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A Combined Statistical and Structural Based Representation for Texture Edge Detection

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Abstract: In this study, texture edge detection using a combined statistical and structural approach based texture representation is presented. Observable textures can be characterized by a set of primitives and their placement rules. Accordingly, a set of texture primitives are proposed for the representation of small region and the entire texture image is considered to be consisting of these proposed set of primitives. The distribution of these primitives is obtained as the global descriptor for the texture image, namely, the texture primitive spectrum. In this study, the usage of the texture primitive spectrum has been shown effective for the texture edge detection. Texture edge detection is defined as segmenting the texture image into mutually exclusive regions. The edge detection has been attempted for 2 different class of texture images, namely, deterministic (texture region is consisting of a single primitives distributed over the entire region) type of textures and non deterministic type of textures. In the first category, the texture primitives are replaced with the corresponding primitive numbers and conventional edge detection is performed on these array of numbers to detect the edges. For the second category, texture descriptors are obtained for a larger window size and conventional edge detection with these descriptor is performed and the edges are detected.With all these experiments and results, the usage of the proposed descriptors are effective and are promising.

Key words: Texture, local global descriptor, texture primitives, primitive spectrum, deterministic and non deterministic textures-edge detection, segmentation

INTRODUCTION

Texture edge detection is considered as one of the important problems in texture analysis which is one of the major focused areas of research for the past two decades in Computer vision group. The main idea behind this effort implies from the fact that most of the surface properties, remote sensed data, abraded surfaces etc. are of texture in nature. There are very few algorithms have been proposed so far for the texture analysis. The reason is that there was no unique definition or feature for the texture. With their own perspectives, a number of definitions for texture have been proposed and used by various researchers in their context of analysis. Few schemes for texture analysis have been suggested, either they are based on statistical or structural approaches. Using statistical approaches, several schemes have been suggested right from literatures such as co-occurrence matrix (Haralick, 1979) run length matrix based (Galloway, 1975), auto correlation, auto regression (Gool *et al*., 1983) MRF based (Chen, 1998) moments based (Tuceryan, 1992). In texture analysis problems, first step is to represent the textural contents and to extract the textural features which are subsequently used for solving other related problems. The features are, in other words obtained either by local analysis or by global analysis of the entire image. Most of the well referred studies in literature treated the texture images globally and the global descriptors were discussed. He and Li Wang, 1990) proposed the texture analysis method quantifying local texture information as well as global textural contents by the texture number scheme. Texture analysis is generally attempted statistically, or structurally or spectrally (Gonzalez and woods, 1995).

In structural approach, the texture region is defined to have a constant texture if a set of local statistics or other local properties of the image are constant, slowly varying or approximately periodic (Ehrich and Foith, 1978). An image texture is described by the number and types of its (tonal) primitives and the spatial organization or layout of the primitives. Textures could be rated as coarse, micro, macro, regular, periodic, aperiodic, directional, random, or stochastic (Richards and Polit, 1974).

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Texture analysis is an important step during low level analysis of textured images. Texture is defined as a structure composed of a large number of more or less ordered, similar elements or patterns. Observable textures can be characterized by the primitives and placement rules(Ehrich and Foith, 1978). The main idea of our research is from the intuitive suggestion offered by this fact. Any texture image can be generated by a set of primitives and their placement rules. Conversely any texture image, is identified or perceived to consist of primitives and their regular or random occurrences. If it is possible to find out the set of primitives and how they occur or the frequency of occurrences of such primitives, we are succeeding in the representation of texture image. The success of any texture analysis scheme is inferred from the way it captures the textural features and the uniqueness. The textural properties of texture images carry more useful information for the discrimination purposes, it is important to develop features for texture based on suitable quantitative representation of some of these properties. Since the frequency of occurrences of such primitives is computed for the entire image, the representation becomes global descriptor. Other recent approaches for texture analysis and synthesis may be referred from Turner (1986), Tuceryan and Jain (1990), Chang *et al*. (2004) and Paul (2006). Radius and angular histogram features obtained by computing Discrete Fourier Transform of the texture image signal was used for content based image retrieval (Wang *et al*., 2004). A texture representation is designed which is invariant to any geometric transformation that can be locally approximated by a sparse set of affine models (Svetlana *et al*., 2003).

A set of texture primitives are proposed with unique labeling. It is under the assumption that any texture image will have the combinations of these primitives. Hence, the entire texture image can be conveniently represented by the primitive spectrum. i.e., the frequency of occurrences of the primitives. The primitive spectrums have been obtained for a number of Bench mark images collected form Brodatz and VisTex images. Sample primitive spectrums have been presented in the Umarani and Radhakrishnan (2006). Using the proposed scheme of representing texture locally by texture primitives and globally by the primitive spectrum, the supervised and un supervised texture classification has been successfully attempted (Umarani and Radhakrishnan, 2006). Further, it has also been established that with a set of placement rules, many texture images have been generated with any predefined size. The main advantages of our proposal over the texture number scheme proposed in (Hi and Wang, 1990) are as follows. Since the texture numbers ranging from 0 to 6560, the feature vector consists of 6561 numbers. This is considerably larger when compared to our proposed scheme where in only 92 primitives have been shown adequate. Since the feature vector length is only 92, the time complexity is very much reduced. The texture numbers are identified even if the region is not textured, whereas in the proposed scheme all the proposed texture primitives have been subjected for the texture presence test. This test is based on statistical design of experiments approach and the presence is ensured by the test (Bishop and Nair, 1939).

The main objective of this study is to propose suitable edge detection methods for deterministic and non deterministic type of texture images with the local and global descriptors proposed by combining the statistical and structural approaches for texture representation. The efficacy of the proposed texture primitive spectrum has also been shown effective in the case of textured edge detection.

The idea of texture primitive is obtained from the intuitive suggestion given by Julesz (1981) In his study, he proposed that the first order and second order statistics computed out of the texture images are defined as the features. These features are either directly computed or derivable. Conversely, if the primitives have the said features and are used for constructing the texture images, they are discriminable (Julesz, 1981) . Further, he proposed that two textures are not discriminable if their second order statistics are identical. With this background intuitive suggestion given, the proposed approach for texture representation by the set of primitives are illustrated in the following section.

Texture primitives and representation: In this study, the presence of texture is detected by proposing a statistical design of experiments based method. This is obtained based on the significant orthogonal effects due to spatial variations of gray levels. It is shown that an image region is represented by a set of orthogonal polynomials and the computed orthogonal effects are decomposed in to 2 sets. The first set is considered to be contributing towards the presence of texture and the second one is for the noise. Suitable mathematical model and statistical tests for detecting the texture presence is presented in this study. Then a set of primitives are presented which are used as local descriptor. Finally any texture image is represented using the frequency of occurrence of the primitives called the Texture Primitive Spectrum.

Detection of texture presence: Texture is defined as a structure composed of a large number of more or less ordered similar elements or primitives in an image. Textures are normally ranging from micro to macro. A small image region which is a function of two spatial co ordinates, is represented by a set of orthogonal polynomials (Ganesan and Bhattacharyya, 1995). In this representation, the image region is considered to be a linear combination of un correlated (orthogonal) effects due to spatial variations. The uncorrelated effects due to the presence of textures have been separated successfully from those due to the presence of Gaussian noise. The presence of texture in the image region under analysis is detected on the basis of the strength of the appropriate orthogonal effects. Using the subset of orthogonal effects, separation of responses towards texture and noise has been successfully performed and are used for the texture representation. The set of primitives have been successfully used for performing supervised and un supervised classification of natural and bench mark texture images . An average correct classification of 95% has been reported. The details of the mathematical model and the procedure for performing the statistical test has been elaborately described in (Umarani and Radhakrishnan, 2006).

Texture edge detection: In the proposed method, texture edge detection is attempted for 2 classes of texture images. They are namely, deterministic and non deterministic texture images. Any texture image consists of different texture primitives with their placements either regularly or randomly. In the study of deterministic textures, texture images are considered to be consisting of different regions, each filled uniformly with a particular primitive. The texture primitives may be present randomly in the case of non deterministic texture images. The edge detection between different textured regions is performed by adopting suitable techniques as proposed.

Edge detection in deterministic textured images: Deterministic textured images have few texture primitives filled uniformly within each regions. i.e., each textured region within the texture image has been filled with a particular texture primitive. The edge detection in this image refers to detect the boundaries present between the textured regions. If the conventional edge detection operators are applied like Roberts or Sobel edge operators like un textured images, the micro edges within each primitive will be identified. As a result, large number of edges will be detected and the discrimination between intra primitive and with different region will be a great problem. Because of the difficulty involved in identification of the boundaries between different textured regions by using the un textured edge detection methods, a separate method is presented here for detection of edges in textured images.

Firstly, a target image is considered with a number of textured regions. This image is of size N×N. For this image, the occurrences of the primitives and their distribution are obtained from the primitive spectrum as proposed in the previous resaerch. In the study of an ideal situation, there will be n number of peaks present in the primitive spectrum if there are n regions, each filled with correspondingly by a primitive. A simple technique is used where each primitive will be replaced with corresponding primitive number. Thus the original image is transformed in to an array of numbers and each number correspond to the primitive numbers. The array size is N/3×N/3 as each texture primitive is replaced with the corresponding primitive number and the image array size gets scaled down. Any conventional edge detection operator may be applied over this array to find out the edges present between the textured regions. Once the edges are obtained, the edge points are scaled up to superimpose with the original image to obtain the exact edges.

Edge detection in non deterministic textured images: The edge detection scheme as suggested for the case of deterministic images can not be directly applied for the non deterministic texture images. The reasons are there is no regularity in the placement of primitives and various primitives may be present in a single region but the distribution vary between different textured regions. Hence a separate proposal has been suggested.

For the non deterministic texture images, the texture primitives get distributed over the entire image in a random fashion. The conventional edge detection operator can not be applied straight away or the previous technique used for the case of deterministic images, are also not useful. The features extracted over the entire image may be used effectively to find the boundaries present between the textured regions. The primitive spectrum has been superimposed along with the conventional edge operator for finding the boundaries present between the textured regions. In order to have description of the texture based on local properties we have used the texture model that has been described in earlier research. The main criteria for edge detection in textured regions is that the difference in adjacent primitive spectrums of the same textured region is less compared to that of 2 different textured regions. Finally, the edge is detected by computing the root mean square (rms) value of the following $r = \text{sqrt}(r_1^2 + r_2^2)$.

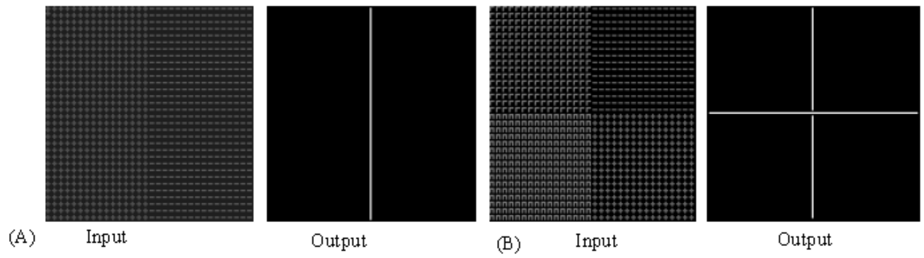

Fig. 1: Texture edge detection (A to B) for deterministic texture images

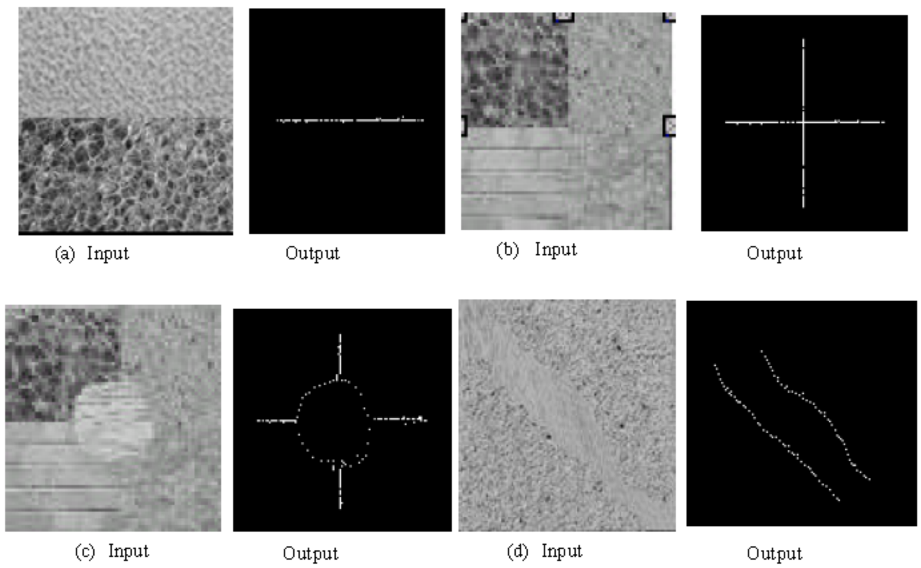

Fig. 2: Texture edge detection (A to D) for non deterministic texture images

where $r_1 = \Sigma \mid v_{x,,y}(i) - v_{x,,y+1}(i) + v_{x+1,,y}(i) - v_{y+1,y+1}(i) \mid$ and

$r_2 = \Sigma \mid v_{x,,y}(i) - v_{x+1,,y}(i) + v_{x,,y+1}(i) - v_{x+1,y+1}(i)$

and $v_{x,,y}$ is the primitive spectrum obtained for the texture region of size 30×30 , centered at x, y coordinates, i is 0varying from 1 to 92 i.e., the primitive number. An approximate threshold T is applied on r to detect the presence of an edge. Since image windows of larger width are considered for computation of the global descriptor called the primitive spectrum for the texture, the detected edges are thickened. The pattern matching thinning algorithm proposed in Chain *et al.* (1987) is applied for thinning the detected textured edges.

RESULTS AND DISCUSSION

The proposed approach has been tested on many composite texture images created using the primitives selected from the set of primitives already proposed (Umarani and Radhakrishnan, 2006). Few sample deterministic texture images are shown in Fig. 1. There are 2 images shown comprising of 2 regions and 4 regions, respectively. Edges are detected as per the above described procedure. Figure 1 (a) has 2 regions, each having filled, correspondingly by the primitive numbers TPi and TPj. In the first step, these primitives are identified and replaced by the corresponding primitive numbers. The edge detected image is also shown in Fig 1. correspondingly. The edges detected are sharp and accurately coincide with the original image. Similarly, for the other image which is also shown in Fig. 1, the edge detection result is presented.

In the study of non deterministic texture images the edge detection experimentation is discussed as follows. There are 4 test images considered and shown in Fig. 2. These images are formed by collecting texture images from Brodatz album. These images are non deterministic because there is no uniformity in the placement of texture primitives. The texture primitives and their occurrences are random and non deterministic. Each image is of size 128×128. Figure 2 (a) has only 2 textured regions. The edge detection procedure has been applied and the edges identified are also shown, correspondingly. Spurious spikes and isolated edge pixels present are eliminated by suitable post processing of the edge detected image. Fig. 2(b) has 4 regions and the edge detected results are also shown. Similarly, for the other 2 images where 5 and 3 egions are present. The result of Fig. 2 (b) is presented to show the efficacy of the proposed methods for even the irregular edges could also be detected accurately.

CONCLUSION

Texture edge detection problem has been addressed in this study. The texture representation both local as well as global descriptors have been discussed and used for the effective segmentation of textured images using suitable edge detection schemes. The usage of conventional edge detection schemes may not be directly applicable to the textured images.

Hence the proposed texture primitive spectrum has been shown applicable along with Roberts's edge detection operator. The results are presented both for the deterministic type and non deterministic type texture images. Using the edge detected algorithms, the target images have been properly segmented into different regions. The results presented for both the deterministic and non deterministic texture images reveal the effectiveness of the proposed local as well as global texture descriptos.The authors are presently working on the classification of skin diseases based on their textural contents, as one of the medical applications.

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