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Retrieving Images and Its Classification by Acumen Mechanism Using Texture Features

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Abstract: *The erudite software mechanism of content-based image representation and retrieval is crystal clear that it is perception-based approach. Here it main pragmatic concept is texture images and propose to model their textural concept. The main dexterous melted to estimate textural feature an namely Complexity, texture strength, coarseness, directionality, contrast, busyness and Textron. The ineffable computational measures are based on autocorrelation function (Associated with original image) An anchored comparison is taken among it statistical and structural methods of texture representation. It elicits which features given vivid performance.*

Kkeywords: Texture Classification, Statistical and Structural features, KNN classifier, Image Retrieval.

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1. Introduction

Texture, which has great impact on human visual perception describe to the spatial distribution of gray-level are considered as the concept of deterministic or random repetition of one or several primitives picture form. Micro textures often have small primitives, and macro textures typically have huge primitives[7]. In the areas of classification, segmentation, and form from practical texture and picture retrieval, texture mechanism is highly helpful.There are various kinds of textural features for image classification have been proposed[1]-[3]. From a segmented region only It will defined texture measure. strategies for analysing textures The two primary giants of computation are spatial techniques and frequency-based approaches. The examination of the spectral density function in the frequency-based domain is the general foundation for our choice of frequency-based approaches. These techniques include the wavelet-based Gabor model and the acumen concept Fourier transform. Techniques for spatial texture analysis can be divided into three categories: statistical, structural, or hybrid methods.

In concerns of concept micro textures, statistical methods produce improved result, whilst structural methods produce better results in terms of concept macro textures. Whether it existing method they are statistical, structural or hybrid, have another drawback not less significant: in the computational cost.

Almost all sorts of textures were perfectly perceived by the human eye. While the automatic processing of these textures is really quite intricate, the human eye could typically perceive the variations between textures reasonably simple.

The overwhelming of computational techniques use mathematical relationships that have no perceptual meaning comprehensible by users, which is the principal reasons of the mismatch between human vision and statistical models

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proposed in literature. In a perceptual approach, to feel or minimize the human visual perception system, one has to neglect the computational techniques to which allow not only the quantitative but also the computational estimation of these perceptual estimation of these perceptual textural features.

2. Texture Representation (Outer Surface)

For Identification of the perceived qualities of texture first step is building mathematical models for texture. The intensity variations in an image which characterize texture are generally due to some underlying physical variation in the scene. There are various methods to represent textures. They anchor the statistical, geometrical, model based and signalprocessing methods.Image texture has a number of perceived qualities which play an vital role in describing texture. Laws et al. [3] identified the following properties as playing an important role in describing texture: uniformity, density, coarseness, roughness, regularity, linearity, directionality, direction, frequency, and phase. For instance, consider frequency which is not independent of density and the property of direction only applies to directional textures. The fact is that the perception of texture has so many different dimensions that is why there is no single method of texture representation which is adequate for the variety of textures.

3.Autocorrelation

The recurrence of texture characteristics in an image is a prominent characteristic of many textures. An image's I(x,y) autocorrelation function can be used to evaluate the texture's fineness or coarseness as well as its degree of regularity.

As per formal logic, an image's mechanism autocorrelation function is as follows:

$$\rho(x,y) = \frac{\sum_{u=0}^{N} \sum_{v=0}^{N} I(u,v) I(u+x, v+y)}{\sum_{u=0}^{N} \sum_{v=0}^{N} I^2(u,v)} \quad (1)$$

This process has everything to do with the texture primitive's size (i.e., the fineness of the texture). The autocorrelation function will diminish progressively if the texture is coarse; otherwise, it will diminish very rapidly. For regular textures, the autocorrelation function will exhibit peaks and valleys.The fig 1 and 2 shows a sample auto correlated image of a given fundus image.

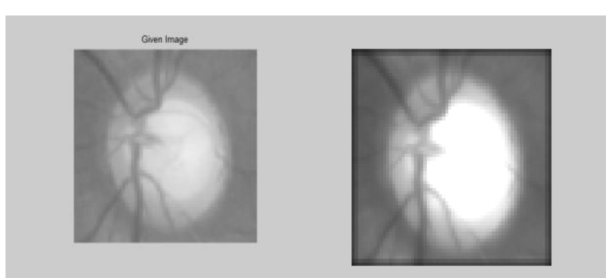

Figure :1 Original Image Figure : 2 Autocorrelated Image

I. THEORY

A. Image Acquisition

Images are compiled and inferred from DRIVE and STARE public databases. The JPEG images are reduced into images of size 128X128pixels. Impassionate comparison A total of 64 images (41 images used to train and 23 images used to test) are included in the dataset.

B. Representation of Textures

By comparing with the various representation methods to meticulous texture – statistical method yields better result for micro texture whereas structural method for macro textures. The initial actual method here is to compare the statistical and structural features extracted to classify normal and abnormal MRI images. Is also to evaluate which features gives better classification of MRI images.

C. Statistical Method by Best Classifier Engine

It is one of the representing extra qualities of texture is the spatial distribution of gray values. The use of statistical features is therefore one of the early methods proposed in the machine vision literature. An image with gray levels is denoted by {$I(xy)$ $0<=x(N$ – 1), 0<=$y(N$ – 1). A large number of texture features have been considered. We have considered six perceptual features, namely complexity, texture strength, coarseness, directionality, contrast and busyness. They are defined as follows.

- *Complexity (dependent on the number of different primitives and different average intensities):*
  The texture means outer surface. But complexity attributes refers to the visual information content of an image. This texture relates or find out many shape edges and lines will be indicated as enigmatic one. So it alludes relationship to the sub attribute (character) busyness and the contrast of an image. Complex texture formed with many differing gray valuation. High solutions to calculation shows with high pragmatic complexity.
- *Texture Strength (clearly definable and visible primitives):* A texture will be indicated to define lucid. Strong textures have a concise appearance. Crassness and the contrast of a texture will define the texture strength in an image. Texture accents calculation and the thickness and the specifiability is the basic pattern of a texture. So does a high solution indicate a strong texture.
- *Coarseness (defined by the size of texture primitives):* It determines the existence oftexture in an image.1 A coarse texture is composed of large primitives and is characterized by a high degree of local uniformity of grey-levels. A fine texture is constituted by small primitives and is characterized by a high degree of local variations of grey-levels.

- *Directionality (rotation (in-) variance):*It quantifies whether obviously influencing an image's orientation is visible. An image may well have one or even more dominant orientations, whatsoever, or a hybrid of these. It is said to be isotropic in the latter instance. Primitive patterns and placement restrictions have an influence on orientation.
- *Contrast (dependent on the intensity difference between neighbouring pixels):*It assesses whether effortlessly one can distinguish between distinct primitives within a texture. A well-contrasted image is one where the basic elements are prominent and instantly identifiable.
- *Busyness or Fineness (described by high spatial frequency of intensity changes):*It refers to the variations from a pixel to its neighbors. A busy texture is one in which the intensity changes occur quickly and dramatically, even though a non-busy texture features moderate, gradual intensity changes.
- *Shape:*To reconstruct the 3D surface geometry from texture information.
- *Resolution (macro- / micro-texture):*Multiresolution approach to using GMRF for texture segmentation appears more effective compared to single resolution analysis (Krishnamachari 1997) et al [15].
- *Regularity:* It is dependent on local sub pattern properties.

D. Structural Method

The structural models of texture is composed by bunch of texture primitives. The texture is processed by the placement of these primitives according to their certain placement rules. The following two major steps consider the Structural texture analysis :

(a) Extraction of the texture elements, and

(b) Inference of the placement rule.

Texture elements can be extracted in many ways. It is useful to define what is meant by texture such as the identification of the periodicity underlying the textural structure and the identification of textons by textrous mechanism. Periodicity can be determined from the image autocorrelation either in special or in the frequency domain. The frequency domain mechanism searches for peaks to identify the fundamental frequencies in the image. The spatial domain approach mechanism searches for peaks related to the correlation shifts which indicate high similarity between the original and shifted image versions. The method proposed for that is based on frequency domain approach which defines periodicity.

II. FEATURE EXTRACTION

Five meticulous features are calculated for each input image, based on characteristics human observers use to recognize abnormal and normal images. They are essence as.

1) To the original image apply autocorrelation function.The autocorrelation function, denoted , for an $f(\delta_i, \delta_j)$ image is defined as follows

$$f(\delta_i,\delta_j)=\frac{1}{(n-\delta i)(m-\delta j)}\times\sum_{i=0}^{n-\delta i-1}\sum_{j=0}^{m-\delta j-1}I(i,j)I(i+\delta i,j+\delta j) \tag{2}$$

Where δ_i and δ_j represent shift on rows and columns.

2.Then, in a separable manner, the strongest Fourier convolution between the autocorrelation function and the gradient of the Gaussian function is computed (according to rows and columns). Then, two functions are obtained (according to rows and columns).

3.Based on these two functions, the following computations are made to determine the computational measurements for each perceptual feature:*4) Complexity:*ore Dependent on the number of different primitives and different average intensities.(according to rows and columns, respectively)

$$\begin{cases}C_x(i,j)=0\\ C_{xx}(i,j)<0\end{cases}$$

$$\begin{cases}C_y(i,j)=0\\ C_{yy}(i,j)<0\end{cases} \tag{3}$$

C_{com}(complexity) is estimated as ,

$$c_{com}=\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}\frac{|i-j|}{n(Pi+Pj)}\left[Pis(i)+Pjs(j)\right], Pi\neq 0, Pj\neq 0 \tag{4}$$

5) Texture strength: The following formula used to find the clearly definable and visible primitives.

$$\begin{cases}C_x(i,j)=0\\ C_{xx}(i,j)<0\end{cases}$$

$$\begin{cases}C_y(i,j)=0\\ C_{yy}(i,j)<0\end{cases} \tag{5}$$

C_{str} (texture strength) is estimated as,

$$Cstr=\frac{\sum_{i=0}^{G-1}\sum_{j=0}^{G-1}(Pi+Pj)(i-j)^2}{\varepsilon+\sum_{i=0}^{G-1}s(i)}, Pi\neq 0, Pj\neq 0 \tag{6}$$

*6) Coarseness:*Initially compute the first derivatives of the autocorrelation function according to rows and columns, respectively. Second, we compute the first derivatives of the obtained functions according to rows and columns. Next detect maxima, we use the following equations (according to rows and columns, respectively)

$$\begin{cases}C_x(i,j)=0\\ C_{xx}(i,j)<0\end{cases}$$

$$\begin{cases} C_y(i,j)=0 \\ C_{yy}(i,j)<0 \end{cases} (7)$$

Cs(coarseness) is estimated as ,

$$C_s = \frac{1}{\frac{1}{2}\times(\frac{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1} Max_x(i,j)}{n}+\frac{\sum_{j=0}^{m-1}\sum_{i=0}^{n-1} Max_y(i,j)}{}} (8)$$

*7)Contrast*To calculate contrast, one can use the amplitude of the gradient of the autocorrelation function according t o the lines and according to the columns.

The amplitude is mostly influenced by two variables:

1.In order to calculate the average amplitude in the autocorrelation function, only pixels that have significant amplitude and are therefore superior to a particular threshold are taken into account.

2. In addition, we also take into account the total number of pixels with significant amplitude.

The average amplitude e is given by

$$M_a = \frac{\sum_{i=0}^{n-i}\sum_{j=0}^{m-i} M(i,j)\times t(i,j)}{N_t} (9)$$

Nt is the amplitude over threshold t, and M(i,j) is the amplitude of pixel(i,j).

C_t (contrast) is estimated as,

$$C_t = \frac{M_a \times N_t \times C_s^{\frac{i}{\alpha}}}{} (10)$$

*8) Directionality:*Regarding directionality**,** The prevailing orientation or orientations and the level of directionality are the two characteristics that need estimation. The general orientation of the primitives that make up the texture is referred to as orientation. The number of pixels with the prevailing orientation is referred to as the degree of directionality, and it is correlated with the visibility of the dominant orientation in an image. The degree of directionality is estimated as,

$$N_{\Theta_d} = \frac{\sum_{i=0}^{n-1}\sum_{j=0}^{m-1} \Theta_d(i,j)}{(n\times m)-N_{\Theta_{nd}}} (11)$$

*9) Busyness:*Busyness is reversely correlated with coarseness. To calculate busyness, apply the formula below**.**

$$B_s = 1 - C_s^{\frac{1}{\alpha}} (12)$$

10) Periodicity: Periodicity in images may exist in various orientations, but two orientations are generally sufficient for determining the basic structure. Higher peaks are the stronger evidence of periodicity. Peaks that correspond to the fundamental frequency harmonics are aligned on a line passing through the autocorrelation centre, and the fundamental frequency is generally defined by the closest peak. The frequency bands located around the fundamental frequencies hold the basic structure information of the texture. Two Gabor filters, with frequency responses centred at the two fundamental frequencies are used to isolate the two bands.

Classification

A K – nearest neighbor (K-NN) is chosen as the classifier engine for its simplicity and good classification performance. The K-NN classifier works which memorizes the entire training data and performs classification only if the attributes of thetest object matches with one of the training examples exactly. The calculated features are trained for both normal and abnormal images which help the detection of normal/abnormal images that are closer to the class defined.

The KNN algorithm works as follows,

```
Input:
      D              //Training data
      K              //No. of neighbours
      t              // Input tuples to classify
Output:
      c              // Classify to which t is assigned.
KNN Algorithm:
     //Algorithm to classify tuple using KNN
     N=Ø;
     //Find set of neighbours, N, for t for each  d ∈ D  do
      If |N|≤K then
       N=N U d;
else if
∀u ∈ N such that sim(t,u) ≥sim(t,d) then
begin
        N=N – u;
        N=N U d;
end
//find class for classification
  c=class to which the most u ϵ N are classified;
```

The classification rate is calculated based on the formula,

$$C.R(\%) = \frac{No.Of\ Images under particular class}{Total No.of\ Images} \times 100 \quad (13)$$

Retrieval

The similarity measure used is based on the Gober coefficient of similarity. The non weighted similarity measure, denoted, can be defined as follows:

$$GS_{ij} = \frac{\sum_{k=1}^{n} S_{ij}^{(k)}}{\sum_{k=1}^{n} \delta_{ij}^{(k)}} \quad (14)$$

Where $S_{ij}^{(k)}$ is the partial similarity between images i and j according to feature k, $\delta_{ij}^{(k)}$represents the ability to compare two images and on feature k. (if $\delta_{ij}^{(k)}$ =1 if images i and j can be compared on feature k and $\delta_{ij}^{(k)}$=0 if not. $\Sigma_{k=1}^{n}\delta_{ij}^{(k)}$=n if images i and j can be compared on all features k.)

III. Results

The drastic analysis on the two texture representation methods statistical and structural are analyzed and inferred. From the texture representation methods implemented, the feature values estimated are compared and performance analysis is carried out.

A. Statistical Method

The statistical method used to extract features such as coarseness, contrast, directionality and busyness. These features are trained and tested for both normal and abnormal images using K-NN classifier engine. It gives 76.92 as classification rate. The features estimated for normal and abnormal images are shown in the table 1,4below.

Table 1.Normal Features Estimated

Images (normal)	**Coarseness**	**Contrast**	**Directionality**	**Busyness**	**Complexity**	**Texture Strength**
1	0.3605	7.5826	0.3911	0.2251	3.2644	12.9003
2	0	0	0.3623	0.3044	6.3111	16.5047
3	0.5541	5.7535	0.4216	0.1372	2.2335	9.8416
4	0.3555	4.7015	0.4135	0.2278	2.2634	10.4295
5	0.4491	6.9879	0.4177	0.1813	2.3267	13.2675
6	0	0	0.2996	0.4874	15.9744	29.7234
7	0.2819	4.935	0.3879	0.2713	3.4978	11.1676
8	0.3131	6.4974	0.4140	0.2515	3.3264	12.3324
9	0.3145	6.753	0.3769	0.2511	3.0451	12.5397
10	0.2949	5.7935	0.4233	0.2630	3.4356	11.7413

B. Structural Method

The periodicity that defines the structural component of the texture is estimated. It is trained and tested for normal and abnormal images using K-NN classifier. It gives 69.23 as classification rate.

Sl. No	Methods	Classification Rate(%)

C. Performance Analysis

The performance analysis is based on the classification rate .It used to compare the feature estimated from the two methods which gives better result.

Table 2. Time Complexity Measures(A bar graph analysis)

Sl. No	Methods	Time(seconds)
1	Statistical Method	3.57
2	Structural Method	3.71
3	Combined Features	3.76

Table 3.Classification Rate Measures.

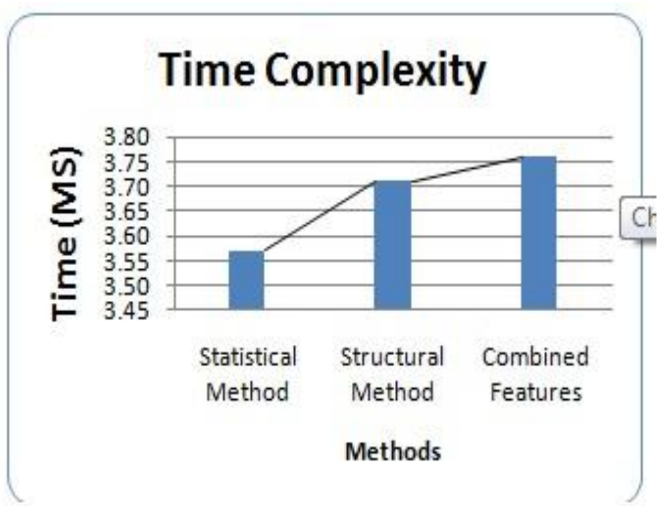

Fig.3 Time Complexity (Data Analysis)

1	Statistical Method	78.84
2	Structural Method	66.73
3	Combined Features	95.46

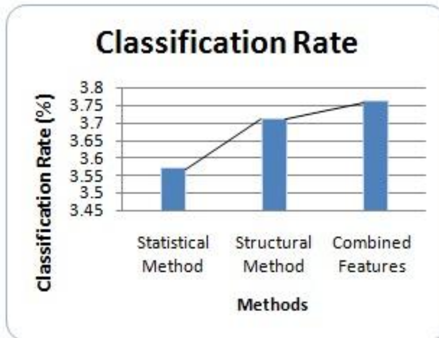

Fig.4 Classification Rate

Table 4.Abnormal Features Estimated

Images (abnormal)	Coarseness	Contrast	Directionality	Busyness	Complexity	Texture Strength
1	0.0244	4.4567	0.1027	0.6045	40.3235	53.635
2	0.0289	4.1516	0.1213	0.5874	29.5309	47.0911
3	0.1690	3.357	0.4533	0.3581	7.4967	11.9519
4	0.64	8.6879	0.4582	0.1055	1.0457	12.4738
5	0.61244	5.5381	0.4502	0.11536	1.1394	8.8791
6	0.43199	5.0282	0.1982	0.5441	33.4721	32.1583
7	0.4314	5.437	0.2131	0.5442	33.4722	33.6572
8	0.4304	4.9044	0.1608	0.5445	33.4408	31.485
9	0.0322	5.3367	0.1608	0.5762	32.4296	47.3644
10	0.3605	5.0019	0.4353	0.2251	3.3736	10.7585

IV. DISCUSSION

In an automated system, the detection of normal and abnormal fundus images has been outlined based five image features by two methods.

V. CONCLUSION

The two giant methods to estimating features are compared based on the classification rate and time takes to perform classification. From the results obtained, it is concluded that when we combine both the statistical and structural features, it gives 93.20%, the better classification results. Thus, the method implemented is capable of distinguish normal and abnormal fundus images. It reduces the manual grading workload or a tool to prioritize patient grading queues. The future work can be extended to add more texture features such as randomness, energy, entropy and so on. The implemented system can be done with another classifier or combined with other classifier engine such as SVM classifier, Bayes classifier, Random forest classifier, ANN etc.

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