Subtexture Components for Texture Description

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Abstract. In this paper the problem of texture description for image browsing or annotation is approached. Previous works in this direction have proposed solutions that have shown to be limited due to the high degree of complexity natural textures can achieve. This problem is solved here by defining textures as a combination of several subtexture components, whose description is simpler since they only have one characteristic element. A computational method based on multiscale filtering with Laplacian of Gaussian is presented to identify the subtexture components of a texture, and a texture description based on these subtexture components attributes is given.

1 Introduction

Texture is an important visual cue for image understanding that still lacks of a standard and general definition in Computer Vision. Texture is necessary for many machine vision applications, and thus several computational approaches to build texture representations have been presented[1] In most cases the representations obtained were directed by specific taks such as image classification [2],image retrieval [3]or image segmentation [4],however psychophysical studies on human texture perception have been the motivation for others [5]. Some texture spaces have been derived from these studies, but for the moment none of the approaches leads to a general texture representation space.

A texture description in textual terms and related to how textures are perceived by human beings is necessary for image browsing or image annotation. In this scope, the MPEG-7 standard, devoted to provide a set of standardized tools to describe multimedia content, proposes a perceptual browsing descriptor (PBC) [6]. In this paper we present a new approach to texture description based on perceptual considerations. We try to extend the PBC descriptor so that it comprehends all the texture information and a wider and adaptable description is obtained.

To this end, the paper is organised as follows. Section 2 sets the background and section 3 defines the concept of subtexture component giving the computational details on how to obtain them. The texture description based on the subtexture components is presented in section 4. Some results are shown in section 5 and finally section 6 presents the conclusions and further work.

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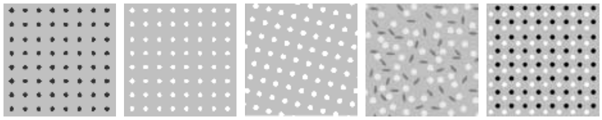


(a) (b) (c) (d) (e)

Fig. 1. Examples of simple textures

2 Background

As mentioned in the introduction, texture does not have a standard definition in Computer Vision. In this paper, a grey-level image is considered to be a texture if it presents homogeneity in its grey-level distribution along the image which is given by the repetition of basic primitives across the image. We will consider an image as a texture when at least four non-overlapped windows can be taken from the image sharing the same texture properties.

Any approach to texture description should be based on how human beings perceive and describe textures. To this end, let us analyse the results that have been obtained in psychophysics on texture perception. Two approaches are confronted as being the basis for an internal visual representation of texture. On one hand, local feature extraction processes have received a hard support from the Julesz's [7] texton theory, and on the other hand, a global spatial analysis has been demonstrated to be necessary by Beck [8]. Examples in figure 1 show that both methods form part of the process by which the human visual system deals with texture: textures in images (a) and (b) are segregable due to differences in the blob contrast, i.e. local features, whereas images (b) and (c) are segregable because of the orientation of the patterns emerging from the texture image. Therefore, not only global methods but also local properties should be taken into account when dealing with texture description.

It can be shown that if textures are regarded as blobs and emergent patterns, the complexity level of textures, both natural and synthetised, is unlimited, like textures in figure 1 (d) and (e), which are made out of combination of different simpler textures, i.e. (e) is obtained by combining (a) and (b). Despite this wide range of complexity degrees in texture, in previous texture descriptors all textures are described with the same number of features. However, if human subjects are asked to describe more complex textures, they will use more words or features than they use for simpler textures.

Another advantage of considering textures as a combination of properties from blobs and emergent patterns is the ability to build objective descriptors. Most of the experiments that have been done to derive the dimensions of the texture space have been based on texture comparison or segregation. Therefore, the results that are obtained might not be suitable for texture description, but for texture comparison. Rao et al, in [9], presented a serie of psychophyiscal experiments concluding there are three main dimensions for texture, namely structure or regularity, scale, and directionality, nonetheless these concepts can

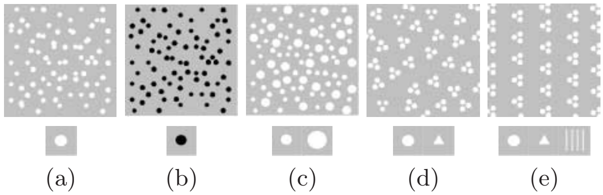


Fig. 2. Textures having different number of subtexture components which are defined by the property presented below each image

not be clear and objective enough for description when both regular and random patterns appear in a texture at the same time. The foregoing discussion makes us consider that a texture descriptor willing to be general and meaningful should fulfil two conditions: (i) different texture degrees of complexity must be taken into account and (ii) textures have to be represented by attributes of their own characteristic elements, and not only by comparison to other textures. These considerations have motivated the introduction of the concept of subtexture component, which is defined in the following section.

3 Subtexture Components

Previous considerations lead us to define a subtexture component of a texture image as a *set of blobs or emergent patterns sharing a common property all over the image*. Then, a texture image will be formed by several subtexture components, each one characterized by only one kind of blobs or emergent patterns. In figure 2 textures with different number of subtexture components are shown. The texture in image (a) has only one subtexture component defined by bright blobs randomly positioned, the image in (c) has two components due to the different size of the bright blobs and in (d) there are also two subtexture components, since there are bright blobs but also triangles emerging from the blobs grouping. Finally, texture in (e) has three subtexture components, since the triangles are positioned forming a stripped emergent pattern.

The fact that textures are understood as a combination of components allows to describe textures in terms of the attributes of their components, instead of describing the whole texture. This approach to texture description fulfils the aforesaid conditions: (i) a texture can be made out of as many subtexture components as necessary, and thus the adaptation to different degrees of complexity is assured, and (ii) the subtexture components can be described in terms of the attributes of its own blobs or emergent patterns, and not by comparison with other textures.

Once this concept has been defined and explained, now the goal is to define a computational approach to automatically extract them since it will be the base of the texture descriptor presented in the following section.

We propose a multiscale filtering approach to obtain the subtexture components, since it allows detecting blobs and emergent patterns with different sizes. The images will be smoothed by a gaussian filter, so that at higher scales the details disappear and only global structures of the image remain. For each scale, blobs will be detected and subtexture components are obtained by gathering those sets of blobs having the same contrast. In [10] the laplacian of gaussian filter was used to detect blobs in texture images; in this case the method will be extended by varying the size of the filter. Filtering with the laplacian of gaussian presents several advantages: (i) if no threshold is considered, the zero-crossings are closed, and thus its duals can be interpreted as blobs, (ii) the multiscale filtering permits tunning with different blob sizes and (iii) the sign of the pixels in the filtered image gives its contrast with the neighbouring pixels, which will be used to determine the contrast of the blobs.

Thus, the first step to obtain the subtexture components is to find the blobs or emergent patterns for a given scale. For a given texture image I, for each scale σ, the smoothed version of the image, S_σ and its Laplacian, L_σ, are calculated:

$$S_\sigma(I) = I * G_\sigma \ ; \ L_\sigma = \nabla^2(I * G_\sigma) = I * (\nabla^2 G_\sigma) = I * LoG_\sigma \tag{1}$$

where G_σ is a gaussian filter with standard deviation ,σ, which takes p values within the range $[\sigma_{min}, \sigma_{max}]$. The zero-crossings of L_σ are the closed edges of the smoothed image; therefore, its duals can be considered as blobs. The following step consits on classifying the blobs according to their contrast [11], which is given by the grey-level values of L_σ in each blob : bright blobs are those verifying $L_\sigma < 0$ and dark blobs those where $L_\sigma > 0$.

At this point, the blobs of an image S_{σ_i} having the same contrast form a subtexture component if they appear uniformly through all the image. Otherwise, it is supposed that the blobs are not characteristic elements of the texture and therefore they are rejected. Thus, for an image I we obtain n subtexture components $\{\mathcal{S}^i\}_{i=1,\ldots n}$ where $n \leq 2p$.

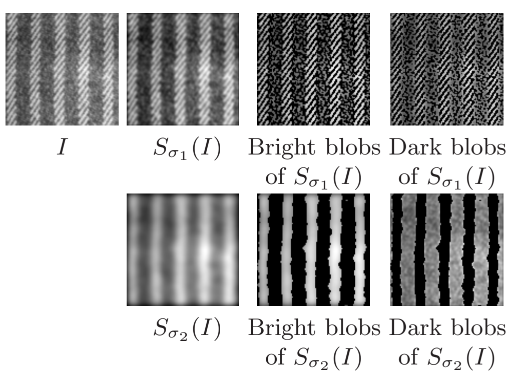


Fig. 3. Extraction of subtexture components by multiscale filtering

The images in figure 3 show different steps to obtain subtexture components. The original image I, the smoothed image and the subtexture components for bright and dark blobs are shown for two different scales, $\sigma_1 = 0.75$ and $\sigma_2 = 3$.

4 Texture Description

Once we have outlined the method to obtain the subtexture components of a texture, let us present the texture descriptor based on their attributes. In [12] the PBC descriptor for a texture image is given by the regularity, two predominant directions and two predominant scales. In our case, we propose to describe a subtexture component $\mathcal{S}^i(I)$ of a texture I by

$$\mathcal{D}(\mathcal{S}^i(I)) = [c, sc, st, d_1, d_2, d_3, d_4] \tag{2}$$

where the meaning of the 7 components is the following:

- c gives the contrast of the blobs, b for bright blobs and d for dark blobs
- sc represents the scale, ranging from 1 (*small*) to 5 (*large*).
- st is the structure, ranging from 1 (*completely random*) to 5 (*structured*).
- d_1, d_2, d_3 and d_4 are the orientations of the predominant directions.

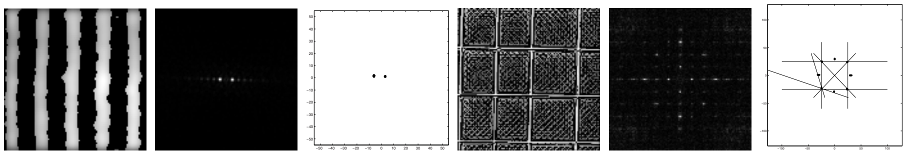
Let us define the steps to compute the subtexture attributes.

Contrast and Scale
In previous section it has been stated that the contrast and scale of the blobs or emergent patterns forming a subtexture component are the attributes that identify it. As it has been shown, the contrast of the blobs has been derived from L_σ, and the scale is directly given by corresponding filter.

In order to estimate the remaining features of the subtexture components we have chosen to calculate the Fourier Spectrum, which has already been used for texture feature extraction [14]. Moreover, there are psychophysical evidences that support frequential analysis plays an important role in human perception of textures [13].

Degree of Structure
In order to determine the degree of structure of a subtexture component, we will study the shape and location of its Fourier Spectrum peaks. Firstly, we will estimate a measure of the stability of them by gradually thresholding the spectrum. Afterwards, we will evaluate the alignement of the peaks by computing a modified Hough transform of the maxima, since only the lines which have been voted by several points are selected. Several measures are extracted from this analysis:

- sp : number of stable peaks (i.e. appearing in 3 or 4 thresholds)
- vsp : number of very stable peaks (i.e. appearing in 5 or more thresholds)
- l : number of straight lines



1.a 1.b 1.c 2.a 2.b 2.c

Fig. 4. Examples of subtexture components analysis for the evaluation of the degree of structure: images 1.a and 2.a are the subtexture components, their spectrums are shown in 1.b and 2.b respectively, and 1.c and 2.c illustrate the maxima and the straight lines obtained from the analysis

The calculation of the degree of structure is then given by a weighted sum of these parameters:

$$st = \alpha \times l + \beta \times sp + \gamma \times vsp \tag{3}$$

The values for $[\alpha, \beta, \gamma]$ have been estimated to be $[0.2, 0.3, 0.5]$ from a preliminar psychophysical experiment where 16 subjects were asked to describe textures in terms of their subtexture components features.

Predominant Orientations

The predominant orientations of the subtexture components are easily detected in the spectrum, since they also appear as predominant orientations in the frequency domain. The spectrum is transformed to polar coordinates and a histogram of the orientations with 8 equally distributed bins is computed. The predominant orientations of the subtexture component are those having more than 20% of the points. This value has also been deduced from the psychophysical experiment mentioned above. The descriptor will take into account up to 4 orientations, since it is difficult to find subtextures with more predominant directions.

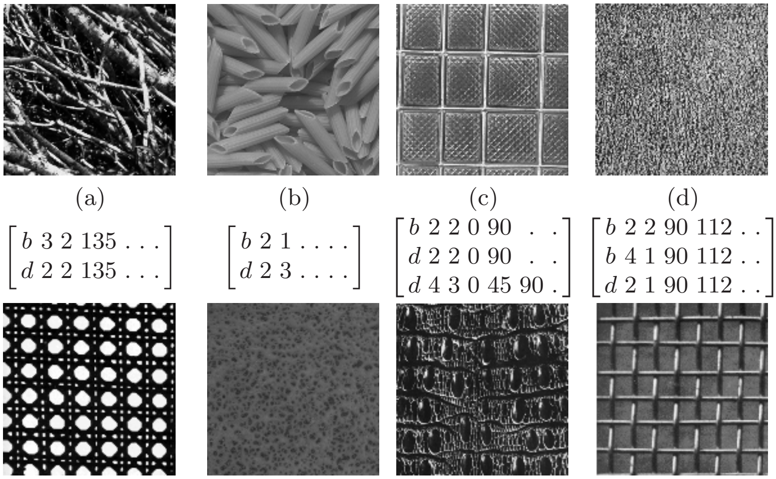
Building the Global Texture Descriptor

Since the presented computational approach can extract more than one component representing the same subtexture, we will firstly apply a selective step that removes redundant subtexture components. This redundancy is easily removed by doing a similarity test. We will denote the number of relevant subtexture components as k.

The texture global descriptor, $\mathcal{GD}(I)$ is a matrix whose rows are the description of the relevant subtextures:

$$\mathcal{GD}(I) = (\mathcal{D}(S^i(I)), \ldots, \mathcal{D}(S^k(I)))^T \tag{4}$$

As it can be seen, the number of rows of the texture descriptor depends on the texture complexity. In next section some examples of texture descriptions are given.



(a) $\begin{bmatrix} b\ 3\ 2\ 135 \ldots \\ d\ 2\ 2\ 135 \ldots \end{bmatrix}$

(b) $\begin{bmatrix} b\ 2\ 1 \ldots . \\ d\ 2\ 3 \ldots . \end{bmatrix}$

(c) $\begin{bmatrix} b\ 2\ 2\ 0\ 90\ .\ . \\ d\ 2\ 2\ 0\ 90\ .\ . \\ d\ 4\ 3\ 0\ 45\ 90\ . \end{bmatrix}$

(d) $\begin{bmatrix} b\ 2\ 2\ 90\ 112\ .\ . \\ b\ 4\ 1\ 90\ 112\ .\ . \\ d\ 2\ 1\ 90\ 112\ .\ . \end{bmatrix}$

(e) $\begin{bmatrix} b\ 2\ 5\ 0\ 45\ 90\ . \\ d\ 2\ 5\ .\ .\ .\ . \\ d\ 5\ 5\ 0\ 45\ 90\ 135 \end{bmatrix}$

(f) $\begin{bmatrix} b\ 1\ 3 \ldots . \\ d\ 1\ 4 \ldots . \\ d\ 3\ 2 \ldots . \end{bmatrix}$

(g) $\begin{bmatrix} b\ 2\ 4\ 90\ .\ .\ . \\ b\ 4\ 4\ 0\ 90\ .\ . \\ d\ 2\ 3\ 90\ .\ .\ . \end{bmatrix}$

(h) $\begin{bmatrix} b\ 2\ 5\ 0\ 90\ .\ . \\ d\ 1\ 5\ 0\ 90\ .\ . \end{bmatrix}$

Fig. 5. Examples of texture descriptions

5 Results

The description of several textures is presented in figure 5, under every image I the corresponding global descriptor $\mathcal{GD}(I)$ is given. For example, image (a) is formed by two subtextures, one made out of bright blobs of medium scale ($sc = 3$) with an almost random structure ($st = 2$) and a predominant orientation of 135°, and another one made out of small dark blobs with the same structure and predominant orientation. On one hand it can be seen that the number of subtexture components that are obtained matches the complexity the texture, images (c) and (e) which can be considered complex textures are described by three components and images (a) and (h), which are much simpler, are described by two components only. On the other hand, we can see that the contrast, degree of structure and orientations of the subtexture components are quite well detected in most cases, whereas the scale needs to be improved. Finally, it can be seen from the examples that the presented texture description is enriched by the fact that subtexture components are treated separately. For instance, in image (g) the horizontal orientation due to the emergent pattern is only detected for a high scale, while the vertical orientation due to small elongated blobs appears at smaller scales.

6 Conclusions and Further Work

This paper has mainly two contributions. Firstly, the concept of subtexture component has been introduced, which allows a texture description that can be interesting both from a computational and a perceptual point of view. Secondly, we have presented a first approach to a computational texture descriptor which is shown to be general enough to give the description of any natural texture.

The fact that the number of subtexture components can vary makes this approach suitable to all levels of texture complexity, which is very important for Computer Vision applications where all types of images can be found. The presented texture descriptor is based on perceivable characteristics of the image without the need of comparison. This is indispensable for applications such as image browsing where images have to be described in terms of its own properties and in a way that makes it easy to go from natural language to computational representations. Further work will be focused on the improvement of the scale detection and on the introduction of more complex information such as the shape of the emergent patterns.

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