AN ASSESSMENT OF PERCEPTUAL BASED TEXTURE FEATURES FOR IMAGE REPRESENTATION AND RETRIEVAL

Proposed study: Texture based feature extraction perceptual Image Retrieval (CBIR) system for Biomedical Sciences (dental related alignments)

Prajakta Prakashrao Hassekar¹ , Dr. Prof. Rajendra R. Sawant²

¹M.E. Scholar, Department of Computer Science and Engg KSIET, Hingoli, S. R .T. M. University Nanded, Maharashtra, India,
²Dr. Prof. Rajendra R. Sawant Department of Computer Science and Engineering KSIET, Hingoli, S. R .T. M. University Nanded, Maharashtra, India,

ABSTRACT

This paper presents a comprehensive survey of perception-based approach of feature extraction methods for Content Based Image Retrieval (CBIR). CBIR is a technique that uses the visual content of a still image to search for similar images in large-scale image databases. CBIR method requires both color and texture features to retrieve digital images from large scale image database, which leads to increase digital image database enormously. On the other hand perception-based approach requires only texture features to retrieve digital images, which can effectively reduce digital image database. In this paper we have considered textured images and studied to model their textural content by a set of features having a perceptual meaning and their application to content-based image retrieval. Process variables or objective functions includes number of control points such as coarseness, directionality, contrast, and busyness used to retrieve virtual image representation of perceptual textural features. So the main intent of this paper is to invent a new method to estimate these perceptual features. And with this application of Texture based Feature Extraction Perceptual Image Retrieval (CBIR) technique and Computational Intelligence, we have also proposed to develop a Knowledge Based Expert system for Biomedical Sciences (dental related alignments).

Keywords: Image processing (CBIR), Perceptual features, Texture retrieval, CBIR for Biomedical Sciences
I. INTRODUCTION

Many educational, commercial and entertainment applications run on the image database to retrieve the user prescribed information on daily basis. And this current era of digital products leads to increase electronic storage capacity enormously, which finally leads to amplify the computing power. As a result this, the challenge is to explore and retrieval of the relevant information in the bulky space of image and video databases. So still there is an uncertainty for How to realize precise retrieval of results and therefore an active research area.

CBIR method requires both color and texture features to retrieve digital images from large scale image database, which leads to increase digital image database enormously. Whereas several image retrieval systems (perception-based approach) rely on only one feature (texture) for the extraction of relevant images, it has been shown that an appropriate combination of relevant features can yield better retrieval performance. So this approach can significantly trim down the database size efficiently and effectively. We are also developing a constructive database for dental related alignments (Biomedical Sciences) based on the recognized Brodatz database to classify large image data set, for the estimated perceptual features measures.

II. LITERATURE REVIEW AND SCOPE OF THE PROPOSED WORK

Several recent content based image retrieval system exploit texture features sets to assist in the retrieval of images. So the texture features has been widely studied and used in literatures since from last few decades. In 1973 research scholars have proposed a methodology to identify objects or regions of interest of texture images which describes some computable textural features based on spatial dependencies, limited to only structural primitives [1]. After six years in 1979 they have concluded structural and statistical generalization which applies statistical approaches and techniques to the structural primitives [2]. After one decade, in 1989 researches have proposed new visual properties of texture features, such as coarseness, contrast, busyness, complexity & texture strength [3]. Then in 2000 researchers have explained a new method to estimate perceptual textural features using the autocovariance function and they have also presented computational measures derived from the autocovariance function to estimate these perceptual textural features. Also they have derived and presented experimental results given from the correspondence between the computational measures and the psychological measures by using psychometric method [4]. They have addressed the fundamental issues of visual content representation and similarity matching in content-based image retrieval and image databases in 2003 [5]. The development has further addressed few issues of texture retrieval by using a perceptual approach based on multiple viewpoints [6]. In 2005 some gentlemen have demonstrated how the use of multiple content representations and their fusion can improve the performance of content-based image retrieval systems. Also they have proposed a new algorithm for texture retrieval based on multiple representations and their results fusion [7]. They have also proposed an approach based on the fusion of retrieval results returned by multiple retrieval strategies to improve the effectiveness of image retrieval from image databases [8]. N. Abbadeni and H. Alhichri have presented a results fusion approach through multiple representations and multiple queries to tackle the problem of invariance in content-based image retrieval [9]. They have proposed an approach based on multiple representations, multiple queries, and the fusion of results returned by these different representations and queries [10]. The new method has considered textured images and proposed to model their textural content by a set of features having a perceptual meaning and their application to content-based image retrieval. Also this method is more effective to estimate a set of perceptual textural features, namely coarseness, directionality, contrast, and busyness. According to this new method computational procedures can be based upon two representations: the original images representation.
and the autocorrelation function (associated with the original images) representation [11]. Researchers have used famous Brodatz database for getting experimental result.

CBIR method relies on both color and texture features, which will be constraint to low budget applications for both space and computing perspective. Even though CBIR is more accurate, an appropriate combination of relevant features can yield similar or better retrieval performance. So scope of the study is aimed to develop a controlled perceptual textural feature based process methodology for nonlinear topological object’s retrieval using experimental and computational intelligence.

III. TEXTURE

Texture plays an important role in human visual perception so it has been widely studied and used in literatures since from last few decades. It is an important characteristic for the psychoanalysis of variety of images. So texture can be defined as a property that represent the surface, topography and structure of an image and as well as a regular repetition of pattern on the surface. Texture refers to the spatial allotment of grey-levels and can be defined as the deterministic or random repetition of one or several primitives in an image. Micro textures refer to textures with small primitives while Macro textures refer to textures with large primitives [11], [12]. Texture analysis techniques have been used in several domains such as classification, segmentation, and shape from texture and image retrieval.

III.1. PERCEPTUAL TEXTURAL FEATURES

There are number of perceptual textural features listed in literatures. The important features that has considered in this study are coarseness, contrast, directionality & busyness. Following are conceptual definitions of all these features [3] [6] [11].

Coarseness refers to the size of the primitives, which represent the texture. It is the most important property of texture. A coarse texture is made up of large primitives and is characterize by a high
degree of local homogeneity of grey-levels. A fine texture is composed of small primitives and is characterized by a high degree of local variation of grey-levels.

**Directionality** deals with the degree of visible dominant orientation in an image. It is a universal property in an image. An image can have one or several governing orientation(s) or no dominant orientation at all. In the latter case, it is said isotropic. The orientation is influenced by the shape of primitives as well as their placement rules.

**Contrast** deals with the degree of clarity with which one can set apart different primitives in a texture. A well contrasted image is an image in which primitives are clearly visible and separable. Contrast can be manipulated by grey-levels in an image, the ratio of white and black in an image, intensity change of frequency of grey-levels.

![Fig 2. Test image from Brodataz database of texture [11]](image1)

![Fig 3. Test images from Biomedical Sciences (Dental) database of texture](image2)
Busyness is associated to spatial frequency of the intensity changes in an image. It refers to the intensity changes from a pixel to its neighborhood. In a busy texture the intensity changes are quick and rush, while they are slow and gradual in non busy textures. If these intensity changes are very small, they risk being invisible. Thus, the amplitude of the intensity changes manipulates the busyness. So we can conclude that busyness has a reverse relationship with coarseness.

Computational simulation of perceptual textural features can be based on two viewpoints: Unique images or the autocorrelation function associated with images. Autocorrelation is a mathematical model for analyzing repetitive patterns, such as the presence of a periodic signal obscured by noise, or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. It is a cross-correlation of a signal with itself. It is frequently used in signal processing for analyzing functions or chain of values, such as time domain signals. The autocorrelation function $f(\delta)$ for an $(n \times m)$ image, so ‘I’ is defined as follows [12]:

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

(1)

Where, $\delta_i$ shows shift on rows & columns respectively.

III. 2 COMPUTATIONAL MEASURE FOR TEXTURAL FEATURES

III.2.1. Brodatz Database

Many of the authors have used Brodatz database for the computational features to retrieve large images. Each of the 112 images of Brodatz database was divided into 9 tiles to obtain 1008 $128 \times 128$ images (112 $\times$ images 9 tiles per image). Such process has some drawbacks. In fact, when the original image is non homogeneous, the resulting tiles are not visually similar. Brodatz database contains an important number of images presenting a medium to high degree of non homogeneity.

![Fig 4. Autocorrelation function corresponding to images of Fig. 2 after their histograms were equalized [11]](image-url)
The autocorrelation $f(i, j)$ is computed on Image $I(i, j)$.
Then, the involvedness of the autocorrelation function and the gradient of the Gaussian function are computed in a separable way (according to rows and columns). Two functions are then obtained (according to rows and columns).
Based on these two functions, computational measures for each perceptual feature are computed as described in the following subsections.

**III.2.2 Coarseness Estimation**
It can be calculated by average number of maxima in an autocorrelation function. Coarse and fine texture measures small and large number of maxima respectively.

**Fig. 5.** Estimation of Non directional edge corresponding to images of Fig. 3 after their histograms were equalized

**Fig. 6.** Coarseness Estimation
• Maxx (i, j) = 1 If pixel (i, j) is a max on rows and Maxx (i, j) = 0 if pixel is not a maximum on rows.
• Maxy (i, j) = 1 If pixel (i, j) is a max on columns and Maxy (i, j) = 0 if pixel is not a maximum on rows.

Coarseness Cs can be written as follows:

$$C_s = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} 1 \cdot \max_{x}(i,j) \cdot \max_{y}(j,i)}{\sum_{i=0}^{n-1} \sum_{j=0}^{m-1} 1}$$  \hspace{1cm} (2)

Denominator gives number of maxima according to rows and columns. It can be calculated on linear scale i.e. 0 to 1.
• If Cs = 1 = less maxima = Coarse Image
• If Cs = 0 = more maxima = Fine Image

### III.2.3 Contrast Estimation

The experiments conclude the value autocorrelation function decreases slowly for no well-contrasted images and decreases quickly for well-contrasted images. So for the estimation of contrast, the amplitude of the slope of the autocorrelation function according to the rows and columns can be used. Function (f) slope of amplitude of average of autocorrelation function depends on-
• Average amplitude in an autocorrelation functions by considering only pixels.
• Quantities of Pixels are having superior amplitude according to rows and columns respectively. (Partial derivatives of the Gaussian).

So the Contrast can be expressed by following equation

$$-C_t = \frac{M_{x,y} \times N_{x,y} \times C_s^2}{n \times m}$$  \hspace{1cm} (3)
\[ M = \sqrt{C_x^2 + C_y^2} \]  

- \( t \) = threshold contrast value of reference image
- \( M_a \) = Average amplitude, represents percentage of pixels having an amplitude superior than threshold “t”.

### III.2.3 Directionality Estimation

It is a measure of dominant orientation(s) and the degree of directionality. Orientation refers to the global orientation of primitives that constitute the texture. It measures the existing orientation in the parent image & its comparison with the orientation derived from autocorrelation function in the form of lines and columns. Directionality is related to the visibility of the dominant orientation(s) in an image, refers to the number of pixels having the dominant orientation(s). For Directionality estimation we can consider only dominant orientations that are present in a sufficient number of pixels.

![Fig 8. Contrast Estimation](image)

So the Contrast can be expressed by following equation –

\[ N_{\theta_d} = \frac{\sum_{i=0}^{n-1} \sum_{j=0}^{n-1} \dot{\theta}_d(i,j)}{(n \times n) - N_{\theta_{nd}}} \]  

- Greater = image is directional
- Lesser = image is non directional

### III.2.3 Busyness Estimation

Busyness is inversely preoperational to the Coarseness. So the Busyness can be expressed by the following equation –

\[ B_s = 1 - C_s^1 \]
As busyness is related to Coarseness, it will not have that much of impact on results when applied in texture retrieval.

III.2.3 Psychometric Method

The psychometric technique used to judge against rankings of images. Rankings of images are derived from the different perceptual textural features analyzed by human subjects. Rank-correlation has been done between the two rankings for each textural feature. The calculation of this rank-correlation is based on Spearman’s coefficient of rank-correlation. For example, if n images are ranked in T different rankings according to some feature, the first quantity called the sum of rank values can be estimated by –

\[
S_i = \sum_{k=1}^{n} f_{ik} R_k
\]  

(7)

Where,
i = ith image and varies between 1 and n.
k = rank and varies between 1 and n.
f_{ik} = number of human subjects which gives ith image for the Rank k.
Rk= reverse order to k and is given by \( R_k = n - k + 1 \).

The sums of rank values \( S_i \) are then ordered decreasingly. The image with the higher sum of rank values \( S_i \) is given position 1, the image with the second higher sum of rank values \( S_i \), is given position 2 and so on. Once the human rankings are obtained, we must determine the correspondence between the human rankings and computational rankings. We can use the well-known Spearman coefficient \( r_s \), of rank correlation defined as:

\[
r_s = 1 - \frac{6D}{n(n^2-1)}
\]  

(8)

\( D = \text{sum of squared differences} = D = \sum_{i=1}^{n} d_i^2 \)
\( d_i = \text{difference between the ranks assigned to the ith image in two different rankings m and l} \)
\( d_i = k_{mi} - k_{li} \)

The value of \( r_s \) should be in between 1 and -1.
- 1 = total correspondence between 2 rankings.
- -1 = total disagreement between 2 rankings.
- 0 = the ranking is orthogonal.

IV. CONCLUSION

In this comprehensive survey we have presented a survey of the most popular perception-based approach of these feature extraction methods. A new proposed perceptual model based on a set of process variables and topological parameters which includes number of control points such as coarseness, directionality, contrast, and busyness has been used to retrieve virtual image representation of perceptual textural features.

Future proposed goal is to compare the surveyed texture feature extraction techniques as well as implement the proposed feature selection methods and to study the combined effect of the multiple feature extraction techniques in image retrieval. The code is currently being written in MATLAB, and the simulations will be done on an image dataset of number of images obtained from the well known web based Brodatz database. We have also proposed to develop a constructive database for dental related alignments or disease (Biomedical Sciences) based on the recognized Brodatz database to classify large image data set, for the estimated perceptual features measures.
So in future with this study, an application of perception-based approach for Content based image retrieval (CBIR) with computational intelligence is aimed to develop a controlled man-machine problem solving process methodology in the hands of the users, with a highly user friendly graphic interface by taking assistance of MATLAB.

REFERENCES


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