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Perceptual approach to a computational colour texture representation for surface inspection

A dissertation submitted by **Ramon Baldrich i Caselles** at Universitat Autònoma de Barcelona to fulfil the degree of **Doctor en Informàtica**.

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a la Montse, l'Alba i el Xavier

Acknowledgement and preliminary note

I know that when using a foreign language it is nearly impossible to use it fluently and perfectly, some times even moderately acceptable is difficult. However I decided to write this thesis in English instead of using my own language because, even with mistakes, it is easier to reach more people. Thus, I will like to acknowledge the people that will read this thesis for being kindly and to read the content and not so much the form, if it is possible. Now, with your consent I will switch to Catalan for a moment.

No perque, de forma establerta, sempre és el primer en aquestes llistes d'agraïments, sóc menys sincer. Gràcies Juanjo per haver-me obligat a fer la tesi. Amb aquesta última històrica et treus un pes de sobre, i jo també.

No hi ha manera possible d'agrair la tasca de na Maria en aquesta tesi, directora i part implicada. Però del que n'estic més satisfet és d'haver acabat aquesta tesi essent més amics que al principi, i això val una tesi i més.

No enumeraré tots aquells amb qui em sento amb deute per haver-me ajudat, o simplement haver estat en el meu entorn, ara i abans. El meu agraïment és per a tots vosaltres.

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Suposo que aquesta tesi tampoc servirà per fer entendre als meus pares i germanes a que coi em dedico, però de totes formes una part també és d'ells.

Per acabar vull fer palés que sense el suport de la Montse, la vitalitat de l'Alba i la simpatia del Xavier hagués estat molt més difícil, si no impossible, fer la tesi. Es mereixen un doctorat en paciència. El millor agraïment és prometre que faré lo impossible per no fer-los-hi tornar a passar una altra època com aquesta.

Abstract

The main goal of this thesis is to deal with the colour texture representation problem from a computer vision point of view. It is easy to demonstrate that the extension of classical grey level methods for texture processing to the three channels of the corresponding colour texture does not succeed in having a human-like behaviour on this visual task. Chromatic induction mechanisms of the human visual system, that has been widely studied in psychophysics, plays an important role on the dependency of the colour perception from its surround. Chromatic induction includes two complementary effects: chromatic assimilation and chromatic contrast. While the former has been psychophysically measured and lately extended to computer vision, some aspects on the last one still remain to be measured. The main contribution of this thesis is a computational operator that simulates the contrast induction phenomena that has demonstrated a coherent behaviour on different texture colour perception problems, since it allows to emphasise colour differences on almost-unimodal colour distributions and consequently improving the segmentation of colour regions. An open problem that will remain open from this work is the psychophysical measurement of the operator parameters, in the same sense as it was done with the s-cielab for the assimilation process.

A perceptually-consistent colour texture computational representation is a goal of extreme importance in automatic colour-textured surface inspection problems, where the classic colorimetric tools does not succeed in given good colour appearance measurements. In this scope, a second contribution is a colour-texture representation based on global colour features considering colour assimilation and local features based on properties of colour blobs considering colour contrast. This representation is applied to an automatic tile classification problem.

Since an important accuracy is needed to measure such small differences, we have devoted a great part of this work to the colour acquisition issue, and to the problem of achieving good colour constancy properties on the acquired images. In this sense, a last contribution of this work has been to define an on-line colour constancy algorithm for a high colour precision scan line camera based on a diagonal linear colour constancy model previously guaranteed by linear transform changing the camera sensitivity properties.

Resum

El principal objectiu d'aquest treball de tesi és tractar el problema de la representació de la textura en color des del punt de vista de la visió per computador. No és difícil demostrar que l'extensió dels mètodes classics de processament de textura per imatges en nivells de grisos a cada un dels tres canals d'una imatge en color no és sinònim d'assolir resultats semblants als de la percepció humana en aquesta tasca. Els mecanismes d'inducció cromàtica del sistema visual humà, que han estat àmpliament estudiats en psicofísica, tenen un paper molt important en la dependència que crea l'entorn en la percepció del color. La inducció cromàtica inclou dos efectes complementaris: l'assimilació cromàtica i el contrast cromàtic. Mentre el primer ja ha estat mesurat des de la psicofísica i extés a la visió per computador, molts aspectes del segon encara queden per fer. La contribució principal d'aquesta tesi és la definició d'un operador computacional que simula el fenòmen del contrast cromàtic i que té un comportament coherent amb el del sistema visual humà en diferents problemes de la percepcció de la textura en color, ja que permet enfatitzar les diferències de color en distribucions que són quasibé unimodals i conseqüentment millorar la segmentació de les petites regions de color. El problema que encara queda obert després d'aquest treball, és la realització de mesures psicofísiques pels paràmetres de l'operador definit, tal com es va fer amb l's-cielab per al procés de l'assimilació.

La definició de representacions computacionals de textura i color que siguin perceptuals és un objectiu de gran importància en els problemes d'inspecció automàtica de superfícies en els que els dispositius de la colorimetria clàssica no permeten donar bones mesures d'aparença de color. La segona contribució d'aquesta tesi, s'emmarca en aquest àmbit, i defineix una representació computacional basada en mesures globals de color que inclouen l'assimilació de color i mesures locals de les propietats de les regions segmentades considerant el contrast cromàtic. Aquesta representació és aplicada al problema de la classificació automàtica de gres porcelànic.

Tenint en compte que s'han de realitzar mesures molt acurades de petites diferències, s'ha dedicat una gran part d'aquest treball al tema de l'adquisició d'imatges en color, i en concret al problema d'aconseguir bones propietats de constància de color a les imatges adquirides. En aquest sentit, la darrera contribució d'aquest treball ha estat la definició d'un algorisme de contància de color en línea per a una càmera lineal amb alta precisió de color. Aquest mètode s'ha basat en el model lineal diagonal de constància de color prèviament garantit amb una transformació lineal que canvia les propietats de la sensibilitat de la càmera.

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Chapter 1

Introduction

The aim of this thesis is the computational representation of two surface properties: colour and texture. To build computational representations of visual information is an essential goal in the computer vision field in which this thesis is framed. A computational texture-colour representation has to allow building automatic descriptions of surfaces that can help in a wide range of computer vision tasks. A large number of works have been reported in the last decades on these two properties separately. But, for the last years the number of works dealing with both properties at the same time is increasing considerably. In this chapter we give a brief review of previous works on colour and texture to put the scope of this thesis within the computer vision field.

1.1 Surface properties

Any natural scene in the world is projected on our retina as a map of different regions that are the projections of 3D surfaces. The properties of these projected surfaces are concrete perceptions derived from specific positioning conditions of the surfaces in the scene and the observer, and the lighting conditions that provoke the neuronal excitation of the visual system. In computer vision, people usually work with the following set of surface properties: shape, orientation, colour and texture. In this work we will only deal with the last two.

Up to this point, we have only revealed one of the two goals of this thesis. The second goal of this thesis is also to develop the engineering background to take the computational texture colour representation to make it works on a real system ready to solve problems of automatic measurement of surface properties in the industry. A wide range of automatisation of industrial problems requires the measurement of coloured surfaces. These measurements are easily solved using calibrated colorimetric devices specially developed to measure colour-homogeneous surfaces. This solution fails when surfaces are coloured textures. Colorimetric measurements on colour texture surfaces give a quantitative measurement that is the result of a colour integration over the surface, and two very different colour textures can give similar measurements even though they have a very different spatial appearance, this is the case for the three

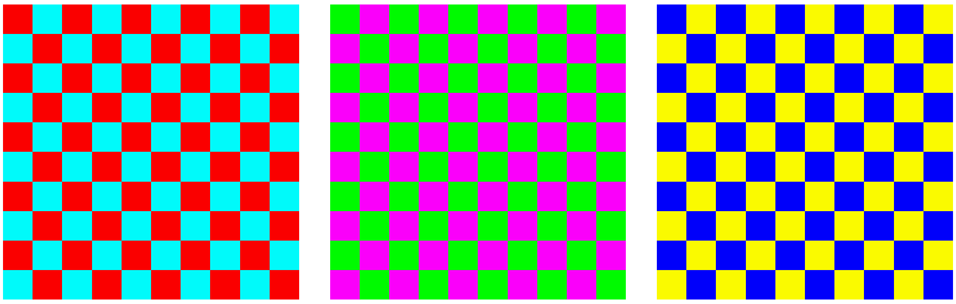


Figure 1.1: Images with the same colour mean but different appearance

images shown in figure 1.1 that share the same colour mean but a very different colour texture appearance.

In the next sections we will give a brief outline on how colour and texture have been treated in computer vision.

1.1.1 Colour

Colour is the visual cue derived from the human visual processing of the electromagnetic radiation that reaches the retina [78]. This process can be seen as a change in representation, which, in general, implies a dimensionality reduction. Although colour has not been given much importance in the first decades of computer vision, since most of the previous work in computer vision has been made for grey level images, the situation has changed and colour has become a very important visual cue for most of the vision tasks, such as object recognition [47], image indexing [100], tracking [66], shape extraction from colour variations [16], etc.

To introduce colour cue in the visual tasks we must take into consideration the variability of this visual stimulus. Colour perception is always dependent on the context: the illuminant, the receptor sensibility and the scene geometry have a great influence on the perceived scene. The human visual system presents a chromatic adaptation ability, which allows avoiding in some sense those context influences over the final perception. Any system doing a visual task involving colour processing should always take into account the colour constancy problem. This problem has been the topic of a lot of research that will be reviewed in chapter 3.

1.1.2 Texture

Texture is the visual cue derived from non-homogeneous surfaces in the scenes. Depending on the surface reflectance, positioning of the observer and lighting conditions, we can obtain different texture images from the same surface. Although there are some recent works dealing with the recovery of the physical reflectance properties of a texture [25, 48] and some other works that have recovered 3D shape information from texture [115, 44], the most traditional approach in computer vision has been the analysis of the texture images without taking considerations on the image formation process. Extensive reviews can be found in [49, 111, 103, 90], where it is shown that texture has been studied for different purposes such as segmentation, classification or synthesis. Despite the large number of works, there is still a lack of a standard texture definition and does not exist a widely accepted texture representation space, as it exists for colour. Interesting works directed to define a standard texture space based on perceptual considerations has to be considered [89, 88, 101], since this kind of work could be the basis to establish a standard computational representation. Before to go deeply on computational representations we will do a short inside on psychophysics theories on texture perception, that have been the basis for some of the works in computer vision.

In psychophysics, the aim has been to understand how the human visual system represents textures and which are the mechanisms used for texture segregation. Texture is one of the most complex visual cues and for the moment there is not a unique accepted theory. Two basic approaches are confronted as being the basis for a visual internal representation of texture. On one hand, feature extraction processes have received a hard support from the Julesz's texton theory [62], and on the other hand a global spatial frequency analysis seems to be indispensable as it has been demonstrated by J. Beck et al in [7]. Let us go deeply in these two approaches.

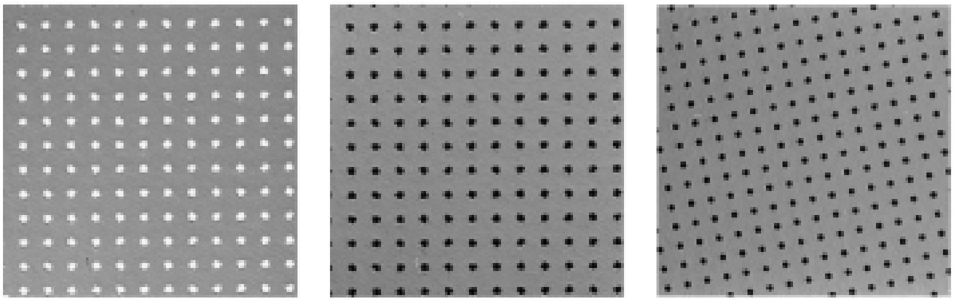
The first approach, the Julesz's texton theory is based on the fact that differences between two textures, are due to differences in the first order statistics, or densities, of the texton attributes, it ignores the positional relationships between adjacent textons. Texton attributes are defined as the blob properties, that is, size and contrast for general blobs, and orientation for elongated blobs. Other textons can be line endings or terminators, but a more exhaustive list of texton has not been developed yet. Although all the texton theory conclusions are based on psychophysical experiments, Julesz associates the feature extractors with simple or complex cortical receptive fields described by Hubel and Wiesel in 1968.

The second approach, leaded by J. Beck [7] and supported by other researchers [52, 51] advocates that, differences on first order statistics of local properties independently of the blob arrangement is not enough to be able to capture the segregation of textures, since in a wide range of cases, differences are due to patterns emerging from the different arrangements of image blobs. In these cases a global spatial-frequency analysis is needed in order to represent different textures.

In figure 1.2 we demonstrate the complementary character of these two approaches. While the textures (a) and (b) can be easily differentiated in the frame of the Julesz's texton theory due to differences on blob contrast; textures (b) and (c) are equals from this theory, since there is no difference in terms of texton attributes. Differences between textures (b) and (c) can be easily derived in the frame of a of a global frequency analysis, for which a difference in emergent orientations can be considered.

Considering the conclusions from psychophysical theories, different approaches have been followed to solve problems involving different visual tasks in computer vision. We briefly summarise the taxonomy proposed by Tuceryan et al in [103]:

Geometrical approach Texture is described by the set of textural primitives that composes the image, therefore a texton isolation step is always needed. Once the basic elements have been extracted, two approaches are essentially used. One



(a) (b) (c)

Figure 1.2: Examples of textures formed by simple blobs and their emergent patterns.

computes statistical properties of the extracted elements and their attributes [105]. The second one extracts the placement rules that organise these shapes in the texture [41], this last approach is called a structural approach.

Model-based approach Texture is considered as the realisation of a concrete mathematical model, hence it is defined by the model parameters. From a methodological point of view this is the most well defined solution, problems can arise from generality, it does not exist a unique model that can represent any natural texture. Interesting texture models can be seen in [1, 54, 61, 87, 23]

Filtering approach Texture is described by the responses of convolving a set of filters with the image. This approach is based on the previous introduced idea of the existence of an spatial-frequency global analysis of the textures in the human visual system. Malik and Perona in [71] proposed a global preattentive texture perception model based on neuro-physiological and psychophysical considerations. A global Fourier-based analysis of textures has been recently proposed in [39] and when spatial dependency is needed the Gabor transform has been used [59, 73].

From all these approaches, different visual tasks can be carried out. In texture segmentation, region-based or edge-based mechanisms have been used, all these methods try to evaluate when two small regions have a uniform texture or, on the contrary, have different textures. The general problem of texture representation has been mainly developed for image retrieval, image annotation or image classification. In all these problems the final goal is to build a feature vector expressing an enough quantitative measure of the image content. The rest of this work will be devoted to study how texture and colour can be combined considering these previous experiences on gray level textures.

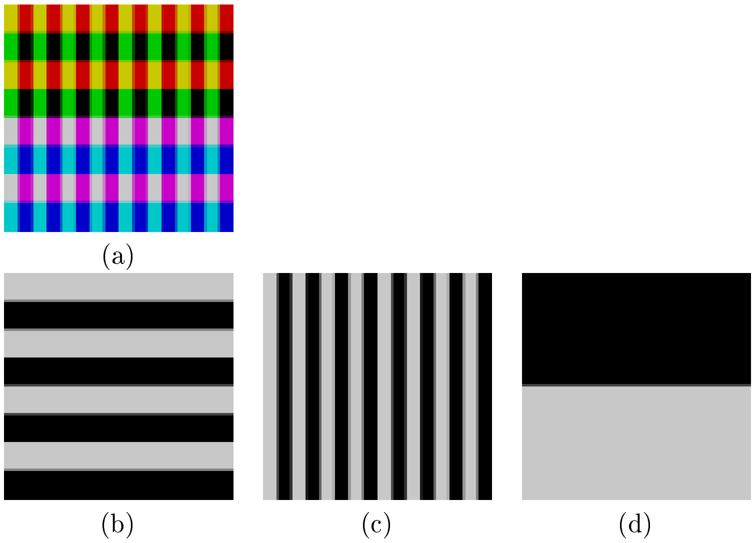


Figure 1.3: (a) A colour image. (b) Red channel of (a), (c) Green channel of (a), (d) Blue channel of (a).

1.2 Colour and Texture

Colour texture representation is a current topic in computer vision. Although both are properties of a surface as we have just introduced, these two visual cues have been usually studied separately. One reason is that while colour is a point feature given by the value of a pixel in several bands or channels, texture has to be modeled as a spatial relationship of the point with its neighbours. The trichromatic representation of colour images taken from common imaging devices has provoked an important dependency, that is probably not the best to deal with these two dependent properties. In figure 1.3 we can see the RGB channel representation of a colour image, where we can observe that the spatial information of the colour image is not present in the separate channels and therefore specific representations have to be constructed in order to deal with both cues at the same time.

The study of colour texture representations has received an increasing attention. The objective of many researchers has been to find co–joint representations of spatial and chromatic information which capture the spatial dependence (in particular, correlation) *within and among* spectral bands. One of the most frequent approaches is the construction of a feature vector mixing grey level texture features and colour features [19, 102]. Another one is to extend classical texture models, such as Markov Random fields and the autocorrelation function, in order to deal with multichannel images [82, 53]. Other works, like [42], convert RGB values into a single code from which texture measurements are computed as if it were a grey scale image. Spatio–chromatic representations are computed in [17, 37] over the smoothed Laplacian of the image, and the structural tensor that is usually used to represent local texture properties is extended to colour images in [113].

Finally, there are some works that have been influenced by known perceptual mechanisms of the human visual system, where the interaction of colour with the spatial frequency of the coloured patterns is considered [84, 80]. These works have considered some important conclusions from psychophysical experiments on colour texture interaction which are the conclusions of some works [2, 85, 109, 119, 118]. The contributions of these works and its application to computer vision will be reviewed in more detail in chapter 4. This perceptual mechanism simulates the colour assimilation phenomenon of the human visual system that is affected by a spatial blurring of the colour representation when looking at colour textures presenting high spatial frequencies.

In this work we will present a complementary operator that will allow simulating the colour contrast phenomenon that appears in the visual system when looking at colour textures presenting low spatial frequencies.

1.3 Thesis Outline

The content of this thesis work has been organised in five chapters. Chapter 1 is the introduction we have done above. We have introduced the thesis goals and a brief introduction on how colour and texture have been studied in computer vision.

Chapter 2 is devoted to explain the design of a colour image acquisition system. Since one of the final goals of this work is to design a vision system able to measure colour appearance on textures as colorimetry does on homogeneous surfaces, we will need to take an special attention to the accuracy and to the stability of the designed system. Is for this reason we will dedicate a complete chapter to the problem of acquiring colour images with a CCD-based sensor.

In chapter 3, we give the basis of a colour image formation and the laws underlying colour constancy theories. Afterwards, a brief review of the most important methods for colour constancy is given. In order to be able to apply a linear diagonal model the spectral sharpening transform is computed once the sensitivities of the camera have been recovered. In the last part of this chapter an on–line colour constancy algorithm for scan line cameras is proposed.

Chapter 4 begins with a review on psychophysical literature, it is directed to establish the basis for the most common colour induction phenomena: assimilation and contrast. Considering the most important conclusions from the previous review, a computational pattern-colour separable model based on the opponent-colour space is derived. The chromatic assimilation model based on a perceptual blurring is introduced, and all the details of the Spatial–CIELAB are explained. In the following sections we propose a chromatic contrast model that is based on a perceptual sharpening. Three types of perceptual sharpening are proposed: local, region and spread. Finally, we show the behaviour of the spread sharpening on some natural textures.

The goal of chapter 5 is to build a computational colour texture representation based on the previous considerations, and to apply it to a pair of automatic surface inspection problems, these are: tile classification and printing quality evaluation. In both cases we will see how the perceptual blurring proposed allows improving the results.

In the last chapter we sum up all the conclusions of this thesis work, and after a short discussion on the results we describe the open research directions that have been outlined from this work.