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LETTER

# Multiprimitive Texture Analysis Using Cluster Analysis and Morphological Size Distribution

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**SUMMARY** A novel method for the primitive description of the multiprimitive texture is proposed. This method segments a texture by the watershed algorithm into fragments each of which contains one grain. The similar fragments are grouped by the cluster analysis in the feature space whose basis is the morphological size density. Each primitive is extracted as the grain of the central fragment in each cluster.

***key words:*** *texture analysis, cluster analysis, size distribution, mathematical morphology*

## 1. Introduction

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 model that the texture is an arrangement of grains derived from a primitive, and estimates the shape of the primitive. We applied the concept of morphological size distribution [4], [5] to the primitive description. We assumed a model of the size density function of a texture. For example, if it is assumed that the target texture contains grains whose shapes are homothetic to a primitive and whose sizes are uniformly distributed, the size density function relative to the structuring element whose shape is homothetic to the primitive will be uniform. This assumption is suitable for most of naturally composed textures, except the textures that are repetitions of an identical grain. We applied the simulated annealing to find 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, contains grains homothetic to one primitive. These approaches are not applicable to the multiprimitive texture, which is a mixture of grains corresponding to two or more distinctive primitives. Sand and Dougherty [7], [8] have proposed several methods to analyze multiprimitive textures using the granulometric moments. Their approach is, however, estimating 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 estimating primitive shapes of multiprimitive textures in case that neither the size densities, 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. Our prospect is that putting similar grains into one group achieves the estimation of primitive by extracting the typical grain from each group. The similarity is measured by the distance in the feature space where the grains are arranged. However, the shape of each grain is often distorted by the segmentation, since adjacent grains often overlap and the segmentation algorithm may cause oversegmentation. To compensate such faults of the segmentation, we apply the morphological size density to create the feature space. The size density of each fragment is calculated, and the fragments are located in the feature space whose basis consists of the size density of each size. The oversegmented grains are clearly distantly arranged in this feature space since their sizes are significantly small. Since the shapes of the non-oversegmented grains are often distorted, the grains corresponding to one primitive scatter in the feature space. However, the following cluster analysis gathers neighborhood grains into a cluster in the feature space. The grains in a cluster are considered to correspond to one primitive. The number of distinctive primitives shapes is estimated as the number of distinctive clusters, and each primitive is estimated by the central grain of each cluster. It is possible that a cluster contains grain corresponding to another primitive because of the shape distortion. However, such faulty grain is hardly extracted as the estimate of primitive, since the average grain in the feature space based on the size density is extracted.

## 2. Method

Our method consists of the following four steps. We

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consider textures that consist of grains. Such a texture as a repeated pattern like woven textile 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 by the watershed algorithm [9] using the center pixels obtained by the distance transformation. 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.

Figures 1 and 2 shows an example; Fig. 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 grains in some cases. The oversegmentation problem will be compensated by the following cluster analysis.

### 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, or the normalized size distribution, 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:

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

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

The size density 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 $3 \times 3$-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 symbol "×" in the space corresponds to each fragment.

### 2.3 Clustering

We apply 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 of the points in the feature space. The two vertical line is connected at the top to indicate the relationship between the two points. The hierarchy of clusters is constructed

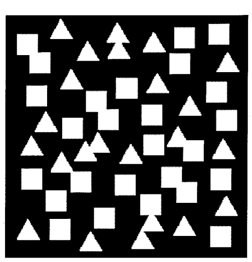


**Fig. 1** An example texture.

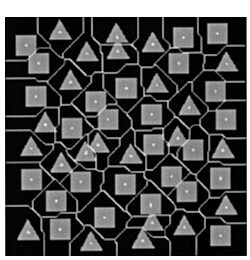


**Fig. 2** Result of segmentation.

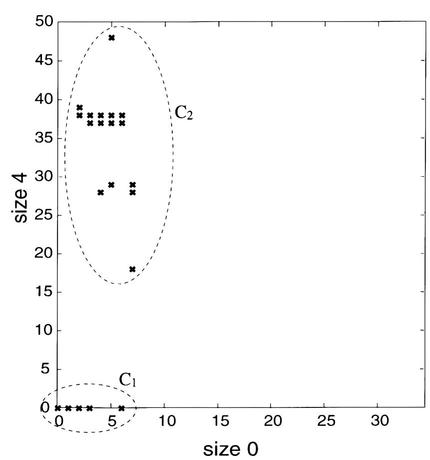



**Fig. 3** Feature space.

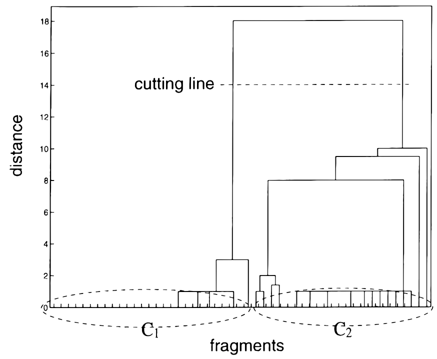



**Fig. 4** Dendrogram.

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. 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. 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 all the points are included in one cluster. Figure 4 shows the hierarchy of the clusters created from the example of Fig. 3.

### 2.4 Separation of Clusters and Estimation 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 coordinate, 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 primitive shapes by extracting the grains in the typical fragments, each of which corresponds to the central point of each cluster in the feature space. Figure 5 shows the estimated primitives in this case. The fragments corresponding to the same primitive scatter in the feature space because of the original variability of the grains as well as the segmentation error like the oversegmentation. However, the primitives can be estimated since the variability is compensated by the collection of scattering points into a cluster and each of the typical grains, which estimate the primitives, is located nearest to the centroid of each cluster in the feature space.

(a) (b)

**Fig. 5** Extracted primitives.

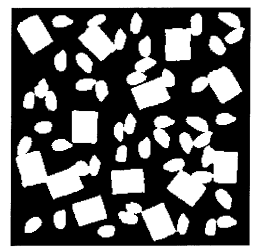


**Fig. 6** An example texture.

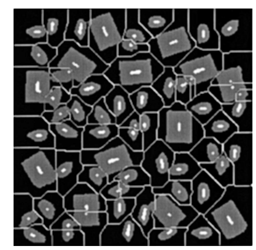


**Fig. 7** Segmentation result.

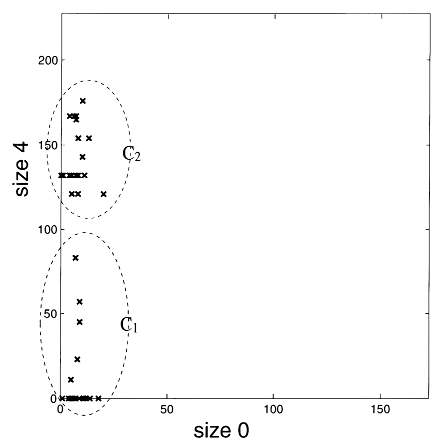



**Fig. 8** Feature space.

## 3. Preliminary Experiment

We carried out a preliminary 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 grains corresponding to two primitives, the rice grain and the plastic bead. This texture is segmented into fragments as shown in Fig. 7. It is found that some beads are oversegmented, for example a bead in the lower left. Figure 8 shows the feature space, whose basis is selected manually and is the set of size densities of size 0 and 4 relative to the $3 \times 3$-pixel square structuring element. 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. Note that the number of beads in the

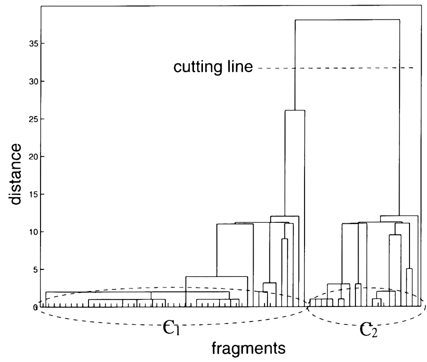
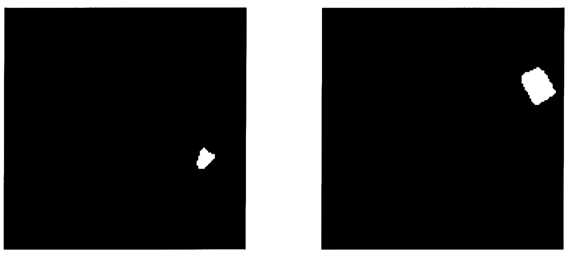



**Fig. 9** Dendrogram.



(a) (b)

**Fig. 10** Extracted primitives.

texture is different from those of the fragments in the cluster $C_1$ and $C_2$. This means that oversegmentation or faulty clustering is happened in the analyzing procedure. Extracted rice grain (a) and typical bead (b), however, successfully estimate the primitives in spite of oversegmentation and distortion, because of the extraction of the average grain of the cluster in the feature space based on the size density.

## 4. Conclusions

In this paper, a novel method of the multiprimitive texture analysis has been proposed. 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 morphological size density 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 central grain of each cluster in the feature space. The extracted grains are considered to be estimates of the primitives. Since the grain shape may be distorted by the segmentation, the grains corresponding to one primitive scatter in the feature space. The following cluster analysis creates clusters of neighborhood fragments in the feature space and each primitive is estimated by the central grain in each cluster.

We have selected the sizes of the size density function for the basis of the feature space manually for obtaining clear cluster discrimination in our preliminary 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. Considering other basis than the morphological size density is also our future work.

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