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Texture Analysis using Markov process with Bayesian Approach

N.Palanivel[1], P.Keerthika[2], K.Yazhini[3], P.Thamizhini[4]

Assistant Professor, Department of CSE, Manakula Vinayagar Institute of Technology, India[1]

UG Student, Department of CSE, Manakula Vinayagar Institute of Technology, India[2,3,4]

Abstract: To analysis the textures in the image and that are identified and distinguished from untextured regions with edges. To represent the textures present in a small image region. Proposed texture analysis methods such as texture Identification, unique representation, description, and classification. The parameters of the model are estimated based on the Bayesian approach. To obtain the significance of the texture based on the classification method we processed two types of classification namely supervised and unsupervised classification.

Keywords: Markov process, Classification, Textured, Untextured.

I. INTRODUCTION

Texture is patterns repeated at one or more scales with more or less regular periodicity, but whose building blocks exhibit local stochastic variations. The texture of a surface is characterized by properties such as fine, coarse, smooth, granulated, rippled, mottled, irregular, random, lineated and so on .Texture Analysis is a particularly natural area for applying statistical methods, because of the stochastic nature of texture variations present in a processed image, which is not available in other real images. Statistical methods have been successfully applied for many years in the area of computer texture analysis. While many texture analysis approach used in computer vision are deterministic and based on heuristics rather than probability models, which leads to the development of a statistical framework, it can be applied to understand, justify, and improve such Texture primitives. A texture primitive is a contiguous set of pixels with some tonal and regional property.

The Texture analysis includes many techniques for the improvement and its clear restoration of the original image such as texture identification, representation, classification, texture segmentation, texture synthesis, object recognition, textured image compression etc.

The texture identification process is the foremost and initial process in texture analysis, which is an important technique for recognition of an image. The texture identification technique implies an identification of each pixel in an image with its complete data such as colour intensity, luminous etc. The repetitions of the texture patterns and its value are identified using the texture identification process.

Texture description compute different texture properties it can be divided into different methods based on texture primitives such as Statistical method are suitable for texture primitive sizes comparable with the pixel sizes, syntactic and hybrid method are more suitable where primitive can be easily determined and their properties are described.

The objective is to represent and describe the resulting aggregate of segmented pixels in a form suitable for further computer processing after segmenting an image into Textures. Two choices for representing a Texture is external characteristics of a texture representation is its boundary and the internal characteristic of a texture representation is its pixels comprising the inner region of the area.

Texture classification process involves two a model for the texture content of each texture class present in the training data, which phases: the learning phase and the recognition phase. In the learning phase, the target is to build generally comprises of images with known class labels. The texture content of the training images is captured with the chosen texture analysis method, which yields a set of textural features for each image. These features, which can be scalar numbers or discrete histograms or empirical distributions, characterize given textural properties of the images, such as spatial structure, contrast, roughness, orientation, etc. In the recognition phase the texture content of the unknown sample is first described with the same texture analysis method. Then the textural features of the sample are compared to those of the training images with a classification algorithm, and the sample is assigned to the category with the best match.

II. RELATED WORK

The literature reveals that a number of approaches have been developed to solve the low-level Texture analysis problems and it can be broadly classified based on the techniques – first-order and second-order statistical properties, modelling this physical variation is very difficult, so texture is usually characterized by the two-dimensional variations and the intensities present in the image. This shows the fact that no precise, general definition of texture exists in the computer vision. One of the defining qualities of texture is the spatial distribution of gray values. The use of statistical features is therefore one of the early approach proposed in the computer vision.

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A large number of texture features have been analysed in the proposed model. The Geometrical Texture analysis is characterized by their definition of texture as being composed of “texture elements” or primitives. This method of analysis usually depends upon the geometric properties of these texture elements. Once the texture elements are identified in the image, there are two major aspects of analysing the texture. First one computes the statistical properties from the extracted texture elements and utilizes them as texture features. The second one tries to extract the placement rule that describes about the texture. Model based texture analysis methods are based on the construction of an image model that can be used not only to describe texture, but also to synthesize it.

Robert M. Haralick et al. [Robe73] is describes some easily computable textural features based on gray tone spatial dependencies, and illustrates their application in category identification tasks of three different kinds of image data.We use two kinds of decisions rules: first is based on the decision regions are convex polyhedral (a piecewise linear decision rule); and the second is based on the decision regions, which are rectangular parallel piped (a min-max decision rule).

In the early stage of the research are purely concentrated on the representation of micro texture preferred the Fourier Power Spectrum methods proposed by Dyer and Rosenfeld [Dyer76], Weskit et al. [Wesk76], and Aulander et al. [Aula83] to characterize the micro level textures present in the images. Dyer and Rosenfeld, A.,[Dyer76] analysis of texture features based on the discrete Fourier power spectrum is used for pattern classification, their performance has been identified and comparatively less effective than that of features based on space-domain gray-level statistics.

Mahmoudi, F., et al. [Mahm03]is proposed a new feature vector for shape-based image indexing and retrieval. This feature classifies image edges based on two factors: their orientations and correlation between neighbouring edges. Hence, it includes information of continuous edges and lines of images and describes major shape properties of images.

Campisi, P., et al. [Camp04]a model based texture classification procedure is modelled as the output of a linear system driven by a binary image. This latter retains the morphological characteristics of the texture and it is specified by its spatial autocorrelation function. The texture features extracted from the ACF of the binary excitation suffice to represent the texture for classification purposes.

Cheng and Bouman[Chen01] proved that multi scale Bayesian approaches have attracted increasing attention for use in image segmentation. Generally, these methods tend to offer improved segmentation accuracy with reduced computational burden. The existing Bayesian segmentation methods use simple models of context designed to encourage large uniformly classified regions.

Krishnamoorthi and Seetharaman[Kris07]propose a family of stochastic models for image compression, where images are assumed to be Gaussian Markov Random Field. This model is based on stationary full range autoregressive (FRAR) process. The advantage of the proposed model is that it helps to estimate the finite number of parameters for the infinite number of orders. We use arithmetic coding to store seed values and parameters of the model as it gives furthermore compression. Different types, both textured and un-textured, images are used for experimentation to illustrate the efficiency of the proposed model and the results are encouraging. It is well recognized that compression ratio achieved by any compression algorithm is dependent upon the content of the input image or the compressibility of the input data.

III. PROPOSED WORK

Classification plays an important role in this texture analysis. To prove the efficiency of the proposed texture analysis scheme, furthermore, an experiment evolution is conducted on the representations of the micro textures present in the target images to classify them.The coefficients are computed based on the model parameters K; α; θ; and f. By testing the homogeneity of variances among the autocorrelation coefficients, textures are identified and are numerically represented the entire image is subjected to texture analysis.

Markov process using Bayesian approach

$$X(k,l) = \sum_{\substack{r=-1 \\ r=q\neq 0}}^{M} \sum_{q=-1}^{M} \frac{K\sin(r\theta)\cos(r\phi)}{\alpha^{r}} X(k+r,\ 1+q) + \varepsilon(k,l)$$

$$= \sum_{\substack{r=-1 \\ r=q\neq 0}}^{M} \sum_{q=-1}^{M} \Gamma_{rq} X(k+r,\ 1+q) + \varepsilon(k,l)$$

Where,

$$\Gamma_{rq} = \Gamma_{r} = \frac{K\sin(r\theta)\cos(r\phi)}{\alpha^{r}},\ \forall q$$

K, α, θ, and ϕ are real parameters. The Γrs are the model coefficients, which are computed by substituting the model parameters K, α, θ, and ϕ in Equation.

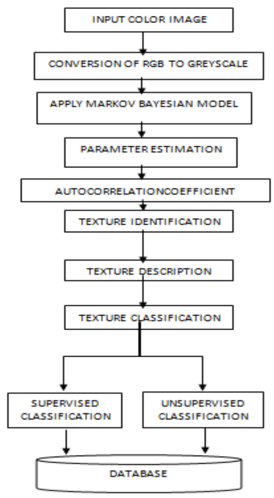

Figure.1 Data Flow Diagram for Texture analysis

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Advantage of Proposed Work

- Bayesian approach is used to enhance the classification performance.
- The accuracy of classification can be increased. The texture analysis is obtained for various image using this approach

IV. MODULES DESCRIPTION

A. Texture Identification

The small image regions are considered by dividing the whole image into various overlapping windows of size 3 × 3. The model coefficients Γrs (r= 1, 2) are determined by applying the estimated parameters K, α, θ and Ø.

$$\Gamma_r = \frac{K \sin(r\theta)\cos(r\phi)}{\alpha^r}, \; r = |p| + |q| + M(M-1)/2$$

B. Texture Representation

To represent the identified micro textures present in a small (local) image region, a simple transformation (ρ× 100) + 100 is applied on the autocorrelation coefficients to obtain decimal numbers, which ranges from 0 to 200, where ρ is the autocorrelation coefficient.

The autocorrelation coefficient falls in the range–1 to +1. The encrypted decimal numbers of the micro texture are quantified as a texture number. This number can be called texnum.

C. Texture Description

A random variable is a value with a given probability distribution. A discrete stochastic process is a sequence or array of random variables, statistically interrelated. Conditional probability *P*[*A*|*B*,*C*] means probability of A given B and C. The autocorrelation coefficient falls in the range–1 to +1. The encrypted decimal numbers of the micro texture are quantified as a texture number. This number can be called texnum.

D. Texture Description

A random variable is a value with a given probability distribution. A discrete stochastic process is a sequence or array of random variables, statistically interrelated. Conditional probability *P*[*A*|*B*,*C*] means probability of A given B and C.

E. Texture Classification

To validate the performance of the proposed texture representation scheme, classification analyses such as supervised and unsupervised are conducted on local descriptors computed on the target image and the reference images.The classification analyses justify and strengthen the proposed scheme in terms of performance, that is, the proposed scheme yields better results than the existing methods.

Supervised Classification

To classify the different types of micro textures present in the target image, the supervised classification is performed on the local descriptors computed on the target image and the reference images Rj, where j =1,2,.. L.

Unsupervised Classification

Closeness is a relative measure, and the minimum distance classifier is used as the measure. The objective minimization function. The closest two clusters are merged and the empty cluster is removed from merging. This procedure is continued until the distance becomes too large between the clusters, that is, all the clusters become mutually exclusive.

$$f_k = \sum_{i=1}^{L}\sum_{j=1}^{N} \varpi_{ij}^{k} \|z_i - c_j\|^2, 1 \le k < \infty$$

where, k is any real number greater than 1, ϖ_{ij} is the degree of membership of z_i in the cluster j, z_i is the ith of d-dimensional measured data, c_j is the d-dimension centre of the cluster, and $\|*\|$ expresses the similarity between measured data and the centre.

V. EXPERIMENTAL RESULTS

In this input image is acquired and then pre-processed that is the colour image is converted to gray scale. This conversion is carried out because to analysis texture accurate extraction.

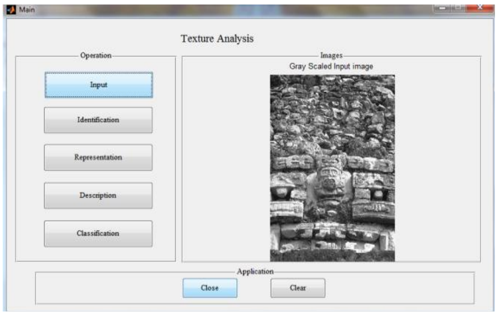

Figure.1 Gray Scaled Input Image

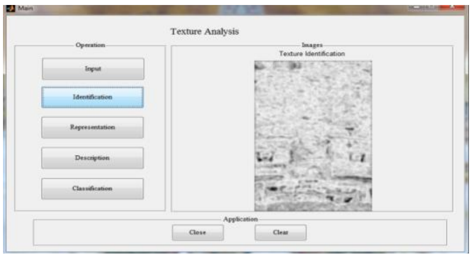

Figure.2 Texture Identification Processes

After conversion to gray scale the texture is identified using the correlation value based on the image with the textum which act as a parameter to identify the texture represent in the image.

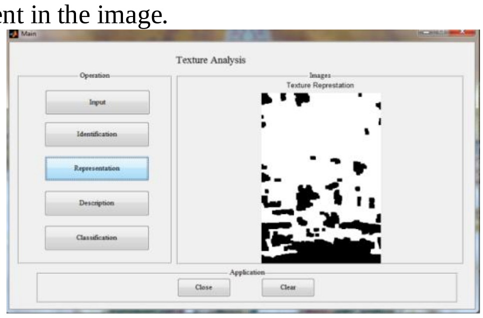

Figure.3 Texture Representation Processes

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In this identified texture is represented using the micro textures present in a small (local) image region, a simple transformation (ρ× 100) + 100 is applied on the autocorrelation coefficients to obtain decimal numbers.

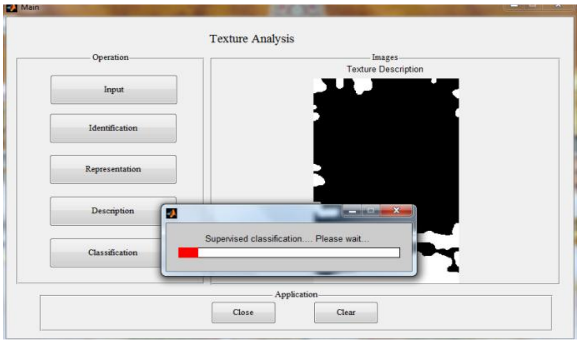

Figure.4 Texture Description Processes

In this the texture represented carried out to describe the random variable with a given probability distribution. A discrete stochastic process is a sequence or array of random variables, statistically interrelated.

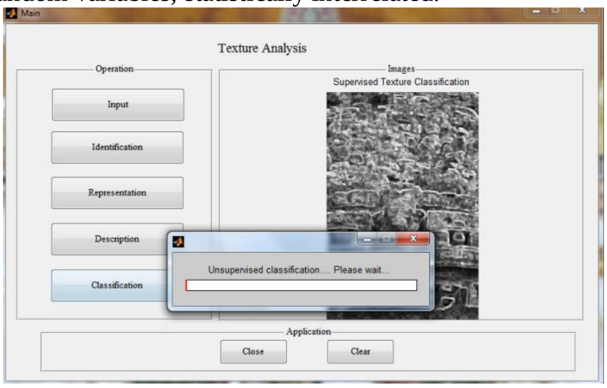

Figure.4 Texture Classification Processes

Using the texture obtained the image classification analyses such as supervised and unsupervised are conducted on local descriptors computed on the target image and the reference images.

V. CONCLUSION

Thus by using Bayesian approach to enhance the classification performance. The accuracy of classification can be increased. The texture analysis is obtained for various image using this approach. These feature are used for a classification of the image based on the significance. A statistical approach is proposed for texture analysis, and the model parameters are estimated based on the Bayesian approach. The model coefficients are computed based on the parameters, and the model coefficients are utilized to derive the autocorrelation coefficients. Based on the computed autocorrelation coefficients, two texture descriptors are proposed: (i) texnum – the local descriptor and (ii) texspectrum –the global descriptor. Decimal numbers are proposed to represent the textures that are in the range from 0 to 200. These numbers uniquely represent the texture primitives, and totally it has 201 components. The textured image under analysis is represented globally by observing the frequency of occurrences of the texnums, called texspectrum. By employing the test of hypothesis on the autocorrelation values, the textures are identified and they are distinguished from untextured regions with edges. The classification analyses such as supervised and unsupervised are performed on the texnum values. The classification analyses justify and strengthen the proposed scheme in terms of performance, that is, the proposed scheme yields better results than the existing methods.

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