Level Based Anomaly Detection of Brain MR Images Using Modified Local Binary Pattern

Abraham Varghese, T. Manesh, Kannan Balakrishnan and Jincy S. George

Abstract The medical imaging technology plays a crucial role in visualization and analysis of the human body with unprecedented accuracy and resolution. Analyzing the multimodal for disease-specific information across patients can reveal important similarities between patients, hence their underlying diseases and potential treatments. Classification of MR brain images as normal or abnormal with information about the level at which it lies is a very important task for further processing, which is helpful for the diagnosis of diseases. This paper focuses on the abnormality detection of brain MR images using search and retrieval technique performed on similar anatomical structure images. Similar anatomical structure images are retrieved using Modified Local Binary Pattern (MOD-LBP) features of the query and target images and the level of the image is identified. The query image is compare with images in the same level and classification is done using the SVM classifier. The result reveals that the classification accuracy is improved significantly when the query image is compared with similar anatomical structure images.

Keywords MOD-LBP · Level identification · Classification

1 Introduction

Magnetic resonance imaging of the brain helps the radiologists to identify abnormal tissues due to bleed, clot, Acute-infarct, tumor, trauma etc. Since brain controls and coordinates most movement, behavior and homeostatic body functions such as heartbeat, blood pressure, fluid balance and body temperature, any injuries to brain affect

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the entire organ. The properties like soft tissue contrast and non-invasiveness of MRI are quite useful to identify any such abnormalities. The purpose of classification of MRI image into normal and abnormal is to find out the subjects with the possibility of having abnormalities or tumors. Many techniques for the classification of MR brain images are depicted in the literature. The feature extraction method for the classification of textures using a GMRF model on linear wavelets is presented (Ramana et al. 2010). These approaches to the texture analysis are restricted to spatial interactions over relatively small neighborhoods. An approach for texture image retrieval is performed in transform domain by computing standard deviation, energy and their combination on each sub band of the decomposed images (Prakash et al. 2012). Ruchika et al (2012) discussed DCT, DWT and Hybrid DCT-DWT based image compression and their performance in terms of Peak Signal to Noise Ratio (PSNR), Compression Ratio (CR) and Mean Square Error (MSE). In all these methods, classification of normal versus abnormal slices is performed without considering the features relevant to similar anatomical structures. In this paper, images are classified as normal or abnormal by giving importance to its anatomical structures so that the accuracy of the classification is improved. MOD-LBP (Abraham et al. 2014) descriptor has been used to retrieve similar MR images from a large database based on a query image. Depending on the 10% of the images retrieved, the level at which the given image lies is determined. Once desired level is identified, the images in that particular level are compared in order to classify it as a normal or abnormal. As the classification is performed by considering the features in the similar anatomical structures too, it is possible to predict the abnormality with higher accuracy.

2 Methodology

The overview of the methodology is given in Fig 1.

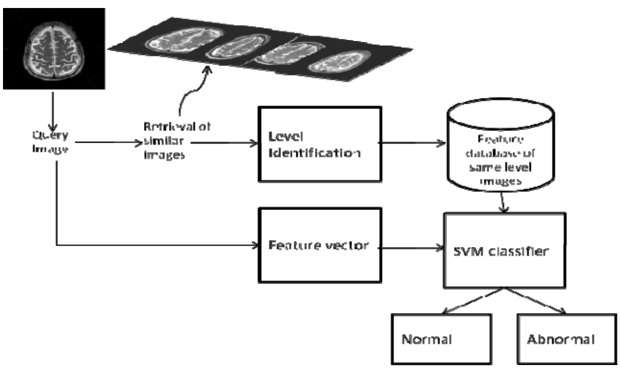


Fig. 1 Overview of Methodology

The similar images are retrieved correspond to a query image using histogram of MOD-LBP. Based on the images retrieved, level of the images is identified. The features of the same level images are given as input to the Support Vector Machine (SVM) and query image is classified as normal or abnormal.

2.1 Retrieval of Similar Images Using MOD-LBP

The procedure for retrieving similar images from the large image database is shown in Fig 2. In the pre-processing stage, the region of interest is extracted using morphological operations. The texture features are extracted using the descriptor MOD-LBP (Abraham et al. 2014) which is computed using the equation

$$MOD-LBP(P,R)=\frac{1}{P}\sum_{i=0}^{P-1}s(g_i-g_c)(g_i-\mu)^2 , \tag{1}$$

on a circular neighborhood with P neighboring pixels and Radius R , where μ is the mean and $\left\{\begin{matrix} s(x)=1, x\geq 0 \\ 0, x<0 \end{matrix}\right\}$. The MOD-LBP image is converted to polar form (r,θ) in order to compensate for rotation and translation in the spatial description of the features by taking centroid as the origin of the image. The output image obtained is of size $N \times N$ with N points along the r-axis and N points along the θ-axis. The pixel value of the non-integer coordinate of the image is estimated using bilinear interpolation. The histogram of MOD-LBP is computed spatially, where the entries of each bin are indexed over angularly partitioned regions. The pixel intensities are brought into the range [0, L], where L is a positive integer and normalized histogram of the image is taken as feature vectors for similarity computation. The similarity computation of 2 images in the database is computed using Bhattacharya coefficient, $d=1-\sum_{i=0}^{L1-1}\sqrt{p(i)q(i)}$ where p and q are normalized histograms with L1-bins. The Bhattacharya coefficient of two exactly similar images is 1, and the dissimilarity increases as it is different from 1. The images in the database are ranked based on this distance measure and the accuracy of the retrieval is computed.

Furthermore, the moment features of MOD-LBP are computed spatially over an angularly partitioned area and performance of the retrieval system is evaluated using the distance function of moment features. In order to achieve an optimum performance, relevance feedback mechanism has been applied by incorporating the user's input in the retrieval process. This is achieved by reweighting the moment features of MOD-LBP based on the relevance of individual features in the retrieval process. An average rank, which shows the closeness of the system performance, is calculated using the formula,

$$Average\ \ Rank = \frac{1}{N_R}\left(\sum_{i=1}^{N_R} R_i - \frac{N_R(N_R-1)}{2}\right) \tag{2}$$

N_R represents number of relevant images and R_i represents the rank at which the ith relevant image is retrieved [Henning & Wolfgang (2001)]. The Accuracy of the retrieval system for a set of queries is also calculated using the formula,

$$Accuracy = \left(1 - \frac{No\ of\ irrelevant\ images\ retrieved}{Total\ no\ of\ irrelevant\ images}\right) \times 100 \tag{3}$$

In the results section, we will illustrate how the average ranking and accuracy make use of, in classifying the retrieval performance at different levels. A comparison has been made between different local measure like LBP (Unay et al 2010), Rotational invariant LBP ($LBP^{ri}{}_{P,R}$), Rotational invariant uniform LBP ($LBP^{riu2}{}_{P,R}$) in retrieving 10 relevant images from 4 different levels. LBP has been used with a window of size 3 (P = 8, R = 1) and window of size 5 (P = 16, R = 2). Bashier et.al. (2012) proposed Local Graph Structure (LGS (8,1)) which is formed with 8 neighbors of a pixel, obtained by moving anticlockwise at the left region of the centre pixel and then right region of the central pixel. If the neighborhood pixel has a higher gray level value, assign the value 1 to the edge connecting the two vertices, else assign a value 0. The MOD-LBP defined in equation (1) has been used in 3 different ways (Histogram features, Moment features, reweighted moment features) in the retrieval process.

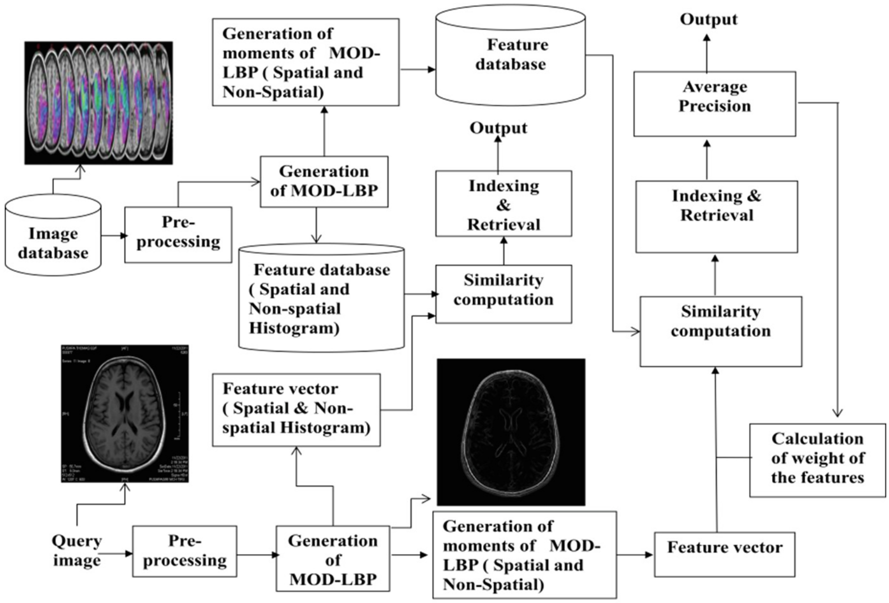


Fig. 2 Image retrieval scheme Level Identification

Based on the most similar and dissimilar images retrieved, the level of the query image is identified using the weights w and 1-w respectively (w $\in$ [0,1]). The level of the query image is computed as the weighted combination of the R_h most similar and R_l most dissimilar retrieval images.

If the database consists of N items ranked in decreasing order of similarity as i = 1, 2 … N given the query, then it calculates four values for each query.

$$
\begin{aligned}
c_{l1} &= w \times \frac{1}{R_h} \sum_{i=1}^{R_h} c1_i + (-1)(1-w) \frac{1}{R_l} \sum_{i=1}^{Rl} c1_i^{'} \\
c_{l2} &= w \times \frac{1}{R_h} \sum_{i=1}^{R_h} c2_i + (-1)(1-w) \frac{1}{R_l} \sum_{i=1}^{Rl} c2_i^{'} \\
c_{l3} &= w \times \frac{1}{R_h} \sum_{i=1}^{R_h} c3_i + (-1)(1-w) \frac{1}{R_l} \sum_{i=1}^{Rl} c3_i^{'} \\
c_{l4} &= w \times \frac{1}{R_h} \sum_{i=1}^{R_h} c4_i + (-1)(1-w) \frac{1}{R_l} \sum_{i=1}^{Rl} c4_i^{'}
\end{aligned} \tag{4}
$$

where c1, c2, c3,& c4 assumes the value 1, if the R_h most similar images belong to the respective levels, and it assumes the value -1, if the R_l most dissimilar images belong to the respective levels. The level of the query image is identified by the maximum value of c_{l1}, c_{l3}, & c_{l4}. i.e. if c_{l1} has got the maximum value, the query image belongs to the level 1($l1$).

2.2 Classification

Support Vector Machines (SVMs) are feed forward networks with a single layer of nonlinear units. It is capable of solving complex nonlinear classification problems. It solves these problems by means of convex quadratic programming (QP) and also the sparseness resulting from this QP problem. The learning is based on the principle of structural risk minimization. Instead of minimizing an objective function based on the training samples (such as mean square error), the SVM attempts to minimize the bound on the generalization error (i.e., the error made by the learning machine in the test data not used during training). As a result, an SVM tends to perform well when applied to data outside the training set. SVM achieves this advantage by focusing on the training examples that are most difficult to classify. These "borderline" training examples are called support vectors. SVM provides an accurate classification although the training time is very high (Othman et al. 2011).

Once the level of the image is identified using similar and dissimilar images retrieved, the query image is compared with images in the same level. The 50% of the images from both normal and abnormal images has been used for training using SVM classifier and remaining for testing. It improves the accuracy of classification as it gives importance to the similar anatomical structure of the images

The performance of the proposed method is evaluated in terms Sensitivity, specificity and Accuracy.

Sensitivity=TP/TP+FN
Specificity=TN/TN+FP
Accuracy=TP+TN/TP+TN+FP+FN where,
TP (True Positives) – correctly classified positive cases,
TN (True Negative) – correctly classified negative cases,
FP (False Positives) – incorrectly classified negative cases,
FN (False Negative) – incorrectly classified positive cases

3 Results

The proposed system has been implemented on a Brain Web dataset [BrainWeb]. Input dataset consists of axial T1 weighted bias 0% and bias 40% images (290 normal and 290 abnormal images). The 52 images from level 1, 64 images from level 2, 44 images from level 3, and 72 images from level 4 are used for level identification.

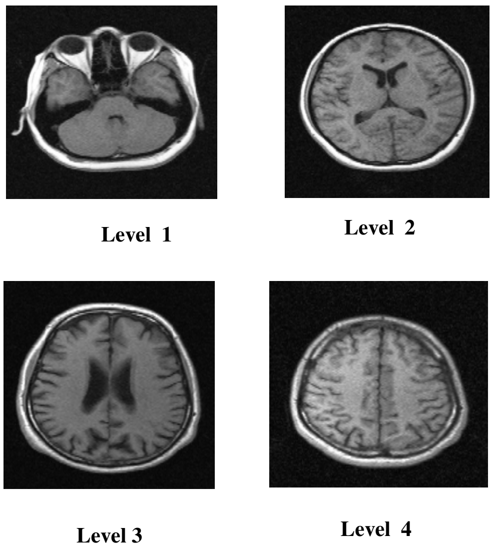
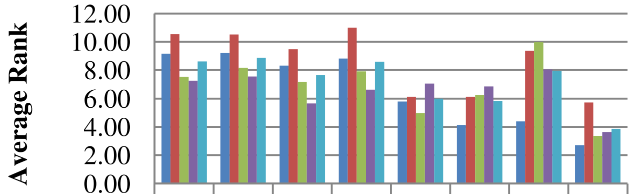


Fig. 3 Different Levels of T1 weighted axial MR slices

3.1 Similarity Retrieval

Ten images from each levels as shown in Fig 3 are randomly chosen as query image and accuracy of the retrieval is calculated based on the first 10 mostly relevant images retrieved. The performance of the retrieval is compared with different local measures and the result is shown in Fig 4. It is observed that LGS performs better compared to LBP (8,1) and LBP (16,2) and moment features of MOD-LBP. But spatial histogram of MOD-LBP outperforms LGS. An optimum performance can be achieved by incorporating users feedback into the retrieval system. An Average rank of 3.86 is obtained by reweighting the moment features based on the performance of the individual features in the retrieval process.



	a)	b)	c)	d)	e)	f)	g)	h)
L1	9.16	9.21	8.33	8.82	5.80	4.13	4.39	2.72
L2	10.5	10.5	9.49	11.0	6.13	6.14	9.36	5.72
L3	7.53	8.17	7.17	7.93	4.98	6.25	9.98	3.36
L4	7.26	7.55	5.65	6.64	7.06	6.85	8.05	3.65
Average	8.62	8.87	7.66	8.60	5.99	5.84	7.95	3.86

Fig. 4 Comparison of different local measures for retrieving 10 relevant images from 4 different levels. a) $LBP^{ri}_{8,1}$ b) $LBP^{riu2}_{8,1}$ c) $LBP^{ri}_{16,2}$ d) $LBP^{riu2}_{16,2}$ e) *LGS(8,1)* f) Spatial Histogram Of *MOD-LBP(8,1)* using 18 angular regions g) Spatial Moments of *MOD-LBP(8,1)* using 18 angular regions h) Reweighting the moment features 5 times.

The Fig. 5 (a),(b), (c) ,(d), show the most similar 10 images and most dissimilar 10 images correspond to a randomly chosen image from each level based on histogram of MOD-LBP computed spatially on 4 angular regions.

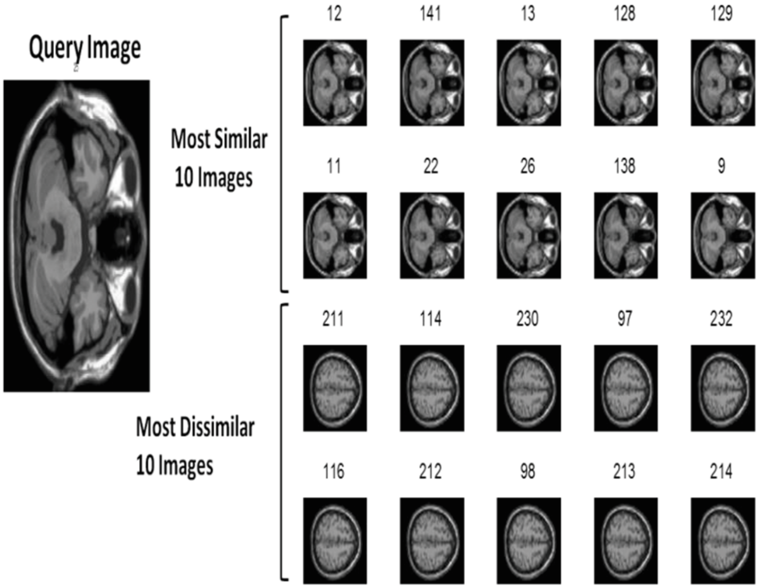


Fig. 5(a) Most Similar and Dissimilar images in Level 1

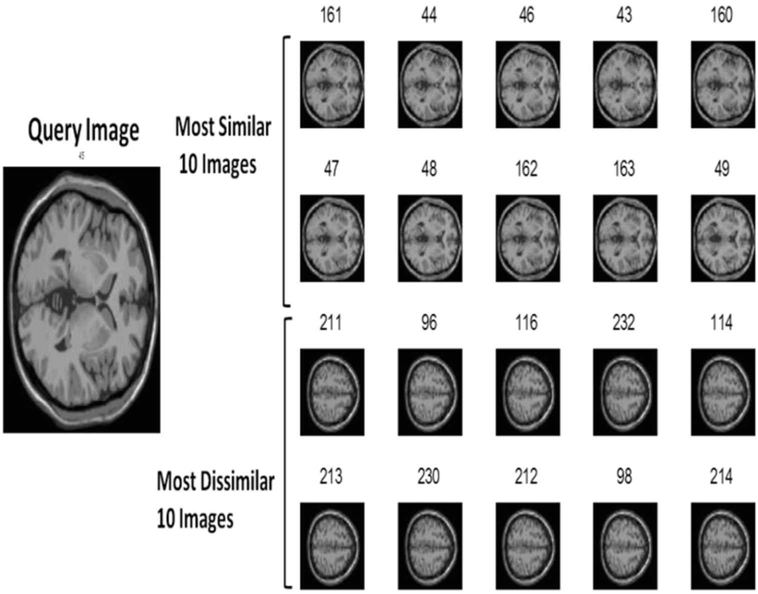


Fig. 5(b) Most Similar and Dissimilar images in Level 2

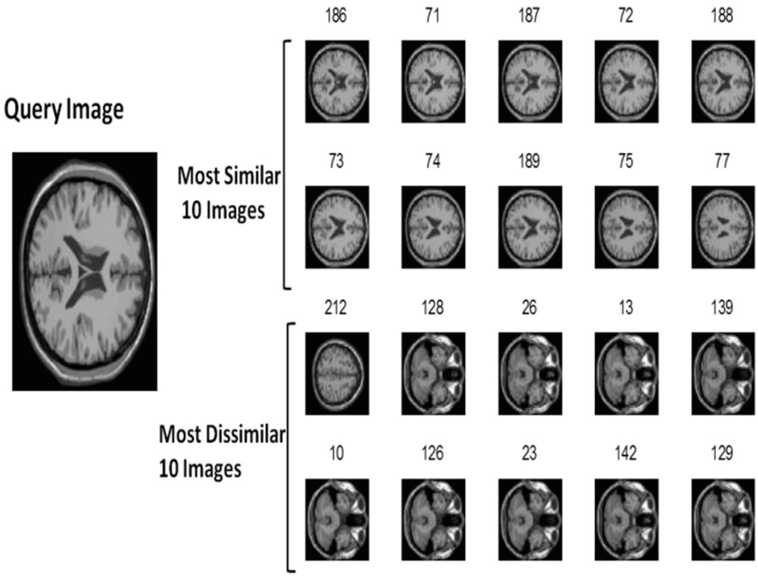


Fig. 5(c) Most Similar and Dissimilar images in Level 3

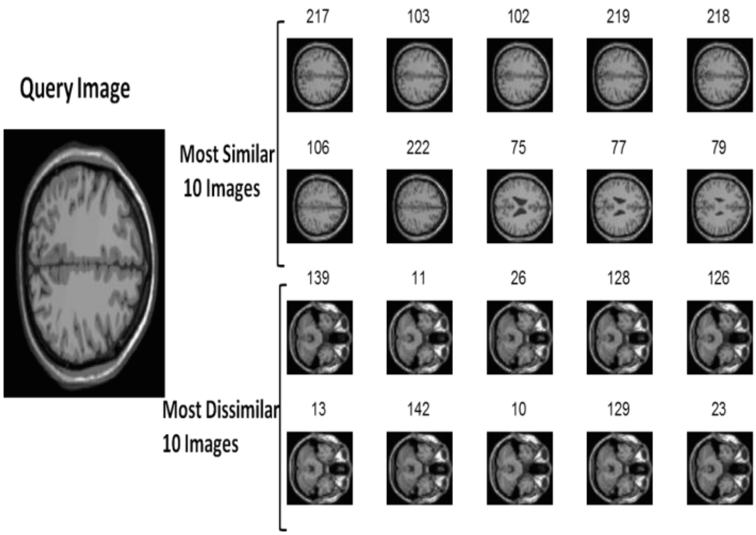


Fig. 5(d) Most Similar and Dissimilar images in Level 4

Accordingly, the level of the query image is identified using 10 retrieved similar and dissimilar images with weight w = 0.5.

The Table 1 shows the accuracy of level identification on BrainWeb data set.

Table 1 The accuracy,sensitivity,and specificity of Level Identification

Level	TP	TN	FP	FN	\Sensitivity	Specificity	Accuracy	Sensitivity
					TP/(TP+FN)	TN/(TN+FP)	(TP+TN)/ (TP+FN+TN+FP)	TP/(TP+FN)
1	26	90	0	0	100%	100%	100%	1
2	32	84	0	0	100%	100%	100%	2
3	20	94	0	2	91%	100%	98%	3
4	36	78	2	0	100%	98%	98%	4

It shows that all the images in the level 1 and level 2 are identified correctly in the respective levels and no images in the other levels are identified as level 1 or level 2. But in level 3, two images out of 22 images are not correctly identified. At level 4 all images are correctly classified, but 2 images in level 3 are identified as level 4 images. Once the level is identified, the query image is compared with images in the same level for classification as normal or abnormal using SVM classifier with linear kernel. The 50% of the images randomly chosen for training and remaining is used for testing. This has been repeated 100 times and mean of the accuracy is calculated using histogram of MOD-LBP and Moment of MOD-LBP as features.

The Table 2 shows the table of sensitivity, specificity and accuracy of the classification.

Table 2 The Mean of the accuracy of the classification on level based and non-level based image dataset using SVM with linear kernel.

Features	Measures	Non-level based images	Levels				
			1	2	3	4	Total
Histo-gram of MOD-LBP	Sensitivity	74.69%	85.15%	97.12%	99.00%	98.78%	95.01%
	Specificity	76.00%	87.31%	99.06%	99.73%	98.33%	96.11%
	Accuracy	75.34%	86.23%	98.09%	99.36%	99.22%	95.73%
Moments of MOD-LBP	Sensitivity	84.50%	85.46%	99.62%	99.36%	100%	96.11%
	Specificity	84.52%	90.62%	98.12%	99.00%	99.97%	96.93%
	Accuracy	84.51%	88.04%	98.80%	99.18%	99.94%	96.49%

The results show that the accuracy of the anomaly detection on a level based image dataset is much higher compared to non-level based image data set. The mean of the accuracy of the classification using histogram of MOD-LBP features improve the accuracy of the classification from 75.34% to 95.73% when the image database is switched to level based from non-level based image data set. A further improvement is observed using moments of MOD-LBP features.

4 Conclusion

This paper focuses on the application of similar slice retrieval to efficient abnormality detection. The level of the image is identified from the most similar and most dissimilar images retrieved correspond to a query image. Once the level is identified, the query image is compared with images in the same level for normal-abnormal classification. The method is robust to rotation and translation misalignment of images. The results show that there is a significant improvement in the accuracy of classification if the query image is compared images with similar anatomical structures. This can be useful to identify the possibilities of certain diseases at the early stage itself provided enough data set is available for comparison.

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