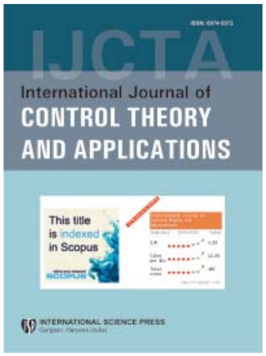

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Support Vector Machine Based Classification and Detection of Iron Accumulation in Brain using Susceptibility Weighted Images

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Abstract: Accumulation of iron in brain results in iron overload. It is due to many disorders and in some cases leads to organ damage. In clinical practice, susceptibility weighted imaging (SWI) is used to differentiate iron regions in brain images. The main objective of this paper is to partition iron region and precisely quantify brain iron. In the preprocessing stage, the noise in the image is eliminated using Gaussian filter. Then fuzzy c-means algorithm is used for segmentation of iron region in the SWI brain image. In the feature extraction step, the statistical features namely Haralick's texture features are computed for the brain image. In addition to statistical features, two shape features like geometric moment and eccentricity are also determined. Support Vector Machines classifiers play an important role in our proposed method which effectively classifies the brain images based on iron regions. The overall accuracy of the SVM based proposed method of classification is above 93.05%.

Keywords: *Susceptibility weighted Imaging; Gaussian; Haralick's texture features;*

1. INTRODUCTION

Automatic diagnostic techniques are becoming very important in the diagnosis of medical images. These systems are applied to a variety of medical data [1]. Susceptibility Weighted Images (SWI) provides valuable information in the diagnosis and subsequent treatment of patients with neurologic disorders [2]. However, based on the expertise of the radiologists the diagnosis process may be time consuming. This limitation is overcome by automatic diagnostic techniques which are nowadays becoming more significant. Soft computing techniques are adapted with digital image processing methods to provide a great deal in visual interpretation of SWI images [3]. A unique contrast is obtained by tissue magnetic susceptibility differences using SWI based techniques. This unique contrast obtained differs when compared to that of spin density values, T1, T2, and T2* [2].

The magnitude image which is contrast enhanced is combined with the phase image which is very sensitive to iron accumulation. As age increase, there is a sudden increase in the accumulation of iron in brain. The basal ganglion is an important region in brain which shows more iron deposition. Various neurodegenerative diseases indicate that the iron content level in the central part of nervous system is abnormal [4] [5]. Regulation of iron content in brain is very important. Globus pallidus region also shows high iron content in brain.

The primary objective of the proposed research is to develop an automated system for the detection and classification of iron content in brain. For this purpose, a step by step methodology is presented in this paper. Initially in the preprocessing step, the noise is removed from the SWI image. Analysis of various filtering algorithms for removal of Gaussian and Rician noise was performed but a better performance as achieved in the case of Gaussian filter [6].

After noise removal, the iron region in SWI brain image is segmented using fuzzy c-means (FCM) method. A comparison performed on various segmentation algorithms indicates that the FCM algorithm achieves a faster clustering rate [7].

Feature extraction is performed after segmentation. Two important features namely texture and shape features are extracted from the segmented brain image. For texture feature analysis, Haralick's features are used and for shape features the geometric moment and eccentricity are determined.

The Support Vector Machine classifier has two phases namely is the training and classification phase. A dataset of 40 abnormal and normal images are first trained. After training, the SVM classifier correctly classifies the image as normal or abnormal. The normal image is the SWI brain image with no iron region detected and abnormal image is detected with iron regions. The overall accuracy of the SVM based proposed method o classification is above 93.05%.

2. METHODOLOGY

The input data set includes Susceptibility Weighted images of brain with iron content (abnormal) and without iron content (normal). The proposed methodology as described in figure 1, for detection and classification of iron content in brain is categorized into four steps:

1. Preprocessing
2. Segmentation
3. Feature Extraction
4. Classification

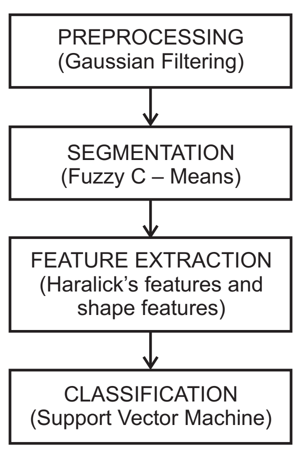

Figure 1: Proposed methodology for iron detection in brain

3. PREPROCESSING

The quality of SWI brain images are greatly affected by two types of noise namely, Rician and Gaussian noise. Noise removal enhances the visual appearance of the brain image. The main goal of this preprocessing step is to enhance the quality of the image. The Gaussian filter or image blurring filter is the most widely used filter which is used for smoothing operation.

Gaussian function implies the impulse response of the Gaussian filter. This function is designed such that when a decrease of rise or fall period occurs, the input value provided to the step function is not increased. This results in the minimum possible group delay because no overshoot is given to the step function.

The Gaussian function is used for calculating the transformation to apply to each pixel in the image. For one dimension, the equation of a Gaussian function is given by:

$$G(x) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-x^2}{2\sigma^2}} \tag{1}$$

Comparison of various filtering algorithms based on their performance shows that Gaussian filter is better for removal of Gaussian and Rician noise from SWI brain images [6].

4. SEGMENTATION

The segmentation step aims at partitioning the iron region from the given image. For the purpose of segmentation, various algorithms have been developed and implemented. Similarity based and discontinuity based are the two properties adapted in many segmentation methods. The primary requirement of the clinical diagnosis of SWI images is to use an efficient algorithm that results in accurate segmentation of SWI brain images.

Among the various segmentation algorithms like fuzzy *c*-means, *k*-means, region growing methods and atlas guided approaches, the fuzzy *c*-means algorithm showed better results. The fuzzy *c* - Means (FCM) image segmentation algorithm is considered to be a powerful tool for performing clustering which uses unsupervised learning. J.C.Bezdek et.al [8] developed the FCM algorithm. An important role is played by membership grade in the algorithm. The extent to which each data element is to be included to a cluster in the image is specified by the membership grade.

Assume the data set, $x = [x_1, x_2, \ldots, x_f]^T$. The performance index or the objective function for segmentation of data is reduced by fuzzy c-means algorithm as explained by [9].

$$J_m(u, v) = \sum_{i=1}^{c} \sum_{k=1}^{f} u_{i,k}^m \| x_k - v_i \|^2 \tag{2}$$

In equation (2), f denotes the total number of data inputs in vector X, c represents the total number of clusters, u_{ik} represents element of the partition matrix U. The size of the matrix U is $(c \ x \ f)$ which contains the membership function v_i is the center of the i^{th} class. The weighting factor denoted by m is responsible for controlling the fuzzy membership function. The fuzzy *c*-Means method partitions the vector represented by X into c fuzzy subsets. Here u_{ik} represents the memberships of x_k in class denoted by i.

The steps for FCM algorithm are explained below [10]:

1. The first step is the initialization phase which includes the following:
   a) The image is scanned across each line to generate vector X that contains the picture element values represented by the gray levels of the given image.
   b) The centers of clusters represented by vector $V^{(0)}$ are randomly initialized.
   c) Repeat iteration $t = 1$ till the algorithm has converged.
2. In the second step, the membership matrix $U^{(t)}$ of element u_{ik} is calculated as:

$$u_{ik} = \left(\sum_{j=1}^{c} \left(\frac{\| x_k - v_i \|}{\| x_k - v_j \|} \right)^{\frac{2}{m-1}} \right)^{-1} \tag{3}$$

3. Vector $V^{(t)} = [v_1, v_2, \ldots\ldots, v_c]$ is computed as:

$$v_i = \frac{\sum_{k-1}^{d} u_{ik}^{m}}{\sum_{k-1}^{d} u_{ik}^{m}} \tag{4}$$

4. Test for convergence: if $\|V^{(t)} - V^{(t-1)}\| > \varepsilon$,
   a) Increment the iteration t by value one and then go to the Step 2, else algorithm has converged.
   b) ε is a positive value that denotes the threshold chosen.

The main objective of fuzzy clustering is to partition the given data into a collection of clusters. Each and every data point is assigned membership values corresponding to each cluster. The fuzzy clustering algorithm allows the clusters to grow into their natural shapes [11].

5. FEATURE EXTRACTION

Feature extraction plays a vital role in the area of image processing. The features are extracted from the segmented image which will be useful in classification and detection of iron content in images. In this paper, two types of features namely texture and shape features are extracted. The Haralicks's texture features and two shape features namely geometric moment and eccentricity are computed.

Haralick's features are statistical features that are computed over the entire brain image. The overall texture of the image is described using entropy and sum of variance. Based on Haralick's features, Chaddad et al [12] proposed an approach for detection and classification of cancer cells in colon. The most distinctive parameters were selected for cancer cells. A study to investigate the effectiveness of using Haralick's features to differentiate between normal and abnormal images is explained by Fleet et al [13].

Statistical texture methods determines the spatial distribution of gray values, by finding local features at each point in the image and inferring a set of statistics from the distributions of the local features. In 1973, Haralick et al. described the Gray Level Cooccurrence Matrix (GLCM) and texture features [14]. Computation of feature extraction using Haralick's features comprises of two steps. In the intial step, the GLCM is determined, and in the second step, the texture features based on the GLCM are calculated.

The nine texture descriptors are presented in (5) to (14), where Ng is the number of gray levels, p_d is the normalized symmetric GLCM of dimension Ng x Ng, and $p_d(i, j)$ is the $(i, j)^{th}$ element of the normalized GLCM [14].

1. Contrast is the intensity variation between reference pixel and its neighbor.

$$\text{Contrast} = \sum_i \sum_j (i-j)^2\, p_d\,(i, j) \tag{5}$$

2. Homogeneity describes the closeness of the distribution of elements in the GLCM to the diagonal of GLCM.

$$\text{Homogeneity} = \sum_i \sum_j \frac{1}{1+(i-j)^2}\, p_d\,(i, j) \tag{6}$$

3. Entropy is the degree of disorder present in the image.

$$\text{Entropy} = -\sum_i \sum_j p_d\,(i, j) ln\, p_d\,(i, j) \tag{7}$$

4. Energy is derived from the Angular Second Moment (ASM). The ASM measures the local uniformity of the gray levels.

$$\text{Energy} = \sqrt{\text{ASM}} \tag{8}$$

where $\text{ASM} = \sum_i \sum_j p_{d^2}(i, j)$

5. Correlation feature shows the linear dependency of gray level values in the cooccurrence matrix:

$$\text{Correlation} = \sum i \sum j\, p_d(i, j) \frac{(i-\mu_x)(j-\mu_y)}{\sigma_x \sigma_y} \tag{9}$$

Where μ_x, μ_y and σ_x, σ_y are the means and standard deviations.

6. Moment 1 (m_1) is the mean which is the average of pixel values in an image and is given by

$$m_1 = \sum i \sum j\, (i-j) p_d(i, j) \tag{10}$$

7. Moment 2 (m_2) is the standard deviation and can be represented as

$$m_2 = \sum i \sum j\, (i-j)^2\, p_d(i, j) \tag{11}$$

8. Moment 3 (m_3) provides the degree of asymmetry in the distribution and is defined as

$$m_3 = \sum i \sum j\, (i-j)^3\, p_d(i, j) \tag{12}$$

9. Moment 4 (m_4) measures the relative peak or flatness of a distribution and is also known as kurtosis.

$$m_4 = \sum i \sum j\, (i-j)^4\, p_d(i, \mathrm{j}) \tag{13}$$

In addition to Haralick's features, two shape features namely geometric moment and eccentricity are also determined. Geometric Moment is computed from weighted averages of the image pixel intensities usually chosen to have some attractive property or interpretation. When normalized, they can be considered as a probability distribution. If $f(x, y)$ is a digital image, the central moment is defined as follows:

$$\mu_{pq} = \sum_x \sum_y (x-x')^p (y-y')^q f(x, y) \tag{14}$$

Eccentricity: An approximate measure of eccentricity of an object is given by:

$$e = \frac{(\mu 20 - \mu 02)^2 + 4\mu 11 \mu 11}{(\mu 20 + \mu 02)^2}$$

6. CLASSIFICATION

The basic idea behind Support Vector Machine (SVM) classifier algorithm is that vectors that are computed are mapped nonlinearly to a feature space of very high dimension. A linear separation surface is created in this feature space to classify the training data by minimizing the margin between the vectors of the two classes. Once the decision surface which partitions the space into two subspaces is obtained, the training process stops. Different classes of the training data are described by the subspaces produced during training. After the training process is over, the test data is mapped to the feature space. Based on the presence of iron region the feature space is defined.

7. EXPERIMENTAL RESULTS

Two input datasets of 60 SWI brain images (normal-without iron content and abnormal-with iron content) were included. The input image is mainly corrupted by Gaussian and Rician noise and is denoised more efficiently by Gaussian filter. Thus the output of the preprocessing step is the Gaussian filtered image. The segmentation of iron region in brain is performed using FCM clustering method.

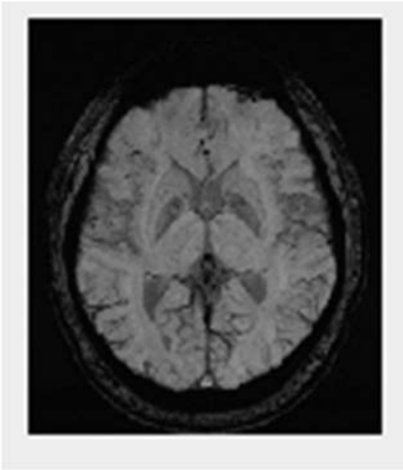

Figure 2: Original Image

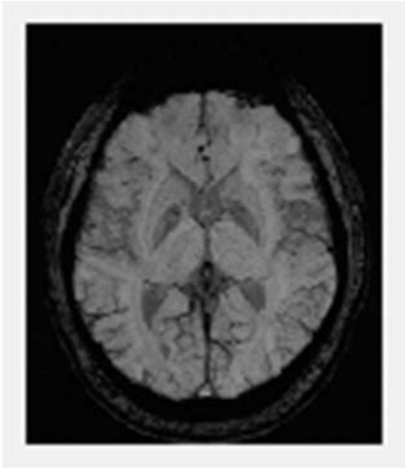

Figure 3: Image corrupted by Gaussian and Rician noise

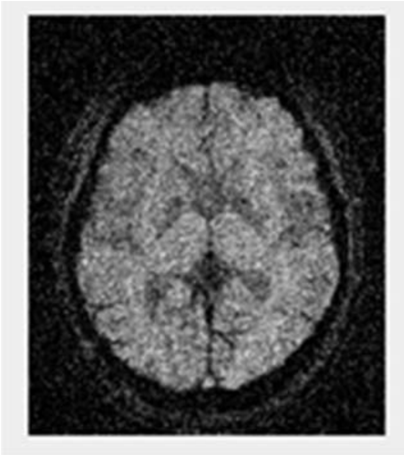

Figure 4: Gaussian Filtered Image

Figure 5: Fuzzy C-Means segmented image

Figure 6: Dilated Image

The Fuzzy *c* – Means image is then dilated to expand the shapes contained in the segmented image as shown in Fig 6.

All the nine Haralick's features are extracted along with the shape descriptors namely geometric moment and eccentricity.

Table 1
Average of Haralick's texture features for normal and abnormal images

Sl. No.	*Texture Features*	*Average value (Abnormal image)*	*Average value (Normal image)*
1.	Homogeneity	0.75	0.70
2.	Energy	0.532	0.541
3.	Correlation	0.010	0.012
4.	Contrast	192.04	196.68
5.	Entropy	3.11	3.18
6.	Moment m1	0.64	–0.52
7.	Moment m2	201.35	216.09
8.	Moment m3	6713	–7234
9.	Moment m4	1592347	1307524

The proposed method achieved a mean specificity of 92.7%, and the mean sensitivity was 93.4%. The overall mean accuracy is calculated to be 93.05%. Table 3 shows the classification results for various subjects.

8. CONCLUSION

The proposed research work focuses on classification of SWI brain images based on the presence or absence of iron content. Fuzzy C-Means segmentation algorithm followed by support vector machine classification is done successfully using Matlab. This helps radiologists to a greater extent in the diagnosis of iron accumulation in brain iron using SWI images.

The accurate results of FCM algorithm extract the iron region from SWI brain images effectively. The FCM method was implemented because it is simpler and provides faster clustering rate than other methods. The SVM uses Haralick's features and shape descriptors for better classification of iron accumulation in SWI brain images.

REFERENCES

[1] Ubeyli ED, "Adaptive neuro-fuzzy inference systems for automatic detection of breast cancer", Journal of Medical Systems, 33(5) : 353-8, 2009.

[2] Haacke E.M., S. Mittal, Wu Z., J. Neelavalli, Cheng N.Y., "Susceptibility-Weighted Imaging : Technical aspects and clinical applications, Part I", American Journal of Neuroradiology, vol 30:19 –30, Jan 2009.

[3] M. Rastgarpour and J. Shanbehzadeh, "Application of AI techniques in medical image segmentation and novel categorization of available methods and tools", Proceedings of the International MultiConference of Engineers and Computer Scientists Volume 1, Hong Kong, March 16-18, 2011.

[4] Harder S. L., Hopp K. M., Ward H., Neglio H., Gitlin J., Kido D., "Mineralization of the deep gray matter with age: a retrospective review with susceptibility-weighted MR imaging", American Journal of Neuroradiology, vol. 29:176 –83, 2008.

[5] Gelman B. B., "Iron in CNS disease", Journal of Neuropathology and Experimental Neurology, vol 54:477– 86, 1995.

[6] Beshiba Wilson, Julia Punitha Malar Dhas, "A Classified overview of Filtering Techniques for Susceptibility Weighted Images of Brain", International Conference On Advances In Engineering And Applied Sciences (ICAEAS-2015), April 2015.

[7] Beshiba Wilson, Julia Punitha Malar Dhas, "An Experimental Analysis of Fuzzy C-Means and K-Means Segmentation Algorithm for Iron Detection in Brain SWI using Matlab", International Journal of Computer Applications, (0975 – 8887) Volume 104 – No 15, October 2014.

[8] Bezdek, J. C., "Pattern Recognition with Fuzzy Objective Function Algorithms", New York: Plenum Press, 1981.

[9] Bezdek J.C., "Pattern recognition with fuzzy objective function algorithms", Plenum Press, New York, 1981.

[10] Mitra Basu, "Gaussian-based edge-detection methods - A survey", IEEE Transactions on Systems, Man, and Cybernetics - Part C (Applications and Reviews), Vol. 32, No.3, Aug 2002.

[11] Pal N.R, Pal K, Keller J.M. and Bezdek J.C, "A Possibilistic Fuzzy c-Means Clustering Algorithm", IEEE Transactions on Fuzzy Systems, Vol. 13, No. 4, Pp. 517–530, 2005.

[12] A. Chaddad, C. Tanougast, A. Dandache, and A. Bouridane, "Extraction of haralick features from segmented texture multispectral bio-images for detection of colon cancer cells," in Proceedings of the 1st International Conference on Informatics and Computational Intelligence, pp. 55–59, Indonesia, December 2011.

[13] B. D. Fleet, J. Yan, D. B. Knoester, M. Yao, J. R. Deller Jr., and E. D. Goodman, "Breast cancer detection using haralick features of images reconstructed from ultra wideband microwave scans," in Clinical Image-Based Procedures. Translational Research in Medical Imaging, vol. 8680 of Lecture Notes in Computer Science, pp. 9–16, Springer International, Cham, Switzerland, 2014.

[14] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," IEEE Transactions on Systems, Man and Cybernetics, vol. 3, no. 6, pp. 610–621, 1973.