Magnetic Resonant Image Segmentation using trained K-means Clustering

Anil D. Kumbhar and A.V.Kulkarni

Abstract—**Magnetic Resonant Image segmentation is an indispensable process in the visualization of human tissues, particularly during clinical analysis. In this paper, we describe a method for segmentation of White matter and Gray matter from real MR images using a LM-k-means technique. After preprocessing, a simple unsupervised clustering system like k-means is taken and made into a supervised system by using Levenberg-Marquardt optimization technique. It was inferred that a k-means system does not arrive on its own at the means which will give a good segmentation. Hence the LM algorithm trains it for that purpose. The results are compared with that of a k-means system and they show a considerable improvement with a much higher precision.**

Index Terms—**Magnetic Resonant Images, image segmentation, Gray matter, White matter, k-means, Levenberg Marquardt optimization.**

I. 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].

Anil D. Kumbhar is with Smt. Kashibai Navale College of Engineering , Pune University,Pune-411041, India.
Dr.A.V.Kulkarni is with D.Y.Patil college of Engg., Pimpri Pune, Pune University.

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 antree 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 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 attempt to classify GM and WM using a trained k-means system. K-means is an unsupervised clustering system which partitions 'n' observations into 'k' clusters in which each observation belongs to the cluster with the nearest mean. We show how the results are not satisfactory when k-means are applied directly to a MRI classification system. To improve the results, we use Levenberg-Marquardt (LM) algorithm to train the k-means classifier. The results are shown to improve greatly.

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.

II. BUILDING BLOCKS

As mentioned above, we use a trained k-means classifier. So in this section we will go through the basics of a k-means clustering system. We train the system using LM algorithm. Hence, we will give a brief on these topics and later explain

how they have been integrated.

A. K-means Classification

K-means clustering algorithm was developed by J. MacQueen (1967) and then by J. A. Hartigan and M. A. Wong around 1975. K-means algorithm is one of the simplest partitions clustering method. More advanced algorithms related to k-means are Expected Maximization (EM) algorithm, Self-Organization Map (SOM), Learning Vector Quantization (LVQ). A usual k-means classifier aims at classifying 'n' observations into 'k' partitions based on the features provided. K-means has a very simple algorithm which is stated as follows:

1. Initialize means. Let's assume these as μ_1, μ_2, … , μ_k
2. Assign each observation to the cluster with the closest mean.
3. Update the means by moving it to the center of the cluster.
4.

It can be summarized as an algorithm for partitioning (or clustering) N data points into K disjoint subsets S_j containing N_j data points so as to minimize the sum-of-squares criterion

$$J = \sum_{j=1}^{K} \sum_{n \in S_j} |x_n - \mu_j|^2 \qquad \text{-(1)}$$

where x_n is a vector representing the nth data point and μ_j is the geometrical center of the data points in S_j. In our system, this k-means algorithm is used in conjunction with the Levenberg-Marquardt algorithm which is explained below.

B. Levenberg- Marquardt Algorithm

The Levenberg-Marquardt (LM) algorithm is an iterative technique that locates the minimum of a multivariate function that is expressed as the sum of squares of non-linear real-valued functions [23, 24]. It outperforms simple gradient descent and other conjugate gradient methods in a wide variety of problems. LM can be thought of as a combination of steepest descent and the Gauss-Newton method. When the current solution is far from the correct one, the algorithm behaves like a steepest descent method: slow, but guaranteed to converge. When the current solution is close to the correct solution, it becomes a Gauss-Newton method.

We will not go into the mathematical details of the algorithm since we are focusing on the application point of view. The function to be minimized can be given as

$$f(x) = \frac{1}{2} \sum_{j=1}^{m} r_j^2(x) \qquad \text{-(2)}$$

Using the LM algorithm, the updating of the parameters can be found as

$$x_{i+1} = x_i - (H + \lambda diag\, |H|)^{-1} \nabla f(x_i) \qquad \text{-(3)}$$

where H is the hessian of $f(x)$. The algorithm is as follows

1. Do an update as directed by the rule above.
2. Evaluate the error at the new parameter vector.
3. If the error has increased as a result the update, then retract the step (i.e. reset the weights to their previous values) and increase λ by a factor of 10 or some such significant factor. Then go to (1) and try an update again.
4. If the error has decreased as a result of the update, then accept the step (i.e. keep the weights at their new values) and decrease l by a factor of 10 or so.

III. PROPOSED SYSTEM

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

A. 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.
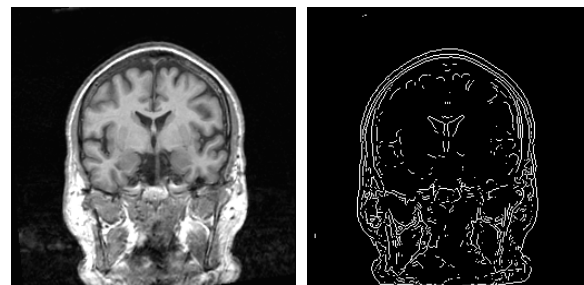
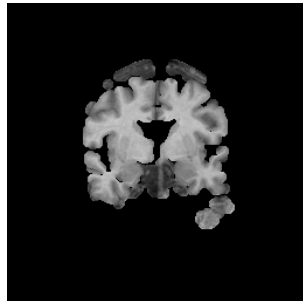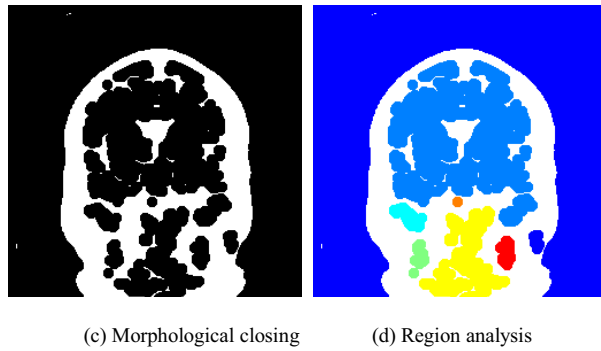(a) Original Image   (b) Edge detected

(c) Morphological closing   (d) Region analysis

(e) Segmented brain

Fig. 1: Preprocessing

B. Training the K-means classifier

We observed through experimentation that if the right means are given to the k-means system, the GM and WM can be classified to a very high precision. Hence, the task would be to find the precise means which would give this optimum classification. With the dataset we used, the manually segmented images for each brain slice is provided. These are used for training. For this training, LM algorithm was used.

1. Three means (background, white matter and gray matter) are initialized randomly.
2. The image is clustered according to these means.
3. The error between the manually segmented image and the clustered image is found and given as error to the LM system. The objective of the system is of course to minimize this error.
4. If the error is decreasing, the means are updated, the Jacobian and Hessian are updated according to the new means and λ value is downscaled by a factor.
5. If the error is increasing, the means are left as they are and the λ value is up scaled by the same factor.
6. Steps 2-5 are repeated till the max. number of iterations are reached or till the error reached a

minimum.

IV. EXPERIMENTAL RESULTS

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. We will first demonstrate the inefficiency of a standalone k-means system for the task. In general, the algorithm does not achieve a global minimum of J over the assignments. In fact, since the algorithm uses discrete assignment rather than a set of continuous parameters, the "minimum" it reaches cannot even be properly called a local minimum. When the system is applied to a MR image, the results obtained are as follows.
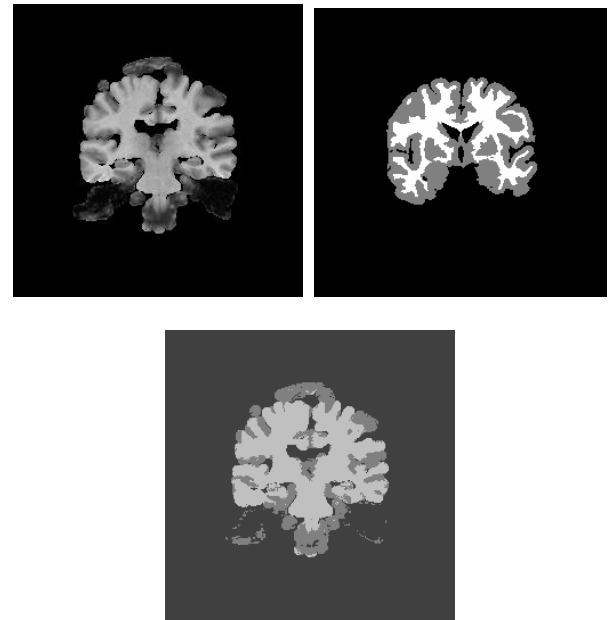

Fig. 2: (a) Preprocessed image, (b) manually segmented image (c) k-means segmented image

It can easily be seen that the result of the k-means system in Fig. 2(c) are extremely inaccurate when compared with the manually segmented image in Fig. 2(b). We divided the database into two sets for training and testing respectively. After preprocessing, each image was sequentially fed to the LM system. The results obtained on training are shown below. The entire 3D brain has been divided into 60 slices. We will show the segmentation results of some of those slices.
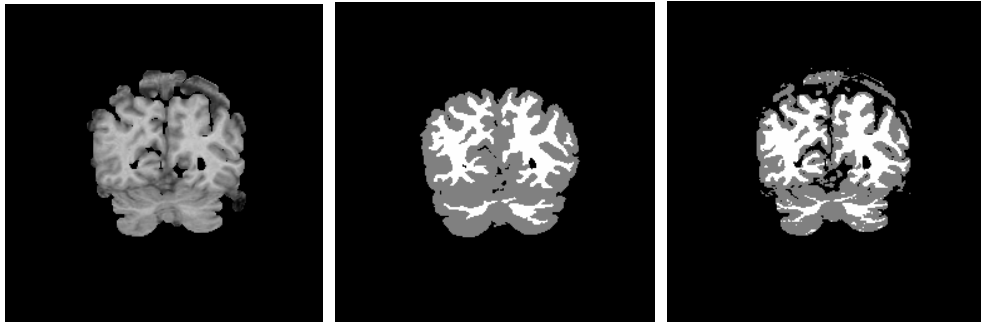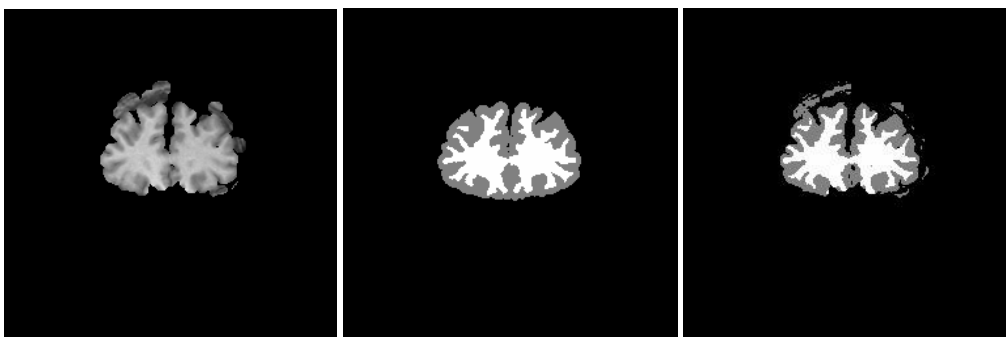
(a) Pre-processed 15th slice (b) manual segmentation (c) LM-k-means segmentation
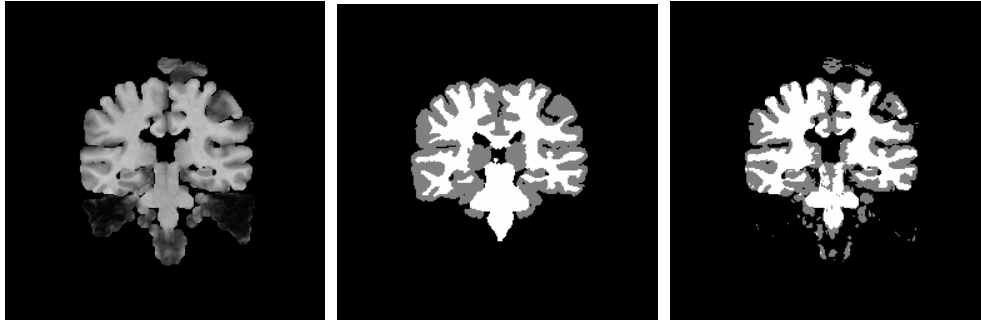
(a) Pre-processed 26th slice (b) manual segmentation (c) LM-k-means segmentation
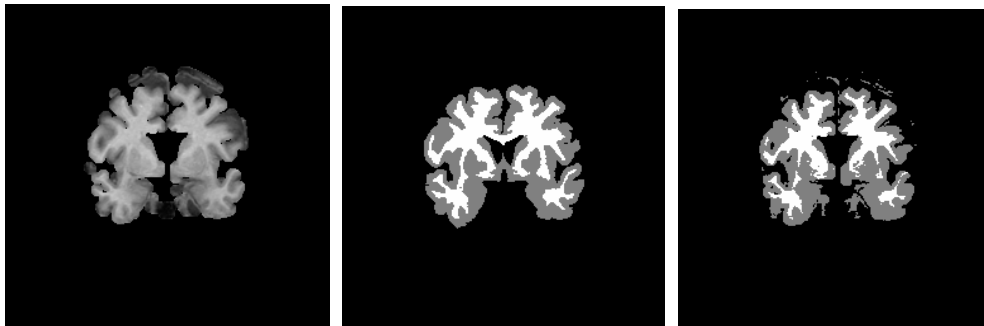
(a) Pre-processed 36th slice (b) manual segmentation (c) LM-k-means segmentation

(a) Pre-processed 45th slice (b) manual segmentation (c) LM-k-means segmentation

Fig. 3: Results of proposed system

The above results when compared with the results of the k-means system show a very big improvement.
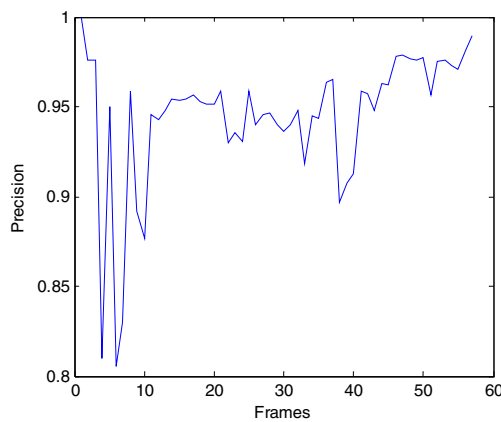
Fig. 4: Precision of the proposed system

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 satisfactory.

V. CONCLUSION

The system presented in this work has demonstrated a very good precision for segmentation of real images. It has taken a simple method like k-means which gave very unsatisfactory results and refined it through a training process to improve the results greatly. A drawback of this technique 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 this project will be to take care of these discrepancies.

REFERENCES

[1] Wei Zhang; Cheng Li; Yu-zhu Zhang, "A new hybrid algorithm for image segmentation based on rough sets and enhanced fuzzy c-means clustering", IEEE International Conference on Automation and Logistics, 2009. ICAL '09. Page(s): 1212 – 1216

[2] Mahmoodabadi, S.Z.; Alirezaie, J.; Babyn, P. "A novel Diffusion-Weighted Image analysis system for pediatric metabolic brain diseases", 4th International IEEE/EMBS Conference on Neural Engineering, 2009. NER '09. Page(s): 722 - 725

[3] Xinyu Du; Yongjie Li; Dezhong Yao, "A Support Vector Machine Based Algorithm for Magnetic Resonance Image Segmentation", Fourth International Conference on Natural Computation, 2008. ICNC '08. Volume: 3 2008 , Page(s): 49 – 53.

[4] Kasiri, K.; Kazemi, K.; Dehghani, M.J.; Helfroush, M.S., "Atlas-based segmentation of brain MR images using least square support vector machines", 2nd International Conference on Image Processing Theory Tools and Applications (IPTA), 2010. Page(s): 306 – 310

[5] Keihaninejad, S.; Heckemann, R.A.; Gousias, I.S.; Aljabar, P.; Hajnal, J.V.; Rueckert, D.; Hammers, A., "Automatic volumetry can reveal visually undetected disease features on brain MR images in temporal lobe epilepsy", IEEE International Symposium on Biomedical Imaging: From Nano to Macro, 2010. Page(s): 105 - 108

[6] Wentao Wang; Cong Chen, "Dirichlet Markov Random Field Segmentation of Brain MR Images", 4th International Conference on Bioinformatics and Biomedical Engineering (iCBBE), 2010. Page(s): 1–4

[7] Bourouis, S.; Hamrouni, K.; "An Efficient Framework for Brain Tumor Segmentation in Magnetic Resonance Images" Image Processing Theory, Tools and Applications, 2008. IPTA 2008. Page(s): 1 - 5

[8] Li Chenling; Zeng Wenhua; Zhuang Jiahe, "An improved AntTree algorithm for MRI brain segmentation", IT in Medicine and Education, 2008. ITME 2008. IEEE International Symposium on, 2008 , Page(s): 679 - 683

[9] Liu Zhidong; Lin Jiangli; Zou Yuanwen; Chen Ke; Yin Guangfu, "Automatic 3D Segmentation of MRI Brain Images Based on Fuzzy Connectedness", ICBBE 2008. The 2nd International Conference on Bioinformatics and Biomedical Engineering, 2008. Page(s): 2561 – 2564

[10] http://www.bic.mni.mcgill.ca/brainweb/

[11] C.A. Cocosco, V. Kollokian, R.K.-S. Kwan, A.C. Evans : "BrainWeb: Online Interface to a 3D MRI Simulated Brain Database"

[12] Nasien, D.; Haron, H.; Yuhaniz, S.S.; "Support Vector Machine (SVM) for English Handwritten Character Recognition", Second International Conference on Computer Engineering and Applications (ICCEA), 2010 Publication Year: 2010 , Page(s): 249 - 252

[13] Bellili. A, Gilloux.M, Gallinari. P, "An MLPSVM combination architecture for offline handwritten digit recognition", International Journal on Document Analysis and 6 Recognition. Pages 244-252. Springer Berlin / Heidelberg.

[14] Das, A.; Bhattacharya, M., "A Study on Prognosis of Brain Tumors Using Fuzzy Logic and Genetic Algorithm Based Techniques", International Joint Conference on Bioinformatics, Systems Biology and Intelligent Computing, 2009. IJCBS '09. Page(s): 348 - 351

[15] Myung-Eun Lee; Soo-Hyung Kim; Wan-Hyun Cho; Soon-Young Park; Jun-Sik Lim, "Segmentation of Brain MR Images Using an AntColony Optimization Algorithm", Ninth IEEE International Conference on Bioinformatics and BioEngineering, 2009. BIBE '09. Page(s): 366 - 369

[16] Chen, V., Su Ruan, "Graph cut segmentation technique for MRI brain tumor extraction", 2nd International Conference on Image Processing Theory Tools and Applications (IPTA), 2010 Page(s): 284 – 287.

[17] De, A.; Das, R.L.; Bhattacharjee, A.; Sharma, D., "Masking Based Segmentation of Diseased MRI Images", 2010 International Conference on Information Science and Applications (ICISA), Page(s): 1 – 7

[18] Pal, N. R., Bezdek, J. C., Tsao, E. C., "Generalized clustering networks and Kohonen ' s self-organizing scheme". IEEE Transactions on Neural Networks, 4(4), pp.549–557, (1993).

[19] Taxt T., Lundervold A.,Fuglaas B., Lien H., Abeler V. " Multispectral analysis of uterine corpus tumors in magnetic resonance imaging". Magnetic Resonance in Medicine. 23,pp.55-76,(1992).

[20] Karsch, K.; Qing He; Ye Duan, "A Fast, Semi-automatic Brain Structure Segmentation Algorithm for Magnetic Resonance Imaging", IEEE International Conference on Bioinformatics and Biomedicine, 2009. BIBM '09. Page(s): 297 – 302

[21] Xia Zheng,; Mo Dai,; Mingquan Zhou,; Gauss-Hermite moments application in medical image segmentation, 5th Intl. Conf. on Visual Information Engineering, 2008. VIE 2008. Page(s): 1 – 5

[22] Jianzhong Wang; Di Liu; Lili Dou; Baoxue Zhang; Jun Kong; Yinghua Lu; "Graph theory based algorithm for magnetic resonance brain images segmentation", 8th IEEE International Conference on BioInformatics and BioEngineering, 2008. BIBE 2008. Page(s): 1 - 5

[23] K. Levenberg, "A method for the solution of certain problems in least squares, Quart. Appl. Math., 1944, Vol. 2, pp. 164–168.

[24] D. Marquardt, "An algorithm for least-squares estimation of nonlinear parameters," SIAM J. Appl. Math., 1963, Vol. 11, pp. 431–441.