A Novel Brain MRI Analysis System for Detection of Stroke Lesions using Discrete Wavelets

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Abstract—Development of computer aided detection techniques for brain disorder has been gaining significant importance in the past few years. Out of the various brain diseases, stroke stands first for the reason behind fatality and disability. Significant features extracted from brain MR images, along with machine learning techniques could identify discriminative patterns for automatic detection of ischemic stroke. This research aims at examining the wavelet based statistical features for characterizing such abnormal lesion structures. Five different wavelet functions, namely daubechies, symlet, coiflet, de-meyer and bi-orthogonal wavelets were extensively analyzed for different normal and abnormal datasets. The wavelet co-efficients were calculated for different levels and statistical parameters were extracted from it as features. These features were trained using support vector machines for automatic classification. Experiments indicate that the accuracy of the proposed system was around 98%.

***Index Terms*—Ischemic Stroke; Wavelet Decomposition; Texture; SVM.**

I. INTRODUCTION

Recent statistical report released by World Health Organization indicated that approximately one billion people were affected by various neurological diseases, such as stroke, Wilson's disease, Parkinson's disease (D) and many others. Out of these disorders, stroke stands first for the reason behind disability and death in both adults and aged people. Ribo Ge et al. reported that the accuracy of medical diagnosis for these neurological disorders depends largely on the interpretation of medical images [1]. Out of the various brain imaging modalities, Magnetic Resonance Imaging (MRI) was considered as an accurate modality of high quality in visualizing the brain tissues because of its high contrast to soft tissues and non-invasive acquisition [2].

Once the images were available after radiological examination, the basic step is to segment the region of interest (ROI) for characterizing its properties. Several methods for segmenting the ROI, like region based approaches, contour based approaches, and many others were presented in the last few years. Region-based segmentation algorithms function by grouping pixels of similar intensity together from the neighborhood. Gargouri et al developed a technique to identify the region of interest by utilizing Maximum entropy thresholding and Otsu's multilevel thresholding [3]. Then, the Iterative Closest Points (ICP) was employed for the matching purpose. Chaudhari et al. developed a method for brain MRI segmentation by using entropy based texture features [4]. Saad et al. utilized region wise histograms for segmentation purpose [5]. Region growing techniques basically identify a connected region based on either edge based details or intensity information by adopting manual selection of a seed point inside the target region [6]. Matesin et al. presented a seeded region-growing based segmentation technique in order to obtain a fast labeling of the background details, gray matter, white matter, CSF and stroke lesions [7].

When the input image was segmented and the region of interest is recognized, the following step is to extract significant features from the segmented region. These features will act as the representatives for the entire image. An approach using geometrical, intensity-based and local image descriptor features was extracted to describe the cerebral micro bleeds in brain MRI images [8]. In the last few decades, texture features were considered to be one of the prominent features in medical images. A few vital properties for image description and interpretation are uncovered through observing the texture pattern of the images for example, granularity, smoothness, coarseness, periodicity, geometric structure and many others. The gray level co-occurrence matrix (GLCM) was usually utilized to concentrate the composition of texture based statistical information from an image [9]. Goswami et al. presented an approach for abnormality detection from brain MRI images using GLCM texture features and hybrid neuro-fuzzy classifier [10]. A scheme for computer aided detection of ischemic stroke utilizing texture features were introduced by Hema Rajini et al. [11]. The input images were bisected into two halves by following the midline. Then texture features were extracted on each half and compared to detect the lesion. An approach to define the area of ischemic stroke lesion was introduced by utilizing statistical methods and probability likelihood. This approach partitioned the information into 2 zones: normal and abnormal areas of the brain [12].

The features extracted from the segmented region must be trained with a suitable algorithm in order to develop a classification system. The supervised learning models were prepared with different algorithms like Artificial Neural Networks (ANN), Support Vector Machines (SVM) and so on.

Bagher-Ebadian et al. presented an approach for anticipating the last degree of the ischemic infarction using artificial neural networks. In this technique, the last degree of the lesion was determined from T1-Weighted, T2-Weighted, Diffused Weighted training images [13]. Mougiakakou et al. presented a computer-aided diagnosis system of carotid atherosclerosis

[14]. It was based on statistical measures obtained from the ultrasound image and classification was done through neural networks. Hachaj et al. proposed a neural network (NN) classifier for identifying the type of abnormality from brain perfusion maps [15]. Prakash et al. introduced a method for segmentation of acute infarction from diffusion weighted images. In this method, a probabilistic neural network along with an adaptive gaussian mixture model [16].

The support vector machine (SVM) is another broadly utilized supervised learning methodology for image classification. An approach using support vector machines with imaging and clinical features was utilized to determine the symptomatic intracranial hemorrhage (SICH) with good accuracy [17]. Padma et al. proposed a method for classifying brain tissues from CT images using SVM and wavelet based texture features [18]. Another novel method was introduced to detect the differences in group brain image groups based on spatially regularized SVM [19]. Another support vector machine based classifier was trained by Oskar et al. on expert-segmented examples and it is used to classify formerly unseen images [20].

II. Materials And Methods

The proposed methodology utilizes wavelet transform based statistical texture features for characterizing the ischemic stroke lesions. At first, the input MRI slices were subjected to global thresholding based method to remove the bony portions of the skull region. Then, Otsu's segmentation was applied to localize the region of interest. First and second order statistical features from different levels were extracted from the segmented region. These vectors were trained using Support Vector Machines to build up the classification system. The architecture of the proposed approach was presented in Figure 1.

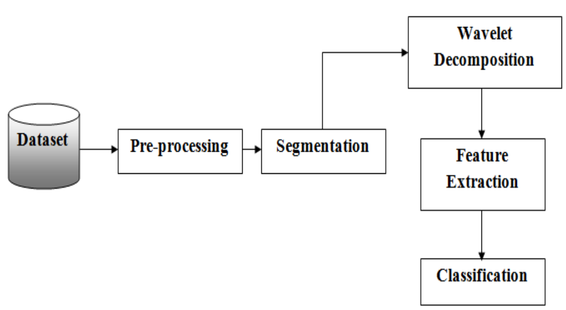


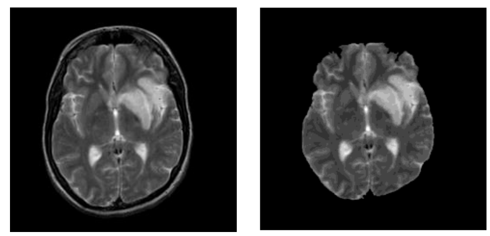
Figure 1: Overview of the proposed system.

A. Data Acquisition

A total of 45 MRI datasets were collected from various online and offline sources. 17 T2-MRI datasets were acquired from Global Health City, Chennai and the remaining datasets were downloaded from ISLES contest [21-22]. The format of the input MRI slices were in Neuroimaging Informatics Technology Initiative (NIfTI) and Digital Imaging and Communication in Medicine (DICOM). The proposed experiments were all carried out with axial slices.

B. Preprocessing

Separating the bony portions of the skull from the brain tissues is a vital pre-processing step in the processing of MRI images. In this work, thresholding based approach is applied to remove the skull portions from the brain images [23]. Initially, the input MRI slice is converted to a binary image by applying global thresholding. Then the largest connected component with respect to the bony threshold is computed. Later, a mask was formed which will suppress the largest connected component and retain the other inner details of the image. This mask is finally convolved with the original image to produce the skull stripped image. The corresponding results of pre-processing stage are presented in Figure 2.

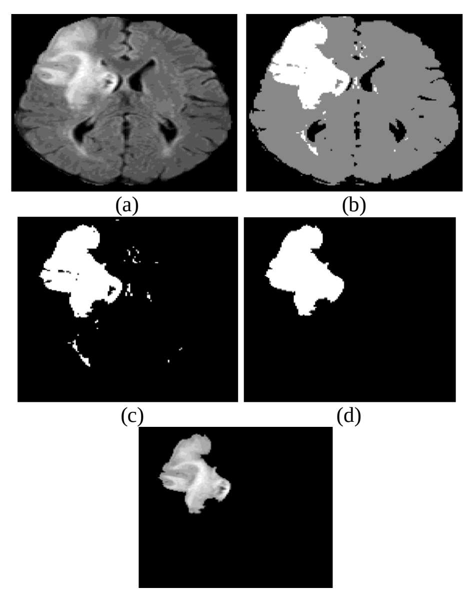


(a) (b)

Figure 2: (a) Input MRI slice (b) Skull stripped image after pre-processing.

C. Segmentation

The objective of segmentation is to transform the representation of an image into some other form that is more meaningful and easier to analyze. It enhances certain essential features or suppresses some unwanted details which were intended for further processing. Vidyarthi et al. applied Otsu's segmentation to brain MR images for extracting the tumor structures [24]. It basically segments the image using a bi-modal histogram, which will differentiate the foreground and background pixels. This method was applied to the preprocessed image and the resulting observations along with segmented region of interest (ROI) were presented in Figure 3.



(e)

Figure 3: (a) Preprocessed image (b) segmented map (c) lesion part (d) localized lesion part after post- processing (e) segmented ROI.

D. Feature extraction

The wavelet transform confines the energy of the signal in a combined space-scale domain. It is essentially a small wave like structure that will decompose a given signal with respect to translated and scaled versions of it. Wavelet decompositions were helpful in the time-frequency analysis of non-stationary signals for recognizing the details of the singularities. In this research, five different wavelet functions were applied to the input MRI images for examining the properties of the lesion structures. The 2D-discrete wavelet transform of an image f(x,y) of size ‘M’ X ‘N’ was presented in Equations (1) and (2).

$$W_{\varphi}(j_0, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \varphi_{j_{0,m,n}}(x,y) \tag{1}$$

$$W_{\gamma}^{i}(j, m, n) = \frac{1}{\sqrt{MN}} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) \gamma_{j.m,n}^{i}(x,y), \quad i = \{H, V, D\} \tag{2}$$

where ‘j_0’represents the starting scale, ‘$W_{\varphi}(j_0,m,n)$’ defines the approximation coefficients of f(x,y) at scale j_0, ‘$W_{\gamma}(j,m,n)$’ coefficients add horizontal ‘H’, vertical ‘V’ and diagonal ‘D’ details for scales $j \geq j_0$.

Five different wavelet functions namely daubechies, de-meyer, bi-orthogonal, symlet and coiflet were applied to the input images. The level of decomposition was maintained to be ‘3’. The detail level coefficients along the vertical, horizontal and diagonal directions describe the edge activity of the image, the approximation coefficients concentrate on the inner details of the image. The de-meyer wavelet decomposition for the segmented ROI was presented in Figure 4.

Once the wavelet decomposition was completed, statistical features could be extracted from each level for characterizing the properties of the images. In this work, four first and second order statistical features were extracted from the segmented regions. The first order features include mean, standard deviation, skewness and kurtosis. The second order statistical features include energy, entropy, homogeneity and contrast parameters. The second order features were represented in Equations (3) to (6). The second order features were derived based on the co-occurrence matrix ‘G’.

$$Energy = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (p(i,j))^2 \tag{3}$$

$$Entropy = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} p(i,j).\ \mathrm{Log}(p(i,j)) \tag{4}$$

$$Contrast = \sum_{n=0}^{G-1} n^2 \left(\sum_{i=1}^{G-1} \sum_{j=1}^{G-1} p(i,j) \right), |i-j| = n \tag{5}$$

$$Homogeneity = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} \frac{p(i,j)}{1 + |i-j|} \tag{6}$$

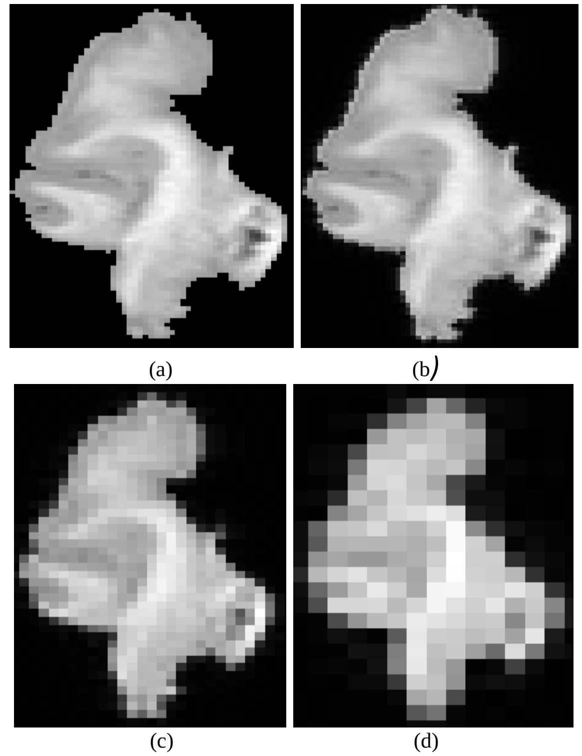


Figure 4: (a) Input image (b) Level-1 Approximation (c) Level-2 Approximation (d) Level-3 Approximation

E. Classification

The first and second order statistical features were extracted from the images and stored as feature vectors. These features must be trained with a suitable algorithm in order to develop a classification system. In this research, support vector machine was utilized for classification. It accepts feature vector as input and finds out to which class it actually belongs to. Let the feature vectors of a given training set X be $x_i, i = 1,2,3 \ldots . M$.

The training set could belong to any one of the two classes $ώ_1$ and $ώ_2$. SVM utilizes the training data to find an optimal hyperplane of maximum margin that could separate these two classes. This hyperplane can be given as per the Equation 7. The radial basis kernel function employed for finding the hyperplane was given in Equation (8).

$$g(x) = W^T x + W_0 = 0 \tag{7}$$

$$K(x, x_i) = \exp\left(\frac{-||x - x_i||^2}{\sigma^2}\right) \tag{8}$$

where σ and k determine the scaling of the inputs in the kernel function.

III. Results And Discussion

The experiments were carried out on Intel(R) i5 processor. The CPU core frequency was 2.3 GHZ and the capacity of the RAM was 4 GB. For the execution environment, MATLAB R2012b. 5-fold cross validation was utilized in this study i.e. the input dataset was partitioned into 5 sets randomly. Each time, any one of the five sets is used for testing case, the remaining 4 sets were used for training purpose.

The performance of each wavelet based detection scheme was validated based on sensitivity, specificity and accuracy. Sensitivity calculates the percentage of positives which were correctly recognized. Specificity computes the proportion of negatives that were correctly recognized as such. Accuracy measures how well the classifier predicts both positives and negatives. The sensitivity, specificity and accuracy are calculated as given in Equations (9) to (11).

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{9}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{10}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{11}$$

where:

- TP = True positives: samples which were correctly identified
- TN = True negatives: samples which were incorrectly identified
- FP = False positives: samples which were correctly rejected.
- FN = False negatives: samples which were incorrectly rejected

Each wavelet function was validated using 5-fold cross validation. The corresponding observations were projected in Table 1. The total number of training and testing samples considered in this work was 160 and 64 respectively.

Table 1. Performance comparison of 5-fold cross validation for each wavelet function.

Type of Wavelet	Fold	Correctly classified	Misclassified	Accuracy
Daubechies	1	63	1	98.43
	2	62	2	96.87
	3	63	1	98.43
	4	63	1	98.43
	5	63	1	98.43
Symlet	1	60	4	93.75
	2	61	3	95.31
	3	61	3	95.31
	4	61	3	95.31
	5	61	3	95.31
Coiflet	1	60	4	93.75
	2	60	4	93.75
	3	61	3	95.31
	4	60	4	93.75
	5	61	3	95.31
De-meyer	1	63	1	98.43
	2	63	1	98.43
	3	63	1	98.43
	4	63	1	98.43
	5	63	1	98.43
Biorthogonal	1	60	4	93.75
	2	61	3	95.31
	3	60	4	93.75
	4	60	4	93.75
	5	63	1	98.43

These observations indicate that both daubechies and de-meyer wavelet functions exhibited better performance than the other wavelet functions. A comparative analysis of accuracy obtained for each wavelet function based classifier was presented in Figure 5.

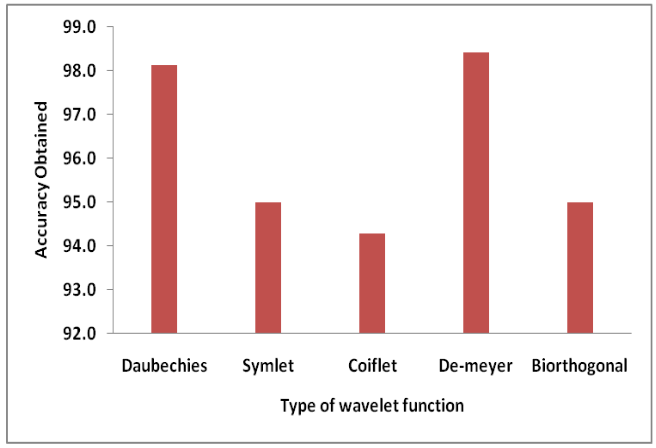


Figure 5: Accuracy obtained for each wavelet function

IV. Conclusion

Computed aided detection of stroke lesions from brain MRI helps in identifying the severity level of the affected tissues for effective treatment. The properties of these abnormal structures were generally complex and non-linear in nature. This research aims at examining the various wavelet based statistical features for automated detection of ischemic stroke lesions. An extensive analysis was carried out with five different wavelet functions, namely daubechies, symlet, coiflet, de-meyer and bi-orthogonal wavelets. These experimental observations indicate that both daubechies and de-meyer wavelet functions exhibited better performance than the other wavelet functions. Specifically, de-meyer wavelet based lesion detection achieved an overall accuracy of 98.43%. In future, it is planned to validate the results of the proposed system by utilizing a wider datasets and also to improve the accuracy further by analysing appropriate techniques.

References

[1] Ribo Ge and Hailong Shen, "Researching on Feature Extraction of Brain CT Image", *International Journal of Signal Processing, Image Processing and Pattern Recognition*, vol. 6, No. 5, pp. 39-48, 2013.

[2] Jeena, R.S. and Sukesh Kumar, "A Comparative Analysis of MRI and CT Brain Images for Stroke Diagnosis", *Proceedings/International Conference on Microelectronics, Communication and Renewable Energy*, pp.1-5, 2013.

[3] Gargouri F, Ben Hamida INA and Chtourou K, "Automatic localization methodology dedicated to brain tumors based on ICP matching by using axial MRI symmetry", *Proceedings /International Conference on Advanced Technologies for Signal and Image Processing*, pp.209-213, 2014.

[4] Chaudhari A.K. and Kulkarni J.V, "Local entropy based brain MR image segmentation", *Proceedings/IEEE 3rd International Conference on Advance Computing*, pp.1229-33, 2013.

[5] Saad N.M, Abu-Bakar SAR, Muda S, Musa Mokji, "Segmentation of brain lesions in diffusion-weighted MRI using thresholding

technique", *Proceedings/IEEE International Conference on Signal and Image Processing Applications*; pp. 249-254, 2011.

[6] Jafari M. and Kasaei S, "Automatic brain tissue detection in MRI images using seeded region growing segmentation and neural network classification", Australian *Journal of Basic and Applied Sciences.* vol. 5, no. 8, pp.1066-79, 2011.

[7] Matesin, M. Loncaric, S. and Petravic, D, "A rule-based approach to stroke lesion analysis from CT brain images", *Proceedings/International Symposium on Image and Signal Processing and Analysis*; pp.219-223, 2001.

[8] Ghafaryasl, B. Van der Lijn, F. Poels M, "A computer aided detection system for cerebral microbleeds in brain MRI", *Proceedings/IEEE International Symposium on Biomedical Imaging*, pp.138-141, 2012.

[9] Norhashimah Mohd Saad, S.A.R Abu Bakar, Abdul Rahim Abdullah, Lizawati Salahuddin, Sobri Muda, Musa Mokji, "Brain lesion segmentation from diffusion-weighted MRI based on adaptive thresholding and gray level co-occurence matrix", *Journal of Telecommunication, Electronic and Computer Engineering*, vol. 3, no. 2, pp. 1-13, 2011.

[10] Goswami, S. And Bhaiya, LKP, "A hybrid neuro-fuzzy approach for brain abnormality detection using GLCM based feature *extraction", Proceedings/International Conference on Emerging Trends in Communication, Control, Signal Processing & Computing Applications*; p.1-7, 2013.

[11] Hema Rajini, N. and Bhavani, R, "Computer aided detection of ischemic stroke using segmentation and texture features", *Measurement*, vol. 46. pp.1865, 2013.

[12] Fueanggan, S. Chokchaitam, S. and Muengtaweepongsa, S, "Automatic detection of ischemic stroke area from CT perfusion maps Cerebral Blood Volume and Cerebral Blood Flow", *Proceedings/International Symposium on Signal Processing and Communications Systems*, p.1-6, 2011.

[13] Hassan Bagher-Ebadian, Kourosh Jafari-Khouzani, Panayiotis D. Mitsias, Mei Lu, Hamid Soltanian-Zadeh, Michael Chopp, James R. Ewing, "Predicting final extent of ischemic infarction using artificial neural network analysis of multi-parametric MRI in patients with stroke", *PloS One.* vol. 6, no. 8, pp. e22626, 2011.

[14] S.G. Mougiakakou, S. Golemati, I. Gousias, Nicolaides AN, Nikita KS. "Computer-aided diagnosis of carotid atherosclerosis based on ultrasound image statistics, laws' texture and neural networks", *Ultrasound Med Biol*. vol. 33, no. 1, pp. 26-36, 2007.

[15] Hachaj, T. and Ogiela, M.R, "Neural Network Approach for Identification of Selected Brain Perfusion Abnormalities", *Proceedings/Innovative Mobile and Internet Services in Ubiquitous Computing*, pp. 52-57, 2012.

[16] Prakash K N Bhanu, Gupta V, Bilello M, "Segmentation, and image property study of acute infarcts in diffusion weighted images by using a probabilistic neural network and adaptive Gaussian mixture model", *Academic Radiology*.vol.13, pp.1474–84, 2006.

[17] Paul Bentley, Jeban Ganesalingam, Anoma Lalani Carlton Jones, "Prediction of stroke thrombolysis outcome using CT brain machine learning", *NeuroImage Clinical*. Vol. 4, pp. 635–40, 2014.

[18] Padma, A. and Sukanesh R, "SVM Based Classification of Soft Tissues in Brain CT Images using Wavelet Based Dominant Gray Level Run Length Texture Features", *Middle-East Journal of Scientific Research*. vol. 13, no. 7, pp. 883-88, 2013.

[19] Rémi Cuingnet, Charlotte Rosso, Stéphane Lehéricy, "Spatially Regularized SVM for the Detection of Brain Areas Associated with Stroke Outcome, *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2010; Lecture Notes in Computer Science*, vol. 6361, pp.316-23, 2010.

[20] Oskar Maier, Matthias Wilms, Janina von der Gablentz, "Ischemic stroke lesion segmentation in multi-spectral MR images with support vector machine classifiers", *Proceedings/SPIE 9035 Medical Imaging*, p.12 pages.

[21] https://www.virtualskeleton.ch/ISLES/Start2015

[22] http://www.isles-challenge.org/

[23] R. Menaka, R. Karthik, Shivangi Gupta, Archit Mishra, "Ischemic Stroke Detection from MRI Diffusion images using bifurcation analysis of texture features and fuzzy based segmentation", International journal of tomography and simulation, vol. 28, no. 2, pp. 117-125, 2014.

[24] Vidyarthi, A. and Mittal, N, "A hybrid model for extraction of brain tumor in MR images", Proceedings/ International Conference on Signal Processing and Communication (ICSC), pp. 202-206, 2013.