Unsupervised Image Segmentation Using Textural Features

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***Abstract*—In this study, a method was developed for the segmentation of the texture patterns in images containing multi-texture pattern. To distinguish these textures from one another, the image was divided into sections, and the textural features of each section were extracted using Gabor filters and gray level cooccurrence matrices. These features were analyzed using AGNES clustering algorithm and each section was assigned to a cluster. Segmentation was performed by marking as many different textural sections as the number of clusters formed on the actual image. The performance of the developed method was tested using the images obtained from Describable Textures Dataset database. The method made 37 correct segmentations for 40 images. In images with two different texture patterns, there were no incorrect segmentations. In 3 of the 32 images with three or four different texture patterns, incorrect segmentation was performed. Due to the sectioning of the image, borders between the texture patterns could not be precisely distinguished.**

***Index Terms*—textural analysis, image segmentation, gray level coocurence matrix, Gabor filters, unsupervised clustering algorithms, image processing**

I. Introduction

Image segmentation is one of the main problems of image processing and computer vision. The complexity of the image makes it hard to resolve this problem. One of the most studied fields is the analysis and classification of texture patterns in digital images [1]. The majority of the methods developed for image segmentation fail to segment the images based on their textural features. In segmentation of the images containing. multi-texture patterns, parameters such as the direction, width, and density of the texture pattern should be considered.Thus, studies have been performed to develop different methods to analyze texture images. Texture analysis methods have been performed in many areas, from the security systems to fingerprint analysis, from detecting errors on various materials to disease detection through medical images [2]-[4]. Features obtained from the texture patterns with these methods are evaluated using various classification or clustering algorithms. As a result of this evaluation, processes such as detection and segmentation are performed [5]-[8].

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Gabor filters, one of the texture analysis methods, are suitable to perform texture analysis on colored images. By applying a group of selected Gabor filters with directions and frequencies with different parameters on the image of an input, textural features are obtained [9]-[11].

GLCM, described by Haralick in 1979, is a two-dimensional matrix in which the frequency of gray level combinations of the pixels that constitute an image are tabulated by analyzing their binary neighborhoods. Features of the textural pattern are obtained via calculations based on this matrix. GLCM is suitable for texture analysis on gray level images [12], [13].

Clustering is the task of grouping the objects with similar characteristics in a dataset. Objects can be represented as dots on a two dimensional plane. Clusters are defined in a way that they can define their constituting objects in the best possible way. Clustering is used for various purposes such as finding the natural classes of the objects [14], [15].

AGNES (Agglomerative Nesting) is an unsupervised clustering algorithm that operates in a bottom-up manner and is designed by Kaufmann and Rousseeuw. At the beginning, each object is regarded as a cluster. The clustering process continues by combining the clusters with the most proximity. When there aren't any objects left unassigned to a cluster, clustering process ends. One of the advantages of the AGNES clustering algorithm is that it is not necessary to specify the number of clusters to be created in advance [16]. In addition, since it is unsupervised, the cost of the calculation is less.

In this study, a method was developed to perform the segmentation of images containing multi-texture patterns with high success rate and low calculation cost. In Section 2, the texture analysis algorithms used in this method and the features obtained are explained. Image datasets, and performed experiments and their results are found in Section 3. In Section 4, information about the future studies is provided.

II. Developed Method

In the developed method, while texture analysis can be performed on colored images using Gabor filters, the image has to be converted to gray level image for GLCM. Both images are divided into small areas of equal size. Using Gabor filters on colored image, textural features are obtained for each area. For areas on the same coordinate, GLCMs are formed using the gray level image. Textural

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features are calculated using these GLCMs. Two groups of features obtained for each area are recorded in a separate vector. The obtained feature vectors are clustered with the AGNES clustering algorithm. A color is specified for each cluster and each area is marked with a frame in the color of the enclosing cluster. The block diagram of the developed method is shown in Fig. 1.

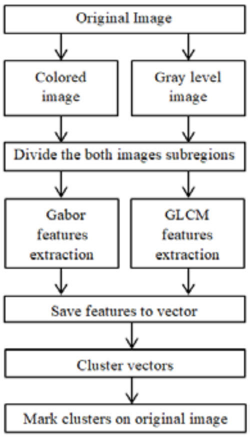

Figure 1. Block diagram of developed method.

A. Gray Level Cooccurrence Matrix

GLCM is generated based on the analysis of two neighboring pixels according to their values. The first of the analyzed pixels is called the reference pixel, and the second is called the target pixel. The direction of the neighborhood analysis is important to generate GLCM. When GLCM is generated, analyses can be performed based on the neighbors of the reference pixel in eight directions. However, in general, the analysis is performed with the pixels found on the same row or column with the reference pixel. While the analysis can be performed with the closest neighbor, it can also be done with a neighbor at a distance specified by a distance vector denoted by a "*d*" symbol [6], [12], [13].

The distance vector specifies the position of the target pixel relative to the reference pixel. This position is specified as direction and distance. If the neighborhood of the reference pixel to the first pixel to its right is to be analyzed, the distance vector is specified as (0, 1) or east direction. The target pixel is attained by incrementing the row number by 0 and the column number by 1 relative to the reference pixel. In the image matrix, all pixels from the upper left corner to the lower right corner are sequentially examined as reference pixels.

The size of the GLCM matrix determined by the bit depth of the gray level of the analyzed texture image. GLCM obtained from an eight-bit gray level image would be 8*8, whereas GLCM obtained from a sixteen-bit gray level image would be 16*16. At 256-bit gray level, a GLCM of 256*256 would be generated. Large GLCM dimensions might cause many elements to have 0 value. Since this would reduce the statistical validity and make the interpretation hard, the image can be reduced to lower gray levels [6], [12], [13].

The element on the first row and first column of the GLCM shows the number of neighborhoods where both the reference pixel and the target pixel have the value 1 in the analyzed texture image. In Fig. 2, generation of GLCM from a texture image matrix is shown [13].

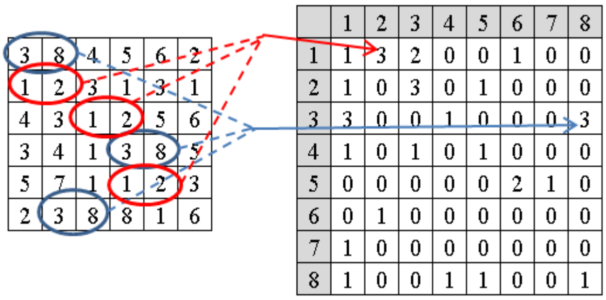

Figure 2. Generation of GLCM matrix [10].

Since GLCM is a statistical probability matrix, matrix values should be between 0 and 1. Thus, a normalization is done by dividing each element of the matrix by the sum of the matrix values. It is calculated by using the normalization equation (1) where $Co_{i,j}$ represents the GLCM element in ith row and jth column.

$$P_{i,j} = \frac{Co_{i,j}}{\sum_{i,j=1}^{n} Co_{i,j}} \quad (1)$$

B. Gabor Filters

Research has shown that the Human Vision System (HVS) is sensitive to both specific orientation and to spatial frequencies. For texture analysis, wavelets are capable of generating the sensitivity of the HVS to frequency and direction. Gabor filter-based feature extraction is performed using a Gabor filter bank consisting of filters with different frequencies and directions.

The Gabor filter design is generally made by first describing the highest frequency as (f_m), total number of frequencies as (n_f) and the total number of directions as (n_o), and then creating filters based on the combination of frequency and direction parameters. Gabor filter-based feature extractors transfer images from their actual space to a feature space where they are represented by their own features. In Gabor filter (2), λ is the wavelength of the sinusoidal multiplier, ϴ is the angle value between 0 and 360 degrees that indicates the normal orientation of the parallel lines of the gabor function, ω is the cosine multiplier of the Gabor function, σ is the standard deviation of the Gaussian multiplier, γ is the width to height ratio (aspect ratio) that determines the ellipsoidality of the Gabor function [9]-[11], [17]-[19].

$$G_{\lambda\theta\varphi\sigma\gamma} = e^{-\frac{\acute{x}^2+\gamma^2\acute{y}^2}{2\sigma^2}} \cos\left(2\pi\frac{\acute{x}}{\lambda}+\varphi\right) \quad (2)$$

$$\acute{x} = x\cos\theta + y\sin\theta$$

$$\acute{y} = -x\sin\theta + y\cos\theta$$

C. Features Extracted Using GLCM

For the analysis of texture patterns, five different features are extracted from the gray level cooccurrence matrix [10]. The features calculated using the GLCM generated upon the neighborhood analysis of this matrix are presented in Table I.

TABLE I. FEATURES EXTRACTED USING GLCM

No	Textural Features
1	Contrast (Con)
2	Energy (Ene)
3	Entropy (Ent)
4	Homogeneity (Hom)
5	Moment (Mom)

Contrast: The contrast value obtained from the GLCM calculations is different from a regular digital image contrast value. The GLCM contrast value indicates the difference between the reference pixel and the target pixel in the texture image under analysis. GLCM diagonals do not indicate contrast since the reference and target pixels are equal. The GLCM contrast value is calculated by (3). For a GLCM of G * G dimensions, i and j denote the GLCM row and column number, and Co(i, j) denotes the value of the GLCM element in those coordinates.

$$\text{Con}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \text{Co}(i,j)(i-j)^2 \tag{3}$$

Energy: Energy is the measure of uniformity of a texture. The energy can be obtained at high values in matrices with an ordered array and a regularly repeating pattern. The energy is calculated using (4).

$$\text{Ene}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \text{Co}(i-j)^2 \tag{4}$$

Entropy: The entropy property of a texture image gives the content information. Unspecified, wide spaces have little content information. The scattered areas where the pixel values vary give more content information. Entropy is calculated using (5).

$$\text{Ent}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} -\text{Co}(i,j)\log(\text{Co}(i,j)) \tag{5}$$

Homogeneity: Homogeneity is also known as the Inverse Difference Moment.

$$\text{Hom}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{1}{1+(i-j)^2}\text{Co}(i,j) \tag{6}$$

Moment: Moment value is a measure of the regular reproducibility of the texture. Moment is calculated using (7).

$$\text{Mom}= \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{(Co(i,j))^2}{1+|i-j|} \tag{7}$$

Features obtained from each section of the image are recorded and analyzed using clustering algorithm. As a result of this analysis, each region is assigned to a cluster.

D. Features Extracted Using Gabor Filters

Extracts of a symmetric and antisymmetric kernel filter for each point on the image can be combined in a single value called Gabor energy. Gabor energy is closely related to the local power spectrum. This feature can be defined using (8).

$$e_{\lambda,\theta}(x,y) = \sqrt{r^2_{\lambda,\theta}(x,y) + r^2_{\lambda,\theta-\left(\frac{1}{2}\right)\pi}(x,y)} \tag{8}$$

Real and virtual parts of the complex moments of the local power spectrum are features that provide information on the presence or absence of dominant texture orientations. This feature calculation is found in (9).

$$C_{mn}(x,y) = \iint (u+iv)^m(u-iv)^n p_{u,v}(x,y)\,du\,dv, \quad m,n \in N \tag{9}$$

$$u = \frac{1}{\lambda}\cos\theta,\ \ v = \frac{1}{\lambda}\sin\theta, \quad p_{u,v}(x,y) = p_{\lambda,\theta}(x,y)$$

Total m+n, which is called the complex moment array, is related with the number of dominant orientations in the texture.

E. AGNES Clustering Algorithm

Features extracted from GLCMs and Gabor filters that belong to image regions are recorded in a separate feature vector. These vectors are then clustered using AGNES clustering algorithm. A frame color is determined for each cluster. The regions that belong to a cluster are marked on the actual image using the same frame color.

TABLE II. EXPERIMENTAL RESULTS FOR SIZE OF 120*120

Number of Textures	Number of Images	Accurate Clustering	Incomplete Clustering	Over-Clustering
2	8	8	-	-
3	16	14	1	1
4	16	12	2	2
Total	40	34	3	3

TABLE III. EXPERIMENTAL RESULTS FOR SIZE OF 48*48

Number of Textures	Number of Images	Accurate Clustering	Incomplete Clustering	Over-Clustering
2	8	8	-	-
3	16	15	1	-
4	16	14	1	1
Total	40	37	2	1

III. EXPERIMENTAL STUDIES

In order to measure the performance of the developed method, tests were performed using 40 images obtained from Describable Textures Dataset (DTD) database [20]. Selected images contain two, three or four different texture patterns. Using the developed method by dividing subregions size of 120*120, eight images containing two different texture patterns were successfully segmented. Fourteen of the 16 images containing three different texture patterns were successfully segmented, one of the remaining two was segmented as two different texture patterns whereas the other one was segmented as three different texture patterns. In images containing four different patterns, twelve correct clustering were achieved. Incomplete clustering occurred in two cases, over-clustering occurred in two cases. The success of the experiments is increased when the images were divided into smaller size of 48*48 subregions. Computational cost and process time are increased using size of 48*48 subregions. Experiment results for 120*120 and 48*48 subregions are presented in Table II and Table III respectively. In Fig. 3, the result for an image with four different texture patterns can be seen for 120*120 subregions. Four sections obtained by clustering are marked with green, orange, yellow and blue.

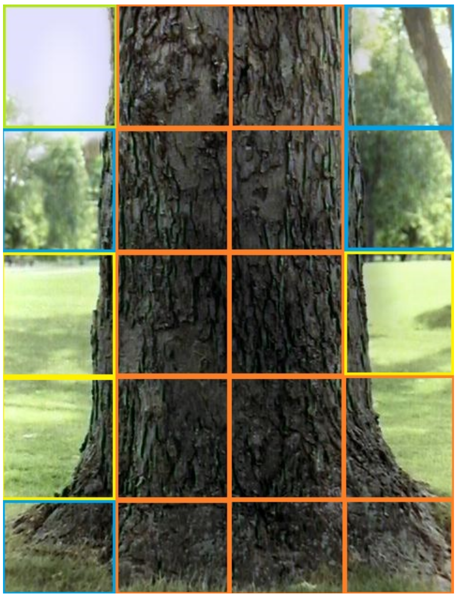

Figure 3. The result obtained for an image containing four different texture patterns using 120*120 subregions.

IV. Conclusion and Future Work

In this paper, a method was developed as a preliminary study for the segmentation of images that contain multi-texture pattern. The developed method has been successful in detecting the number of different texture patterns in a given image. Since the method analyzes the actual image by dividing it into fixed segments, the borders of the texture patterns cannot be precisely detected. To eliminate this problem, a more precise segmentation can be performed by including other texture analysis methods and artificial intelligence algorithms into the novel method. Also flexible shape and size regions can be applied on multitextural images for dividing to subregions.

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