Chapter 6

Conclusions and open research directions

Before to come in the details of the main contributions of this work we should review which was the aim of this thesis in its initials. The goal was twofold:

- From an engineering perspective, it was to solve the problems of an automatic inspection system of colour texture surfaces, when the final target is to get quantitative measures of general colour texture properties. We were mainly addressed to the grading of polished ceramic tiles.

- From a scientific perspective, it was to define robust computational colour texture representations that allow to derive similarity judgements which are coherent with human perception and represent enough sound information to allow complex classification tasks.

Taking in mind these two goals, the essential contributions of this work can be summed up in three:

1. A perceptual sharpening operator has been proposed, whose behaviour tries to simulate the chromatic contrast effect demonstrated by the human visual system.

2. A complete computational representation for colour texture has been formulated. It compiles colour representations that consider spatial operations to move chromaticities in a perceptual sense, with a feature vector computed on the modified colour representation that combines global and local features.

3. An on-line colour constancy algorithm for a colour scan line camera that removes dependencies on spatial and temporal variations of lighting conditions, to be used in industrial inspection processes in computer vision.

The main advantages of every contribution will be analysed in the following paragraphs.

The first contribution can be understood as a perceptual pre-processing step that modifies the colour distribution of an image depending on the spatial relations of the image content. The modified distribution presents good properties for being segmented accordingly to the colour appearance of the image blobs.

Even when the number of colours in a scene is not very large, and due to the smoothing effects introduced by the acquisition system, it is common to have unimodal colour distributions for images where a concrete number of colour are perceptually segregated without effort. Unimodality introduced problems at the time to take a colour classification decision within the image. To build sharpened images with a colour distribution where the unimodality has been broken and a clear mixture of different gaussians have appeared accordingly with the number of the perceived image colours can introduced interesting properties for general colour segmentation and for coloured-blob segmentation.

As has been demonstrated in different works on texture perception, as the Julesz texton theory, the attributes of the image blobs have an essential contribution for any texture representation. An efficient blob segmentation is an unavoidable step before computing any local property, as blob size, orientation, chromaticity or contrast.

The proposed computational representation presents the ability to compile the image content properties as a result of a vision process that combines different observations of the same scene or what we could call an integrated colour multi-scale representation. Properties obtained from the images perceptually blurred will represent the image appearance from a distant observer positioning, on the other hand, properties obtained from the images perceptually sharpened will represent the image appearance from an attentive process of the observer across the image and from a close observer positioning to the target. The proposed local features are the same as those used to represent gray-level texture images.

Finally, the on-line colour constancy algorithm developed has more practical than theoretical implications. A linear diagonal model is applied and adapted to the special constraints of a scan line camera. Although its inherent simplicity, it is completely indispensable for any real application where a classification catalog pretends to be stored for a long-term period.

On the basis of the scientific work in this thesis, two practical derivations have been addressed on inspection problems:

1. Ceramic tile classification: We have established the basis for a future system for fully automatic system in this scope. A simplification of the general schema defined for colour texture has been used to grade a large set of samples of ceramic tiles, validating this approximation.

2. Printing quality inspection: We have defined the first steps to quantify the banding effect in commercial printers. This is done using the properties of the defined operators, which improve the colour distribution of the images considering spatial relationships. This takes us to a better interpretation of the degree of banding error.

Once, we have enumerated and commented the most important contributions of this work, let us enumerate other minor contributions and conclusions we want to highlight from all the work:

- Several acquisition architectures has been tested and analysed before to get a final solution. In this work we analyse a list of possibilities and common problems arising when a digital colour acquisition problem is posed. The central conclusions we want to enumerate are the importance of designing criteria that have to take into account when defining such an architecture:

  - The complexity or almost the impossibility of acquiring an homogenously illuminated surface with a matrix camera.
  - The problems on the sensor calibration of some commercial cameras.
  - The high red-sensibility of commercial CCD's that sometimes implies to introduce special filter corrections at the sensor input, resulting in an loss of light intensity.
  - The spatial non-homogeneities introduced by the optic systems: chromatic aberrations, vignetting effects, etc.
  - The non-homogeneous profile provided by light line fiber optics.
  - The influences of spectral distributions of the lamps when they are combined with other problems enumerated before, e.g, the red spectral distribution of a tungsten halogen lamp, added to the special sensibility of CCD's to red inputs increases the needs of filtered inputs.

- Some important corrections are needed when working with CCD cameras with high colour precision, as it is the removing of the dark current. While this is a common matter in astronomy where high precision is also required for photometric measurements, it is not as common in computer vision.

- A diagonal linear model, or Von Kries adaptation model, is the simplest solution to deal with the colour constancy problem. However, most of the commercial CCD cameras does not include completely sharpened sensors. To guarantee the suitability of this diagonal model we have built the sensor transformation that assures sharpened responsivities for a specific line scan camera.

- To compute the sharpening transformation the sensitivities of the camera sensors have been recovered. The method used has been based on a least-square approach. The main problems concluded from this methodology arises from the need of design information of the CCD that should be provided by the camera manufacturer that is not always available, and the need to introduce important constraints due to the generality of the basis functions.

- A wide review of psychophysical bibliography has been done to deal with the perceptual implications of the colour induction phenomena. Although there is an increasing number of works that deal with this issue, there are still some measurements that should be done, in order to be able to have a tabulation on how chromaticities of a large set of basic colours change in front of a large set of inductors. This should be done for a wide set of different spatial frequencies conditions.

Doing research and engineering activities provokes to open new issues to address. In our case some of the future research directions are

- To find a model to combine contrast and assimilation induction in a scene. As we are involved in computer vision it converts to a perceptual sharpening/blurring problem. Our first thought is that a multiresolution approach is needed to select those areas of the image assigned to each effect.

- Sharpening operators have been defined to simulate perceptual human vision but their parameters are left open. Although we have demonstrate their usefulness, psychophysical work is needed to evaluate the validity of this model to match the Human Visual System. In this case the magnitudes and ratios between parameters have to be investigated.

- To go deeply into the field of dynamic clustering to give response to many industrial applications where the clustering has to be done without a priori information. Although with the current results, the on–line surface inspection can be done, the training process of the classifier has to be simplified to be operative.

There also exists open engineering problems that have to be studied

- In the case of ceramic tile inspection, to collect and analyse the prior and posterior samples of the creation of a new grade is created by the production line. Without these data it is not possible to address the problem of a true on–line inspection.

- In the case of printing quality quantification, larger tests have to be done to validate the first results presented, and to evaluate the weight of the proposed parameters in the final quantisation.

- To look for new methods to recover camera sensor sensitivities in a high demanding application. These methods should keep the process as simple as possible for being feasible their use in industrial problems.

- To investigate the effects of the optics distortions in the recovery of the sensor sensitivities, and thus on the final spectral sharpening transform.

Appendix A

Classification method

As our interest is the capacity of the representation of texture and colour information simultaneously, we will not focus on the classification methods. Although there exists many classification approaches [26], considering the nature of the problem we found that a discriminant analysis method was a correct chose. We will need a set of samples to characterise the classes (the learning set) that will be selected randomly from the whole set of each class.

Discriminant analysis can cope with problems where the main characteristics of classes are not a priori known, prototyping classes from the learning sets. The selection criterion of these prototypes has to provide the maximum discrimination ratio overall the learning set. Moreover, distribution of features is unknown, so we have to use a non-parametric discriminant analysis method [63, 74]. One of the methods that fits these constraints is the one based on Fisher discriminant functions. With Fisher's approach there is no need of a priori knowledge of data and it is able to select the best representation maximising the ratio between the inter-class covariance and the intra-class covariance. A linear transform $\mathbf{W}$ is applied over the feature vector $\mathbf{x}$ of a particular image obtaining a new representation, $\mathbf{y} = \mathbf{W}^t\mathbf{x}$, in a new space where discrimination capability has been maximised.

The linear transformation, $\mathbf{W}$, which optimises the discrimination, is obtained by calculating the most significant eigen vectors of the matrix $\mathbf{S}_w^{-1}\mathbf{S}_b$, assuring the maximisation of the following ratio:

$$\frac{\mathbf{W}^t\mathbf{S}_b\mathbf{W}}{\mathbf{W}^t\mathbf{S}_w\mathbf{W}} \ , \tag{A.1}$$

where $\mathbf{W}^t$ stands for the transpose of $\mathbf{W}$, $\mathbf{S}_w$ is the within data sparse matrix defined as:

$$\mathbf{S}_w = \sum_{i=1}^{c} \sum_{\mathbf{x}_k \in C_i} (\mathbf{x}_k - \mu_i)(\mathbf{x}_k - \mu_i)^t \ , \tag{A.2}$$

where c is the number of possible classes and C_i is the set of vectors that are used as learning samples in the i class.The $\mathbf{S}_b$ matrix is the between class sparse matrix, which is defined as:

$$\mathbf{S}_b = \sum_{i=1}^{c} N_i(\mu_i - \mu)(\mu_i - \mu)^t \ , \tag{A.3}$$

where μ_i is the mean vector of the samples of the i class, N_i is the number of learning samples in the i class and μ is the global mean vector.

We extract the feature vector from an input image, $\mathbf{x}$, and we assign it to the j class if

$$|\mathbf{W}^t\mathbf{x} - \mathbf{W}^t\mu_j| < |\mathbf{W}^t\mathbf{x} - \mathbf{W}^t\mu_i| \qquad \forall\, i \neq j \ . \tag{A.4}$$

A previous step on the classification process is to choose those variables that are significative of the data. Many variables can be used but few of them will be uncorrelated or will be homogenous inside each group. The best way to that is to choose the combinations of variables that best classifies the learning set of samples. This is very time consuming and can not be carried out for many variables. Statistics broach this problem with a stepwise approximation. It begins by selecting the individual variable which provides the greatest univariate discrimination. Then all the remaining variables are paired with the selected one to select the pair that best discriminates the data. This procedure is done until there is no more variables or the contribution to the classification is meaningless. Some test can be done to look for the best discriminating variable, but is has been shown that the results are nearly the same and conclusions vary slightly. We have used SPSS statistical software to do the classification process, which implements Wilks's lambda to test variables:

$$\lambda = \frac{\mid \mathbf{S}_w \mid}{\mid \mathbf{S}_w + \mathbf{S}_b \mid}$$

where $\mid A \mid$ denotes determinant of matrix A. The best discriminatory value is 0 and 1 when variables are useless. Further details on the classifier can be found in [26, 74, 63].

Appendix B

Tile samples

In this appendix we depict some samples of the ceramic tiles models used in section 5.6.

commercial name	number of pigments	number of grades	number of tiles
Duero	2	12	120
Tiber	4	10	120
Cinca	3	3	50
Orinoco	3	11	101
Ohio	2	7	72
Mijares	3	3	51

Table B.1: List of model tiles used in the ceramic tile classification problem.

Figure B.1: Tiber model. Classes are presented on rows.

Figure B.2: Duero model. Classes are presented on rows.

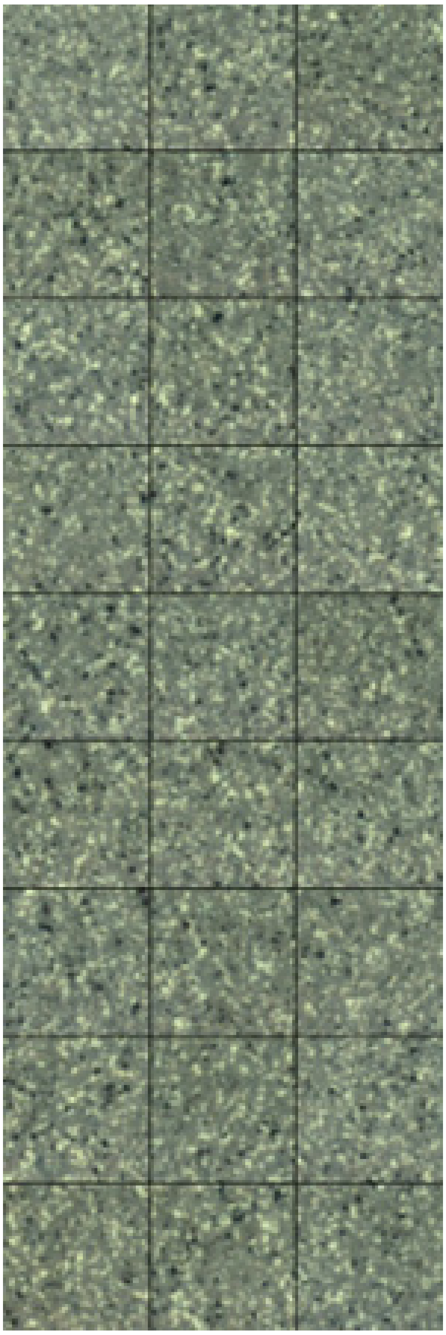

Figure B.3: Cinca model. Classes are presented on columns.

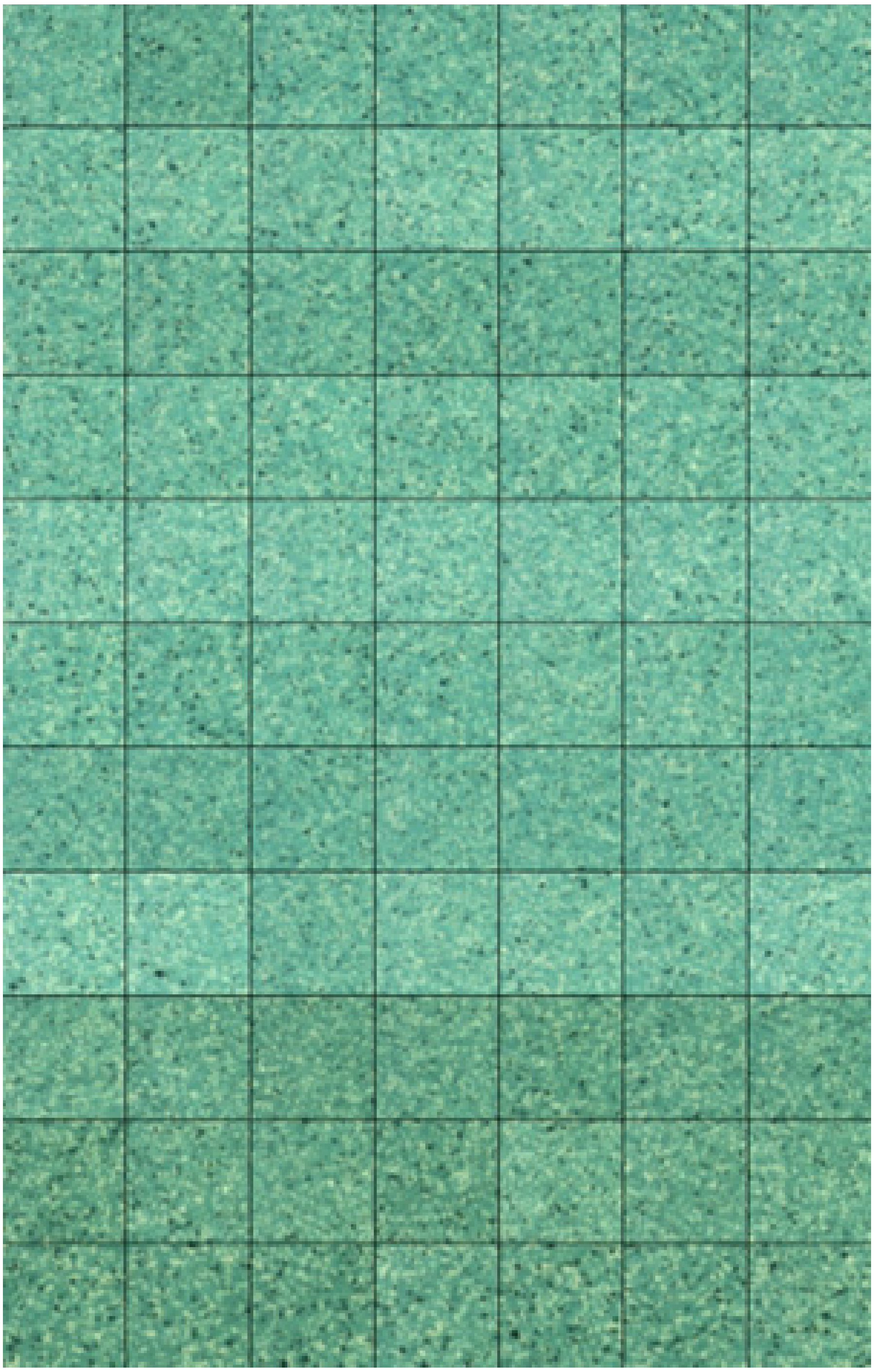

Figure B.4: Orinoco model. Classes are presented on rows.

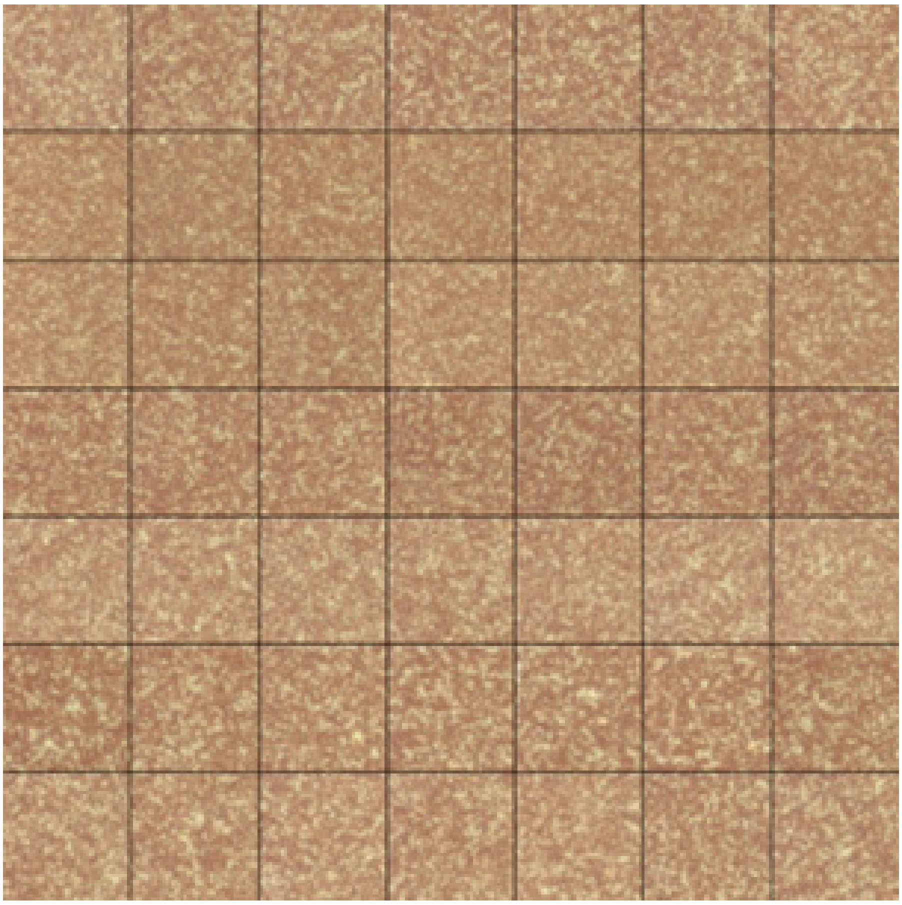

Figure B.5: Ohio model. Classes are presented on rows.

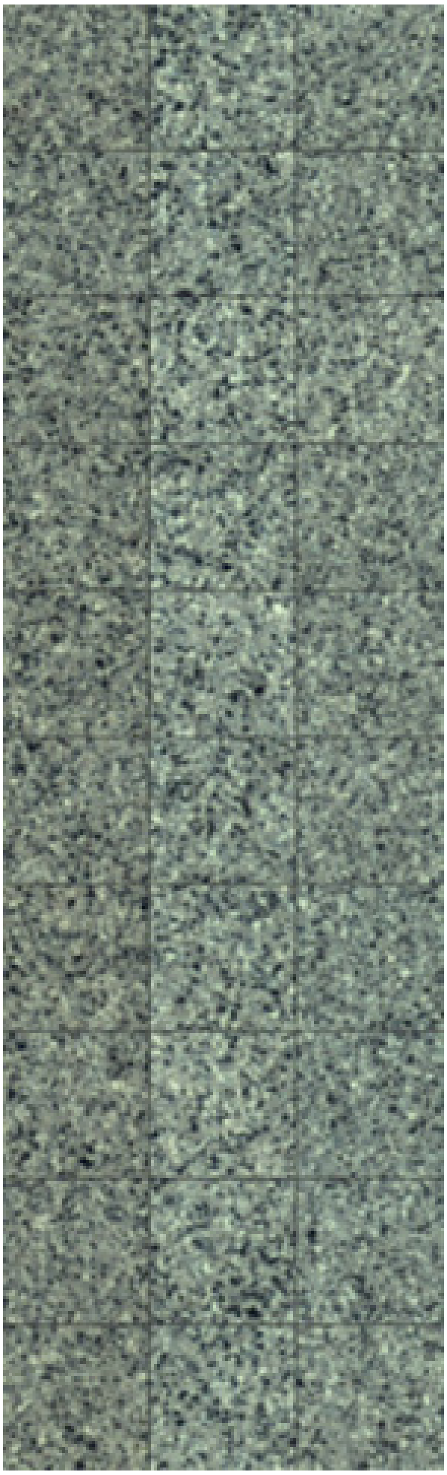

Figure B.6: Mijares model. Classes are presented on columns.