ENERGY EFFICIENT COOPERATIVE NODE MANAGEMENT

FOR

WIRELESS MULTIMEDIA SENSOR NETWORKS

by

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Submitted in Fulfillment of the
Requirements for the Degree
Doctor of Philosophy (Ph. D.)

Doctoral Program: Computer Architecture

Supervised by

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Barcelona, 2013

ABSTRACT

In Wireless Multimedia Sensor Networks (WMSNs) the lifetime of battery-operated visual nodes is limited by their energy consumption, which is proportional to the energy required for sensing, processing, and transmitting the data. The energy consumed in multimedia sensor nodes is much more than in the scalar sensors; a multimedia sensor captures images or acoustic signals containing a huge amount of data while in the scalar sensors a scalar value is measured (e.g., temperature). On the other hand, given the large amount of data generated by the visual nodes, both processing and transmitting image data are quite costly in terms of energy in comparison with other types of sensor networks. Accordingly, energy efficiency and prolongation of the network lifetime has become a key challenge in design and implementation of WMSNs.

Clustering in sensor networks provides energy conservation, network scalability, topology stability, reducing overhead and also allows data aggregation and cooperation in data sensing and processing. Wireless Multimedia Sensor Networks (WMSNs) are characterized for directional sensing, the Field of View (FoV), in contrast to scalar sensors in which the sensing area usually is uniform and non-directional. Therefore, clustering and the other coverage-based techniques designed for WSNs, do not satisfy WMSNs.

In WMSNs, sensor management policies are needed to assure balance between the opposite requirements imposed by the wireless networking and vision processing tasks. While reducing energy consumption by limiting data transmissions is the primary challenge of energy-constrained visual sensor networks, the quality of the image data and application, QoS, improve as the network provides more data. In such an environment, the optimization methods for sensor management developed for wireless sensor networks are hard to apply to multimedia sensor networks. Such sensor management policies usually employ the

clustering methods which form clusters based on sensor neighbourhood or radio-coverage. But, as it was mentioned, because of the main difference between directional sensing region of multimedia sensors and the sensing range of scalar sensors, these schemes designed for WSNs, do not have efficiency for WMSNs. Moreover, sensor management strategies of WSNs do not consider the event-driven nature of multimedia sensor networks, nor do they consider the unpredictability of data traffic caused by a monitoring procedure.

This thesis, first, present a novel clustering mechanism based on the overlapping of the FoV of multimedia nodes. The proposed clustering method establishes clusters with grouping nodes that their FoVs overlap at least in a minimum threshold area. Two styles of cluster membership are offered by the mechanism depending on the desired network application; Single Cluster Membership (SCM) and Multi Cluster Membership (MCM). The name of MCM comes from the fact that a node may belong to multiple clusters, if its FoV intersects more than one cluster-head (CH) and satisfies the threshold area while in SCM each node belongs to exactly one cluster.

Then, the proposed node management schemes designed for WMSNs are presented; the node selection and scheduling schemes manage the acts of the multimedia sensor nodes in a collaborative manner in clusters with employing the mentioned clustering method. Intra-Cluster Cooperation (ICC) and Intra&Inter-Cluster Cooperation (IICC) use the SCM and MCM clusters respectively. The monitoring period is optimized and the sensing region is divided among clusters and multimedia tasks are performed applying cooperation within and between clusters. The objective is conserving the residual energy of nodes to prolong the network lifetime.

Finally, a hybrid architecture for WMSNs in order to energy efficient collaborative surveillance is proposed. The proposed mechanism employs a mixed random deployment of acoustic and visual sensor nodes. Acoustic sensors detect and localize the occurred event/object(s) in a duty-cycled manner by sampling the received signals and then trigger the visual sensor nodes covering the objects to monitor them. Hence, visual sensors are warily scheduled to be awakened just for monitoring the object(s) detected in their domain, otherwise they save their energy.

Section B. 4 of Chapter I introduces the contributions of this thesis.

Keywords:

Wireless Multimedia Sensor Network (WMSN); Clustering; Energy Efficiency; Node Management; Field of View (FoV); Network Architecture; Cooperation; Monitoring; Scheduling; Visual Sensor; Acoustic Sensor.

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INTRODUCTION

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A. *PROBLEM STATEMENT AND MOTIVATION*

Wireless Sensor Networks (WSN) [1,2] are considered as autonomous and self-organized systems consisting of a large number of small, inexpensive, battery-powered communication sensor nodes deployed throughout a physical space. These networks are mainly used for gathering information related to the surrounding environment (*e.g.*, temperature, humidity, light, *etc*.), and for transmission of the gathered data to a base station (*i.e.*, sink), for further processing. Typically, a sensor node is a tiny device that includes three basic components: a sensing subsystem for data acquisition from the physical surrounding environment, a processing subsystem for local data processing and storage, and a wireless communication subsystem for data transmission. In addition, a power source supplies the energy needed by the device to perform the programmed task. This power source often consists of a battery with a limited energy budget. In addition, it is usually impossible or inconvenient to recharge the battery, because nodes are deployed in a hostile or unpractical environment. On the other hand, the sensor network should have a lifetime long enough to fulfill the application requirements. Accordingly, energy conservation in nodes and maximization of network lifetime are commonly recognized as key challenges in the design and implementation of WSNs.

In recent times there has been increased interest in video surveillance and environment multimedia monitoring applications. Visual information may be captured from the environment using CMOS cameras embedded in wireless sensor nodes. Wireless Multimedia Sensor Networks (WMSN) [3,4], should be able to process in real-time, retrieve or fuse multimedia data. The availability of low-cost hardware and developments in low power CMOS digital cameras are enabling the development of embedded multimedia nodes and having dense deployments of low cost, low power and low resolution camera sensors in WMSNs to sense and monitor the environment especially in some applications that employ a random deployed network such as battlefield surveillance, environment monitoring, biological detection and agricultural fields.

The main difference between multimedia sensor networks and other types of sensor networks lies in the nature of how the image sensors perceive information from the environment. Most scalar sensors provide measurements as 1-dimensional data signals. However, image sensors are composed of a large number of photosensitive cells. One measurement of the image sensor provides a 2-dimensional set of data points, which we see as an image. The additional dimensionality of the data set results in richer information content as well as in a higher complexity of data processing and analysis. In addition, a camera's sensing model is inherently different from the sensing model of any other type of sensor. Typically, a scalar sensor collects data from its vicinity, as determined by its sensing range. Multimedia nodes are characterized by a directional sensing model, called Field of View (FoV, see Figure 1), and can capture images of distant/vicinal objects/scenes within its FoV from a certain direction. The object covered by the camera can be distant from the camera and the captured images will depend on the relative positions and orientation of the cameras towards the observed object [5-8]. Because of non-coincidence between neighborhood and sensed region by multimedia nodes, coverage-based techniques in WSN do not satisfy WMSN requirements.

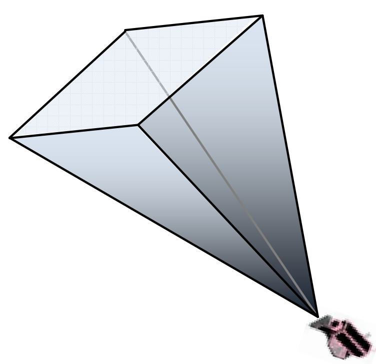


Figure 1. The Field of View (FoV) of a multimedia sensor node

Experimental measurements have shown that generally data transmission is very expensive in terms of energy consumption, while data processing consumes significantly less [9]. The energy cost of transmitting a single bit of information is approximately the same as that needed for processing a thousand operations in a typical sensor node [10]. The energy consumption of the sensing subsystem depends on the specific sensor type. In some cases of scalar sensors, it is negligible with respect to the energy consumed by the processing and, above all, the communication subsystems. In other cases, the energy expenditure for data sensing may be comparable to, or even greater (in the case of multimedia sensing) than the energy needed for data transmission. In general, energy-saving techniques focus on two subsystems: the communication subsystem (i.e., energy management is taken into account in the operations of each single node, as well as in the design of networking protocols), and the sensing subsystem (i.e., techniques are used to reduce the amount or frequency of energy-expensive samples).

According to the mentioned specifics of multimedia sensors, the amount of power consumed in the sensing subsystem of a multimedia sensor node is considerably more than of a scalar ordinary sensor. For example, a temperature sensor [11] as a scalar sensor consumes 6μW for sensing the environment. To have a view of multimedia sensors power consumption, table 1 shows the power consumed by four classes of cameras that are available today either as prototypes or as commercial products. At the lowest end of the spectrum is tiny Cyclops [12] that consumes a mere 46mW and can capture low resolution video. CMU-Cams [13] are cell-phone class cameras with on-board processing for motion detection, histogram computation, etc. At the high-end, web-cams can capture high-resolution video at full frame rate while consuming 200mW, whereas Pan-Tilt-Zoom cameras are re-targetable sensors that produce high quality video while consuming 1W. It is noticeable that the mentioned power amounts are the power consumed by the camera sensors without considering the power consumed by the host motes, see [14] for a survey of visual network platforms.

On the other hand, given the large amount of data generated by the multimedia nodes, both processing and transmitting image data are quite costly in terms of energy, much more so than for other types of sensor networks. Furthermore, multimedia sensor networks require large bandwidth for transmitting image data. Thus both energy and bandwidth are even more constrained than in other types of wireless sensor networks. In-node processing can help to avoid transmitting all data gathered by the multimedia nodes toward the sink or the base station and thus reduces the traffic and resource usage of the network. The constraint of power and processing ability also limit nodes to accomplish complicated processing on the huge amount of the sensed multimedia data [15].

Table1. Power consumption of different classes of multimedia sensors

Multimedia Sensor	Power for image capturing	Capability in image capturing
Cyclops	42 mW	Fixed angle lens, 352×288 at 10 fps
CMU-Cam	200 mW	Fixed angle lens, 352×288 up to 60 fps
Web-Cam	200 mW	Auto focus lens, 640×480 at 30 fps
High-end PTZ Camera	1 W	Pan-tilt-zoom lens, 1024×768 up to 30fps

As it was mentioned before, duo to developments in camera sensors, having a dense network consisting of low power, low resolution multimedia sensors has become applicable. This kind of deployment has more performance than sparse networks of high power, high resolution cameras particularly for randomly deployed networks. However, overlapping FoVs in dense deployments yield wasting of power in the network because of redundant sensing of the area [7].

In redundantly deployed multimedia sensor networks, a subset of cameras can perform continuous monitoring and provide information with a desired quality. This subset of active cameras can be changed over time, which enables balancing of the cameras energy consumption, while spreading the monitoring task among the cameras. In such a scenario the decision about the camera nodes activity and the duration of their activity is based on sensor management policies. Sensor management policies define the selection and scheduling (that determines the activity duration) of the camera nodes activity in such a way that the visual information from selected cameras satisfies the application specified requirements while the use of camera resources is minimized. Various quality metrics are used in the evaluation of sensor management policies, such as the energy-efficiency of the selection method or the quality of the gathered image data from the selected cameras. In addition, camera management policies are directed by the application; for example, target tracking usually requires selection of cameras that cover only a part of the scene that contains the non-occluded object, while monitoring of large areas requires the selection of cameras with the largest combined FoV.

In multimedia sensor networks, sensor management policies are needed to assure balance between the opposite requirements imposed by the wireless networking and vision processing tasks. While reducing energy consumption by limiting data transmissions is the primary challenge of energy-constrained visual sensor networks, the quality of the image data and application, QoS, improve as the network provides more data. In such an environment, the optimization methods for sensor management developed for wireless sensor networks are hard to apply to multimedia sensor networks. Such sensor management policies usually employ the clustering methods which form clusters based on sensor neighbourhood or radio-coverage. But, as it was mentioned, because of the main difference between directional sensing region of multimedia sensors and the sensing range of scalar sensors, these clustering schemes and other coverage-based techniques designed for WSNs, do not satisfy WMSNs, [5]. Moreover, sensor management strategies of WSNs do not consider the event-driven nature of multimedia sensor networks, nor do they consider the unpredictability of data traffic caused by a monitoring procedure. Thus, more research is needed to further explore sensor management for multimedia sensor networks.

B. THE CONTRIBUTIONS OF THE THESIS

In this thesis, the objective is to proceed to design node management schemes for WMSNs to establish cooperative coverage, monitoring and in-network processing, and to increase the capability of energy conservation in the nodes. The lifetime prolongation is achieved through cooperation of sensor nodes and avoiding redundant sensing or processing.

Before bringing up the contributions of the thesis, it is noticeable that in all the works from which the following contributions have been resulted, we have designed the solutions without any knowledge of the targets or events in the sensing area. We have employed low resolution, low power and low price sensor nodes with the fixed lenses without the capability of motility or mobility. The nodes have been deployed in random manner.

B. 1. MULTIMEDIA NODE CLUSTERING

The first contribution of the thesis is clustering multimedia nodes in a WMSN. An approach for multimedia node clustering is proposed that satisfies FoV constraints. The membership criterion for joining to a cluster is FoV overlapping areas between nodes in contrast to radio or distance neighbourhood, i.e., nodes having enough common area in their FoVs are grouped in the same cluster. We compute the overlapped areas, if the overlapped area of two nodes' FoV is relatively wide, they act similarly from the coverage point of view and thus are selected as members of the same cluster. The clusters are established with the possibility of having common nodes among them or to be totally disjoint.

Single Cluster Membership (SCM) and Multiple Cluster Membership (MCM) are defined as two kinds of node membership in clusters. In SCM, each node belong to exactly one cluster and thus clusters are disjoint without any common node between them; this kind of membership is a base for coordination and cooperation within the established clusters. Nevertheless, in MCM clusters can have common nodes. A node can be a member of multiple clusters if can satisfy the clustering criteria. Therefore, by this kind of membership, not only we can establish cooperation within the clusters but also between the clusters having intersections at the cost of a more complex algorithm for nodes and clusters coordination.

The proposed method is the first clustering scheme in the literatures appropriated for WMSNs considering the FoV specifics and characteristics. The publications [Alaei-1], [Alaei-5], [Alaei-9] and [Alaei-10] correspond to the clustering approach and related membership schemes; (for the list of publications see Section B.4, next page).

B. 2. ENERGY-EFFICIENT COLLABORATIVE NODE MANAGEMENT

Planning energy-efficient collaborative node management mechanisms (selection and scheduling), within and between the established clusters is the second contribution. The established clusters are managed to schedule the members to collaboratively survey the sensing area in a duty-cycled manner. With this collaborative monitoring, clusters avoid acquisition of redundant and correlated data and thus not only the sensing subsystem of the nodes save its energy, but also the transmission and processing subsystems meet an optimized amount of data to be transmitted/processed.

Intra Cluster Cooperation (ICC) and Intra&Inter Cluster Cooperation (IICC), are the scheduling methods established on the clusters created by respectively SCM and MCM. According to the desired application of the multimedia sensor network, overlapping clusters or disjoint clusters will be employed and scheduled by the appropriate scheduling approach.

Also, in another manner of node management, we schedule the members of disjoint clusters, calculating an optimized monitoring period for each cluster and a time interval for cluster members depending on the cluster size and the clustering scale. Therefore, the period and the interval of each cluster are proprietary for that cluster and are calculated from its cluster-size and clustering scale. In other word, each cluster has its own period and interval although all clusters work concurrently.

We will see in next chapters the efficiency of the proposed schemes in energy conservation and performance of monitoring. The works [Alaei-1], [Alaei-3], [Alaei-4], [Alaei-5], [Alaei-6], [Alaei-8] and [Alaei-11] correspond to the mentioned node management policies.

B. 3. A HYBRID ACOUSTIC-VISUAL ARCHITECTURE FOR WMSNS

The third is a hybrid collaborative architecture, applying cooperation between acoustic and visual sensor nodes; acoustic sensor nodes perform object detection and object localization while visual sensors have the responsibility of object monitoring. The main objective is to increase the energy conservation capability in visual sensor nodes in a surveillance mechanism. Both acoustic and visual sensors are clustered and managed by the proposed approach. Acoustic sensors detect and localize the occurred event/object(s) in a duty-cycled manner by sampling the received signals and then trigger the visual sensor nodes covering the objects to monitor them. Hence, visual sensors are warily scheduled to be awakened just for monitoring the object(s) detected in their domain, otherwise they save their energy. In fact, acoustic sensors play the role of assistants for visual sensors to detect and localize the occurred objects/events consuming much less energy than which is required for doing these procedures by visual sensors. Therefore, the visual sensors are saving their energy in the sleep mode unless an object/event is detected and localized in their FoV. Moreover, in the proposed scheme, data transmission is replaced with in-node processing as much as possible.

The results will show how this collaboration between acoustic and visual sensor nodes increases the energy efficiency of the network and prolong thr network lifetime. The works [Alaei-2] and [Alaei-7] correspond to this contribution.

B. 4. LIST OF PUBLICATIONS

Book Chapter:

[Alaei-1]. Mohammad Alaei, Jose M. Barcelo-Ordinas, Book Chapter: "Power Management in Sensing Subsystem of Wireless Multimedia Sensor Networks," Wireless Communications and Networks-Recent Advances, Dr. Eksim (Editor), ISBN 979-953-307-394-0, INTECH, March 2012.

In Journals:

[Alaei-2]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "An Acoustic-Visual Collaborative Hybrid Architecture for Wireless Multimedia Sensor Networks," International Journal of Adaptive, Resilient and Autonomic Systems (IJARAS), to appear in 2014.

[Alaei-3]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "A Collaborative Node Management Scheme for Energy-Efficient Monitoring in Wireless Multimedia Sensor Networks," Wireless Networks Journal (Springer), DOI 10.1007/s11276-012-0492-6, 2013.

[Alaei-4]. I. T. Almalkawi, Mohammad Alaei, M. Guerrero-Zapata, Jose M. Barcelo-Ordinas, J. Morillo-Pozo, "Energy Efficiency in Wireless Multimedia Sensor Networks," IEEE MMTC e-letter, Volume 6, Number 12, December 2011.

[Alaei-5]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "A Method for Clustering and Cooperation in Wireless Multimedia Sensor Networks," Sensors Journal (MDPI), Vol 10, Issue 4, pp. 3145-3169, March 2010.

In Conferences:

[Alaei-6]. M. Cesana, A. C. Redondi, N. Tiglao, A. M. Grilo, Jose M. Barcelo-Ordinas, Mohammad Alaei, P. Todorova, "Real-time Multimedia Monitoring in Large-Scale Wireless Multimedia

Sensor Networks: Research Challenges," The 8th Euro-NF Conference on Next Generation Internet (NGI 2012), Sweden, June 2012.

[Alaei-7]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "A Hybrid Cooperative Design for Energy-Efficient Surveillance in Wireless Multimedia Sensor Networks," 18th European Wireless Conference (EW 2012), Poznan, Poland, April 2012.

[Alaei-8]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "Priority Based Node Selection and Scheduling for Wireless Multimedia Sensor Networks," IEEE 6th International Conference on Wireless and Mobile Computing, Networking and Communications (IEEE WiMob 2010), Niagara Falls, Canada, October 2010.

[Alaei-9]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "MCM: Multi-Cluster-Membership Approach for FoV-Based Cluster Formation in Wireless Multimedia Sensor Networks," the 6th ACM International Wireless Communication & Mobile Computing Conference (IWCMC 2010), Caen, France, June 2010.

[Alaei-10]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "Node Clustering Based on Overlapping FoVs for Wireless Multimedia Sensor Networks," IEEE Wireless Communications and Networking Conference (IEEE WCNC2010), Sydney, Australia. April 2010.

[Alaei-11]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "A Cluster-based Scheduling for Object Detection in Wireless Multimedia Sensor Networks," The 5th ACM International Symposium on QoS and Security for Wireless and Mobile Networks (ACM Q2Swinet 2009), Tenerife, Canary Islands, Spain, October 2009.

C. *STRUCTURE OF THE THESIS*

The thesis is organized as follows. After the first chapter which shows the problem statement, motivation and contributions, in Chapter II the basic concepts of directional sensor networks are discussed. These preliminaries are used in the next chapters; as it was mentioned before, directional sensor networks have some characteristics which make them and their challenges different from other sensor networks. To have a preface of this kind of sensor nodes, in this chapter we mention the directional sensing models, constraints and then challenges of directional sensors, and finally, the coverage and node management development principals in this field which is directly related to our work in the next sections.

Chapter III reviews the state of the art in the field of coverage and node management mechanisms for wireless directional sensor networks. The solutions are divided in three categories as following: (i) network lifetime prolonging solutions, (ii) target-based coverage solutions and (iii) area-based coverage solutions. The works of each category are discussed exploiting principles of coverage and node management developments mentioned in Chapter II.

Chapter IV proceeds to our proposed method for node clustering for wireless multimedia sensor networks. The chapter starts with some preludes and then introduces the parameters specified for the method (such as clustering scale and overlapping degree). In next sections, the chapter describes the calculation procedure of finding the overlapped polygons between node FoVs and computing the area of the discovered overlapped polygons. The chapter continues with the approach of establishing and formation of clusters and node membership criterions and its manners. Single cluster membership (SCM) and multi cluster membership (MCM) are two membership schemes applied in the procedure of clustering. The chapter is continued with the results of the proposed clustering method, presenting the number of clusters, cluster size and membership degree for different node densities and clustering scales with several curves and diagrams.

Chapter V presents the proposed distributed node management (selection and scheduling) approaches for cooperative monitoring: Intra-cluster cooperative scheme (ICC) and Intra&inter cluster cooperative scheme. Both of them have been designed based on the clustering method presented in chapter IV; ICC is a scheme of management with applying cooperation within the clusters for monitoring while IICC applies cooperative monitoring not only within clusters but also between clusters. ICC is proposed for the clusters created by SCM and IICC is adopted for MCM clusters of chapter IV. After an introduction and some definitions, a mathematical idealized central model as the global collaborative model is presented to have a base case for comparison and evaluation of the proposed management schemes. Then, the mentioned node management approaches are explained and discussed with details in the next sections of the chapter. Comparisons and evaluations are performed based on the mentioned idealized model considering energy conservation development, coverage and overheads for both ICC and IICC.

Chapter VI describes the proposed time division schedule for clusters created by SCM to prolong the monitoring periods. The chapter begins with an introduction and then proceeds to details of computations of its offered monitoring period and the time interval between activating of cluster members. The calculations are based on the cluster sizes thus each cluster will have its own monitoring period and node intervals. Evaluation of the schedule scheme is performed considering its developing effect on power conservation.

An acoustic-visual collaborative hybrid architecture is proposed in Chapter VII. The architecture containing random deployments of acoustic and visual sensors is described after introduction and definitions. Then, the surveillance procedure consists of object detection, object localization and object monitoring is explained; object detection and localization are performed by acoustic sensor nodes and object monitoring is accomplished by the visual sensors which are awakened by the acoustic nodes. Evaluations and discussions from energy conservation and overhead points of view show the advantages of the proposed architecture and surveillance mechanism. Chapter VIII concludes the research presented on this thesis and paths for future work.

Chapter II

PRELIMINARIES

A. SENSING MODELS FOR DIRECTIONAL SENSORS

B. CHARACTERISTICS AND CONSTRAINTS OF A DIRECTIONAL SENSOR NODE

C. TECHNICAL CHALLENGES OF DIRECTIONAL SENSOR NETWORKS

D. COVERAGE ENHANCEMENT PRINCIPLES IN DSNS

A. *SENSING MODELS FOR DIRECTIONAL SENSORS*

Sensor nodes may have different types of sensors. Sensors, such as temperature, humidity, infrared, and video, are selected based on the requirements of the application. There are several attributes for categorizing available sensors. One of them is the sensing model of the sensor. In the literature, sensing model has been defined as either to express the sensitivity or the capability of the sensor [16]. Two subcategories for sensing model are defined: Mathematical sensing model and physical sensing model.

The mathematical sensing model describes the sensitivity model [17] of the sensor. Theoretically, a sensor either covers a point or not. This simple model is called as the binary sensing model. Most of the researchers assume that sensors sense according to the binary model. However, a more realistic model, the probabilistic model, expresses the detection of a target within the sensing range of a sensor according to a probability function. Sensors, which sense according to a probabilistic model, may not detect the event, even if the event occurs within the sensing range (R_S).

Physical sensing model gives information about the sensing direction of the sensor node. There are two different physical sensing models: omni-directional and directional. Normally, sensor nodes equipped with traditional sensors like temperature, humidity, and magnetic sensors are able to sense with 360°. Thus, omni-directional sensing can also be named as traditional sensing. This type of sensors covers a unit of circle with a radius (R_S), i.e. they have only one working direction. Directional sensors work in a specified direction at a given time t. They may adjust their working direction based on the requirements of the application (e.g., Pan Tilt Zoom sensors). This ability of the node is called motility.

Unlike an omni-directional sensor, a directional sensor, such as infrared, ultrasound and video sensor, has a finite angle of view and thus cannot sense the whole circular area. Directional sensor nodes may have several working directions and may adjust their sensing directions during their operation. The sector covered by a directional sensor node S is denoted by a 4-tuple (P, Rs, W_d, α). P is the position of the sensor node, R_S is the sensing radius, W_d is the working direction and α is the angle of view. The common directional sensing capability for 2D spaces is illustrated in Figure 2. The special case of this model, where α = 360º can be described as omni-sensing model.

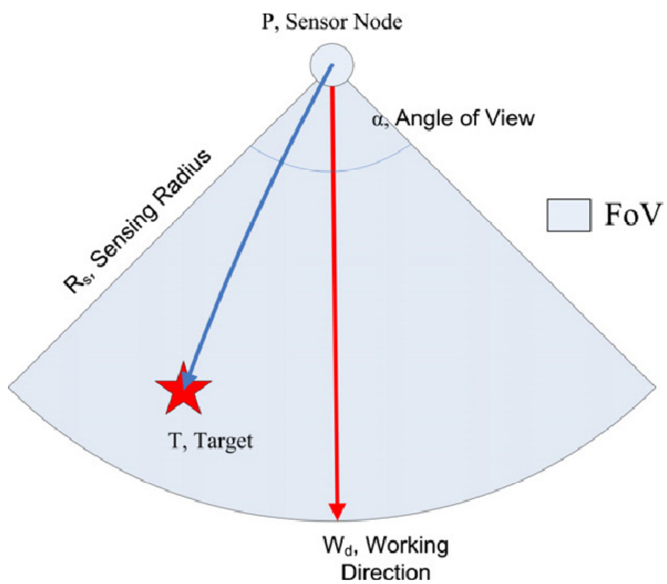


Figure 2. A directional sensor node senses a unit of sector described with the position (P), the working direction (W_d), the sensing radius (R_S), and the angle of view (α). A target (T) may be covered if it is located within the FoV of the node.

B. Characteristics and Constraints of a Directional Sensor Node

A directional sensor node has unique characteristics which cause new challenges when formulating solutions for DSN problems or designing DSN applications. In this section, we observe the characteristics of a directional sensor node, which directly affect the coverage problem.

B.1. Angle of View

Research in traditional sensor networks is based on the assumption of having omni-directional sensors with an omni-angle sensing coverage. However, directional sensors have a limited angle of sensing coverage due to technical constraints and/or cost considerations. The size of the angle of view may theoretically change from 1º to 360º. If the angle equals to 360º, the sensing model of the node can be described as omni-directional. DSNs consisting of sensor nodes with smaller angle of view require excessive number of nodes to achieve a given coverage ratio.

B.2. Working Direction

The direction to which a directional sensor faces is the working direction of this sensor. In DSNs, sensors may have different working directions after a random deployment. In this case, orientation of sensors is required, to maximize the coverage. Moreover, due to external effects or application- specific queries in DSNs, sensor nodes may need to change/re-orient their working direction over time. Also, nodes may fail due to battery outage or external effects which should be handled by a dynamic update of the working directions. Adjusting working directions can be performed via local information exchange among sensors.

B.3. Line of Sight

Multimedia coverage could be occluded by any obstacle such as trees, and buildings, present in the deployment environment [7]. This fact is described as the occlusion effect. The FoV of video sensors highly depends on the size and distance of the obstacles. Video sensors can only capture useful images when there is a line of sight between the event and the sensor itself [3]. Hence, coverage models developed for traditional wireless sensor networks are insufficient for the deployment planning of multimedia sensor networks.

B.4. MOTILITY

Actuation yields a significant improvement in coverage, especially when two or more simple forms of actuation are combined together. There are three defined motions for video sensor nodes. pan, tilt and zoom. Motility [18] represents these three motions which occur along any of x, y, and z axes. It relies on reduced complexity motion primitives to reconfigure the network in response to environmental change.

Researches show that motility and mobility can significantly improve the coverage ratio of the network. Nevertheless, networks consisting of motile/mobile directional sensor nodes require not only high power but also high budgets due to the considerable production cost of those nodes. The gap between the costs has definitely decreased and will continue to decrease in the future. However, there will always be a reasonable cost ratio between static, motile and mobile nodes. Thus, we believe that hybrid directional sensor networks consisting of heterogeneous sensor nodes should also be considered for additional coverage performance to balance the coverage gain ratio and the cost of the network.

C. TECHNICAL CHALLENGES OF DIRECTIONAL SENSOR NETWORKS

Directional sensor networks (DSNs) inherit all the technical challenges introduced by the traditional WSNs [16]. In addition, they introduce new ones that are unique to them. Studies about DSNs have primarily focused on the following items:

C.1. COVERAGE

Obtaining data from the environment is the main function of wireless sensor applications. Each application has different goals and collects different types of data. However, most of the sensor applications aim at maximum coverage with minimum number of sensors. Thus, the coverage problem in wireless sensor networks has been researched extensively in the past decades. This problem has some subcategories, such as area coverage, target coverage, k-coverage, each of which requires different strategies for the solution.

C.2. NETWORK LIFETIME

Sensor nodes suffer mostly from their limited battery capacity. Due to the small size of existing batteries, sensor nodes do not last as long as desired. Thus, research community have studied several solutions for prolonging the network lifetime of WSNs. Energy-aware MAC layers and routing protocols [19-21], cross-layer design [22], various deployment strategies [23], base-station positioning algorithms [24-27] have been proposed to minimize the energy consumption of regular WSN activities.

Reducing the energy consumption of communication, which is relatively higher compared to other energy consuming activities, is the main focus of researchers. Since directional sensor nodes may have several working directions, rotatable mechanical design is required to utilize all working directions. Physical movement consumes definitely much more power than other activities [28]. Therefore, physical activities like rotating a sensor node around its axes or moving it to another position should be well planned to minimize the related energy consumption.

C.3. NETWORK TRAFFIC

Message traffic directly affects the network lifetime of sensor networks. The more messages are delivered, the more energy is consumed. Therefore, a sensor network should minimize its message traffic. There are two types of messages. application-specific messages and network-specific messages. Application-specific messages contain only the data sensed from the environment. On the other hand, network-specific messages consist of the information such as the position, the status, the working direction, the angle of view, the sensing range, and the residual energy of the sensor node.

To minimize the communication burden, i.e. to maximize the network lifetime, delivering redundant messages should be avoided. In-network processing is the common method for minimizing redundant data about the environment. However, this process cannot be applied to the network-specific messages. Network-specific messages are exchanged especially during the initial setup of the network. Each sensor node determines its position and the position of its neighbors via network-specific messages. Repositioning algorithms aim at calculating the final position of the sensor nodes. These algorithms work iteration-based which require excessive message traffic. There are two approaches for repositioning algorithms: (i) physical movement and (ii) virtual movement after each iteration.

In WSNs, using physical movement strategy, sensor nodes change their position physically after each step. Conversely, with the virtual movement strategy, sensor nodes move to their final destination after the iteration process ends. This strategy minimizes physical energy consumption albeit an increase in the message traffic of the network. Since communication process consumes less power than physical movement, virtual movement strategy outperforms physical movement strategy in terms of the network lifetime [29].

D. COVERAGE ENHANCEMENT PRINCIPLES IN DSNS

Coverage quality is closely related to the deployment strategy. Deployment strategies for DSNs do not differ from the strategies applied to the traditional sensor networks. Directional sensor networks can be deployed in two distinct ways: (i) controlled deployment and (ii) random deployment.

In controlled deployment, directional sensors are orderly placed following a pre-processed plan. In this approach, the coverage is maximized with a minimum number of sensors, reducing the final cost of the sensor number of sensors, reducing the final cost of the sensor network. This deployment strategy is usually opted for indoor applications, such as the surveillance of an art gallery which is deployed according to a plan, mostly do not have overlapping and occlusion problems.

Compared to the deterministic deployment, the random deployment is easy and less expensive for large directional sensor networks, and may be the only feasible option in remote or inhospitable environments. Moreover, to compensate for the lack of exact positioning and to improve the fault tolerance, nodes are typically deployed in excess, and thus redundant sensors usually arise. This type of deployment certainly causes overlapped areas and occluded regions. Thus, the coverage problem for randomly deployed directional sensor networks is very popular in recent years.

Researchers have proposed several coverage enhancing solutions for randomly deployed directional sensor networks. We believe that the theoretical coverage probability formulation could help the researchers to evaluate the performance of their proposed solutions. The theoretical coverage probability for directional sensing can be formulated using the sensing range, the angle of view of the sensor, the number of sensor nodes and the size of the targeted area [6]. In directional sensor networks, the following five main principles can be used for attaining high coverage rates;

- Deployment of excessive number of directional sensors
- Exploiting the motility of directional sensors

- Exploiting the mobility of directional sensor nodes
- Redeployment
- Hybrid solution

D.1. REDUNDANT DEPLOYMENT

Like traditional sensor networks, deploying more directional sensor nodes than theoretically necessary will cover more regions. However, sensor applications, where sensor nodes are deployed randomly, cannot guarantee 100% coverage. Thus, it is impossible to determine the number of redundant sensor nodes. Moreover, this technique requires very high budgets.

D.2. ADJUSTMENT OF WORKING DIRECTION, SENSING RADIUS, AND ANGLE OF VIEW

Since the probability of overlapped regions for directional sensor nodes is high, many of the studies focus on adjusting the working directions of the deployed sensor nodes. Their main goal is to both minimize the occlusion effect and the overlapped regions. This technique was examined in several studies with different assumptions [7,30-32]. To reposition a directional sensor (video, infrared, etc.) after the initial deployment, the sensor node should contain a mechanical hardware which enables the sensor to rotate 360° around its center. Although adjusting sensor parameters may heal coverage holes or help to cover more target points, increasing sensing radius and/or changing the angle of view has a cost in terms of energy depletion and budget [33].

D.3. DEPLOYMENT OF MOBILE DIRECTIONAL SENSOR NODES

Mobility is very important for sensor networks, since it may heal several network problems [34], including coverage and connectivity. A certain number of nodes may lose their functionality due to sensor node-specific reasons, such as running out of battery or damages originated from the environment. Thus, there may occur non-reachable regions during the network lifetime. The only way to cover these regions is to relocate the nearest mobile nodes. There are several solutions using mobility for the coverage problem in omni-directional sensor networks [29,35,36]. Also, the idea of moving a directional sensor node to a different location has been studied in [37]. A directional sensor node with mobility feature is expensive and more prone to failures. Moreover, moving a sensor node only 1m consumes almost 30 times more energy than transmitting 1KBytes of data. Despite of these disadvantages mobility increases the adaptability of the sensor network. Though motility has a significant improvement on coverage, just rotating the sensor node does not supply full coverage. To heal the coverage holes, coverage problems for DSNs need also consider the mobility.

D.4. REDEPLOYMENT

Considering that the random deployment of sensor nodes is performed via an airplane or a catapult, deploying additional nodes to the estimated positions is extremely difficult. Thus, in the monitored area, there will be many redundant nodes. Moreover, each attempt for redeployment will cost more due to the nature of available redeployment methods [34,38].

D.5. HYBRID SOLUTION

Sensor networks with static nodes are rigid after the initial deployment. Conversely, mobile sensor networks have the ability to adapt themselves to dynamic changes in the topology, target tracking and etc. However, the cost of mobile sensor nodes is very expensive compared to the cost of the static nodes. Thus, researchers proposed a new type of a sensor network, called the hybrid sensor network. They believe that a balance can be achieved by using a combination of static and mobile nodes, while still ensuring sufficient coverage.

Chapter III

BACKGROUND

A. INTRODUCTION

B. NETWORK LIFETIME PROLONGING SOLUTIONS

C. TARGET-BASED COVERAGE IMPROVEMENT SOLUTIONS

D. AREA-BASED COVERAGE IMPROVEMENT SOLUTIONS

A. INTRODUCTION

In the previous section, we observed the coverage and node management enhancing principles for directional sensor networks. The related research works exploit those principles and propose unique solutions for coverage optimizing and node scheduling in DSNs. Which principle could be applied to a specific application is dictated by the requirements of that application. However, research community have basically focused on two general solutions; adjusting the working directions of the sensor nodes and scheduling the working durations of sensors. A directional sensor node may theoretically work in N different directions. The main goal for determining the best working direction of a directional sensor node is to find a direction, where the occlusion effect and overlapped areas are minimized. Thus, the directional sensor node serves with high efficiency. On the other hand, adjustment of working directions is not enough to prolong the network lifetime, since there may be some redundant nodes, which cover the same area and/or targets. Some scheduling algorithms manage nodes in order to save energy. Available studies in directional sensor networks can be categorized into the following types.

- Network lifetime prolonging solutions
- Target-based coverage solutions
- Area-based coverage solutions

B. NETWORK LIFETIME PROLONGING SOLUTIONS

Due to their limited battery capacity sensor nodes have to manage their energy consuming activities. They should avoid unnecessary energy consumption during their operation to increase the network lifetime. Scheduling sensor nodes is the common way of prolonging network lifetime in directional sensor networks [39] as in WSNs [40-42]. The main goal of sensor scheduling algorithms is to shut off redundant sensor nodes and make them active when necessary.

Coverage enhancement algorithms organize the working directions of sensor nodes and determine a set of active nodes once after the initial deployment. However, active nodes need to be replaced by inactive nodes repeatedly and vice versa. Thus, several scheduling algorithms [43,44] have been proposed to increase the network lifetime of DSNs.

Ai and Abouzeid have proposed a new protocol [45], Sensing Neighborhood Cooperative Sleeping (SNCS), which performs dynamic scheduling among sensors depending on the amount of residual energy. SNCS protocol consists of two phases; scheduling and sensing. Each sensor node becomes active in each scheduling phase. Afterwards, the status of each sensor node is determined according to the result of the DGA algorithm. After the final decision, the inactive sensor nodes turn off their sensing and communication units and remaining active sensors perform their tasks. These two steps are repeated periodically. DGA algorithm uses the residual energy of a sensor as its priority. The residual energy is calculated based on the behavior of the node, such as transmitting, receiving, or sleeping. There is a trade-off between coverage enhancement and network lifetime prolonging. SNCS aims at achieving energy balancing across the network, while providing a solution to the MCMS problem.

Similar to the SNCS protocol, WT-Greedy and WT-Dist algorithms [46] take the residual lifetime of each sensor into consideration, while computing the set of non-conflicting directions of the sensors. Some interested targets with known locations are deployed in the plan and the sensors which are tunable camera sensors, scattered close to these targets. WT-Greedy is a centralized solution where the work time of each cover set is determined as a fixed value, Δt. This algorithm finds the uncovered target t_u that can be covered by minimal number of directions and assigns it to the sensor S_i with the longest residual lifetime. Then, the sensor adjusts its working direction to cover that target. This algorithm terminates after the residual lifetime of all the sensors drops below Δt. On the other hand, WT-Dist is a distributed algorithm with two stages; the deploying stage and the monitoring stage. The deploying stage is the same as the DCS-Dist algorithm. In the monitoring stage, a sensor probes the states of its neighbors and decides its working direction so that the maximum number of targets are covered. The simulation results show that the coverage percentage drops afterwards, since both algorithms aim at prolonging network lifetime while maximizing coverage. However, WC-Dist' drop is faster than WT-Greedy as the first one is a distributed solution.

The authors, in [31], examined the trade-off between coverage and network lifetime. They proposed to shut off the nodes, whose overlap ratio is greater than a predefined value. On the other hand, for waking up the nodes, they used a correlation degree, i.e. the distance between the related node and its neighbors. Their algorithm runs once after the initial deployment and terminates after the network reaches an equilibrium. The authors have increased the coverage ratio by 3% where they were able to shut off 40% of the deployed sensor nodes. Their results also show that the coverage ratio can be enhanced much with small number of the sensor nodes, whereas the network lifetime is prolonged with a large number of redundant sensor nodes.

Wen et al. proposed a distributed protocol, Neighbors Sensing Scheduling (NSS), determining whether sensors sleep or work, based on their local information. This protocol generates multiple cover sets from the sensor nodes and each cover set works for a predefined optimal time duration to prolong the network lifetime. A sleeping node decides to wake up if its remaining energy is more than its neighbors. Conversely, an active node changes its status as inactive if each of the targets around it is covered, i.e., if it becomes a redundant node. To compare the performance of their protocol with a centralized algorithm, designed for omni-directional sensor networks, Greedy-MSC [47], the authors set the angle of view to 360°. The numerical results show that NSS achieves a similar performance to the Greedy-MSC. Moreover, this distributed solution is more scalable with its low communication overhead.

A couple of work in video sensor networks apply image processing techniques to find the sensors whose FoVs are the same or similar. Bai and Qi developed a so-called Extend Speeded-UP Robust Features (E-SURF) image comparison algorithm [48] based on two feature extraction schemes, SURF [49] and SIFT. They aim at removing redundancy through semantic neighbor selection in video sensor networks and they achieved 90% coverage with more than doubled network lifetime. The results show that E-SURF is computationally faster than SURF and it also has a low communication overhead compared to SURF.

In most of the aforementioned solutions, sensor nodes basically utilize their residual lifetime whether to become active or inactive in each round. In studies based on target coverage they also check the status of their neighbors' targets to sleep or to wake up. Both coverage enhancement and network lifetime prolonging are essential to DSNs. Researchers should aim at balancing the two critical network goals.

Newell et al., in [32], propose a distributed solution for efficiently selection and scheduling camera sensors. The idea is for each camera sensor to utilize a number of scalar sensors which detect an event within its FoV and exchange this information with the neighboring camera sensors to determine the possible coverage overlaps. Counting the number of scalar sensors detecting an event is the way to determine the size of the event area. Based on such information, the camera sensors which hear from a higher number of scalar sensors will be given priority in being turned on.

The work [50] addresses the multiple directional cover sets (MDCS) problem of organizing the directions of sensors into a group of non-disjoint cover sets to extend the network lifetime. Assuming some targets with known locations are deployed in the area and a number of directional sensors are randomly scattered close to these targets, one cover set in which the directions cover all the targets is activated at one time. Cai et al. prove the MDCS to be NP-complete and propose some algorithms for this problem.

In [51], Dagher et al. provide an optimal strategy for allocating parts of the monitored region to the cameras for the purpose of power-constrained distributed transmission. The optimal fractions of regions covered by every camera are found in a centralized way at the base station. The cameras use JPEG2000 to encode the allocated region such that the cost per bit transmission is reduced according to the fraction received from the base station.

Zamora and Marculescu [52] explore distributed power management of camera nodes based on coordinated node wake-ups to reduce the energy consumption. The proposed policy assumes that each camera node is awake for a certain period of time, after which the camera node decides whether it should enter the low-power state based on the timeout statuses of its neighboring nodes. Alternatively, camera nodes can decide whether to enter the low-power state based on voting from other neighboring cameras. In [53], a multicamera monitoring system to share the physical risk, is introduced. The authors increase robustness to unpredictable events by adding redundancy with multiple cameras focusing on a common scenery of interest. They propose an interleaved sampling strategy to minimize per-camera consumption by distributing sampling tasks among all neighboring cameras. Under the proposed sampling configuration, they propose video coding methods to compress correlated video streams.

C. TARGET-BASED COVERAGE SOLUTIONS

Some sensor applications are only interested in stationary target points, such as buildings, doors, flags, and boxes, whereas other applications aim at tracking mobile targets like intruders. Stationary targets can be located anywhere in the observed area. To cover only the interested targets instead of the whole area, researchers have defined target-based coverage problems. In some studies, researchers name the target coverage approach as point coverage [54]. Unlike the area coverage, this issue puts emphasis on how to cover the maximum number of targets.

In target coverage, each target is monitored continuously by at least one sensor. However, some DSN applications may require at least k sensors for each target in order to increase the reliability of the network. k-coverage problem has been formulated based on this requirement. In addition, k-barrier coverage [55] is used to detect an object, that penetrates the protected region. In this case, the sensor network would detect each penetrating object by at least k distinct sensors before it crosses the barrier of wireless sensors. It aims at minimizing the number of sensors that form such functionality.

A considerable number of studies have focused on the maximization of covered stationary targets with a minimum number of sensors. In [46], the authors call a subset of directions of the sensors as a cover set, in which the directions cover all the targets. The problem of finding a cover set in a DSN is named as the directional cover set problem. They propose a centralized algorithm, DCS-Greedy, and a distributed algorithm, DCS-Dist, that determines the working directions of sensor nodes while covering maximum number of targets. Both proposed algorithms basically accept the number of targets M, the number of sensors N and the number of directions per sensor W as input. They define two sets, the set of targets and the set of directions that cover at least one target in the set of targets. Their pivot policy is to find a direction to cover the target that can be covered by a minimal number of directions.

DCS-Dist algorithm is proposed for the large-scale applications where centralized solutions are ineffective. In this algorithm, a sensor node repositions itself only based on the information from its neighbors. The algorithm consists of two stages, the deployment stage and the decision stage. In the deployment stage, each target is labeled with a priority number indicating by how many directions of sensor nodes it is being covered. The more times a target can be covered by the directions of a sensor and its neighbors, the lower priority it is assigned to. In the decision stage, a sensor node looks for uncovered targets with highest priorities while assessing messages received from its neighbors. The time complexity of DCS-Greedy algorithm is $O(N^2WM)$, whereas the time complexity of the DCS-Dist algorithm is O(NWM). Experimental results show that DCS-Greedy algorithm has a higher possibility to find a cover set, and has a greater coverage percentage than the DCS-Dist algorithm.

Ai and Abouzeid have proposed the Maximum Coverage with Minimum Sensors (MCMS) problem [45]. Given a set of targets $T = \{t_1, t_2, \ldots, t_m\}$ and a set of n homogenous directional sensors, each of which has p possible orientations, MCMS aims at maximizing the number of covered targets while minimizing the number of activated directional sensors. The authors first show that the MCMS problem is NP-hard by proving that MCMS is a sub-problem of MAX_COVER [56], a classic NP-complete problem. The decision version of the MAX_COVER problem can be stated as follows. Given a set of targets T and a collection C of subsets, MAX_COVER problem searches for a subcollection of C with u subsets which cover at least v elements in T. For the MAX_COVER problem, any u subsets $\varphi_1, \varphi_2, \ldots, \varphi_u$, are picked from C. Then, for each subset $\varphi_i (1 \leq i \leq u)$, p copies of itself are constructed and rewritten as $\varphi_{i1}, \varphi_{i2}, \ldots, \varphi_{ip}$ similarly to that in the MCMS problem. Such an expanded subcollection can be used as the input to the MCMS problem.

In [45], the authors also describe the sensing model of a directional sensor and the Target In Sector test where the decision is made if a target is located within the FoV of the related sensor or not. They have presented an exact Integer Linear Programming (ILP) formulation and two greedy algorithms, Centralized Greedy

Algorithm (CGA) and Distributed Greedy Algorithm (DGA). ILP formulation takes the number of directional sensors n, the number of targets m, and the number of orientations available for each directional sensor p, as input. The objective function of this formulation maximizes the number of targets to be covered and imposes a penalty by multiplying the number of sensors to be activated by a positive penalty coefficient ε whose value must be small enough ($\varepsilon \leq 1$) to guarantee a unique solution.

Although ILP formulation chooses optimal working directions for the directional sensor nodes, it is not scalable for large problem instances. For large-scale networks, the authors present a polynomial-time heuristic greedy algorithm rather than giving an LP-relaxation algorithm to the MCMS problem.

CGA is a centralized solution for the MCMS problem. In each iteration, CGA searches for an inactive sensor and its orientation where the number of covered targets is maximized, and then activates the chosen node and its working direction. Random choices are made for any ties. This algorithm runs in loops and terminates if there are no more targets to be covered or no more unselected directional sensors remain. Since there are at most n loops, the time complexity of CGA is $O((m + 1)n^2p)$.

DGA is a distributed solution for MCMS where only local information is taken into account. Although this algorithm cannot perform as good as the centralized methods, it is computationally more scalable and requires less message traffic. In the DGA algorithm, each node assigns itself a unique variable, called as priority. Sensor nodes make their decisions based on the priority level of their neighbors located within $2R_S$. Sensor nodes with higher priority levels choose their working direction first. These nodes look for the direction where the number of covered targets is at maximum. In each iteration, nodes within the same communication range exchange their priorities, location and orientation information. A transition timer prevents a sensor with zero targets from finalizing its decision.

According to the simulation results, ILP outperforms CGA and DGA in terms of coverage ratio, whereas DGA activates the largest number of sensors in most of the scenarios with 150 sensors or more. To evaluate the performance of their distributed algorithm the authors chose OGDC algorithm [57] which outperforms other existing distributed solutions [58-60] for omni-directional sensor networks. They achieved omni-directional sensing model, a special case of directional sensing model, by setting the value of p to 1 in order to compare their algorithm with OGDC. The results show that in most cases the coverage ratio of DGA is better than the coverage ratio of OGDC.

In [61], two new direction optimizing algorithms, greedy direction adjusting (GDA) and equitable direction optimizing (EDO) algorithms, have been proposed. GDA algorithm optimizes directions according to the amount of covered targets, whereas EDO algorithm adjusts the directions of nodes to cover the critical targets and allocates sensing resources among nodes fairly to minimize the coverage difference between nodes. To minimize covering collision, shown in Figure 3, equivalent coverage model is presented. The basic idea of EDO is estimating the utilization for each sensor via constructing a target-direction mapping which contains the target number and the status of the target as whether or not being covered by neighboring sensors. In contrast to GDA, EDO improves coverage by 30% on average.

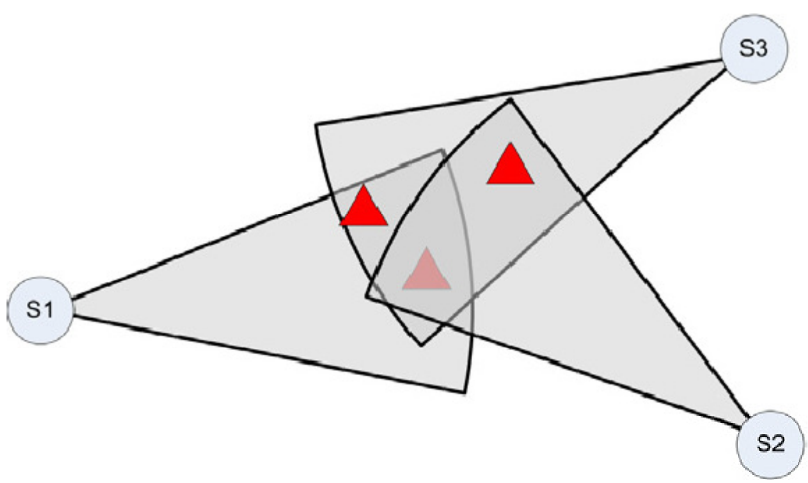


Figure 3. Covering collision occurs when a target is covered by more than the minimum required number of sensors. In this figure, all targets should be covered only by one sensor, whereas they were covered by at least two sensors yielding to covering collision [61].

Similar to previously described solutions, the proposed algorithm in [62] looks for possible orientations of sensor nodes to cover targets as much as possible. Weighted Centralized Greedy Algorithm (WCGA) chooses the orientations with the larger weights. This algorithm takes three inputs, the set of all targets, the sensors and their orientations. It outputs the set of selected orientations. The authors define two weight functions, target weight and orientation weight. They also describe the Maximally be Covered Number (MCN) for each target. MCN is the maximal number of sensor nodes that cover the related target. In the target weight function ($w(t_k)$), given in Equation (1), a target with a small MCN, that is a target covered by less number of sensors will have a greater weight. The authors discovered that priority adjusting of the MCN and the amount of targets in the orientation according to the density of sensors could improve the target coverage rate. WCGA algorithm improves the coverage rate and decreases the number of active sensors compared to the CGA algorithm. The weight function determines how much the improvement will be:

$$w(t_k) = \frac{1/\alpha m}{M(t_k)} \tag{1}$$

where m is the total number of targets and a is the positive factor to adjust the weight ($w(t_k)$) of the target tk. $M(t_k)$ represents the maximal number of sensor nodes that cover the target tk.

Individual targets may be associated with different priorities. The authors, in [63], propose the priority-based target coverage problem and they aim at selecting a minimum subset of directional sensors that can monitor all targets, satisfying their prescribed priorities. A genetic algorithm was offered to solve this minimum subset problem. This genetic algorithm has been run on MATLAB, since it provides strong optimization toolboxes. The simulation results show the effects of various factors including the sensing radius, angle of view, and the targets on the subset of sensors. With an increasing sensing range, the number of sensors decreases to acquire the same coverage ratio. On the other hand, an increment on the sensing angle reduces the number of sensors, but relatively less than enlarging the sensing range.

In [64], Osais et al. discuss directional sensor placement problem in a different way. They present an ILP model, where both a set of control points and a set of placement sites for sensors are defined previously. The objective is to place sensors in the sensor field such that every control point is covered by at least one sensor and the overall cost of the sensors is minimum. The impact of the three parameters of a directional sensor node, i.e. sensing range, FoV and orientation, has been examined thoroughly, since these parameters have significant impact on the overall cost of the DSN. Contrary to the other available solutions, the sensors in this model might have unequal sensing ranges and angle of views. Their experimental results show that if the number of potential placement sites increases, the total cost of the DSN will generally decrease and the number of required sensors will be reduced by as high as 95%.

D. AREA-BASED COVERAGE SOLUTIONS

This section is about the research on the enhancement of area-coverage in DSNs. Some studies [63] refer to area coverage as field coverage. Enhancing area coverage is very important for DSNs to fulfill the specified sensing tasks. The objective is to achieve maximal sensing region with a finite number of sensors. Some of the published papers, especially early ones, use the ratio of the covered area to the overall deployment region as a metric for the quality of the coverage [65]. However, some work focuses on the worst-case coverage, usually referred to as the least exposure. Worst-case coverage aims at measuring the probability that a target would travel across an area or an event would happen without being detected [66].

Grid-based coverage approach [67] has been used to simulate area coverage problems for DSNs. Each vertex on the grid represents a point in the monitored area. The grid resolution shows with how much detail an area is simulated. However, increasing grid resolution causes coverage optimization algorithms to run longer.

Several solutions [30,31,68-71] and algorithms have been proposed to enlarge the covered area with a minimization of the occlusion and overlapping. The study in [30] is one of the pioneer works on coverage enhancement in DSNs. The authors present a new method based on a rotatable directional sensing model. They propose to divide a directional sensor network into several components, called as sensing connected sub-graphs (SCSGs). Partitioning a directional sensor network into several SCSGs is dividing and conquering a centralized issue into a distributed one, thus decreasing the time complexity. The number of SCSGs, ns, reflects the performance of the area coverage. The less ns is, the worse the coverage rate becomes, i.e., the more coverage holes occur. They also model each sensing connected sub-graph as a multi-layered convex hull set to address the enhancing coverage problem. Once forming a multi-layer convex hull set in each SCSG, the sensing directions of nodes are rotated to obtain the maximal sensing coverage. To achieve less overlapping area between two neighboring directional nodes on the same convex hull, the directional node repositions itself on the reverse direction of the interior angle-bisector. The interior angle bisector is calculated based on the position of two neighbor nodes as shown in Figure 4.

Their algorithm consists of three steps. (i) depth-first search for finding SCSGs (ii) Graham algorithm for the construction of multi-layer convex hull set for each SCSG (iii) rotation of the sensing directions according to the corresponding interior angle-bisectors. Given n directional nodes, calculated k convex hulls in a convex hull set and m nodes in a SCSG, the time complexity of each step is $O(n^2)$, O(kmlogm), and O(n) respectively.

The numerical results show that the coverage rate increases with an increase in the sensing radius Rs. However, once the value of Rs exceeds a threshold, coverage rate turns to be inversely proportional to R_S. The same results were also observed by the relationship of coverage rate to the angle of view (a). The proposed algorithm optimizes the scale of node deployment by quantifying the requirements of deploying directional sensors for a given coverage rate.

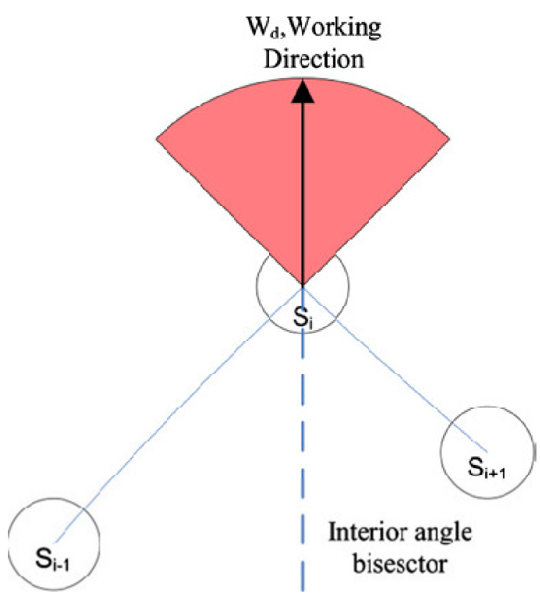


Figure 4. Interior angle bisector

Cheng et al. describe the area-coverage enhancement problem as Maximum Directional Area Coverage (MDAC) problem and prove the MDAC to be NP-complete [70]. They propose one distributed scheduling algorithm, named Dgreedy, for the MDAC. Their objective is to maximize the area coverage of a randomly deployed DSN. In their study, the authors define two new concepts, virtual sensor and virtual field. A virtual sensor represents one working direction of a directional sensor, whereas a virtual field is a minimal region that is formed by the intersection of sensing regions of a number of virtual sensors. The idea behind presenting a distributed solution is that it is computationally more scalable and does not incur high communication overhead as required by a centralized solution.

For every directional sensor, Dgreedy algorithm chooses the least overlapped direction as its working direction. The authors assume that sensing neighbors are definitely located within $2R_S$ distance. Similar to the possible solutions in target-based coverage enhancement, each sensor was assigned a unique priority to put the sensing neighbors into an order. Higher priority sensing neighbors make their decision earlier than lower priority neighbors. The authors observe that the scarce sensors are highly critical to achieve maximal coverage, thus they utilize the number of sensing neighbors to differentiate the priority. Simulation results show that Dgreedy algorithm outperforms the Random algorithm. The performance improvement becomes obvious especially when the number of sensors increase, since the ratio of overlapped area is greater in a dense network.

The theory of the virtual potential field has already been applied to the coverage enhancement problems in omni-directional mobile sensor networks [36,72]. Zhao and Zeng [31] has adapted this approach to wireless multimedia sensor network for coverage improvement. They proposed an electrostatic field-based coverage-enhancing algorithm (EFCEA) to enhance the area coverage of WMSNs by turning sensors to the correct orientation and decreasing the coverage overlap of active sensors. They also aim at maximizing the network lifetime by shutting off as much redundant sensors as possible based on the theory of grid approach, and waking them up according to a correlation degree. The grid's number covered by every neighbor represents the value of an electric charge. The repel force between two sensors is defined according to the Coulomb's law of the electrostatic field theory. This force is applied to the centroid of every sense sector (see Figure 5). The resultant force F_i to the sensor i's centroid is calculated then by the following formula:

$$F_i = \sum_{j=1}^{m} k * \frac{q_{ij}}{R_S^2} r_O \quad (2)$$

where k is a constant describing the strength of the field, r_O is a vector of unit length and describes the direction of the force. R_S represents the distance of two sensor nodes. q_{ij} describes the size of the area covered by the neighboring sensor nodes, whereas m is the number of neighboring nodes. A sensor node becomes stable after the composition of the forces caused by all neighbors is less than a predefined threshold ε.

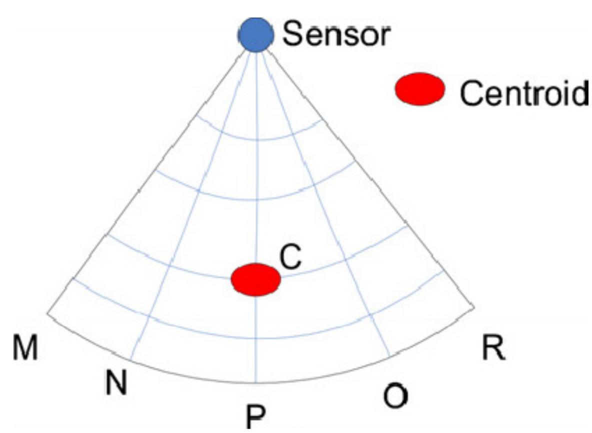


Figure 5. Centroid of a video sensor node

The performance of EFCEA algorithm depends on the number of the deployed sensors. If it is small, the coverage ratio can be enhanced much, whereas the coverage ratio does not increase significantly when there are already a large number of sensors. However, in the latter case, many redundant sensors go into sleeping and the lifetime of WMSNs is prolonged along with the higher coverage ratio.

In [68], the authors name the above mentioned coverage problem as optimal coverage problem in directional sensor networks (OCDSN). Like other studies, they aim at covering maximal area while activating as few sensors as possible.

They propose a greedy approximation algorithm to the solution of the OCDSN problem, based on the boundary Voronoi diagram. The Voronoi diagram is an important data structure in computational geometry, which is a fundamental construct defined by a discrete set of points [73]. By constructing the Voronoi diagram of a directional sensor network one could find the maximal breach path of this network. This path shows the weakest parts of the network and the probability of target detection is at minimum along this breach. The authors introduce an assistant sensor that can obtain the global information by traveling the edges of Voronoi diagram. While moving, the assistant sensor senses whether being covered by active sensors per unit time. If not, it checks whether there is an inactive directional sensor within its sensing circle in time. This condition ensures that an inactive sensor with the shortest Euclidean distance to the edge will be chosen. Then, the inactive sensor is woken up and it selects its orientation as to make the borderline of its sensing sector to go through the assistant sensor.

Given n sensors, the best known algorithms for the generation of the Voronoi diagram have O(nlogn) complexity, whereas the assistant sensor needs O(n) complexity to traverse all edges of the Voronoi diagram. For each edge, the assistant sensor may detect n sensors in the worst case. Thus, the total time of their algorithm is: $O(n\log n) + O(n^2)$.

The effect of the number of sensors, sensing ranges and angle of views on the coverage ratio have been examined by the authors via several tests executed in MATLAB. Overall, the simulation results show that their algorithm outperforms the Random algorithm.

Some sensor applications require high reliability. Therefore, monitored points need to be covered by k sensors. This type of coverage problems is defined as k-coverage problems. Some researchers have focused on k-coverage problems in directional sensor networks [74,75]. In [74], Fusco and Gupta address the problem of selecting a minimum number of sensors and assigning orientations such that the given area or the set of target points is k-covered. The authors design a simple greedy algorithm that delivers a solution that k-covers at least half of the target points using at most $M \cdot \log k |C_j|$ sensors, where $|C_j|$ is the maximum number of target points covered by a sensor and M is the minimum of sensor required to k-cover all the given points.

Ma et al. have proposed a 3D sensor coverage-control model with tunable orientations [69]. They developed a virtual potential-field based coverage-enhancing scheme to improve the coverage performance. The virtual-force-analysis based area coverage enhancing algorithm (VFA-ACE) determines the new working directions of directional sensors according to the neighborhood forces. These forces are applied to the centroid of the 3D covered area. VFA-ACE terminates when all centroid points are stable, i.e. the DSN reaches to the equilibrium.

The global area coverage optimization is clearly an NP-hard problem. Since the authors cannot find the analytic relationship between the optimization objective and the tunable parameters, they select the heuristic optimization technique, Simulated Annealing (SA) algorithm, to optimize the area coverage-enhancing for 3D directional sensor networks. The SA is a global optimization method that tries to find optimal solution in the candidate solution space. Both of the proposed algorithms, VFA-ACE and SA-ACE, have been implemented on a 3D simulation platform 3Dsenetest 1.0. The simulation results show that SA-ACE algorithm can achieve faster convergence speed.

Wang and Cao, in [76], study the problem of constructing a camera barrier. They propose a method to select camera sensors to form a camera barrier, and present redundancy reduction techniques to effectively reduce the number of cameras used. They also present techniques to deploy cameras for barrier coverage in a deterministic environment, and analyze and optimize the number of cameras required for this specific deployment under various parameters. Similarly, the policy followed in the work [77] to conserve energy is finding the most valuable event areas among all the event areas (i.e., the ones leading to the most utility) to monitor, subject to resource constraints. Thus, only a partition of the area is covered by a subset of devices activated at any time slot.

Sometimes, the quality of a reconstructed view from a set of selected cameras is used as a criterion for the evaluation of camera selection policies. Park et al., in [78], use distributed look-up tables to rank the cameras according to how well they image a specific location, and based on this, they choose the best candidates that provide images of the desired location. Their selection criterion is based on the fact that the error in the captured image increases as the object gets further away from the center of the viewing frustum while the resource constraints are not considered.

A similar problem of finding the best camera candidates is investigated in [79]. In this work, Soro and Heinzelman propose several cost metrics for the selection of a set of camera nodes that provide images used for reconstructing a view from a user-specified view point. Two types of metrics are considered: coverage aware cost metrics and quality-aware cost metrics. The coverage-aware cost metrics consider the remaining energy of the nodes and the coverage of the indoor space. The quality-aware cost metrics favor the selection of the cameras that provide images from a similar view point as the user's view point.

Chapter IV

NODE CLUSTERING FOR WIRELESS MULTIMEDIA SENSOR NETWORKS

A. INTRODUCTION

This chapter presents the proposed clustering method for wireless multimedia sensor networks. The method is the first approach of clustering based on the field of view of multimedia nodes. Following, the details of finding the overlapped polygon between FoV of multimedia nodes, calculating the area of discovered polygons and then cluster establishment and membership schemes are presented. The results of the clustering method, cluster-size, number of clusters and membership-degree are defined and showed for different node densities and clustering scales. The publications [Alaei-1], [Alaei-5], [Alaei-9] and [Alaei-10] (see Chapter I, Section B.4) correspond to this chapter.

Multimedia sensors, such as cameras, are multidimensional sensors that can capture a directional view. We assume wireless multimedia sensor nodes with fixed lenses providing a θ angle FoV (see Figure 6), densely deployed in a random manner. The assumption of fixed lenses is based on the current WMSN platforms [14]. Almost all of them (SensEye, MicrelEye, CITRIC, Panoptes, Meerkats [80-84]) have fixed lenses and only high powered PTZ cameras have movement capabilities. We assume that sensors are aware of their position.

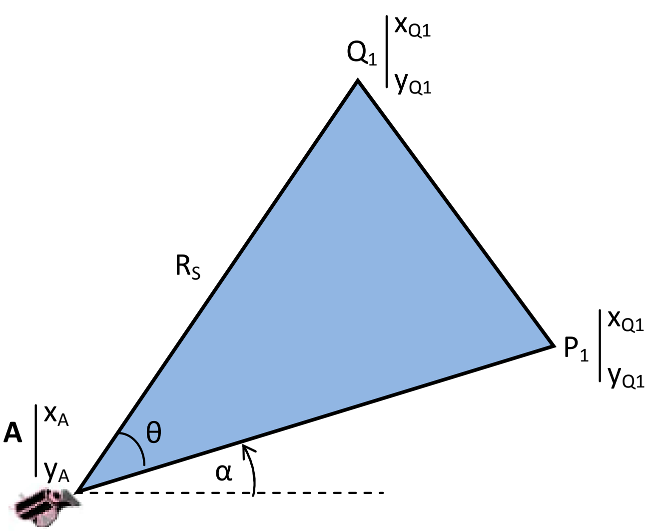


Figure 6. The Field of View (FoV) of a node located at the point A (x_A, y_A) with the orientation α. Each node is equipped to learn its location coordinates and orientation. The coordinates of the other vertices of the FoV are calculated in the clustering procedure.

We consider a monitor area with N wireless multimedia sensors, represented by the set $S = \{S_1, S_2, ..., S_N\}$ randomly deployed. Each sensor node is equipped to learn its location coordinates and orientation information via any lightweight localization technique for wireless sensor networks.

B. OVERLAPPING AREAS BETWEEN FOV OF MULTIMEDIA NODES

It is obvious that there is no overlap between FoV of two nodes if the Euclidean distance between them is more than $2R_S$. Otherwise, it is possible to have overlapped regions between their FoV depending on the orientation angles α. For calculating the FoV overlapping area of two nodes, we first survey the intersection of triangles that are representatives of their FoVs. Second, if they intersect each other, we find the intersection polygon and at last, compute the area of the polygon. An example of the intersection polygon of two FoV belonging to nodes $A = (x_A,y_A)$ with orientation α_1 and $B = (x_B,y_B)$ with orientation α_2 is illustrated in Figure 7.

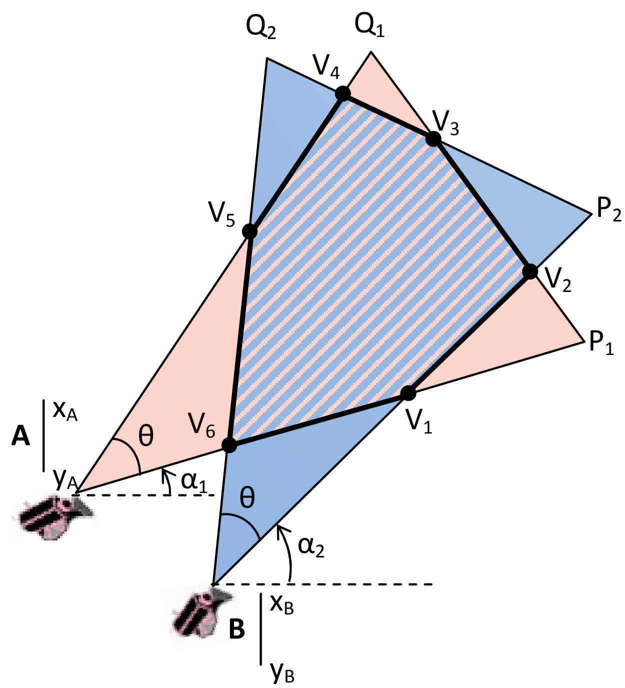


Figure 7. An example of the intersection polygon of two FoVs, $(V_1V_2\ldots V_6)$

For this purpose, in the first step, we define the equations of the sides of each triangle using the vertex coordinates of each triangle. The coordinates of the main vertex A (see Figure 6) are known according to the location of the node in space. The coordinates of vertex P_1 and Q_1 are:

$$x_{P_1} = x_A + R_S \cdot \cos(\alpha) \tag{3}$$

$$y_{P_1} = y_A + R_S \cdot \sin(\alpha) \tag{4}$$

$$x_{Q_1} = x_A + R_S \cdot \cos((\alpha + \theta) \bmod 2\pi) \tag{5}$$

$$y_{Q_1} = y_A + R_S \cdot \sin((\alpha + \theta) \bmod 2\pi) \tag{6}$$

We can determine the equation of a line from the coordinates of two points of the line or from the coordinates of one point and the gradient of the line. Thus, using the coordinates of A, P_1 and Q_1, we can determine the equations of the three sides of the FoV triangle:

$$\overline{P_1Q_1}:\ y - y_{P_1} = \frac{y_{Q_1} - y_{P_1}}{x_{Q_1} - x_{P_1}} \cdot (x - x_{P_1}) \tag{7}$$

$$\overline{AP_1}:\ y - y_A = (x - x_A) \cdot \tan(\alpha) \tag{8}$$

$$\overline{AQ_1}:\ y - y_A = (x - x_A) \cdot \tan((\alpha + \theta) \bmod 2\pi) \tag{9}$$

In the second step, we calculate the intersection of each side of each triangle to all sides (*i.e.*, the perimeter) of the other triangle. An intersection point V of two lines representing two sides of the FoVs will be a vertex of the overlapped polygon if it lies among the vertices associated with those two sides. As illustrated in Figure 3, the line representing AP_1 of the FoV of node A intersects the line that represents BP_2 of the FoV of node B in point V_1. V_1 can be considered as a vertex of the intersection polygon because V_1 is located between A and P_1 and also between B and P_2. The desired condition (C_{ACCEPT}) for an intersection point V to be an acceptable vertex of the polygon is stated in Equation (10). This subject is noticeable because any two anti-parallel lines obviously have an intersection point in a two dimensional space. On the other hand, each side of a FoV is a segment of a line. Figure 8 shows examples of non-acceptable intersection points:

$$\begin{aligned} C_{ACCEPT} = {} & (\mathrm{Min}(x_A, x_{P_1}) \le x_V \le \mathrm{Max}(x_A, x_{P_1})) \wedge \\ & (\mathrm{Min}(x_B, x_{P_2}) \le x_V \le \mathrm{Max}(x_B, x_{P_2})) \end{aligned} \tag{10}$$

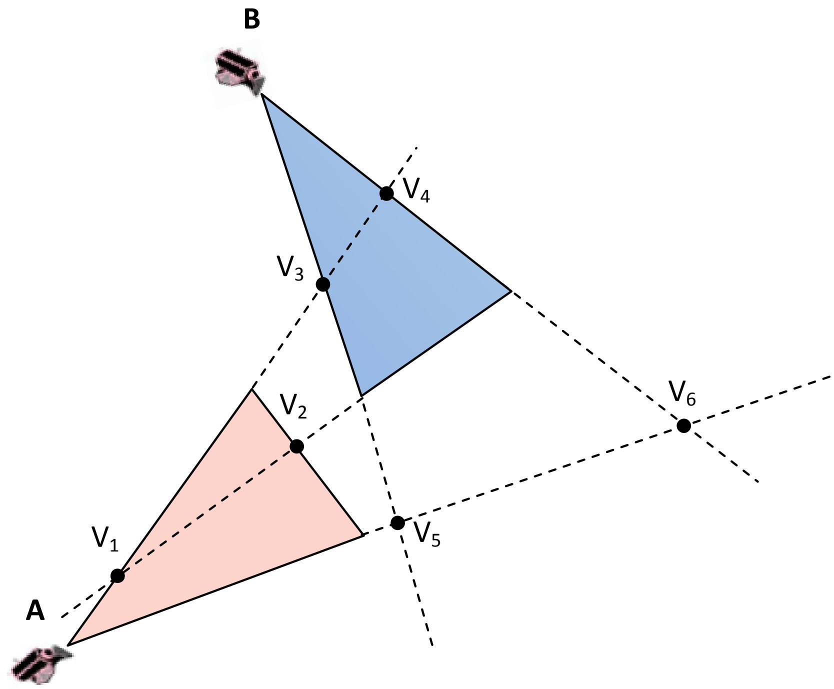


Figure 8. Non-acceptable intersection points, each two anti-parallel lines have an intersection point but the point have to satisfy Equation (10) to be a vertex of the intersection polygon.

The intersection of each side of one triangle with all sides of another triangle consists of at most two points. Figure 7 shows the case in which each side of each triangle intersects the perimeter of the other one in exactly two points V_i and V_j, becoming the segment V_iV_j one of the sides of the intersection polygon. However, there are other situations in which the intersection of one side of a triangle with the perimeter of another triangle occurs only at one point, resulting in that one of the vertices associated with that side lies within the second triangle and will become one of the vertices of the polygon (see Figure 9).

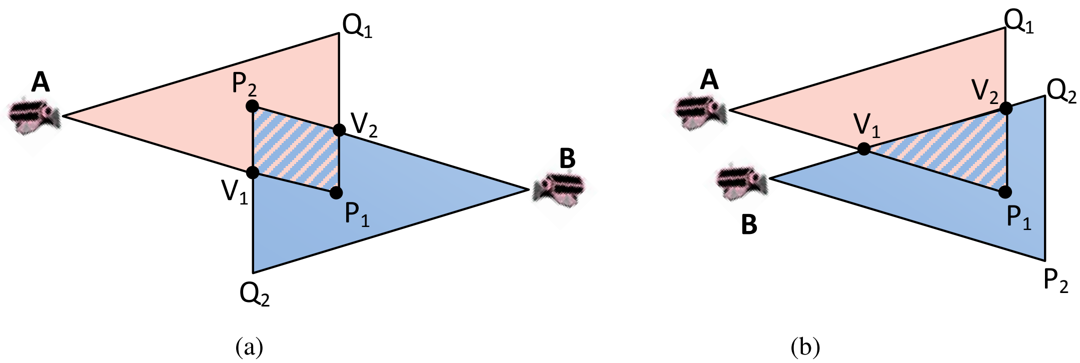


Figure 9. Examples of side intersection in only one point, for instance AP_1 intersect the perimeter of the other triangle in only V_1 in both (a) and (b).

In the third step, a decomposition approach is used for calculating the area of the overlapped polygon in a 2D-plane. Let a polygon (W) be defined by its ordered vertices $V_i = (x_i,y_i)$ for i = 0,...,n with $V_n = V_0$. Also, let P be a reference point in the 2D-plane. For each edge V_iV_{i+1} of the polygon W, form the triangle $\Delta_i = PV_iV_{i+1}$. Then, the area of the polygon W is equal to the sum of the signed areas of all the triangles Δ_i for i = 0,...,n–1:

$$A(W) = \sum_{i=0}^{n-1} A(\Delta_i) \quad \text{where} \quad \Delta_i = PV_i V_{i+1} \tag{11}$$

$A(\Delta_i)$ refers to the area of triangle Δ_i. Notice that, for a counter-clockwise oriented polygon, when the point P is on the left side of an edge V_iV_{i+1}, the area of Δ_i is positive; whereas, when P is on the right side of an edge V_iV_{i+1}, the area Δ_i is negative. If the polygon is oriented clockwise, then the signs are reversed. This computation gives a signed area for a polygon and similar to the signed area of a triangle, is positive when the vertices are oriented counter-clockwise around the polygon, and negative when oriented clockwise. We refer to [85] for a detailed description of the algorithm for calculating the area of a 2D polygon.

C. CLUSTER FORMATION AND MEMBERSHIP PROCEDURE

Let us consider a monitoring area with N wireless multimedia sensors, represented by the set $S=\{S_1,S_2,...,S_N\}$ randomly deployed. As it was mentioned before, sensor nodes are equipped to learn their location coordinates and orientation information. Each camera sensor notifies the sink of its location and orientation after node deployment via sending a message. The cluster formation and membership procedure, which is executed in a centralized manner by the sink, computes areas of overlapping FoVs between nodes and then decides about their membership. The membership criterion for joining to a cluster is FoV overlapping areas between nodes, i.e., nodes having enough common area in their FoVs are grouped in the same cluster.

Before describing the membership and cluster formation procedure, let us define:

- *Clustering scale* (γ), as the threshold of overlapping FoVs for membership, defines the minimum area of a node's FoV which is required to be overlapped with the CH of a cluster to be accepted as a member of the cluster. The clustering scale is set at the beginning of the clustering algorithm to a value which is determined by the user. Depending on the application, we define a proper value for this scale which will be the threshold of overlapping between nodes' FoV for clustering them.
- *Overlapping degree* (η) of a sensor node (S_i) is the number of network nodes which have overlapping with the sensor node at least in an area determined by the clustering scale.

We bring up two policies for membership of nodes in clusters; *Single-Cluster-Membership (SCM),* allows a node to be a member of only one cluster. Therefore, a node can only belong to one cluster and thus clusters are disjoint. But, in *Multi-Cluster-Membership (MCM),* Nodes join to any cluster with which they have enough overlapping FoV. So, nodes can belong to more than one cluster, or in other words, established clusters are not necessarily disjoint and they may have intersection with common nodes. As we will see later, employing of MCM and

SCM depends on the desired application of WMSNs; the nodes of the clusters established by SCM can collaborate in the clusters (intra cluster collaboration), while the clusters resulted by MCM, have intersection and thus not only cluster members cooperate in the application but also the clusters potentially can cooperate by their common nodes (intra and inter cluster collaboration). Following, let us proceed to the details of the formation and membership procedure.

1) Set the Clustering scale (γ) to a predefined value.
2) The overlapping degree of the network nodes is calculated and then the nodes list is sorted according to their overlapping degree with a descending order ($S=\{S_1,\ldots,S_N\}$), Algorithm 1, lines 3-10.
3) The first un-clustered node in the nodes list (S), is selected for establishing a new cluster. The node is assigned as a member and as CH of the established cluster, Algorithm 1, lines 13-15.
4) For MCM, All sensor nodes of the network, S_i (i=1…N), both un-clustered nodes which have not been assigned as member of any other cluster and also clustered nodes which are currently member of other clusters, except for the previous CHs (because the CHs have previously been tested with all other nodes), are tested for membership in the established cluster. But, for SCM, only un-clustered nodes are tested for membership. The test is performed based on the following criterion: if the overlapped area between the FoV of CH and the candidate node is larger than the area determined by the clustering scale, the node is assigned to the new established cluster, Algorithm 1, lines 16-18, 23, 24.
5) If the joined node to the established cluster belongs to more than one cluster, it is set as a common node and the established cluster name is added in its mother cluster list for inter-cluster collaboration, Algorithm 1, lines 19-22.
6) If at least an un-clustered node exists in the network, the algorithm starts a new iteration with a new cluster (step 3), Algorithm 1, lines 11, 25, 26.

The sink, after executing the cluster formation procedure, notifies each CH about its cluster-ID and what are the members of the cluster. Then, each CH sends a packet to the members of his cluster notifying them about the cluster which they belong to.

As it was mentioned before, the cluster formation procedure has a centralized architecture; The main reasons in choosing a central architecture are the following: (i) In a centralized architecture the nodes should notify to the sink their location, A_i, and its orientation, α_i, (i = 1,…,N). For a distributed architecture, each node should notify to the rest of the nodes about its location and orientation. Note that this notification can be done using any energy efficient sensor routing protocol and only is necessary at bootstrap phase. All phases of the clustering algorithm are executed only one time, right after node deployment. (ii) In many WSN applications, the sink has ample resources (storage, power supply, communication and computation) availability and capacity which make it suitable to play such a role. (iii) Collecting information by a sink node is more power efficient compared to spreading this information to each and every other node within the network. (iv) Having the global view of the network at the sink node facilitates provision algorithms for closer-to-optimal cluster determination; the global knowledge can be updated at the sink when new nodes are added or some nodes die. Such maintenance tasks can be regarded as a normal routine for the sink. (v) Finally, using a centralized scheme can relieve processing load from the sensors in the field and help in extending the overall network lifetime by reducing energy consumption at individual nodes.

We note that the cluster formation procedure is executed only once after network deployment. If a node joins the network hereinafter, it has to notify its position and orientation to the sink. Then, the sink will determine its membership in the established clusters in the network by calculating the intersection between the FoV of the new node and the CHs. The sink sends a notification packet to each CH which the membership test proves that can accept the new node. Therefore, the clustering mechanism supports the scalability of the network. Algorithm 1 shows the procedure of formation and membership whose complexity is $O(N^2)$.

Let us proceed to an instance of the cluster formation procedure. Figure 10 illustrates a random deployment of five nodes, S={S_1,S_2,S_3,S_4,S_5}, as a small instance of a sensor network. Firstly, right after deployment, nodes notify the sink their location and orientation. The clusters established by the clustering algorithm on these nodes are: C_1={S_1,S_4}, C_2={S_2,S_3,S_4}, C_3={S_5,S_3}. When the algorithm starts with S_1 as the first CH and establishes a cluster for that, it finds that the only node having enough overlapping with S_1 to be grouped in the same cluster is S_4. Since the next un-clustered node is S_2, C_2 is established with S_2 as CH and all the network sensors are tested for membership in C_2 except for the previous CHs (S_1), because S_1 has been tested with all other nodes previously for cluster membership. The nodes S_3, S_4 join to C_2 because of their satisfying overlapping with S_2 although S_4 is previously a member of C_1. In the next iteration, the algorithm starts with the next un-clustered node, S_5, resulting in the cluster C_3={S_5,S_3}. Therefore, we observe that S_4 is a common node between C_1, C_2 and also S_3 is a common between C_2, C_3. In the Single Cluster-Membership (SCM) scheme, [10], a node already assigned to a cluster is not tested when a new cluster is created. As a comparison with SCM, we may observe the clusters established by SCM on these nodes will be C_1={S_1,S_4}, C_2={S_2,S_3}, C_3={S_5}.

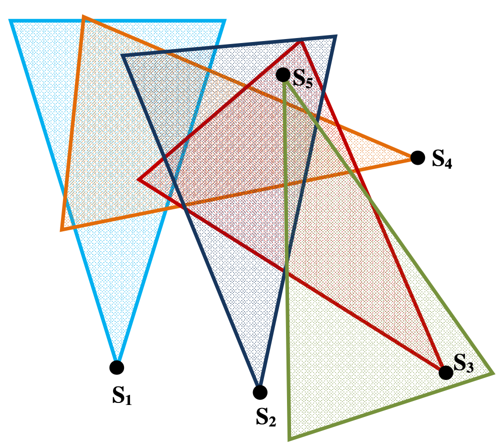


Figure 10. An example of five multimedia nodes deployment; In order to cluster the nodes, MCM results in C_1={S_3,S_2,S_5}, C_2={S_4,S_1,S_2}, and SCM results in C_1={S_1,S_4}, C_2={S_2,S_3}, C_3={S_5}.

Algorithm 1. Cluster formation and membership procedure

The algorithm pseudo code

N: Number of nodes in the network

SV: Status Vector, a vector with size N consisting one component for each node showing the status of node (Un-clustered (0), Clustered (1), Cluster Head (2) and Common Node (3))

k: Index of established clusters

$\mathbf{S_j}$**:** A multimedia sensor node

$\mathbf{D_{mn}}$**:** Overlapped area between FoVs of nodes m,n

$\boldsymbol{\eta}(\mathbf{S_m})$**:** Overlapping degree of the node S_m

$\mathbf{C_k}$**:** The cluster number k

$\mathbf{MC_i}$**:** Mother Cluster list of the node S_i, a list showing the clusters including S_i

$\mathbf{CH_k}$**:** The CH of the cluster number k

γ: Clustering scale

```
Set the clustering scale (γ)
SV ← <0,…,0>
k=1
For ∀S_m , m=1,...,N
   For ∀S_n , n=1,...,N
      Find intersection polygon of FoVs of S_m , S_n
      Compute D_ij // overlapped area between S_m, S_n //
   End-For
   Calculate η(S_m)
   Sort the nodes list according to η(S_m) with descending order, (S={S_1,…,S_N})
End-For
While ( ∏_{i=1}^{N} SV_i = 0)
      Establish a new cluster (C_k)
      SV_i ← 2 // i is the number of  first un-clustered node in SV //
      Add k in the MC_i
      CH_k ← i // Set S_i as the CH of the cluster C_k //
      For ∀S_j | (SV_j≠ 2)  // all nodes except for the CHs //
         If (D_ij ≥  γ.FoV)
            Add S_j in C_k
            If (SV_j =1) // previously clustered node //
                Add k in the MC_j ,  SV_j ← 3 // set as a common node //
            Else
                Add k in the MC_j , SV_j ← 1 // set as a clustered node //
         End-If
      End-For
      k←k+1
End-While
```

C.1. CLUSTER MAINTENANCE

For cluster maintenance, CHs utilize the message exchanging approach; each CH periodically sends messages to the cluster members and each member acknowledges the message notifying its residual energy level. As the CH consumes more amount of energy than the other cluster members, in order to prevent depleting its energy and losing it soon, the role of heading is periodically turned among cluster members. Based on the responds of energy polling, the node with the highest level of energy is selected as the new CH. When a node dies, the CH will reconfigure any parameter related to the cluster. For a common node which belongs to several clusters, the mother-cluster having minimum size among all its mother-clusters is responsible of its maintenance. In Section C of Chapter V, we will see that with the message exchanging mechanism used for cluster maintenance, other necessary information related to the network application such as timings (for synchronization) will be transmitted between cluster members and CHs in the same packet used for cluster maintenance. We use the proposed scheme in [86] for message exchanging, cluster maintenance and synchronization.

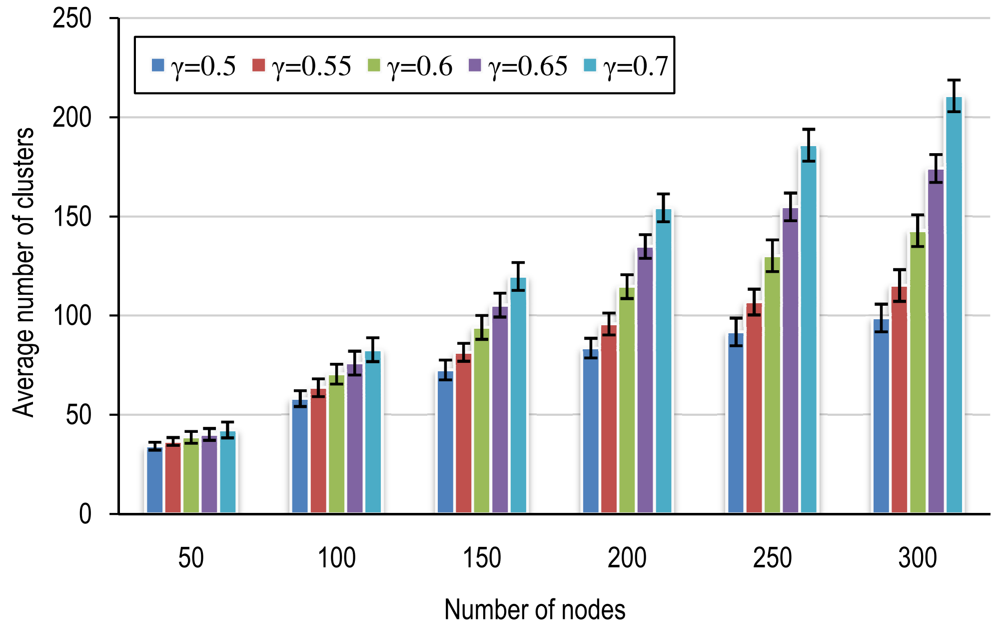
D. CLUSTERING RESULTS

The average of results of 50 independent running tests of the clustering algorithm in C++, are shown following; each test corresponds to a different random deployment. For this purpose, all sensor nodes have been configured with a FoV vertex angle θ=60º, FoV radius of 20m and the transmission range of nodes is assumed as 40m. A sensing area 120m×120m has been used and sensor densities were varied to study the system performance from sparse to dense random deployments.

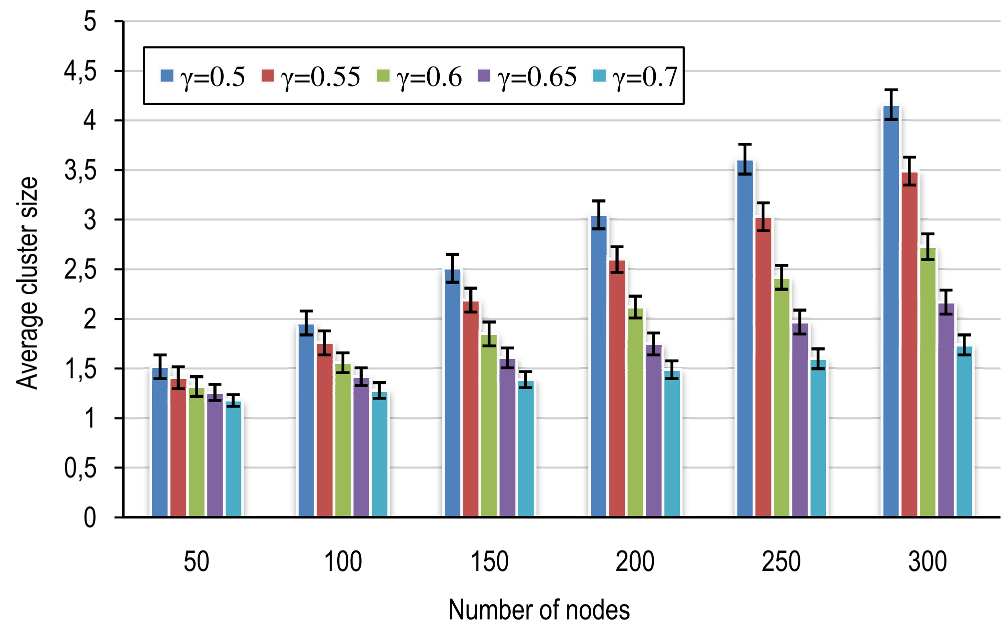
D.1. NUMBER OF CLUSTERS AND CLUSTER SIZE

Figures 11.(a),(b) respectively illustrate the average number of clusters and the average cluster-size for MCM in terms of node density for different clustering scales. High clustering scales restrict membership of nodes in clusters because to be a member of a cluster, the node's FoV must overlap the CH's FoV at least as much as the area that the defined clustering scale (γ) determines. So, the clustering scale is a key factor to decide about membership of nodes in clusters. It shows the minimum required overlapping FoVs between the CH and any other cluster member; i.e., the two nodes have to overlap in more than γ % of their FoV. High values of γ mean that the mechanism is very restrictive to accept a node as a cluster member resulting in a high number of clusters with low cluster-sizes. Lower values of γ will yield lower number of clusters with larger cluster-sizes.

Figure 12 shows the number of clusters having only one node (single nodes) in a network clustered by both MCM and SCM for different node densities. In MCM, many of the single nodes of SCM join to the other established clusters since the nodes can join to multiple clusters. As the figure shows, in the sparse deployments the number of single nodes is relatively large while with increasing node density, single nodes are decreased because of increasing in FoVs overlapping. We may observe that MCM decreases the number of single nodes with joining them to the previously established clusters and this creates the capability of collaboration for these nodes in the clusters.



(a)



(b)

Figure 11. (a) Average number of clusters, (b) Average cluster-size of MCM, with several clustering scales (γ), for different node densities

It is important to stress that the monitored area by a single node is equal to its FoV, thus, when a node captures an image, it monitors an area equivalent to its FoV of which a percentage equivalent at least to the γ coincides with the other members of the cluster. Considering a cluster of only two nodes with a clustering scale of for instance γ=0.5, means that at least 50% of the FoV of each member is covered by the other one, thus, the maximum cluster coverage domain is 1.5·FoV. When a member takes a picture, this one comprises a FoV that at the same time corresponds with at least 50% of the other node's FoV. We will use these properties of common covering to establish collaboration in clusters for covering the sensing area in Chapter V.

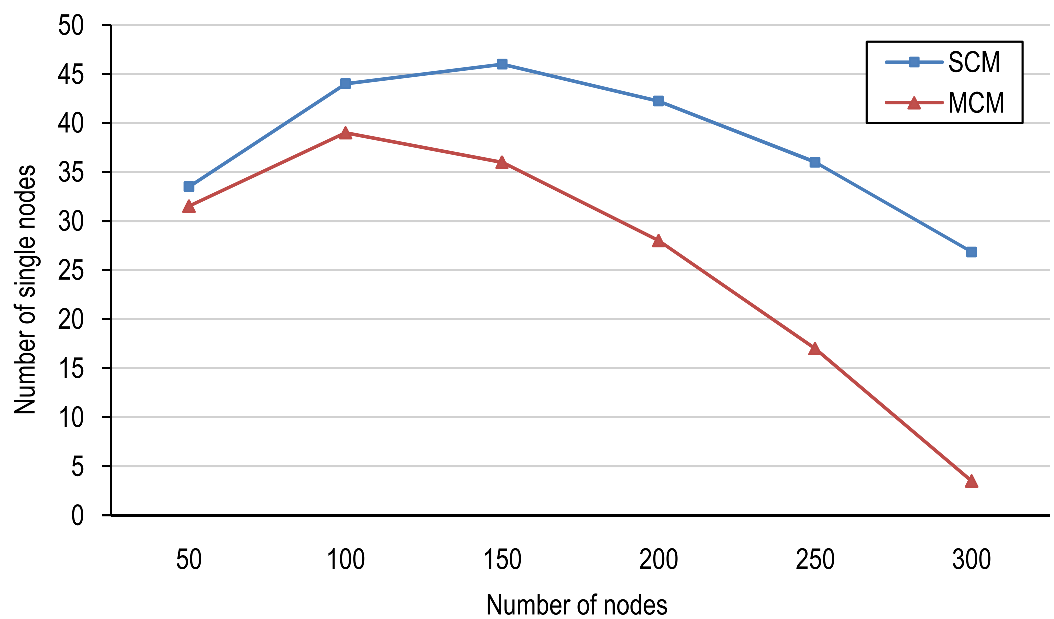


Figure 12. Average number of clusters with only one node (single nodes) in a clustered network by MCM and SCM with γ=0.6 for different node densities. In MCM, many of single nodes of SCM join to other established clusters.

Figure 13 shows the difference of average size of established clusters by the clustering algorithms, MCM and SCM. Intersection of clusters in MCM and having common nodes make an increment in the size of clusters. With increasing of the network node density, overlapping areas between node FoVs are increased and thus the number of common nodes between clusters in MCM is raised. As it can be observed in the figure, in a network consisting of 300 nodes clustered with a clustering scale of 0.5, each cluster established by MCM, in average, has one node more than clusters of SCM. Nevertheless, in a sparse network clustered there is almost no difference between MCM and SCM. The interesting point of this curve is that SCM algorithm has higher number of isolated nodes than MCM algorithm. This is due to the fact that a given isolated node may overlaps with nodes already clustered but the isolated node does not overlap with the CH of that cluster, and thus it is not clustered.

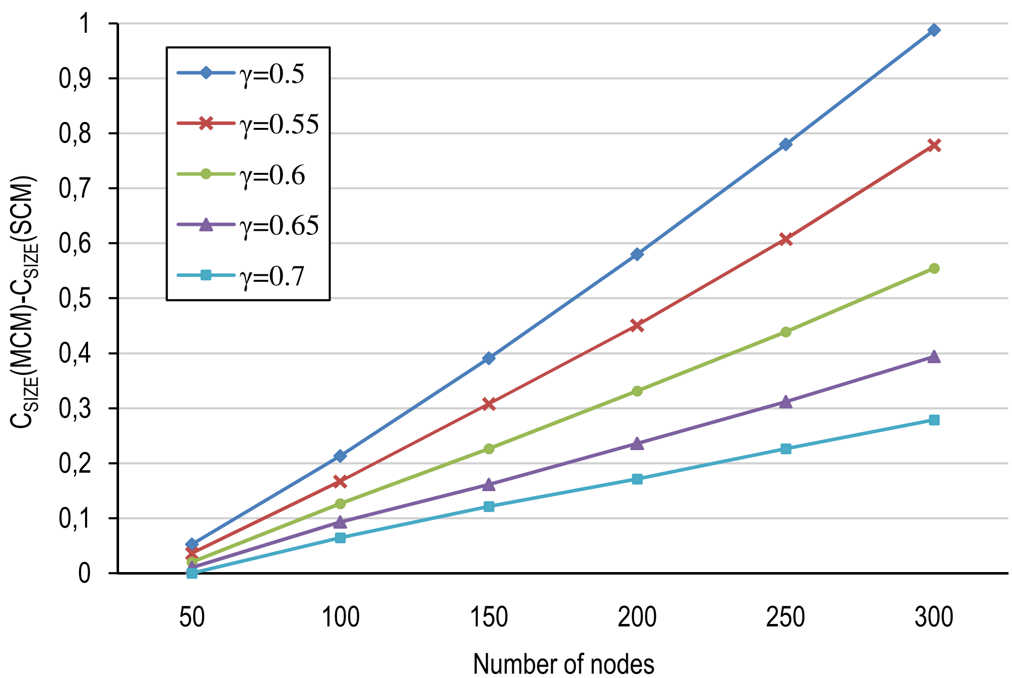


Figure 13. Difference between the average size of clusters established by MCM and SCM with several clustering scales (γ) for different node densities

D.2. MEMBERSHIP DEGREE

Figure 14 illustrates the average number of clusters to which a given node belongs; we have called this parameter as the node membership-degree (M_D), and according to the definition, this is equal or greater than 1. As the figure shows, higher clustering scales result in lower membership-degrees. Obviously, the higher the density of nodes, the more overlapping among nodes and therefore the higher membership-degree offered by MCM.

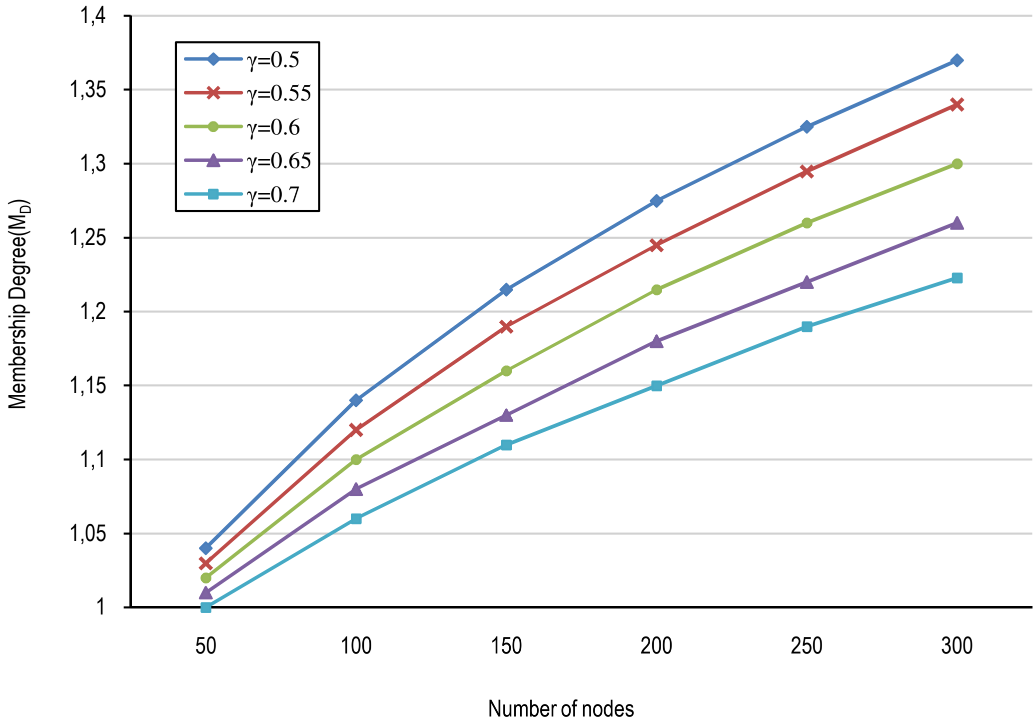


Figure 14. Average Membership-Degree (M_D) of nodes clustered by MCM with several clustering scales (γ), for different node densities

E. CONCLUSIONS

This chapter presented our proposed clustering method based on the similarity of the multimedia nodes from the coverage point of view. Wide overlapping of field of view of the nodes is the criterion of membership in clusters. Single cluster membership (SCM) and multi cluster membership (MCM) are the two styles of membership procedure in the clustering mechanism.

As the results show, high clustering scales restrict membership of nodes in clusters because to be a member of a cluster, the node's FoV must overlap the CH's FoV at least as much as the area that the defined clustering scale (γ) determines. So, the clustering scale is a key factor to decide about membership of nodes in clusters. High values of γ mean that the mechanism is very restrictive to accept a node as a cluster member, resulting in a high number of clusters with low cluster-sizes and low membership degree for the nodes. Lower values of γ will yield lower number of clusters with larger cluster-sizes and higher membership degree.

In MCM, many of the single nodes of SCM join to the other established clusters since the nodes can join to multiple clusters. In the sparse deployments the number of single nodes is relatively large while with increasing node density, single nodes are decreased because of increasing in FoVs overlapping. With increasing of the network node density, overlapping areas between node FoVs are increased and thus the number of common nodes between clusters in MCM is raised.

Selection of the node membership style (MCM or SCM) in the clustering mechanism depends on the desired application from the clustered WMSN. In an application which disjoint and non-overlapping clusters are needed, SCM plays its role while MCM can create clusters with common nodes having the potential of collaboration between clusters for an application.

This chapter with presenting the clustering method whose criteria directly consider the specific characteristics and constraints of WMSNs, solves the problem of coverage based clustering of this kind of networks. As it was mentioned in the Section A of Chapter I, and in Chapter III, all the existing clustering schemes for WSNs consider the neighborhood or data transmission range for clustering.

Because of the main difference between directional sensing region of multimedia sensors and the sensing range of scalar sensors, these clustering schemes and other coverage-based techniques designed for WSNs, do not satisfy WMSNs. In contrast, the proposed clustering mechanism in this chapter is quite adapted with WMSNs and thus covers the mentioned lack. As clustering is the base of many node management necessities, the proposed mechanism can play a key role for coverage based techniques in WMSNs.

The publications whose contributions correspond to this chapter are as follows.

[Alaei-1]. Mohammad Alaei, Jose M. Barcelo-Ordinas, Book Chapter: "Power Management in Sensing Subsystem of Wireless Multimedia Sensor Networks," Wireless Communications and Networks-Recent Advances, Dr. Eksim (Editor), ISBN 979-953-307-394-0, INTECH, March 2012.

[Alaei-5]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "A Method for Clustering and Cooperation in Wireless Multimedia Sensor Networks," *Sensors Journal* (MDPI), Vol 10, Issue 4, pp. 3145-3169, March 2010.

[Alaei-9]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "MCM: Multi-Cluster-Membership Approach for FoV-Based Cluster Formation in Wireless Multimedia Sensor Networks," the 6th ACM International Wireless Communication & Mobile Computing Conference (IWCMC 2010), Caen, France, June 2010.

[Alaei-10]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "Node Clustering Based on Overlapping FoVs for Wireless Multimedia Sensor Networks," IEEE Wireless Communications and Networking Conference (IEEE WCNC2010), Sydney, Australia. April 2010.

Chapter V

NODE SELECTION AND SCHEDULING PROCEDURES FOR ENERGY EFFICIENT COLLABORATIVE MONITORING

A. INTRODUCTION

The proposed mechanisms of node management (selection and scheduling) for collaborative monitoring are described by this chapter. The procedures aim to conserve the energy of network nodes as much as possible thus to prolong the network lifetime. To this purpose, they coordinate cluster members of the disjoint clusters created by SCM (Chapter IV), to cooperatively sense and process the sensing area. For the clusters established by MCM, the cooperation is not only applied within the clusters but also the cluster modules cooperate for monitoring.

The importance and novelty of this chapter comes from the fact that most of the existent node management approaches in the scope of WSNs are designed for managing scalar sensors without considering the constraints of multimedia sensors, particularly the directional sensing region (FoV) of the nodes. Moreover, sensor management strategies of WSNs do not consider the event-driven nature of multimedia sensor networks, nor do they consider the unpredictability of data traffic caused by a monitoring procedure. A few work which are performed previously in this field for WMSNs, assume a very special conditions for the nodes and area, for example having the planed deployed nodes with the capability of mobility and turning the lenses, also targets with pre-known or predictable locations like a barrier. The methods proposed in the present chapter have been designed for random deployment of low power low resolution static multimedia sensors having a fixed lens, without any knowledge of the targets or their locations. Our published works corresponding to the contents of this chapter are: [Alaei-3], [Alaei-4], [Alaei-6] and [Alaei-8], (see Section B. 4, Chapter I).

Surveillance and monitoring have been the primary applications of multimedia networks, where the monitoring of large, even remote and inaccessible areas is performed by high number of multimedia sensors over a long period of time. Since sensors usually provide raw data, acquiring important information from collected image data requires some processing like object detection in nodes. Since WMSNs are so resource constraint, in these applications, energy efficient operations are particularly important in order to prolong monitoring over an extended period of time. For this purpose, resource-aware camera management policies and wireless networking aspects are integrated with monitoring specific tasks. Usually, sensor nodes are duty-cycled to capture images and do the desired processing task (for example, object detection) periodically.

This chapter is aimed to propose cluster-based sensor management policies (selection and scheduling), and show how nodes and clusters can be coordinated and how much network lifetime is prolonged by using the clustering mechanism proposed in the previous section for collaborative monitoring. However, we also note that the clustering scheme offers the possibility of coordinating concurrently cluster members for multi-view monitoring of the same area/object. In this way, each member takes the view from its perspective at the cost of all cluster members spend simultaneously sensing, processing and transmission energy. In this case, the network trades power saving with multi-view monitoring.

We divide the environment sensing task in clusters of overlapping FoVs. Each cluster covers a region by its members with a certain degree of overlapping; as regards an event can happen in each of these regions, all clusters sense their domains concurrently by their members in a collaborative manner. A general cooperating mechanism works as follows:

- In each cluster, the CH is programmed to periodically select and schedule cluster members to monitor the sensing area in a duty-cycled manner.
- Each selected node, when is awakened, captures an image from its unique perspective, then surveys the presence of a new object/event in the captured image, and in the case of detection sends it - depending on the application objective - to the sink.
- During each monitoring period (T), the awakened and sleeper nodes spend their energy proportional to their working state, (see Figure 15). The figure shows the energies consumed in the monitoring (E_M) and sleeping (E_S) modes by a node. Awakened members that monitor the area in the current period, consume their energy for monitoring (capturing and detection) while other nodes of the network that remain in the sleep mode during T, just use the

power of the sleeping state. For instance, assuming T=3s, using Cyclops as the camera sensor, E_M and E_S respectively correspond to 31.6mJ and 3mJ, [80].

- Common nodes, i.e., nodes that belong to more than one cluster, can potentially be awakened by more than one CH and when a common node is awakened, captures an image that belongs to more than one cluster area. Thus, any defined scheduling algorithm has to be able to schedule efficiently common nodes because if a common node is continuously scheduled by different CHs will deplete fast its battery.

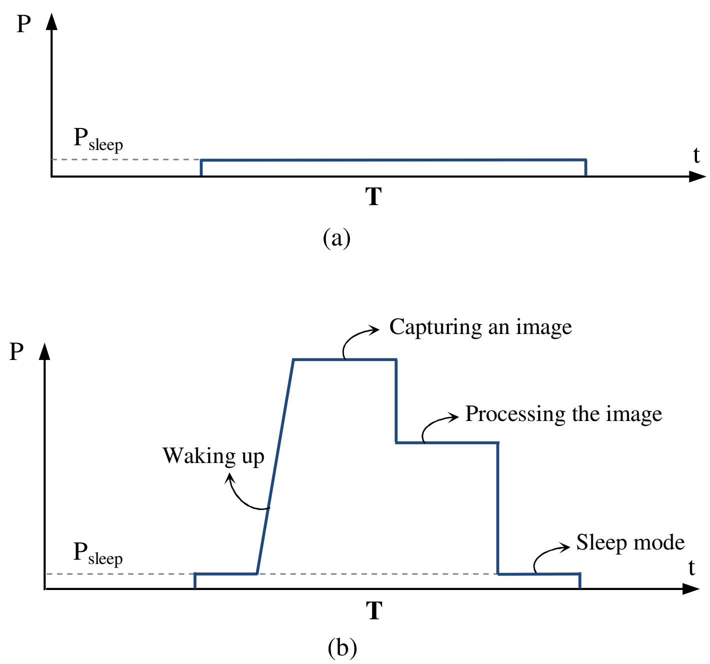


Figure 15.(a). E_S, the energy consumed by a sleeper node during the monitoring period (T), the node consumes P_{sleep} during the period, (b). E_M, The energy consumed by an activated node for monitoring the area during the period T, consisting of the energy used for waking up, capturing image, processing the captured image (in our case, Object Detection) and remaining in sleep mode until the next period.

In this chapter, we propose two specific procedures for node management in order to monitor the environment collaboratively by WMSNs. In the first mechanism, called **Intra-Cluster Collaborative Scheme (ICC)**, collaboration is defined only for members of the same cluster and is thought for those clustering algorithms that cluster nodes in such a way that a node can only belong to one cluster. That means that all the clusters are disjoint and non-overlapping. An example of this kind of disjoint clustering algorithms is SCM (Chapter IV). In the second mechanism that is based on MCM, called **Intra and Inter-Cluster Collaborative Scheme (IICC)**, collaboration is defined for nodes that belong to the same cluster and also for clusters that have intersection (Chapter IV). That means that there will be collaboration within all clusters and also between the overlapping clusters for monitoring the environment. Both of the proposed monitoring schemes are distributed and localized in clusters. To be distributed and localized are important properties of a node selection mechanism, as they adapt well to a scalable and dynamic network topology and also they yield efficient resource consumption for node management. Finally, monitoring is organized in duty-cycled periods, and the set of active sensor nodes is decided at the beginning of each monitoring period.

In order to have a base case for comparison and evaluation of the schemes, we introduce an idealized central model, called **Global Collaborative model (GC)**, in which there is a global centralized entity with information about all energy states of all the sensors in the network. Based on this information, the best subset of network nodes in terms of energy efficiency is selected for the current monitoring period with the restriction that only one active node from each cluster is selected.

We stress that we are concerned with designing the node selection and scheduling mechanism, and do not address the problem of selecting which protocol is used for data gathering. Without loss of generality, to efficiently transmit data from the detector sensors to the sink, a mechanism like PEGASIS [87] can be used.

B. GLOBAL COLLABORATIVE MODEL (GC)

Let us consider an idealized global node selection model with full information and the energy level of any sensor node of the network. Let N be the total number of nodes in the network and M the total number of clusters. We associate to each node *j* (with j=1,2,…,N) the decision variable x_j:

$$x_j = \begin{cases} 1, & \text{if node j is selected} \\ 0, & \text{otherwise} \end{cases}$$

We refer to their vector as $\mathbf{x}=[x_1,\ldots,x_N]^T$ and $\mathbf{x^k}$ indicates the vector **x** at the monitoring period T_k. Moreover, let **A** represent the membership matrix, i.e. $\mathbf{A}\in R^M \times R^N$. The coefficients of matrix A are defined as follows:

$$a_{ij} = \begin{cases} 1, & \text{if node j belongs to cluster i} \\ 0, & \text{otherwise} \end{cases}$$

Let E^k_j be the residual energy at each node j at monitoring period T_k and let $\mathbf{E^k}$ be the residual energy vector $\mathbf{E^k}=[E^k_1,\ldots,E^k_N]^T$. The initial conditions are $\mathbf{E^0}= [E^0_1,\ldots,E^0_N]^T$. Then, for selecting an optimal set of nodes to be awakened and monitor the sensing area in T_k, the model works as follows:

For every monitoring period T_k (k=0,1,2,...):

Step 1: Maximize $\sum_{j=1}^{N} w_j E_j^k x_j^k$, where $w_j = \sum_{i=1}^{M} a_{ij}$

s.t. $Ax^k = 1$

$x_j^k \in \{0,1\}$

Step 2: $E^{k+1} = E^k - E_M x^k - E_S(1 - x^k)$

$k++$

At step 1, the objective function assures that those nodes with more amount of residual energy are selected for monitoring in the monitoring period T_k. The algorithm obtains the best node assignment subject to the condition that only one node at each cluster is selected. The weight w_j in the objective function is the number of clusters which the node j belongs to. When a common node is selected, it monitors the area as a representative of a number of w_j clusters, thus, in the procedure of calculating the sum of residual energy of candidate nodes to be selected for monitoring, the common node's energy has to be added w_j times; if we do not consider w_j, a common node with a high level of residual energy will be ignored while from each of the overlapping clusters related to that common node, a member with a less amount of energy than the common node, will be selected. For example, let us assume C_1 and C_2 as overlapping clusters with the node S_1 as their common node having 2J of energy at T_k, also S_2, S_3 with residual energy at T_k equal to 1.5J, are respectively members of C_1 and C_2. Without considering w_j, the nodes S_2, S_3 are selected from C_1 and C_2 because the sum of energy of the selected nodes in this case is 3J which is higher than of the case selecting S_1 (2J) for both clusters. To avoid this miss selection, we apply w_j and thus the procedure selects S_1 for T_k because its weight is of 2 and maximizes the objective energy summation function to 4J.

In step 2, the assignment vector ($\mathbf{x}^k$) is used to update the residual energy vector according to the energy spent in monitoring, E_M, or the energy spent for sleeping, E_S, (see Figure 15).

As it was mentioned before, GC is an idealized central model for node selection. In a practical case of selection and scheduling, a centralized architecture necessitates all the nodes to send their amount of residual energy to the central entity to decide about node selection. Moreover, the selection results have to be transmitted by the central entity toward the nodes. These required data transmissions not only increase the traffic of the network, especially around the central entity, but also consume a considerable amount of energy in nodes. Thus, following we distribute the GC procedure in all the clusters while the CHs are designated for executing the procedure in each cluster. We will see in Section E.3 that the overhead is kept low in the proposed collaborative schemes.

C. INTRA-CLUSTER COLLABORATIVE SCHEME (ICC)

In this section, we propose an implementation of a node selection approach for a network clustered by SCM that clusters multimedia sensor nodes in disjoint and non-overlapping clusters. Each node belongs to exactly one cluster and thus w_j in the objective function of Section B, for all nodes is equal to 1. So, the objective function aiming to select high energy level nodes along with the condition of selecting one node from each cluster, cause to select the node having the maximum level of energy in each cluster.

Accordingly, the monitoring procedure based on disjoint node clustering will be as follows:

1) At the beginning of each monitoring period (T) in each cluster, the member having the maximum residual energy level is selected and awakened by its CH as the representative of the cluster for monitoring the environment while the other members of the cluster are kept in the sleep mode.
2) The awakened member captures an image from its FoV and surveys the presence of an object/event and go back to the sleep mode.
3) Each CH records the current energy level of all members of its cluster in a register and periodically refreshes that.

Since in every monitoring period, each CH determines a member to monitor the area, the number of assigned nodes of the network to be awakened is the same as the number of clusters in the network. The scale of collaboration in each cluster depends on the cluster size; in a cluster with more number of nodes, each node can save more amount of energy during the times it sleeps while the other cluster members are sequentially activated and monitor the area. The single nodes in the network that do not have enough overlap with others to join to the established clusters are programmed to awake every T to monitor their area and will be the first ones to die.

When a sensor node detects a new object/event, it notifies the CH and also sends the captured image toward the sink. Therefore, in addition to the energy consumed by nodes during the monitoring period (T) (E_M for active nodes and E_S for sleeper nodes), some amount of energy is consumed in network nodes for packet sending and forwarding of detected data and thus the residual energy of nodes is affected by that. Hence, the CHs need to update their registers with new values of residual energy level (E_R) of the nodes. To this purpose and also for synchronization, the current energy level and the timing information of cluster members are sent to CHs in the same packet transmitted by the message exchanging procedure utilized for cluster maintenance introduced in Section C.1 of Chapter IV. In this way, each CH in addition to maintenance of its cluster, periodically synchronizes the cluster members and refreshes its register with update energy information values of its cluster members. As it was mentioned in Section C.1 of Chapter IV, the role of CH is turned among cluster members according to their residual energy.

Since the clusters are disjoint, the monitoring scheme only offers intra-cluster collaboration (ICC). Figure 16 illustrates an example of 5 clusters established by SCM on 11 nodes. Figure 17 corresponding to Figure 16, shows how the cluster members are selected as representatives of clusters in each monitoring period under the ICC algorithm. Nodes S_8 and S_9 are awakened every T since they belong to the clusters with only one member (single nodes) while in other clusters consisting of several nodes, the members collaboratively monitor the area. For instance, in the cluster C_4 consisting of nodes S_4, S_5, S_6 and S_7, each node will be awakened every $4 \cdot T$, being this cluster the one with the most energy saving potential among the clusters of the example. Finally, in Algorithm 2, the intra-cluster collaborative procedure is showed.

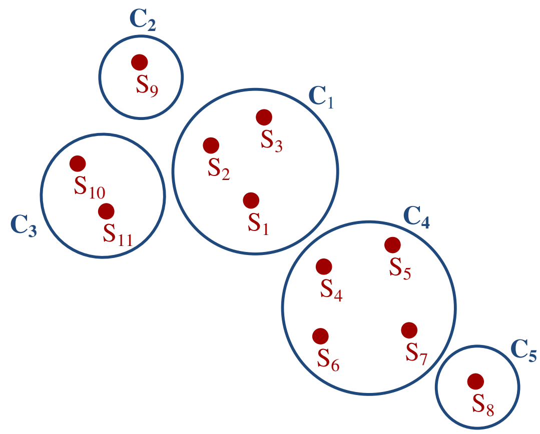


Figure 16. An example of disjoint clusters established on 11 nodes, single nodes that do not have enough overlapping with other nodes, make clusters with only one member.

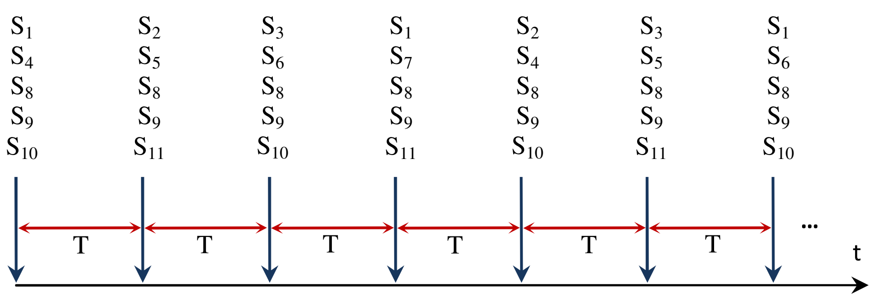


Figure 17. The selected nodes by Intra-Cluster Collaborative scheme (ICC) to monitor the sensing area

Algorithm 2. Distributed Intra-Cluster Collaborative (ICC) scheduling

The algorithm pseudo code

A: Active node
T: The monitoring period
$\mathbf{E_R}$: The residual energy in the node

1: **For all** C_j: *// All clusters in parallel //*
2: A ← node with the maximum E_R
3: CH awakens A
4: Delay (T)
5: **Goto 2**
6: **End-For**

D. INTRA AND INTER-CLUSTER COLLABORATIVE SCHEME (IICC)

Multi-Cluster-Membership (MCM), (Section C of Chapter IV), allows overlapping clusters. In other words, clusters intersect each other by common nodes that belong to more than one cluster. For example, Figure 18 illustrates the clusters created by MCM on the nodes of Figure 16. In this section, we propose an implementation of a node selection approach (IICC) for a network clustered by MCM. In order to define a selection and scheduling scheme for monitoring, we have to take into account that selecting nodes that only belong to one cluster will yield intra-cluster monitoring. However, selecting a node that belongs to more than one cluster means that the common node monitors simultaneously the area corresponding to the clusters the node belongs to; we call this collaboration as inter-cluster collaboration. It is clear that in the ICC scheme (Section C) one node per cluster is awakened per monitoring period while in IICC scheme there can be a number of awakened sensors less or equal than the number of clusters. Thus, better power savings can be achieved defining a more optimal node selection scheme able to decide which common and non-common nodes have to be awakened at every period. Similar to ICC, IICC is distributed in the clusters while the CHs are designated for executing the procedure in each cluster.

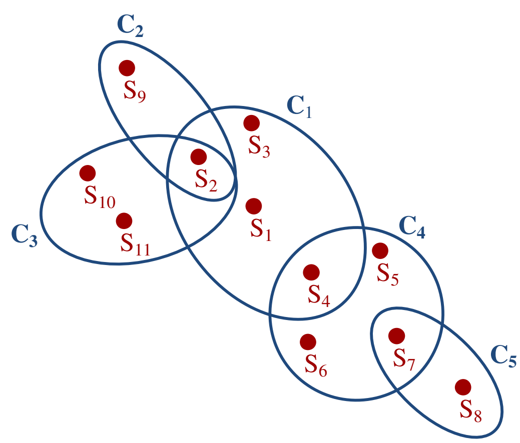


Figure 18. Overlapping clusters resulted from MCM. S_2, S_4, S_7: Common nodes as the linkages for inter-cluster coordinating.

Introducing inter-cluster collaboration is challenging as it can be observed in Figure 18 in which several nodes act as common nodes. Let us consider node S_2 that belongs to clusters C_1, C_2 and C_3, and the cardinality (i.e., number of members) of the clusters are: $|C_1|=4$, $|C_2|=2$, $|C_3|=3$. Selecting nodes as it was done in Section C would imply that node S_2 would be awakened more times than the other nodes, (see Figure 19). For example, using the notation $C_x=\{S_y\}$ (i.e., cluster C_x awakes node S_y), in the first T: $C_1=\{S_1\}$, $C_2=\{S_2\}$, $C_3=\{S_2\}$, in the second period T: $C_1=\{S_2\}$, $C_2=\{S_9\}$, $C_3=\{S_{10}\}$ and in the third period T: $C_1=\{S_3\}$, $C_2=\{S_2\}$, $C_3=\{S_{11}\}$, etc. As it can be observed, the clusters have no knowledge of which nodes are awakened by other clusters and thus S_2 is consecutively awakened by the clusters this node belongs to (its mother-clusters). That means that common nodes are selected in a non-optimal way, more times than others, due to the lack of inter-cluster coordination.

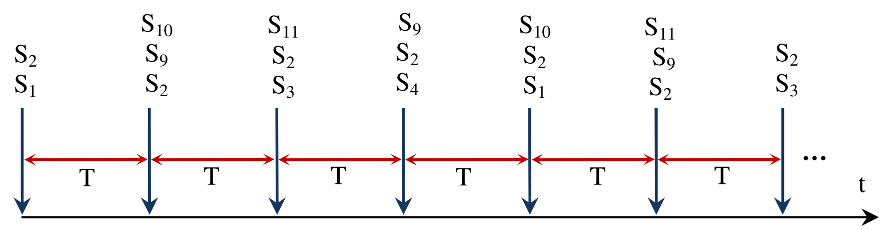


Figure 19. An example of timing for monitoring the area of clusters C_1, C_2, C_3 using a sequential mechanism (Only nodes of clusters C_1, C_2 and C_3 have been illustrated.)

The key point of a more optimal node selection procedure for this kind of cluster memberships is that one in which common nodes are selected more times than others since they cover areas for several clusters but not so many times to deplete their batteries faster than other members of the clusters this nodes belongs to (mother-clusters). Thus, we aim to design a selection scheme to monitor the environment in a collaborative manner satisfying the following conditions:

- Awakening the minimum number of nodes in each period of monitoring meanwhile activating a node from each cluster.
- Prolonging the network lifetime and balancing the energy level of nodes.
- Avoiding of covering repeated FoVs in consecutive monitoring periods.

We observe that this mechanism aims to obtain as close results as the global scheduler (GC) with the difference of being a distributed structure in clusters instead of a centralized algorithm, in Sections A and B, the preference of distributed algorithm has been discussed. For this purpose, we define two levels of priority for each multimedia node. The sum of the two priority values of each node determines its priority to monitor the environment for each monitoring period.

$$P_j = P_j^{L_1} + P_j^{L_2} \tag{12}$$

The *first level of priority*, P^{L_1}, is a static value during each monitoring period and aims to choose the nodes with highest residual energy and membership-degree for monitoring the environment during the current monitoring period. So, that is determined from the residual energy in the node and also the membership-degree of the node. A node with high membership-degree (membership-degree is equivalent to the weight, w_j, defined in the objective function in GC scheme, Section B) is a member of a larger number of clusters than other nodes, thus, it can monitor the area on behalf of more number of clusters and yielding in high power savings for members of its mother clusters. Therefore, selecting a high membership-degree node always is advantageous since it represents high number of clusters and yields minimum number of awakened nodes. However, the remainder energy of a node is quite important to select it for monitoring. Each awaken node spends its energy for monitoring the area (E_M). Thus, in addition to representing all clusters with the minimum number of awakened nodes, awakening nodes having high level of residual energy is a criterion. Let P_j^{L1}, the first level of priority for node j be:

$$P_j^{L_1} = \frac{E_{R_j}}{E_M} + w_j, \forall S_j \tag{13}$$

where E_R is the residual energy, E_M is the energy consumed by an active node during period T (Figure 15), E_R/E_M is the number of times that the node can monitor the area from its perspective considering its residual energy, and w_j is the membership-degree of the node S_j

The *second level of priority*, P^{L_2} , is chosen to avoid selecting the same FoVs in consecutive monitoring periods (T), and also to prefer selecting nodes from different clusters in the current T. The P^{L_2} is preset at the end of each T and may be decreased during each T according to the following rules:

1) When a member of a cluster (C_i) is selected, all other members of the cluster get a negative unit of priority (see Equation (14)) to decrease their priority and allow members of other clusters to be selected, when there are qualified appropriate nodes in other clusters.

$$P_j^{L_2} = P_j^{L_2} - 1, \forall S_j \in C_i \tag{14}$$

2) If a node was selected in the previous period for monitoring the environment, in the current period the node has a negative unit in its second level of priority. The aim followed of adding this negative unit is to avoid sensing the same FoVs in consecutive periods of monitoring when we can find other members having high priority to be selected for monitoring the area. At the end of each monitoring period, P^{L_2} is preset for the next period (Equations 15,16); normally for all the nodes, the second level of priority preset with 0 then the nodes activated in the current T get a negative unit in their second level of priority for the next T:

$$P_j^{L_2} = 0, \forall S_j \tag{15}$$

$$P_j^{L_2} = P_j^{L_2} - 1, \text{if } S_j \in \text{CSS} \tag{16}$$

where CSS is the Covering Sensors Set, the set of nodes activated in the current monitoring period.

The IICC scheduling scheme works as follows: At the beginning of each monitoring period (T), based on the summation of the two levels of priority, the CHs select and assign the members of Covering Sensors Set, CSS, (which is the set of nodes which are selected to be active in the current T) of nodes having highest priorities to represent all clusters, (Algorithm 3, lines 9-11, 20, 29). Note that for initializing, the first level of priority is calculated according to Equation (2) from the initial energy of the nodes (Algorithm 3, lines 4-6) and the second level is preset (Algorithm 3, line 3), and then, at the end of each monitoring period, the levels are re-computed and prepared for the next monitoring period according to the residual energy of nodes, (Algorithm 3, lines 31-34), also, the second level of priority may change during a monitoring period according to Equation (14), (Algorithm 3, lines 23-25). Each cluster has a representative in the CSS while a selected node may represent more than one cluster according to its membership-degree. All the nodes of the CSS are awakened by their CHs for monitoring in the current T, (Algorithm 3, line 30). In the case of a common node, (Algorithm 3, lines 12-19), it is awakened by the CH of its smallest mother-cluster. Awakened nodes monitor the area from their perspective and go to the sleep mode again, (Algorithm 3, line 36).

During each monitoring period, CSS nodes and sleeper nodes spend their energy proportional to their working state: members of the CSS that monitor the area in the current period consume their energy for monitoring (E_M), while other nodes of the network that remain in the sleep mode during the T just use the power of sleeping state (E_S), (see Figure 15). Thus, at the end of each period, the level of energy in all nodes of the network is reduced. Each CH records the current energy and also the first level of priority of all its cluster members in a register and refreshes that in each monitoring period with the new values to prepare for the next period, (Algorithm 3, lines 33,34). Exchanging messages for synchronization, getting up-to-date residual energy values (E_R), maintaining clusters and turning the CH role, is done as mentioned in Section C. The second level of priority of each node is preset at the end of each period for the next period according to Equations (15,16), (Algorithm 3, lines 31,32).

Figure 20 shows the selected CSSs awakened in several monitoring periods under the proposed algorithm. As it can be observed, in each period the awakened nodes cover all the clusters of Figure 12. Algorithm 3 shows the IICC procedure.

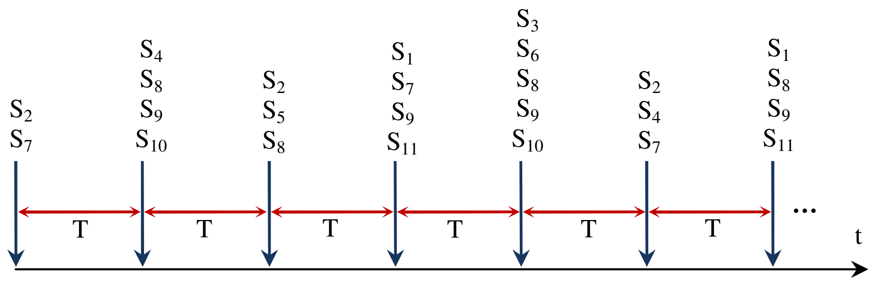


Figure 20. The selected covering sensor sets (CSS) to monitor the area with Intra and Inter-Cluster collaboration

Algorithm 3. Distributed Intra and Inter-Cluster Collaborative scheduling

The algorithm pseudo code

CCV: Covered Cluster Vector of size M (number of clusters), that shows the covered clusters by the selected multimedia nodes.

PVL1: Level one Priority Vector of size N (number of nodes) that consists of the first level covering priority value of each multimedia node in the network.

PVL2: Level two priority Vector of size N that consists of the second level covering priority value of each multimedia node in the network.

E_{init}: The initial energy of each node

E_M: The energy consumed by an activated node during the monitoring period, T

M_D: Membership-Degree

CSS: Covering Sensors Set, that consists of the activated sensor nodes covering all clusters.

CCN: The Candidate Covering node for joining to CSS

E_S: The energy consumed by a sleeper node during the monitoring period, T

CCV ← <0,…,0>
PVL1 ← <0,…,0>
PVL2 ← <0,…,0>
For all (S_j) *// sensor nodes //*
    $PVL1_j = E_{init}/E_M + w_j$
End-For
CSS ← ∅
i ← 1
Repeat:
If (CCV_i ==0)
  CCN ← the node with maximum priority ($P_j = PVL1_j + PVL2_j$) belonging to C_i
  If CCN is a common node belonging to some other clusters (C_k)
    For each (C_k)

Algorithm 3 (continue)

        If there is a node (S_h) in C_k having higher priority than CCN
            CCN ← S_h with the highest priority
            Goto 11
        End-If
      End-For
    End-If
    CSS = CSS ∪ {CCN}
    For all clusters including CCN (C_p)
      $CCV_p \leftarrow 1$
      For all nodes belonging to C_P
        $PVL2_l = PVL2_l - 1$
      End-For
    End-For
 End-If
 $i \leftarrow (i+1) \bmod M$
Until ($\forall CCV_r == 1, r=1,2,3,\ldots,M$)
The related CHs activate nodes of CSS

// Preparing for the next period: //

PVL2 ← <0,…,0> *// Reset second level of priority //*
For $\forall S_t \in$ CSS: $PVL2_t \leftarrow PVL2_t - 1$
For $\forall S_t \in$ CSS: $PVL1_t \leftarrow PVL1_t - E_M / E_M$
For $\forall S_t \notin$ CSS: $PVL1_t \leftarrow PVL1_t - E_S / E_M$
Delay (T)
The related CHs take nodes of CSS to sleep mode
Goto 7

E. COMPARISONS AND EVALUATIONS

In order to evaluate the proposed distributed scheduling algorithms (ICC and IICC), we compare them with the idealized central base model (GC, Section B) in the environment of C++. For this purpose, GC is executed on a network clustered with SCM having disjoint and non-overlapping clusters, as an idealized central Intra-Cluster Collaborative scheme and we name that GC ICC. Similarly, GC IICC is the GC on network clustered by MCM having Intra and Inter Cluster Collaboration. On the other side, to show the effect of collaboration offered by these proposed approaches, we use an un-collaborative duty-cycled periodic monitoring mechanism similar to [80] in which the sensor nodes are woken up periodically to capture an image and detect the presence of new objects in the area independent of each other.

For generality in all the scheduling algorithms, we assume that during each monitoring period (T), active nodes execute a monitoring procedure; each of them captures an image from its perspective of the area and accomplishes an object detection procedure to survey the presence of objects or events. The object detection procedure is performed via simple frame differencing, when a node detects an object or event, the image is sent toward the sink. Without loss of generality, we assume a low power, low resolution and low cost CMOS camera, Cyclops [12], as the camera sensor and MICAII [88] as the host mote in the multimedia nodes. Cyclops has a fixed angle lens and capture images with 352×288 pixels at the rate 10 fps with consuming 42 mW power. MICAII, in average, consumes 33mW in active mode and 75µW in its sleep mode. All sensor nodes have been configured with a FoV vertex angle θ=60º, FoV radius of 20m and the transmission range of nodes is assumed as 40m. A sensing area 120m×120m, in which nodes are randomly deployed, has been used and the sensor densities were varied to study the performance of the mechanisms from a sparse deployment of 50 nodes to a dense network consisting of 300 nodes. For clustering the nodes in ICC and IICC, a clustering scale of 0.6 has been defined. The averages of results of 50 independent running tests of the algorithms are shown in the figures and discussions of the following subsections; each test corresponds to a different random deployment.

E.1. POWER CONSERVATION DEVELOPMENT DUE TO COLLABORATIVE SCHEMES

We remark that we only evaluate the energy consumed by the sensing and processing subsystems which perform the monitoring procedure. Figure 15 showed the energy consumption model for nodes in the active and sleeping modes. According to the figure, the energy consumed by an active node in the monitoring procedure, consists of the energy consumed for waking up, taking an image and processing the image (object detection). The energy consumed by multimedia nodes in the monitoring procedure is many times higher than in scalar sensors. If the result of detection is negative, there is not any transmission originated from this node. If an object/event is detected, then the node produces a set of packets (i.e., the processed image) to be transmitted toward the sink.

With the collaboration offered by the proposed monitoring methods, and decreasing the number of monitoring nodes with overlapping coverage areas and thus decreasing the amount of generated data during each T, obviously not only the energy consumed for monitoring in the sensing and processing subsystems is decreased but also the communication subsystem meets an optimized amount of generated data to be transmitted. Therefore, the proposed methods also advantage in power conservation in the communication subsystem rather than the un-collaborative monitoring. However, we remark that traffic characterization of the communication subsystem is out of the scope of this work and we do not proceed to measure the energy consumed in the communication subsystem in the collaborative and un-collaborative methods.

In the case of un-collaborative monitoring, [80], all nodes are programmed to periodically wake up and monitor the area with a period of time T in a duty-cycled manner. Thus, the nodes consume their stored energy according to their sleep and active modes during each period. Each node sleeps during the time $T\text{-}T_M$ in each period, where T_M is the monitoring time taken for capturing an image and surveying the presence of an object/event by the node. We assume that the initial amount of stored energy in all nodes is the same. Thus, as the level of energy in all nodes is decreased with the same rate per monitoring period, the lifetime of the nodes will be the same.

Figure 21 shows the average number of awakened nodes for monitoring the area during each monitoring period in terms of node density for all the mentioned idealized and practical cases. The density of the network is varied from a sparse deployment with 50 nodes to a dense case of 300 nodes that covers 95% of the area. In the un-collaborative monitoring, during each period, all sensor nodes will wake up to monitor the area while in the collaborative methods, during each period, every cluster selects and awakes one representative for monitoring. Thus, in distributed ICC and GC ICC, the number of active nodes is equal to the number of established clusters (N_C) in the network while in GC IICC scheme because of collaboration between clusters, the number of active nodes is equal to (N_C/M_D) which is less than of ICC with a ratio of $1/M_D$, where M_D is the membership-degree. Distributed IICC have slightly more active nodes than GC IICC in a monitoring period because of its policies in the second level of priority; Distributed IICC avoids sensing the same FoVs in consecutive periods of monitoring, also, sometimes the qualified high priority nodes from the same cluster are selected (for example, one of them is a common node). In a sparse deployment, overlapping between nodes and also clusters is less than dense ones, being then, the potential of collaboration in sparse networks lower than in dense networks. As it can be observed from the figure, the difference between the number of active nodes in collaborative schemes and also the difference between both of them and the un-collaborative scheme raises with increasing the density of the network. This is the result of increasing the collaboration potential.

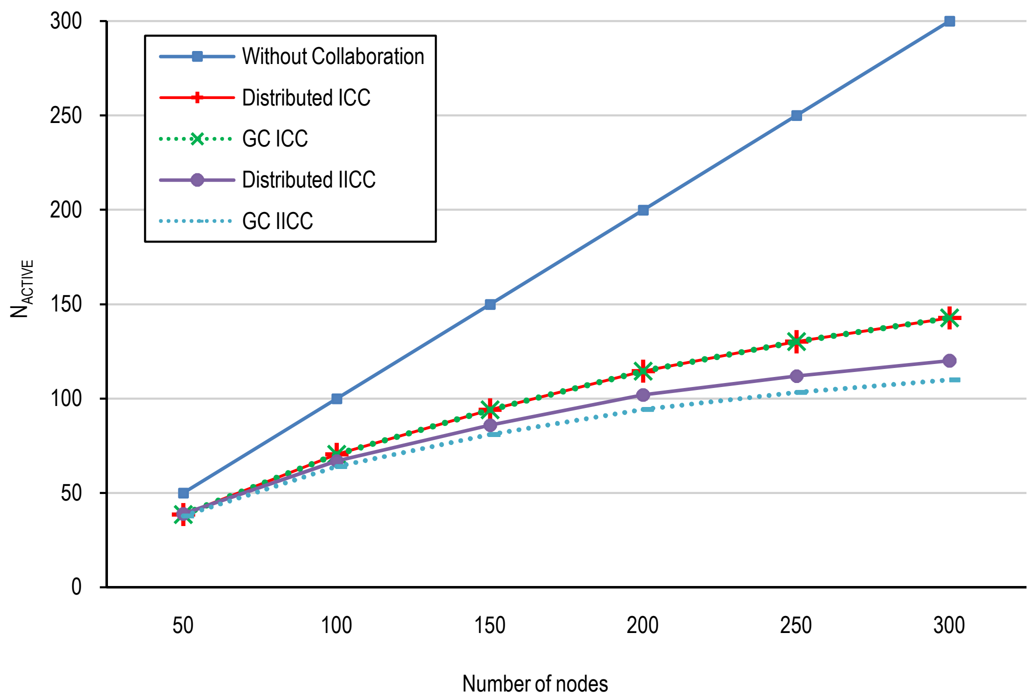


Figure 21. Average number of awakened nodes during a monitoring period (T) for both proposed collaborative methods (clustered with γ=0.6), and the un-collaborative scheme for different node densities in the sensing area

Equation (17) indicates the amount of consumed energy for monitoring in a network since the starting time of monitoring to a given time (t):

$$E(t) = \frac{t}{T} \cdot (N_{Active} \cdot E_M + (N - N_{Active}) \cdot E_S) \tag{17}$$

where N_{Active} is the number of active nodes during a monitoring period, N is number of network nodes. For the un-collaborative monitoring, N_{Active} is equal to N, for ICC is the same as N_C and in IICC is reduced to N_C/M_D. Thus Equation (17) is re-written as Equations (18), (19) and (20) for un-collaborative, ICC and IICC schemes respectively:

$$E(t) = \frac{t}{T} \cdot N \cdot E_M \tag{18}$$

$$E(t) = \frac{t}{T} \cdot (N_C \cdot E_M + (N - N_C) \cdot E_S) \tag{19}$$

$$E(t) = \frac{t}{T} \cdot \left(\frac{N_C}{M_D} \cdot E_M + \left(N - \frac{N_C}{M_D}\right) \cdot E_S\right) \tag{20}$$

Figure 22 shows the number of alive nodes in terms of time in a network consisting of 250 multimedia nodes clustered with a clustering scale of 0.6, for the un-collaborative and collaborative methods. We can see that in the un-collaborative mechanism, the network is alive with all of its nodes until their energy will be spent completely. After each T, the level of stored energy in all nodes of the network decrease uniformly and thus the network will die with all of its nodes after the specific number of T (i.e., $T_b = T \cdot E_{init}/E_M$),) which depends on: first, the amount of initial stored energy in nodes, second, the characteristics of the mote and the embedded multimedia sensor in the nodes, thirdly, the monitoring period of nodes (T).

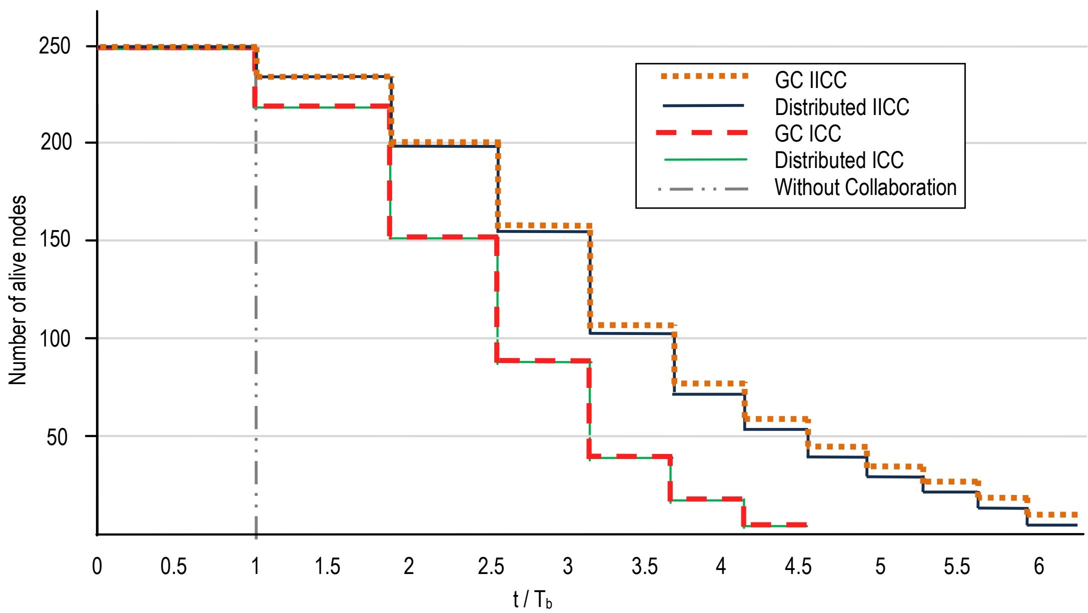


Figure 22. Number of alive nodes in terms of time, for both proposed collaborative monitoring methods in a network consisting of 250 nodes clustered with γ=0.6, and for the un-collaborative scheme

In order to compare the schemes, we normalize the time axis of the figure by T_b. For the collaborative schemes, each down step of the diagram indicates losing some nodes of the network. As the figure shows, the network monitoring the environment with IICC algorithm has alive nodes until $6.5\cdot T_b$. Single nodes (clusters having only one node; i.e., nodes do not have enough overlap with others in the membership test) are the first set of dying nodes (i.e., dying at T_b). Then, members of clusters of size two die at $1.83\cdot T_b$ and clusters of size three die at $2.52\cdot T_b$ and the network continues with larger clusters. As it is observed from the figure, bigger clusters can keep their nodes for a longer time than sparse ones because of having more collaboration capability among the members/clusters. Using ICC scheme also achieves a good increment in lifetime of clusters, $4.5\cdot T_b$ for big clusters with respect the un-collaborative scheme. However, the efficiency is not such good as the IICC scheme.

In the IICC algorithm, overlapping among clusters makes an enhancement in the size of clusters and the collaboration between clusters increases their lifetime. As it can be observed in Figure 22, at each time, the number of alive nodes in the network with IICC is larger than of ICC. As explained in the former section, IICC benefits from an intelligent schedule of the nodes belonging to more than one cluster. As in GC IICC, the number of awakened nodes during a monitoring period is slightly less than of distributed IICC (see Figure 21), there is a slight difference between the number of alive nodes in the network with GC IICC and distributed IICC. But, the number of alive nodes with GC ICC is the same as of distributed ICC because of their conformity.

Particularly, many of the single nodes in SCM which die at the T_b in the ICC method, are joined to other clusters by MCM. These nodes cooperate with other cluster members in IICC and thus work for a considerable longer time. Figure 12 showed the number of clusters with single nodes in MCM and SCM.

E.2. COVERAGE OF THE SENSING AREA

The coverage area of the clusters is centered by the FoV of the cluster head because the FoV of each cluster member overlap with the FoV of CH at least in an area which the clustering scale determines (Section C, Chapter IV). Hence, the cluster members are around the CH with a high degree of overlapping among them; when some nodes are the members of the same cluster, the FoV of each of them not only highly overlap the FoV of the CH but also they overlap each other particularly in dense deployments. When a member is awakened to take an image, it captures from several FoVs of the cluster, mainly from the CH. On the other hand, in IICC, the FoV of awakened nodes from different clusters are quite disjoint or do not overlap in a considerable area because if they could overlap each other in a wide area, they would be the members of the same cluster.

We calculated the area covered by all the nodes deployed in the sensing area (Section E) and the average of area covered by the awakened nodes by the proposed methods, during a period of T. Table 2 shows the average percentage of covered area for different node densities for the un-collaborative manner, in which all the network nodes are awakened to monitor the environment in each T, and for the collaborative schemes clustered with different clustering scales. Obviously, with increasing the number of nodes in the network the area under covering of the nodes is increased for each scheme. As the table shows, for each node density, the area covered by the un-collaborative scheme during each T is more than of the collaborative schemes at the cost of awakening all the network nodes at each T to monitor the area. It is worth to notice that activating all the nodes highly results in redundant monitoring; for example, in a network consisting of 300 nodes the sum of FoVs of nodes is 3.8 times of the covered area by the nodes which is 95% of the sensing area. But, collaborative schemes reach to the mentioned levels of coverage in the table with activating considerably less number of nodes than the un-collaborative scheme (see Figure 21) by intra and inter cluster coordination. Therefore, with a dense random deployment, we can put all the sensing area under the covering of sensor nodes and then with scheduling the nodes, the area is covered during each monitoring period with a high level of coverage avoiding redundant sensing.

As Table 2 shows, higher clustering scales result in greater percentage of covered area. The reason is behind of the fact that higher clustering scales yield establishing more number of clusters (Section D.1, Chapter IV), and with increasing of the number of clusters, the number of awakened nodes during each monitoring period and consequently the covered area are increased. However, it is worth to notice that increasing of the number of awakened nodes in monitoring periods, grows the power consumed for monitoring and thus decreases the lifetime of the network nodes. Obviously, more number of nodes saving their energy in the sleep mode (less number of awakened nodes), results in more amount of energy conserved in the network and thus longer lifetime of the network.

Table 2. Average percentage of covered area for different node densities for the un-collaborative and both distributed collaborative schemes (clustered with different clustering scales). It is worth to notice that in the un-collaborative scheme all the deployed nodes are awakened during each monitoring period while the collaborative schemes awaken a number of selected nodes according to Figure 21.

Scheme / Deployed nodes	Un-Collaborative	Distributed ICC			Distributed IICC		
		γ=0.5	**γ=0.6**	**γ=0.7**	**γ=0.5**	**γ=0.6**	**γ=0.7**
50	54%	41.5%	46%	50.5%	40%	45%	50%
100	75%	59%	68.5%	72%	56%	65%	69%
150	85%	67%	78.5%	81%	64%	75%	78.5%
200	90%	71.5%	85%	87%	68.5%	82.5%	85.5%
250	93%	73%	87%	89%	70%	85%	87.5%
300	95%	74%	88.5%	90.5%	71.5%	87%	89.5%

Figure 23 shows the number of alive nodes in terms of time for Distributed IICC, in a network consisting of 250 nodes clustered with different clustering scales. The time axis of the figure has been normalized with T_b similar to Figure 22. As Figure 23 shows, the number of alive nodes for the case of γ=0.5 is the largest in the set of three cases at any time since with γ=0.5, the number of established clusters is the minimum

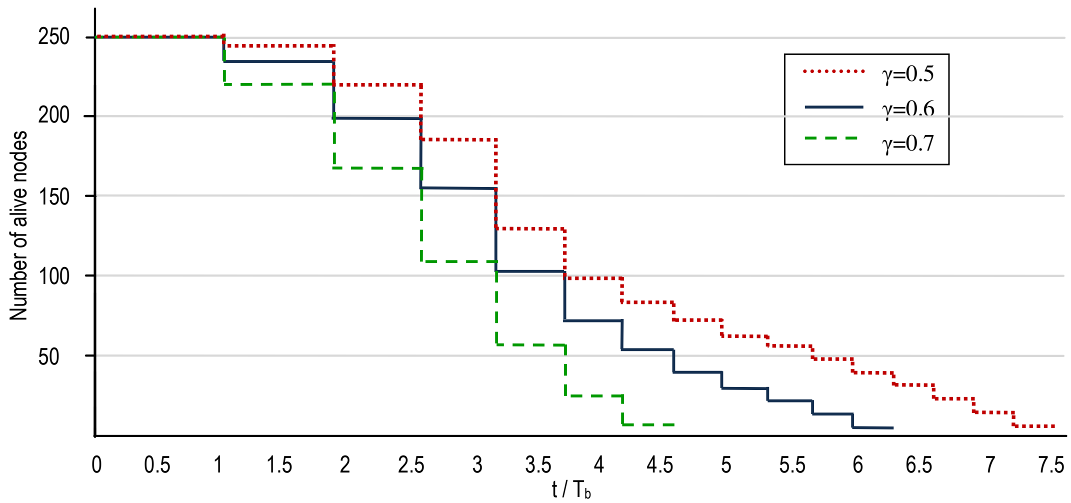


Figure 23. Number of alive nodes in terms of time for Distributed IICC in a network consisting of 250 nodes clustered with different clustering scales

According to Table 2 and Figure 23, there is a trade-off between coverage ratio and network lifetime for selection a value for clustering scale. The appropriate value depends on the application desired from the network, to reach more coverage of the sensing area, higher clustering scale is selected at the cost of consuming more amount of energy for monitoring.

Table 3 shows the ratio of coverage of the area in terms of the time for a network consisting of 250 nodes scheduled by Distributed IICC with γ=0.6. The table shows how the coverage ratio gradually decreases with depleting the nodes' energy and losing them during the time.

In order to compensate for the decrement of coverage level in collaborative schemes rather than un-collaborative monitoring, we can decrease the T to alternate the monitoring nodes as fast as is needed in the desired application; in this way, if an object is not detected in the current T, it will be covered in the next T by other members particularly in IICC that avoid sensing the same FoVs in consecutive monitoring periods by its second level of priority when there are other members having high priority.

Table 3. Coverage ratio in terms of the time for a network consisting of 250 nodes scheduled by Distributed IICC with γ=0.6

Coverage ratio	**Number of alive nodes**	**t/T_b**
85%	250	1
79%	233	1.9
69%	200	2.5
58%	155	3.1
46%	102	3.7
36%	70	4.2
28%	52	4.5
22%	41	4.9
16%	31	5.3
11%	22	5.6
6%	12	5.9

The coverage area of IICC is a little less than of ICC while the difference of the number of their active nodes (Figure 21) is more considerable than their difference in the percentage of covering the area. The reason is that in ICC some of the active nodes during a T overlap each other while they belong to different clusters and monitor the area at the current T on behalf of their clusters; in ICC a node can be a member of only one cluster even if that has enough overlapping with several CHs. This redundant monitoring is prevented by inter-cluster coordination in IICC with its common nodes but the coverage is slightly decreased also. Note that in ICC, clusters do not have common nodes while the FoVs of clusters have intersection. But, in IICC the clusters have common nodes and the intersections of their FoVs are the regions under the coverage of common nodes.

E.3. OVERHEADS

The proposed node management mechanisms impose some extra communications within the clusters and sometimes between the intersecting clusters. As it was mentioned before, in both schemes, distributed ICC and IICC, CHs use a message exchanging scheme within clusters for member synchronization, cluster maintenance and getting up-date values of residual energy of cluster members in a periodical manner. Distributed IICC sometimes obligates CHs (when a CH is deciding about a common node to be an active node) to know the priority level of the members of other mother-cluster(s) of the common node. For this case, the CH connects to the CH of the common-node's mother-cluster(s) to obtain all required information of all members. So, in distributed IICC method, in addition to message exchanging within clusters, some node information is communicated between intersecting clusters. Figure 24 shows the average of total number of overhead packet transmissions in distributed ICC and IICC during each period for a network clustered with a clustering scale of 0.6 for different node densities. As it was mentioned, all packet transmissions of ICC and major of IICC are performed within the clusters, the difference of number of packet transmissions between IICC and ICC is the packets communicated between intersecting clusters, thus, all of them are done with one or two hops.

For example, in the case of 300 nodes network, totally, 375 packets are transmitted within clusters for both ICC and IICC and 111 packets are communicated between intersecting clusters for IICC. These packet transmissions are the cost of nodes management to reduce the number of active nodes during each monitoring period (Figure 21) and thus power saving in nodes. However, the cost of transmitting these numbers of packets (with one or two hops) is much lower than the cost of taking a picture, then processing and sending the picture packets toward the sink by the nodes. It is worth to notice that reducing the active nodes in monitoring periods, not only results in saving energy of the sensing subsystem of the nodes kept in sleep modes, but also the amount of generated data in monitoring periods is reduced and thus communication and processing subsystems meet an optimized amount of data to be transmitted/processed.

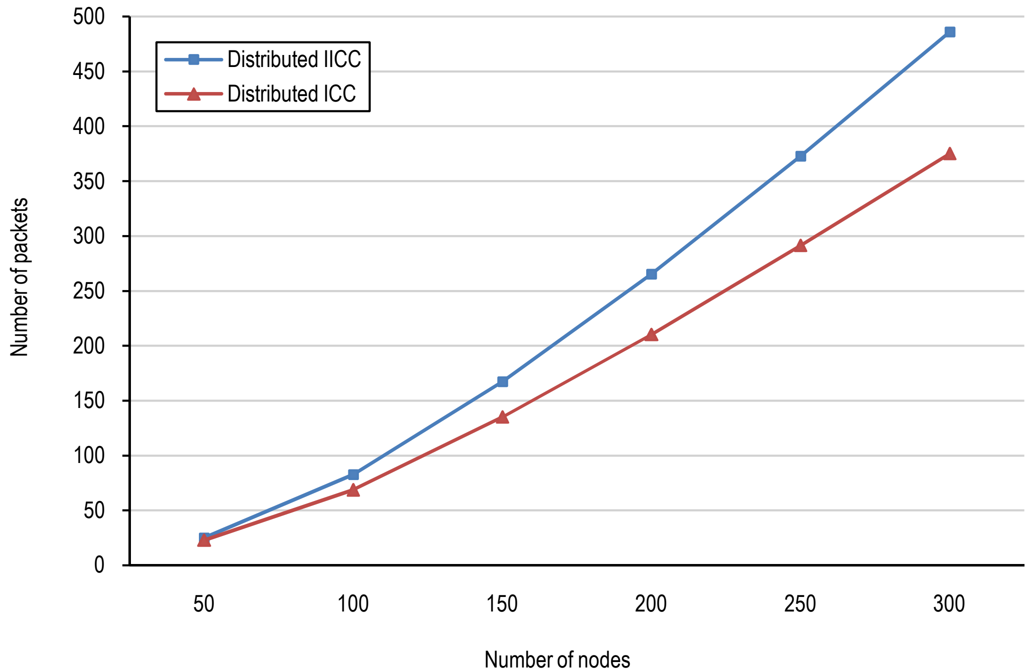


Figure 24. Average number of packet transmissions for overheads, (synchronization, cluster maintenance and getting up-date values of residual energy of cluster members), during each period for both distributed ICC and IICC, in a network clustered with γ=0.6, for different node densities

Figure 25 illustrates the amount of energy consumed in the network due to the mentioned overheads (see Figure 24) of distributed IICC during each monitoring period (T). Also, the figure shows the amount of energy saved in each T by this scheme with respect to the un-collaborative scheme. According to Figure 21, the number of awakened nodes by distributed IICC during each T is considerably less than of the un-collaborative scheme. By keeping unnecessary nodes in sleeping mode, IICC saves an amount of E_M-E_S energy (see Figure 15) during each T for each node kept in sleep mode. It is clear that the energy consumed for overheads is negligible in comparison to the saved energy and also to the energy required by multimedia sensing and processing tasks.

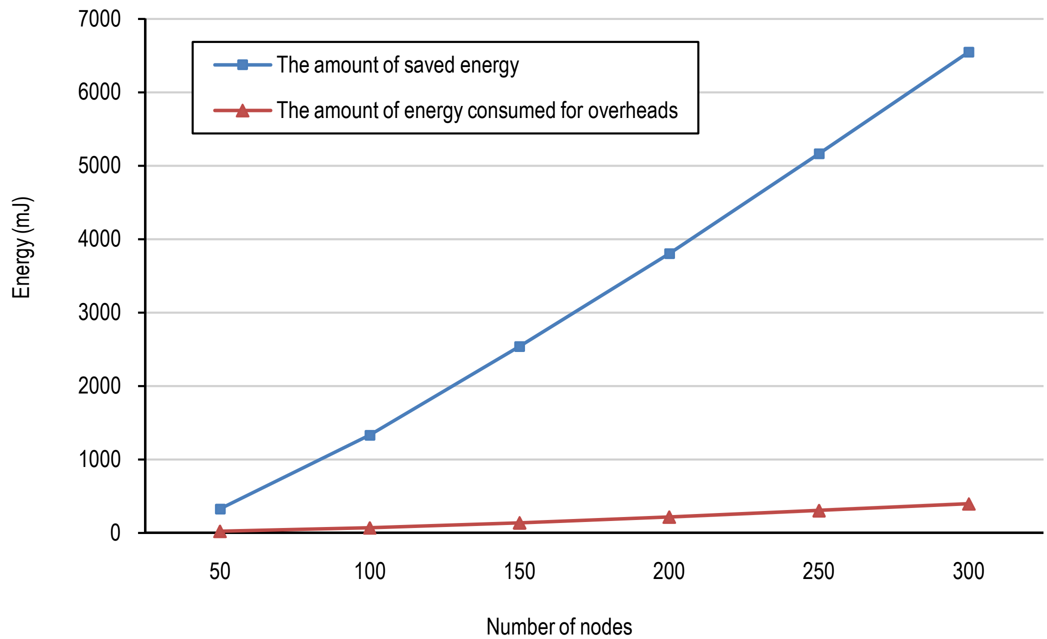


Figure 25. The average amount of energy saved in network during each monitoring period (T) by distributed IICC (clustered with γ=0.6), and the energy consumed for overheads, (synchronization, cluster maintenance and getting up-date values of residual energy of cluster members), during each T for different node densities

F. CONCLUSIONS

In this chapter the methods of node selection and scheduling in order to energy efficient monitoring were presented. ICC offers intra cluster cooperation for the clusters established by SCM (Chapter IV), while IICC offers intra and inter cluster cooperation in MCM clusters.

According to the results of the proposed schemes, both of collaborative schemes considerably raise the energy conservation capability of the nodes thus increase the network lifetime. In ICC the number of active nodes during each monitoring period is equal to the number of established clusters (N_C) in the network while in IICC scheme because of collaboration between clusters, the number of active nodes is less than of ICC. In consequent, both the difference between the number of active nodes in collaborative schemes and also the difference between both of them and the un-collaborative scheme raises with increasing the density of the network. This is the result of increasing the collaboration potential.

It is worth to notice that activating all the deployed nodes highly results in redundant monitoring especially in the dense deployments; for example, in a network consisting of 300 nodes the sum of FoVs of nodes is 3.8 times of the covered area by the nodes which is 95% of the sensing area. But, collaborative schemes reach to high levels of coverage with activating considerably less number of nodes than the un-collaborative scheme by intra and inter cluster coordination. Therefore, with a dense random deployment, we can put all the sensing area under the covering of sensor nodes and then with scheduling the nodes, the area is covered during each monitoring period with a high level of coverage avoiding redundant sensing.

Higher clustering scales result in greater percentage of covered area. The reason is behind of the fact that higher clustering scales yield establishing more number of clusters, and with increasing of the number of clusters, the number of awakened nodes during each monitoring period and consequently the covered area are increased. However, it is worth to notice that increasing of the number of awakened nodes in monitoring periods, grows the power consumed for monitoring and decrease the lifetime of the network nodes.

Therefore, there is a trade-off between coverage ratio and network lifetime for selection a value for clustering scale. The appropriate value depends on the application desired from the network, to reach more coverage of the sensing area, higher clustering scale is selected at the cost of consuming more amount of energy for monitoring.

The coverage area of IICC is a little less than of ICC while the difference of the number of their active nodes is more considerable than their difference in the percentage of covering the area. The reason is that in ICC some of the active nodes during a T overlap each other while they belong to different clusters and monitor the area at the current T on behalf of their clusters; in ICC a node can be a member of only one cluster even if that has enough overlapping with several CHs. This redundant monitoring is prevented by inter-cluster coordination in IICC with its common nodes but the coverage is slightly decreased also.

The proposed node management mechanisms impose some extra communications within the clusters and sometimes between the intersecting clusters. In both schemes, distributed ICC and IICC, CHs use a message exchanging scheme within clusters for member synchronization, cluster maintenance and getting up-date values of residual energy of cluster members in a periodical manner. The results and related diagrams shows the energy consumed for overheads is negligible in comparison to the saved energy by the schemes, and also to the energy required by multimedia sensing and processing tasks.

This chapter offered the solution of an important need in the field of sensor node management for WMSNs. Many approaches have been proposed to optimize scheduling of wireless scalar sensor nodes in the literature. But, the optimization methods for sensor management developed for wireless sensor networks are hard to apply to multimedia sensor networks. Such sensor management policies usually employ the clustering methods which form clusters based on sensor neighbourhood or radio-coverage. But, as it was mentioned before, because of the main difference between directional sensing region of multimedia sensors and the non-directional sensing range of scalar sensors, these schemes and other coverage-based techniques designed for WSNs, do not satisfy WMSNs. Here, the proposed node management mechanisms and the clustering method on which the management schemes are based, are totally designed considering the FoV and the constraints of multimedia sensor nodes.

It is worth to notice that due to the proposed methods, the sensing subsystems of the network nodes are coordinated to optimize the number of active nodes during each monitoring period and to avoid redundant and correlated sensing. Consequently, the amount of generated data in monitoring periods is reduced and thus the processing and communication subsystems meet an optimized amount of data to be processed and/or transmitted. Therefore, the capability of saving energy for the three subsystems is raised and the network lifetime is considerably prolonged.

The publications presenting the contributions corresponding to this chapter contents are as the list below.

[Alaei-3]. Mohammad Alaei, Jose M. Barcelo-Ordinas, “A Collaborative Node Management Scheme for Energy-Efficient Monitoring in Wireless Multimedia Sensor Networks,” Wireless Networks Journal (Springer), DOI 10.1007/s11276-012-0492-6, 2013.

[Alaei-4]. I. T. Almalkawi, Mohammad Alaei, M. Guerrero-Zapata, Jose M. Barcelo-Ordinas, J. Morillo-Pozo, “Energy Efficiency in Wireless Multimedia Sensor Networks,” IEEE MMTC e-letter, Volume 6, Number 12, December 2011.

[Alaei-6]. M. Cesana, A. C. Redondi, N. Tiglao, A. M. Grilo, Jose M. Barcelo-Ordinas, Mohammad Alaei, P. Todorova, “Real-time Multimedia Monitoring in Large-Scale Wireless Multimedia Sensor Networks: Research Challenges,” The 8th Euro-NF Conference on Next Generation Internet (NGI 2012), Sweden, June 2012.

[Alaei-8]. Mohammad Alaei, Jose M. Barcelo-Ordinas, “Priority Based Node Selection and Scheduling for Wireless Multimedia Sensor Networks,” IEEE 6th International Conference on Wireless and Mobile Computing, Networking and Communications (IEEE WiMob 2010), Niagara Falls, Canada, October 2010.

Chapter VI

A TIME DIVISION CLUSTER BASED SCHEDULE FOR SCM CLUSTERS

A. INTRODUCTION

This chapter describes a schedule designed for SCM clusters. The goal is to optimize the monitoring period for each cluster depending on the number of its members and the clustering scale. By this way, each cluster will have its specific period which will be the period of its cluster members to monitor their region. Moreover, for each cluster a time interval is calculated to be the time slot between activating the cluster members. So, each member of a given cluster monitors the area with the cluster´s period while during the sleep of each member, all other cluster members awake and monitor in an intermittent way with the time slot between them. As we will see in the next sections, this scheduling scheme yields a development in power conservations in nodes and thus network lifetime with optimizing the monitoring period. The publications [Alaei-1], [Alaei-5] and [Alaei-11] (see Section B. 4, Chapter I), correspond to the contents of this chapter.

Let us consider as baseline mechanism, a non-collaborative duty-cycled scheme in which every node independently awakes with a period of time T (see Figure 26.a) and senses the area (i.e., takes a picture and performs object detection) without coordination among nodes as in [80]. The objective of the proposed collaborative mechanism in this chapter is to produce a cluster-based duty-cycled scheduler based on Single-Cluster-Membership (SCM, chapter IV) in which: (i) Each node is awakened and senses the area with a reliable period of $T_P>T$ taking advantage of the overlapping among nodes in the cluster, thus, saving energy and increasing network lifetime. Each cluster will have its own T_P, determined according to the cluster-size and the clustering scale (γ). All clusters concurrently sense their domains. (ii) During the sleeping period of each member of a given cluster, other nodes belonging to the cluster are awakened with intervals of $T_{interval} < T$ ($T_{interval}$ is equal to: T_P/C_{size}) sequentially in an intermittent manner by the cluster head, (see Figure 26.b). Accordingly, each cluster has its own $T_{interval}$ in terms of its T_P and its cluster-size.

B. CLUSTER-BASED T_P AND $T_{INTERVAL}$ COMPUTATION

Let us see the potential of cooperative node monitoring in clusters in terms of sensor area coverage. We define the Maximum Cluster Coverage Domain (MCCD) parameter for a cluster as the maximum monitoring area which is covered by that cluster. Since each cluster is established considering a clustering scale equal to γ, the MCCD can be computed as follows (C_{size} is the size of the cluster):

$$\begin{aligned} MCCD &= \gamma \cdot A_{FoV} + (1-\gamma) \cdot A_{FoV} \cdot C_{size} \\ &= (C_{size} - \gamma \cdot (C_{size} - 1)) \cdot A_{FoV} = \beta \cdot A_{FoV} \end{aligned} \tag{21}$$

where:

$$1 \le \beta = C_{size} - \gamma \cdot (C_{size} - 1) \tag{22}$$

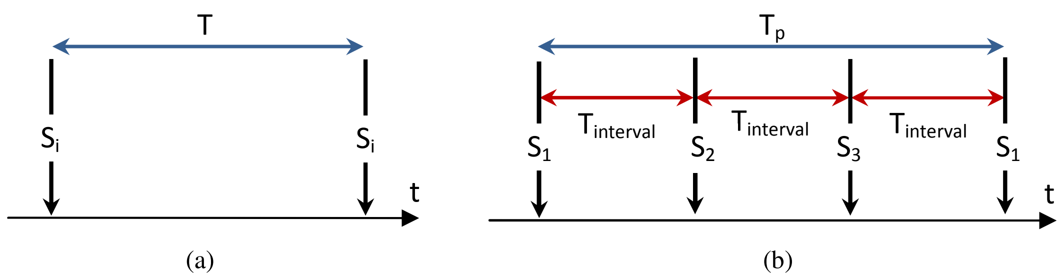


Figure 26. (a) Period of awakening a given node in the un-collaborative scheduling. (b) Scheduling for a cluster consisting of three members (S_1, S_2, S_3)

The effective cluster covering domain can be inferior to the MCCD calculated by (21) since some nodes can overlap more than the region determined by γ. Since MCCD gives us an upper bound on the area covered by the cluster, using MCCD will allow us worst-case dimensioning. Factor β represents the increment of area that the cluster senses with respect to an individual sensor. When each node of a cluster obtains an image from its FoV, a part of the related MCCD with a ratio at least equal to 1/β respect to the MCCD is captured whereas this part includes overlapped areas of other nodes in the cluster. Sensing the environment by each member delivers information not only from the FoV of the active node but also from some overlapped parts of other nodes in the same cluster: at least $\gamma \cdot A_{FoV}$ of the area is common to the cluster head and more than $1/\beta$ of the MCCD is monitored. For example, in a cluster consisting of just 2 members, assuming a clustering scale of $\gamma = 0.5$, the MCCD is $1.5 \cdot A_{FoV}$. Thus, when each of the two members of the cluster is activated and monitors the environment, an area of one FoV is captured that is at least 2/3 of the whole MCCD of the cluster.

In order to compute T_P we will consider the MCCD area. By awaking each member of a given cluster, in average, a part of the related MCCD with a ratio equal to $1/\beta$ is captured (Equation (22)). Note that the MCCD is an area of $\beta.A_{FoV}$ and is sensed by C_{size} overlapping members, thus sensing the environment by each node delivers information not only from the FoV of the awakened node but also from some overlapped parts of the FoV of other nodes in the same cluster. Then, we may define the node duty-cycle period as:

$$T_P = T \cdot \frac{C_{size}}{\beta} = T \cdot \frac{C_{size}}{C_{size} - \gamma \cdot (C_{size} - 1)} \qquad (23)$$

Note that the T_P is proprietary for each cluster in terms of its cluster-size and clustering scale. As it was mentioned before, the MCCD calculated by Equation (21) is the maximum covering domain of a cluster while the effective cluster covering domain may be less than MCCD since some members of a given cluster may overlap more than the region determined by γ. Consequently, a given cluster can cover an area less than $\beta \cdot A_{FoV}$. Thus, using β gives us the lowest period T_P and thus the most reliable one since lower values of β would increase the period T_P. On the other hand, members of a cluster are awakened sequentially to sense their environment in an intermittent way with the time intervals equal to $T_{interval}$ between them:

$$T_{interval} = \frac{T_P}{C_{size}} = \frac{T}{C_{size} - \gamma \cdot (C_{size} - 1)} \leq T \qquad (24)$$

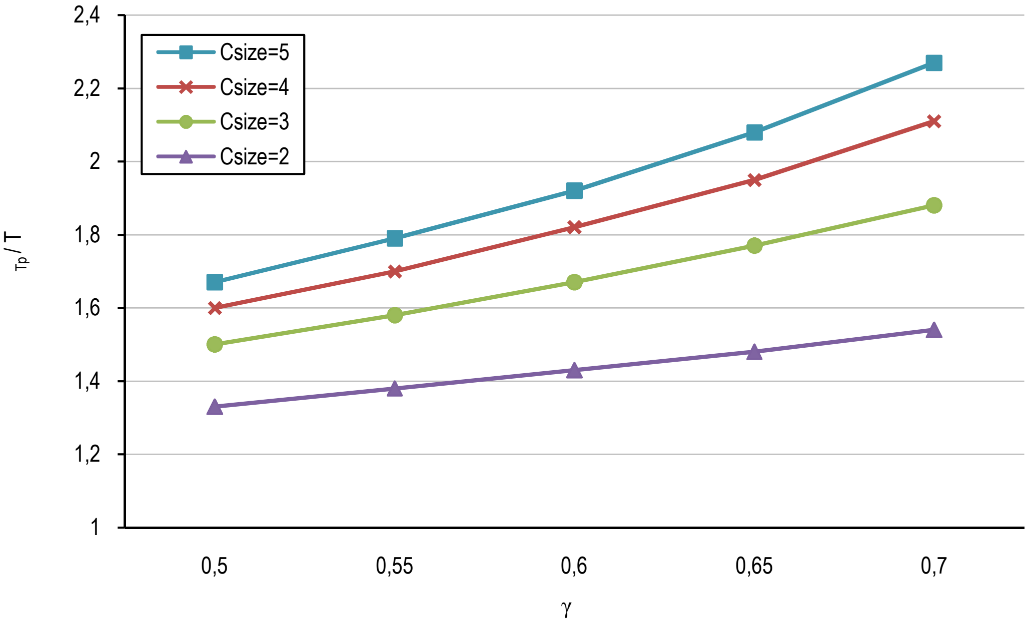
Let us consider Figure 26.b and for example a cluster with three members, $C = \{S_1, S_2, S_3\}$, cluster-head S_1 and $\gamma = 0.5$. Every node will be awakened every $T_P = 1.5 \cdot T$ seconds and the area will be monitored every $T_{interval} = 0.5 \cdot T$ seconds. As can be observed, every sensor is awakened with a period higher than the non-collaborative scheme but the area is monitored more times. Then, the area duty-cycled frequency is increased while the sensor duty-cycled frequency is reduced. Algorithm 4 shows the procedure.

Algorithm 4. Cluster-based cooperative scheduling for object detection

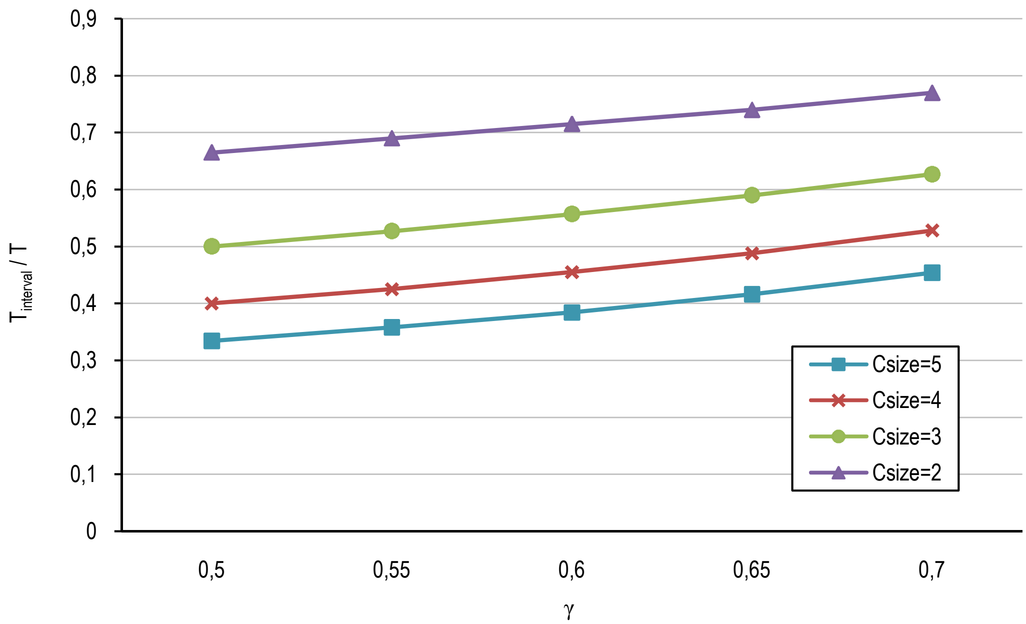
The algorithm pseudo code

1: **For all** C_j // all clusters in parallel //
2: i = 0 // start with the first member of each cluster //
3: Wake up member number i
4: Capture an image and then call object detection
5: **If** (detection==true)
6: Send the image to sink
7: **End-If**
8: Delay ($T_{interval}$) *// each cluster has a proprietary $T_{interval}$ //*
9: i = i+1(mod C_{size}) *// select next node of the cluster //*
10: **Goto 3**
11: **End-For**

Figure 27 shows the evolution of T_P and $T_{interval}$ as a function of γ for several C_{size}. Both parameters are normalized by T. We first have to notice that for different cluster-sizes, $T \leq T_P \leq T/(1-\gamma)$; thus, the duty-cycle frequency at which a specific node is awakened is decreased by a factor between 1 and 1-γ , depending on the value of C_{size}. On the other hand, a member of the cluster will be on duty every $T_{interval}$ seconds. Note that $T_{interval}$ will be shorter than T and will be decreased as C_{size} increases. This means that the area is monitored more frequently although every sensor monitors with lower frequency than in the case of un-clustered mechanism (the baseline). The reason is justified in how the clusters are formed; any sensor of the cluster overlaps with the cluster-head by at least an area of $\gamma\cdot A_{FoV}$. Thus, when a sensor enters in duty, he will monitor an area equal to $\gamma\cdot A_{FoV}$ overlapped with the cluster head and an area equal to $(1-\gamma)\cdot A_{FoV}$ which in the worst case, does not overlap with any other member of the cluster.



(a)



(b)

Figure 27. (a) Sensor node duty-cycle period T_p/T, (b) Cluster duty-cycle period $T_{interval}/T$.

C. POWER CONSERVATION EVALUATION

To evaluate the proposed scheduling scheme in terms of power conservation, we compare the cooperative scheduled scheme with an architecture consisting of N nodes performing object detection without coordination among them as [12,80,83], in which, nodes are independently awakened with a time period of T. We note that the evaluation is over the sensing subsystem and the communication subsystem is not taken into account.

The energy consumed in the network for object detection by N nodes during a duty-cycle interval of T in the non-collaborative scheduling is:

$$E = N \cdot (T_{sleep} \cdot P_{sleep} + E_{w\_up} + E_{cap} + E_{detect}) \qquad (25)$$

where T_{sleep} and P_{sleep} are the period and power consumption for a node in sleep mode. E_{w_up}, E_{cap} and E_{detect} respectively are the energies consumed in waking up a node, capturing a picture and performing object detection.

Let us now consider the cooperative scheduling algorithm in a clustered tier/network. Both, the interval between waking up consecutive nodes in the same cluster and the period of waking up a given node are functions of the cluster-size of the cluster which the nodes belong to. In one hand, in clusters with high cluster-size, $T_{interval}$ is short and thus cluster duty-cycle frequency is increased. On the other hand, higher number of nodes in the cluster causes longer periods T_P for awaking a given node of the cluster and thus yields an enhancement for power conservation in cluster's members. Assuming average cluster-size for all clusters in the tier/network, T_P will be:

$$T_P = \frac{T \cdot \mu_{C_{size}}}{\mu_{C_{size}} - \gamma \cdot (\mu_{C_{size}} - 1)} \qquad (26)$$

where T is the base period for waking nodes in the base un-coordinated tier.

Figure 28 shows the evolution of T_P normalized by T (*i.e.*; μ_{Csize}/β) for several node densities and clustering scales, γ. We may observe that the node average duty-cycle frequency is reduced by factors that are, for example, on the order of 0.78 for a 200 node network and a scale factor of $\gamma = 0.6$.

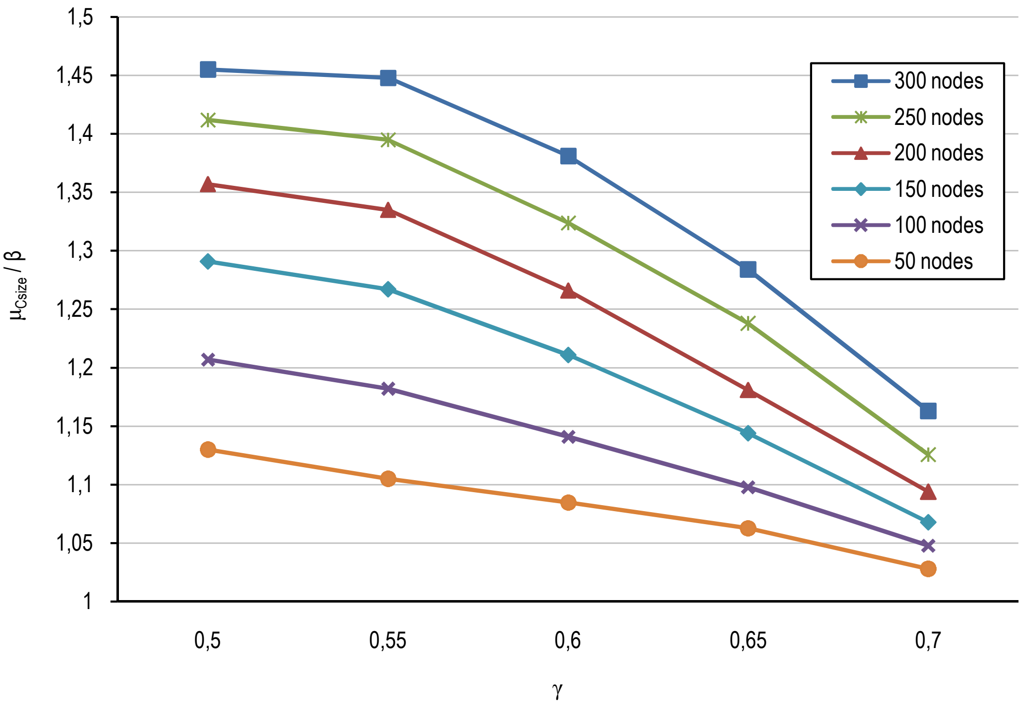


Figure 28. The average of coefficient μ_{Csize}/β for several node densities and clustering scales (γ)

Consequently, the total amount of averaged consumed energy by nodes for object detection in the coordinated tier during T_P will be:

$$E_P = E + N \cdot P_{sleep} \cdot (T_P - T) \tag{27}$$

From (26) and (27) we have:

$$E_P = E + \frac{\gamma \cdot T \cdot (\mu_{C_{size}} - 1)}{\mu_{C_{size}} - \gamma \cdot (\mu_{C_{size}} - 1)} \cdot N \cdot P_{sleep}$$

So:

$$\frac{E_P}{T_P} = \frac{E \cdot (\mu_{C_{size}} - \gamma \cdot (\mu_{C_{size}} - 1))}{T \cdot \mu_{C_{size}}} + \frac{\gamma \cdot (\mu_{C_{size}} - 1) \cdot N \cdot P_{sleep}}{\mu_{C_{size}}}$$

$$\frac{E_P}{T_P} = (1 - \frac{\mu_{C_{size}} - 1}{\mu_{C_{size}}} \cdot \gamma) \cdot \frac{E}{T} + \frac{N \cdot \gamma \cdot (\mu_{C_{size}} - 1)}{\mu_{C_{size}}} \cdot P_{sleep}$$

where $(0 < \gamma < 1)$ and $(\mu_{C_{size}} > 1)$

Therefore, the consumed power is:

$$P_P = \lambda \cdot P + \sigma \cdot P_{sleep} \tag{28}$$

where:

$$\lambda = (1 - \frac{\mu_{C_{size}} - 1}{\mu_{C_{size}}} \cdot \gamma) \quad , \; 0 < \lambda < 1$$

$$\sigma = \frac{N \cdot \gamma \cdot (\mu_{C_{size}} - 1)}{\mu_{C_{size}}} \quad , \; 0 < \sigma < \gamma \cdot N$$

Parameter P in Equation (28) is the power consumed in the network with the base un-coordinated mechanism. The consumed power in our scheme (P_P) is reduced by a factor λ with respect to P. The λ factor depends on the average cluster-size and the clustering scale factor. As can be observed from Equation (28) increasing μ_{Csize} produces lower values of λ, and thus a saving in energy with respect the uncoordinated system. For example a $\mu_{Csize} = 1.5$ (100 nodes with $\gamma = 0.5$) produces a $\lambda = 1 - \gamma/3 = 0.83$ while a $\mu_{Csize} = 2.15$ (200 nodes with $\gamma = 0.5$) produces a $\lambda = 1–0.53 \cdot \gamma = 0.73$. The other term ($\sigma \cdot P_{sleep}$) in Equation (28) is due to the fact of taking nodes to sleep mode in during ($T_P > T$) and then nodes sleep $T_p – T$ more time than in the un-clustered scheme.

Figure 29 illustrates the impact of factor λ in Equation (28) in terms of node densities for several clustering scales. From this figure we can see that in high node densities, the factor λ is more beneficial since μ_{Csize} is higher and thus there is more potential of cooperation among nodes.

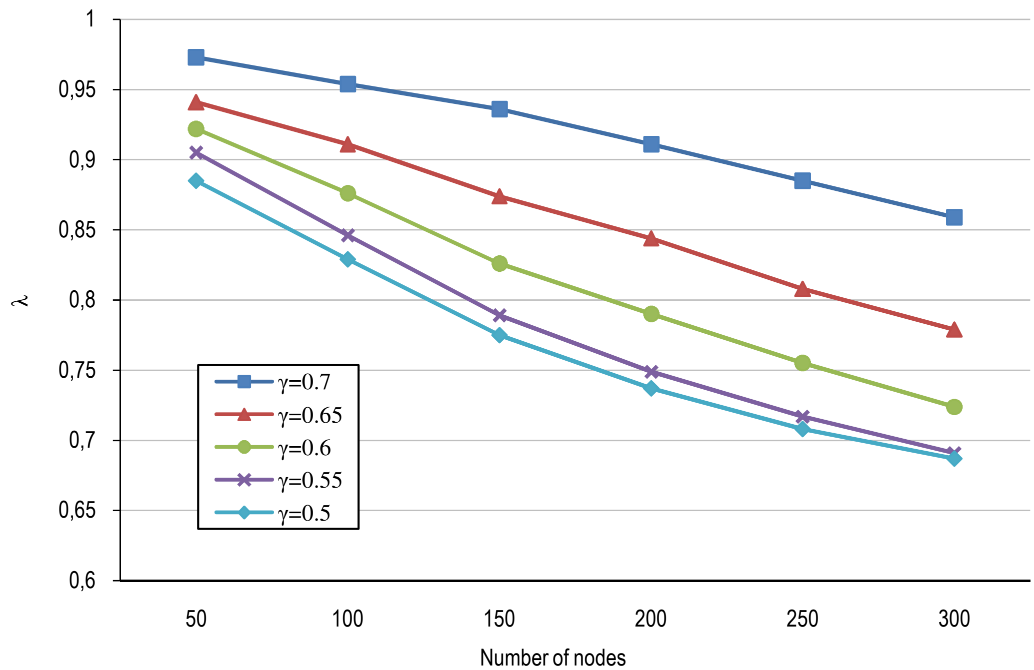


Figure 29. Factor λ in cooperative scheduling for several clustering scales

Figure 30 shows the consumed power (P) in the un-coordinated network (baseline) for object detection in four cases of period of duty-cycle for different node densities. The consumed power has been computed for nodes consisting of Cyclops as camera sensor embedded in the host MICAII [88], similar to [80].

For instance, in the case without coordination, the power consumed in a tier consisting of 200 nodes that performs object detection with a duty cycle of T=5 second, is 1.344 watts. In the coordinated network with the same number of nodes and a clustering scale of 0.5, the power consumed by the network would be reduced by a factor λ of 0.737 (see Figure 29) at the cost of increasing 52.60 mW, ($\sigma \cdot P_{sleep}$). This means a power consumption of $1.344 \cdot 0.737 + 0.0526 = 1.043$ Watts implying a reduction of 22.39%. Thus, in this case, the Prolongation Lifetime Ratio (PLR) would be of 1.344/1.043 = 1.289.

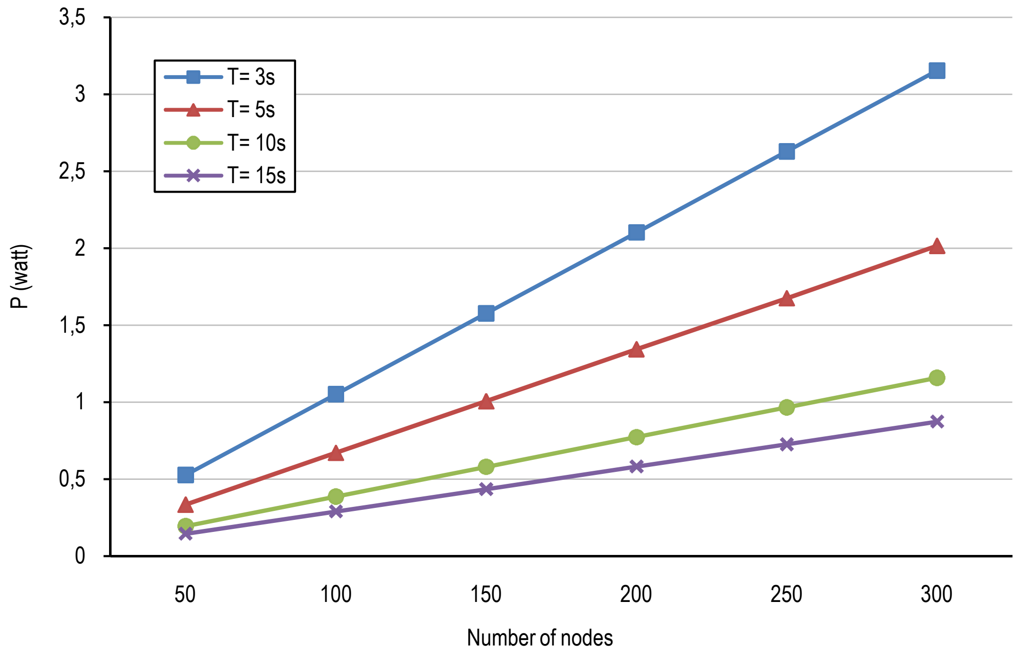
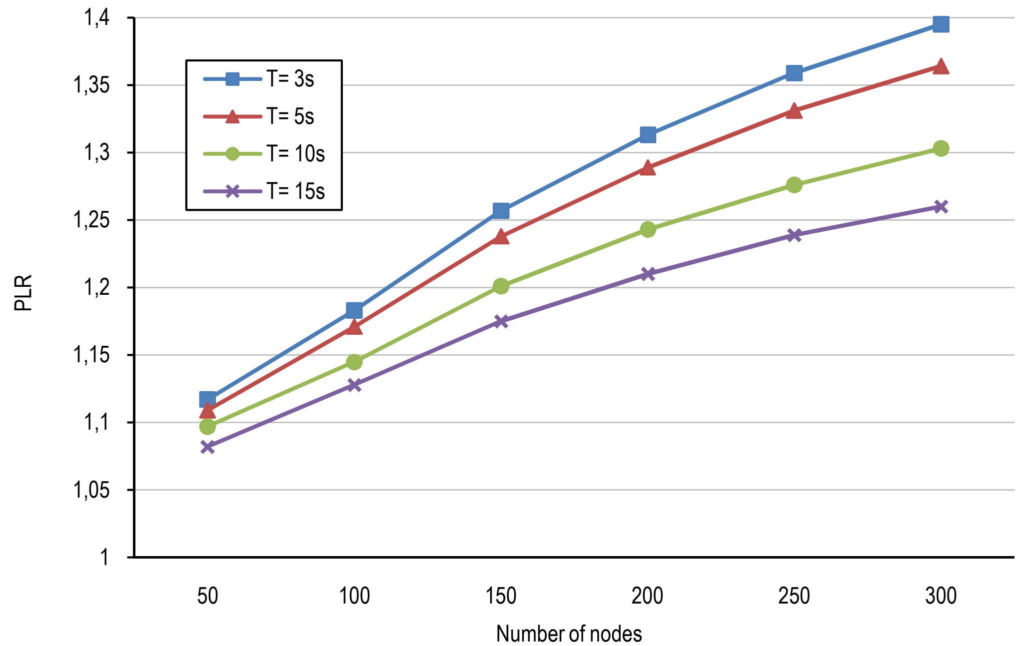
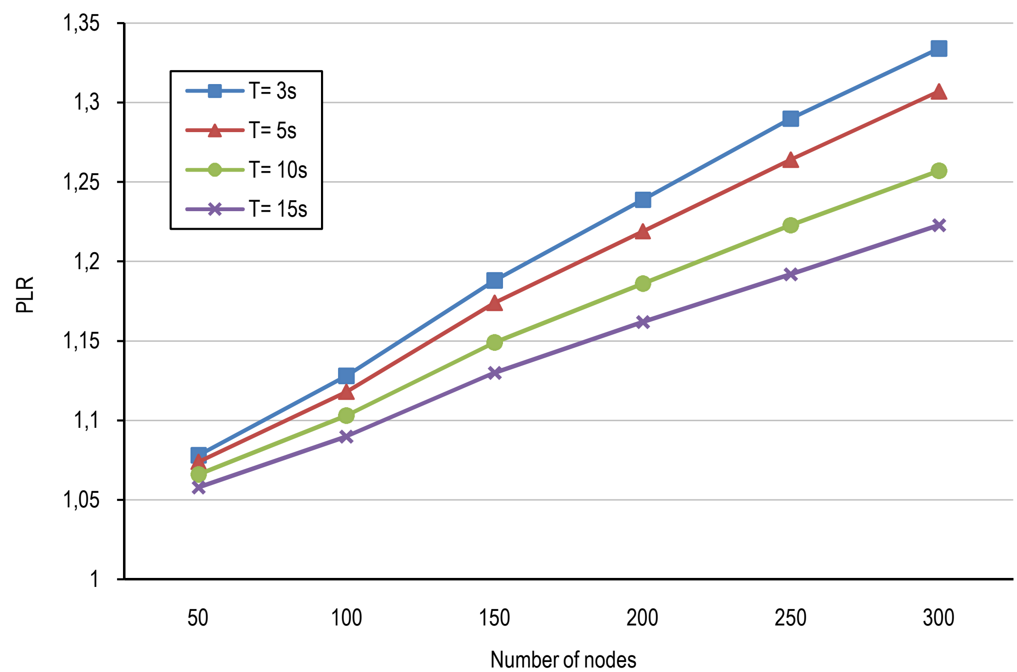


Figure 30. Consumed power (P) for a non-cooperative tier/network of nodes consisting of Cyclops.

Figure 31 shows the prolongation lifetime ratio assuming a clustering scale of 0.5 and 0.6 for different node densities in four cases of duty-cycle (T). Networks with high number of nodes have higher capability for cooperation and thus their nodes can conserve considerable amount of energy comparing to sparse networks and consequently, have longer prolonged lifetime. The figure indicates the more prolongation lifetime for dense networks.



(a)



(b)

Figure 31. Prolongation Lifetime Ratio (PLR) for different node densities in the clustered tier with a clustering scale equal to (a) 0.5, (b) 0.6, in four states of base awakening period

Finally, the lifetime increment in a deployment of 250 nodes is shown in Figure 32. The lifetime is normalized to L_t, the time to which all nodes would deplete their batteries without coordination. This lifetime only is due to sensing and thus forwarding and other tasks are not taken into account. We assume that all nodes under an uncoordinated duty-cycle scheme will die at the same time with a difference of T seconds among them (*i.e*, $L_t \pm T$). Note, that if we include the radio subsystem, the lifetime of every node would be less than L_t. Moreover, L_t will depend on the initial energy stored in the nodes. As can be observed, single nodes (clusters having only one node) are the first set of dying nodes (i.e., dying at L_t). Then, cluster members of clusters of size two nodes die at 1.3·Lt and clusters of size three die at $1.43 \cdot L_t$. We may observe, thus, increments of 30% and 43% in the lifetime of the sensors for these cluster sizes.

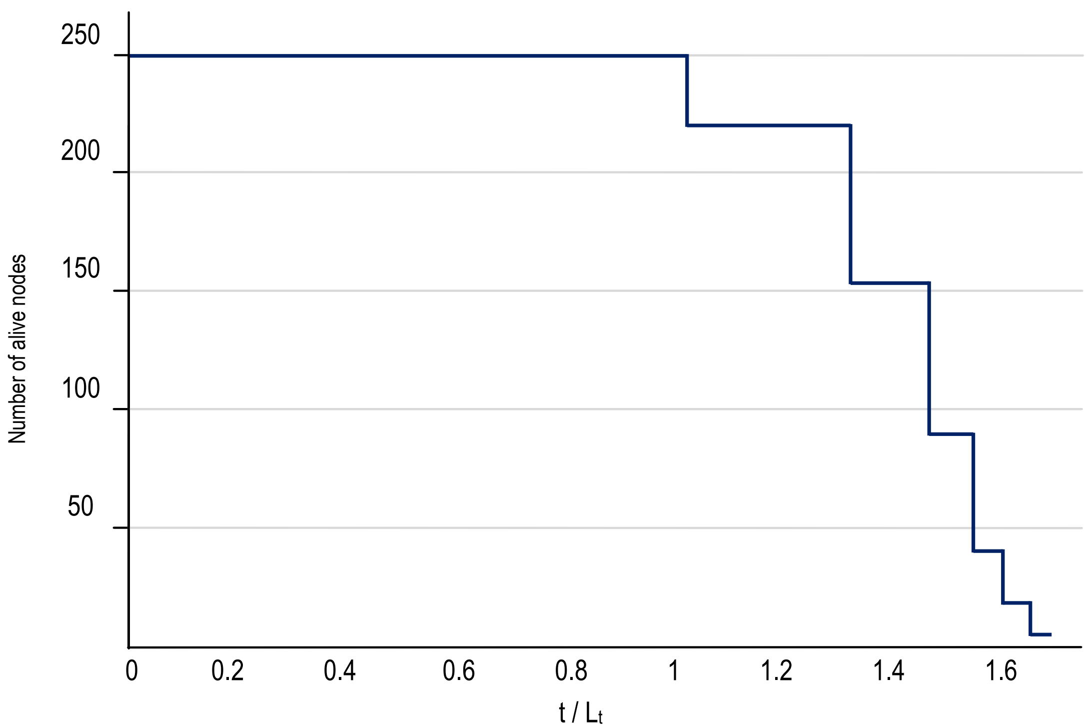


Figure 32. Lifetime of nodes in a network with 250 nodes, single nodes are the first set of dying nodes (*i.e.*, dying at L_t). Larger clusters can save more amount of energy and be alive for a longer time.

D. CONCLUSIONS

This chapter presented a scheduling approach for disjoint clusters which optimize the monitoring period of each node depending on the size of the cluster which the node belong to and the clustering scale. Cluster members awake to monitor their region in a serial manner with a specific time interval between them.

The calculations prove that larger cluster-sizes yield higher coefficient of reducer of consuming power in the network. Also, results show that the networks with higher node density have higher capability for cooperation since have larger cluster sizes and thus their nodes can conserve considerable amount of energy comparing to sparse networks and consequently, have longer prolonged lifetime. Single nodes (clusters having only one node) are the first set of dying nodes (i.e., dying at L_t). Then, cluster members of clusters of size two nodes die at 1.3·Lt and clusters of size three die at $1.43 \cdot L_t$. We may observe, thus, increments of 30% and 43% in the lifetime of the sensors for these cluster sizes.

The proposed scheduling method prolongs the network lifetime which is one of the main constraints of WMSNs. The consuming power of wireless sensor nodes is supplied by a non-rechargeable embedded battery. On the other hand, because of the huge amount of multimedia data, all the applications on them (sensing, processing or transmitting) are quite power costly. It is noticeable that multimedia data, for example an image, consists of at least 1KB while a scalar data like a temperature degree contains one or two Bytes. Therefore, always conserving energy of the nodes is our problem to maintain the network for a longer time. The described work in this chapter is a response to this problem.

Our publications which their contributions correspond to this chapter contents are as follows.

[Alaei-1]. Mohammad Alaei, Jose M. Barcelo-Ordinas, Book Chapter: “Power Management in Sensing Subsystem of Wireless Multimedia Sensor Networks,” Wireless Communications and Networks-Recent Advances, Dr. Eksim (Editor), ISBN 979-953-307-394-0, INTECH, March 2012.

[Alaei-5]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "A Method for Clustering and Cooperation in Wireless Multimedia Sensor Networks," Sensors Journal (MDPI), Vol 10, Issue 4, pp. 3145-3169, March 2010.

[Alaei-11]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "A Cluster-based Scheduling for Object Detection in Wireless Multimedia Sensor Networks," The 5th ACM International Symposium on QoS and Security for Wireless and Mobile Networks (ACM Q2Swinet 2009), Tenerife, Canary Islands, Spain, October 2009.

Chapter VII

An Acoustic-Visual Collaborative Hybrid Architecture for WMSNs

A. *INTRODUCTION*

Employing other kind of sensor nodes to be assistant of visual sensors in the multimedia tasks, is a way of keeping the visual sensors from depleting their residual energy. In this chapter we establish a collaborative surveillance mechanism in a multimedia architecture based on both acoustic and visual sensor nodes. All sensor nodes are deployed randomly. Acoustic sensor nodes perform object detection and object localization while visual sensors have the responsibility of object monitoring. The main objective is to increase the energy conservation capability in visual sensor nodes in a surveillance mechanism with employing acoustic sensors to collaborate with visual sensor nodes.

Acoustic sensors sense a broad sampling range and the energy consumed by an acoustic sensor in both sensing and processing modes is considerably less than of the visual sensors as well as the complexity of computation on the audio data sensed by them is less than image data processing in visual sensor nodes. Accordingly, designating the acoustic nodes to detect and localize the objects instead of visual sensor nodes, allows the visual nodes to save their energy. So that, a visual sensor node is awakened by acoustic sensors only if an object/event, which has been detected and localized by acoustic sensors, lies in its FoV; the node monitors the object, sends the captured images and finally goes to sleep mode again when the object leaves its FoV. Also, in-node processing is utilized instead of data communication as much as possible.

[Alaei-2] and [Alaei-7] are the publications corresponding to the contents of this chapter, (see Section B. 4, Chapter I).

B. HYBRID ARCHITECTURE OF VISUAL AND ACOUSTIC SENSORS

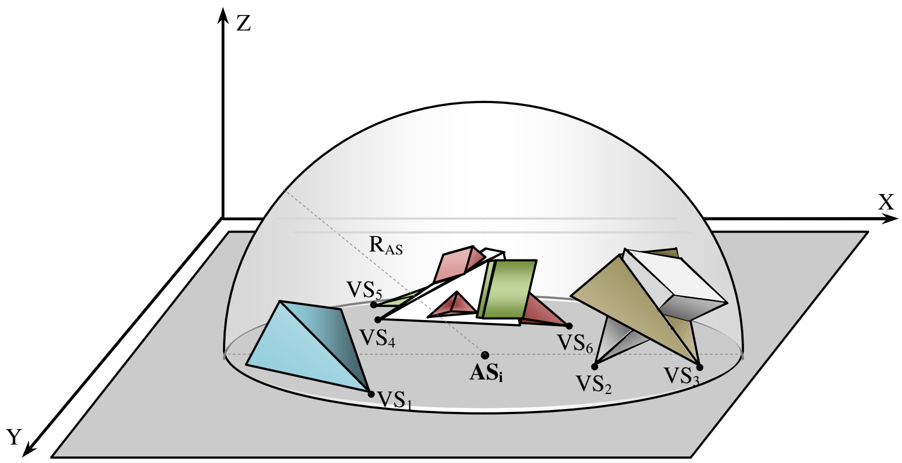
The proposed multimedia sensor network is composed of stationary acoustic and visual sensor nodes. All sensor nodes are randomly deployed in a three-dimensional sensing field. It is assumed that each node is equipped to learn its location information via any lightweight localization technique for wireless sensor networks.

Each acoustic sensor node is equipped with one microphone. The way that acoustic signal propagates with the distance from the source is dependent on the size and shape of the source, the surrounding environment, prevailing air currents and the frequencies of the propagating acoustic signal. We assume the acoustic signal propagation in the free air and the acoustic source acts as an omni-directional point. An additive white Gaussian noise from the environment, n(t), which is assumed to be uncorrelated with the source acoustic signal, affects on the propagated acoustic signals.

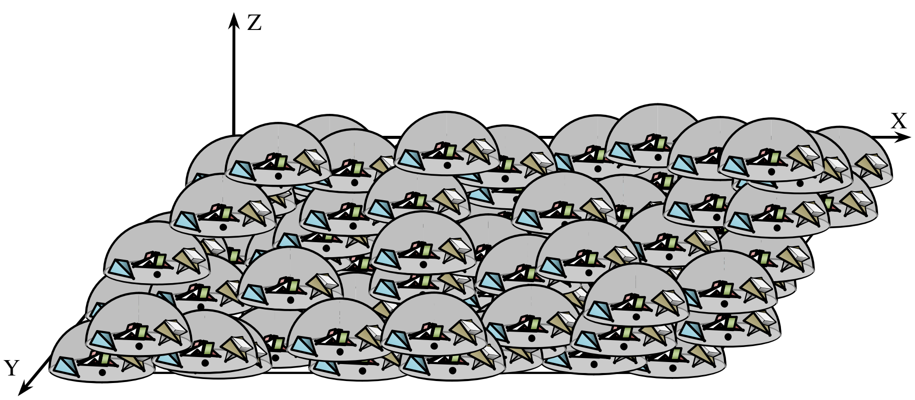
$$r(t) = s(t) + n(t) \tag{29}$$

Each visual sensor node includes a low power, low resolution and low price CMOS camera with a fixed lens. Each visual node can capture images from its directional FoV which is dependent on the position and orientation of the node in the sensing field. Figure 33 illustrates the sensing region of an acoustic sensor node (AS_i) and some visual sensor nodes (VS_j, j=1,…,6) deployed around that on the floor. As the figure shows, visual sensors monitor some parts of the sensing region of the acoustic sensor.

We employ acoustic sensors to detect object/events based on the sound propagated by them and then to calculate the position of the objects in the sensing area. When an object is detected, acoustic sensor nodes around the detector, collaboratively compute the object position based on the amount of energy received by each of them from the propagated acoustic signal of the object. To this purpose, as we will see in Section D.2, an enough dense deployment of acoustic sensor nodes is required to have a sufficient number of nodes participating in computation of the position of an occurred object/event in any part of the sensing area.



(a)



(b)

Figure 33. a) An example of sensing region of acoustic and visual sensor nodes which are deployed on the floor, b) A given random deployed network

Visual sensor nodes are employed to monitor the detected objects. Obviously, an object would be captured in images if it lies within the FoV of visual sensor(s). Thus, to reach a high level of visual covering of the sensing area, we densely deploy the visual sensor nodes; a denser network covers higher percentage of the sensing area.

Since we utilize dense deployments of both acoustic and visual sensors, to prevent energy wasting of redundant overlapping sensing and processing, nodes are clustered. Acoustic sensors are clustered by the scheme HEED, introduced in [89] and visual sensor nodes are clustered by SCM (Section C, Chapter IV). In both clustering algorithms, the nodes having a considerable common sensing area are grouped in the same clusters. So, the cluster members sense the area similarly and thus can alternate in sensing task. Since the acoustic sensing range is a globe, the distance between nodes can indicate their common sensing area; when two acoustic sensor nodes are close enough, their sensing globe have a considerable common area. But, in visual sensor nodes the FoV is directional and thus vicinity of nodes in not the criteria of clustering. Two adjacent visual nodes can have such orientations that their FoVs do not have any intersection point. So, for the visual nodes, the overlapping FoV of nodes has to be calculated to cluster them. For example, in Figure 33.b some visual nodes FoV overlap each other.

C. HYBRID COLLABORATIVE SURVEILLANCE

The proposed algorithm consists of three phases: Object Detection, Localization and Monitoring. Detection and localization phases are performed by the acoustic sensor nodes and the monitoring phase is accomplished by the visual sensor nodes. Following, we proceed to each phase in details.

C.1. OBJECT DETECTION

During the detection phase, acoustic sensors are sensing the environment for detecting a probable object or event. The environment sensing task is divided among acoustic clusters. In each cluster, the cluster members are awakened by the cluster-head in an intermittent way with a sensing time period (T_S). So, all acoustic clusters are sensing the environment in parallel and independent of each other, by one active node in each cluster at every T_S.

Each sensor senses its range in its intermittence period (T_S) in a duty-cycled manner while all the other cluster members are in the sleep mode of sensing subsystem. Each awakened node samples its sensed signal to distinguish an object/event or the noise of environment; in the case of object/event detection, goes to localization phase otherwise goes to the sleep mode.

C.2. OBJECT LOCALIZATION

When an object/event is detected by an active acoustic sensor node, which is mentioned after this as the detector node, object localization is started. During this phase, the detector along with its neighbors calculates the object coordinates in the sensing field. For this purpose, the detector broadcasts an awakening message to all its neighboring acoustic sensor nodes to wake up and sense the environment for receiving acoustic signals from the detected object. As we will see later, in order to locate the object/event, multiple energy values of received signals are required. Each of the detector neighbors that sense a signal of the object, acknowledge the detector node with its coordinates in the sensing area and the received energy level value from the object. If the number of received information by the detector from the neighbors is enough to calculate the position of the object, the detector calculates the coordinates of the object in the sensing area and broadcasts that to all of visual clusters deployed in its neighborhood.

Following, we proceed to the procedure of finding the object coordinates. Let there be multiple acoustic sensor nodes which receive signal of the object emitting omni-directional acoustic signal. The energy of the signal received by the acoustic sensor number i (AS_i) over the time interval (T_A) is expressed as follows [90]:

$$Y_i^{T_A} = g_i \cdot \frac{Y_O^{T_A}}{|P_O - P_i|^2} + N_i^{T_A} \tag{30}$$

In (30), $Y_O^{T_A}$ denotes the energy emitted by the object during the time interval. P_O and P_i are respectively the position of the object and AS_i in the sensing area, g_i is the gain factor of the sensor node and N is the noise energy added during T_A.

For the object as a point source of the signal s(t), the energy emitted during T_A is denoted by $E[s^2(t)]$, where $E[\cdot]$ is the function of expected value and is applied on the sampled values of s(t) during T_A.

$$Y_O^{T_A} = E[s^2(t)]_{t_1}^{t_M} = \frac{\sum_{k=1}^{M} s^2[t_k]}{M}, t_k \epsilon [0, T_A] \tag{31}$$

Based on the central limit theorem and the assumptions, n(t) in the sensor node can be approximated well using a normal distribution with a positive mean value. Therefore, the energy of the pure received signal can be calculated in the sensor node, as follows (32,33).

$$r_i[t_k + \tau_i] = x_i[t_k + \tau_i] - n_i[t_k + \tau_i] \tag{32}$$

where τ_i indicates the delay of propagating signal from the object to the sensor number i (AS_i).

$$Y_i^t - n_i^t = E\left[r_i^2(t)\right]_{t_1+\tau_i}^{t_M+\tau_i} = \frac{\sum_{k=1}^{M} r_i^2[t_k + \tau_i]}{M} \tag{33}$$

From (30) and (33), we have:

$$|P_O - P_i|^2 = \frac{g_i \cdot \sum_{k=1}^{M} s^2[t_k]}{\sum_{k=1}^{M} r_i^2[t_k + \tau_i]} \tag{34}$$

In (34), the value of $\sum_{k=1}^{M} s^2[t_k]$ and also $|P_O - P_i|^2$ which has three components, P_O=(X_o,Y_o,Z_o), are unbeknownst. Therefore, to calculate the object position, P_O, in the area, we need four equations like (34). For this purpose, the object has to be sensed by at least four acoustic sensors to achieve and solve a four-equation system.

C.3. OBJECT MONITORING

As it was mentioned in the previous subsection, after object localization, the visual clusters in the neighborhood of the detector node, receive the notification and the object coordinates sent by the detector. Then, the notified cluster heads test whether the coordinates lie in their sensing domains, as each cluster head knows the coordinates of vertices of its cluster member FoVs, this test is performed simply. If a visual cluster head finds the object coordinates in its domain, acknowledges to the detector node and also awakens those cluster members which cover the object to periodically capture images from their FoV until the object leaves the cluster domain. Leaving the cluster domain by the object is known by the background subtraction procedure which is employed in the monitoring phase; if the result of subtraction of the captured image and the initial FoV of the visual node is null, the object has left the FoV.

If any of the visual clusters neighboring the detector node does not find the object coordinates in their sensing domain, and thus the detector does not receive any acknowledgement, this means that the object is not covered by any of the visual sensors. In this case, the detector sends a message to the sink notifying the position of the object in the sensing area.

Algorithm 5. The cooperative surveillance procedure

The algorithm pseudo code

AC: Acoustic Cluster
ACH: Acoustic Cluster Head
AS: Acoustic Sensor
RN_j: Radio Neighborhood of AS_j
P_O: Position of the Object
VC: Visual Cluster
VCH: Visual Cluster Head
VS: Visual Sensor
T_M: Time period of Monitoring by visual sensors
T_S: Time period of Sensing and sampling by acoustic sensors
AC_{size}: Acoustic Cluster size

j=0
For all AC_i, i=1…N *// All acoustic clusters in parallel //*
  ACH_i awakens AS_j
  AS_j senses the environment
  If (detection)
    AS_j awakens all $AS_k \in RN_j$
    Each AS_k which detects the object, sends the sensed energy information and its location to AS_j
    AS_j calculates the P_O
    AS_j broadcasts P_O to all $VC_r \in RN_j$
    In **each** VC_r:
      VCH_r awakens all $VS_l \mid P_O \in FOV_l$
      Repeat
        Each VS_l captures an image and subtracts with its background
        Each VS_l sends the resulted image to VCH_r
        VCH_r mosaics the received images
        VCH_r sends the resulted image to the sink
        Delay (T_M)
      Until (the object leaves the sensing domain of VC_r)
  End-If
  Delay (T_S)
  j=j+1(mod AC_{size})
End-For

In the clusters covering the object, the captured images are sent to the sink by the cluster head. In order to reach the minimum data transmission and maximum level of energy saving, we apply the following techniques on the captured images in clusters: (1) *Background Subtraction,* each image captured by a visual node is subtracted with an initial background image of node's FoV view. So, the subtracted image only consists of the detected object and considerably has less number of pixels than the primary image taken by the node. Also, as it was mentioned before, background subtraction is performed to know when an object leaves the node's FoV. Each cluster member accomplishes subtraction after image capturing and sends the resulted image to the cluster head. (2) *Image Mosaicing,* [91], the cluster head mosaics all the images received from the cluster members (and also its own image), and sends the resulted image to the sink, instead of sending multiple images disjointly. As the subtracted images in the visual sensor nodes are not massive and do not have a huge amount of pixels, mosaicing them and transmitting the resulted image (as the cluster image) by the cluster head is applicable. Algorithm 5 shows the proposed surveillance procedure.

D. DISCUSSIONS AND EVALUATIONS

In this section we proceed to some discussions and comparison the proposed algorithm with other mechanisms of energy efficiency in surveillance and monitoring for WMSNs. For the evaluation, we simulate the proposed environment with C++ using the technical parameters of the products which are mentioned following.

We utilize eXtreme Scale Mote (XSM), [92], for sensing and detection of acoustic signals. XSM platform includes an Atmel ATmega 128L microcontroller and a 4Mbit serial flash memory in its processing subsystem which we use for sampling and processing the signal. The sensing range of acoustic sensors is 40m. The visual sensor nodes consist of MICAII [88] as the mote, a low power, low resolution CMOS camera, Cyclops [12] and Xilinx Spartan 6 low power FPGA [93] which is used for in-node vision processing, background subtraction and mosaicing. All visual sensors have been configured with a FoV vertex angle $\theta=60^{\circ}$ and R_S of 20m. All acoustic and visual sensor nodes are randomly deployed in a sensing field spanning an area of 120m×120m.

D.1. ENERGY CONSUMPTION

D.1.1. ACOUSTIC CLUSTERS

Since in every acoustic cluster the environment sensing task is turned among the members in a serial manner, larger numbers of nodes in the clusters yield higher potential of energy saving in cluster members for environment sensing and thus prolong the cluster lifetime. Considering AC_{size} as the number of nodes belonging to an acoustic cluster, E_S the energy consumed for sensing the environment during T_S and E_P the energy consumed by a sleeper node during T_S, the ratio of *Lifetime Prolongation* (LP) in the cluster is:

$$\mathrm{LP} = \frac{\mathrm{E_S} \cdot \mathrm{AC_{size}}}{\mathrm{E_P} \cdot (\mathrm{AC_{size}} - 1) + \mathrm{E_S}} \tag{35}$$

To observe the average lifetime prolongation in the acoustic sensor nodes of the network, let us consider $\overline{\mathrm{AC}_{\mathrm{size}}}$ as the average of established acoustic clusters size. Thus, the average of lifetime prolongation ($\overline{\mathrm{LP}}$) in acoustic sensor nodes is:

$$\overline{\mathrm{LP}} = \frac{\mathrm{E_S} \cdot \overline{\mathrm{AC}_{\mathrm{size}}}}{\mathrm{E_P} \cdot (\overline{\mathrm{AC}_{\mathrm{size}}} - 1) + \mathrm{E_S}} \tag{36}$$

As it was mentioned before, during the T_S, each active node senses the environment by its sensing subsystem and the node's processing subsystem surveys the presence of object/event in the sensing range of the node. Finally, the active node goes back to the sleep mode. So, considering a duty-cycle system:

$$\mathrm{T_S} = \mathrm{T_{on}} + \mathrm{T_{sleep}} \tag{37}$$

$$\mathrm{T_{on}} = \mathrm{T_{srartup}} + \mathrm{T_{samples}} \tag{38}$$

where $T_{startup}$ is the time required for the subsystem to stabilize after power is applied. The sampling time, $T_{samples}$, is the time required for sampling the signal to achieve an acceptable signal-to-noise ratio while the processing subsystem is observing to detect an object/event.

For the employed acoustic sensors, with the parameters $T_{startup}$=1ms, $T_{samples}$=32ms and T_S=1s, the average power consumed by an active node during T_S is of 370 µW, and the power consumed by a sleeper node is of 33 µW. Thus, the offered average lifetime prolongation ratio ($\overline{\mathrm{LP}}$) by the acoustic sensors architecture is: $370 \cdot \overline{\mathrm{AC}_{\mathrm{size}}}/(33 \cdot \overline{\mathrm{AC}_{\mathrm{size}}} + 337)$. Table 4 shows the offered $\overline{\mathrm{LP}}$ values for different average cluster sizes. As the table indicates, denser established clusters yield higher degrees of energy efficiency. Therefore, to achieve a higher level of energy conservation and prolonging the network lifetime, a larger number of members in clusters is required. On the other hand, for calculating the position of objects in the area, at least four detections by acoustic sensors are necessary (Section C.2). Consequently, a dense deployment of acoustic sensor nodes is a base demand of the proposed algorithm.

Table 4. Lifetime Prolongation values of acoustic sensor nodes for different average cluster- sizes

$\overline{\mathbf{AC_{size}}}$	5	6	7	8	9	10	11	12
$\overline{\mathbf{LP}}$	3.68	4.15	4.56	4.93	5.25	5.55	5.81	6.06

D.1.2. VISUAL CLUSTERS

In the proposed mechanism, at any monitoring period, the maximum number of active visual sensors is a whole cluster (VC_{size}) per object. As only the visual sensors which cover the detected object are awakened, the proposed algorithm offers a considerable development in saving energy of visual nodes. In order to cover 95% of the sensing field, we deploy 300 visual nodes in the sensing area resulting average visual cluster size equal to 2.67 (chapter IV). Table 5 shows the number of awakened visual nodes at each monitoring period respectively for an uncooperative monitoring system in which, nodes independently and periodically wake up and capture images [80], the FoV-based clustered mechanism (Chapter V) in which the visual nodes cooperate in monitoring, and the proposed (acoustic-visual cooperative) algorithm. On the other hand, in-node processing (background subtraction and image mosaicing) lower the amount of data communicated in the network. In each T_M, the cluster-head sends a mosaiced image toward the sink instead of all the images captured by the cluster members. Thus, the energy consumed by the network nodes for forwarding image packets to the sink, in average, is reduced with a ratio of 1/2.67.

Table 5. Number of active visual nodes at each monitoring period

Uncooperative scheme	N (All nodes asynchronously) (300 for 95% vision covering)
Visual Cooperative scheme	N_{VC} (Number of visual clusters) (112.36 for 95% vision covering)
Proposed algorithm	VC_{size} per object (2.67 per object for 95% vision covering)

D.2. OVERHEADS

D.2.1. ACOUSTIC CLUSTERS

Clustering and cluster maintenance for the acoustic sensor nodes consume less than 4% of the dissipated energy of the network [89]. As the algorithm describes, when an object/event is detected by an acoustic cluster, some data exchanging and in-node processing are triggered by the acoustic nodes in order to calculate the object position. Then, the coordinates of the object is broadcasted to all neighboring visual sensor nodes. Table 6 shows the rate of resource usages per object/event detection. It is worth to notice that in-node processing is much more energy-efficient than transmitting data between nodes. Here, in-node processing is utilized instead of data communication as much as possible.

Table 6. Overhead of resource usage per object/event detection

Overhead	Message broadcasting	Packet transmission	Total energy for in-node processing
Amount of allocated resources	2 times from detector (1-hop)	Number of detector´s neighbors (at least 4packet) (1-hop)	35 μJ

D.2.2. VISUAL CLUSTERS

The clustering algorithm utilized to group visual sensor nodes is a central algorithm which is executed by the sink (Chapter IV). However, within the clusters, a periodical message exchanging between cluster-head and cluster members for cluster maintenance is used. The clustering overhead is of $2 \cdot N_{VC} \cdot (VC_{size}-1)$ one-hop packet transmissions per clustering maintenance period (T_C). Since the visual node energy usage is not uniformly continuous-i.e., is based on detection of an object/event in their FoV-, the T_C is set with a relative large value of 2s.

Background subtraction and image mosaicing are the added tasks in visual nodes to lower data communications. The programmed FPGA embedded in nodes is responsible for vision in-node processing. For this purpose, the FPGA consumes

6.81mW during 28.16ms per image taken by Cyclops with a resolution 352×288 pixels and a frequency of 4MHz. Therefore, the maximum energy consumed for in-node processing by a visual cluster is of 2.67×0.192=0.51mJ per image. Table 7 summarizes the overheads in the visual clusters.

Table 7. Overheads of resource usage in the visual clusters

Overhead	Packet transmission	Total energy for in-node processing
Amount of allocated resources	$2 \cdot N_{VC} \cdot (VC_{size}-1)$ per T_C, one-hop (375 packet per T_C for 95% vision covering)	$VC_{size} \cdot$ 0.192 mJ by cluster per image (51 mJ per image for 95% vision covering)

E. ENERGY EFFICIENCY DEVELOPMENT

Figure 34 illustrates the total energy consumed by the network per monitoring period (T_M) for uncooperative [80], visual cooperative and the proposed mechanism considering all the aspects mentioned in Sections D.1 and D.2. We assume a T_M for visual sensors of 2s. Without lose of generality, we consider one object in the sensing area for the three cases. As the figure shows, a considerable amount of network energy is saved since acoustic sensors undertake detection and localization procedures consuming much less amount of energy than of visual sensors require.

As it was mentioned in Section C.2, an object has to be detected by at least four acoustic sensors to be localized. So, a network requirement is the deployment of a density of acoustic sensors such that within the neighborhood (with a radius of R_{AS}, 40m) of each point of the sensing area, at least four sensors exist. The worst case for satisfying this condition is the corners of the sensing area, considering this case and assuming uniformly random node deployment, we have to deploy at least one acoustic node per 100π m^2. Thus, in our sensing field at least 46 acoustic sensors have to be randomly deployed. We deploy 60 acoustic sensors in the sensing field while the density of visual sensors is varied from a sparse case with 50 nodes to a dense deployment of 300 nodes (see Figure 34).

Increasing the density of visual sensors raises the capability of covering the area for monitoring. Deploying 50 visual sensors covers 54% of our sensing area while the coverage rise to 95% with employing 300 visual sensors (Table 2, Chapter V). It is worth to notice that in the proposed mechanism, an object/event is detected and localized by the acoustic nodes independent of visual nodes density; the object position coordinates are sent to the sink if it is not covered by the visual sensors. But, the two other schemes shown in the figure depend on the density of visual sensors. As the figure indicates, the proposed mechanism is so energy affordable even employing a dense deployment of visual sensors. The reason stands on the fact that visual sensors are warily scheduled to be awakened just for monitoring the object(s) detected in their domain, otherwise, they save their energy.

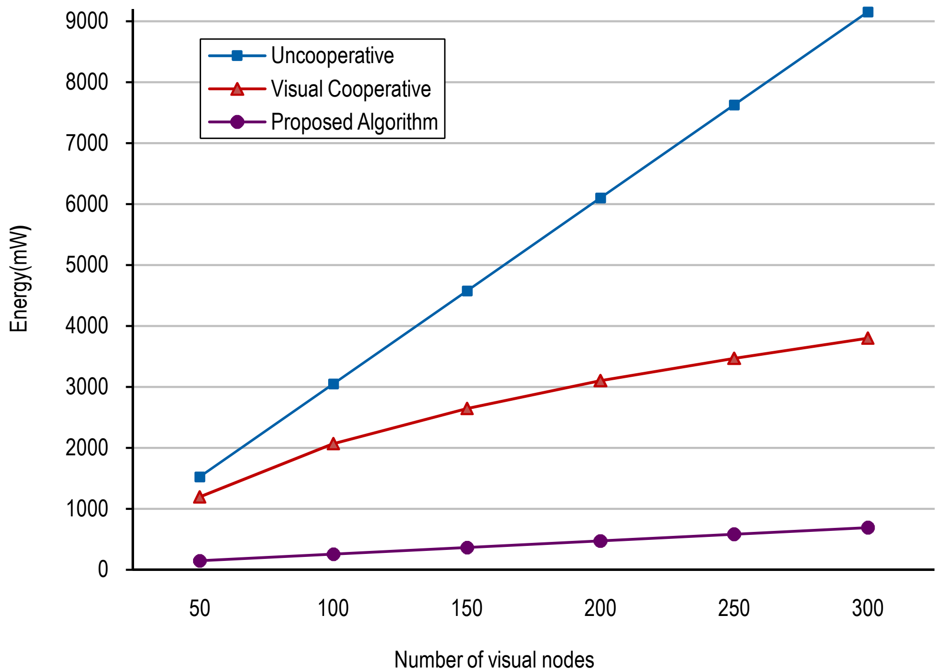


Figure 34. Energy consumed by the network per T_M for uncooperative, visual cooperative and the proposed acoustic-visual surveillance mechanism

F. CONCLUSIONS

This chapter presented an establishment of hybrid collaboration between multimedia sensor nodes to survey the environment. Acoustic and visual sensors are employed to collaborate in the proposed approach. The main objective is saving energy and prolonging the lifetime of visual sensors through assisting of acoustic sensors. Object detection and object localization are the tasks considered for the acoustic sensors and monitoring is the job of the visual sensor nodes. In fact, acoustic sensors play the role of assistants for visual sensors to detect and localize the occurred objects/events consuming much less energy than which is required for doing these procedures by visual sensors. Therefore, the visual sensors are saving their energy in the sleep mode unless an object/event is detected and localized in their FoV. Moreover, in the proposed scheme, data transmission is replaced with in-node processing as much as possible.

As the figures and tables show, a considerable amount of network energy is saved since acoustic sensors undertake detection and localization procedures consuming much less amount of energy than of visual sensors require. The proposed mechanism is so energy affordable even employing a dense deployment of visual sensors. The reason stands on the fact that visual sensors are warily scheduled to be awakened just for monitoring the object(s) detected in their domain, otherwise, they save their energy. Data transmission between acoustic and visual sensors, and in-node processing consisting the calculations of object localization in acoustic clusters, background subtraction and image mosaicing in visual clusters are the overheads imposed to the mechanism. The amount of energy consumed for overheads is negligible comparing to the energy saved by the mechanism.

Following, the publications corresponding to this chapter contents is mentioned.

[Alaei-2]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "An Acoustic-Visual Collaborative Hybrid Architecture for Wireless Multimedia Sensor Networks," International Journal of Adaptive, Resilient and Autonomic Systems (IJARAS), to appear in 2014.

[Alaei-7]. Mohammad Alaei, Jose M. Barcelo-Ordinas, "A Hybrid Cooperative Design for Energy-Efficient Surveillance in Wireless Multimedia Sensor Networks," 18th European Wireless Conference (EW 2012), Poznan, Poland, April 2012.

Chapter VIII

CONCLUSIONS AND FUTURE WORK

A. CONCLUSIONS

B. FUTURE WORK

A. CONCLUSIONS

This thesis presented a novel clustering mechanism based on the overlapping of the FoV of multimedia nodes. The proposed clustering method establishes clusters with grouping nodes which their FoVs overlap at least in a minimum threshold area. SCM and MCM are the membership schemes offered by the clustering method.

As the results show, high clustering scales restrict membership of nodes in clusters because to be a member of a cluster, the node's FoV must overlap the CH's FoV at least as much as the area that the defined clustering scale (γ) determines. So, the clustering scale is a key factor to decide about membership of nodes in clusters. High values of γ mean that the mechanism is very restrictive to accept a node as a cluster member, resulting in a high number of clusters with low cluster-sizes and low membership degree for the nodes. Lower values of γ will yield lower number of clusters with larger cluster-sizes and higher membership degree. Selection of the node membership style (MCM or SCM) in the clustering mechanism depends on the desired application from the clustered WMSN. In an application which disjoint and non-overlapping clusters are needed, SCM plays its role while MCM can create clusters with common nodes having the potential of collaboration between clusters for an application.

Chapter IV with presenting the clustering method whose criteria directly consider the specific characteristics and constraints of WMSNs, solves the problem of coverage based clustering of this kind of networks. As it was mentioned in the Section A of Chapter I, and in Chapter III, all the existing clustering schemes for WSNs consider the neighborhood or data transmission range for clustering. Because of the main difference between directional sensing region of multimedia sensors and the sensing range of scalar sensors, these clustering schemes and other coverage-based techniques designed for WSNs, do not satisfy WMSNs. In contrast, the proposed clustering mechanism in this chapter is quite adapted with WMSNs and thus covers the mentioned lack. As clustering is the base of many node management necessities, the proposed mechanism can play a key role in coverage based techniques in WMSNs.

Then, the proposed node management schemes designed for WMSNs were described. The node selection and scheduling schemes manage the acts of the multimedia sensor nodes in a collaborative manner in clusters with employing the mentioned clustering method. ICC and IICC use the SCM and MCM clusters respectively. The monitoring period is optimized and the sensing region is divided among clusters and multimedia tasks are performed with applying cooperation within and between clusters.

According to the results of the proposed schemes, both of ICC and IICC considerably raise the energy conservation capability of the nodes thus increase the network lifetime. In ICC the number of active nodes during each monitoring period is equal to the number of established clusters (N_C) in the network while in IICC scheme because of collaboration between clusters, the number of active nodes is less than of ICC. In consequent, both the difference between the number of active nodes in collaborative schemes and also the difference between both of them and the un-collaborative scheme raises with increasing the density of the network. This is the result of increasing the collaboration potential.

There is a trade-off between coverage ratio and network lifetime for selection a value for clustering scale. The appropriate value depends on the application desired from the network, to reach more coverage of the sensing area, higher clustering scale is selected at the cost of consuming more amount of energy for monitoring.

The proposed node management mechanisms impose some extra communications within the clusters and sometimes between the intersecting clusters. In both schemes, distributed ICC and IICC, CHs use a message exchanging scheme within clusters for member synchronization, cluster maintenance and getting up-date values of residual energy of cluster members in a periodical manner. The results and related diagrams shows the energy consumed for overheads is negligible in comparison to the saved energy by the schemes, and also to the energy required by multimedia sensing and processing tasks.

Chapters V and VI offered the solution of an important need in the field of sensor node management for WMSNs. Many approaches have been proposed to optimize scheduling of wireless scalar sensor nodes in the literature. But, the optimization methods for sensor management developed for wireless sensor networks are hard to apply to multimedia sensor networks. Such sensor management policies usually employ the clustering methods which form clusters based on sensor neighbourhood or radio-coverage. But, as it was mentioned before, because of the main difference between directional sensing region of multimedia sensors and the non-directional sensing range of scalar sensors, these schemes and other coverage-based techniques designed for WSNs, do not satisfy WMSNs. Here, the proposed node management mechanisms and the clustering method on which the management schemes are based, are totally designed considering the FoV and the constraints of multimedia sensor nodes.

A hybrid architecture for WMSNs in order to energy efficient collaborative surveillance was proposed in Chapter VII. The proposed mechanism employs a mixed random deployment of acoustic and visual sensor nodes. Acoustic sensors detect and localize the occurred event/object(s) in a duty-cycled manner by sampling the received signals and then trigger the visual sensor nodes covering the objects to monitor them.

In fact, acoustic sensors play the role of assistants for visual sensors to detect and localize the occurred objects/events consuming much less energy than which is required for doing these procedures by visual sensors. Therefore, the visual sensors are saving their energy in the sleep mode unless an object/event is detected and localized in their FoV. Moreover, in the proposed scheme, data transmission is replaced with in-node processing as much as possible.

The proposed mechanism is so energy affordable even employing a dense deployment of visual sensors. The reason stands on the fact that visual sensors are warily scheduled to be awakened just for monitoring the object(s) detected in their domain, otherwise, they save their energy. The amount of energy consumed for overheads is negligible comparing to the energy saved by the mechanism.

It is worth to notice that due to all the proposed node management methods, the sensing subsystems of the network nodes are coordinated to optimize the number of active nodes during each monitoring period and to avoid redundant and correlated sensing. Consequently, the amount of generated data in monitoring periods is reduced and thus the processing and communication subsystems meet an optimized amount of data to be processed and/or transmitted. Therefore, the capability of saving energy for the three subsystems is raised and the network lifetime is considerably prolonged.

B. FUTURE WORK

The work performed in this thesis opens several perspectives that can be addressed in the future:

Since sensor management policies depend on the underlying networking policies and vision processing, future research lies in the intersection of finding the best trade-offs between these two aspects of visual sensor networks. Additional work is needed to compare the performance of different camera node scheduling sensor policies, including asynchronous (where every camera follows its own on-off schedule) and synchronous (where cameras are divided into different sets, so that in each moment one set of cameras is active) policies. From an application perspective, it would be interesting to explore sensor management policies for supporting multiple applications utilizing a single visual sensor network.

Object occlusion, which happens when a camera loses sight of an object due to obstruction by another object, is an unavoidable problem in visual sensor networks. Although in most cases the positions of moving occluders cannot be predicted, still it is expected that a multicamera system can handle the occlusion problem more easily due to providing multiple object views. The real challenge in visual sensor networks however, is to avoid losing the tracked object due to occlusions in the situation when not all cameras are available for tracking at the same time. Thus, future research should be directed toward examining the best sensor management policies for selecting camera nodes that will enable multiple target views, thereby reducing the chances of occlusion while using the minimum number of cameras. The mentioned sensor management policy would be based on the proposed clustering method in this thesis, because the clusters yielded by this clustering method consist the nodes with highly overlapping FoVs thus for each cluster, the cluster members can have multiple views of the objects within their overlapped domain.

In the future we can expect to see various applications based on multimedia wireless networks, where camera nodes will be integrated with other types of sensors, such as audio sensors, PIRs, vibration sensors, light sensors, and so forth.

By utilizing these low-cost and low-power sensors, the lifetime of the camera nodes can be significantly prolonged. However, many open problems appear in such multimedia networks. The first issue is network deployment, whereby it is necessary to determine network architecture and the numbers of different types of sensors that should be used in a particular application, so that all of the sensors are optimally utilized while at the same time the cost of the network is kept low. Such multimedia networks usually employ a hierarchical architecture, where ultra-low power sensors (such as microphones, PIRs, vibration, or light sensors) continuously monitor the environment over long periods of time, while higher-level sensors, such as cameras sleep most of the time. When the lower-level sensors register an event, they notify higher-level sensors about it. Such a hierarchical model tends to minimize the amount of communication in the network. However, it is important to reduce the number of false and missed alarms at the low-level sensors, so that the network reliability is not jeopardized. Thus, it is important to precisely define an event at the lower level sensors that cameras can interpret without ambiguity.

Motility and mobility can significantly improve the coverage ratio of the network. Nevertheless, networks consisting of motile/mobile directional sensor nodes require high budgets due to the considerable production cost of those nodes. The gap between the costs has definitely decreased and will continue to decrease in the future. However, there will always be a reasonable cost ratio between static, motile and mobile nodes. Thus, we believe that hybrid directional sensor networks consisting of heterogeneous sensor nodes should also be considered for additional coverage performance to balance the coverage gain ratio and the cost of the network.

BIBLIOGRAPHY

[1] Akyildiz, I.F; Su, W.; Sankarasubramaniam, Y.; Cayirci, E. Wireless sensor networks: A survey. Comput. Netw. 2002, 38, 393–422.

[2] Chong, Y.; Kumar, S.P. Sensor networks: Evolution, opportunities, and challenges. Proc. IEEE 2003, 91, 1247–1256.

[3] Akyildiz, I.F; Melodia, T.; Chowdhury, K.R. A survey on wireless multimedia sensor networks. Comput. Netw. 2007, 51, 921–960.

[4] Akyildiz, I.F; Melodia, T; Chowdhury, K.R. Wireless multimedia sensor networks: applications and testbeds. Proc. IEEE. 2008, 96, 1588–1605.

[5] Soro, S. & Heinzelman, W. (2005). On the coverage problem in video-based wireless sensor networks. Proceedings of the 2nd IEEE International Conference on Broadband Communications and Systems (BroadNets), pp. 932–939, ISBN 0-7803-9276-0, Boston, MA, USA, October 3–7, 2005

[6] H. Ma, Y. Liu, On coverage problems of directional sensor networks, in: Lecture Notes in Computer Science: Mobile Ad-hoc and Sensor Networks, vol. 3794, 2005, pp. 721-731.

[7] Tezcan, N. & Wang, W. (2008). Self-orienting wireless multimedia sensor networks for occlusion-free viewpoints. Computer Networks, vol. 52, issue 13, (September 2008), pp. 2558–2567, ISSN 1389-1286

[8] Adriaens, J.; Megerian, S. & Potkonjak, M. (2006). Optimal worst-case coverage of directional field-of-view sensor networks, Proceedings of the 3rd IEEE Communication Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (IEEE SECON), pp. 336–345, ISBN 1-4244-0626-9, Reston, VA USA, September 25–28, 2006

[9] Raghunathan, V.; Schurghers, C.; Park, S. & Srivastava, M. (2002). Energy-aware Wireless Microsensor Networks. IEEE Signal Processing Magazine, Vol. 19, Issue 2, (March 2002), pp. 40-50, ISSN 1053-5888

[10] Pottie, G. & Kaiser, W. (2000). Wireless Integrated Network Sensors. Communication of theACM, Vol. 43, N. 5, (May 2000), pp. 51-58

[11] http://www.ti.com/product

[12] Rahimi, M.; Baer, R.; Iroezi, O.I.; Garcia, J.C.; Warrior, J.; Estrin, D. & Srivastava, M. (2005). Cyclops: in situ image sensing and interpretation in wireless sensor networks, Proceeding of the 3rd ACM Conference on Embedded Networked Sensor Systems (SenSys05), pp.192–204, ISBN 1-59593-054-X ,San Diego, CA, USA, November 2–4, 2005

[13] Rowe, A.; Rosenberg, C. & Nourbakhsh. I. (2002). A Low Cost Embedded Color Vision System. Proceedings of the international IEEE/RSJ Conference on Intelligent Robots and Systems (IROS 2002), pp. 208-213, ISBN 0-7803-7398-7, Lausanne, Switzerland, Sep.30-Oct.4, 2002

[14] Tavli, B.; Bicakci, K.; Zilan, R. & Barcelo-Ordinas, J.M. (2011). A Survey of Visual Sensor Platforms. Journal on Multimedia Tools and Applications, ISSN 1573-7721, June 2011

[15] M. Tahir, R. Farrell, “Optimal communication-computation trade off for wireless multimedia sensor network lifetime maximization,” In proc. of the IEEE Wireless Communications & Networking Conf. (WCNC), pp. 2514-2519, Hungary, 2009.

[16] A. Ghosh, S.K. Das, Coverage and connectivity issues in wireless sensor networks: a survey, Pervasive and Mobile Computing 4 (3) (2008) 303–334, doi:10.1016/ j.pmcj.2008.02.001

[17] E. Onur, C. Ersoy, H. Delic, L. Akarun, Surveillance wireless sensor networks: deployment quality analysis, Network, IEEE 21 (6) (2007) 48–53, doi:10.1109/MNET.2007.4395110.

[18] A. Kansal, W.J. Kaiser, G.J. Pottie, M.B. Srivastava, Actuation techniques for sensing uncertainty reduction, Tech. rep. (March 2005).

[19] K. Akkaya, M. Younis, A survey of routing protocols in wireless sensor networks, Ad Hoc Networks (Elsevier) 3 (3) (2005) 325–349.

[20] H. Tian, H. Shen, T. Matsuzawa, Coverage-enhancing algorithm for directional sensor networks, in: Lecture Notes in Computer Science: Network and Parallel Computing, vol. 3779, 2005, pp. 461–469, doi:10.1007/11577188.

[21] I. Demirkol, C. Ersoy, F. Alagoz, Mac protocols for wireless sensor networks: a survey, IEEE Communications Magazine 44 (4) (2006) 115–121.

[22] T. Melodia, M.C. Vuran, D. Pompili, The state of the art in cross-layer design for wireless sensor networks, in: Proceedings of EuroNGI Workshops on Wireless and Mobility, Springer Lecture Notes in Computer Science 3883, Como, Italy, 2005.

[23] Y. Mohamed, K. Akkaya, Strategies and techniques for node placement in wireless sensor networks: a survey, Ad Hoc Networks 6 (4) (2008) 621–655. http://dx.doi.org/10.1016/ j.adhoc.2007.05.00.

[24] E. Oyman, C. Ersoy, Multiple sink network design problem in large scale wireless sensor networks, in: Proc. of the IEEE Intl. Conf. on Communications, Paris, France, 2004, pp. 3663–3667.

[25] J. Pan, L. Cai, Y. Hou, Y. Shi, S. Shen, Optimal base-station locations in two-tiered wireless sensor networks, IEEE Transactions on Mobile Computing 4 (5) (2005) 458-473.

[26] Z. Vincze, R. Vida, A. Vidacs, Deploying multiple sinks in multi-hop wireless sensor networks, in: Proc. of the IEEE Intl. Conf. on Pervasice Services (ICPS'07), Istanbul, Turkey, 2007, pp. 55–63.

[27] Y. Lin, Q. Wu, X. Cai, X. Du, K.-H. Kwon, On deployment of multiple base stations for energy–efficient communication in wireless sensor networks, Hindawi Intl, Journal of Distributed Sensor Networks (2010), doi:10.1155/2010/563256.

[28] K. Dantu, M. Rahimi, H. Shah, E. Babel, A. Dhariwal, G.S. Sukhatme, Robomote: enabling mobility in sensor networks, in: Proc. of IEEE/ACM

Intl. Conf. on Information Processing in Sensor Networks (IPSNSPOTS), 2005, pp. 404–409.

[29] G.G. Wang, G. Cao, P. Berman, T.F. La Porta, Bidding protocols for deploying mobile sensors, IEEE Transactions on Mobile Computing 6 (5) (2007) 563–576. http://dx.doi.org/ 10.1109/TMC.2007.1022.

[30] D. Tao, H. Ma, L. Liu, Coverage-enhancing algorithm for directional sensor networks, in: Lecture Notes in Computer Science: Mobile Adhoc and Sensor Networks, vol. 4325, 2006, pp. 256–267.

[31] J. Zhao, J.-C. Zeng, An electrostatic field-based coverage-enhancing algorithm for wireless multimedia sensor networks, in: Proc. of IEEE Intl. Conf. on Wireless Communications, Networking and Mobile Computing (WiCom'09), Beijing, China, 2009, pp. 1–5, doi:10.1109/WICOM.2009.5302443.

[32] A. Newell, K. Akkaya, Self-actuation of camera sensors for redundant data elimination in wireless multimedia sensor networks, 2009, pp. 1–5, doi:10.1109/ICC.2009.5199448.

[33] Y. Osais, M. St-Hilaire, F. Yu, The minimum cost sensor placement problem for directional wireless sensor networks, in: Proc. of. IEEE Intl. Conf. on Vehicular Technology (VTC'08), Calgary, Canada, 2008, pp. 1–5, doi:10.1109/VETECF.2008.289.

[34] Y. Yang, M. Cardei, Movement-assisted sensor redeployment scheme for network lifetime increase, in: Proc. of ACM Intl. Symposium on Modeling, Analysis, and Simulation of Wireless and Mobile Systems (MSWiM'07), 2007, pp. 13–20, doi:http://doi.acm.org/ 10.1145/1298126.1298132.

[35] S. Chellappan, W. Gu, X. Bai, D. Xuan, B. Ma, K. Zhang, Deploying wireless sensor networks under limited mobility constraints, IEEE Transactions on Mobile Computing 6 (2007) 1142–1157. http://doi.ieeecomputersociety.org/10.1109/TMC.2007.1032.

[36] N. Heo, P. Varshney, Energy–efficient deployment of intelligent mobile sensor networks, IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans 35 (1) (2005) 78–92, doi:10.1109/TSMCA.2004.838486.

[37] C.-K. Liang, M.-C. He, C.-H. Tsai, Movement assisted sensor deployment in directional sensor networks, in: Proc. of Intl. Conf. on Mobile Ad-Hoc and Sensor Networks, 2010, doi:10.1109/ MSN.2010.42

[38] P. Xingyu, Y. Hongyi, Redeployment problem for wireless sensor networks, in: Proc. of Intl. Conf. on Communication Technology (ICCT'06), 2006, pp. 1–4, doi:10.1109/ICCT.2006. 341957.

[39] H. Yang, D. Li, H. Chen, Coverage quality based target-oriented scheduling in directional sensor networks, 2010, pp. 1–5, doi:10.1109/ICC.2010.5501996.

[40] J. Deng, Y.S. Han, W.B. Heinzelman, P.K. Varshney, Balanced-energy sleep scheduling scheme for high-density cluster-based sensor networks, Computer Communication 28 (14) (2005) 1631–1642. http://dx.doi.org/10.1016/j.comcom.2005.02.019.

[41] J. Deng, Y.S. Han, W.B. Heinzelman, P.K. Varshney, Scheduling sleeping nodes in high density cluster-based sensor networks, Mobile Networks and Applications 10 (6) (2005) 825–835. http:// dx.doi.org/10.1007/s11036-005-4441-9.

[42] W. Mo, D. Qiao, Z. Wang, Lifetime maximization of sensor networks under connectivity and k-coverage constraints (2006).

[43] J. Wang, C. Niu, R. Shen, A utility-based maximum lifetime algorithm for directional sensor network, in: Proc. of IEEE Intl. Conf. on Wireless Communications, Networking and Mobile Computing (WiCom'07), Shanghai, China, 2007, pp. 2424–2427, doi:10.1109/WICOM. 2007.604.

[44] A. Makhoul, R. Saadi, C. Pham, Adaptive scheduling of wireless video sensor nodes for surveillance applications, in: Proc. of ACM Workshop

on Performance Monitoring and Measurement of Heterogeneous Wireless and Wired Networks (PM2HW2N'09), Tenerife, Canary Islands, Spain, 2009, pp. 54–60, doi:http://doi.acm.org/10.1145/ 1641913.1641921.

[45] J. Ai, A.A. Abouzeid, Coverage by directional sensors in randomly deployed wireless sensor networks, Journal of Combinatorial Optimization 11 (1) (2006) 21–41, doi:10.1007/s10878-006-5975-x.

[46] Y. Cai, W. Lou, M. Li, Cover set problem in directional sensor networks, in: Proc. of IEEE Intl. Conf. on Future Generation Communication and Networking (FGCN'07), Washington, DC, USA, 2007, pp. 274–278, doi:http://dx.doi.org/10.1109/ FGCN.2007.94.

[47] M. Cardei, D.-Z. Du, Improving wireless sensor network lifetime through power aware organization, Wireless Networks 11 (3) (2005) 333–340. http://dx.doi.org/10.1007/ s11276-005-6615-6.

[48] Y. Bai, H. Qi, Redundancy removal through semantic neighbor selection in visual sensor networks, in: Proc. of ACM/IEEE Intl. Conf. on Distributed Smart Cameras (ICDSC'09), Como, Italy, 2009, pp. 1–8, doi:10.1109/ICDSC.2009.5289402.

[49] H. Bay, A. Ess, T. Tuytelaars, L. Van Gool, Speeded-up robust features (surf), Computer Vision and Image Understanding 110 (3).

[50] Y. Cai, W. Lou, M. Li and X.Y. Li, "Energy Efficient Target-Oriented Scheduling in Directional Sensor Networks," IEEE Transactions on Computers, Vol. 58, No. 9, pp. 1259-1274, September 2009.

[51] J. C. Dagher, M. W. Marcellin, and M. A. Neifeld, “A method for coordinating the distributed transmission of imagery,” IEEE Transactions on Image Processing, vol. 15, no. 7, pp. 1705– 1717, 2006.

[52] N. H. Zamora and R. Marculescu, “Coordinated distributed power management with video sensor networks: analysis, simulation, and prototyping,” In Proc. of the ACM/IEEE Conf. on Distributed Smart Cameras (ICDSC ’07), pp. 4–11, 2007.

[53] Z. Chen, G. Barrenetxea and M. Vetterli, "Share Risk and Energy: Sampling and Communication Strategies for Multi-Camera Wireless Monitoring Networks," In proc. of the 31st IEEE Int. Conference on Computer Communications (IEEE INFOCOM 2012), Orlando, Florida USA, March 25 - 30, 2012.

[54] M. Cardei, M. Thai, Y. Li, W. Wu, Energy–efficient target coverage in wireless sensor networks, 3 (2005) 1976–1984, doi:10.1109/INFCOM.2005.1498475.

[55] S. Kumar, T.H. Lai, A. Arora, Barrier coverage with wireless sensors, in: Proc. of ACM Intl. Conf. on Mobile computing and networking (MobiCom'05), 2005, pp. 284–298, doi:http://doi.acm.org/10.1145/ 1080829.1080859.

[56] D.S. Hochbaum, Approximating covering and packing problems: set cover, vertex cover, independent set, and related problems (1997) 94–143

[57] H. Zhang, J. Hou, Maintaining sensing coverage and connectivity in large sensor networks, Ad Hoc & Sensor Wireless Networks 1 (1–2).

[58] D. Tian, N.D. Georganas, A coverage-preserving node scheduling scheme for large wireless sensor networks, in: Proc. of ACM Intl. Workshop on Wireless Sensor Networks and Applications (WSNA'02), 2002, pp. 32–41, doi:http://doi.acm.org/10.1145/570738.570744.

[59] X. Wang, G. Xing, Y. Zhang, C. Lu, R. Pless, C. Gill, Integrated coverage and connectivity configuration in wireless sensor networks, in: Proc. of ACM Intl. Conf. on Embedded Networked Sensor Systems (SenSys'03), 2003, pp. 28–39, doi:http://doi.acm.org/10.1145/ 958491.958496.

[60] F. Ye, G. Zhong, S. Lu, L. Zhang, Peas: a robust energy conserving protocol for long-lived sensor networks, in: Proc. of IEEE Intl. Conf. on Network Protocols, 2002, pp. 200–201.

[61] J. Wen, L. Fang, J. Jiang, W. Dou, Coverage optimizing and node scheduling in directional wireless sensor networks, in: Proc. of IEEE Intl. Conf. on Wireless Communications, Networking and Mobile Computing (WiCom'08), Dalian, China, 2008, pp. 1–4, doi:10.1109/WiCom.2008.984.

[62] U.-R. Chen, B.-S. Chiou, J.-M. Chen, W. Lin, An adjustable target coverage method in directional sensor networks, in: Asia-Pacific Conference on Services Computing, Los Alamitos, CA, USA, 2008, pp. 174–180, doi:http://doi.ieeecomputersociety.org /10.1109/APSCC. 2008.37.

[63] J. Wang, C. Niu, R. Shen, Priority-based target coverage in directional sensor networks using a genetic algorithm, Computers and Mathematics with Applications 57 (11-12) (2009) 1915-1922, doi:10.1016/j.camwa.2008.10.019.

[64] Y. Osais, M. St-Hilaire, F. Yu, Directional sensor placement with optimal sensing range, field of view and orientation, in: Proc. of. IEEE Intl. Conf. on Wireless and Mobile Computing (WIMOB'08), Avignon, France, 2008, pp. 19–24, doi:10.1109/ WiMob.2008.88.

[65] C.-F. Huang, Y.-C. Tseng, The coverage problem in a wireless sensor network, Mobile Networks and Applications 10 (2005) 519-528.

[66] S. Meguerdichian, F. Koushanfar, M. Potkonjak, M. Srivastava, Coverage problems in wireless ad-hoc sensor networks, in: Proc. Of IEEE Intl. Conf. onf Computer and Communications (INFOCOM'01), vol. 3, 2001, pp. 1380-1387, doi:10.1109/INFCOM. 2001.916633.

[67] H. Chen, H. Wu, N.-F. Tzeng, Grid-based approach for working node selection in wireless sensor networks, in: Proc. Intl. Conf on Communications, vol. 6, Paris, France, 2004, pp. 3673-3678, doi:10.1109/ICC.2004.1313228.

[68] J. Li, R.-C. Wang, H.-P. Huang, L.-J. Sun, Voronoi based area coverage optimization for directional sensor networks, in: Proc. of Intl. Symposium

on Electronic Commerce and Security (ISECS'09), vol. 1, Nanchang, China, 2009, pp. 488–493, doi:10.1109/ISECS. 2009.116.

[69] H. Ma, X. Zhang, A. Ming, A coverage-enhancing method for 3-D directional sensor networks, in: Proc. of IEEE Intl. Conf. on Computer Communications (INFOCOM'09), Rio de Janerio, Brazil, 2009, pp. 2791–2795, doi:10.1109/INFCOM 2009.5062233.

[70] W. Cheng, S. Li, X. Liao, S. Changxiang, H. Chen, Maximal coverage scheduling in randomly deployed directional sensor networks, in: Proc. of Intl. Conf. on Parallel Processing Workshops (ICPPW'07), Xi-An, China, 2007, pp. 68–68, doi:10.1109/ ICPPW.2007.51.

[71] C. Kandoth, S. Chellappan, Angular mobility assisted coverage in directional sensor networks, 2009, pp. 376–379, doi:10.1109/NBiS.2009.69.

[72] G. Wang, G. Cao, T.L. Porta, Movement-assisted sensor deployment, IEEE Transactions on Mobile Computing 5 (6) (2006) 640–652, doi:10.1109/TMC.2006.80.

[73] F. Aurenhammer, Voronoi diagrams—a survey of a fundamental geometric data structure, ACM Computing Surveys 23 (3) (1991) 345–405. http://doi.acm.org/ 10.1145/116873. 116880.

[74] G. Fusco, H. Gupta, Selection and orientation of directional sensors for coverage maximization, in: Proc. of IEEE Intl. Conf. on Sensor, Mesh and Ad Hoc Communications and Networks (SECON'09), Rome, Italy, 2009, pp. 1–9, doi:10.1109/SAHCN. 2009.5168968.

[75] Y. Wu, J. Yin, M. Li, Z. En, Z. Xie, Efficient algorithms for probabilistic k-coverage in directional sensor networks, in: Proc. of IEEE Intl. Conf. on Intelligent Sensors Networks and Information Processing (ISSNIP'08), Sydney, Australia, 2008, pp. 587–592, doi:10.1109/ ISSNIP.2008.4762053.

[76] Y. Wang, G. Cao, "Barrier Coverage in Camera Sensor Networks, " In proc. of the 12th ACM International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc 2011), Paris, France, May 16-19, 2011.

[77] X. Fang, D. Yang and G. Xue, "Strategizing Surveillance for Resource-Constrained Event Monitoring," In proc. of the 31st IEEE Int. Conference on Computer Communications (IEEE INFOCOM 2012), Orlando, Florida USA March 25 - 30, 2012.

[78] J. Park, P. Bhat, and A. Kak, “A look-up table based approach for solving the camera selection problem in large camera networks,” In Proc. of the International Workshop on Distributed Smart Cameras (DCS ’06), 2006.

[79] S. Soro and W.Heinzelman, “Camera selection in visual sensor networks,” In Proc. of the IEEE Conf. on Advanced Video and Signal Based Surveillance (AVSS’07), pp. 81-86, 2007.

[80] Kulkarni, P.; Ganesan, D.; Shenoy, P.; Lu, Q. SensEye: A multi tier camera sensor network. In Proceedings of the 13th ACM International Conference on Multimedia (ACM MM 2005), Singapore, November 6–11, 2005; pp. 229–238.

[81] Kerhet, A.; Magno, M.; Leonardi, F.; Boni, A.; Benini, L. A low-power wireless video sensor node for distributed object detection. J0urnal of Real-Time Image Process. 2007, vol 2, pp. 331-342.

[82] P. Chen, P.; Ahammed, P.; Boyer, C.; Huang, S.; Lin L.; Lobaton, E.; Meingast, M.; Oh, S.; Wang, S.; Yan, P.; Yang, A.Y.; Yeo, C.; Chang, L.C.; Tygar, D.; Sastry, S.S. CITRIC: A low-bandwidth wireless camera network platform. In Proceedings of the 2nd ACM/IEEE International Conference on Distributed Smart Cameras (ICDSC 2008), Palo Alto, CA, USA, September 7–11, 2008; pp. 1–10.

[83] Feng, W.C.; Kaiser, E.; Shea, M.; Feng, W.C; Baillif, L. Panoptes: scalable low-power video sensor networking technologies. ACM Trans. Multimed. Comput. Commun. Appl. 2005, 1, 151–167.

[84] Margi, C.B.; Lu, X.; Zhang, G.; Stanek, G.; Manduchi, R.; Obraczka, K. Meerkats: A power-aware, self-managing wireless camera network for wide area monitoring. In Proceedings of International Workshop on Distributed Smart Cameras (DSC 06) in conjunction with SenSys06, Boulder, CO, USA, October 31, 2006; pp. 26–30.

[85] Area of triangles and polygons (2D &3D), Available online: http://www.softsurfer. com/algorithm_archive.htm (accessed on January 2009).

[86] S. Ganeriwal, R. Kumar, S. Adlakha, M. Srivastava, "Network-wide time synchronization in sensor networks," Technical Report, Networked and Embedded Systems Lab, Electronic Engineering Dep., UCLA, 2003.

[87] S. Lindsey, C. S. Raghavendra, "PEGASIS: Power Efficient Gathering in Sensor Information Systems," In proc. of the IEEE Aerospace Conference, pp. 1125-1130, Big Sky, Montana, March 2002.

[88] Crossbow Technology, "http://www.xbow.com"

[89] O. Younis, and S. Fahmy, "HEED: A hybrid, energy-efficient distributed clustering approach for Ad Hoc sensor networks," IEEE Transactions on Mobile Computing, Vol. 3, No. 4, pp. 366-379, October-December 2004.

[90] L. Kinsler, A. Frey, A. Coppens, and J. Sanders, Fundamentals of Acoustics, JohnWiley and Sons, New York, NY, USA, 1982.

[91] D.S. Vinod, R. Akshatha and M. Bhat, Shiva Prakash, "Intensity based image mosaicing," International Journal of Education and Information Technologies, Vol. 1, Issue 2, pp. 121-126, 2007.

[92] P. Dutta, M. Grimmer, A.Arora, S. Bibyk, and D. Culler, "Design of a wireless sensor network platform for detecting rare, random, and ephemeral events," In proceedings of 4th International Conference on Information Processing in Sensor Networks (IPSN'05-SPOTS Track), pp. 497-502, Los Angeles, California, USA, April 25-27, 2005.

[93] Spartan-FPGA Family, http://www.xilinx.com/products