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Image Retrieval Based on Structural & Statistical Methods of Texture

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I. INTRODUCTION

Images now play a crucial role in fields as diverse as medicine, journalism, advertising, design, education, entertainment, etc. Technology, in the form of inventions such as photography and television, has played a major role in facilitating the capture and communication of image data. But the real engine of the imaging revolution has been the computer, bringing with it a range of techniques for digital image capture, processing, storage and transmission through internet. The creation of the World-Wide Web in the early 1990s, enabling users to access data in a variety of media from anywhere on the planet, has provided a further massive stimulus to the exploitation of digital images. The number of images available on the web was recently estimated to be between 10 to 60 million [41], which some observers consider to be a significant underestimate.The process of digitization does not itself make image process and is expected to provide a high percentage of relevant images in response to user query [38].The presence of large volumes of digital repositories leads to many schemes of indexing and retrieval of such data (e.g.,QBIC [2, 8], Netra [31],VisualSeek [43], Chabot [33], Blobworld [3], photobook [37], etc). In all these cases, the user is interested in seeking the most similar images to his query.

In content-based retrieval systems the features of an image query are used to search for similar features of images in the database [24, 27, 28, 56].The CBIR has been applied for many purposes [25] in law enforcement and crime prevention, such as significant descriptor. LBP based models often shows promising performances in texture analysis and have been widely used in related applications, such as texture segmentation [26], facial expression collections easier to manage. The need for efficient storage and retrieval of images recognized by managers of large image collections such as picture libraries and design archives for many years was reinforced by a workshop sponsored by the USA's National Science Foundation in 1992 [21]. All these factors have created numerous possibilities and finally created interest among the researchers towards the design of an efficient and accurate Content Based Information Retrieval (CBIR) system. That's why the technological advances and growth in CBIR has been unquestionably rapid during the last five years.

2. LITERATURE SURVEY

There has been a lot of interest in content-based image retrieval using visual features over the last decade. An overview of work in this area can be found in [10, 29, 40, 44, 54, 55]. CBIR is like an information filter

fingerprint recognition, face recognition [30], DNA matching, shoe sole impressions [9], and surveillance systems [7]. Some of the popular methods to characterize color information in images are color histograms [13, 47], color moments [46], and colorcorrelograms [17]. Though all these methods provide good characterization of color, they have the problem of high-dimensionality. The present thesis uses an LBP based approach for efficient image retrieval. LBP approach captures the local features of the image efficiently, accurately and significantly. LBP [51, 52, 53] is proved as an extremely versatile and

recognition [42], shape localization [19] texture classification [11, 12], face recognition [1], dynamic texture recognition [58], and object recognition [59]. Based on LBP new operators are derived such as

Local Ternary Patterns (LTP) [48], Local Quinary Patterns (LQP) [34], Centralized Binary Patterns (CBP) [9] etc. Based on the above research on LBP the present thesis derived new versions of LBP that reduced the dimensionality of LBP and for efficient image retrieval.

Building Blocks of the CBIR

In content-based image retrieval systems, a desirable image is retrieved, from the large collection of images stored in the image database, based on their visual content. This process is usually performed automatically without human intervention. The visual content of an image is represented by common attributes which are called features. They include 'shape of the image' [49], 'colour histogram of the image' and 'texture of the image'. Colour feature is the most commonly used visual feature for image retrieval. Color is the most extensively used visual content for image retrieval [17, 18, 20, 31, 36, 45, 47, 57].

Texture is another important feature of an image that can be extracted for the purpose of image retrieval. Human vision perceives scenes with variations of intensity and color which form certain repeated patterns called texture. A texture is a measure of the variation of the surface intensity, and quantifying properties such as uniformity, density, roughness, regularity, linearity, frequency, phase, directionality, coarseness, randomness, fineness, smoothness, granulation etc. This special variation in pixel intensities is useful in a variety of applications such as analysis of satellite images in industrial surface inspection, remote sensing, CBIR and bio-medical image analysis. Texture is very important in quality control since many inspection decisions are based on the appearance of the texture of the material. There exist two main approaches for texture analysis. They include structural and statistical approaches.

The traditional statistical approaches to texture analysis such as Gray level Co-occurrence Matrices (GLCM), second order statistics, Gaussian Markov Random Fields (GMRF), local linear transforms [4, 5, 6, 14, 22] and run length matrix [39] are restricted to the analysis of spatial interactions over relatively small neighborhoods on a single scale. As a consequence, their performance is best for the analysis of micro-textures only [26]. Moreover, they are single resolution techniques, resulting in poor performance for texture analysis. He and Wang [15] proposed a texture spectrum based method, which stated that a texture image is considered as a set of small texture units, which characterize the local texture information for a pixel and its neighbourhoods and then used a clustering algorithm for unsupervised classification. Statistics of the primitives can be computed as the texture features. However, most of existing methods are more or less sensitive to the changes in rotation, scale, or illumination of images.

In the structural approach, texture is considered as the repetition of some primitives with a certain rule of placement. The traditional Fourier spectrum analysis is often used to determine the primitives and the placement rule [16, 32]. In the theory of textons, Julesz formalized the way in which human perception is able to discriminate textures in a pre-attentive way [22,23, 50]. The local binary pattern (LBP) operator first introduced by Ojala et al. [35], is a robust but theoretically and computationally simple approach. It brings together the separate statistical and structural approaches to texture analysis of both stochastic micro textures and deterministic macro textures simultaneously.

One of the fundamental problems of Computer Vision, Image Processing and Pattern Recognition is how to describe and represent a shape. Good shape representation and description schemes are of paramount importance in developing efficient image compression, image data retrieval, content based video processing, shape matching, object recognition algorithms. A good shape representation should provide an accurate and complete description of the given shape. Finding and representing an efficient shape is one of the problems associated with shape.

3. Problem Statement

Derivation of a new image retrieval models to overcome the dimensionality problem of LBP and usage of integrated retrieval model that combines the shape features (using textons) with structural and statistical features of textures.

4. Objectives of the Present Studty

1. To overcome the high dimensionality problem of LBP (with 256 and 58 patterns).
2. To address the problem of non-considering NULBP's, which occupy 77 % of LBP and treating them as miscellaneous class.
3. To derive an efficient image retrieval method by considering all uniform (ULBP) and non–uniform (NULBP) transitions of LBP by reducing overall dimensionality.
4. To derive a new model of image retrieval by integrating the transitions on Local Binary Pattern (LBP) with textons and Grey Level Co-occurrence Matrix (GLCM). (To derive a new integrated model that is based on statistical and structural properties of texture for efficient image retrieval.)
5. Efficient usage of textons which are represented with definite placement rules with emerging patterns sharing a common property all over the image in image retrieval.
6. To derive a 2-dimensional dual uniform LBP

matrix (DULBPM) for efficient texture image retrieval.

5. Organization of the Thesis

To meet the objectives and the problem statement the present thesis is proposed to divide in to six chapters.

The first chapter gives the introduction, literature survey and basic blocks of image retrieval, objectives and problem statement.

The second chapter is proposed to deal with LBP, since the approaches of the present thesis are based on this approach. In this chapter various issues related to LBPand its variants in-terms of advantages and disadvantages will be discussed in depth.

All the proposed methods of the present thesis are experimented on 480 numbers of images with four groups i.e. Tire, Animal fur, Car and Leaf textures. Each group consists of 120 numbers of images**.** These texture images i.e**.** Tire, Animal fur, Car and Leaf are collected from Google data base with a resolution of 256 x 256.

The third chapter of the thesis derived a method based on the histogram of transitions (from 0 to 1 or 1 to 0) on LBP and it is called as Histogram of Texture Features on LBP (HTF-LBP). One of the current theoretically significant, simple and very effective texture descriptor that describe local structure efficiently and precisely is the '*Local Binary Pattern'* (LBP). Today LBP and its variants are applied in many areas. One of the disadvantage with LBP is it derives a total of 256 patterns out of which 58 are the Uniform LBP (ULBP) and remaining are Non Uniform LBP (NULBP).The ULBP holds the fundamental characteristic and most of the textures predominantly contain ULBP . The disadvantage with ULBP is one should consider 58 pattern features for any classification or retrieval etc. The ULBP approaches completely ignored the NULBP and grouped them into miscellaneous class. This leads to lot of complexity. To overcome this, present research of the thesis in chapter three designed a new method for retrieval based on Histogram of transitions (from 0 to 1 or 1 to 0) on LBP. The LBP will have only 0, 2, 4, 6 and 8 transitions from 0 to 1 or 1to 0 on 8-bit circular LBP. These 5 transitions forms five texture features. The histogram of transitions (from 0 to 1 or 1 to 0) on LBP is represented as Histogram of Texture Features on LBP (HTF-LBP) in the third chapter .The proposed HTF-LBP method is experimented on various images collected from Google data base. The experimental result indicates the efficiency of the proposed HTF-LBP method over the various methods. One of the disadvantages of LBP is its weights and they can be ordered differently in 8 different ways as shown in Fig.1. The proposed HTF-LBP overcomes this also.

2^{0}	2^{1}	2^{2}
2^{7}		2^{3}
2^{6}	2^{5}	2^{4}

2^{7}	2^{0}	2^{1}
2^{6}		2^{2}
2^{5}	2^{4}	2^{3}

2^{6}	2^{7}	2^{0}
2^{5}		2^{1}
2^{4}	2^{3}	2^{2}

2^{5}	2^{6}	2^{7}
2^{4}		2^{0}
2^{3}	2^{2}	2^{1}

2^{4}	2^{5}	2^{6}
2^{3}		2^{7}
2^{2}	2^{1}	2^{0}

2^{3}	2^{4}	2^{5}
2^{2}		2^{6}
2^{1}	2^{0}	2^{7}

2^{2}	2^{3}	2^{4}
2^{1}		2^{5}
2^{0}	2^{7}	2^{6}

2^{1}	2^{2}	2^{3}
2^{0}		2^{4}
2^{7}	2^{6}	2^{5}

Fig.1: *Different ways of representing LBP weights.*

The proposed HTF-LBP method finds the histogram of transitions on LBP on the entire image. The five texture features i.e F_1, F_2, F_3, F_4 and F_5 represents the histogram of 0,2,4,6 and 8 transitions on LBP respectively. The overall image retrieval performance based on the proposed HTF-LBP method is shown in Table 1 and it is also shown in the form of bar graph in Fig.2.

Table 1: *Retrieval performance of different texture databases based on HTF-LBP.*

Texture Databases	Retrieval rates
Tire	80
Animal fur	90
Car	100
Leaves	100

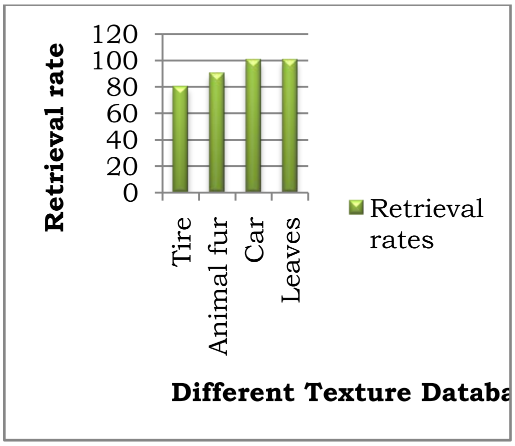

Fig.2: *Bar graph representation of retrieval performance.*

The fourth chapter of the thesis will be presenting a new model of texture image retrieval by integrating the transitions on Local Binary Pattern (LBP) with textons and Grey Level Co-occurrence Matrix (GLCM). The present thesis initially derived transitions that occur from 0 to 1 or 1 to 0 in circular manner on LBP. The transitions reduce the 256 LBP codes into five texture features. This reduces the lot of complexity. The LBP codes are rotationally variant. The proposed circular transitions on LBP are rotationally invariant. Textons,which represents the local relationships, are detected on this. The GLCM features are evaluated on the texton based image for efficient image retrieval.

The proposed TTLBP model aims to overcome rotational variance problem and to reduce the large number of codes that are derived by LBP. The proposed TTLBP model consists of five steps as given below.

Step 1: Color Quantization of 7-bit Binary Code using RGB color space.

Step 2: Representation of the Texture image by the number of circular transitions from 0 to 1 or 1 to 0 on LBP instead of LBP codes or numbers.

Step 3: Texton detection on transitioned number LBP Texture Image.

Step 4: Evaluation of the GLCM features on the Texton based Transitioned LBP (TTLBP) texture Image.

The proposed TTLBP using GLCM features evaluated the integrated texture features using the GLCM features contrast correlation, energy and homogeneity. The overall image retrieval performance based on the proposed TTLBP method is shown in Table 2 and it is also shown in the form of bar graph in Fig.3.

Table 2: *Retrieval rates of different textures by the proposed TTLBP method.*

Texture Databases	Retrieval rates
Animal fur	60
Rubber	66.66
Leaf	66.66
Car	73.33
Average retrieval rate	**66.7**

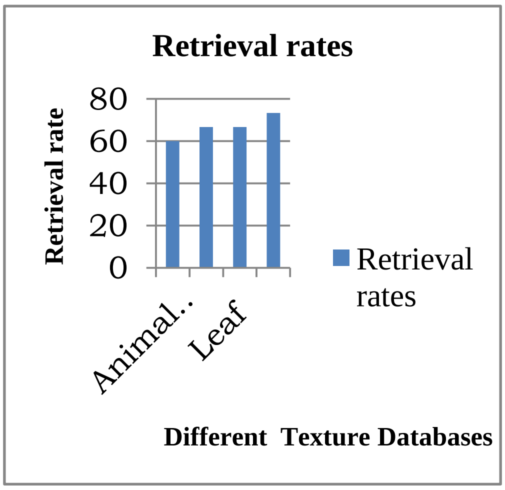

Fig.3: *Bar graph representation of retrieval rate of different texture databases.*

Texture Databases	Retrieval rates 0-0 transition	Retrieval rates 0-2 transition	Retrieval rates 2-0 transition	Retrieva l rates 2-2 transitio
Animal fur	33	60	60	33.33
Rubber	40	66.66	53.33	33.33
Leaf	46.66	66.66	66.6	40
Car	73.33	86.6	93.3	46.6
Average retrieval	53.3	69.98	68.3	38.315

Texture image retrieval plays a significant and important role in these days, especially in the era of big-data. The big-data is mainly represented by unstructured data like images, videos and messages etc. An efficient method of image retrieval that reduces the complexity of the existing methods is need of the big-data era. The present paper proposes a new method of texture retrieval basedon local binary pattern (LBP) approach. One of the main disadvantage of LBP is it generates 256 different patterns on a 3x3 neighborhood and a method based on this for retrieval needs 256 comparisons which is very tedious and complex.The retrieval methods based on uniform LBP's which consists of 59 different patterns of LBP is also complex in nature. To overcome this, the present research dividedLBP into dual LBP's consisting four pixels each. The present work is an extension of the work proposed in research three. The present research based on this dual LBP derived a 2-dimensional dual uniform LBP matrix (DULBPM) that contains only four entries. The texture image retrieval is performed using these four entries of DULBPM. The proposed method is evaluated on the animal fur, car, leaf and rubber textures.

Table 3: *Retrieval rates of different transitions based on DULBPM entries.*

Texture Databases	Retrieval rates 0-0 transition	Retrieval rates 0-2 transition	Retrieval rates 2-0 transition	Retrieval rates 2-2 transition
Animal	33	60	60	33.33
Rubber	40	66.66	53.33	33.33
Leaf	46.66	66.66	66.6	40
Car	73.33	86.6	93.3	46.6
Average	53.3	69.98	68.3	38.315

The sixth chapter presents the conclusions and future scope.

5. Conclusions

The need for efficient content based image retrieval (CBIR) has increased tremendously in many applications areas such as biomedicine, military, commerce, education, and web image classification and whatsApp. CBIR is highly challenging because of the large size of the database, the difficulty of understanding images, both by people and computers, the difficulty of formulating a query, and the problem of evaluating the results. Efficient indexing and searching of large-scale image data bases remain as an open problem. The automatic derivation of semantics from the content of an image is the focus of interest of the present research on image databases.

The Content-based image retrieval systems allow the user to iteratively search image databases looking for those images which are similar to a specified query image. Selection and ranking of relevant images from image collections remains a problem in content-based image retrieval. Image retrieval has been an active research topic in recent years due to its potentially large impact on both image understanding and Web image search. 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.

LBP is a powerful and significant tool that holds and extracts the local texture features in a powerful manner. LBP is a local texture operator with low computational complexity and low sensitivity to changes in illumination and it is easy to use and understand. Though LBP has proved itself as a powerful tool in many image processing applications however only few researchers used LBP in image retrieval. To fill this gap the present research on CBIR used LBP model only i.e. extracted texture features for CBIR.

To overcome the dimensionality and complexity problem in considering the patterns of LBP, the present thesis designed a new method for retrieval based on histogram of transitions (from 0 to 1 or 1 to 0) on LBP (HTF-LBP). The LBP will have only 0, 2, 4, 6 and 8 transitions from 0 to 1 or 1to 0 on 8-bit circular LBP. These 5 transitions forms five texture features. The histogram of transitions (from 0 to 1 or 1 to 0) on LBP is represented as histogram of texture features on LBP (HTF-LBP).The proposed HTF-LBP is a simple method of image retrieval. The main advantage of the present method is, it considered all the 256 LBP features by reducing them into 5 features based on the number of transitions. The present method has overcome the disadvantage of considering all NULBP into one label called miscellaneous. The proposed HTF-LBP is rotationally invariant whereas the features based on LBP code are rotational variant because LBP weights can be represented in 8-different ways.

The present HTF-LBP method reduced lot of complexity in representing number of texture features if one considered the ULBP or NULBP. The experimental results indicate a good image retrieval rate by the present HTF-LBP method.

The present thesis derived a new image retrieval model of texture image retrieval by integrating the transitions on Local Binary Pattern (LBP) with textons and Grey Level Co-occurrence Matrix (GLCM). The proposed texton based transitioned LBP(TTLBP) model, aims to overcome rotational variance problem and to reduce the large number of codes that are derived by LBP. The proposed TTLBP model consists of five steps. The proposed circular transitions on LBP are rotationally invariant. Textons, which represents the local relationships, are detected on this. The GLCM features are evaluated on the texton based image for efficient image retrieval. The proposed TTLBP image retrieval model achieved a retrieval rate of 60%, 66.66%, 66.66% and 73.33% for animal fur, rubber, leaf and car textures respectively. This method created a new direction in image retrieval model by integrating shape features with structural and statistical model of texture.

Texture image retrieval plays a significant and important role in these days, especially in the era of big-data. The big-data is mainly represented by unstructured data like images, videos and messages etc. An efficient method of image retrieval that reduces the complexity of the existing methods is need of the big-data era. To address this, the present thesis divided LBP into dual LBP's consisting four pixels each. The present research based on this dual LBP derived a 2-dimensional dual uniform LBP matrix (DULBPM) that contains only four entries. The texture image retrieval is performed using these four entries of

DULBPM.The DULBPM is a 2x2 2-D matrix i.e. it consists of 4 entries only and DULBPM entries are initialized to zero. The texture retrieval is performed separately based on Euclidian distance between query texture image and feature or database texture images using individual entries of DULBPM. That is based on 0 versus 0, 0 versus 2, 2 versus 0, 2 versus 2 circular bitwise transitions of CLBP and DLBP. From the experimental results it is clearly evident that the retrieval based on DULBPM (2, 0) and DULBPM (0, 2) entries shown higher performance nearly with an average retrieval rate of 70%.

The present thesis compared all the proposed methods of CBIR and listed in Table 3 and also graphically represented in Fig.4. From the tables and graphs it is observed that the proposed HTF-LBP outperforms the remaining three proposed methods. The reason for this is may be textons are not formed well on the LBP transitions.

Thus the present thesis created a new direction to those working in the area of image retrieval and LBP, on how to reduce the overall dimensionality and complexity without losing and texture features and by not treating NULBP's as miscellaneous and to make the proposed methods to be more suitable to real time applications and also to big data applications like image analytics etc.

Table.3: *Comparison of retrieval rates of proposed methods.*

Texture Databases	Retrieval rates of Histogram of texture features(HTF-LBP)	Retrieval rates of Texton Based Transitioned LBP	Retrieval rates 0-2 transition of DULBP	Retrieval rates 2-0 transition of DULB
Animal fur	80	60	60	60
Rubber	90	66.66	66.66	53.33
Leaf	100	66.66	66.66	66.6
Car	100	73.33	86.6	93.3
Average retrieval rate	80	66.7	69.98	68.3

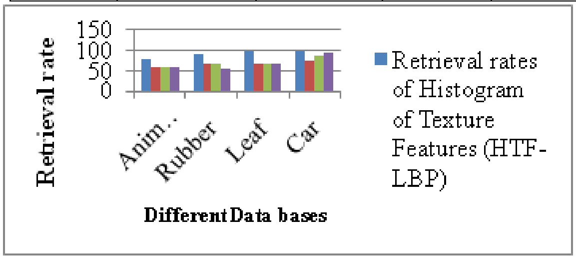

Fig.4: *Bar graph representation of comparison.*

6. FUTURE SCOPE

The present methods can be extended in wavelet domain. The proposed methods of the present thesis can be extended to other applications in the field of image processing like face recognition, age classification, medical imaging etc. To improve further results the present methods can be extended by using pre-processing techniques.

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