ISSN: 2349-6495(P) | 2456-1908(O)

A Fast Object Recognition Using Edge Texture Analysis for Image Retrieval

S.S.Sarmila, P.Shyamala

Department of Computer Science and Engineering, K.L.N. College of Engineering, Siva Gangai, Tamil Nadu, India

Abstract— *A Robust Object Recognition for Content Based Image Retrieval (CBIR) based on Discriminative Robust Local Binary Pattern (DRLBP) and Local Ternary Pattern (LTP) analysis. The Robust Object Recognition using edge and texture feature extraction. The extension of Local Binary Pattern (LBP) is called DRLBP. 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. LBP is defined as an ordered set of binary comparisons of pixel intensities between the center pixel and its eight surrounding pixels .DRLBP features identifying the contrast information of image patterns. The proposed features preserve the contrast information of image patterns. The DRLBP discriminates an object like the object surface texture and the object shape formed by its boundary.*

Keywords— Content Based Image Retrieval (CBIR), Local Binary Pattern (LBP), Discriminative Robust Local Binary Pattern (DRLBP), Local Ternary Pattern (LTP).

I. INTRODUCTION

Image retrieval techniques are useful in many image-processing applications. Content-based image retrieval (CBIR) systems work with whole images and searching is based on comparison of the query. General techniques for image retrieval are color, texture and shape. These techniques are applied to get an image from the image database.

They are not concerned with the various resolutions of the images, size and spatial color distribution. Hence all these methods are not appropriate to the art image retrieval. Moreover shape based retrievals are useful only in the limited domain. The content and metadata based system gives images using an effective image retrieval technique. Many other image retrieval systems use global features like color, shape and texture. But the prior results say there are too many false positives while using those global features to search for similar images. Hence we give the new view of image retrieval system using both content and metadata.

There will be multitude of objects in images and it can be recognized by a normal human eye with little effort, still the image of the objects may vary somewhat in different viewpoints. It is a fact that it varies in different sizes and scales or even when they are translated or rotated. If the objects are partially obstructed, it can be easily recognized. It is a risky task when it comes to computer vision. Different approaches to the idea have been implemented over several decades. Category recognition and detection are the two parts of the object recognition. The function of category recognition is to classify an object into one of several categories which are already defined. The necessity of detection is that it differentiates objects from the background. There are various object recognition difficulties. Basically, the objects have to be recognized against cluttered, noisy environments or backgrounds and also it has to detect

other objects various contrast and illumination environments. Accurate feature representation is an important stage in an object recognition system as it improves performance by differentiating the object from the background or other objects in various lightings and scenarios.

II. RELATED WORK

Object recognition features are categorized into two groups- sparse and dense representations. For sparse feature representations, interest-point detectors are used to identify structures such as corners and blobs on the object. A feature is created for the image patch around each point. Popular feature representations include Scale-Invariant Feature Transform(SIFT), Speeded Up Robust Feature , Local Steering Kernel Principal Curvature-Based Regions, Region Self-Similarity features Sparse Color and the sparse parts-based representation.

Dense feature representations, which are extracted at fixed locations densely in a detection window, are gaining popularity as they describe objects richly compared to sparse feature representations. Various feature representations such as Wavelet Haar-like features Histogram of Oriented Gradients (HOG), Extended Histogram of Gradients Feature Context, Local Binary Pattern(LBP), Local Ternary Pattern (LTP),Geometric-blur and Local Edge Orientation Histograms have been proposed over recent years. Dense SIFT has also been proposed to alleviate the sparse representation problems.

ISSN: 2349-6495(P) | 2456-1908(O)

Junjie Cai [1] proposed model is a new attribute-assisted reranking method based on hyper graph learning. We first train several classifiers for all the pre-defined attributes and each image is represented by attribute feature consisting of the responses from these classifiers. Different from the existing methods, a hyper graph is then used to model the relationship between images by integrating low-level features and attribute features.

Gulfishan Firdose Ahmed[20]: The image retrieval that is based on artificial notes labels images by using text firstly, in fact it has already changed image retrieval into traditional keywords retrieval. There are two problems remain in this method. On the one hand, it brings too heavy workload. On the other hand, it still remains subjectivity and uncertainty. Because the image retrieval that is based on artificial notes still remains insufficiency

Rasika Raikar [21]:A proposed model is edge-texture feature for recognition that provides discrimination which is Discriminative Robust Local Binary Pattern and Local Ternary Pattern. Discriminative Robust Local Binary Pattern and Local Ternary Pattern help in discrimination of the local structures that Robust Local Binary 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.

Amit Satpathy[22]: A propose two sets of novel edge-texture Features, Discriminative Robust LBP (DRLBP) and LTP. The proposed features solve the issues of LBP, LTP and RLBP.They alleviate the intensity reversal problem of object and back ground. Furthermore, DRLBP discriminates local structures that RLBP misrepresent. In addition, the proposed features retain the contrast information of image patterns. They contain both edge and texture information which is desirable for object recognition.

III. PROPOSED SYSTEM

An object has mainly two separate cues for discriminating from other objects. And the two cues are namely the object surface texture and the object shape. The object shape is formed by its boundary. Since the boundary provide higher contrast between the object and the background than the surface texture, the boundary is very essential. Additional discriminatory information can be bought by differentiating the boundary from the surface texture, this is because the shape information is contained in the boundary. The histogramming of LBP codes only checks the frequencies of the codes instead of the weight of the code. Also all the codes have same weight. This makes it very difficult to discriminate

a weak contrast local pattern and a strong contrast one. To compensate this, edge and texture information is fused and represented as a single by modifying the way the codes are histogrammed.

The primary goal of the research work is to reduce the computation time and user interaction. The conventional Content Based Image Retrieval (CBIR) systems also display the large amount of results at the end of the process this will drove the user to spend more time to analyze the output images. In the proposed method it was computing texture feature and color feature for compute the similarity between query and database images. This integrated approach will reduce the output results to a certain levels based on the user threshold value.

The secondary goal is to reduce semantic gap between high level concepts and low level features. Generally the content based image retrieval systems compute similarity between the query image and the database images. Hence there might be chances for unexpected results at the end the retrieval process. The novel clustering technique cluster the output images and select one representative image from each clusters.

A third goal is to evaluate their performance with regard to speed and accuracy. These properties were chosen because they have the greatest impact on the implementation effort.

A final goal has been to design and implement an algorithm. This should be done in high-level language or Matlab. The source code should be easy to understand so that it can serve as a reference on the standard for designers that need to implement real-time motion detection.

Advantages:

- Visual features, such as color, texture, and shape information, of images are extracted automatically
- Similarities of images are based on the distances between features
- Robust Illumination Changes with Low Complexity and Retain Contrast Information.

IV. METHODOLOGY

A.PREPROCESSING:

Each image added to the collection is analyzed to compute a color histogram, which shows the proportion of pixels of each color within the image. The color histogram for each image is then stored in the database. At search time, the user can either specify the desired proportion of each color (75% olive green and 25% red, for example), or submit an example image from which a color histogram is calculated.

B.RGB to Gray Scale CONVERSION:

Conversion from GRAY SCALE space to RGB space is more complex. And, given to the nature of the hue information, we will have a different formula for each sector of the color triangle.

ISSN: 2349-6495(P) | 2456-1908(O)

C.FEATURE EXTRACTION AND ANALYSIS

There are several distance formulas for measuring the similarity of color histograms. In general, the techniques for comparing probability distributions, such as the kolmogoroff-smirnov test are not appropriate histograms for color. This is because visual perception determines similarity rather than closeness of the probability distributions.

V. IMPLEMENTATION

LBP ALGORITHM:

```
lbpout = zeros (max_row, max_col);
for i = 1:max_row
 for j = 1:max_col
A = Cinp(i:i+L-1, j:j+L-1);
 cA= Cinp(i:i+L-1, j:j+L-1);
 dA = A-A(C,C);
 dA(dA>=0) = 1;
 dA(dA<0)  = 0;
lbpout(i,j) = dA(1,1) + dA(1,C)*2 +            dA(1,L)*4
+ dA(C,L)*8 + dA(L,L)*16 + dA(L,C)*32 + dA(L,1)*64
+ dA(C,1)*128;
 end;
 end;
```

DRLBP ALGORITHM:

```
ii=1:1:2^(B-1)
Hrlbp(ii) = hlbp (ii)+hlbp((2^B)-1-ii);
hdlbp(ii) = abs(hlbp(ii)-hlbp((2^B)-1-ii));
end
for jj=1:1:Nbins
if (jj<=2^(B-1))
hdrlbp (jj) = hrlbp(jj);
else
hdrlbp(jj) = hdlbp (jj-2^(B-1));
end
end
mbins = drlbpmap.Mbins;
drmap = drlbpmap.map_table;
for k=1:1:mbin;
bcor = find(drmap==k-1);
drlbp_h (k) = sum (hdrlbp (bcor));
End
drlbp_nh = drlbp_h. /sum (drlbp_h);
Figure ('Name','LBP Code','Menu Bar','none');
Imshow (lbpout,[]);
figure('Name','DRLBP Histogram','Menu Bar','none');
Bar (drlbp_nh,0.5);
```

LTP ALGORITHM:

```
load Rfeatures;
Qfeature = drlbp_nh(:);
```

VI. PERFORMANCE EVALUATION

A.SIMILARITY MEASUREMENT:

$$d(h,g) = (h-g)^t A(h-g)$$

The cross distance formula considers the cross-correlation between histogram bins based on the perceptual similarity of the colors represented by the bins. And the set of all cross-correlation values are represented by a matrix A, which is called a similarity matrix.

B.PERFORMANCE ANALYSIS:

The Performance of retrieval result is measured by Precision and Recall.

$$\text{Precision} = \frac{\text{Number of Relevant images Retrived}}{\text{Total number of images Retrived}}$$

$$\text{Recall} = \frac{\text{Number of Relavant images Retrived}}{\text{Total number of relevant images in database}}$$

The precision measures the hit-rate that the class of the retrieved images is the same as that of input reference image from the whole database. The recall measures the capability of finding the images with the same class from the whole class of images in the database. The effective retrieval system has the highest recall and precision rates.

Recall Rate

$Rec = Rp/20$

Rp is represent Number of images retrieved positive.

Precision Rate

$Pre = Rp/N$

N is represent the total no of retrieved Images.

VII. RESULTS AND DISCUSSION

Mat lab 7 is used to find out the features extracted by using the techniques DRLBP, DRLTP and Curvelet transform. Performance of the system is evaluated by using two parameters. They are namely precision rate and recall rate. The number of relevant images retrieved to that of the total images retrieved is defined as the precision rate [3]. Similarly recall rate can also be defined. It is the total number of relevant images retrieved to that of the total number of relevant images. The findings of the proposed method is as follows.Fig 3 shows the query image. It is this image which is considered for feature extraction.The techniques are carried out and their corresponding histograms are plotted.

The diagram shows the DRLBP and DRLTP histograms respectively. It is observed that different images are obtained at the time of retrieval. The number of images retrieved is shown in table 1. Analyzing table 1 it is clear that the LBP, LTP, RLBP, RLTP shows comparatively less number of images retrieved. Whereas in the case of DRLBP and DRLTP much more similar images are obtained. 11 to 12 images are retrieved from the group of image.

Fig.1: Input image

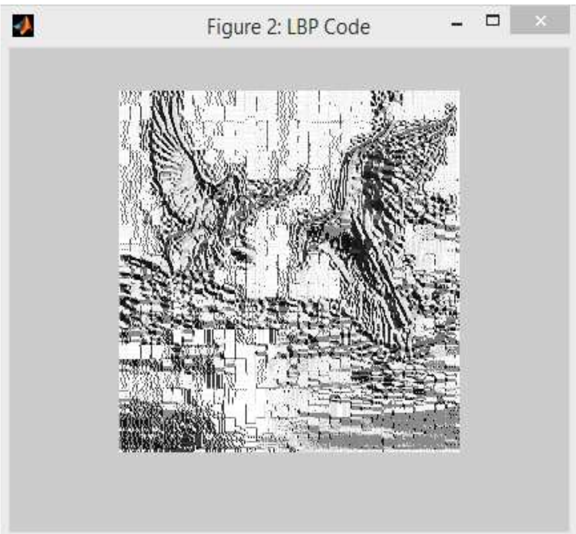

Fig.2: Gray scale mined input image

The Normalised DRLBP Histogram measures taken between the extracted features of the input image and that of all the sample images in the database 16 images are retrieved based on the highest similarity.

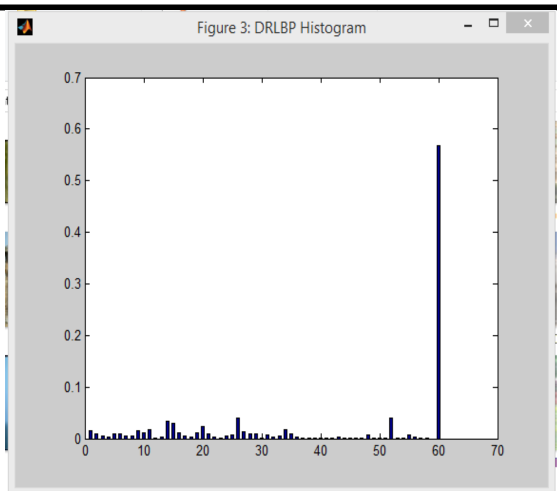

Fig.3:Discriminative Robust Local Binary Pattern Histogram

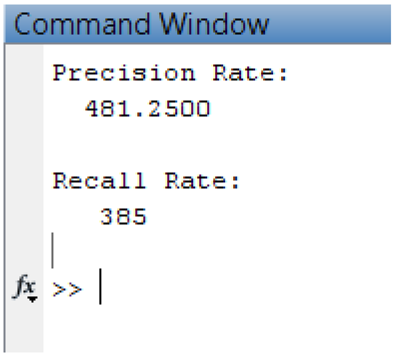

Fig.4:The command window in matlab for precision rate and recall rate

Table 1 shows the comparison of all techniques. Table displays the total number similar images obtained, precision rate and recall rate .DRLBP and DRLTP techniques shows 11 and 12 images retrieved from reference images.

The transform, similar images are obtained indicating better efficiency. The performance parameters are obtained by manually entering the number of retrieved images. And hence the output is obtained in commend window. The outputs in command window is plotted in the table 1.

Table.1:The value for the retrieved images

NUMBER OF RETRIVED IMAGES	PRECISION RATE	RECALL RATE	TEST IAMGES
56	350	280	MOUNTAIN
67	418.25	335	BUTTERFLY
61	381.25	338.88	PLANE
77	481.20	427.77	HORSE
80	500	400	BULIDING

For the purpose of analysis user is prompted again to give in the number of true positives. Using this number performance of the algorithm is analyzed.The measured performance parameters such as precision and recall rate are displayed on command window.

VIII. CONCLUSION

The project presents the robust object recognition using edge and texture feature extraction. The system proposes new approach in extension with local binary pattern and ternary pattern called DRLBP and 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 binary pattern (DRLBP) is used for different object texture and edge contour feature extraction process. With the different efficient methods and techniques used here it helps to retrieve all the similar images corresponding to the input image given in a successful way.

REFERENCES

[1] Junjie Cai,Zheng-Jun Z"ha,Meng Wang, Shiliang Zhang, and Qi Tian (2015),"An Attribute-Assisted Reranking Model for Web Image Search", IEEE transactions on image processing, vol. 24, no. 1,

[2] A. Fernández, M.Álvarez, and F. Bianconi,(2012) "Texture descriptionthrough histograms of equivalent patterns," J. Math. Imag. Vis., vol. 45,no. 1, pp. 1–27.

[3] T. Ahonen, A. Hadid, and M. Pietikainen,(2014) "Face description with local binary patterns: Application to face recognition," IEEE Trans. PatternAnal. Mach. Intell., vol. 28, no. 12, pp. 2037–2041, Dec.

[4] A. Hadid,(2014) "The local binary pattern approach and its applications toface analysis," in Proc. 1st Workshops Image Process. Theory, ToolsAppl., Nov. pp. 1–9.

[5] S. Liao, M. Law, and A. Chung,(2011"Dominant local binary patterns for textureclassification," IEEE Trans. Image Process., vol. 18, no. 5,pp. 1107–1118, May.

[6] S.Agarwal,A.Awan, and D. Roth,(2011) "Learning to detect objects in imagesvia a sparse, part-based representation," IEEE Trans. Pattern Anal. Mach.Intell., vol. 26, no. 11, pp. 1475–1490.

[7] H.Bay, A. Ess, T. Tuytelaars, and L. J. V.Gool,(2010) "Speeded-up robustfeatures (surf)," Comput. Vis. Image Understand., vol. 110, no. 3,pp. 346–359.

[8] O.Boiman, E. Shechtman, and M. Irani,(2010) "In defense of nearest-neighborbased image classification," in Proc. IEEE Int. Conf. Comput. Vis.Pattern Recognit., Jun. 2008, pp. 1–8.

[9] P.Brodatz,(2010) "Textures: A Photographic Album for Artists and Designers".New York, NY, USA: Dover Publications.

[10] B.Caputo,E. Hayman, and P. Mallikarjuna,(2008) "Class-specific materialcategorisation," in Proc. IEEE Int. Conf. Comput. Vis., vol. 2,pp. 1597–1604.

[11] J.Chen et al., (2010) "WLD: A robust local image descriptor," IEEE Trans.Pattern Anal. Mach. Intell., vol. 32, no. 9, pp. 1705–1720.

[12] N. Dalal and B. Triggs,(2009) "Histograms of oriented gradients for humandetection," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit, pp. 886–893.

[13] H. Deng, W. Zhang, E. Mortensen, T.Dietterich, and L. Shapiro,(2010) "Principal curvature-based region detector for object recognition," inProc. IEEE Int. Conf. Comput. Vis. Pattern Recognit. Pp. 1–8.

[14] P. Dollar, C. Wojek, B. Schiele, and P. Perona, "Pedestrian detection: An evaluation of the state of The art, (2012)" IEEE Trans. Pattern Anal. Mach.Intell., vol. 34, no. 4, pp. 743–761.

[15] L.Fei-fei, R. Fergus, and P. Perona, (2010)"One-Shot learning of object categories," IEEE Trans. Pattern Anal. Mach. Intell., vol. 28, no. 4, pp. 594–611.

[16] R. Fergus, P. Perona, and A. Zisserman,(2008) "Object class recognition by unsupervised scale-Invariant learning," in Proc. IEEE Int. Conf.Comput. Vis. Pattern Recognit., vol. 2., pp. 264–271.

[17] J. Gall and V. Lempitsky,(2009) "Class-specific hough forests for object detection," in Proc. IEEE Int. Conf. Comput. Vis. Pattern Recognit., pp. 1022–1029.

[18] C. Geng and X. Jiang, (2010) "Face recognition based on the multi-scalelocal image structures," Pattern Recognit., vol. 44, nos. 10–11, pp.2565–2575.

[19] G. Griffin, A. Holub, and P. Perona, (2007)"Caltech-256 object category dataset," California Inst. Technol., Pasadena, CA, USA: Tech. Rep.7694.

[20] Gulfishan Firdose Ahmed, Raju Barskar (2011) "A Study on Different Image RetrievalTechniques in Image Processing "International Journal of Soft Computing and Engineering (IJSCE) ISSN, Volume-1, Issue-4.

[21] Rasika Raikar1, Shivani Pandita(2015) "Discriminative Robust Local Binary Pattern based Edge Texture Features for Object Recognition "International Journal of Scientific Engineering and Research (IJSER) Volume 3 Issue 8.

[22] Amit Satpathy,"LBP-Based Edge-Texture Features for Object Recognition"ieee transactions on image processing,vol.23,no.5.
[23] Z. Guo, L. Zhang, and D. Zhang (2010) "A completed modeling of localbinary pattern operator for texture classification," IEEE Trans. ImageProcess., vol. 19, no. 6, pp. 1657–1663.
[24] S. Li, R. Chu, S. Liao, and L. Zhang,(2008) "Illumination invariant facerecognition using near-Infrared images," IEEE Trans. Pattern Anal.Mach. Intell., vol. 29, no. 4, pp. 627–639.