Analysis of Feature Extractor and Classifier for Magnetic Resonant Image Segmentation

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Abstract

Diagnostic imaging is a critical tool in healthcare sector. There are various modalities such as Magnetic resonance imaging (MRI), computed tomography (CT), digital mammography, and others, to provide an insight of subject's body, noninvasively in order to facilitate stakeholders to take decision in diagnosis. Additionally, in medical research, these technologies has been playing centre role in most of the health care studies and experiments. Being a critical component in imaging systems, MRI system has been active area for researchers in computational intelligence and image processing. One of the most important problems in image processing and analysis is segmentation and same is true for biomedical imaging. The main objective of segmentation is separating the pixels associated with different types of tissues like white matter (WM), gray matter (GM) and cerebrospinal fluid (CSF). In this paper, we present the analysis of various features to be used for segmentation process. Additionally, the classifiers such as SVM and Neural Network have also been compared here. The main objective of this paper is to determine the best candidate for the optimized feature and classifier to be used in segmentation process.

Keywords: *Magnetic Resonant Images, Image segmentation, Wavelet, Neural Network, SVM, k-means clustering*

1. Introduction

Magnetic resonance imaging (MRI) plays an important role in detection of neurodegenerative signs. MRI which uses NMR i.e. Nuclear Magnetic Resonance is an effective diagnostic tool in the study of human brain. Segmentation of the anatomic structures from medical images is a challenging process for a number of reasons. These structures exhibit considerable variability from one person to another. They are non-rigid and complex in shape, and there is an absence of explicit shape models that capture the deformations in anatomy. A number of methods have been proposed in recent times for segmentation of White Mater (WM) and Gray Matter (GM) to provide locations of important functional regions of the brain, as required for optimal surgical planning or medical therapy. Apart from these applications, there is brain tumor segmentation [7], [20], [16], detection of pediatric metabolic diseases [2], detection of Hippocampal sclerosis (HP) in patients with medical temporal lobe epilepsy [5].

Segmentation techniques can be categorized in three classes: threshold-based, edge or boundary-based and region-based techniques. In threshold based techniques [9], local pixel intensities with additional filtering and clustering are considered. Edge-based technique is by far the most common method of detecting boundaries and discontinuities in an image. In region-based techniques [7], similarity conditions are checked between neighboring pixels and regions are grown. Later on similarity conditions are checked between and within regions and they merged or split. Various classifications techniques have been used such as SVM [3], [4], k-means were used in [18] and [19] and Fuzzy-c-means clustering (FCM) algorithm which allows pixels to belong to multiple classes with varying degrees of membership. [1], [21], variations and optimization of ant-tree clustering were used [8], [15], FCM was combined with genetic algorithms and neural networks to detect tumors in [14] etc. The work can be divided as fully automatic which

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include [3], [8], [9], [21], [22] while others were semi-automatic [7], [20] which requires some user interaction. A number of attempts at 3D segmentation have been made as in [7], [9], [20] which is done to increase accuracy of the segmentation system. However, we will focus on the 2D segmentation in this work.

In this paper, we present the analysis of various features to be used for segmentation process. Additionally, the classifiers such as SVM and Neural Network have also been compared here. The main objective of this paper is to determine the best candidate for the optimized feature and classifier to be used in segmentation process.

The rest of the paper is organized as follows. In section II, we describe the basics of k-means and LM algorithm. In section III, our proposed system is described. Experimental results have been discussed in IV and finally conclusion and future work in section V.

2. ROI Extraction

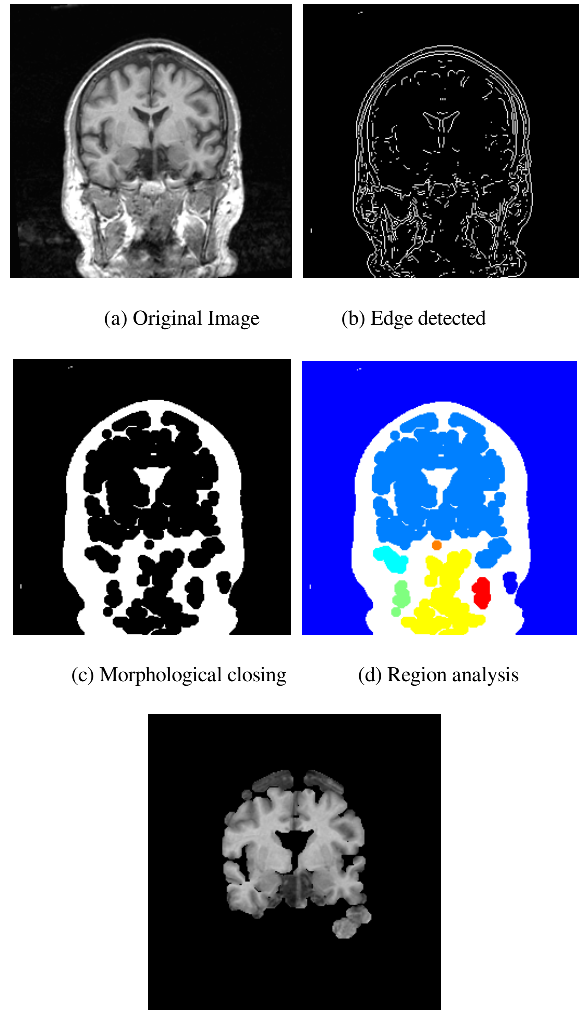
Before the classification step, there is a pre-processing step. In this, we aim to separate the brain from the rest of the skull.

2.1 Preprocessing

In the original images from [10] 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 area as depicted in Fig. 1(a). Hence the brain area needs to be segmented from this region which can later be fed to the classification system. This preprocessing stage consists of finding edges using a gradient operator. The operator of choice is Sobel's edge detector. Then some morphological closing is performed so that all gaps in the edges are properly closed. Then region analysis is performed to find connected regions. This is followed by morphological operators which effectively segment out the brain area. For segmenting out the brain region, two criteria are checked, (1) It should be the first or second largest region as the background can be considered as the largest region and (2) it should be the region with the highest solidity since the background will have a very low solidity. The results of each step are shown below.

3. Image Segmentation

The basic image segmentation processing is shown in figure 2. Here feature extraction process plays crucial role and selecting proper set of features to represe4nt the pixel can affect the performance of segmentation process.



(a) Original Image (b) Edge detected

(c) Morphological closing (d) Region analysis

(e) Segmented brain

Fig. 1: Preprocessing

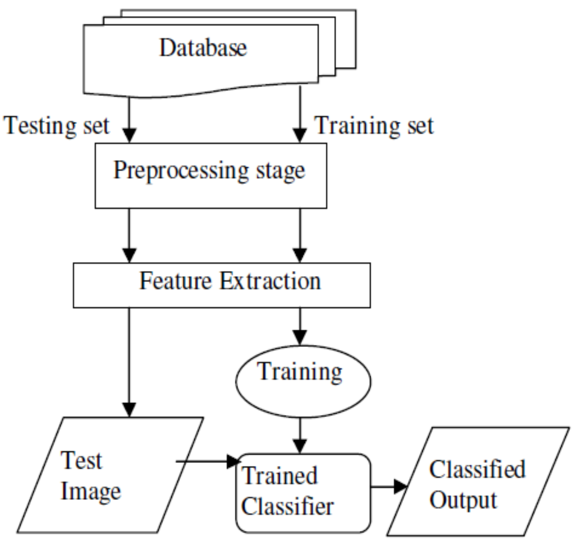


Fig. 2: System Flowchart

The possible features for segmentation process are intensity, position of pixel and wavelets. The detail description for wavelet has been given below.

4. Wavelet Decomposition

Wavelet transform 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. This is the main advantage of wavelet Transform over FT & STFT. WT is used to mainly analyze 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. We have used Mallat's algorithm [25] , to calculate the wavelet coefficients in order to reduce the computation, it is also called as "Fast Wavelet Transform". Its computational flow diagram is shown in figure 3. The algorithm needs the computations of wavelet coefficients up to fourth level. Each level has three directional components, namely, horizontal, vertical and diagonal. As the fingerprint images carries oscillatory patterns, coefficient after fourth level insignificant information about the pattern.

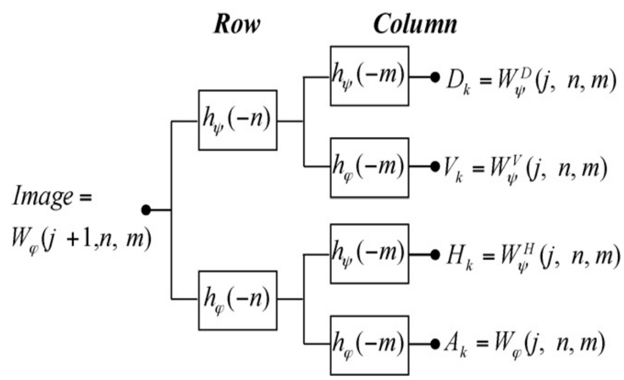


Fig. 3: Wavelet decomposition

4. SVM Classifier

The concept of Support Vector Machine was introduced by Vapnik [23]. 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.

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

corresponding to decision functions,

$$f(x)=sign((w.x)+b) \tag{2}$$

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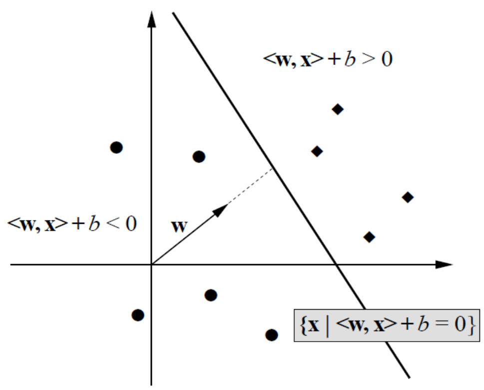

Fig. 4. Linear hyper-plane separating two classes (black dots and black diamonds)

Here we have two sets i.e. X and Y corresponding to input and output. X can correspond to detection of a certain object v/s the absence of that object. Y corresponds to {1,-1} where 1=occurrence of the object, and -1=absence of the object. Hence the training set will correspond to $(x_1, y_1), (x_2, y_2)...(x_N, y_N)$. In order to learn the classifier, we need to have $y = f(x, \alpha)$, where ∝ symbolizes the parameters of the function. Hence, if we are choosing our model for a set of hyperplanes in $\mathbb{R}^N$, we have

$$f(x, \{w, b\}) = sign(w.x + b) \qquad (3)$$

Define the "margin" of a separating hyperplane to be $d_+ + d_-$. For the linearly separable case, the support vector algorithm simply looks for the separating hyperplane with largest margin. This can be formulated as follows:

$$x_i.w + b \geq +1, \text{ for } y_i = +1$$

$$x_i.w + b \leq -1, \text{ for } y_i = -1$$

In order to construct such an optimal separating hyperplane, it is required to solve the following optimization problem:

minimize: $w^T w$ (4)

subject to:

$$y_i(w^T x_i + b) \geq 1$$

For linearly inseparable case, the constraints must be relaxed. Any point falling on the wrong side is considered an error. We must simultaneously maximize the margin and minimize the error. Hence, a non-negative slack variable z_i is added as a weighted penalty term in the objective as follows:

minimize: $w^T w + C\sum_{i=1}^{l} z_i$ (5)

subject to:

$$y_i(w^T x_i + b) + z_i \geq 1$$

C is called the penalty parameter. For every occurrence of a point on the wrong side, it is multiplied C times. Hence, higher the penalty parameter, stricter the system is and lower is the tolerance.

For non-linear cases as shown in Fig. 5, a quadratic function such as the circle pictured is needed

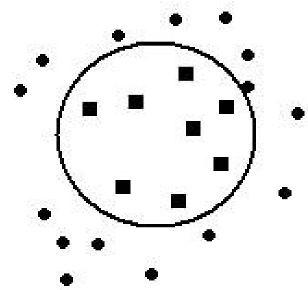

Fig. 5: Example requiring a quadratic discriminant

A classical method of converting linear classification algorithm to non-linear classification algorithm is to simply add attributes to the data that are non-linear functions of the original data. This is performed by the use of *kernels*. There are various kernels available but the most basic ones are linear $x_i^T x_j$, polynomial $(\gamma x_i^T x_j + r)^d, \gamma > 0$, Gaussian or radial base function $\exp(-\gamma \| x_i - x_j \|^2), \gamma > 0$, and sigmoid $\tanh(\gamma x_i^T x_j + r)$.

5. Neural Network

A multi-layer perceptron feedforward is trained based on the back error propagation algorithm. In addition, an adaptive learning rate, momentum, batch training and Nguyen & Widrow weights initialization techniques [4] are also applied to improve the neural network learning time and convergence capability. 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 6.

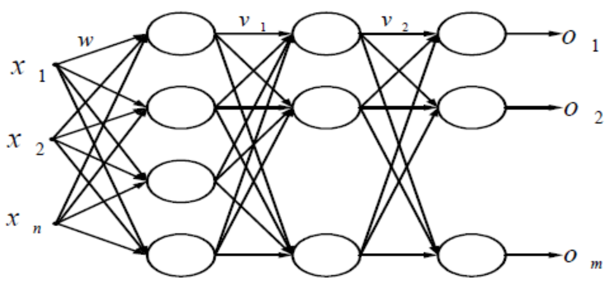

Fig. 6: Multilayer Neural Network

6. Experimental Results and Discussion

The datasets are Real data taken from the Center for Morphometric Analysis at Massachusetts General Hospital [10]. The dataset consists of T1-weighted 256x256 16-bit image slices through the brain and their manual segmentation.

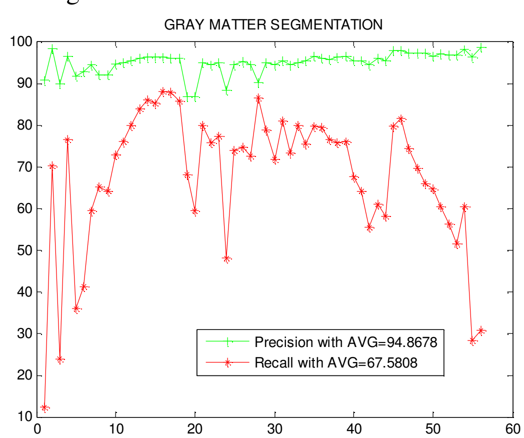

Fig. 7: Precision and Recall Results with SVM for GM with Intensity and Position in feature vector

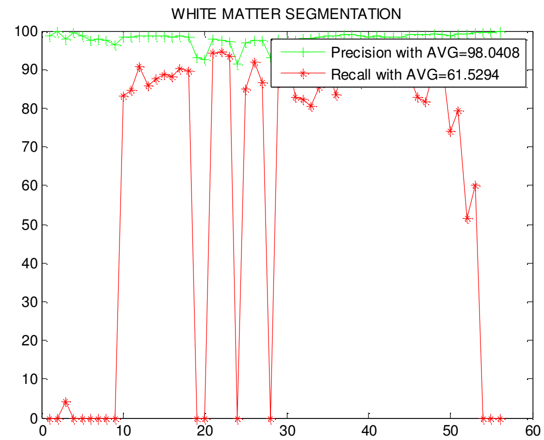

Fig. 8: Precision and Recall Results with SVM for WM with Intensity and Position in feature vector

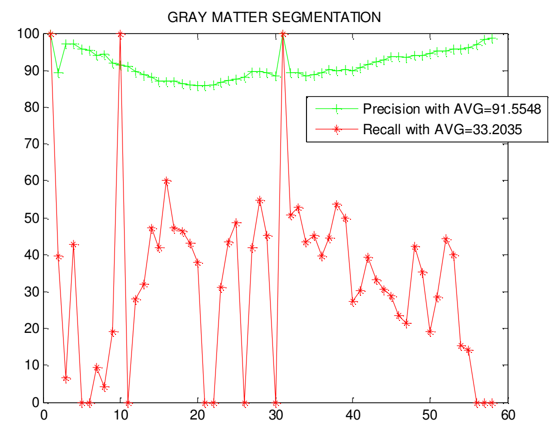

Fig. 9: Precision and Recall Results with SVM for GM with Intensity, Position and wavelet coefficients in feature vector

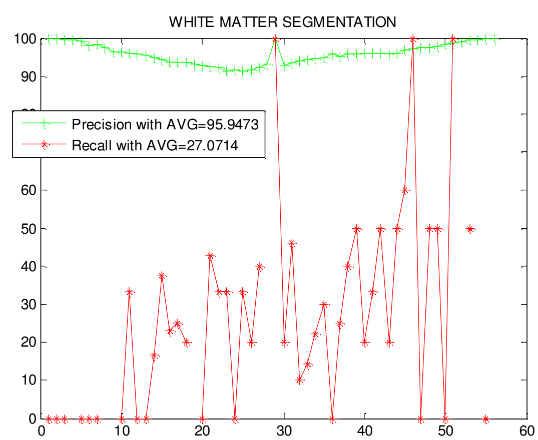

Fig. 10: Precision and Recall Results with SVM for WM with Intensity, Position and wavelet coefficients in feature vector

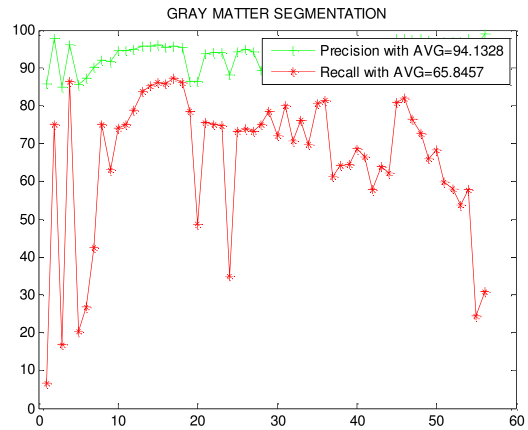

Fig. 11: Precision and Recall Results with Neural Network for GM with Intensity and Position in feature vector

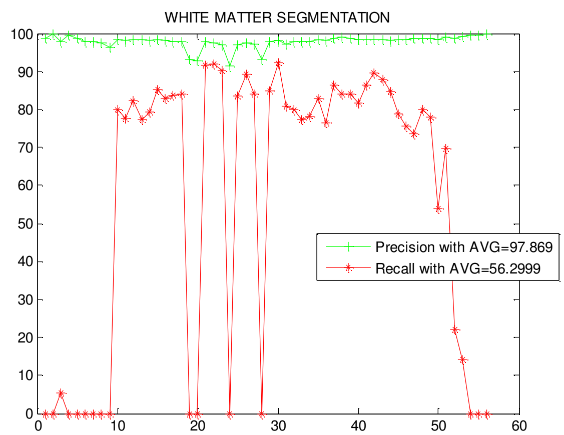

Fig. 12: Precision and Recall Results with Neural Network for WM with Intensity, Position and Wavelets Coefficients in feature vector

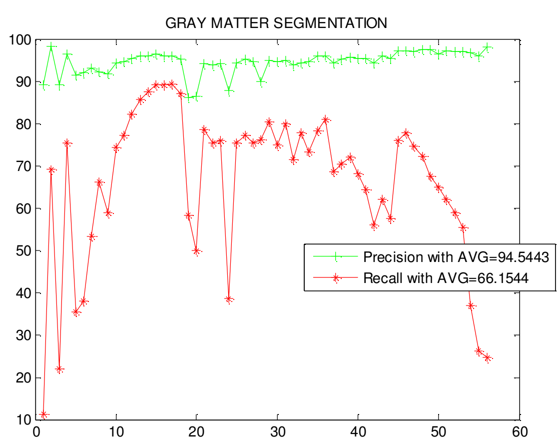

Fig. 13: Precision and Recall Results with Neural Network for WM with Intensity and Position in feature vector

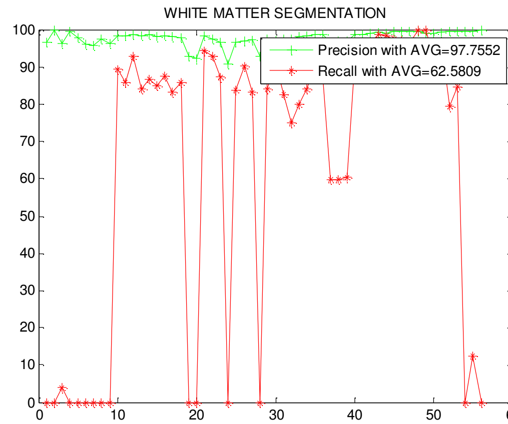

Fig. 14: Precision and Recall Results with Neural Network for WM with Intensity, Position and Wavelets Coefficients in feature vector

The above graph gives the precision for each of the 60 frames. The troughs in the graph represent the points at which the pre-processing result was faulty which shows that this system is quite dependant on the pre-processing stage. But the overall precision for all the frames seems to be sati.

To summarize the results, the table I shows the results for all combinations for features as intensity, position and wavelet coefficients with the classifiers as SVM and Neural Network. The result shows that most of the time precision values approach to ideal value. However, recall values are significantly down and shows the degradation in results due to several factors , out of them improper pre-processing being a dominant factor. While using simple features like intensity and position, SVM classifier outperforms over the neural network. The neural network shows improved results when all three features, intensity, position and wavelets coefficients, are sued in feature vector as compared to SVM classifier. It is also visible from results that discrimination capability of feature and classifier is more in case of white matter than gray matter.

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

Feature type	Classifier	Precision (%)		Recall (%)	
		GM	WM	GM	WM
Intensity and Position	SVM	94.86	98.04	67.58	61.52
Intensity and Position	Neural Network	94.54	97.86	66.15	56.29
Intensity , position and Wavelets	SVM	91.55	96.10	33.20	27.07
Intensity , position and Wavelets	Neural Network	94.13	97.75	65.84	62.58

4. 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. The automated system based on MRI imaging has been researched by several researcher groups. In this paper, we attempted to analyze the performance of segmentation in MRI images with simple features and complex representations. We also compared the performance obtained with two popular classifiers such as SVM and neural network. The result shows the superiority of neural network over the SVM. It also shows that inclusion of wavelet features in case of neural network improves the segmentation capability of MRI segmentation system. A drawback with these techniques is the dependency on the preprocessed image. This needs to be reduced. This can be done by adding a factor which will take into consideration the position and connectivity. The future scope of our research work will be to take care of these discrepancies.

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