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An Enhanced Center Symmetric Local Binary Pattern Technique for Image Retrieval Using Euclidean Distance

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Abstract-

In recent years, image mining techniques enters and plays a vital role in various fields. The fast improvement in the information technology various methods has been appear to process and store these information, issues in data retrieval and huge volume. Image retrieval has been developed into a very dynamic explore the part will focus on how to extract and retrieve the images. An assortment of methods has been proposed for image retrieval and each technique has advantages and drawbacks. The difficulty in procedure and other problem involve the performance of existing system which makes inadequate. In this paper image retrieval with feature are extracted based on features such as contrast, energy, homogeneity and the threshold value calculated separately stored in feature database. The feature is generated and matching is done by Euclidean distance which is used to measure distance between two images. The experimental results shows that CSLBP method provides better retrieval rate when compared with the existing methods in terms of retrieval, precision and recall.

Keywords-LBP, ILBP, MBLBP, CSLBP, Euclidean, Precision, Recall.

1. INTRODUCTION

Today, information has a great value and the amount of information has been expansively growing during last few years. Especially, text databases are rapidly growing due to the increasing amount of information available in electronic forms.

Generally, data mining is the process of analyzing data from different perspectives and summarizing it into useful information. That type of Information can be used to increase revenue, cuts costs or both. It allows users to analyze data from many different dimensions or angles, categorize it and summarize the relationships identified.

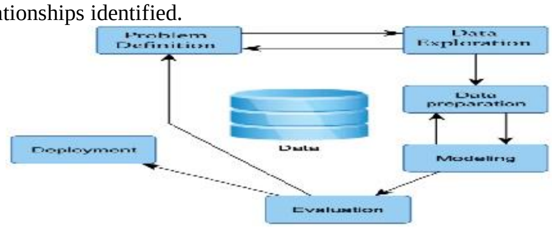

Fig 1.1 Steps in Data mining

Data Mining Techniques

There are several core techniques are used in data mining, to describe the type of mining and data recovery operation. The most common techniques used in the field of data mining are as follows.

Association

Association is a data mining function that discovers the probability of the co-occurrence of items in a collection. The relationships between co-occurring items are expressed as association rules. Association (or relation) is probably the better known and most familiar and straightforward data mining technique. Association makes a simple correlation between two or more items, often of the same type to identify patterns.

Classification

Classification is a data mining function that assigns items in a collection to target categories or classes. The goal of classification is to accurately predict the target class for each case in the data. For example, a classification model could be used to identify loan applicants as low, medium or high credit risks.

Clustering

Clustering is a data mining (machine learning) technique used to place data elements into related groups without advance knowledge of the group definitions. Popular clustering techniques include k-means clustering and expectation maximization (EM) clustering. Support Vector Machines that analyze data used for classification and regression analysis. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. When data are not labeled, supervised learning is not possible and an unsupervised learning approach is required, which attempts to find natural clustering of the data to groups and then map new data to these formed groups. Clustering is useful to identify different information because it correlates with other examples to see where the similarities and ranges agree.

Artificial Neural Networks

Artificial Neural Networks are relatively crude electronic models based on the neural structure of the brain. The brain basically learns from experience. It is natural proof that some problems that are beyond the scope of current computers are indeed solvable by small energy efficient packages. This brain modeling also promises a less technical way to develop machine solutions. Some Non-linear predictive models learn through training and resemble biological neural networks in structure.

1.2 Image Retrieval

An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords or descriptions to the images so that retrieval can be performed over the annotation words. Manual image annotation is time-consuming, laborious and expensive, to address this, there has been a large amount of research done on automatic image annotation. Additionally, the increase in social web applications and the semantic web have inspired the development of several web-based image annotation tools.

Image retrieval is an important topic in the field of pattern recognition and artificial intelligence. Generally speaking, there are three categories of image retrieval methods:

i. Text-based
ii. Content-based
iii. Semantic-based

The text-based approach the images need to be manually annotated by text descriptors which requires much human labor for annotation and the annotation accuracy is subject to human perception. Image retrieval is an extension to traditional information retrieval. Approaches to image retrieval are derived from conventional information retrieval and are designed to manage the more versatile and enormous amount of visual data that exist.

Low-level visual features such as color, texture, shape and spatial relationships are directly related to perceptual aspects of image content. Since it is usually easy to extract and represent these features and fairly convenient to design similarity measures by using the statistical properties of these features, a variety of content-based image retrieval techniques have been proposed in the past few years.

Image retrieval systems attempt to search through a database to find images that are perceptually similar to a query image. CBIR is an important alternative and complement to traditional text-based image searching and can greatly enhance the accuracy of the information being retrieved. It aims to develop an efficient visual-content-based technique to search, browse and retrieve relevant images from large-scale digital image collections.

1.3 Content Based Image Retrieval (CBIR)

The term Content-Based Image Retrieval (CBIR) seems to have originated in 1992, when it was used by T. Kato to describe experiments into automatic retrieval of images from a database, based on the colors and shapes present. Since then, the term has been used to describe the process of retrieving desired images from a large collection on the basis of syntactical image features.

Content-based image retrieval has become a prominent research topic because of the proliferation of video and image data in digital form. The main goal of CBIR resides in its efficiency during image indexing and retrieval, thereby reducing the need for human intervention in the indexing process. The computer must be able to retrieve images from a database without any human assumption on specific domain. The fundamental operation applied on the image databases are matching and determining whether the data is present or not. Matching is not expressive enough for multimedia data and database systems.

Various systems have been introduced for content-based image retrieval (CBIR) systems that operate in two phases: indexing and searching. In the indexing phase, each image of the database is represented using a set of image attribute, such as texture and layout. The extracted features are stored in a visual feature database. In the searching phase, when a user makes a query, a feature vector for the query is computed. Using a similarity criterion, this vector is compared to the vectors in the feature database. The image most similar to the query (or images for range query) is returned to the user. Visual feature extraction is the basis of any content-based image retrieval technique. Widely used features include color, texture, shape and spatial relationships.

Texture based retrieval

In general, matching of texture based image is carried out with the similarity between the areas of the images with similar texture. Various techniques have been used for measuring texture similarity is by calculating the relative brightness of selected pairs of pixels from each image. From these it is possible to compute some measures for the texture images such as the degree of contrast, coarseness, directionality, regularity or periodicity and randomness. Texture queries can be formulated in a similar manner to color image queries, by selecting examples of desired textures from a palette or by supplying a query image. The system then retrieves images with these texture measures that are close to the query image.

Edge based retrieval

The edges in an image are usually referred as abrupt changes in some physical properties, geometrical illumination and reflectivity. Mathematically, a discontinuity may be involved in the function representing physical properties. Various methods have been proposed to extract the specific features of edges. Once the edge map has been arrived from the query image, the edge features are extracted and stored in the feature database for the image retrieval. In order to improve the efficiency of image retrieval system with low-level features, edge features are extracted and included, since salient features are embedded in the edges.

Shape based retrieval

The ability to retrieve images based on shape is perhaps the most obvious requirement at the primitive level. Unlike texture, shape is a fairly well defined concept and there is considerable evidence that natural objects are primarily recognized by their shape. Queries are then answered by computing the same set of features for the query image and retrieving those stored images whose features are most closely match to the query.

Color based retrieval

Several methods for retrieving images on the basis of color have been described, but most of the methods use the same basic principle. Each image added to the collection is analyzed to compute a color histogram, which shows the proportion of each color pixels within the image. The color histogram for each image is then stored in the database. The matching process retrieves images whose color histograms are similar to the query image.

Semantic based retrieval

Semantic based retrieval is a high-level image retrieval system. In the semantic based retrieval technique, semantic meanings are used to retrieve relevant images. Typically, certain form of knowledge base is required in the semantic based retrieval systems. The ideal CBIR system from a user perspective would involve what is referred to as semantic retrieval, where the user makes a request like find pictures of dogs. This type of open ended task is very difficult for the computers to complete. Semantic analysis is also considered in the biometric system to recognize the objects.

2. RELATED WORKS

Ahonen et al., [1] proposed an efficient image representation based on local binary pattern texture features. The image is divided into several regions from which the LBP feature distributions are extracted and concatenated into an enhanced feature vector to be used as descriptor.

Felicitas et.al. [2] proposed a fuzzy index for edge evaluation without considering a binarization step. In order to process all detected edges, images are represented in their fuzzy form and all calculations are made with fuzzy set operators between the images to be compared. By using these metrics synthetic images will give better results and it is not used for real images.

Content Based Image Retrieval (CBIR) is a technique used for extracting relevant images from the image database based on the input query image. The most challenging aspect of CBIR is to bridge a gap between low-level feature and high-level features. In the early works, Query-By-Image-Content (QBIC) was the first CBIR system [3].

Heikkil et al.,[4] discussed an efficient texture-based method for modeling the background and detecting moving objects from a video sequence. Each pixel is modeled as a group of adaptive local binary pattern histograms that are calculated over a circular region around the pixel. The approach provides us with many advantages compared to the other methods. Experimental results clearly justify this model.

Huang et al., [5] developed a method based on accurate localization of representative points which is crucial to many analysis and synthesis problems. Active shape model is a powerful statistical tool for alignment. However, it suffers from variations of pose, illumination and expressions. To analyze the mechanism of active shape model, to realize the ability of normal profiles and to describe the local appearance pattern is very limited. For efficient appearance pattern representation, the local binary pattern is used and extended to describe the local patterns of key points.

Masily [6] developed this method which is very similar to that of LBP. The only difference is that vicinity pixels lie on an ellipse relating to the central pixel rather than on a circle.

Ojala et al., [7] used three standard approaches to automatic texture classification which make use of features based on the Fourier power spectrum, first-order statistics of gray level differences and second-order gray level statistics. Feature sets of these types, all designed analogously, and were used to classify two sets of terrain samples. It was found that the Fourier features generally performed more poorly, while the other feature sets all performed comparatively well.

The photo book system is a set of interactive tools for browsing and searching images [8]. It consists of three sub-books they are the appearance photo book, shape photo book and texture photo book, which can extract the shape and texture, respectively. Users can query for an image based on the corresponding features in each of the three sub-books or on a combination of different mechanisms with a text-based description.

Pooja et al. [9] developed a canny and Sobel edge detection algorithm for extracting the shape features from the images. After extracting the shape feature, the classified images are indexed and labeled for retrieval of the images from the smaller image database.

Rong et al. [10] describes that bridging the semantic gap between the low-level features and the high-level semantics is within the interface between the user and the system, other research direction is towards improving aspects of CBIR systems by finding the latent correlation between low-level visual features and high-level semantics and integrating them into a unified vector space model.

Rui. et al., [11] discussed a comprehensive survey of the technical achievements in the research area of image retrieval, especially content-based image retrieval, an area that has been so active and prosperous in the past few years. The survey covering the research aspects of the three fundamental bases of content-based image retrieval namely image feature representation and extraction, multidimensional indexing and system design. Furthermore, based on the state-of-the-art technology available now and the demand from real-world applications, open research issues are identified and future promising research directions are suggested.

Smeulders et al., [12] presented a review of 200 references in content-based image retrieval and the working conditions of content-based retrieval: patterns of use, types of pictures, the role of semantics and the sensory gap. This review focuses on image processing for retrieval sorted by color, texture and local geometry. Features for retrieval are discussed next, sorted by: accumulative and global features, salient points, object and shape features, signs and structural combinations thereof. Similarity of pictures and objects in pictures is reviewed for each of the feature types, in close connection to the types and means of feedback the user of the systems is capable of giving by interaction.

Smith et al., [13] discussed a digital image and video libraries require new algorithms for the automated extraction and indexing of salient image features. Texture features provide one important cue for the visual perception and discrimination of image content. They used this approach for automated content extraction that allows efficient database searching using texture features. The algorithm automatically extracts texture regions from image spatial-frequency data which are represented by binary texture feature vectors.

Zhao et al., [14] extended the LBP to the completed modeling of local binary patterns (CLBP), which is composed of the center gray level, sign components and magnitude components. The authors concluded that the CLBP has better texture feature extraction capabilities than the standard LBP.

3. Existing Methodology

The image retrieval includes several techniques such as filtering, feature extraction and classification of image.

3.1 Local Binary Pattern (LBP)

A Local binary pattern (LBP) is a type of feature used for classification in computer vision. LBP [8] was first described in 1994. It has since been found to be a powerful feature for texture classification based on the assumption that texture has locally two complementary aspects of a pattern and its strength. The basic version of the local binary pattern operator works in a 3 × 3 pixel block of an image. The pixels in this block are threshold by its center pixel value, multiplied by powers of two and then summed to obtain a label for the center pixel.

3.2 Improved Local Binary Pattern (ILBP)

Jin et al. [17] pointed out that LBP could miss the local structure information under some circumstances. For instance, LBP operator can only get 256 of all 511 patterns for a 3x3 neighborhood, as the central pixel is not considered. In order to obtain the complete information, they proposed an Improved LBP (ILBP) which compares all the pixels (including central pixel) with the mean of all the pixels in the kernel. Later ILBP was extended to the neighborhoods of any sizes instead of the original 3x3 [16].

3.3 Multi Block Local Binary Pattern (MBLBP)

Multi Block Local Binary Pattern is used to obtain texture pattern for every pixel by considering a local region of size 3 × 3, 9 × 9, 15 × 15 etc. with center pixel. Computation of MBLBP for 3 × 3 local region is equivalent to the ordinary LBP. Local region of other sizes can be decomposed into equally sized regions. Hence, the average sum of pixel intensity for every sub regions is calculated which is then threshold with the center region average value. MBLBP values are computed in a similar manner as in LBP which exhibits more distinctive features.

4. Proposed Methodology

The texture features are extracted from the input image. The texture feature extraction is an important process to make efficient retrieval. Though various models and methods are available, they are not sufficient for providing accuracy in retrieval process. The important steps involved in the proposed technique are identification and localization of block wise features of the image. The extraction of geometrical image features in local binary pattern. The proposed CS-LBP local binary pattern technique is experimented. There by a novel technique for image retrieval using texture feature is proposed.

4.1 Center Symmetric Local Binary Pattern

The recognition of object in PASCAL database. The original LBP was very long its feature is not robust on flat images. In this method, instead of comparing the gray level value of each pixel with the center pixel, the center symmetric pairs of pixels are compared. CS-LBP is closely related to gradient operator. It considers the grey level differences between pairs of opposite pixels in a neighborhood. So CS-LBP take advantage of both LBP and gradient based features.

4.2 Feature Extraction

The features are located to compute the feature sets for classification. Here five feature sets are calculated for feature extraction. The feature set 1 are contrast of the image, feature set 2 is correlation features, feature set 3 is energy features of an image, feature set 4 is entropy image features and feature set 5 is homogeneity features of the image.

Contrast Feature Set

Contrast measures how the values of the matrix are distributed and number of local changes reflecting the image clarity and texture of shadow depth. Large Contrast represents deeper texture. The feature set is generated with the contrast by the equation 3.9 for the image block. The feature set of the input image under analysis is represented as follows,

$$\text{Featureset}_{\text{contrast}} = \sum\sum (k-m)^2 V(k,m) \qquad ......(4.1)$$

Correlation Feature Set

The feature set is generated with the correlation feature of the blocks of the input image under analysis and is computed as follows,

$$\text{Featureset}_{\text{Correlation}} = \frac{\sum_{k,m} (k-\mu)(m-\mu) V(k,m)}{\sigma^2} \qquad .... (4.2)$$

Energy Feature Set

The feature set is consisting of a texture feature based on energy contributed by all image blocks. The energy computed by equation 3.8

$$\text{Featureset}_{\text{Energy}} = \sum_k \sum_m V(k,m)^2 \qquad ..... (4.3)$$

Entropy Feature Set

The feature set is generated with the entropy as a measure for all the image blocks. Entropy measures the randomness in the image texture. A minimum entropy value indicates that the co-occurrence matrix values are uniform. Then, the maximum entropy implies that the gray distribution in the image is random. The feature set of the input image under analysis is represented as follows,

$$\text{Featureset}_{\text{Entropy}} = \sum_k \sum_m V(k,m) \log V(k,m) \qquad ....(4.4)$$

Homogeneity Feature Set

The feature set is generated with the homogeneity measure for all the block images of the input image under analysis and computed as follows,

$$\text{Featureset}_{\text{Homogeneity}} = \sum_{k,m} \frac{V(k,m)}{1+|k-m|} \quad .....(4.5)$$

Where

V is co-occurence matrix and

(k, m) is gray-level value at the Coordinate

« = kV(k,m) (weighted pixel average)

± =weighted pixel variance

Finally the feature database is established to store the feature set of all the images available in IDB. The final feature set/vector is formed by the feature values derived by the equations 4.1 to 4.5 and represented as below

$$\text{Featureset}_{\text{CSLBPF}} = \left\{ \begin{array}{l} \text{Featureset}_{\text{Energy}}, \text{Featureset}_{\text{contrast}}, \\ \text{Featureset}_{\text{Entropy}}, \text{Featureset}_{\text{Correlation}}, \\ \text{Featureset}_{\text{Homogeneity}} \end{array} \right\} \quad .... (4.6)$$

5. ALGORITHM

The process of the image retrieval takes place in two phases and defined as algorithm I and II.

Algorithm I

// generating feature sets //

Input: Input image of size (M x N) from IDB.
Output: Feature database.

Begin

Step1: *Read an image from the image database (IDB) of size.*
Step2: *Partitioning the input image into k non-overlapped blocks, each of size (n x n).*
Step 3: *Perform procedure_ threshold ( )*
Step4: *Repeat Step 2 through step3 for all blocks of the input image.*
Step5: *Generate feature set as mentioned in equation 4.6.*
Step6: *Store the feature set into the feature database.*
Step7: *Repeat Step 1 through Step 6 for all the images in IDB.*
End

Algorithm II

//Retrieving top *m* relevant images corresponding to the target image //

Input: Target Image (T_i) of size (M x N) and images from IDB
Output: List the top m relevant images corresponding to the target image.

Step1: *Read the Target image (T_i).*
Step2: *Partitioning the Target image by k non-overlapped blocks of size (n × n)*
Step3: *Perform procedure threshold_feature ( )*
Step4: *Repeat Step 2 through Step 3 for all blocks of the target image.*
Step5: *Generate feature set as mentioned in equation 4.6.*
Step6: *Perform* ***procedure Euclidean_dist ( )***

{

Compute the distance measures for number of images from IDB with the target image using the equation 4.7.

}

Step7: *Retrieve the top m relevant images from the image database.*
End

Procedure _ threshold ( )

{

Step 1: Input M, N //size of input image
Step 2: Read the image with even row and column
Step 3: Convert gray scale values into matrix.
Step 4: Apply sorting for an array by using step 3.
Step5: Find out the middle gray scale values of lower range and upper range.
Step6: Find out the average value of middle gray scale values and take whole number in sorted array and also known as threshold value.
Step7: Convert binary matrix by using threshold value.
Step8: Repeat step 3 to step 7 for all images in the database.
Step9: Return

}

6. Experiments and Results

The proposed feature extraction is experimented with the images collected from the standard database CORAL consisting of 1000 images as shown in fig.6.1 and generated feature set images considered for this experiment are of the size.

Fig.6.1 Sample Images

Euclidean Distance

To find the similarity measures between the images, various metrics are used to measure the distance between features of the images. Some of the well known distance metrics used in for image retrieval is presented below. The Euclidean Distance is calculated as below

$$d_E(x_1, x_2) = \sqrt{\sum_{i=1}^{i=n} \left(x_1(i) - x_2(i)\right)^2} \quad \ldots (4.7)$$

Where x1(i) is the feature vector of input image i and x2(i) is the feature vector of the target image i in the image database.

In the texture based image retrieval system Euclidean distance is used to find the distance between the features vectors of the target image and each of the image in the image database. The difference between two images can be expressed as the distance'd' between the respective feature vectors Fs(Ii) and Fs(It). From the given input image Ii and the target image It the Euclidean Distance is calculated as,

$$d_E\left(Fs(I_i),Fs(I_t)\right)=\sqrt{\sum_{i=1}^{i=n}\left(Fs(I_i)-Fs(I_t)\right)^2} \quad \ldots (4.8)$$

Where Fs(Ii) is the feature set of the input image Ii, Fs(It) is the n-dimensional feature vector of the target image It respectively.

The performance of a retrieval system can be measured in terms of its recall and precision.

$$\text{Recall} = \frac{\text{Number of relevant images retrieved}}{\text{Total Number of relevant images}} \quad .....(4.9)$$

$$\text{Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Total Number of images retrieved}} \quad .....(4.10)$$

Category	LBP	ILBP	MBLBP	Proposed CSLBP
Buses	77.14	77.10	81.56	82.57
Dinosaurs	78.02	77.93	79.31	83.29
Elephants	50.74	62.96	68.55	68.94
Flowers	80.56	84.91	69.90	72.71

Table 6.1 Comparison Results in terms of Precision

From the above Table 6.1 shows the precision for the proposed technique and existing technique respectively. Hence, the proposed technique is also efficient for image retrieval.

Category	LBP	ILBP	MBLBP	Proposed CSLBP
Buses	71.20	73.17	75.87	80.27
Dinosaurs	80.34	82.28	83.38	85.59
Elephants	28.81	31.36	31.21	32.01
Flowers	64.35	69.13	70.56	71.08

Table 6.2 Comparison Results in terms of Recall

From the above Table 6.2 shows the recall for the proposed technique and existing technique respectively. Hence, the proposed technique is also efficient for image retrieval.

Model	Retrieval Rate
LBP	72.61
ILBP	76.97
MBLBP	75.33
Enhanced CSLBP	78.87

Table.6.3 Image Retrieval Rate

The Table 6.3 shows that recognition percentage of the query images with CSLBP. The experimental results show that the CSLBP produces higher retrieval accuracy of 78.87%. The performance was evaluated using the Euclidean distance classification is analyzed and proposed CSLBP method is better for image retrieval.

7. Conclusion

In this paper, enhanced centre symmetric local binary pattern based image retrieval with block wise texture features has been proposed. The feature vector of the images in IDB is generated using the proposed technique and a feature database is established. The Euclidean distance has been computed to measure the similarity between the images based on the distance the images are retrieved. The CSLBP method produces better retrieval results with 78.87% accuracy compared with existing methods where Local Binary Pattern, Improved Local Binary Pattern and Multi-block Local Binary Pattern. The proposed CSLBP is experimented and compared with existing models the proposed technique gives better results.

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