Image Segmentation based on Inter-feature Distance Maps

Susana Álvarez [a,1] Xavier Otazu [b] and Maria Vanrell [b]
[a] *Departament d'Enginyeria Informàtica i Matemàtiques*
[b] *Centre de Visió per Computador*

Abstract. In this paper we present an unsupervised colour-texture segmentation method. The novelty of this new approach relies on the definition of the inter-feature distance map, which combines different textural properties, either those due to chromaticity variations or those due to intensity changes. The proposed framework works on a multi-channel representation that directly depends on the basic colours perceived in an image, trying to avoid the spatial correlation of usual 3D representations of colour. The textural information derived from intensity changes is added to the multi-channel representation and finally, chromaticity and intensity are combined with the inter-feature distance maps. The behaviour of the approach is tested on a set of natural and synthetic images to demonstrate the capabilities to deal with some representative types of colour-textures which are suggested in this work.

Keywords. colour and texture segmentation.

1. Introduction

Automatic segmentation of image has been a key issue to deal with image understanding. Colour and texture are key properties for image segmentation. Both are due to physical properties of object surfaces and to the geometric conditions of scene and observer.

In computer vision there have been different approaches to deal with these two visual cues on digital images [1,2,3,4,5]. An essential difference amongst these approaches rely on where, within the overall process, texture and colour are combined, and how it is done. The essential difference between colour and texture relies on the fact of colour is a punctual property while texture is an spatial property, it implies that computational combination is not an evident step. In [1] and [2], colour and texture are combined in the first steps of the process; the first one computes a perceptual blurring based on psychophysical studies about colour appearance [6]; the second one is based on the gaussian model of colour images, introduced in [7]. On the other hand, in [3]image pixels are labelled with colour descriptor, in [5] pixel label depends on image descriptors (colour and texture) and in both, regions are derived with different classification methods. A last and very common approach is based on a filtering step, usually Gabor filters, applied to the monochrome image [4] or on colour channels of the image, as it is done in [2], then

[1]Correspondence to: Susana Alvarez, Universitat Rovira i Virgili, Tarragona, Spain ; E-mail: salvarez@etse.urv.es.

combination is just given by the local properties of filters within each channel and no inter-channel combination is derived. A common step in some of these methods [2,3], is to incorporate a region merging process that achieves the final region segmentation based on their respective features, a key issue for a good performance relies on the selection of a set of parameters to take merging decisions, this is usually a hard task considering the inherent variability of digital images in general purpose applications. Finally, we want to note that on all these approaches there is not a unique procedure to evaluate the performance of the algorithms, since in general is the final goal of each application that usually establish the best performance criteria.

In this paper, we deal with the same problem, that is colour-texture segmentation, where the main differences between all the referred approaches and our method are: the way we combine colour and texture features and the use of the inter-feature distance map which performs part of the final clustering process. We outline the essential steps of our approach, that relies on the definition of the inter-features distance map. Since we can not give specific criteria to evaluate general performance at the moment, we propose to establish some assumptions about how a segmentation should be done depending on specific properties of colour-texture images. Hence, images fulfilling these specific assumptions, will be the guide to analyse the performance of the method and will be de guide for the algorithm requirements (section 2).

To this end, in this paper we propose an unsupervised colour-texture segmentation method. A Global scheme of this proposal is given in figure 1 where it can be seen that colour signal is divided into luminance and chrominance components to process them separately. With chrominance components we perform a basic chromaticity segmentation (explained in section 3), and we apply Gabor filtering to the luminance component to obtain texture features (detailed in section 4). In the next step, section 5, we extract texture features of each class colour obtained in the chromaticity segmentation. At the last step, in section 6, we perform a first clustering of the pixels nearby a feature with the computation of the inter-feature distance map and finally an inter-feature clustering achieves the image segmentation.

2. Colour and texture

A colour texture region in an image is an specific projection of a scene surface on the image plane. From the image point of view a colour texture region is given by the spatial repetition of spatio-chromatic patterns that are due to different physical properties derived from the image surfaces.

A colour texture can be given by a surface of homogeneous colour and different observation conditions across this surface, which are provoked by the surface roughness. An example of this kind of textures is given in figure 2.(a), a synthetic version of a similar effect is given in figure 2.(b), in both cases texture is essentially due to differences on the intensity channel and not on the chromaticity channel.

Other colour textures are due to texture elements of different chromaticities, such as those textures in figure 2, (c) and (d). Texture (c) is emerging from the random repetition of different colour patterns, we can synthesize an extreme case of this kind of texture by building a colour image with constant intensity in all the points and texture is just provoked by chromaticity differences across the image, one of this cases is shown in image (d).

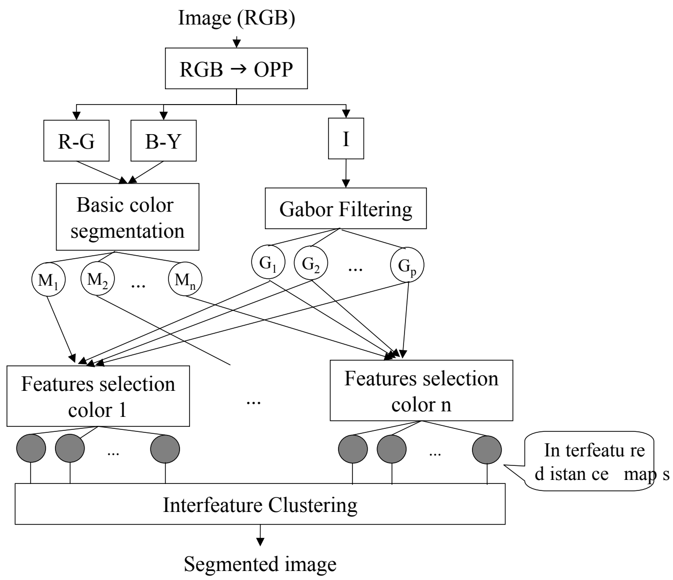


Figure 1. General scheme of our proposal.

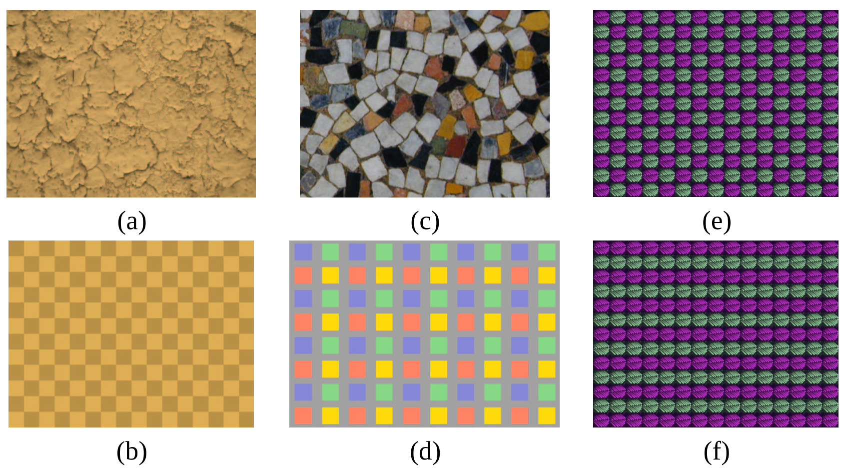


Figure 2. (a) Natural texture provoked by surface roughness. (b) Synthetic texture with homogeneous chromaticity and a texture provoked by intensity properties. (c) Colour texture essentially given by changes on chromaticity properties. d) Synthetic colour texture with different chromaticities and homogeneous intensity. (e),(f) Two different textures where differences are due to location of textural elements.

Finally, in figures 2,(e) and (f), we present two textures with equivalent intensity and chromaticity properties, textural differences are due to different spatial distribution, that is, different location of textural patterns.

We propose a colour-texture segmentation method, that has been defined to be able to segregate all the types of textures above mentioned.

3. Basic chromaticity segmentation

In order to assure that all kind of textures can be segmented, the first step of our approach is to separate chromaticity and intensity properties of image points. To this end, we will use an opponent colour space for the representation of colour, since this space have been shown as one of the most well suited to the human colour visual system [8,9,10] to predict the colour representation of patterned surfaces. This opponent colour space represents colour information on three axis: one for the intensity and two for chromaticity, these are the red-green and blue-yellow components. Starting from an RGB image we apply de following transform to obtain opponent colour components:

$$\begin{pmatrix} \text{I} \\ \text{RG} \\ \text{BY} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 \\ 1 & \text{-1} & 0 \\ 1 & 1 & \text{-2} \end{pmatrix} \cdot \begin{pmatrix} \text{R} \\ \text{G} \\ \text{B} \end{pmatrix} \tag{1}$$

Since in our case we want to process only chromaticity information, we used blue-yellow and red-green components to perform a colour classification in terms of the basic colours we can segregate. To achieve this goal, we use a type of neural network named Self-Organizing-Map (SOM) [11,12], which is a widely used technique to perform clustering tasks [4,13]. In this case we will use a SOM of 11 nodes (number of output classes), in order to assure that at least the eleven basic colour terms suggested in [14] are completely represented in this multi-channel chromaticity representation of our image.

This first segmentation defines the spatial distribution of the different colour labels throughout the image and allows us to define a spatial support: a mask (M_i), for every colour with the aim to analyse the texture features present in every colour class.

4. Intensity Gabor Filtering

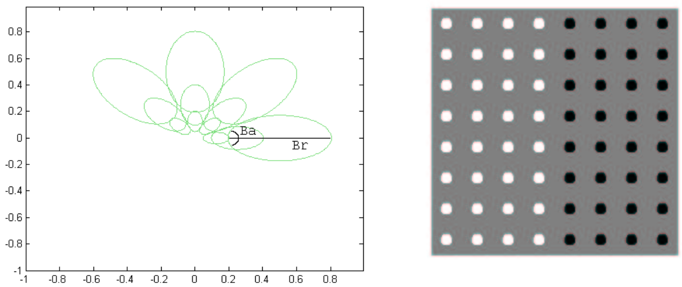
Once, chromaticity and intensity have been separated, in this step we deal with the textural properties given by differences on intensity changes, independently of their chromaticity. At this stage, we are considering the basic elements, usually referred as textons [15] or blobs, which are repeated all over the image. Perception of this textons is influenced by its spatial frequency properties. Characterization of these frequency properties is usually performed by tools like Fourier Transform, Gabor filters, Wavelet Transform, etc., being Gabor filters [16] increasingly used for textural analysis tasks [4,17,18,19,20,13,21].

In our case, we use Gabor filters in order to extract blob features from the intensity image (luminance plane). The Gabor filter used [22] is:

$$g(x,y) = a^2\, T\, \exp\left[-\pi a^2 \left(x'^2 + T^2 y'^2\right)\right] + 2\pi j f x' \tag{2}$$

where:

$$a = k * f; \;\; k = \sqrt{\frac{\pi}{\ln 2}}\,\frac{2^{Br}-1}{2^{Br}+1}; \;\; T = \sqrt{\frac{\pi}{\ln 2}}\,\frac{1}{k}\,\tan\frac{Ba}{2}$$



(a) (b)

Figure 3. (a) Contours magnitude, in the frequency plane, of the filter responses for different Gabor filters. (b) Example of two different textures formed by black and white blobs on a uniform background.

$$x' = x\ cos\theta + y\ sen\theta;\ \ y' = -x\ sin\theta + y\ cos\theta$$

The location of each filter is determined by two parameters: the radial frequency f and the orientation θ. Ba and Br parameters are frequency and orientation bandwidth of Gabor filters. The 2-D Gabor filter coverage on the frequency plane can be seen in figure 3.(a) where a given subset of frequencies and orientations are shown [18]. Filters of different orientation sensitivities are obtained varying their angular locations θ in the frequency plane, and different frequencies varying their radial distances f.

To describe all the blobs related to a certain spatial frequency all the filters with the same frequency f should be combined along orientation θ. In order to assure the segregation of textures defined by black and white blobs (see Fig. 3.(b)), we need to preserve the sign of the filter responses. It can be accomplished by splitting Gabor filtered signals into two parts: positive and negative values, that is usually referred as a half-wave rectification.

Applying this Gabor analysis to the image intensity channel, we obtain Gabor intensity features which describe all the spatial and luminance information of image blobs, which are given by the intensity channel.

5. Feature selection

Gabor features from intensity image can help us to distinguish textures which are defined by intensity variations. In contrast, as explained in section 2, there are textures with homogeneous intensity but with different chromaticity information. In this case, using just the Gabor intensity features does not allow to differentiate this kind of textures. To achieve this goal it is necessary to combine intensity features with chromaticity information. The chromaticity information is represented by binary masks denoted as M_i, where i represents a basic colour (section 3), and intensity features are obtained from the Gabor filtering in data sets G_k, where k represents an specific Gabor filter (section 4). Then if we apply every colour mask to the Gabor intensity features we can isolate, for every basic colour, its Gabor intensity features (M_iG_k).

After that, in order to achieve binary features needed in the next step, and in addition to reduce the number of features, we use a SOM. For every basic colour i we introduce its Gabor intensity features in a SOM, giving us a new set of binary features MF_{ij} which describe the intensity information for the colour i. This allows us to perform a textural analysis of features of each basic colour channel.

6. Inter-feature distance map

As explained in section 2, texture is defined by the spatial distribution of intensity and chromaticity information. This spatial distribution has been captured in the new features MF_{ij}, then, analysing for every MF_{ij} the spatial interaction between the textural features, we can obtain the different textures. The spatial interaction is analysed using distance maps. To obtain the distance map of a feature image, first we compute the Euclidean distance transform of the binary feature. For each pixel the distance transform assigns a number that is the distance between that pixel and the nearest nonzero pixel of the image, then all the pixels which value is greater than certain distance are set to zero. As a result since MF_{ij} are intensity textural features of a certain colour i, the distance map allows to perform an analysis of the spatial interaction between different colours and different textured areas.

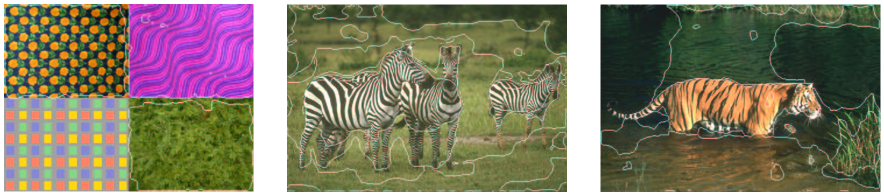
Obtaining a distance map for every MF_{ij} textural features and grouping them in a stack, we obtain a multidimensional dataset $D(MF_{ij})$ that describes the inter-features interaction which, in turn, define more complete texture features. These inter-feature distance maps allow to compactly describe all the elements that can provoke a colour texture, i.e. chromaticity information, intensity variations and the spatial distribution and interaction between these textural features.

The multidimensional dataset $D(MF_{ij})$ is a complete colour texture descriptor. This descriptor can be used to perform the final segmentation of our original textured colour image if used as the input feature dataset of a classification process. This classification step is again performed by a SOM that achieves the inter-feature clustering of the descriptors $D(MF_{ij})$ and distinguishes the different texture types and delivers a finally classified image.

7. Results

As we have already mentioned, we do not have an objective procedure to evaluate the obtained segmentation. Our main goal in this work is to check the feasibility of our method in segmenting the different kind of textures we have introduced in section 2. To this end, we will show some of the results we have obtained in some images.

In figure 4.(a), we can see the result of a mosaic image composed by three natural texture and one synthetic image. With this example we can see that our method is able to get a segmentation when we have four different types of texture. The textures on the left side of the mosaic are textures provoked by differences in chromaticities, the texture in the top presents changes on the intensity channel, however the bottom texture the intensity channel is constant and texture is just due to chromaticity channels, we can see that in both cases, the segmentation has been well done. On the other hand, textures on the left side present less chromaticity changes, and again the method has succeed in giving a correct segmentation.



(a) (b) (c)

Figure 4. Segmentation results.

(a) (b)

Figure 5. (a) Segmentation of gorilla image 3x1 classes. (b) Segmentation of gorilla image 2x2 classes

The natural images shown in 4.(b) and (c), are presenting textures of both types, that is, just intensity variations as in the (c) image, or intensity and chromaticity variations as in (b) image.

Another point we want to note about the behaviour of this algorithm, is that the final step provided by the SOM, allows to get different degrees of segmentation, when we increase the number of classes we obtain a more accurate representation of the image details, this can be seen in 5.(a) and (b).

8. Conclusions and Further work

In this paper we have given a first outline of a new approach that tries to combine colour and texture by applying a different process on chromaticity and intensity properties. The method is based on an opponent colour representation, from which a multi-channel representation of basic colour terms is derived. The chromaticity properties are preserved on these channels or binary masks of basic colour terms. These masks are combined with the responses of an spatial-frequency analysis performed on the intensity plane, which is based on a Gabor decomposition. In order to combine both, inter-feature distance maps are computed on this combined description. Finally, a self-organising map is computed to obtain a global classification of image pixels, considering all the computed colour and textured combined properties.

We want to note, that it is a first outline of a new framework in the pursuit of an unsupervised segmentation of colour textures that can minimise the number of parameters that need to be tuned for any image segmentation, and that allow any kind of image texture, either the textural properties are due to intensity, chromaticity or spatial arrangements. Some improvements need to be done essentially on the feature selection step of the proposed method.

References

[1] M. Mirmehdi, M. Petrou: Segmentation of Color Texture. IEEE Trans. PAMI 22, No. 2, 142–159,(2000)

[2] M.A. Hoang, J.M. Geusebroek: Measurement of color texture. Proc. Advance School for Computing and Imaging (ASCI),75–82. (2002).

[3] Y. Deng, B.S. Manjunath: Unsupervised Segmentation of Color-Texture Regions in Images and Video. IEEE Trans. PAMI(23), No. 8. 800–810.(2001).

[4] N.W. Campbell, B. T. Thomas,T. Troscianko: Segmentation of Natural Images using Self-Organising Feature Maps. British Machine Vision Conference, 223–232, (1996).

[5] C. Carson, S. Belongie, H. Greenspan, J. Malik: Blobworld: image segmentation using Expectation-Maximization and its applications to image querying. IEEE Trans. PAMI 24, 8. 1026–1038.(2002).

[6] X. Zhang and B.A. Wandell: A spatial extension of cielab for digital color image reproduction. Proc. Soc. Information Display Symp. (1996).

[7] J.M. Geusebroek, R. van der Boombaard, A.W.M. Smeulders and A. Dev: Color and Scale: The spatial structure of color images. Sixth European Conference on Computer Vision. 331–341.(2000).

[8] B.A. Wandell: Foundations of Vision. Sunderland, Massachusetts, USA: Sinauer Associates Inc., (1995).

[9] A. Poirson and B.A. Wandell, The Appearance of Colored Patterns: Pattern Color Separability, JOSA A, 10, 2458 (1993).

[10] A.B. Poirson and B.A. Wandell: Pattern-Color Separable Pathways Predict Sensitivity to Simple Colored Patterns, Vision Research, 36, 515 (1996).

[11] T. Kohonen: Self-Organization and Associative Memory. Springer Verlag, Berlin. 3rd edition, (1989).

[12] T. Kohonen: Self-Organizing Maps. Springer Verlag, Berlin. 2nd edition, (1997).

[13] S.Y. Lu, J.E. Hernandez and G.A. Clark: Texture Segmentation by Clustering of Gabor Feature Vectors. Int. Conf. Neural Networks (IJCNN), 683–688 (1991).

[14] B. Berlin and P. Kay: Basic Color Terms: Their Universality and Evolution, University of California Press, Berkeley, (1969)

[15] Julesz, B., Bergen, J.R.: Textons, the fundamental elements in preattentive vision and perception of textures. Bell Systems Techn. Journal, 62:1619-1645, (1983).

[16] D. Gabor: Theory of communication. J. IEE, 93:429–457,(1946).

[17] C. Grigorescu, N. Petkov and M.A. Westenberg: contour Detection Based on Nonclassical Receptive Field Inhibition, IEEE Tr. on Image Processing, 12, 7 , 729–737 (2004).

[18] S.R. Fountain, T.N. Tan: Extraction of Noise Robust Rotation Invariant Texture Features via Multichannel filtering. Int. Conf. on Image Processing (ICIP), 197–200 (1997).

[19] A. Jain, G. Healey: A Multiscale Representation Including Opponent Color Features for Texture Recognition, IEEE Trans. Image Processing, 7, 1, 124-128 (1998).

[20] A.C. Bovik, M. Clark, and W.S. Geisler: Multichannel Texture Analysis Using Localized Spatial Filters, IEEE Trans. PAMI, 12, 1, 55–73 (1990).

[21] A. Teuner, O. Pichler, B.J. Hosticka: Unsupervised texture segmentation of images using tuned matched Gabor filters. IEEE Trans. Image Processing, 4, 2. 863–870,(1995).

[22] J.A. Aznar Casanova: Análisis multiescala y multiorientación de imágenes mediante un banco de filtros de Gabor-2D, Cognitiva 12, 2, 223–246, (2000).