MULTIPRIMITIVE TEXTURE ANALYSIS USING CLUSTER ANALYSIS AND SIZE DENSITY FUNCTION

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Abstract A novel method of the multiprimitive texture analysis is proposed. This method segments a texture using the watershed algorithm into fragments each of which contains one grain. The size density function of each fragment is calculated, and the fragments are located in the feature space each of whose basis is the size density of a size. The shape of each grain is distorted by the segmentation if the grains overlap, and the watershed algorithm may cause the over-segmentation. Thus the fragments containing grains corresponding to one primitive scatter in the feature space. However, the following cluster analysis collects neighborhood fragments in the feature space into a cluster. The grains in a cluster are regarded as corresponding to one primitive. The number of distinctive primitives shapes is obtained as the number of distinctive clusters, and each primitive is obtained as the central fragment of each cluster.

Keywords: texture analysis, cluster analysis, size distribution, size density function.

1. Introduction

Texture recognition and discrimination are important aims of image processing, as well as object shape recognition in images. A lot of texture analyzing

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methods have been proposed, and the texture classification and segmentation are main objectives among them. The texture classification and segmentation requires characterization of textures, i.e. evaluation of features describing local or global characteristics of the target texture.

According to [1], the texture characterization approaches can be divided into four categories: statistical, geometrical, model-based and signal processing. We have recently investigated several approaches that are categorized into geometrical ones [2][3]. The geometrical approach considers a texture to be composed of primitives, and attempts to describe the shapes of primitives. We applied the concept of morphological size distribution [4][5] to the primitive description. We assumed a distribution of grain sizes in a texture. For example, we assume that the target texture contains grains whose shapes are homothetic to one primitive and whose sizes are uniformly distributed. In this case, the size density function relative to such structuring element that is homothetic to the primitive will be uniform. We employed the simulated annealing for finding the optimal structuring element that makes the size density function uniform.

Our method above, as well as other geometrical approaches [6], assumes that the target texture, or the target area of texture, is composed of one primitive. These approaches are not applicable to the multiprimitive texture, which is composed of two or more distinctive primitives. Sand and Dougherty [7][8] have proposed several methods to analyze multiprimitive textures using the granulometric moments. Their approach estimates the mixture proportion and sizing parameters of primitives with the assumption that the shapes of primitives and their size density functions are known. We propose, in this paper, a method of extracting typical primitive shapes of multiprimitive textures in case that neither the size densities of primitives, mixture proportion, nor sizing parameters are known. This method at first segments a texture by the watershed algorithm into the fragments each of which contains one grain. The size density function of each fragment is calculated, and the fragments are located in the feature space each of whose basis is the size density of a size. The shape of each grain is often distorted by the segmentation if the grains overlap, and the watershed algorithm may cause the over-segmentation. Thus the fragments containing grains corresponding to one primitive scatter in the feature space. However, the following cluster analysis collects neighborhood fragments in the feature space into a cluster. The grains in a cluster are regarded as corresponding to one primitive. The number of distinctive primitives shapes is obtained as the number of distinctive clusters, and each primitive is obtained as the central fragment of each cluster.

2. Method

Our method consists of the following four steps. We consider textures that consist of grains. Such a texture as a repeated pattern like woven textiles is out of our scope.

2.1 Segmentation

To segment a texture into the fragments each of which contains one grain, we find the center of each grain at first. The distance transformation is applied for this purpose. The distance transformation assigns the distance from the outline to each pixel inside a white-pixel object in a binary image. If a distance transformed object is convex, the maximum of distance transform is the connected set of central pixels in this object; Otherwise two or more separate local maxima are found in the object, and each of them is the center of each convex part yielded by dividing the original object. We apply the distance transformation to the suitably binarized target texture, and pick up the local maxima of the distance transform. We find the centers of grains by this operation.

We draw boundaries between the fragments using the watershed algorithm [9] with the center pixels obtained above. The watershed algorithm obtains the boundaries by tracking local minima as if the water tracked the valley in terms of regarding the distance transforms as the heights from the ground. The boundaries segment the texture into the fragments each of which contains one grain.

Figure 1 and 2 shows an example; Figure 1 is the target binary texture. We apply the distance transformation, the extraction of local maxima, and the watershed algorithm, and then obtain the boundaries as shown in Fig. 2. Since the watershed algorithm segments an object into convex parts, overlapped grains are divided into each grain. This segmentation, however, divides one original grain into two or more fragments in some cases. The over-segmentation problem will be compensated by the following cluster analysis.

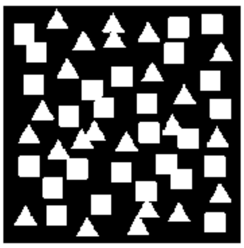


Figure 1. An example texture.

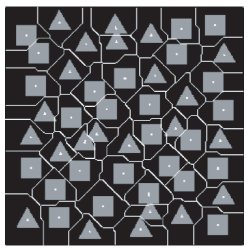


Figure 2. Result of segmentation.

2.2 Size distribution and location of fragments in the feature space

We calculate the morphological size distribution of each fragment using a certain structuring element. The size density function of discrete size r for the image object X relative to the structuring element B, denoted $p_{X,B}(r)$, is defined as follows:

$$p_{X,B}(r) = \frac{A(X_{rB}) - A(X_{(r+1)B})}{A(X)}, \tag{1}$$

where $A(X)$ denotes the area of X, X_B denotes the morphological opening of X by B, and rB is the $r-$times homothetic magnification of B, defined as follows:

$$rB = B \oplus B \oplus \ldots \oplus B \quad ((r-1) - \text{times of } \oplus). \tag{2}$$

$$0B = \{0\}. \tag{3}$$

where $\oplus$ denotes the Minkowski set addition. The size density function of size r indicates the relative residual area that is contained in the opening X_{rB} but not contained in $X_{(r+1)B}$.

Each fragment is located in the feature space whose basis consists of the size density function of several sizes. Figure 3 shows an example of the location. The shape of structuring element is the 3×3-pixel square in this example. The feature space is two dimensional, where the horizontal coordinate corresponds to size $r = 0$ and the vertical one corresponds to size $r = 4$. Each point denoted by the symbol “x” in the space corresponds to each fragment.

2.3 Clustering

We employ the hierarchical clustering in our method, and illustrate the hierarchy by a dendrogram. We at first select the closest point pair in the feature space, and create the initial cluster of this pair. The selected points are arranged on the horizontal coordinate of the dendrogram, and a vertical line is drawn upward from each point to the height corresponding to the distance between these points in the feature space. The two vertical lines are connected at the tops to indicate the relationship between the two points. The hierarchy of clusters is constructed by the iteration of the followings:

1) Selecting the point-point pair, point-cluster pair or cluster-cluster pair whose distance is currently the smallest of all the pairs that have not selected yet. The distance of a point-cluster pair is defined as the smallest distance between the point outside the cluster and a point in the cluster, and the distance of a cluster-cluster pair is defined as the smallest distance between a point in one cluster and a point in the other cluster.

2) Creating the cluster of the selected pair. The tree structure of the dendrogram is drawn in the same manner as the initial cluster.

These steps are iterated until the largest cluster containing all the points is created. Figure 4 shows the hierarchy of the clusters created from the example of Fig. 3.

2.4 Separation of clusters and extraction of primitives

Dividing the hierarchy into several clusters that are significantly distant, we obtain the clusters each of which contains the grains corresponding to a distinct primitive. Since the dendrogram indicates the distances between the clusters as the heights on the vertical axis, this division is equivalent to cutting the dendrogram at a height, as shown by the dashed line in Fig. 4. In this case we find that the texture contains two distinct clusters, i.e. two distinct primitives. The obtained clusters, denoted C_1 and C_2, correspond to the ovals C_1 and C_2

shown in Fig. 3, respectively. We find the typical primitive shapes by extracting the grains in the typical fragments, each of which corresponds to the point closest to the centroid of each cluster in the feature space. Figure 5 shows the extracted primitives in this case. The fragments corresponding to a common primitive scatter in the feature space because of the original variability of the grains as well as the segmentation error like the over-segmentation. However, the typical primitive is extracted since the variability is compensated by the collection of scattering points into a cluster and each of the typical grains, which resemble the primitives, situates closest to the centroid of each cluster in the feature space.

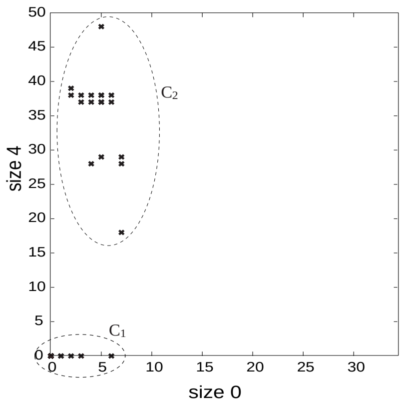


Figure 3. Feature space.

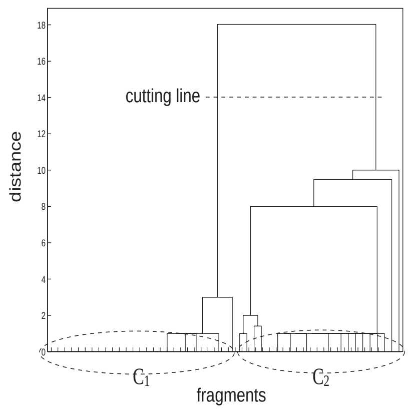
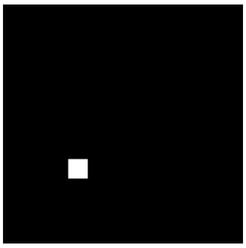


Figure 4. Dendrogram.



(a)

(b)

Figure 5. Extracted primitives.

3. Experiment

We carried out an experiment of this method using a practical texture. Figure 6 shows an example of a practical texture, which is already binarized. This is a mixture of two primitives, a rice grain and a plastic bead. This texture is segmented into fragments as shown in Fig. 7. It is found that some beads are over-segmented. Figure 8 shows the feature space, whose basis is the set of size densities of size 0 and 4 relative to the 3x3-pixel square structuring element. The basis is selected manually in the current experiment for obtaining clear cluster discrimination in our experiment. Figure 9 shows the dendrogram, which is divided into two clusters C_1 and C_2. Figure 10 shows the typical grains extracted from the two clusters. A typical rice grain (a) and a typical bead (b) are successfully extracted as the primitives.

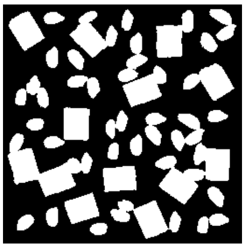


Figure 6. An example texture.

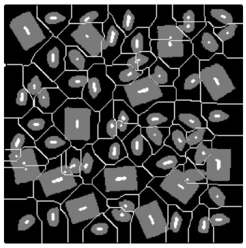


Figure 7. Segmentation result.

4. Conclusions

In this paper, we have proposed a novel method of the multiprimitive texture analysis. This method consists of the following procedures: 1) segmenting a texture by the watershed algorithm into the fragments each of which contains one grain, 2) calculating the size density function of each fragment, 3) locating the fragments in the feature space whose basis is the size density of each size, 4) creating distinctive clusters of the points in the feature space, and 5) extracting the fragment closest to the centroid of each cluster in the feature space. The extracted fragments have typical grains corresponding to the primitives. Since

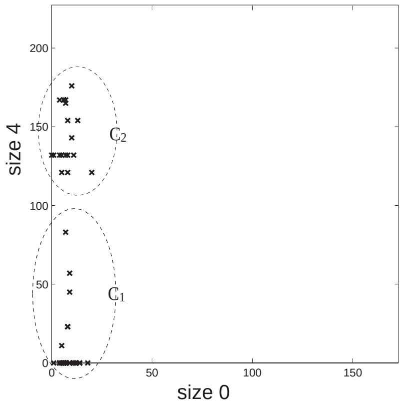


Figure 8. Feature space.

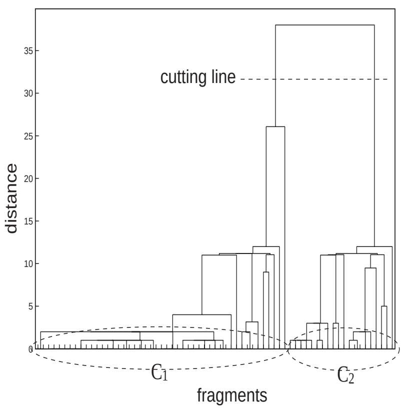
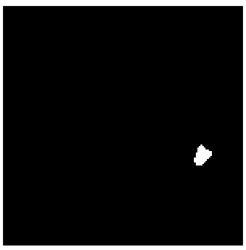
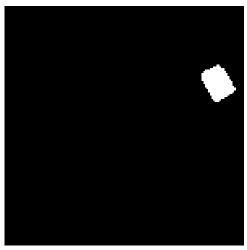


Figure 9. Dendrogram.



(a)



(b)

Figure 10. Extracted primitives.

the grain shape may be distorted by the segmentation, the fragments containing the grains corresponding to one primitive scatter in the feature space. The following cluster analysis creates clusters of neighboring fragments in the feature space and each primitive is obtained as the grain in the fragment closest to the centroid of each cluster.

We have selected the sizes for the basis of the feature space manually for obtaining clear cluster discrimination in our current experiment. It is an important problem how to construct the basis. One idea is constructing the basis using the size density function of all the sizes at first, and then reducing the dimension of the feature space by some statistical method. We are now working on this. Moreover, the examination of the robustness against noises and grain overlapping should be our future work.

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