DOMAIN SPECIFIC CBIR FOR HIGHLY TEXTURED IMAGES

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ABSTRACT

It is A Challenging Task To Build A Cbir System Which Primarily Works On Texture Values As There Meaning And Semantics Needs A Special Care To Be Mapped With Human Based Languages. We Have Consider Highly Textured Images Having Properties(Entropy, Homogeneity, Contrast, Cluster Shade, Auto Correlation)And Have Mapped Using A Fuzzy Minmax Scale W.R.T. Their Degree(High, Low, Medium)And Technical Interpetation.This Developed System Is Performing Well In Terms Of Precision And Recall Value Showing That Semantic Gap Has Been Reduced For Highly Textured Images Based Cbir.

KEYWORDS

CBIR; fuzzyminmax; recall; precision; Texel; texture

1. INTRODUCTION

Content Based Image Retrieval system is that system in which the retrieval is based on the content which is numerical in nature. The word "content" here means in mathematical terms, the color values, the texture features or other statistical numerical values that can be calculated from the metrics of the image. Therefore, a system that works to store and retrieve such content and to retrieve such content is known as CBIR.This unit of information is basically a numerical value and hard to interpret in terms of human understanding. Therefore, there is an urgent need to remove the barriers to have a streamlined retrieval system which works for humans and with humans. There is a growing interest in CBIR because of the limitations inherent in metadata-based systems, as well as the large range of possible uses for efficient image retrieval E.g. texture value which measures the look for visual patterns in images and how they are spatially defined. Textures are represented by' texels'[1] which are placed into a number of sets, depending on how many textures are detected in that image. Texture is a difficult concept to represent in human based languages Texture is a difficult concept to represent. The identification of specific textures in an image is achieved primarily by modeling texture as a two-dimensional gray level variation. The relative brightness of pairs of pixels is computed such that degree of contrast, regularity, coarseness and directionality may be estimated. However, the problem is in identifying patterns of co-pixel variation and associating them with particular classes of textures such as silky, or rough. A Texel is similar to a pixel (picture element) because it represents an elementary unit

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in a graphic. But there are differences between the Texel's in a texture map and the pixels in an image display. In special instances, there might be a one-to-one correspondence between Texel's and pixels in some parts of the rendition of a 3-D object. But for most, if not all, of a 3-D rendition, the Texel's and pixels cannot be paired off in such a simple way. There are three major categories of texture-based techniques, namely probabilistic/statistical, spectral and structural approaches. Probabilistic methods treat texture patterns as samples of certain random fields and extract texture features from these properties. Spectral approaches involve the sub-band decomposition of images into different channels and the analysis of spatial frequency content in each of these sub-bands in order to extract texture features. Structural techniques model texture features based on heuristic rules of spatial placements of primitive image elements that attempt to mimic human perception of textural patterns.

Texture based feature extraction techniques such as co-occurrence matrix, Fractals, Gabor Filters, variations of wavelet transform, other transform have also been widely used [2], [3]. In Gray level Co-occurrence matrix (GLCM), the texture features from gray scale image are extracted [4]. As per GLCM, the following texture features are considered for identifying differentiating textures of images properties

1.1 **Entropy**: Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as

```
p = -pixel Count .* log (pixel Count)
p (isnan(p)) = []
p (isinf(p)) = []
EntropyValue = -sum (p)
```

pixelCount are the total number of pixels in image region, calculated from the histogram of the gray image region and the variable p means temporary variable to calculate entropy. Entropy can also be shown as:

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-sum (p.*log2 (p))
```

Where p contains the histogram counts. Image (I) can be a multidimensional image. If I have more than two dimensions, the entropy function treats it as a multidimensional grayscale image and not as an RGB image.

1.2 **Homogeneity**: The homogeneity consists of two parts- the standard deviation and the discontinuity of the intensities at each pixel of the image. The standard derivation S_{ij} at pixel P_{ij} can be written as

$$S_{ij} = \sqrt{\frac{1}{n_w} \sum_{I_w \epsilon W_d(P_{ij})} (I_w - m_{ij})^2}$$

Where m_{ij} is the mean of n_w intensities within the window W_d (P_{ij}), which has a size of d by d and is centered at P_{ij}.

A measure of the discontinuity D_{ij} at pixel P_{ij} can be written as:

$$D_{ij} = \sqrt{G_X^2 + G_y^2}$$

where G_x and G_y are the gradients at pixel P_{ij} in the x and y direction. Thus, the homogeneity H_{ij} at P_{ij} can be written as

$$H_{ij} = 1 - (S_{ij}/S_{max})X(D_{ij}/D_{max})$$

1.3 **Contras**t: Contrast is the difference in luminance and/or color that makes an object (or its representation in an image or display) distinguishable. In visual perception of the real world, contrast is determined by the difference in the color and brightness of the object and other objects within the same field of view. The maximum contrast of an image is the contrast ratio or dynamic range. It is mathematically defined as:

$$\frac{\text{Luminance Difference}}{\text{Average Luminance}}$$

1.4 **Cluster Shade**: Cluster shade[8] and cluster prominence are measures of the skewness of the matrix, in other words the lack of symmetry. When cluster shade and cluster prominence are high, the image is not symmetric with respect to its texture values. It is defined as follows:

$$\sum_{i,j}^{i,j}\left((i-\mu_i)+(j-\mu_j)\right)^3 C(i,j)$$

where

$C\,(i,j)$ is the *(i,j)*the entry in a co-occurrence matrix C

$\sum_i$ means $\sum_{i=1}^{i=M}$ where M is the number of rows

$\sum_j$ means $\sum_{j=1}^{j=N}$ where N is the number of columns

$\sum_{i,j}$ means $\sum_i \quad \sum_j$

μ_i is defined as: $\mu_i = \sum_i i \sum_j C(i,j)$

μ_j is defined as: $\mu_j = \sum \quad j \sum \quad C(i,j)$

1.5 **Auto Correlation**: In any time series containing non-random patterns of behavior, it is likely that any particular item in the series is related in some way to other items in the same series. This can be described by the autocorrelation function and/or autocorrelation coefficient.

The correlation of two continuous functions f(x) and g(x) can be defined as:

$$f(x).g(x) = \int \left(f(a).g(x \mid a)\right)dx$$

If *f(x)* and *g(x)* are the same functions, *f(x).g(x)* is called autocorrelation function.
For a 2D image, its autocorrelation function (ACF) can be calculated as:

$$f(x,y).g(x,y) = \int \left(f(a,b).g(x+a,y+b)\right)dx$$

Where *f(x,y)* is the two-dimensional brightness function that defines the image, and a and b are the variables of integration. Like the original image, the ACF is a 2D function. Although the dimensions of the ACF and the original image are exactly the same, they have different meaning. In the original image, a given coordinate point (x, y) denotes a pixel position, while in the ACF, a given coordinate point (a,b) denotes the endpoint of a neighbourhood vector.

2. PROPOSED SYSTEM

For reducing the semantic gap, we have developed fuzzy sets and associated each instance with its degree and interpretation as follows:

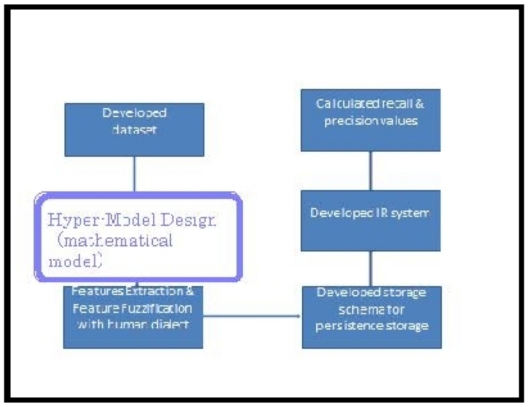

Fig.1 The flowchart of the proposed algorithm

1. Development of a representative data set of textured images.
2. Study of various linguistic descriptors (Fuzzy Sets) based on the domains of textured images.
3. Use of Fuzzy Sets collected in step 2; development of color and texture feature sets for the said data set developed in step 1as follows:-

I. Get texture properties fuzzy sets for each feature (Entropy/Energy, Autocorrelation, Cluster shade, Contrast, Homogeneity).

II. For each texture properties fuzzy set, develop a decision making function which indicates the membership of each element of the fuzzy set.

III. If ' X ' is a universe of discourse and x is a particular element of X (Texture Data image dataset), then a fuzzy set A defined on X may be written as a collection of ordered pairs $\tilde{A} = \{(x, \mu_{\tilde{A}}(x))$, x belongs to texture feature(s)} where each pair $(x, \mu_{\tilde{A}}(x))$ is called a singleton [5]. It can also be represented as: $\tilde{A}=\sum \mu_{\tilde{A}} (x_i) / x_{i;}$

IV. Where 'X' may be a set having boundaries defined by Max, Min, Mean, Mim and Mam for all the texture features. The Entropy/Energy values fall in the range [0,1] and this range is divided into four separate regions namely low, medium, high and very high. The fuzzy boundaries obtained are further associated with human dialect for defining textures into smooth, regular and coarse categories and then degree with interpretation

4. Development of a storage schema which maps the Hyper Model and texture feature sets developed in step 3.
5. Development of an interface for storing the highly textured images information w.r.t. previous steps in the database.
6. Development of a structured query based on which information of texture images can be retrieved.
7. Development of an application for running the queries developed in step 6.
8. Calculation of precision and recall values.

3. RESULTS AND INTERPRETATION

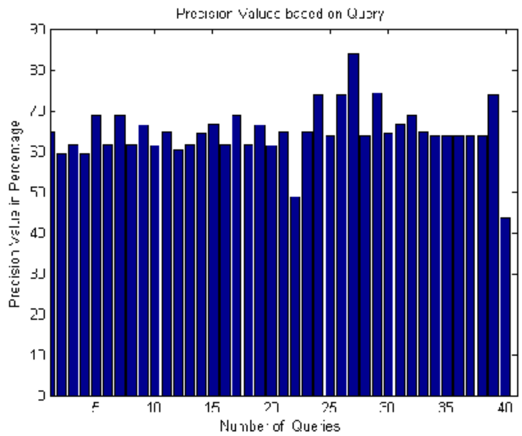

Figure 2. PRECISION GRAPH:

The precision [6] values of the proposed system are as shown in Fig 2, where the precision value (in percentage) for each query has been calculated .it is shown as a bar. The framework applied in the proposed system is for different queries that run on the image instance dataset and the standard situation where competing results are obtained on the same data. The shape of the graph shows that the precision value remains in a bracket of 48-70% and the graph query produces significant amount of results from the total database. So based on the formula of precision, it can be understood that close to 2/3rd of the results are relevant from the total results. the overall average precision value which is calculated to be 70.2%, it can be inferred that the system is able to retrieve results close to what the user is expecting. So degree of semantic gap reduction can be inferred and understood.

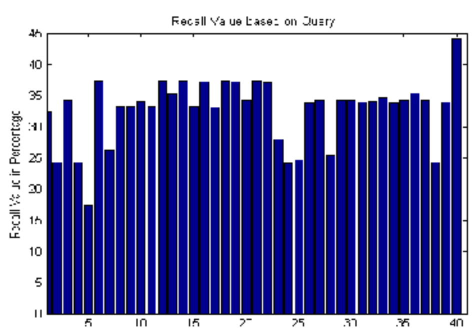

Figure. 2 RECALL GRAPH:

The recall [6] value of any system will be high if the selection process of the dataset images have been done very carefully .If the dataset has high quality of images, highly significant and relevant to the technical subject based on which the user is trying to find a unit of information, the recall value will normally be good enough to satisfy user needs. So it can be seen from Fig 3, that for unique queries, 1/3rd of the database remains relevant and contributes towards results. Also, the image instances content stored in the domain dataset of interest is indexed and is searchable. Based on the formula for recall, the average recall value calculated is 35%.

Retrieval algorithm can fall into one of the two cases as given below.

Case1: The algorithm has higher precision values at lower recall percentage than at higher recall percentage levels. This implies that the algorithm does not retrieve as well (in terms of numbers), but rank its retrieved results set well. It can identify good relevance in its ranking metric, but does not match well to retrieve all or many relevant/irrelevant result sets. This algorithm is more selective.

Case 2: The algorithm has lower precision values at higher recall levels than at lower recall levels. This implies that the algorithm retrieves well, but does not rank the retrieved image instances result high enough. It does not have a good relevance ranking metric, but is able to search and retrieve well. This algorithm has junkie results and is not stable. Based on the interpretation of the precision and recall values, the proposed system is the first case algorithm.

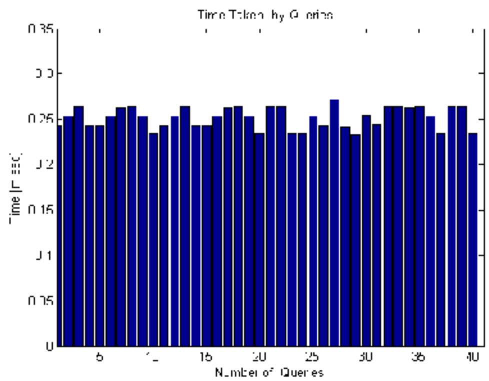

Figure. 4 Time taken by queries:

This pertains to the time taken for the system to bring results. Current technological advances are in direction of intelligence augmentation by using information just in time to take decision and solve many real time problems and issues. Therefore, it is important to look into the time aspect of retrieval to check the performance. Fig 3 shows the time taken by the queries. From the graph for retrieving the data, one can have a visualization of minimum and maximum value of time in mill seconds.

4. CONCLUSION

The precision value obtained by the proposed method is close to 70% which is fairly good enough as it shows that the user is getting $2/3^{rd}$ of the information quite relevant out of the total results retrieved for the query inquired by the user. The recall value obtained by the proposed method is close to 35% which reflects that the image quality and the associated information fed into the system while developing its database is significant in aiding technical work for the said textured what user is looking for is good. In the proposed algorithm, the execution time of the query fed by the user ranges from 0.2434 to 0.2527 milliseconds**.**

5. FUTURE WORK

In further development of the CBIR [7], many other multi-model feature extraction algorithms must be used to make it rich in terms of both low level and high level concepts and then one can also explore the need of the machine learning algorithms if the size of the dataset increases many folds. Then, for building next generation CBIR, next focus must also be on incorporating algorithms that are helping to reduce sensory gap also.

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