The use of Boolean model for texture analysis of grey images

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Abstract

We generalise here the use of the 1D Boolean model for the analysis of grey textures. Each grey image is first histogram-equalised with 8 grey levels. The pixels that constitute each grey level are used to form a binary image. Each of these binary images is separately analysed with the help of the 1D Boolean model and features are extracted from it. The final texture recognition is performed on the basis of these features. 100% recognition rate is achieved for an image database of Brodatz textures that consists of 48 model textures coming from 16 different classes and 16 test textures, one from each class.

1. Introduction

The aim of the work described in this paper is to investigate the properties of the Boolean model [6][1][3] for describing grey textures.

The basic principles of the Boolean model and its application to binary texture classification are explained in section 2. In section 3 we describe how the model was used to classify 16 different grey textures. We shall present our conclusions in section 4.

2. Binary image analysis

The Boolean random set model [6] can be used for describing and creating texture images. For this purpose, a texture is assumed to consist of a large number of certain primitive shapes. The Boolean model consists of two independent statistical processes, a shape process and a point process. The outcomes of the shape process determine the shapes of the primitives, and the outcomes of the point process determine where these shapes appear. In a typical realization of a Boolean model, shapes tend to overlap each other.

In the one-dimensional case, the shapes of the Boolean model are simply line segments. For each segment the left end-point is considered to be the origin of the shape. From this origin the shape is said to *emanate* to the right.

The locations of the origins of the shapes in a Boolean model are the outcomes of a point process with probability p. This probability is called the *marking probability* and is one of the parameters of the Boolean model. The other parameter describes the length of the line segments, which are distributed according to some discrete distribution function $C(k)$ which represents the probability that a line segment has length less than or equal to k, with $C(0) \equiv 0$ [1].

The marking probability and the segment length distribution together form the one-dimensional Boolean model. They can be combined in one expression for the probability that a given line segment of length less than or equal to k emanates from a given point. This probability is given by the distribution function $F(k)$ [3].

$$F(k) = 1 - p + p\,C(k), \qquad \text{for } k = 0, 1, \ldots \tag{1}$$

To analyse binary texture images, we transform each image in a string of pixels and estimate the parameters of the Boolean model.

To enhance the variety of parameters that we estimate we use several Boolean models to compare two images. These models correspond to:

1. Horizontal, vertical and the four Hilbert scannings to obtain different strings of pixels for each image.

2. Direct and inverse video. When we say "Direct video" we mean that the parameters are estimated considering white runlengths as being the shapes of the Boolean model, while the black ones are the background. When we say "Inverse video" we mean that the white runlengths of the image are considered as the background and the black runlengths as the shapes of the Boolean model.

3. The distribution $C(k)$ was chosen to be Normal, Gamma, Beta, Rayleigh, Maxwell and Poison.

In order to classify textures, we need to compare two Boolean models characterised by marking probabilities p_1 and p_2 respectively, and probability distributions $C_1(k)$ and $C_2(k)$ respectively. To obtain an overall similarity measure between two models, we count as positive the similarity measure between their corresponding probability density functions (the derivatives of $C_1(k)$ and $C_2(k)$) and as negative the difference between their marking probabilities. Further, these two terms may be weighted using constants δ_f and δ_p. We defined the similarity measure between the two probability density functions as the area of their overlap. Thus, a combined similarity measure may be defined in the following way:

$$S(p_1, C_1, p_2, C_2) = -|p_1 - p_2| + \sum_{k=1}^{\infty} Min\,\{C_1(k) - C_1(k-1), C_2(k) - C_2(k-1)\} \quad (2)$$

The similarity function S takes values in the interval [-1,1], where 1 means that the two Boolean models are identical and -1 means that they are totally different.

When the texture images are described using all available Boolean models corresponding to different scannings and colour assignments, a test image may be classified in several different ways as described in [2], where the MAXMIN criterion performed the best. According the MAXMIN criterion the similarity measure between a test image and each model image is given by the minimum similarity measure over all the Boolean models that are considered. The test image is finally identified with the model that maximises this measure.

Experiments carried out using 32 different classes of binary textures obtained from [4] achieved a 100% rate of correct classification, when the horizontal and vertical scannings were used together with the Normal distribution for $C(k)$. When using Hilbert scannings and/or other distribution functions the classification accuracy was lower, but always achieved rates between 85% and 96% [2].

These results lead us to abandon the Hilbert scannings as well as most of the probability distributions we investigated. Thus, for the classification of grey level images presented in the next section we are considering only the Boolean models obtained using horizontal and vertical scannings combined with direct and reverse video. We also choose the Normal probability distribution and the MAXMIN classification criterion because they all provided the best results for binary images [2].

3. Grey Images

We consider a grey level image as a set of binary slices, having one slice per each grey level. For each slice the pixels with the appropriate grey level are defined as covered while the rest of pixels are defined as uncovered.

Usually, grey level images can contain 256 different grey levels. In order to reduce the number of slices that we need for each image, we can quantise the number of grey levels allowed in each image. To quantise an image we fix a set of intervals in the grey level range and all pixels within each interval are assigned the same grey value. However, if the interval set is prefixed for all images, for some of them we may find intervals with no pixels assigned. This would lead to empty slices for such images. To solve this problem, we will not use a fixed set of intervals for all images, but a fixed number of intervals for all images. For each image, we fix a set of intervals in such a way that the same number of pixels falls inside each interval. That is, we compute an interval-equalised quantised image.

Once each image has been quantised to the desired number of grey levels, we can characterise it applying the method described in section 2 to each binary slice. All the parameters of the Boolean models obtained for each slice are used to describe the whole image. In all we have 12 parameters per slice: p and the μ and σ of $C(k)$ for the 4 possible Boolean models that combine horizontal and vertical scannings with direct and inverse video.

In order to classify grey level texture images whose features have been calculated using the Boolean model for each slice we have tried several methods:

1. Voting system. In order to classify a test image each slice is classified separately. Each binary slice is compared with the corresponding slices of the model images, and is classified using the MAXMIN criterion as explained in section 2. When a slice is classified in a class, this class obtains one vote. When all the slices have been classified, the grey level image is classified in the most voted class.

2. Similarity average. To obtain a similarity measure between a test image and a model, each binary slice in the test image is compared with the corresponding slice in the model as described in section 2. The final similarity measure for the grey image is computed as the average of the similarity of all the slices. After comparing the test image with all the models, the image is classified with the class that provided the highest similarity measure.

3. Hierarchical method. The first slice of the test image is compared with the corresponding slice of all the model images. Those model images that provided the lowest similarity measure are eliminated and are no more considered for this image. Every time a slice is considered, a set of model images is eliminated, so when all slices have been considered only one model class remains. The test image is classified to that class.

4. Mixed method. As a first step, we use the hierarchical method to eliminate those model images that provide a similarity measure lower than a threshold. After that, only the model images that were not eliminated are considered in combination with the voting system or the similarity average method.

To check the performance of the classification methods defined we have created an image database of Brodatz textures with 16 images of size 256×256 pixels. There are among them some textures similar to each other, as well as homogeneous and directional textures. Each image is divided in 4 quarters of size 128×128. Three of them are used as model images and the other one as a test image.

In order to classify each test image, we first quantise it to obtain 8 binary slices from it. To characterise each binary slice we used the horizontal and vertical scannings and the Normal probability distribution for covered runlengths because they provided the best results in the binary experiments described in section 2. Also, the MAXMIN similarity criterion was used because it performed the best in the binary case.

For the hierarchical method, 4 model images were eliminated in each step, and the one which provided the highest similarity for the last slice was selected. For the mixed methods a threshold of 0.5 was selected. Table 1 shows the classification accuracy for all the classification methods defined for grey level images.

Classification method	Classification rate
Voting system	100.0%
Similarity average	100.0%
Hierarchical	87.5%
Mixed (H. + Voting)	100.0%
Mixed (H. + Sim. av.)	100.0%

Table 1. Classification accuracy obtained for grey level images.

We can note from the results that only the hierarchical method failed in the classification while the other methods achieved a 100% classification rate. This is due to the fact that in the hierarchical method we always eliminate image models, even though they may score quite high. For example, a certain binary slice, say the 3rd darkest, may have similar statistics in all textures. All scores then will be very similar and by eliminating the worst 2, we may actually eliminate the model texture which is the correct class for the test image under consideration. However, in the mixed methods we eliminate only those image models that provided small similarity values, so we never eliminate the correct model, and we obtained the same classification accuracy with both the voting system and the similarity average method in less CPU time.

4. Conclusions

Although real textures are not strings wrapped to form 2D patterns, it seems that the Boolean model can be used to properly describe and classify binary textures as well as grey level textures. Using discrete Normal probability distributions to characterise the shape process and combining horizontal and vertical scannings to introduce spatial and directional properties to the model, we achieved good results when applied to binary textures [2].

In this paper, we showed that the one-dimensional Boolean method can also be applied for grey level textures when a grey level image is considered as a set of binary slices, one per each grey level in the image. A quantisation process allows us to obtain a histogram-equalised image with a reduced number of grey levels in the image. We proposed different classification criteria to be used with grey level images. Only the hierarchical method does not seem adequate for our purposes, while all the other classification methods provided a 100% classification accuracy. The mixed methods were able to achieved a 100% correct classification rate requiring less computational effort.

The advantage of the method of horizontal and vertical raster scanning of images is that it can be applied to irregularly shaped textured patches that have to be classified. This allows it to be used in applications of searching large image databases.

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