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Fusion at Features Level for MRI Image Segmentation

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***Abstract* — Diagnostic imaging is an important tool in healthcare applications. So far, Magnetic resonance imaging (MRI), computed tomography (CT), digital mammography, and others, are providing easy means to physicians for examining patient's condition and take decision over the particular diagnosis. Recently, MRI has become most preferred imaging modalities, especially, in brain and heart related diagnostic. Due to advances in computing hardware and its easy availability, the performance of MRI system has been improved dramatically since its inception and is able to provide fast imaging, better resolution, immunity to artifacts and cheaper cost. One of the most important problems in image processing and analysis is segmentation and same is true for biomedical imaging. Segmentation is generally a two-step process; feature extraction and classification. In this paper, we have analyzed the segmentation performance for fusion of features such as wavelet, histogram of gradients (HOG) and linear binary pattern (LBP). The classification carried out with two different classifiers; support vector machine (SVM) and neural network. the results presented in terms of precision and recall obtained in segmentation experiments for white matter and gray matter from MRI images. The result confirms the appropriateness of use of new features like HOG and LBP.**

***Keywords* — Fusion at feature Level, MRI segmentation, Wavelet, LBP, HOG.**

I. Introduction

Use of medical images acquired from imaging modalities is the once of the important step towards the medical diagnostic and treatment. The tasks such as identification of diseases, surgical planning, medical reference, research and training are heavily rely on the analysis and findings from MRI images. In general, the observations associated with images may involve measurements of the biological parameters, such as density of particular type/s of tissues. Therefore, effective and meaningful analysis and classification of these images are vital. The annotation of MRI images representing subject's anatomical structure is conventionally done manually. However, manual annotation suffers from limited knowledge of annotator, inconsistency, time consuming. The solution to overcome this problem is to use of automated software to analyse the biological parameters or diagnostic parameters of interests without human interaction. In today's interconnected world, computerized automated annotation can be used in collaborative manner to include the medical expert's advice without having him/her physically present in place. The high quality expertise can be seamlessly acquired across the globe at reduced cost. Thus, segmentation of various tissues in anatomical structure appears in given MRI image is an important issue in computer aided diagnostic and healthcare systems.

The possible extended applications for the segmentation methods using images processing are described below:

A. Diagnosis System

General objectives of diagnosis system using MRI image processing can be:

- localizing the objects of interest, i.e. different organs
- taking the measurements of the extracted objects, e.g. tumors in the Image
- interpreting the objects for diagnosis

B. Functional MRI (FMRI)

The brain functioning need continuous supply of glucose and oxygen, which are supplied by CBF. Several studies and experiments indicated that within the brain, there are heterogeneous distributions of blood, with grey matter receiving several times more flow per gram of tissue than white matter [1]. This distribution in terms of CBF (cerebral blood flow) which is the rate of delivery of a particular mass of tissues and oxygen metabolism has resulted into blood oxygenation. The magnetic resonance (MR) signal is sensitive to this change because deoxyhemoglobin (dHb) is paramagnetic and the presence of dHb reduces the MR signal at rest. During activity in brain, MR signal will increase slightly. This MR signal increase during brain activation has now been measured during wide range of sensory, motor and cognitive tasks due to change in blood oxygenation. Thus, functional MRI measures blood–oxygenated-level– dependent (BOLD) signal changes caused by regional hemodynamic adjustments in response to changes in neuronal activity. The statistical analysis of blood oxygen level dependent (BOLD) is a critical part of the brain mapping with functional magnetic resonance imaging. Aim of such analysis is to produce an image identifying the region which shows significant signal change in response to the task.

C. Cardiac MRI (CMRI)

An investigation of biomechanical processes in normal and abnormal heart muscle are vital to understand the cardiovascular disease and therapeutic interventions on ventricular performance. To identify the abnormal motion of heart in diseases associated with heart itself and lung, there should be straightforward dynamic model of normal motion of the heart during normal functioning. In order to measure, myocardial strain or modelling wall motion, for clinical assessment, it crucial to localize the same point of heart surface on two images acquired at different parts of cardiac cycle. Two most common techniques used in MRI to measure myocardial motion are myocardial tagging and myocardial velocity mapping.

In any of the healthcare application mentioned above, there is tremendous need of identifying the location par particular tissue type. This requires the segmentation for the MRI image and in brain MRI image, segmentation process carried out mainly to separate out the white and gray matter along with CBF. Various approaches has been reported in literature for segmentation of brain, where main objective is separating the pixels associated with different types of tissues like white matter, gray matter and cerebrospinal fluid (CSF). Of these, semi-automated methods that employ only sequence of image processing techniques are not preferred because they rely heavily on human interaction for accurate and reliable segmentation. Fully automated methods, on the other hand, are free from any human interference and can segment the brain with high precision by using computational intelligence in association with image processing algorithms. In this paper, we analyse the importance of different feature types such as wavelet, HOG, LBP etc. The classification of tissue types was archived with two different types of classifiers namely, SVM and neural network.

The remaining part of the paper is organized as follows. In section II, we described briefly how MRI segmentation achieved in existing literature. Various types of features are presented in section III. In section IV, we have discussed two classifiers, SVM and neural networks. Quantitative performance and its discussion is provided in section V. Finally, paper is concluded highlighting the outcome of this paper.

II. Proposed System

One of the most important problems in image processing and analysis is segmentation. Various approaches have been reported in literature for segmentation of brain MRI images, where main objective is separating the pixels associated with different types of tissues like white matter, gray matter and cerebral fluid (CBF) as shown in figure 1. There are two ways to handle the segmentation in anatomical images. Semi-automated methods, that employ only sequence of image processing techniques, are not preferred because they rely heavily on human interaction for precise and reliable segmentation. Fully automated methods, on the other hand, are free from any human interference and can segment the brain with high precision by using computational intelligence in association with image processing algorithms. Thus, automated MRI segmentation has great importance in research and clinical applications.

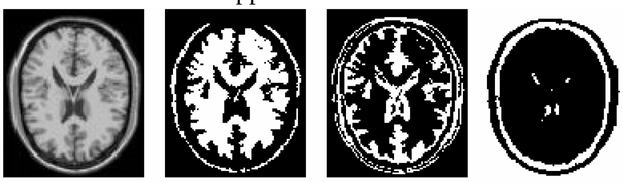

Fig.1. From left to Right, 1) MRI Image, 2) WM, 3) GM and 4) CSF

An interesting approach depicted in [6] has used the information fusion approach. The information is obtained from image as well as expert's knowledge. This information is in the form of morphology, topology and constitution of tissue. This approach was supplemented by fuzzy logic. In diagnostic application point of view, separating or segmenting healthy tissue and tumour is crucial task. This task can be achieved by segmentation method presented in [7], which is based on probabilistic approach, expectation maximization (EM) algorithm. Another work on probabilistic approach has been presented in [8], where variant of EM algorithm is employed.

The PCA and ICA have been used to model the variants of primary shapes and applying it for pattern recognition problems. There has been study to use PCA and ICA combinely to segment the MRI images in [9]. Similarly, SVM and Radial Basis Function (RBF) based Adaboost method have been applied to MRI image for white matter lesion in one of the work presented in [10] and it is found that Adaboost method is faster than SVM method.

An adaptive mean shift has been a powerful algorithm for segmentation and is used in segmentation of MRI brain images in work reported in [11, 12]. A novel method for simultaneous segmentation and registration is presented in [13]. This algorithm can be carried out by a statistical modelling framework. First, the authors segment the medical volume data using the geometric active model with level set theory and then extract the region of an object from a given volume data. Second, they use a hidden Markov model and the conditional likelihood function to statistically model a problem that aligns the extracted object with other volume data. Brain structural volumes can be used for automatically classifying subjects into categories like controls and patients. One of the recent papers [14] aims to automatically separate patients with temporal lobe epilepsy (TLE) with and without hippocampal atrophy on MRI, pTLE and nTLE, from controls, and determine the epileptogenic side.

Additionally, advances in computational intelligence, machine learning has made researchers to explore the new techniques for meaningful segmentation. It will be interesting to note the effectiveness of methods based on computational intelligence over the earlier methods. We expect to have more reliability, accuracy over classical methods. The generalized framework system for the application based on MRI segmentation is shown in fig. 2.

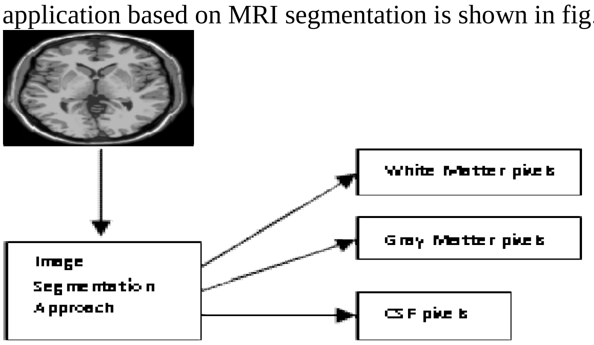

Fig.2. MRI segmentation system

III. Features Extraction

A. *Wavelet:*

The main advantage with wavelet transform (WT) over fourier transform (FT) and short time FT is that it gives good resolution in time as well as frequency domain. It also gives locations of different frequency spectral components during that particular instant of time. WT is the good tool to analyse the non stationary signals, i.e., whose frequency response varies in time. Wavelet transform is used as an alternative approach to STFT in order to overcome the resolution problem i.e. STFT is able to give band of frequency spectral components in a particular interval of time. Time-scale wavelet coefficients are given by $W(a,b)=\int_{\infty}^{\infty} f(t)\frac{1}{\sqrt{a}}\overline{\psi(\frac{t-b}{a})}dt$

where,
x(t) = Input signal which is to be transformed
ψ (t) = Mother wavelet
b = Time shift parameter
a = Scaling parameter

1/sqrt(a)=normalizing factor which ensures that energy of $\psi(t)$ remains constant for all values of a & b. The wavelet coefficients W(a,b) are normally calculated using Mallat's algorithm [15] in order to reduce the computation, it is also called as "Fast Wavelet Transform" and is shown in figure 3. The algorithm needs the computations of wavelet coefficients up to N level. Each level has three directional components, namely, horizontal, vertical and diagonal.

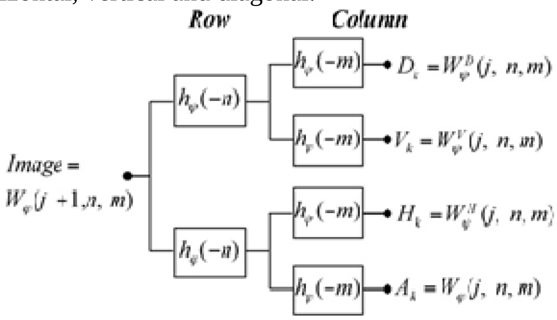

Fig.3. Wavelet Feature Extraction

B. HOG:

In existing set of various features, HOG is one of the local descriptors that have been applied efficiently in variety of problems of computer vision [16, 17]. The image is decomposed into local regions and from each local region gradient orientation and its magnitude are calculated. In each bin of gradient orientation of histogram, corresponding magnitudes are accumulated for the local region. It is believed that HOG is robust to illumination variation for recognition problems [18]. Here, we calculated HOG for each pixel.

C. LBP:

After using linear binary pattern (LBP) first time for measuring the local image contrast [19], it has been applied in several pattern classification problems [20, 21]. To calculate LBP, each pixel is assigned with a label by a type of binary pattern obtained in 3x3-neighborhood pixels by thresholding neighborhood pixel intensity with center pixel. The distribution of these binary patterns in local region is used as a feature representation, describing the nature of texture exist in that region. Here, we calculated LBP for each pixel of MRI images to decide whether the pixels belongs to white/gray matter tissue of not.

IV. Classifiers

D. SVM:

The concept of Support Vector Machine was introduced by Vapnik [22]. SVM is used for both classification and regression problems based on Statistical Learning Theory (SLT).SVM constructs models that are complex enough it contains a large class of neural nets, radial basis function (RBF) nets, and polynomial classifiers as special cases. Yet it is simple enough to be analyzed mathematically, because it can be shown to correspond to a linear method in a high dimensional feature space nonlinearly related to input space.

SV classifiers are based on the class of hyperplanes. The optimal hyperplane is defined as the one with the maximal margin of separation between the two classes as shown in figure 4.

$$w.x+b=0, w\in \mathbb{R}^N, b\in \mathbb{R} \qquad (1)$$

Corresponding to decision functions,

$$f(x)=sign((w.x)+b) \qquad (2)$$

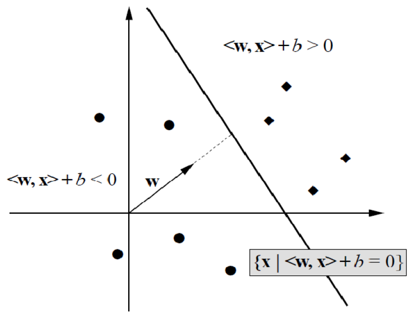

Fig.4. Linear hyper-plane separating two classes (Black dots and black diamonds)

Thus, in SVM main objective is to find out the decision function or boundary function for two classes from the given data. In training stage this function is calculated and then this trained function is used to classify the given data into two classes.

B. Neural Network:

A multi-layer perceptron feed forward is trained based on the back error propagation algorithm. To use neural network, the feature vector is applied to the input layer of the network. With known input-output mapping, the weights of each layer are adjusted so that error between output layer and actual known outputs would be reduced. This is called as training phase. With this trained network with optimum set of weights in each layer obtained from supervised training, feature vector extracted from unknown sample is applied and output of classification is inferred from the values of the output layer nodes. The Multilayer neural network is shown in figure 5.

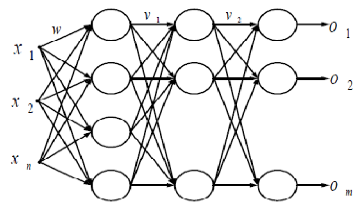

Fig. 5: Multilayer Neural Network

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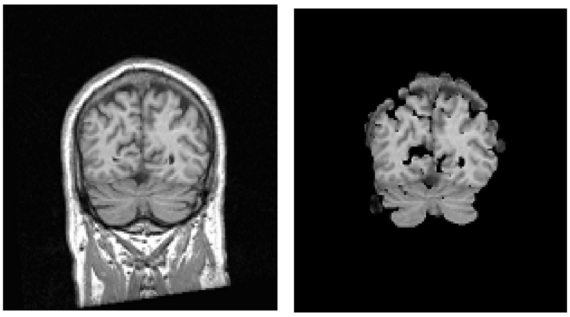
V. Experimental Results and Discussion

The dataset has real data taken from the Center for Morphometric Analysis at Massachusetts General Hospital [23]. The dataset consists of T1-weighted 256x256 16-bit image slices through the brain and their manual segmentation.

In the dataset, original images are T1-weighted 3D coronal brain scans after it has been positionally normalized. They represent slices through the brain and hence consist of ground truth which includes the entire face anatomy. Thus, segmentation algorithm needs to first separate out the brain area from the acquired MRI image before passing through it to the segmentation process. In this pre-processing stage, gradient operator used to find the edges. For this purpose, we used Sobel's edge detector. In order to ensure the properly closing of edges, morphological processing is employed. This is further processed with region analysis to find the connected regions, which are again processed with morphological operators to ensure perfect closing of gap in the edges. The example of this region of interest (ROI) extraction from original image is shown in figure 6.



a) b)
Fig.6. ROI extraction: a) Original input image; b) ROI

The performances of segmentation in terms of precision and recall values are presented in the table I. The experiments were performed for different combinations of features, wavelet transform, HOG and LBP. It is visible in the result that recall values are showing much variation as per the features included in fusion. From the table, it can be said that performance with neural network is superior to that with SVM classifier. While fusing the different features, wavelet features works better with LBP than with HOG. In fact HOG and LBP together does not give promising results and inclusion of wavelet feature in fusion scheme is very much essential. There is one more important observation from the table is that recall value with fusion of all the three features (WT+HOG+LBP) for gray matter segmentation is worst among all the fusion schemes, whereas that for white matter segmentation is best. Thus, selecting WT+HOG+LBP as a best fusion scheme is not that straightforward. With this drawback of WT+HOG+LBP, fusion scheme with WT+LBP proves to be best for the segmentation of gray matter and white matter both.

The results obtained here is primarily very much dependent on the first stage pre-processing which involves the ROI extraction from MRI acquired image. Thus, these fusion based performances can be further enhanced by using more reliable ROI extraction technique.

Table I: Performance results for different features fusion schemes and classifiers in terms of precision and recall

Fusion Scheme	White Matter				Gray Matter			
	Neural Network		SVM		Neural Network		SVM	
	Precision	Recall	Precision	Recall	Precision	Recall	Precision	Recall
WT+HOG+LBP	97.43	59.71	95.98	37.11	92.45	51.21	91.55	32.79
WT+HOG	97.58	62.66	95.97	26.46	90.80	43.60	91.48	31.80
WT+LBP	97.52	64.03	95.97	33.67	91.74	45.57	91.52	32.63
HOG+LBP	97.70	61.87	97.42	56.33	91.67	42.48	92.39	54.84

V. Conclusion

Because of heterogeneous nature of tissues in the anatomical structure across the subjects, it's become challenging to the physicians to segment the brain tissues in white and gray matter. Segmentation is generally a two-step process; feature extraction and classification. In this paper, we have analysed the segmentation performance for fusion schemes with features such as wavelet, histogram of gradients (HOG) and linear binary pattern (LBP). The classification carried out with two different classifiers; support vector machine (SVM) and neural network. The results presented in terms of precision and recall obtained in segmentation experiments for white matter and gray matter from MRI images. The result confirms the appropriateness of use of new features like HOG and LBP along with wavelet features. However, the performance can be further improved with ROI extraction pre-processing.

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