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DRLTP Based Object Recognition for Image Retrieval Systems

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ABSTRACT: The project presents the robust object recognition using edge and texture feature extraction. The system proposes new approach in extension with local ternary pattern called DRLTP. By using these methods, the category recognition system will be developed for application to image retrieval. The category recognition is to classify an object into one of several predefined categories. The discriminative robust local ternary pattern (DRLTP) is used for different object texture and edge contour feature extraction process. It is robust to illumination and contrast variations as it only considers the signs of the pixel differences. The proposed features retain the contrast information of image patterns. They contain both edge and texture information which is desirable for object recognition. The DRLTP discriminates an object like the object surface texture and the object shape formed by its boundary. The boundary often shows much higher contrast between the object and the background than the surface texture. Differentiating the boundary from the surface texture brings additional discriminatory information because the boundary contains the shape information. These features are useful to distinguish the maximum number of samples accurately and it is matched with already stored image samples for similar category classification. The simulated results will be shown that used discriminative robust local ternary pattern has better discriminatory power and recognition accuracy compared with prior approaches.

KEYWORDS: Test image, Pre-processing, Feature Extraction, Database Training, Classification, Parameter analysis.

I. INTRODUCTION

The need for efficient content-based image retrieval has increased tremendously in many application areas such as biomedicine, military, commerce, education, and web image classification and searching. Currently, rapid and effective searching for desired images from large-scale image database becomes an important and challenging research topic [5,6]. Content-based Image Retrieval (CBIR) technology overcomes the defects of traditional text-based image retrieval technology, such as heavy workload and strong subjectivity. It makes full use of image content features (color, texture, shape, etc.), which are analyzed and extracted automatically by computer to achieve the effective retrieval [7]. Using a single feature for image retrieval cannot be a good solution for the accuracy and efficiency. High-dimensional feature will reduce the query efficiency; low-dimensional feature will reduce query accuracy, so it may be a better way category recognition and detection are 2 parts of object recognition. The objective of category recognition is to classify an object into one of several predefined categories. The goal of detection is to distinguish objects from the background. There are various object recognition challenges. Typically, objects have to be detected against cluttered, noisy backgrounds and other objects under different illumination and contrast environments. Proper feature representation is a crucial step in an object recognition system as it improves performance by discriminating the object from the background or other objects in different lightings and scenarios.

Many applications require simple methods for comparing pairs of images based on their overall appearance. For example, a user may wish to retrieve all images similar to a given image from a large database of images. Color histograms [10, 11] are a popular solution to this problem, the histogram describes the gray-level or color distribution for a given image, they are computationally efficient, but generally insensitive to small changes in camera position. Color histograms also have some limitations. A color histogram provides no spatial information; it merely describes which colors are present in the image, and in what quantities. In addition, color histograms are sensitive to both compression artifacts and changes in overall image brightness. For the design of histogram based method the main things we require are appropriate color space, a color quantization scheme, a histogram representation, and a similarity

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metric [12]. A digital image in this context is a set of pixels. Each pixel represents a color. Colors can be represented using different color spaces depending on the standards used by the researcher or depending on the application such as Red-Green-Blue (RGB), Hue-Saturation-Value (HSV), YIQ or YUV etc. [13]

This kind of a textual-based image retrieval system always suffers from two problems: high priced manual annotation and inaccurate and inconsistent automated annotation. On the other hand, the cost associated with manual annotation is prohibitive with regards to a large-scale data set [8]. So the retrieval methods based on text or keywords for the digital multimedia apparently can't meet the demand that human being get multimedia information exactly.

II. RELATED WORK

Invariant Color Histogram Theo Gevers et al., (2004) proposed a robust histogram from photometric color invariants (invariant to illumination, shading, highlights and inter reflections) for object recognition. The histograms are computed by the variable kernel density estimators. The variable kernel density estimator is given in equation (5) Here, kernel K is a function satisfying . The kernel centered on Xi, has its own scale parameter. For color images, the scale parameter is a function of the RGB-values and the color space transform. This histogram is invariant to illumination, shading, highlights and reflections.

Dominant Color In region based image retrieval, the regions are segmented and the features are extracted for the regions. Due to the inaccuracy of the segmentation, the average color of a segmented region may be different from that of the original region. To obtain the dominant color of the image, first the histogram is obtained and then the bin with the maximum size is taken as the dominant color of the region. When the segmented region does not have a homogeneous color, then, the average color will not be a good choice for the color feature (Ying Liu, et al., 2008).

Texture Features The identification of specific textures in an image is achieved primarily by modelling texture as a two-dimensional gray level variation. Textures are characterized by differences in brightness with high frequencies in the image spectrum. They are useful in distinguishing between areas of images with similar color (such as sky and sea, or water, grass). A variety of methods has been used for measuring texture similarity; the best- established depend on comparing values of what are well-known as second-order statistics estimated from query and stored images. Essentially these estimate the relative brightness of picked pairs of pixels from each image. From these it is possible to measures the image texture such as contrast, coarseness, directionality and regularity [7] or periodicity, directionality and randomness [8].

III. PROPOSED ALGORITHM

We have proposed a novel edge-texture feature for recognition that provides discrimination which is Discriminative Robust Local Ternary Pattern [1] which helps in discrimination of the local structures that Robust Local Ternary Pattern seems to misrepresent. Also, the proposed features tend to retain the contrast information of the image patterns. They comprises of both edge and texture information which seem desirable for object recognition.

An object has 2 distinct states for differentiation from other objects - the object surface texture and the object shape formed by its boundary. The boundary often shows much higher contrast between the object and the background than the surface texture. Differentiating the boundary from the surface texture brings additional discriminatory information because the boundary contains the shape information. Local Ternary Pattern does not provide differentiation between a weak contrast local pattern and a strong contrast pattern. It mainly captures the object texture information. The histogramming of LTP codes only considers the frequencies of the codes i.e. the weight for each code is the same. This makes it difficult to provide differentiation between a weak contrast and a strong contrast local pattern. To mitigate this, we propose to fuse edge and texture information together in a single representation by further modifying the way the codes can be histogrammed. Figure 1 shows Block Diagram representation.

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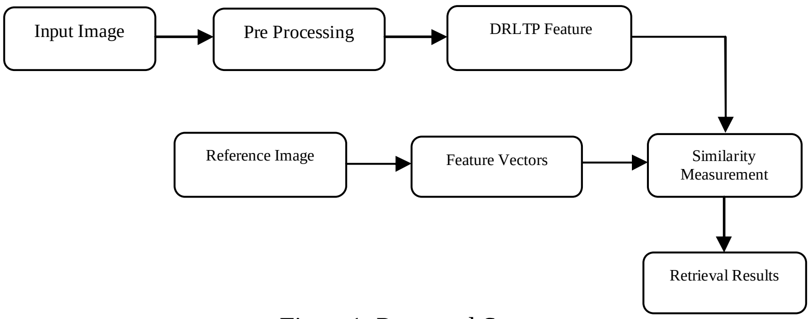

Figure1. Proposed System

The LTP code [1] at (x, y) is calculated as follows:

$$LTP_{x,y} = \sum_{b=0}^{B-1} s'\left(p_b - p_c\right)3^b \quad (1)$$

$$s'(z) = \begin{cases} 1 & z \geq T \\ 0 & -T < z < T \\ -1 & z \leq -T \end{cases}$$

LTP code is divided into "upper" and "lower" LBP codes. The ULBP [1] and LLBP [1] is calculated as follows:

$$ULBP = \sum_{b=0}^{B-1} f(p_b - p_c)\,2^b \qquad (2)$$

$$f(z) = \begin{cases} 1, & z \geq T \\ 0, & \text{otherwise} \end{cases}$$

$$LLBP = \sum_{b=0}^{B-1} f'(p_b - p_c)2^b \qquad (3)$$

$$f(z) = \begin{cases} 1, & z \leq -T \\ x, & \text{otherwise} \end{cases}$$

By doing so, the dimensionality of the feature is reduced from 6561 bins to 512 bins. Using uniform LBP code representation, the number of bins is further reduced to 118 bins. The RLTP code is divided into "upper" and "lower" LBP codes. The URLBP [1] is calculated as follows:

$$URLBP = \sum_{b=0}^{B-1} h(RLTP_{x,y,b})\,2^b \qquad (4)$$

$$h(z) = \begin{cases} 1, & z = 0 \\ 0, & \text{othrewise} \end{cases}$$

Where RLTPx,y,b represents the RLTP state value at the bth location. The "lower" code, LRLBP [1] is computed as follows:

$$LRLBP = \sum_{b=0}^{B-1} h'(RLTP_{x,y,b})2^b \qquad (5)$$

$$h'(z) = \begin{cases} 1, & z = -1 \\ 0, & \text{otherwise} \end{cases}$$

Here, LRLBP only has 7 bits as the state at (B-1)th location of RLTP is always 0 or 1. Consider a LTP histogram for M×N image block. The value of the kth bin of the weighted LTP histogram [1] is as follows:

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$$h_{ltp}(k) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \omega_{x,y}\,\delta(LTP_{x,y,}k) \qquad (6)$$

It is not difficult to see that the RLTP histogram [1] can be simply created from above equation as follows:

$$h_{rltp}(k) = \begin{cases} h_{ltp}(k), & k = 0 \\ h_{ltp}(k) + h_{ltp}(-k), & 0 < k < \dfrac{3^B + 1}{2} \end{cases} (7)$$

Where $h_{rltp}(k)$ is the kth bin value of RLTP. we consider the absolute difference between the bins representing a LTP code and its inverted representation to form Difference of LTP [1] histogram as follows:

$$h_{dltp}(k) = |h_{ltp}(k) - h_{ltp}(-k)|, \quad 0 < k < \frac{3^B+1}{2} \qquad (8)$$

Where $h_{dltp}(k)$ is the kth bin value of DLTP. RLTP and DLTP are concatenated to form Discriminative Robust LTP [1] as follows:

$$h_{drltp}(l) = \begin{cases} h_{rltp}(l), & 0 \le l < \dfrac{3^B + 1}{2} \\ h_{dltp}\left(l - \dfrac{3^B + 1}{2}\right), & \dfrac{3^B + 1}{2} \le l < 3^B \end{cases}$$

DRLTP produces different features for the structures. It also resolves the issue of brightness reversal of object and background. Consider the ULBP and LLBP codes for an image block. The value of the sth bin, 0 < s < 2B, of URLBP can be generated from ULBP [1] and LLBP [1] codes as follows:

$$h_{urlbp}(s) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \omega_{x,y}\delta(\max(ULBP, LLBP), s) \quad (9)$$

$$h_{lrltp}(t) = \sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \omega_{x,y}\delta(\min(ULBP, LLBP), t) \quad (10)$$

The split LBP histograms, UDLBP and LDLBP, for DLTP can also be generated from the ULBP and LLBP codes. For every LTP code whose ULBP and LLBP representations are swapped, the corresponding values of UDLBP and LDLBP bins are decremented by 1 accordingly. Otherwise, the bins are incremented by 1. The sth bin value, 0 < s < 2B, of UDLBP [1] is expressed as follows:

$$h_{udlbp}(s) = \left|\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} \omega_{x,y}\delta'(\lambda(ULBP, LLBP), s)\right| \quad (11)$$

$$\lambda(p,q) = \begin{cases} p, & p > q \\ -q, & p < q \end{cases}$$

$$\delta'(m,n) = \begin{cases} 1 & m = n, m > 0 \\ -1 & |m| = n, m > 0 \\ 0 & \text{otherwise} \end{cases}$$

The function λ (•) determines whether the ULBP and LLBP codes are being swapped. If a swap occurs, the negative maximum code is assigned to the result. The function $\delta'(\bullet)$ checks the value output from λ with s. If the value is positive and matches s, the sth bin value is incremented. Otherwise, it is decremented. The tth bin value of LDLBP [1] is determined as follows:

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$$h_{ldlbp}(t) = \left| \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} \omega_{x,y}(\lambda'(ULBP, LLBP), t) \right| \quad (12)$$

$$\lambda'(p,q) = \begin{cases} q, & p \geq q \\ -p, & p < q \end{cases}$$

$$\delta''(m,n) = \begin{cases} 1 & m = n, m \geq 0 \\ -1 & |m| = n, m, 0 \\ 0 & \text{otherwise} \end{cases}$$

The function $\lambda'(\bullet)$ determines whether the ULBP and LLBP codes are being swapped. If a swap occurs, the negative minimum code is assigned to the result. The function $\delta''(\bullet)$ checks the value output from λ' with t. If the value is zero or positive and matches t, the tth bin value is incremented. Otherwise, it is decremented. The URLBP, LRLBP, UDLBP and LDLB histograms are then concatenated to form DRLTP.

Euclidean Distance Classifier: Here the Euclidean distance classifier is used to classify the different objects. It is a minimum distance classifier [2]. The minimum distance classifier is used to classify unknown image data to classes which minimize the distance between the image data and the class in multi-feature space. Using the given set of values minimum distance can be found. In testing, for every expression computation of Euclidean distance (ED) is done between new image (testing) Eigenvector and Eigen subspaces, to find the input image expression classification based on minimum Euclidean distance is done The formula for the Euclidean distance [2] is given by,

$$ED = \sqrt{\sum (x_2 - x_1)^2} \quad (13)$$

Where, x2 stands for query image feature and x1 stands for corresponding feature vector database.

IV PARAMETER ANALYSIS:

The System saves and presents a sequence of images ranked in decreasing order of similarity or with the minimum distances is returned to the user. To evaluate the efficiency of the proposed system precision [2] and recall [2] rates are to be calculated where,

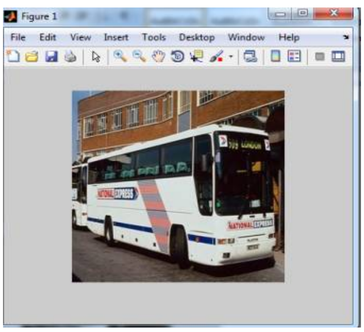
$$\text{Precision} = (IR / IT) \quad (14)$$

IR=No Of Relevance Images Retrieved, IT=Total Number of Images Retrieved on the screen

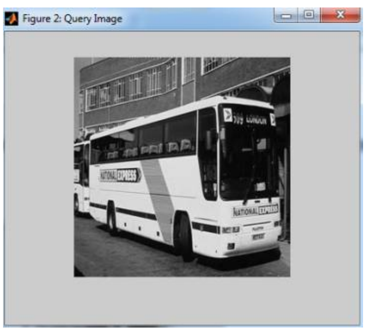
$$\text{Recall} = IR / IRB \quad (15)$$

IR=No Of Relevance Images Retrieved, IRB=Total Number of relevant Images in the database

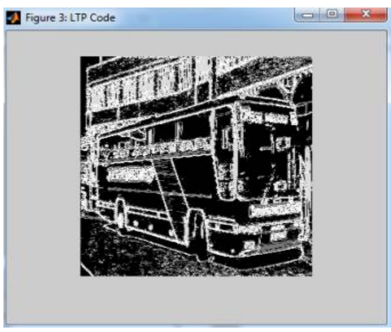
V. RESULTS



a) input image



b) pre-processed image



c) LTP

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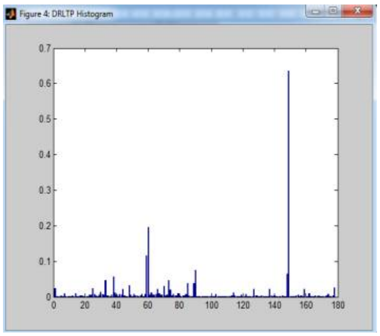
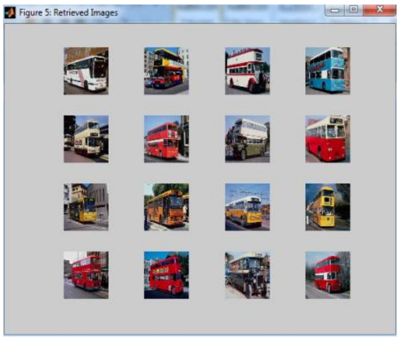
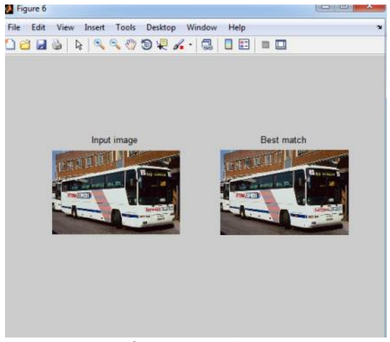


d) DRLTP histogram

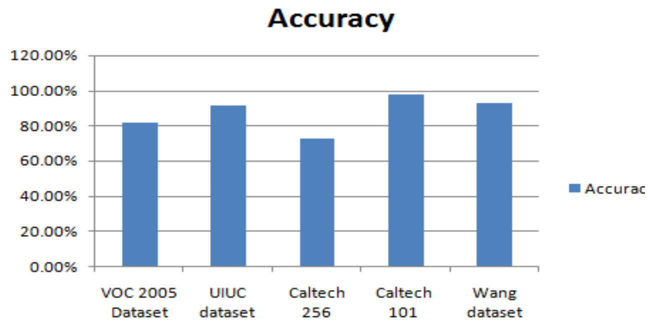


e) DRLTP Retrieved images



f) Best match

We had applied various dataset to our proposed method and calculated accuracy, below we had tabulated in detail.



DRLTP		
S.no	**Database**	**Accuracy**
1	VOC 2005 Dataset	81.91%
2	UIUC dataset	91.64%
3	Caltech 256	72.51%
4	Caltech 101	97.91%
5	Wang dataset	92.69%

VI. CONCLUSION

In this system features extracted are found robust to image variations that are caused due to the intensity inversion and they also provide discrimination to the image structures which are within the histogram block. The Interclass variations are also reduced. The Proposed system provides efficient recognition and helps to alleviate the issues of Local Ternary Pattern, Robust Local Ternary pattern. And our system is giving more relevant image extraction accuracy then existing system. Also we had applied various dataset to our proposed method and calculated accuracy.

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