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TEXTURE ANALYSIS OF FACES OF TWINS BY USING IMAGE PROCESSING TECHNIQUES

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***Abstract**: Texture Analysis has been an active area of research over the past twenty five years. Today, texture analysis plays an important role in many tasks ranging from remote sensing to bio-medical image analysis. Textures, the repeated patterns, have different frequency components along different orientations. Texture analysis is important in many applications like image database retrieval, industrial, agricultural and bio-medical applications. Texture analysis and classification are based on three different approaches; statistical, spectral and structural. We have proposed statistical approaches for analyzing the faces of twins and the components on the faces.*

***Keywords**: texture, remote sensing, orientations, retrieval bio-medical , faces of the twins etc.*

I. INTRODUCTION

Identical twins are also known as monozygotic twins. They result from the fertilization of a single egg that splits into two. Identical twins share all of their genes and are always of the same sex. In contrast, fraternal or dizygotic twins result from the fertilization of two separate eggs during the same pregnancy. They share half of their genes, just like any other siblings. Fraternal twins can be of the same or different sexes. Identical twins are natural clones. Because they start out with the same genes, they can be used to investigate how much heredity contributes to individual people. This is the Nature vs. nurture question.

Studies with twins have been quite interesting. If we make a list of characteristic traits, we find that they vary in how much they owe to heredity. For example:

- Eye colour: entirely inherited.
- Weight, height: partly inherited, partly environmental.
- Which language do they speak: entirely environmental.

The insight we gain from studying the twins helps us to better understand how nature and nurture works together. Today technologies are well-studied, but research shows they have many drawbacks which decrease the success of the methods applied. The frequently used and most common biological traits in the field of biometrics are face, finger, and iris. Identifying identical twins is crucial for all biometric systems. The systems that cannot handle identical twins have a serious security hole. The present work is first of its kind in the literature and the result is found to be very fruitful.

II. TEXTURE ANALYSIS

Texture analysis refers to a class of mathematical procedures and models that characterize the spatial variations within imagery as a means of extracting information. Texture is an aerial construct that defines local spatial organization of spatially varying spectral values that is repeated in a region of larger spatial scale. Thus, the perception of texture is a function of spatial and radiometric scales. Descriptors providing measures of properties such as *smoothness*, *coarseness* and *regularity* are used to quantify the texture content of an object.

Since an image is made up of pixels, texture can be defined as an entity consisting of mutually related pixels and group of pixels. This group of pixels is called as texture primitives or texture elements (texels). Here, we provide a brief description of a number of texture analysis techniques and some examples.

III. APPROACHES TO TEXTURE ANALYSIS

Mathematical procedures to characterize texture fall into two major categories, 1.Statistical and 2. Syntactic. Statistical approaches compute different properties and are suitable if texture primitive sizes are comparable with the pixel sizes. These include Fourier transforms, convolution filters, co-occurrence matrix, spatial autocorrelation, fractals, etc. Syntactic and hybrid methods are suitable for textures where primitives can be described using a larger variety of properties than just tonal properties; for example shape description. Using these properties, the primitives can be identified, defined and assigned a label. For gray-level images, tone can be replaced with brightness. Texture Image Classification using Gabor Statistical Features (GSF) and Wavelet Statistical Features was studied by [Sabeenian and Palanisamy, 2010]. Wavelet based Features for Texture classification is studied by [Hiremath and Shivashankar, 2006]. This paper discusses some of the simple statistical approaches for texture analysis.

IV. STATISTICAL APPROACHES

Statistical methods analyze the spatial distribution of gray values, by computing local features at each point in the image, and deriving a set of statistics from the distributions of the local features. Texture Based Weed detection in agricultural field using MRCSF was developed by [Sabeenian and Palanisamy, 2009]. The reason behind this is the fact that the spatial distribution of gray values is one of the defining qualities of texture. Depending on the number of pixels defining the local feature, statistical methods can be further classified into first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics. The basic difference is that first-order statistics estimate properties (e.g. average and variance) of individual pixel values, ignoring the spatial interaction between image pixels, whereas second- and higher-order statistics estimate properties of two or more pixel values occurring at specific locations relative to each other.

A. First-order statistics based approach

First order texture measures are statistics calculated from the original image values, like variance, and do not consider pixel neighborhood relationships. Histogram based approach to texture analysis is based on the intensity value concentrations on all or part of an image represented as a histogram. Common features include moments such as mean, variance, dispersion, mean square value or average energy, entropy, skewness and kurtosis. Variance in the gray level in a region in the neighborhood of a pixel is a measure of the texture. However, the Standard Deviation could also be used instead of variance. The histogram can be easily computed from the image. The shape of the histogram provides many clues to the characteristics of the image. For example, a narrowly distributed histogram indicated the low-contrast image.

Texture analysis based solely on the gray level histogram suffers from the limitation that it provides no information about the relative position of pixels to each other. Therefore we cannot distinguish between them using first order statistical analysis.

B. Spatial frequencies based Texture Analysis

Image texture can also be represented as a function of the tonal and structural relationships between the primitives. Tone is based mainly on pixel intensity (gray values) properties in the primitives while the structure is the spatial (location) relationship between the primitives. Effects of special frequency specific adaptation and target duration on the visual perception were conducted by [Mayer and Maguire, 1981]. An effect of spatial frequency overlap on face recognition was analyzed by [Liu et. al., 2000]. Recognition of face is affected by similarity in spatial frequency range to a greater degree than within-category object recognition was justified by [Chaudhuri et al., 2004]. Spatial frequency is a measure of the repetitive placement of identical texture elements (texels) in the image. How low spatial frequencies are useful in perceiving the faces is studied by[Goffaux and Rossion 2006]. Spatial frequency gives spatial distribution of gray values. One method of measuring spatial frequency is to evaluate the autocorrelation function of a texture. The autocorrelation function of an image can be used to assess the amount of regularity as well as the fineness/coarseness of the texture present in the image.

C. Co-occurrence matrices

Spatial gray level co-occurrence estimates image properties related to second-order statistics which considers the relationship among pixels or groups of pixels (usually two). The size of co-occurrence matrix will be the number of threshold levels. Classification of textures using Gaussian Markov random fields was developed earlier by [Chellappa and Chatterjee , 1985]. When we consider neighboring pixels, the distance between the pair of pixels is 1. However, each different relative position between the two pixels to be compared creates a different co-occurrence matrix.

D. Edge frequency based Texture Analysis

The total length of all the edges in a region could also be used as a measure of the coarseness or complexity of a texture. Edges can be detected either as micro edges using small edge operator masks or as micro edges using large masks. Operators like Robert's operator or sobel's operator can be used for this purpose. Using gradient as a function of distance between pixels is another option. Several edge properties may be derived from first order and second-order statistics of edge distributions. They are coarseness: edge density is a measure of coarseness. The finer the texture, the higher the number of edges present in the texture edge image.

Contrast: High-Contrast textures are characterized by large edge magnitude.

Randomness: Randomness may be measured as entropy of the edge magnitude histogram.

Directivity: An approximate measure of directivity may be determined as entropy of the edge direction histogram. Texture classification via conditional histograms was studied by [Montiel et al., 2005]. Directional textures have a significant number of histogram peaks, directionless textures have a uniform edge direction histogram.
Linearity: Texture linearity is indicated by co-occurrence of edge pairs with the same edge direction at constant distances and edges are positioned in the edge directions.
Periodicity: Texture periodicity can be measured by cooccurrence of edge pairs of the same direction at constant distance in a direction perpendicular to the edge directions
Size: Texture size measure may be based on co-occurrences of edge pairs with opposite edge directions at constant distance in a direction perpendicular to the edge directions
The first three measures are derived from first order statistics and the last three are derived from the second order statistics.

E. Primitive length texture analysis

A texture can be described by the features of gray level, length and direction of the pixels and primitives. The direction in the above can be described as the continuous probabilities of length and the gray-level of primitives in the texture.

F. Fractal based texture analysis

Fractals measure geometric complexity, which could be used to describe many spatial patterns of textures. Conceptually, the word `fractal' refers to complex patterns that recur at various scales but are independent of scales.

G. Other statistical methods

A powerful tool for structural texture analysis is provided by mathematical morphology. The mathematical morphology approach looks for spatial repetitiveness of shapes in a binary image using structure primitives. Thus this approach stresses the shape properties of the texture primitives. Due to the assumption of the binary textured images, this approach is often successful for granulated materials, which can be segmented by thresholding.
The texture transform represents another approach for texture analysis. The general idea is to construct an image I where the pixels I(x, y) describe a texture in some neighborhood of the pixel f(i, j) in the original textured image f. In addition, a priori knowledge can be used to guide the transformation and subsequent texture recognition and segmentation.
The peak and Valley Method is based on detection of local extrema of the brightness function in vertical and horizontal scans of a texture image. Fine structures have a large number of small sized extrema , coarse textures have a smaller number of larger sized local extrema – Higher peaks and deeper valleys.
A modified peak and valley approach is to consider the sequence of peaks and valleys above as a Markov Chain in which the transition probabilities of an m^{th} order chain represent $(m-1)^{th}$ order Statistics of textures.

V. FORMULATION OF THE PROBLEM

The faces of twins are downloaded from the web site http://www.twinsdays.org/pictures/. The data set contains 60 pairs of grey scale face images of twins. The size of each image is 256x256. Sample of the images are shown below in figure 1. All the faces are facing the camera.

VI. METHODOLOGY

After collecting the data in jpeg file form, we have preprocessed the images to have the same resolution and then resized all the images in to 256 x 256 size and converted all of them to a grey scale raw image to reduce the memory requirement. Experiment is conducted to analyze row, column and spatial frequency to understand how pixel intensities are distributed in these directions on each of the faces. Spatial Frequency is a measure of the overall activity level in an image. For an MxN image F, with the gray value at pixel position (m,n) denoted by F(m, n) and is computed by

$$\mathrm{SF} = \sqrt{CF^2 + RF^2} \qquad 1$$

where CF & RF are column frequency and row frequency respectively and are given by

$$\mathrm{CF} = \sqrt{\left(\frac{1}{MN}\sum_{n=1}^{M}\sum_{n=2}^{N}(F(m,n) - F(m-1,n))2\right)} \qquad 2$$

$$\mathrm{RF} = \sqrt{\left(\frac{1}{MN}\sum_{n=1}^{M}\sum_{n=2}^{N}\big(F(m,n) - F(m,n-1)\big)^2\right)}. \qquad 3$$

Study is also carried out to understand the variation in row , column and spatial frequency of the objects on the faces such as eyes, nose and mouth. To achieve this, these components are extracted with the help of PSP5 software. Image size of mouth and eyes are fixed with pixels 200x50, and that of nose is with pixels 100x 50.

Fig. 1: Sample face data of twins

VII. EXPERIMENTS AND RESULTS

Experiment is conducted with each faces of twins and each time the row, column and spatial frequency are calculated using the VC++ software programmes.

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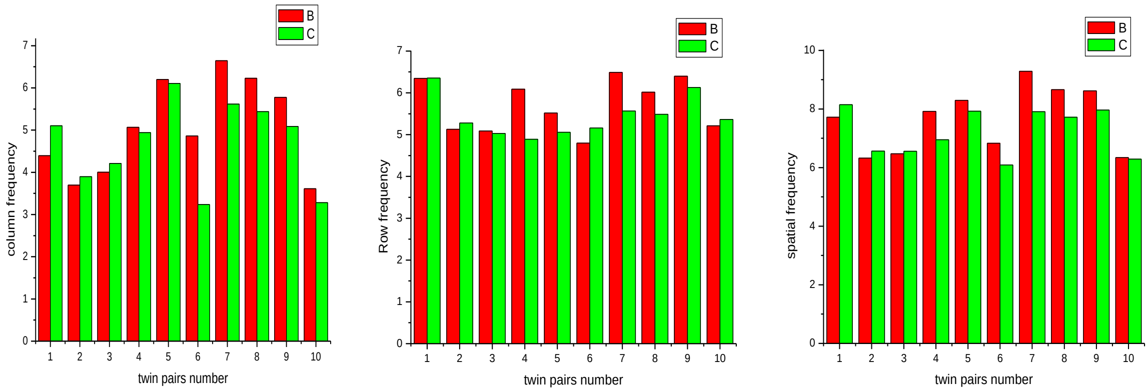

Fig. 2: Column frequency, row frequency and spatial frequency of faces V/s twins pair number

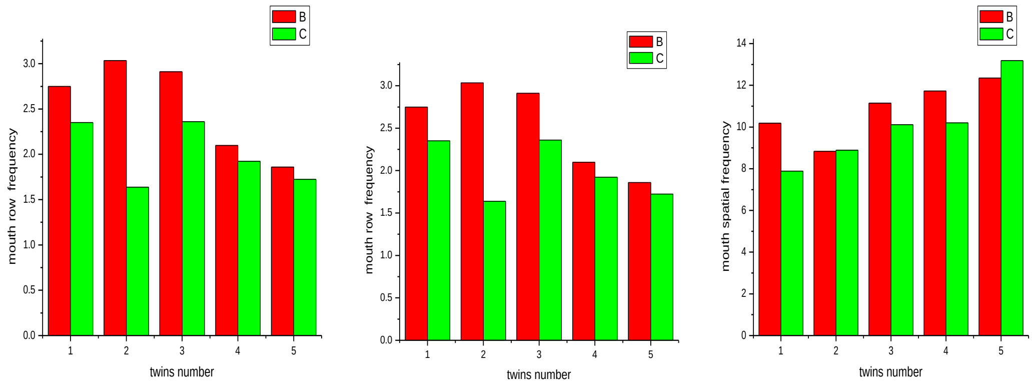

Fig. 3: Variation in row, column and spatial frequency of mouth V/s twins number

The procedure is repeated with the parts of these faces like eyes, mouth and nose to understand the similarity and dissimilarity in the distribution of pixel intensities on components of the faces. After getting the results for all the data set, the results are plotted using origin. 6.1. Software to understand the variations. The resulting graphs are as shown below figure 2, 3, 4, and fig 5. respectively.

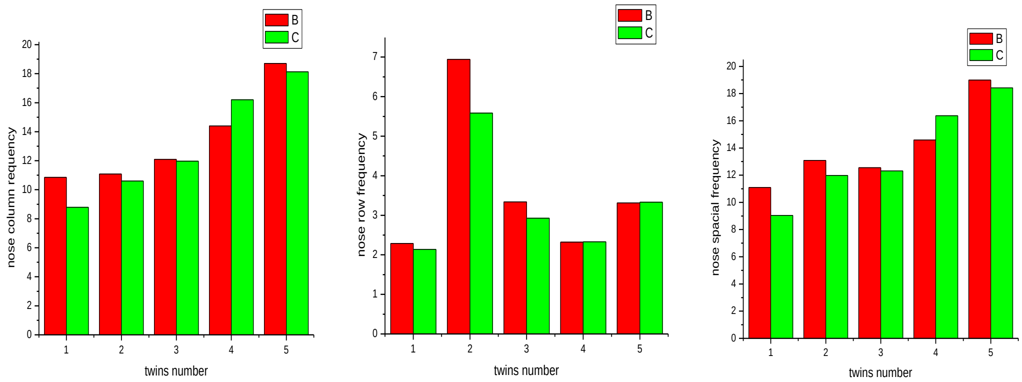

Fig. 4: Variation in row, column and spatial frequency of nose V/s twins number

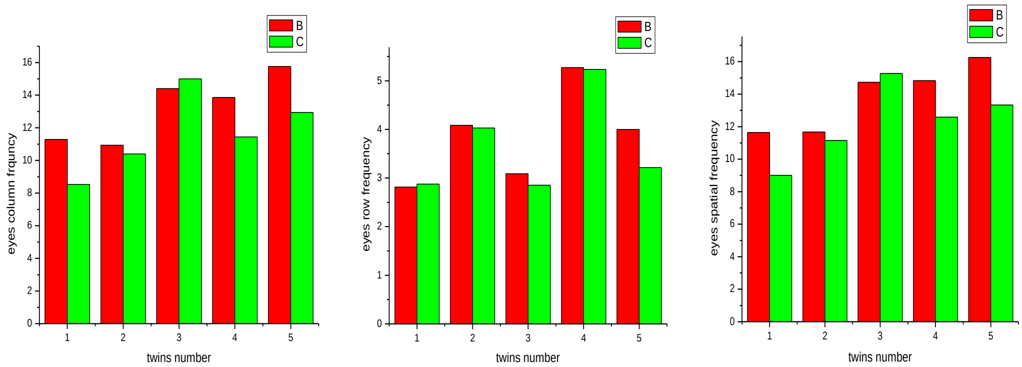

Fig. 5: Variation of column, row and spatial frequency of eyes V/s twins number

twins number	Column frequency (CF)		Row frequency (RF)		Spatial frequency(SF)		% changes in CF, RF and SF		
	A	**B**	**C**	**D**	**E**	**F**	**A- B**	**C-D**	**E-F**
1	9.80894	7.524811	2.74878	2.350378	10.18657	7.88334	23.2862	14.49378	22.61043
2	8.293145	8.689967	3.033156	1.637652	8.830418	8.892931	4.78494	46.00832	0.707928
3	10.76178	9.834942	2.910818	2.359341	11.14849	10.11398	8.612294	18.94577	9.27935
4	11.5429	10.01954	2.097388	1.922319	11.73191	10.20228	13.1974	8.347001	13.0382
5	12.212	13.06846	1.86024	1.72322	12.35287	13.18158	7.013207	7.365716	6.708593

Table 1: Column, row and spatial frequency of faces against twins number and corresponding changes.

Figure 2 represents the variation of column, row and spatial frequency of faces of twins with the twins' number and the corresponding data is represented in Table 1. From Table 1 it is clear that the maximum variation in column frequency of identical twins is 23% and minimum is 4.7%. At the same time maximum variation in row frequency is 46% and minimum is 7.3%. But the maximum variation in spatial frequency is 22% and the minimum is .7% for these identical tested images. The data thus obtained clears that the change is not uniform even in the identical twins. Surprisingly human brain could recognize them as identical twins.

VIII. CONCLUSION

This paper demonstrates the use of row, column and spatial frequency to analyze the variation in textures intensities on the faces of twins. From the graphical representations of these values on the face and the facial components and the data tabled in this article, it is very clear that there is a variation in these values from 3 to 20% for identical twins. It is certainly more in case of non identical twins as they may be of similar sex or dissimilar. Still, the human brain identifies them without confusion. This indicates that the recognition of faces by our mind is not just based on the mathematical formula but is on something else. Variation in intensity of pixels need be considered in analyzing two identical images. This can be used as a tool to distinguish identical images for future works.

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