Texture Classification by Simple Patterns on Edge Direction Movements

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Summary:
The objective of the present paper is to obtain an accurate classification of the textures, which did not introduce undesired merging and to develop a quick, effective and novel algorithm that should be easy to understand and implement. For this the present study advocates a new statistical method based on edge direction movement for classification of textures on the opening of the image. An edge is a property attached to an individual pixel and is calculated from the image function behavior in a neighborhood of that pixel. Based on this assumption the present study calculated the frequencies of Horizontal, Vertical, Right and Left diagonal patterns on edge direction movement for classification of textures. The experimental results on groups and samples of Brodatz textures show validity of the present method.

Key Words:
Opening, Horizontal Patterns, Vertical Patterns, Right Diagonal Pattern, Left Diagonal Patterns.

1. Introduction:

Texture discrimination or classification is the basis for many applications in computer vision. Texture classification is an image processing technique by which different regions of an image are identified based on texture properties. This process plays an important role in many industrial, biomedical and remote sensing applications. Traditionally edges are located at the local maxima of the gradient in the intensity/image feature space. In contrast, the detection and localization of edges (or image boundaries in more general sense) are performed indirectly in the Edge direction method: first by identifying a flow direction at each pixel location that points to the closest boundary; then followed by the detection of locations that encounter two opposite directions of edge flow. Since any of the image attributes such as color, texture, or their combination can be used to compute the edge energy and direction of flow, this scheme provides a general framework for integrating different image features. Edges are local preprocessing methods, that has the property of splitting of local neighborhoods which may also lead into different small regions based on texture properties.

The term 'edge' also stands for a local luminance change for which a gradient can be defined and which is of sufficient strength to be considered important in a given task. Examples of edge detectors are operators that incorporate linear filtering [3, 8, 14, 20], local orientation analysis [10, 21], fitting of analytical models to the image data [4, 9, 12] and local energy [7, 13, 15, 23]. Some of these methods were biologically motivated [13, 14, 20, 23]. Since these operators do not make any difference between various types of edges, such as texture edges vs. object contours and region boundaries, they are known as non-contextual or, simply, general edge detectors. Other studies propose more elaborate edge detection techniques that take into account additional information around an edge, such as local image statistics, image topology, perceptual differences in local cues (e.g. texture, color), edge continuity and density, etc. Examples are dual frequency band analysis, statistical analysis of the gradient field [1, 22], anisotropic diffusion [2, 5], complementary analysis of boundaries and regions [17-19], use of edge density information [6] and biologically motivated surround modulation [11, 16].

The optimality of an edge detector, however, can only be assessed in the context of a well-defined task. That is, the quality of the edge map is directly related to the amount of supportive information it carries into the subsequent processing stages. Since this information is extracted after the edge map was generated, a measure of confidence should be associated with the bottom-up information stream. The Edge direction method utilizes a predictive coding model to identify and integrate the direction of change in image attributes such as color, texture, and phase discontinuities, at each image location. Towards this objective, the value $E(s, \theta)$ is usually computed. This measures the edge energy at pixel s along the orientation θ, $P(s,\theta)$ which is the probability of finding an edge in the direction of θ from s.

Each of the different edge movements, based on their direction represents a pattern. Finally these patterns are used for classification of textures. The paper is organized as follows: In the next section methodology is given.

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Section III describes the results of the proposed method. The conclusions are presented in Section IV.

2. Methodology:

Texture Discrimination using frequencies of edge movements:

Ideally, the description of an image from edge and region primitives must be identical. In practice, the differences are important and we rarely obtain equivalent descriptors from these two primitives. But the present work is strongly based on the principal advantage of the edges, that they are localized in a precise manner. Nevertheless, the application of an edge approach often coincides with a problem of under-detection of certain discontinuities, which create open contours. The strong point of the region extraction approach is the closure of their boundaries and the richness of the information that they convey. However their exact localization remains difficult to obtain. The adapted methodology in the developed system tends to gain compensation between the uniform regions and edges in the image. For this, the classification graph is plotted on the frequencies of number of occurrences of edge movements, but not on edges. These frequencies will overcome the open contour problem of edge detection and exact localization problem of region extraction. Opening is a morphological operation that generally smoothes the contour of an object, breaks narrow isthmuses and eliminates thin protrusions. Because of this reason the proposed method is implemented after opening of the image.

The present paper is based on the assumption that edge is a vector variable with two components, magnitude and direction. The edge magnitude is the magnitude of the gradient, and the edge direction ø is rotated with respect to the gradient direction ψ by -90 degrees. The gradient direction gives the direction of maximum growth of the function. That's why in the present work edge direction movement utilizes a precedence coding model to identify and integrate the direction of change in a given set of image attributes such as brightness and texture, at each image neighboring level of 3 x 3. Based on this assumption the present study outlined a novel technique for classification of textures by using edge direction movement.

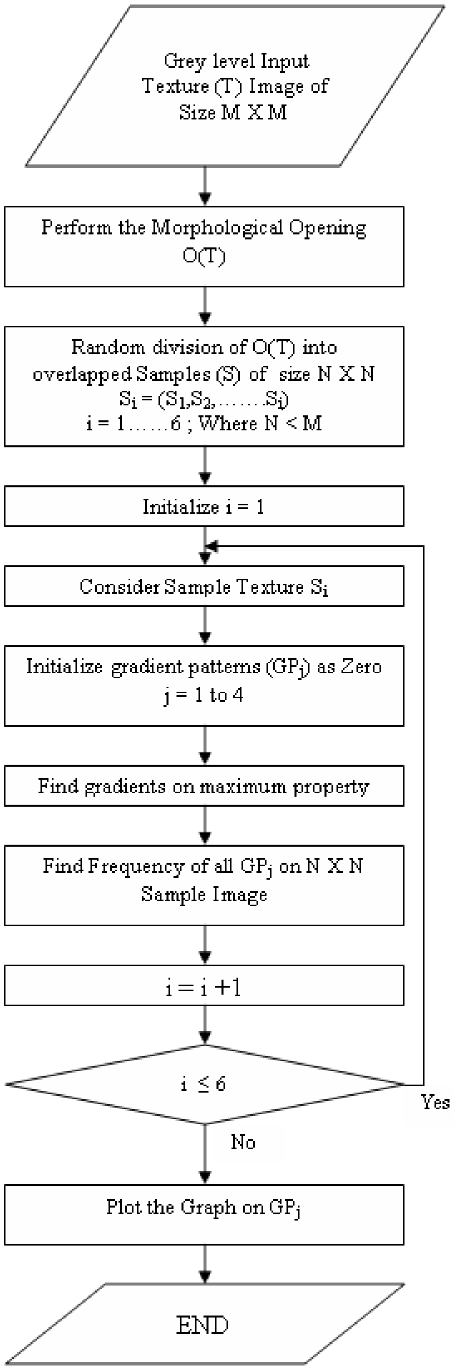

Fig. 1 Block Diagram of entire process.

The novel method of extraction of texture features such as the frequencies of Horizontal, Vertical, Right and Left diagonal patterns on edge direction movements are described in the flow chart shown in Figure 1.

3. Results and Analysis:

The performance of the proposed algorithms for classification of textures is studied on groups of Brodatz textures. Four natural texture images of Brodatz album are considered as one group and they are digitized to a resolution of 200x200. Three texture groups and their combination of Brodatz textures are listed in Table 1. In Table 1 TG_i denotes textures of group i.

Table 1: Texture Groups with their four combinations of textures.

Texture Group No.	Combination of Textures
TG1	Bark, Sand, Raffia, Pigskin
TG2	Straw, Beach Sand, Wood Grain, Grass
TG3	Plastic Bubbles, Bark, Woolen Cloth, Water

These natural images are chosen because they are broadly similar to one another, and are similar to parts of digital images usually encountered in practice, for example, to landscape scenes provided by Earth Observation Satellites.

To implement the method more constructively each Brodatz texture of 200 x 200 resolution has been divided in to six-different overlapped samples 100 x 100. All these samples cover the entire image in an overlapped manner. The main reason for dividing the texture into overlapped samples is to have a comprehensive testing and comparison between the randomly chosen pieces of textures of same size for classification purpose. If we implement on entire texture of 200 x 200, instead of six different samples, then one part of frequency of edge movement pattern will affect overall frequency count. For plotting the graphs the frequency of horizontal and vertical gradient patterns are added into one and right left diagonal pattern frequencies are added into another.

The Fig. 2 and Fig. 3 classifies three classes of textures from TG1 where C1= {Raffia}, C2= {Bark, Sand} and C3= {Pigskin}.

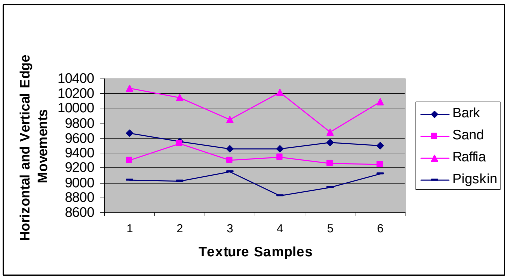

Fig. 2 Classification graph using Horizontal and Vertical Edge Movements for TG1.

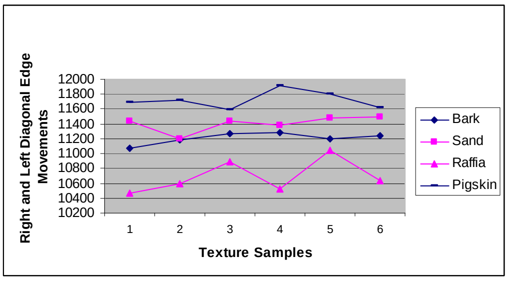

Fig. 3 Classification graph using Right and Left Diagonal Edge Movements for TG1.

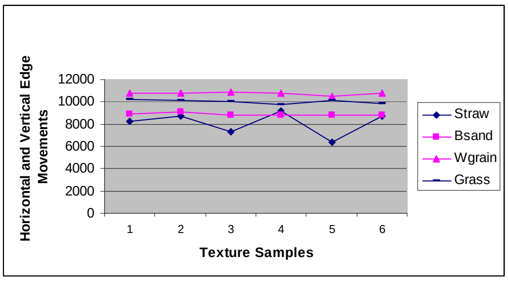

Fig. 4 Classification graph using Horizontal and Vertical Edge Movements for TG2.

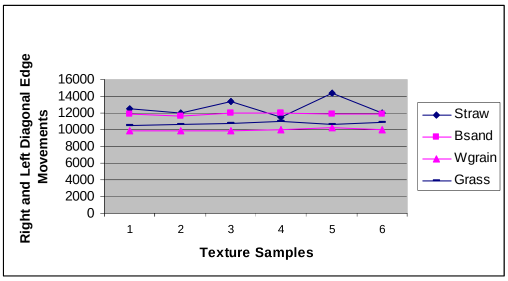

Fig. 5 Classification graph using Right and Left Diagonal Edge Movements for TG2.

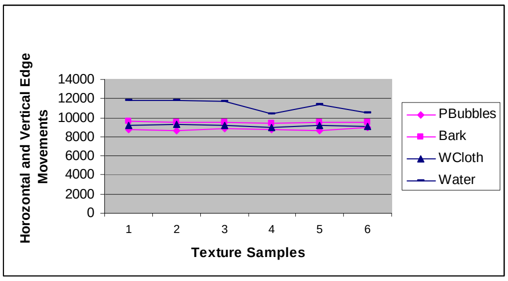

Fig. 6 Classification graph using Horizontal and Vertical Edge Movements for TG3.

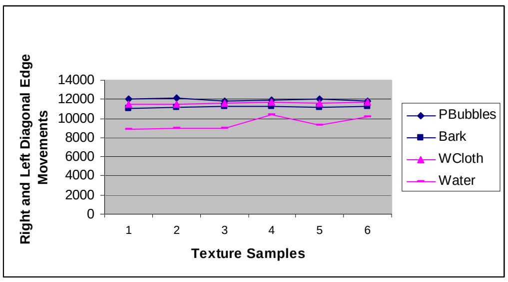

Fig. 7 Classification graph using Right and Left Diagonal Edge Movements for TG3.

The Fig 4 classifies TG2 into two classes where C1= {Wood Grain, Grass}, C2= {Beach Sand, Straw}. However Fig. 5 based on diagonal edge movement patterns classified TG2 into an overlapped classification. The plotted graphs of Fig. 6 and 7 of TG3 classifies the TG3 into two classes C1= {Plastic Bubbles, Bark, Woolen Cloth} C2= {Water}.

4. Conclusions:

The present study of classification is completely based on edge direction movements on a neighborhood. The novelty of the present paper is to utilize edge direction movements as simple linear patterns. The proposed method is powerful because it has shown a clear classification on all six random samples of textures of the same group. Several possible improvements to the proposed method are of interest for future research, for example exploiting a distance function instead of graphs. The developed classification method is automatic, and results are conclusive.

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