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# A Novel Method for Detection of Significant Areas with Low Contrast Boundaries of Images

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## ABSTRACT

The problem of Segmenting Gray scale still images has been addressed in this work and proposed new methods by generating random field for image segmentation and boundary detection for image classification. The present work describes image segmentation at multiple scales. The detected regions are homogeneous and surrounded by closed edge boundaries. Segmentations yield texture and boundary information. Boundary information requires much more effort than texture information. The proposed techniques rely on boundary, textured and non-textured information for image segmentation at multiple scales. The definition of a general purpose segmentation technique has been revealed as being a rather complicated task. This complication is owing to the huge amount of different kind of data that a segmentation technique may have to handle. Previous approaches to multistage segmentation represented an image at different scales using a scale space. However, structure is only represented implicitly in this representation, structures at coarser scales are inherently smoothed, and the problem of structure extraction on is unaddressed. This work argues that the issue of scale selection and structure detection can not be treated separately. A new concept of scale will be presented that represents images structures at different scales, and the image itself. This scale is integrated into a non-linear transform, which makes structure explicit in the transformed domain. Structures that are stable to changes in scale are identified as being perceptually relevant, the transform can be viewed as collecting spatially distributed evidence for edges and regions, and making it available at contour locations there by facilitating integrated detection of edge and regions without restrictive models of geometry or homogeneity. Markov random field theory has been widely applied to the challenging problem of image segmentation. Image segmentation is a task that classifies pixels of an image using different labels so that the image is partitioned into non-overlapping labeled regions. Extraction of regions or objects of interest is usually the first important step in almost every task of image processing and high level image analysis for better understanding. Although it is fundamental, image segmentation a is field in which researchers are facing challenges because most of the real objects have complex shapes, boundaries and true images are often corrupted by noise that cannot be ignored. To tackle the difficult problem of image segmentation, researchers have proposed a variety of methods. In this thesis three textured models have been studied and proposed new methods under these models.

**Keywords:** Helly-Property, Segmentation, Texture model, Neighborhood Spanning Tree, BRF, Markov-Chain-Rule, Edge-Flow, Fuzzy-Logic and Boundary MRF model

## I. INTRODUCTION

Early days of computing, data was numerical. Later, textual data became more common. Today, many other forms of data: voice, music, speech, images, computer graphics, etc. Each of these types of data is signals. A Signal is a function that conveys information. Before going to know about Digital Image Processing, let us discuss the history from where it exists.

First the issue of digital image processing appeared relatively late in computer history, it had to wait for the arrival of the first graphical operating systems to become a true matter. Secondly, digital image processing requires the most careful optimizations and especially for real time applications. As long as people have tried to send or receive the message through electronic media: telegraphs, telephones, television, radar, etc. there has been the realization that these signals may be affected by the system used to acquire, transmit, or process them. Sometimes, these systems are imperfect and introduce noise, distortion, or other artifacts.

Understanding the effects these systems have and finding ways to correct them is the fundamental of signal processing. That is, we specifically introduce the information content into the signal and hope to extract it out later. Sometimes, these man-made signals are encoding of natural phenomena (audio signal, acquired image, etc.), but sometimes we can create them from scratch (speech generation, computer generated music, computer graphics). Finally, we can merge these technologies together by acquiring a natural signal, processing it, and then transmitting it in some fashion. This fashion is called Digital Image Processing.

Vision allows humans to perceive and understand the world surrounding us. Computer vision aims to duplicate the effect of human vision by electronically perceiving and understanding an image. Giving computers the ability to see is not an easy task - we live in a three dimensional (3D) world, and when computers try to analyze objects in 3D space, available visual sensors (e.g., TV cameras) usually give two dimensional (2D) images, and this projection to a lower number of dimensions incurs an enormous loss of information. In order to simplify the task of computer vision understanding, two levels are usually distinguished as Low-level image processing and High-level image processing

Evolution of data communications in the early days was mainly numerical and textual form. Many other forms of data: voice, music, speech, images, computer graphics, etc as specified in([1],[2]) are mostly in the form of electrical or electronic signals. A Signal is a function that conveys information. The concept of digital image processing was introduced relatively late in computer history after the arrival of the first graphical operating systems [3]. More ever, digital image processing requires the most careful optimizations especially for real time applications [4]. Transfer of the messages as signals through electronic media: telegraphs, telephones, television, radar, etc. may be affected by the systems used to acquire, transmit, or process them. Also these systems are imperfect and introduce noise, distortion, or other artifacts leading to necessity of the signal processing [5]. Accordingly, we specifically introduce the information content into the signal to extract it out later by encoding natural phenomena (audio signal, acquired image, etc.), but also generated from scratch (speech generation, computer generated music, computer graphics). Ofllate these technologies are merged together by acquiring a natural signal, processing it, and then transmitting it in some electronic form. This form is called Digital Image Processing.

Computer vision aims to duplicate the effect of human vision by electronically perceiving and understanding an image ([1],[6]). Incurring an enormous loss of information in due processing. In order to simplify the task of computer vision processing, two levels are usually distinguished viz: Low-level image processing and High-level image processing. Low level images processing methods usually use very little knowledge about the content of image. In the case of the later, it is usually provided by high-level algorithms. Low level methods often include image compression, pre-processing methods for noise filtering, edge extraction, image sharpening and boundary detection for image classification and analysis. High-level image processing is based on knowledge, goals, and plans of how to achieve those goals, and artificial intelligence methods are widely applicable. In this thesis low level image processing methods have been studied for image segmentation and classification of images.

## II. RELATED WORK

The problem of Segmenting Gray scale still images has been addressed in this work and proposed new methods by generating random field for image segmentation and boundary detection for image classification. In the image processing literature there exist many different definitions of image segmentation. Actually, almost each author has coined one. The definition used throughout this work is the following: segmentation is a process that divides completely an image into a set of homogeneous, connected regions related to the objects in the scene. Therefore, the result of segmentation is a labeled image corresponding to label at different region. Note that the above definition is rather vague since it fixes neither the criterion of homogeneity to be used nor the algorithm to be applied. The range of frameworks in which segmentation is nowadays utilized is so wide that a more concrete definition would not apply for all of them. Indeed, almost each discipline dealing with images uses some kind of segmentation as low level processing. Moreover, the success of the segmentation algorithm often determines the success or failure of the overall image analysis algorithm. The large range of possible images is not the only fact that makes segmentation a difficult task. Some problems arise when validating a segmentation or comparing it with other results. The first problem comes from the fact that two different projections are carried out, when acquiring a picture. Physical world, which is a three dimensional space, is mapped into an image, which is a two dimensional space. A possible solution for solving this machine handicap is to try to emulate the human visual system. There has been a large number of studies in this field, but very little has been concluded due to the difficulty of the problem. Most of these studies have handled the problem from a qualitative or philosophic viewpoint, without giving a quantitative model or theory for characterizing the human visual system. Furthermore, when some 'theories have been built for a specific environment, their application to more general or realistic situations have failed. Hence, their results do not help to implement computer vision algorithms. • Gradient operators: basically, these algorithms use a discrete approximation of the gradient or of the laplacian operators. The approximation of the gradient in each direction (directional difference) is performed by means of the convolution of a small kernel with the image. A scalar measure of the local gradient can be estimated in different ways: taking the maximum, the absolute value or the magnitude of the gradient. Changing the size of the kernels, theirs weights and the estimate, one can obtain different gradient operators: Roberts [18], Sobel [24], Prewitt [25], etc... Another possible approach is to substitute linear convolutions for morphological operators [26,27]. All these algorithms have the problem of being very sensitive to noise. In order to solve this problem a new theory of edge detection has been proposed [35], which leads to methods combining image filtering and laplacian operators. These methods yield more robust estimations of the gradient and therefore, less noisy edges.

* Template matching: in this approach, a set of kernels is used in parallel (selecting the output of one filter for

each pixel) rather than by combination (obtaining a result by combining all the outputs, as in the previous approach). Thus, a set of templates, each one representing a kind of edge (different directions), is applied on every point of the image. At each point, the template producing the highest correlation gives the edge characteristics at this point. Several sets of templates have been proposed, for instance the so called Kirsh template [29] or the Frei&Chen template [30].

• Edge fitting: the basis of this approach is the assumption that an edge can be modeled as a step discontinuity. Using this model, regions in the image whose edge fitting error is small are sought. The parameters of the model which better fits this region determine the position, orientation and magnitude of the edge. Two main techniques have been developed following this idea, namely Hueckel [31] and Nalwa and Binford [32]. It has to be pointed out that these techniques require more computation than the above presented techniques while not improving their performance.

Statistical techniques here, the detection of an edge are treated as a hypothesis testing. A line going through a window is said to be an edge if the two sets of pixels that it forms on its sides can be defined as two different regions. The study has to be carried out for different orientations in the same window, and the orientation which best accomplishes the two regions hypothesis is chosen. Yakimovsky [33] presented a method using a 7x7 window and normal models for regions. It has to be said that the different methods above presented lead to similar results. As an example of gradient detection, Figure 2.2 shows the morphological gradient of an image. Once the edge detection has been performed, the second step in the segmentation process deals with removing false edges. The necessity of this step is twofold. Firstly, since edge detectors are very sensitive to noise, small spots appear in edge images. This kind of artifacts can be seen in Figure 2.2: on the top right-hand corner the noise has yielded some false edges. Hence, the need of an algorithm for removing small isolated spots. Secondly, almost all the aforementioned techniques yield a gray level image. That is, in edge images the estimated magnitude of the gradient is represented. Therefore, a threshold must be introduced for removing weak gradient points and for obtaining a binary edge image. In Figure 1 some weak gradients can be seen within the coat of the woman.

**Figure 1.** The original woman image and its morphological gradient

The third step of an edge-oriented segmentation tries to solve the problem of having wide edges. In order to obtain segmentation, contours must be represented by one-pixel width edges. Nevertheless, the output of the edge detectors is not constrained to have such width and, due to the image uncertainty, algorithms yield wide edges (this effect can also be observed in Figure 2.2). Thus, a thinning step is mandatory. In segmentation applications, thinning techniques present some problems, e.g.: usually, they do not take into account the original image but just edge images; after thinning, the connectivity of edges may change. Thus, conventional thinning algorithms cannot be used. A review of more suitable thinning techniques for this application can be found in [34], The last step of an edge-oriented segmentation creates a partition of the image from its edge map. This procedure is usually refereed as gap filling, edge linking or boundary detection. It can be carried out just taking into account the information contained in the edge map or combining this information with that of the original image. Anyway, it has to be noticed that whereas the first three steps are mainly filtering and therefore simple, low-level operations, this last step requires the use of some heuristics or assumptions on the kind of boundaries that are wanted. Among these techniques there exist different classes:

boundary refining, the Hough Transform, graph searching, dynamic programming and contour following. A more extensive review of such techniques can be found in [6,17,35].The above four steps are grouped in only two by some authors [6,31]. That is done by taking edge detection, thresholding and thinning as a single procedure. In this way, edge-oriented segmentations are split into a low-level and a high-level stage. The more sophisticate the edge detection, the simpler the boundary detection can be. Edge-oriented segmentations are not simple to use (note that each step in the process presents problems, as well as their concatenation) and, moreover, they do not achieve high performance. In an image, texture is one of the visual characteristics that identify a segment as belonging to a certain class. We recognize many parts of the image by texture. If the texture belongs to a class that has a particular physical interpretation such as grass, hair, water or sand, then it may be regarded as "natural" texture. On the other hand a texture may belong to a class identified by artificial visual characteristics that have a concise mathematical interpretation.

A complete definition of texture has been elusive as there does not exist an all encompassing mathematical model of texture .However from a human perspective we may conjecture that texture is a quality that distinguishes regularity in the visual appearance of local detail [60,61,62]. Texture has been an active area for research of computer vision for over Two decades. There are several areas like petrography, metallographic, and lumber processing, which make extensive use of textural features such as grain shapes, size, and distribution for recognizing and analyzing specimens. Texture is very important in quality control since many inspection decisions are based on the appearance of the texture of the material. There are many different kinds of textures, and these have been classified in the form of taxonomy. Texture is the term used to characterize the surface of a given object or phenomenon and is undoubtedly one of the main features used in image processing, pattern recognition and multispectral scanner images obtained from aircraft or satellite platforms to microscopic images of cell cultures or tissue samples. Texture also plays an important role in human visual perception, medical image processing, and provides information for recognition and interpretation. That's why research on texture analysis has received considerable attention in recent years. An important approach to region description is to quantify its texture content. Although no formal definition of texture exists, intuitively this descriptor provides measures of properties such as smoothness, coarseness, and regularity. Julesz's [63] classic approach for determining if two textures were alike was to embed one texture in the other. If the embedded patch of texture visually stood out from the surrounding texture then the two textures were deemed to be dissimilar. The comparisons relied solely on pre-attentive human visual perception, where the subjects were only given a brief time to view the texture [64].Julesz found that texture with similar first order statistics, but different second-order statistics, were easily discriminated. However Julesz could not find any textures with the same first and second order statistics, but different third order statistics, that could be discriminated.

This led to the Julesz conjecture that "second-order textures are indistinguishable ". This was further substantiated with work on the visual discrimination of stochastic texture fields [53].

However, later caelli, Julesz, and Gilbert [66] did produce second-order textures that could be discriminated with pre-attentive human visual perception .Further work by Julesz [67,54] revealed that his original conjecture was wrong. Instead; he found that the human visual perception mechanism did not necessarily use third –order statistics for the discrimination of these second order textures, but rather used the second order statistics of textures he called textons. These textons he describes as being the fundamentals of texture. Julesz [67,54] found three classes of textons: color, elongated blobs, and the terminators (end-points) of these elongated blobs. Julesz revised his original conjecture to state that, "the human pre-attentive human visual system cannot compute statistical parameters higher than second order. "He further conjectured that the human pre-attentive human visual system actually uses only the first order statistics of these textons.

Since these pre-attentive studies into the human visual perception, psychophyical research has focused on developing physiologically plausible models of texture discrimination .These models involved determining which measurements of textural variations humans are most sensitive to. Textons were not found to be the plausible textural discriminating measurements as envisaged by Julesz [66,55,56].On the other hand, psychophysical research has given evidence that the human brain does a spatial frequency analysis of the image [57,58,59].Therefore a number of models are now based on the responses of orientated filter banks [60,61,62,35].Tamura et.al. [87] and laws[63] identified the following properties as playing an important role in describing texture: uniformity, density, coarseness, roughness, regularity, linearity, directionality, direction, frequency, and phase. However these perceived qualities are by no means independent.

## III. PROPOSED ARCHITECTURE

Image segmentation is a process that partitions an image into its constituent regions or objects. Image segmentation plays an important role in Medical images, Archeology, Astronomy, Geography, Biology, Defense, Law enforcement, problems dealing with machine perception. Effective segmentation of complex images is one of the most difficult tasks in image processing. Various image segmentation algorithms have been proposed to achieve efficient and accurate results. This project explains watershed segmentation. Watershed segmentation is a particularly attractive method. The major idea of watershed segmentation is based on the concept of topographic representation of image intensity. But this method has some drawbacks such as over segmentation, sensitivity to noise, poor detection of significant areas with low contrast boundaries and poor detection of thin structures etc. To overcome these drawbacks, markers will be used on gradient images. Firstly it computes the gradient image and secondly markers applied on gradient image. This method produced good result over conventional methods. The result has been given in the following chapters.

The problem of Segmenting Gray scale still images has been addressed in this work and proposed new methods by generating random field for image segmentation and boundary detection for image classification. The present work describes image segmentation at multiple scales. The detected regions are homogeneous and surrounded by closed edge boundaries. Segmentations yield texture and boundary information. Boundary information requires much more effort than texture information. The proposed techniques rely on boundary, textured and non-textured information for image segmentation at multiple scales. The definition of a general purpose segmentation technique has been revealed as being a rather complicated task. This complication is owing to the huge amount of different kind of data that a segmentation technique may have to handle. Previous approaches to multistage segmentation represented an image at different scales using a scale space. This work argues that the issue of scale selection and structure detection can not be treated separately. A new concept of scale will be presented that represents images structures at different scales, and the image itself. This scale is integrated into a non-linear transform, which makes structure explicit in the transformed domain. Structures that are stable to changes in scale are identified as being perceptually relevant, the transform can be viewed as collecting spatially distributed evidence for edges and regions, and making it available at contour locations there by facilitating integrated detection of edge and regions without restrictive models of geometry or homogeneity. To tackle the difficult problem of image segmentation, researchers have proposed a variety of methods. In this thesis three textured models have been studied and proposed new methods under these models. The main objective of is to compare and evaluate statistical feature parameters on these four methods. The Novel Method described in present study has a potentiality to generate new concepts in design of enhanced Images .This new algorithm for Image segmentation has been implemented using morphological transformations. Improvements achieved when using novel marker selection method are highlighted. In addition to this these methods are also suggested to detect and distinguish among objects and regions in images, to infer perspective, surface orientation, and shape in 3D scenes and as in this chapter to distinguish among features of textures. We design a Q-matrix is the best and easy method for classifying and differentiating the Textures. Therefore we can conclude that the Q-matrix is much better than that of the remaining matrix methods this can be because the method considers all possible neighbors of an element at once. Improvements achieved when using Q-Matrix are highlighted.

## IV. TECHNIQUE PRELIMINARIES

The proposed method consists of five steps. The first step deals with order of placing the weights on a 3x3 neighborhood. The second step computes the sample space by calculating the weights for each neighborhood scanning tree and planar graph. The third step computes the event of interests for segmentation by counting the frequency of occurrence of each neighborhood Spanning tree or planar graph on 3X3 sample space. Fourth step computes the probability of each event under constraints of probability. Fifth step computes the mean and variance and replace each pixel by corresponding variance and choose good threshold for segmentation.

In the present chapter the binary Image weights are represented by using snake like topology. From this the weights of neighborhood spanning trees are computed. Neighborhood Spanning trees are form a unique combination. Then the frequency of occurrence of each neighborhood spanning tree is computed. Based on these frequencies, random numbers are generated by specifying whether neighborhood tree or planar graph is in the mask or not. Based on this probability, calculate mean and variance by mathematical formulae. Chose good threshold method and segment the image. This method gives good classification of images. The comparisons with hyper graph show that the proposed method can give more accurate segmentation results in both high and low noise level regions while preserving subtle boundary information with high accuracy.

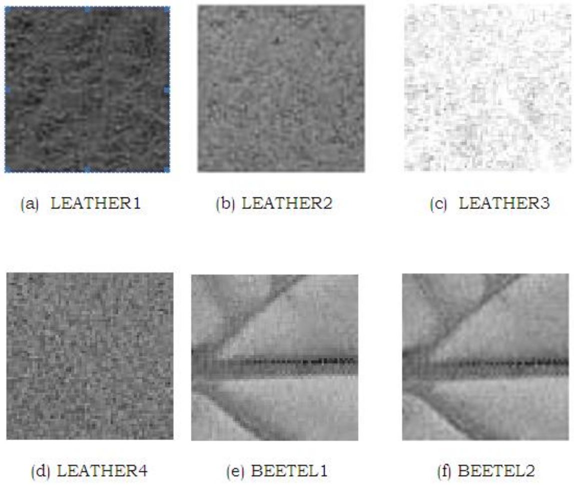
Texture analysis plays an important role in human vision, computer vision, pattern recognition and digital image processing. It is used to detect and distinguish among objects and regions in images [78], to infer perspective, surface orientation, and shape in 3D scenes[79,80], to distinguish among features of textures. Present study compares the texture features based on Grey Level Run Length matrix (GLRLM), Co-occurrence, Neighboring Grey Level Dependence Matrix (NGLDM), and the new matrix method called The Q-matrix which measures the similarities of grey levels. The problem addressed is to determine which features optimize classification rate. Such features may be used in image segmentation, compression and in evaluation of statistical features. Though traditional methods are used for evaluating similarity measures, but large scale objective comparison has not been performed in the past. The main objective is to compare and evaluate statistical feature parameters on these four methods. Two types of textures are studied. The Experimental results indicate good classification for Q-Matrix. One method frequently cited in the literature for texture discrimination is based on the co-occurrence matrix family [11,81]. Which are based on second-order statistics, that is, spatial relationships of pairs of grey values of pixels in digital texture Images. This prominence of second-order statistics in current research can be motivated by Julesz's conjecture, that the human eye uses such statistics as a discriminator between textures [127]. Recently Julesz and Gagolowicz constructed several counter-examples to be Julezs conjuncture. However, these counter examples consist of artificially constructed texture that does not occur naturally. In the present study a new method that is similar than Q-Matrix has been used and various measures have been computed based on this Matrix. A comparison is made among texture features of four methods. The present study evaluates the various statistical texture features based on Q-matrix.

Although neither structural nor statistical methods satisfy this requirement fully, both classes of method, particularly statistical methods, have been widely accepted over two decades. The four matrix methods that we are going to review in that belong to the later approaches of texture analysis i.e., the Statistical Methods. These approaches are considered to be the most powerful method for extracting texture information from images ([83,86]). Little theoretical evidence has been presented which attempts to explain why Statistical approaches of texture analysis are intrinsically more powerful than, say, structural approaches. However, if empirical evidence is considered as a valid measure of algorithm worth, then we need to look no further the literature is ripe with quantitative comparisons of texture methods which conclude in favour of the Statistical Approaches of texture analysis.

## V. EXPERIMENTAL STUDY

In this chapter, A novel method is proposed and named as Q-matrix. Q-matrix is easy to compute because the image gray levels will be reduced to 0 to 8. In the above case Q-matrix has dominated the above matrix methods in discriminating the textures. Q-matrix is a matrix of grey levels that will have a strong influence of neighboring pixels. The above four methods are applied to extract texture features from the different images of the textures taken. The above parameters are evaluated on the output matrices for the textures Leather and Betel and are listed in the tables. The parameters homogeneity, contrast, dissimilarity, angular second moment and entropy are evaluated on four matrices for the same textures and they are listed in the tables. In the tables TLi and TBi indicate Leather Texture and Betel Texture with no i respectively. From the tables graphs are plotted. However the graphs plotted for run length, co-occurrence and Neighboring Grey Level Dependence matrices couldn't discriminate the different textures. The graphs Show some of the results plotted the features extracted from the image-texture metrics against the scale values. Although the features described the image texture very well at a particular parameter, the other parameters did not always show good correlation. The present study we have proposed a novel method and extract texture features from the different images of the textures taken. We have applied the above mentioned four methods on these images and have successfully tried to compare these matrices with each other and have found out which among the four is the best and identifies the texture descriptors more clearly and efficiently.Finally we have detected that the Q-matrix is the best and easy method for classifying and differentiating the Textures. Therefore we can conclude that the Q-matrix is much better than that of the remaining matrix methods this can be because the method considers all possible neighbors of an element at once. So the Q-matrix may be the preferred method for analyzing the carpet wear and other fabrics by many manufacturing companies in future.

The statistical formulation indicates if an image is smooth, rustic, granulated, etc. It is based on a set of features to represent the characteristics of the texture of an image. Those features are contrast, correlation, entropy, etc. They are usually derived from "measurement of the gray level of the image", "it differentiates from the values of gray" or "co occurrence matrix". The characteristics are selected in heuristics form; nevertheless, an image similar to the analyzed one cannot be recreated using some measurement of the set of features. To overcome these limitations structural models have been proposed in the next chapter. The structural technique, on the other hand, indicates the primitive features that exist in the image, such as regularity of parallel lines. Some textures can be seen as two-dimensional patterns, composed of a set of primitives or sub-patterns, which are organized according to a certain rule of positioning. The primitives used are areas of constant gray level, lines, curves and polygons. In the next chapter we have studied structural models for image segmentation and classification. However Q-matrix has two significant weaknesses one is its susceptibility to noise. Second is its inability to capture important second order gray level transition statistics of the form P(I,j), i<>j. To ensure maximal capture of texture information, it is clearly an advantage to use several complementary texture algorithms which extract both rotation-variant and rotation-invariant features at multi scales. The features performed the poorest when compared to structural model based methods. In the next chapter for structural models, new morphological patterns watershed methods have been studied and proposed new method for image segmentations and classification. In this chapter we formulate the problem of processing binary random field images by means of mathematical morphology. In this chapter we employ mathematical morphology in order to develop new structural techniques for the processing and analysis of random shapes modeled as binary random fields. Since, in general, morphological transformations of continuous space binary random fields are not measurable; we suggest morphological operators, thereby effectively implementing our problem in the discrete domain.



(a) LEATHER1 (b) LEATHER2 (c) LEATHER3

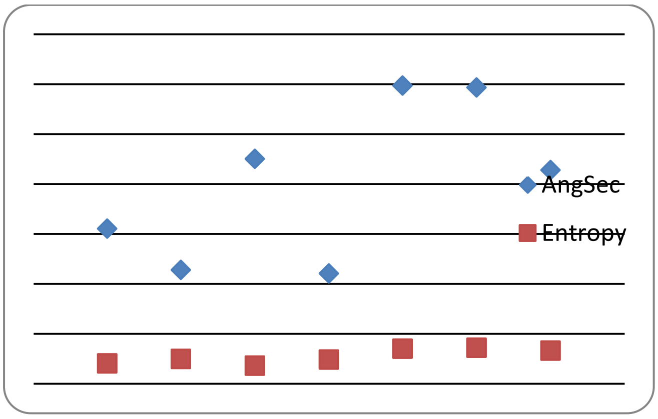
(d) LEATHER4 (e) BEETEL1 (f) BEETEL2

**Figure 2**

**GLCM TABLE**

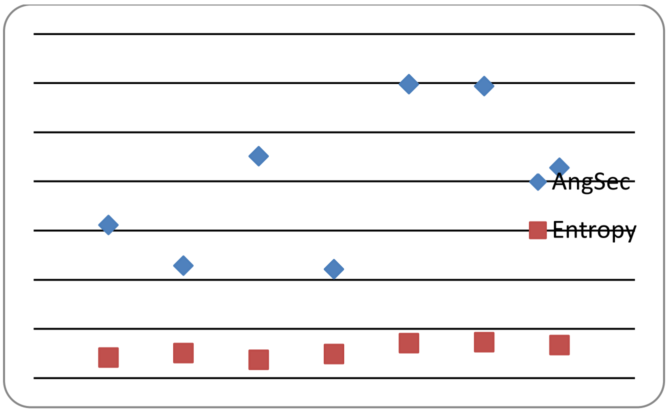
| Texture .no. | N1 Homogeneity | N2 Contrast | N3 Dissimilarity | N4 Ang Sec Movement | N5 Entropy |
|---|---|---|---|---|---|
| TL1 | 45 | 95 | 5 | 21734 | 999 |
| TL2 | 406 | 804 | 8 | 47276 | 5257 |
| TL3 | 93 | 185 | 1 | 8122 | 27192 |
| TL4 | 467 | 977 | 5 | 20680 | 5453 |
| TB1 | 136 | 278 | 6 | 39936 | 5476 |
| TB2 | 255 | 514 | 2 | 8488 | 12840 |
| TB3 | 55 | 218 | 16 | 20199 | 14111 |
| TB4 | 6 | 430 | 12 | 45900 | 7890 |
| TB5 | 21 | 380 | 4 | 25212 | 5925 |

## GLCM GRAPH



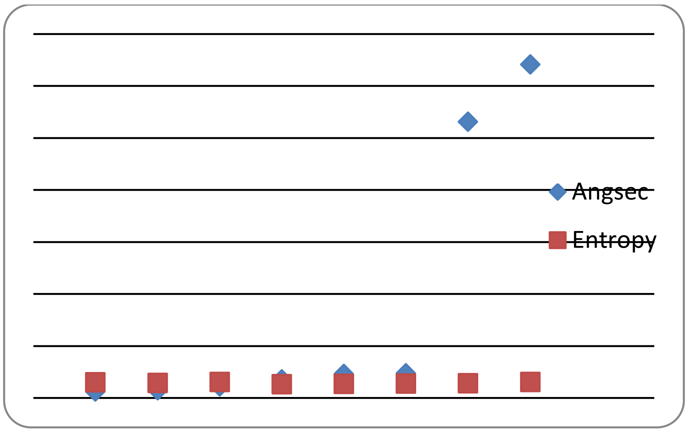

GLRLM TABLE

| Texture .No | N1 Small number Emphasis | N2 Large Number Emphasis | N3 Ang sec Moment | N4 Non-uniformity | N5 Entropy |
|---|---|---|---|---|---|
| TL1 | 0.111 | 25.444445 | 35.0 | 1.296296 | 5.545100 |
| TL2 | 0.179487 | 21.435898 | 75.0 | 1.923099 | 20.454619 |
| TL3 | 0.182796 | 28.470791 | 4579.0 | 15.33538 | 754.868370 |
| TB1 | 0.166667 | 26.916666 | 54.0 | 1.5000000 | 12.476649 |
| TB2 | 0.15 | 27.85 | 84.0 | 2.1000000 | 25.136749 |
| TB3 | 0.244604 | 16.776978 | 147.0 | 8.251999 | 265.064832 |
| TB4 | 0.237530 | 25.657952 | 10209.0 | 24.24993 | 1243.94981 |




GLDM TABLE

| Texture . no | Angsec N1 | Contrast N2 | Entropy N3 | Mean N4 |
|---|---|---|---|---|
| TL1 | 12351 | 33278 | 29653.98 | 994 |
| TL2 | 14341 | 31150 | 28920.82 | 983 |
| TL3 | 21955 | 39326 | 30468.88 | 1007 |
| TL4 | 35207 | 21854 | 26189.93 | 930 |
| TB1 | 46106 | 24318 | 26955.87 | 948 |
| TB2 | 47349 | 25704 | 27301.67 | 954 |
| TB3 | 531140 | 29526 | 28349.02 | 995 |
| TB4 | 641230 | 31278 | 30421.89 | 1002 |




## VI. CONCLUSION

The statistical formulation indicates if an image is smooth, rustic, granulated, etc. [63]. It is based on a set of features to represent the characteristics of the texture of an image. Those features are contrast, correlation, entropy, etc. They are usually derived from measurement of the gray level of the image; it differentiates from the values of gray or co occurrence matrix [64]. The characteristics are selected in heuristics form; nevertheless, an image similar to the analyzed one cannot be recreated using some measurement of the set of features. The structural technique, on the other hand, indicates the primitive features that exist in the image, such as regularity of parallel lines. Some textures can be seen as two- dimensional patterns, composed of a set of primitives or sub-patterns, which are organized according to a certain rule of positioning. Textures like brick walls and mosaics; the primitives used are areas of constant gray level, lines, curves and polygons. The correct identification of those primitives is quite difficult. However, if the textures primitives are identified completely, then it is possible to recreate the texture from the primitives. A work using a structural model is indicated in [59,60]. The stochastic technique is based on the energy properties and it is used mainly to detect global regularity in an image, indicating small peaks of high energy in its spectrum [61]. A texture is assumed to be the realization of a stochastic process, which is governed by some parameters. The analysis is executed, defining a model and considering the parameters. This way, the stochastic processes can be reproduced from the model and associated to the parameters. The estimation of the parameters can serve to classify and to segment textures. This type of model offers a good possibility to recreate realistic examples of natural textures. The next chapter describes the statistical model based methods and compares the texture features based on Grey Level Run Length matrix (GLRLM), Co-occurrence, Neighboring Grey Level Dependence Matrix (NGLDM), and the new matrix method called The Q-matrix which measures the similarities of grey levels. The problem addressed is to determine which features optimize classification rate. Such features may be used in image segmentation, classification and in evaluation of statistical features. Improvements achieved when using Q-matrix method are highlighted. In addition, their main drawbacks are pointed out.

## VII. REFERENCES


[1]. Prof. R. C. Gonzalez, P. Wintz, Digital image processing, Addison-Welsey,Massachusetts,2006.

[2]. Les Kitchen and Azriel Rosenfeld.2007) Digital Image Processing, Addison Wesley

[3]. Jain A.K. (1999) Fundamentals of Digital Image Processing, Prentice Hall.

[4]. Niblack, W. (2005) An Introduction to Digital Image Processing, Strandberg.

[5]. R.C. Gonzalez and R.E. Woods. Digital Image Processing Addison- Wesley, Reading, MA, 2002.

[6]. F. M. Wahl, Digital image signal processing, Artech House, Boston, 2004.

[7]. D.F. Rogers. Procedural Elements of Computer Graphics. McGraw-Hill, New York, 2003.

[8]. T. Pavlidis. Algorithms for Graphics and Image Processing. Computer science press, New York, 2007.

[9]. R. M. Haralick, L. G. Shapiro, "Image segmentation techniques," Computer Vision,Graphics, and Image Processing, vol. 29, pp. 100-132, January 1990.

[10]. M. Bertero, T. A. Poggio, V. Torre, "Ill-posed problems in early vision," Proceedings of the IEEE, vl. 76, pp. 869-887,1999.

[11]. D. Marr, Vision, W. H. Freeman, New York, 2007.

[12]. B. S. Lipkin, "Introduction: Psychopictorics," in Picture Processing andPsychopictorics, B. S. Lipkin and A. Rosenfeld, Academic Press, New York, 1970.

[13]. R.M. Haralick ,Digital step Rdges from zero crossings of second directional derivatives, IEEE transavtions on Pattern Analysis and Machine Intelligence, January (1984).

[14]. Canny, J. (1986) A Computational Approach to Edge Detection IEEE Transactions on Pattern Analysis and Machine Intelligence PAMI No 6, 679-698.

[15]. Bretto, J. Azema, H. Cherifi, and B. Laget. IEEE Transaction on Combinatorics and Image Processing. France, 1997.

[16]. R. Wilson and M. Spann, Image segmentation and uncertainty, Research Studies Press Ltd., Letchmore, Hertfordshire, England, 1988.

[17]. D. Vernon, Machine vision. Automated visual inspection and robot vision, Prentice Hall International (UK) Ltd, 1991.

[18]. L. G. Roberts, "Machine perception of three-dimensional solids," in Optical and Electro-Optical Information Processing, J. T. Tippet et al., MIT Press, Cambridge,MA, pp. 159-197.
[19]. F. Marqués, Procesado de imágenes para la detección de contornos en ecocardiogramas de tipo B, Projecte Fi de Carrera, U.P.C., Barcelona, 1988
[20]. M. D. Levine, Vision in man and machine, New York, McGRaw-Hill, 1985.
[21]. D. H. Ballard, C. M. Brown, Computer vision, Prentice Hall, New Jersey, 1982.
[22]. R. Wilson and M. Spann, Image segmentation and uncertainty, Research Studies Press Ltd., Letchmore, Hertfordshire, England, 1988.
[23]. W. K. Pratt, Digital image processing, Wiley-Interscience, New York, 1991.
[24]. J. M. S. Prewitt, "Object enhancement and extraction," in Picture processing and psychopictorics, B. S. Lipkin and A. Rosenfeld, academic Press, New York, 1970.
[25]. J. Serra, Image analysis and mathematical morphology, Academic Press, London, 1982.
[26]. S. Beucher, Segmentation d'images et morphologie mathématique, PhD Thesis, Paris School of Mines, Paris, June 1990.
[27]. D. Marr and E. Hildreth, "Theory of edge detection," Proc. Roy. Soc. London, B207, pp. 187-217,1980.
[28]. R. Kirch, "Computer determination of the constituent structure of biomédical images," Computers and Biomédical Research, vol. 4, pp. 315-328, 1971.
[29]. W. Frei and C. Chen, "Fast boundary detection: A generalization and a new algorithm," IEEE Trans. Computers, vol. 26, pp 988-998,1977.
[30]. M. F. Hueckel, "An operator which locates edges in digitized pictures," Journal Assoc. Còmput. Mach., vol. 20, pp. 634-637,1973.
[31]. V. S. Nalwa and T. O. Binford, "On detecting edges," IEEE Trans. Pattern Analysis and Machine Inteligence, vol. 6, pp.699-714, 1986.
[32]. Y. Yakimovsky, "Boundary and object detection in real world images," Journal of the Assoc. Computing Machinery, vol. 23, pp. 599-618,1976.
[33]. R. J. Schalkoff, Digital image processing and computer Vvsion, John Willey & Sons, New York, 1989.
[34]. J. J. Gerbrands, Segmentation of noisy images, PhD Thesis, Delf University of Technology, Delft, 1988.
[35]. J. L. Muerle and D. C. Allen, "Experimental evaluation of techniques for automatic segmentation of objects in a complex scene," in Pictorial Pattern Recognition, G. C. Cheng et al., Eds., pp. 3-13, Thompson, Washington, 1968.
[36]. Rosenfeld and A. C. Kak, Digital picture processing, vol. 2, Academic Press, Orlando, Florida, 1982.
[37]. Cocher, Codage d'images à haute compression basé sur un modèle contour-texture, D Thesis, Ecole Polytechnique Fédérale de Lausanne, Lausanne, 1983.
[38]. T. Pavlidis, Structural pattern recognition, Springer, New York 1977.
[39]. S. L. Horowitz and T. Pavlidis, "Picture segmentation by a directed split-and-merge procédure," in Proc. 2nd Int. Joint Conf. on Pattern Recognition, pp. 424-433, 1974.
[40]. K. S. Fu, R. C. Gonzalez and C. S. G. Lee, Robotics: Control, sensing, vision and intelligence, McGraw-Hill, New York, 1987.
[41]. S. L. Horowitz and T. Pavlidis, "Picture segmentation by a tree traversal algorithm,". Journal of the Assoc. Computing Machinery, vol. 23, pp. 368-388, 1976.
[42]. Y. Fukada, " Spatial clustering procedures for region analysis," Pattern Recognition, vol. 12, pp. 395-402, 1980.
[43]. R. Leonard!, Segmentation adaptative pour le codage d'images, PhD Thesis, Ecole Polytechnique Fédérale de Lausanne, Lausanne, 1987.
[44]. P. C. Chen and T. Pavlidis, "Image segmentation as an estimation problem," Computer Graphics and Image Processing, vol. 12, pp. 153-172, 1980.

[45]. P. J. Burt, T. H. Hong and A. Rosenfeld, "Segmentation and esti-mation of image region properties through cooperative hierarc-hical computation," IEEE Transactions on Systems, Man and Cybernetics, vol. 11, pp. 802-809, 1981.

[46]. S. Kasif and A. Rosenfeld, "Pyramid linking is a special case of ISOBATA," IEEE Trans, on Systems, Man and Cybernetics, vol. 13, pp. 84-85, 1983.

[47]. L. A. Zadeh, "Fuzzy sets," Information Control, vol. 8, pp.338- 353, 1965.

[48]. J. C. Bezdek, Pattern recognition with fuzzy objective function algorithms, Plenum, New York, 1981.

[49]. B. Jahne, Digital image processing, Springer-Verlag, Berlin, 1991.

[50]. M. Pietikàinen and A. Rosenfeld, "Image segmentation by texture using pyramid node linking," IEEE Transactions on Systems, Man and Cybernetics,vol.11,pp.822-825, 1981.

[51]. C. Home, Unsupervised image segmentation, PhD Thesis, Ecole Polytechnique Fédérale de Lausanne, Lausanne, 1990.

[52]. R.L Kashyap and R.Chellappa, "Estimation and choice of neigh-bors in spatial interaction models of images", IEEE Transactions on Information Theory, vol. IT 29, no. 1, pp.60 72, 1983.

[53]. B.Julesz, "A theory of preattentive texture discrimination based on first-order statistics of texons," Bibliogical Cybernetic, vol. 41, no.2, pp. 131, 138, 1981.

[54]. C.O.Acuna "Texture Modeling using Gibb's Distributions" Computer Vision, Graphics, and Image Processing : Graphical Models and Image Processing, vol. 54, no.3, pp.210 222, 1992.

[55]. H.Voorhes and T.Poggio," Computing Texture Boundaries in Images", Nature, Vol. 333, pp. 364 367, May 1998.

[56]. J.W.Campbell and J.G. Robson," Application of Fourier analysis to the visibility of gratings", Journal of Physiology, vol.197, pp. 551 566,1968.

[57]. R.L.Devalois, D.G. Albrecht and L.G.Thorell "Spatial-frequency selectivity of cells in macaque visual cortex," Vision Research, vol. 22, pp.545 559,1988.

[58]. M.A.Georgeson, ," Spatial Fourier analysis and human vision," in Tutorial Essays, A Guide to Recent Advances (N.S.Sutherland, ed.), vol. 2, ch. 2, Hillsdale, NJ: Lawrence Erlbaum Associates, 1979.

[59]. R,K.Beatson and W.A. Light,"Fast Evaluation of radial basis functions: methods for two dimensional polyhormonic splines," IMA Journal of numerical Analysi, vol. 17,pp. 343 372, July 1997.

[60]. J.R.Bergen and M.S.Landy," Computational Modeling of visual texture segregation," in Computational Models of Vision Processing (M.S.Landy and J.A.Movshon , eds.), pp.253 271,Cambridge MA: MIT Press, 1991.

[61]. C.Chubb and M.S.Landy, "Orthogonal distribution analysis:a new approach to the study of texture perception" in Computa-tional Models of vision processing (M.S.Landy and J.A.Movshon, eds.), pp.291 301, Cambridge MA: MIT Press,1991.

[62]. K.I.Laws, Textured image segmentation. PhD thesis, University of Southern California, 1980.

[63]. M. Haindl, Texture Synthesis," CWI Quarterly, vol. 4, pp. 305 331, 1991.

[64]. J.M Francos and A.Z. Meiri, "A unified structural stochastic model for texture analysis and synthesis," in Proceedings 5th International Conference on Pattern recognition,(Washington), pp. 41 46, 1988.

[65]. J.M.Coggins, A Framework for Texture Analysis Based on Spatial Filtering. PhD thesi,Computer Science Department, Michigan Stat University, East Lansing, MI, 1982.

[66]. J.K.Hawkins "Textural properties for pattern recognition," in Picture Processing and Psychopictorics (B.Lipkin and A.Rosenfeld,eds.)NewYork Academic Press, 1969.

[67]. W.Richords and A. Polit, "Texture Matching," Kybernetic, vol. 16, no. 3, pp. 155 162, 1974.

[68]. J.Skalnsky, “Image segmentation and feature extraction," IEEE Transactions on Systems, Man, Cybernetics, vol.8,pp. 237 247,Apr 1978.

[69]. S.W.Zucker and K.Kant,"Multiple-level representation for texture discrimination," in Proceedings IEEE Conference on Pattern Recognition and Image Processing, (Dallas, TX),pp.609 614, 1981

[70]. R.Paget and D. Longstaff ," Texture synthesis via a noncausal nonparametric multiscale Markov random field," IEEE Transactions on Image processing, vol. 7, pp. 925 931,June 1998.

[71]. J.E.Besag, “ Spatial Interaction and the statistical analysis of lattice systems" Journal of the Royal Statistical Society, series B, vol. 36, pp.192 326, 1974.

[72]. R. Chellappa, “Two dimensional discrete Markov random fields for image processing", in progess in Pattern Recognition (L.N.Kanal and A. Rosenfeld, eds.) B, vol. 2, pp.79 122,North Holland Pub. Co., 1985.

[73]. R.C. Dubes and A.K.Jain," Random field models in image analysis" journal of Applied Statistics, vol. 16,no. 2, pp.131 164,1989.

[74]. Haralick R., Shanmugam K. and Dinstein I., Textural Features for Image Classification, IEEE trans. on Systems, Man, and Cybernetics, Vol. SMC-3, No.6, pp.610-621, 1973.

[75]. Hsin H., Texture Segmentation Using Modulated Wavelet Transform, IEEE trans. On Image Processing, Vol 8. No.7, 2000.

[76]. Mery D., Da Silva R., CAlova L. and Rebello J., Detection de fallas en piezas fundidas usando metaodologia de reconocimiento de patrones, 3rd Panamerican Conference for Nondestructive Testing, Rio de Janeiro, Brazil, 2003.

[77]. Bader D., Jaja J. and Chellapa R., Scalable Data Parallel Algorithms for Texture Synthesis using Gibbs Ramdon Fields, IEEE Transactions on Image Processing, Vol. 4 No.10, pp. 1456-1460, 1995.

[78]. Pun C. and Lee M., Rotation Invariant Texture Classification Using a Two Stage Wavelet Packet Features Approach, IEE Proc. Vis. Image Signal Process, vol. No 148, No 6, pp 422- 428, 2001.

[79]. .Kaufmann, Los Altos, A, (1982).The Handbook of Artificial Intelligence, Vol.3 (P.R.Cohen and E.A.Feigenbaum, Eds.).

[80]. J.R.Kender,(1980).Shape from Texture, Ph.D. thesis,Tech.No.Rep.No.CMU-CS-81-102,Department of Computer Science, Carnegie-Mellon University.

[81]. C.Sun and W.G.Wee.(1983) Neighbouring Grey level Dependence Matrix on classification.Comput.Vision Graphics Image Process 23, 41-352.

[82]. B.Julesz, (1975) Experiments in the visual perception of texture, Sci. Amer. 232, No.4, , 2-11.

[83]. M.M.Galloway, “Texture analysis using gray level run lengths", Comput. Graph. Image Process., vol.4,pp. 172-179, 1975.

[84]. B.Julesz, “ Texture gradients: The Texton theory revisited", Biol. Cybern., vol. 54, pp. 247-251, 1986.

[85]. B.B.Chaudhuri and N.Sarkar, “ Texture segmentation using fractal dimension", IEEE Trans. Pattern Anal Machine Intell., vol 19, pp, 148- 153, Feb, 1997.

[86]. R.Azencott, J.Wang, and L.Younes," Texture classification using windowed Fourier filters", IEEE Trans Pattern Anal Machine Intell., vol 19, pp, 148-153, Feb, 1997.

[87]. J.Rushing, H.Ranganath, T.Hinke, and S.Graves," Using association rules as texture featurea", IEEE Trans Pattern Anal Machine Intell., vol, pp, 845-858, Aug, 2001.

[88]. R.Srikant, q.Vu, and R.Agarwal, “ Mining association rules with item constraints", in Proc. 3rd int. Conf.Knowledge Discovery and Data Mining; Aug. 1997, pp , 67-73.

[89]. A.Chu, C.M.Sehgal, and J.F.Greenleaf, “Use of gray value distribution of run lengths for texture analysis" Pattern Recognit. Lett., vol, 11, pp. 415-420, 1990.

[90]. R. Adams and L. Bischof, "Seeded region growing" Pattern Anal. Much. Intell, vol. 16, no. 6, pp. 641-647, Jun. 1994.

[91]. Bleau and L. J. Leon, "Watershed-based segmentation and region merging," CV/U, vol. 77, no. 3, pp. 317-370, Mar. 2000.

[92]. J. S. De Bonet and P. A. Viola, "A non-parametric multi- scale sta¬tistical model for natural images," in Advances in Neural Informa¬tion Processing Systems, M. I. Jordan, M. J. Keams, and S. A. Solla, Eds. Cambridge, MA: MIT Press, 1998, vol. 10. L. Breiman, "Bagging predictors," Mach. Learn., vol. 24, no. 2, pp. 123-140, 1996.

[93]. H. Cheng and C. A. Bouman, "Multiscale bayesian segmentation using a trainahle context model," IEEE Trans. Image Process., voj. 10, no. 4, pp. 511-525, Apr. 2001-

[94]. F. S. Cohen, Z. Fan, and M. A. Patel, "Classifcation of rotated and scaled textured images using gaussian markov random field models," IEEE Tram- Pattern Anal. Mach. Inteli, vol.13, no. 2, pp. 192-202, Feb.1991.

[95]. F. Dornaika and H. Zhang, "Granulometry using mathematical inor-plicaiions, Tokyo, Japan, Nov. 2000, pp. 51-54.

[96]. B. Draper, J. Bins, and K. Baek, "ADORE: Adaptive object recogni¬tion," Videre, vol. 1, no. 4. pp. 86-99. 2000.

[97]. R. P. W. Dum, P. Juszczak". P. Paclik, E. Pekalska, D. de Ridder, and D. M. J. Tax, PRTools4, A Matlab Toolbox for Pattern. Recognition. Delft, The Netherlands: Deift Univ. Technol., 2004.

[98]. J. Fan. G. Zeng, M. Body, and M. S. Hacid, "Seeded region growing: An extensive and comparative study," PRL, vol. 26. no. 8, pp. 1139-1156,2005.

[99]. J K. Glocer, D. Eads, and J. Theiler, "Online feature selection for pixel classification," in Proc. ICML, 2005, pp. 249-256.T. Hastie, R. Tibshirani, and J. Friedman, The Elements of Statistical Learning. New York: Springer Verlag, 2001.

[100]. Levner and V. Bulitko, "Machine learning for adaptive image in-terpretation," presented at the I6th Annual Innovative Applicat-ions of Artificial Intelligence Conf., San Diego, CA, 2004.

[101]. Levner and V. Bulitko, "Comparison of machine learned image in¬terpretation systems in (the domain of forestry." in Proc. WACV, 2005, pp. 1:421-1:426.

[102]. O. Lezoray and H. Cardot, "Bayesian marker extraction for color wa¬tershed in segmenting microscopic images," in Proc. 16th Int. Conf. Pattern Recognition, 2002, pp. 739- 742.

[103]. O. Lezoray and H. Cardot, "Cooperation of color pixel classification schemes and color watershed: A study for microscopic images," IEEE Trans. Image Process., vol. 11, no. 7, pp. 783-789, Jul. 2002.