Level Identification of Brain MR Images using Histogram of a LBP variant

Abraham Varghese[1], Reji Rajan Varghese[2], Kannan Balakrishnan[3] , Joseph. S. Paul[4]

[1]Computer Science and Engg, Anna University, Coimbatore.
[2]Co-operative Medical College, Cochin.
[3]Department Of Computer Applications, Cochin University of Science and Technology, Cochin.
[4]Indian Institute of Information Technology and Management, TVM.

Abstract - **Axial brain slices containing similar anatomical structures are retrieved using features derived from the histogram of Local binary pattern (LBP). A rotation invariant description of texture in terms of texture patterns and their strength is obtained with the incorporation of local variance to the LBP, called Modified LBP (MOD-LBP). In this paper, we compare Histogram based Features of LBP (HF/LBP), against Histogram based Features of MOD-LBP (HF/MOD-LBP) in retrieving similar axial brain images. We show that replacing local histogram with a local distance transform based similarity metric further improves the performance of MOD-LBP based image retrieval**

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Keywords –**Average Rank, HF/MOD-LBP, HF/LBP, MOD-LBP, Precision**

I. INTRODUCTION

The increase in volume of images produced across different modalities has resulted in the requirement for locating desired images from a large collection of image database. The problems inherent with traditional methods of image indexing, have led to the emergence of *Content-Based Image Retrieval* (CBIR) systems in which source and target images are compared by their visual content so that it can automatically retrieve all similar images corresponds to the query image minimal human intervention [1],[2],[3].
Content Based Medical Image Retrieval (CBMIR) provides diagnostic support by displaying relevant past cases [4],[5],[6],[7],[8],[9]. The inter-patient search, which can compare multiple patients and retrieve relevant cases among them, will especially help the expert in diagnosis of diseases. Referring similar images of another patient would help the doctor to take accurate decision whenever there is a doubtful case. Medical image retrieval can also be used for research purpose, follow up studies and as a training tool for medical students. In order to identify the cause of pathology, especially in brain related problems, the experts generally focus on a single slice or multiple slices together. In such cases, retrieving the relevant slices from a volume of brain images may be taken as a first step in diagnosis of brain related problems.

Magnetic Resonance Imaging (MRI) is a commonly used modality to image brain as it provides high tissue contrast, and is free from harmful ionizing radiations. Neurologists mostly rely on MRI of the brain for the diagnosis of brain related diseases. The first step in reporting of the MRI consists of reviewing of the cross sectional images at various levels. However, there are many challenges in retrieving similar MR brain images because of inter and intra-patient intensity variation due to imperfect and non-homogeneous magnetic field, misalignment of images due to MR acquisition etc. Devrim et.al [10] has used histogram based features of Local Binary Pattern (LBP) for image retrieval application in MRI. Broadly, their image retrieval algorithms have been grouped into taxonomy of approaches that use spatial gridding versus selective choice of Kanade–Lucas–Tomasi (KLT) feature points. The motivation of this paper is to incorporate gray scale information into LBP so that it acts as a better descriptor .The performance of the histogram based features using MOD-LBP (HF/MOD-LBP), is compared against their counterparts derived using conventional LBP.

II. FEATURE EXTRACTION

A. LBP vs mod-LBP

The Local Binary Pattern (LBP) operator is a simple yet a powerful gray-scale invariant texture primitive, derived from a general definition of texture in a local neighborhood. Due to its discriminative power and computational simplicity, the LBP operator has become a highly popular approach in various computer vision applications, including visual inspection, image retrieval, remote sensing, biomedical image analysis etc. Original LBP is formed by taking difference between the gray value of a pixel (g_c) and the gray values of P pixels (g_k) in a local neighborhood [11].

The LBP is a measure of the spatial structure of local image texture and it is invariant to monotonic gray level changes because just the sign of the differences are considered instead of their exact values. In order to account for the changes in contrast and rotational invariance against grayscale shift too with respect to the window taken, we modify the definition of the LBP to be

$$MOD-LBP = \frac{1}{k}\sum_{i=0}^{k-1} s(g_i - g_c)(g_i - \mu)^2 \qquad (1)$$

where $\mu = \frac{1}{k}\sum_{i=0}^{k-1} g_i$. The concept of variance [12] is a special case of the definition when all neighboring pixels are brighter than the central pixel.MOD-LBP acts as a better descriptor as it encounters information from every pixel in the window chosen.The Fig.1(a-c) shows a T2-weighted axial slice, its LBP, and MOD-LBP respectively.

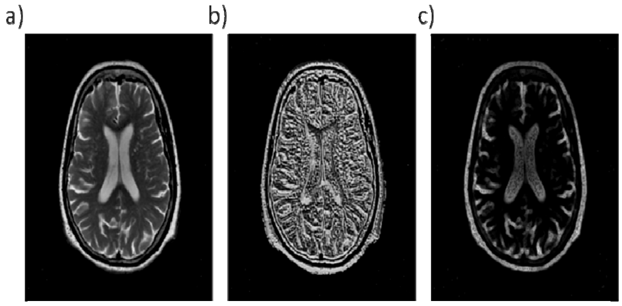

Fig.1: a) T2 weighted image b) LBP of (a), c) MOD-LBP of (a)

B. Histogram of LBP and MOD-LBP

The LBP and MOD-LBP maps of size $N \times N$ obtained using (1) is divided into n disjoint blocks of size $w \times w$. The image is represented using a finite number of discrete classes in the range 1 and NL. Let $H(k)$ specify the no. of pixels having gray-value k, $1 \le k \le NL$, and N_t be the total number of pixels,

$$N_t = \sum_k H(k) \qquad (2)$$

Each block of an image is represented using a feature vector consisting of probability values

$$P(k) = \frac{H(k)}{N_t}, \text{ k = 1 to } NL. \qquad (3)$$

Thus each image can be represented as a collection of feature vectors at n discrete spatial locations. For a query image Q, we define the feature matrix as

$$F^q = \begin{bmatrix} f^q(1,1) & f^q(1,2) & \cdots & f^q(1,NL) \\ f^q(2,1) & f^q(2,2) & \cdots & f^q(2,NL) \\ \vdots & \vdots & \vdots & \vdots \\ f^q(n,1) & f^q(n,2) & \cdots & f^q(n,NL) \end{bmatrix}$$

and that for the P database images as

$$F_i^I = \begin{bmatrix} f_i^I(1,1) & f_i^I(1,2) & \cdots & f_i^I(1,NL) \\ f_i^I(2,1) & f_i^I(2,2) & \cdots & f_i^I(2,NL) \\ \vdots & \vdots & \vdots & \vdots \\ f_i^I(n,1) & f_i^I(n,2) & \cdots & f_i^I(n,NL) \end{bmatrix},$$

for i = 1, 2 …P. The measure of similarity between query and target brain slices is defined using a distance measure,

$$D(F^q, F^I) = \sqrt{\sum_i (f^q(i) - f^I(i))^2} \qquad (4)$$

The distance vector is arranged in ascending order and each image in the database will be assigned an index based on its value in the distance vector. A Rank is assigned to the query image using the formula,

$$Rank = \frac{1}{N_R}\left(\sum_{i=1}^{N_R} R_i - \frac{N_R(N_R-1)}{2}\right) \qquad (5),$$

N_R represents number of relevant images and R_i represents index of the i[th] relevant image retrieved. In order to check the performance of the system, a set of query images from various levels are taken and corresponding ranks are calculated. Each of the query images will be assigned a rank depending on the number of relevant images retrieved. An average value of the ranks will be indicative of the closeness of the system performance to the ideal case. The Accuracy of the retrieval for a set of queries is, Accuracy =

$$\left(1 - \frac{\text{No of irrelevantimagesretrieved}}{\text{Total no of irrelevant images}}\right) \times 100 \qquad (6)$$

is also used to evaluate the performance of the system. The overall procedure is shown in Fig.2.

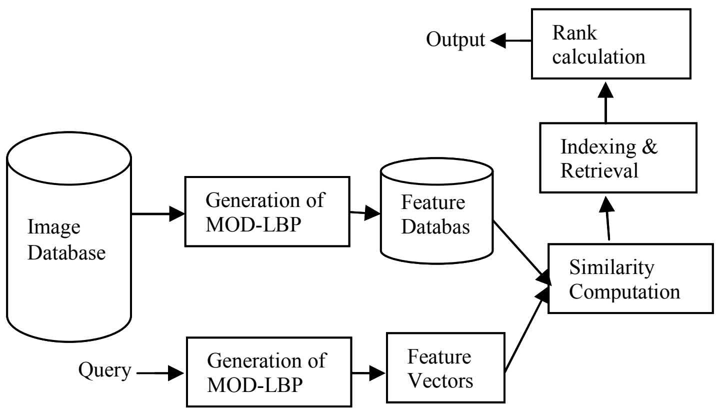

Fig.2: Block diagram of Image Retrieval Scheme

III. RESULTS

We have categorized unregistered T2-weighted Brain MR Images of different subjects into 4 levels, for independently evaluating the performance of the histogram based image retrieval method.

L1- the foramen magnum (The cerebellum with paranasal sinus is present)

L2- Above the fourth ventricle (Caudate nucleus, thalamus, basal ganglia are seen)

L3- mid ventricular section

L4- above the ventricle

A. *HF/LBP vs HF/MOD-LBP on a Clinical Data sets*

The histogram based features are extracted from the database images as well as query image of size 512×512 using (2) & (3). The Average rank and Accuracy are calculated using (5) and (6) for a set of queries in each class using the histogram of LBP and MOD-LBP. Table 1 shows the average rank and accuracy of retrieval of first 5 relevant images for a set of queries (25 query images from L1, 16 images from L2, 23 from L3 and 50 from L4) in each level. It shows that MOD-LBP outperforms LBP in terms of average rank and accuracy for retrieving first 5 relevant images

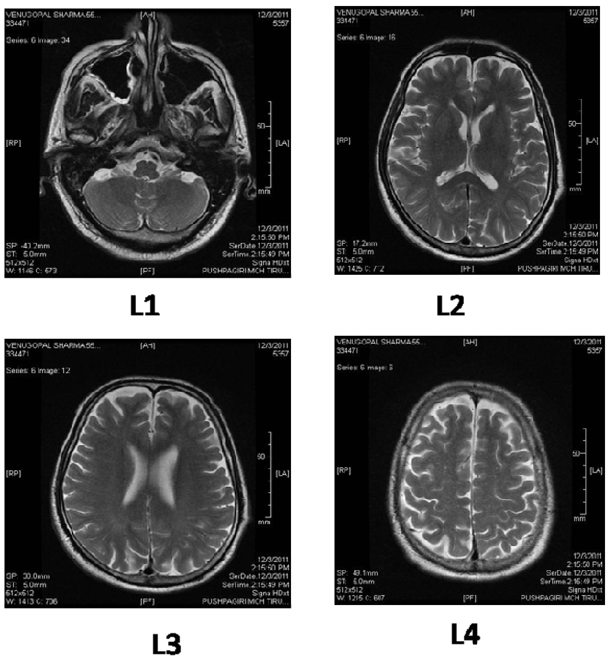

Fig. 3: Axial MR slices of different levels of T2 weighted image

The accuracy using histogram based MOD-LBP increases from 93% to 97% in level 1(L1), 91% to 95% in level 2 (L2), 96.1% to 96.8% in level 3 (L3), and 99.5% to 99.7% in level 4 (L4) compared to histogram based LBP.

B. *BrainWeb: Simulated Brain Database*

T2-weighted axial brain MR images of 1mm thickness, 0% noise and 0% intensity non-uniformity from simulated Brain Database has been used for evaluating the performance of the method. As discussed in section II.A & B, histogram of LBP and MOD-LBP images of the simulated images are formed spatially with a window size 5. The average rank and accuracy is calculated using histogram of LBP images and distance metric of MOD-LBP. The Fig.4 shows the performance in retrieving first 10 relevant images using histogram of LBP and distance metric of MOD-LBP features. The result shows that the accuracy of retrieval using distance metric based Mod-LBP is 99.3% in level 1, 98.6% in level 2, 93.8% in level 3,& 99.9% in level 4 while that using histogram of LBP is 96.2% in level 1, 88.2% in level 2, 91.5% in level 3, and 81.8 in level 4 respectively..

TABLE 1

THE ACCURACY AND AVERAGE RANK OF FIRST 5 RELEVANT IMAGES FOR A SET OF QUERIES IN EACH LEVEL USING HF/ LBP VS HF/MOD-LBP

Level	Method	Measure	No of relevant images retrieved 1	2	3	4	5
L1	HF/MOD	Avg Rank	1.52	1.89	2.29	3.91	5.05
	LBP	Accuracy %	99.7	99.4	99.0	96.4	96.03
	HF/LBP	Avg Rank	1.52	2.07	2.57	4.86	6.77
		Accuracy %	99.7	99.2	98.8	95.1	93.77
L2	HF/MOD-	Avg Rank	3.00	4.69	6.56	7.86	9.10
	LBP	Accuracy %	99.1	97.6	95.8	95.2	94.17
	HF/LBP	Avg Rank	4.19	7.06	9.21	11.9	14.13
		Accuracy %	98.5	96.1	94.4	91.5	90.21
L3	HF/MOD-	Avg Rank	1.57	2.78	3.81	4.79	5.70
	LBP	Accuracy %	99.7	98.6	97.7	96.8	96.17
	HF/LBP	Avg Rank	2.04	4.15	5.41	6.45	7.36
		Accuracy %	99.5	97.5	96.8	96.1	95.39
L4	HF/MOD-	Avg Rank	1.10	1.17	1.25	1.33	1.39
	LBP	Accuracy %	99.9	99.8	99.8	99.7	99.66
	HF/LBP	Avg Rank	1.34	1.44	1.53	1.62	1.72
		Accuracy %	99.8	99.7	99.6	99.5	99.39

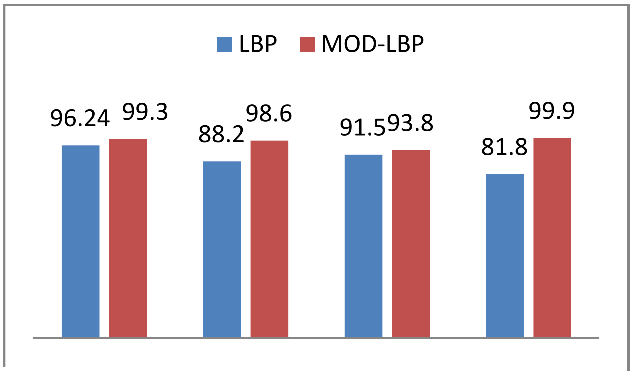

Fig.4: The accuracy in retrieving 10 relevant images using LBP and MOD-LBP

The result of application of our method for retrieval of first 5 images from the database is shown in Fig. 5.

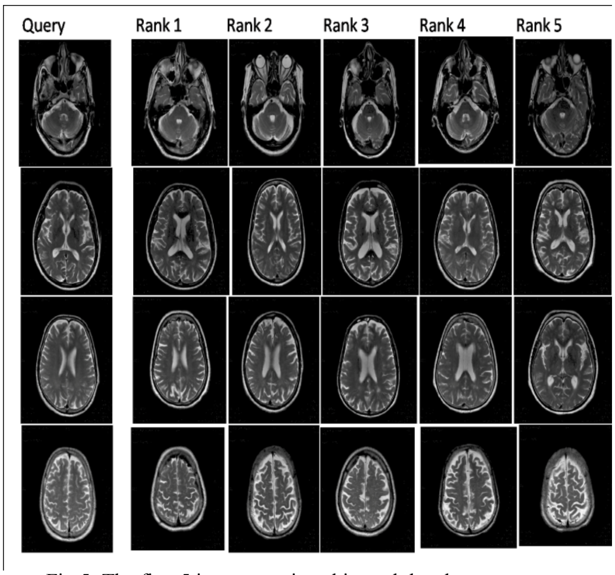

Fig.5: The first 5 images retrieved in each level

IV DISCUSSION AND CONCLUSION

The observations reveal that the histogram based MOD-LBP performs better than histogram based LBP by a factor of 1 to 2 times in terms of average rank. Addition of gray scale information to the LBP enhances the accuracy of the method. The accuracy of retrieval using distance metric based Mod-LBP increases from 96.2% to 99.3% for level 1 images, 88.2% to 98.6% for level 2 images, 91.5% to 93.8% for level 3 images and 81.8% to 99.9% for level 4 images. The accuracy can be improved further by applying a suitable relevance feed mechanism.

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