CT HEAD IMAGES SEGMENTATION USING UNSUPERVISED TECHNIQUES

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ABSTRACT

In this paper, a new approach is proposed for the segmentation of Computed Tomography (CT) head images. The approach consists of two-stage segmentation with each stage contains two different segmentation techniques. The ultimate aim is to segment the CT head images into three classes which are abnormalities, cerebrospinal fluid (CSF) and brain matter. For the first stage segmentation, k-means and fuzzy c-means (FCM) segmentation are implemented in order to acquire the abnormalities. Whereas for the second stage segmentation, modified FCM with population-diameter independent (PDI) and expectation-maximization (EM) segmentation are adopted to obtain the CSF and brain matter. The experimental results have demonstrated that the proposed system is feasible and achieve satisfactory results.

1. INTRODUCTION

Image segmentation is a process of clustering the image data into different structural components based on the features such as intensity, texture and shape. For CT images, there always exist problems such as noise, different objects within the same range of intensity, and partial volume effect. Consequently, these problems create some challenges in developing a reliable automated segmentation and detection system for the CT images. Various approaches of segmentation for CT brain images have been adopted such as case-based reasoning[1], morphological processing with thresholding[2] and clustering algorithm[3] and active contour[4]. However, these segmentation techniques are implemented to the images without considering the abnormalities present in the images.

The main problem for the segmentation of images with the present of the abnormalities is due to the fact that the abnormalities may be too small to form their own clusters. Single segmentation technique alone is insufficient to segment the images into the desired segments. As such, the obtained segmentation results[5,6] have been used with rule-based approach to label the abnormal regions such as calcification, hemorrhage and stroke lesion. Besides, hybrid unsupervised segmentation techniques were also employed to locate the abnormalities[7].

This paper presents the unique concept of segmentation via the combination of the different segmentation techniques at two different stages to obtain more efficient and accurate results.

2. OVERVIEW OF THE SYSTEM

Prior to the segmentation, the system will undergo the preprocessing stage in order to better prepare the images for the segmentation as shown in Fig. 1.

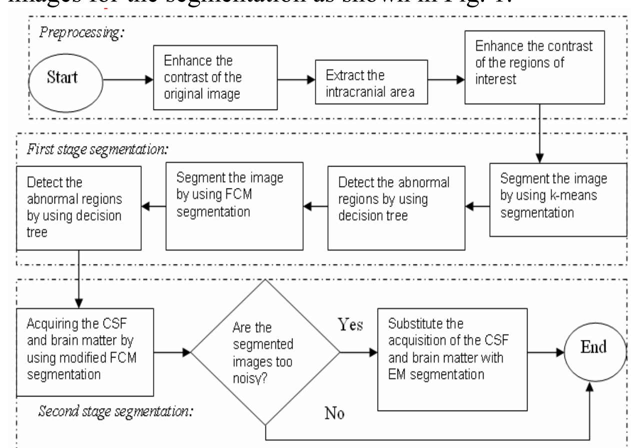


Fig. 1: Flow chart of the proposed system

For the first stage of segmentation, the preprocessed images will undergo the k-means segmentation. Then the segmented images will be converted to binary images in order to obtain the connected components. The connected components will be determined as abnormal or normal regions by using the decision tree. Likewise, the segmented images from FCM segmentation will experience the same process. The

FCM and k-means segmentation in this stage will complement each other to obtain the optimized results.

The second stage segmentation is to acquire CSF and brain matter. Firstly modified FCM with PDI segmentation will be executed. If the results from modified FCM segmentation are satisfactory, the results will be finalized and the process will be terminated. Otherwise, the segmentation results will be omitted and the process will be continued with EM segmentation

3. PREPROCESSING

3.1 Original Image Contrast Enhancement

The acquired original images are low contrast images which lack dynamic range for the region of interest such as intracranial area as depicted in Fig. 2. The histogram of the original image in Fig. 3 consists of several higher and lower peaks, but only the rightmost peak is within the significant range for region of interest. The rest of the peaks correspond to the background. Therefore, the contrast of the region of interest should be improved to increase the visibility of the images. First the curve in Fig. 3 is smoothen by using the convolution operation with a vector which each element the value is 10^{-3} in order to facilitate the process of locating the appropriate upper and lower limits for significant range. The smoothen curve is then transformed into absolute first difference as shown Fig. 4. From Fig. 4, the closest peak on the left and right are automatically determined as lower limit, I_L and upper limit, I_U.

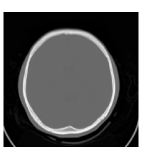


Fig. 2: CT head image

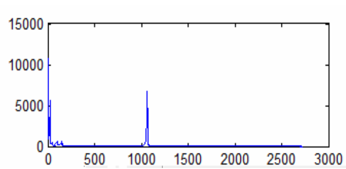


Fig. 3: Histogram of CT head image

Once I_L and I_U are acquired, the contrast of the significant range can be stretched via the linear contrast stretching algorithm as in equation (1).

$$F(i,j) = I_{\max} \frac{(I(i,j) - I_L)}{(I_U - I_L)} \qquad (1)$$

where I_{max}, $I(i,j)$ and $F(i,j)$ denote the maximum intensity in the image, original image and contrast enhanced image respectively. After the contrast stretching, the visibility for the region of interest is improved as shown in the Fig. 5.

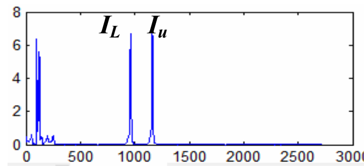


Fig. 4: Histogram of the absolute first difference

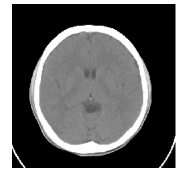


Fig. 5: Contrast enhanced image

3.2 Intracranial Area Extraction

In this section, thresholding technique is applied to extract the intracranial area. The enhanced image from Section 3.1 will be binarized as shown in Fig. 6(a). In order to acquire the intracranial area, the skull will be detected and the hole of the intracranial area will be filled up. The skull can be easily detected as it always appears as the largest region in the obtained binary image.

Then the skull is removed by setting the pixel values for the skull to zero intensity value. After eliminating the skull, the intracranial area can be obtained as shown in Fig. 6(b).

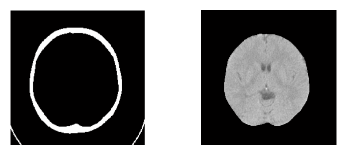


Fig. 6: (a) Thresholded image (b)Intracranial area

3.3 Regions of Interest Contrast Enhancement

The segmentation process of abnormal regions is done separately from the segmentation of CSF and brain matter. By this, the visibility of the abnormal regions can be enhanced. The enhancement is to ensure that abnormal regions are easier to be detected. Similar to Section 3.1, the images are enhanced by using the linear contrast stretching. The appropriate lower and upper limits for contrast stretching are automatically determined from the constructed histogram for the image from Section 3.2. The lower limit, I_L is defined as the peak position of the histogram. The upper limit, I_U is obtained as below:

$$I_U = I_L + I_\alpha$$

where I_α is predefined at 400 found from experimental observation. Then median filter is adopted in order to reduce the "salt and pepper" noise existed in the enhanced image. The example of the abnormal regions after contrast enhancement and "salt and pepper" noise reduction is shown in Fig. 7.

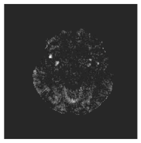


Fig. 7: Abnormalities contrast enhanced image

4. FIRST STAGE IMAGE SEGMENTATION

In this section, the enhanced image from Section 3.3 will be binarized by using the segmentation techniques. The binarization is to acquire the connected components of abnormal regions in the image. The connected components will be utilized for the classification of normal and abnormal regions in the later section. In order to obtain the optimized results, we have attempted on four segmentation techniques which are Otsu thresholding, k-means, FCM and EM segmentation and their results are shown in Fig. 8.

4.1 FCM Segmentation

FCM on the other hand is a method of clustering which allows one pixel to belong to two or more clusters. It is based on minimization of the objective function. The objective function is defined as:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^m \parallel x_i - c_j \parallel^2$$

where ***m*** is any real number greater than 1, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the intensity value of the ***i***th pixel , and c_j is ***j***th cluster center. The algorithm will iterate to optimize the objective function with the update of membership u_{ij} and the cluster centers c_j.

4.2 EM Segmentation

The expectation-maximization (EM) algorithm is a statistical estimation algorithm used for finding maximum likelihood estimates of parameters in probabilistic models, where the model depends on unobserved or missing data.

The procedures of EM segmentation basically involve expectation (E) step and maximization (M) step as:

a) Find the initial values for the maximum likelihood parameters which are means, covariances and mixing weights.

b) In E step, use the probability density function for a Gaussian distribution to compute the cluster probability for every pixel. The multivariate Gaussian conditional density function is written as:

$$f_i(x \mid \theta_i) = \frac{1}{(2\pi)^{d/2} \left|\sum_i\right|^{1/2}} \exp[-\frac{1}{2}(x-\mu_i)^t \sum_i^{-1} (x-\mu_i)]$$

where $\theta_i = (\mu_i, \sum_i)$, x is a d-dimensional feature vector, μ_i is the mean vector and $\sum_i$, $\left|\sum_i\right|$ and $\sum_i^{-1}$ are the d × d covariance matrix, its determinant and inverse respectively.

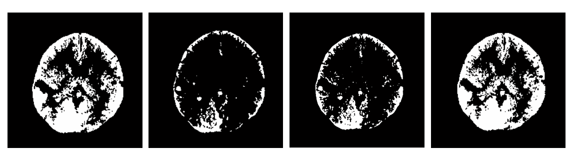
c) In M step, use the probability values obtained in E-step to re-compute the means, covariances and mixing weights.

d) Repeat E-step in (ii) and M-step in (iii).

The algorithm terminates when the difference between the log likelihood for the previous iteration and current iteration fulfills the tolerance.

4.3 Visual Comparison of the Results

The visual evaluation at this stage is adequate as the evaluation is in terms of isolation of abnormal regions from the normal regions. The separation is significant to ensure that the annotation of the abnormal regions can be done. From the visual inspection, Otsu threshold and EM method is not adoptable as the abnormal regions are merged together with the normal region. This cause the separation of abnormal region from normal region becomes not possible.



(a) (b) (c) (d)

Fig. 8: Binary image obtained by
(a) Otsu threshold (b) k-means method
(c) FCM method (d) EM method

The binary images obtained from k-means and FCM segmentation are adoptable as the abnormal regions are not merged with the normal regions. As such, abnormal regions can be well distinguished from the normal regions. That is why for the first stage segmentation only k-means and FCM methods are considered.

5. DETECTION OF ABNORMAL AND NORMAL REGIONS

The detection of abnormal and normal regions is based on the extracted features for respective connected component in the binary image. The extracted features for every connected component are as listed in Table 1. Based on the CT head image we acquired, we take into consideration of a few types of abnormalities which are calcification, hemorrhage, hematoma, lesion and hyperdense lesion. Whereas, other bright regions such as sinus, vessel, midline falx and white brain matter are classified as normal region.

Table 1: Features of the connected component

Feature	Remarks
Area	The number of pixels in the region of the enhanced image in Section 3.1.
mean	The average of pixels in the region of the original image in Section 3.1.
Standard deviation	The standard deviation of pixels in the region of the original image in Section 3.1.
Eccentricity	The value is between 0 and 1. An ellipse whose eccentricity is 0 is actually a circle, while an ellipse whose eccentricity is 1 is a line segment.
Orientation	The angle in degree.
Adjacent neighbor	Whether is skull or not.

For classification of the normal and abnormal region, the decision tree is employed as shown in Fig. 9. The notation $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ denote the mean and standard deviation respectively.

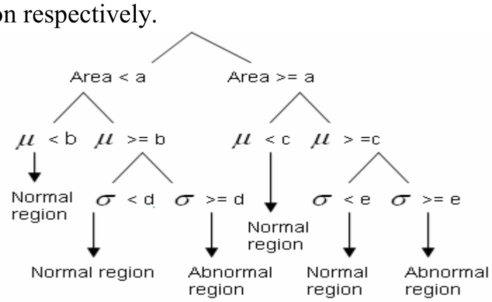


Fig. 9: Decision tree for classification of the regions that not adjacent to skull

Similarly, for the region adjacent to the skull, a similar decision tree is formed but with two extra features which are orientation and eccentricity. The orientation and eccentricity are to detect the midline falx which is the bright area at top and bottom of the intracranial area. This is to ensure that it won't be misclassified as an abnormal region.

6. SECOND STAGE IMAGE SEGMENTATION

For second stage segmentation, the abnormal regions will be excluded from the intracranial area. During this stage, the intracranial area will be partitioned into CSF and brain matter. Initially, the images will experience the FCM with PDI segmentation. The results of segmented images will be evaluated in terms of noise to determine their acceptability. The noisiness is verified in terms of the number of connected components. From the observation of unacceptable results, the threshold for the noise is four hundred number of connected components. If the results are unacceptable, the process will be replaced with EM segmentation instead. Then EM segmentation results will be used as the final segmentation results.

6.1 Modified FCM with PDI Method

The FCM with PDI method aims to balance the contributions of larger and smaller clusters to solve tendency of forming large cluster[8]. The new objective function after modifying the FCM objective function is depicted as:

$$J_m = \sum_{j=1}^{C} \frac{1}{\rho_j^r} \sum_{i=1}^{N} u_{ij}^m \| x_i - c_j \|^2$$

where $\boldsymbol{m}$ and $\boldsymbol{r}$ is any real number greater than 1, ρ_j is the normalizer for cluster j, u_{ij} is the degree of membership of x_i in the cluster j, x_i is the intensity value of the $\boldsymbol{i}$th pixel , and c_j is $\boldsymbol{j}$th cluster center.

7. EXPERIMENTAL RESULTS AND DISCUSSION

The images are acquired from the collaborating hospital and the radiologist has manually labeled abnormal regions in the brain. The total 80 images are sourced from over 30 patients. Out of this, a total of 159 potential abnormal regions are presented.

7.1 Visual Evaluation of Abnormal Regions Classification Results

In this subsection, the assessment is to verify visually whether k-means, FCM or k-means cum FCM segmentation results yield the highest abnormalities detection rate through the decision tree.

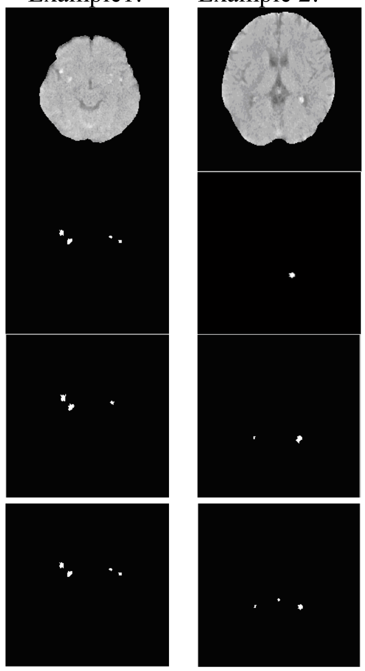


Fig. 10: Detection results of abnormalities

The obtained results of detection are shown in Fig. 10 for the respective methods. From Fig. 10, there is a trade off between FCM and k-means method. For Example 1, k-means method is outdoing the FCM method as less abnormal regions being detected from FCM results. This is caused by the over-segmentation in FCM clustering reduces the average intensity of the pixels in the region and makes it being misclassified as normal region.

However, advantage of FCM method is revealed through Example 2. Example 2 is the image that possesses blurred abnormal regions with intensity too close to the white matter of the brain. When faced with this kind of images, k-means method will have the problem of under segmentation due to the blurriness. This causes the formed abnormal regions to be relatively too small to be detected. However, in this case FCM method perform well by including the more abnormal pixels into each abnormal region compare with k-means method, which make them more obvious for detection.

The results also show that the k-means cum FCM method is superior than any single method as it managed to detect equivalent or more abnormal regions. The superiority is contributed by the second detection using the results from FCM manage to detect more abnormal regions.

7.2 Numerical Assessment Results for First-Stage Segmentation

Besides the visual assessment, the detection results of abnormal regions are also computed numerically in terms of recall. For the classification, recall is derived from the formula below:

$$\text{Recall} = \frac{\text{Numbers of abnormal regions correctly classified}}{\text{Total abnormal regions}}$$

The computed values for recall for k-means, FCM and FCM cum k-means clustering are depicted in Table 2. The recall as it measures the completeness of the classification. The recall for k-means method is higher than FCM method because of the over-segmentation occurs in FCM method. Furthermore, lesser cases as discussed earlier for the advantage of the FCM method in example 3 are encountered which reduce the value of recall.

Table 2: Classification results for abnormalities

Method	Recall
k-means	0.849
FCM	0.805
k-means & FCM	0.912

Overall, the result of recall shows that FCM cum k-means method outperform the rest of the methods. The outperformance around 6% FCM cum k-means method compared to k-means method in the recall does make some significant improvement of the classification. This is contributed by the second detection that manages to find some residual abnormal regions from FCM results which have not been located during the first detection from k-means results. At the same time, excluding the detected abnormal regions from k-means method has overcome the over-segmentation problem from the subsequent detection by FCM method.

7.3 Visual Assessment Discussion for Second-Stage Segmentation

In order to obtain accurate results, the experiments have been conducted on three unsupervised segmentation methods which are FCM, modified FCM with PDI, and EM segmentation. One of the advantages of the unsupervised segmentation is it does not require any training. The results for respective methods are shown in Fig. 11. In this section, the segmented results are evaluated visually as it is difficult to evaluate the accuracy of segmentation numerically.

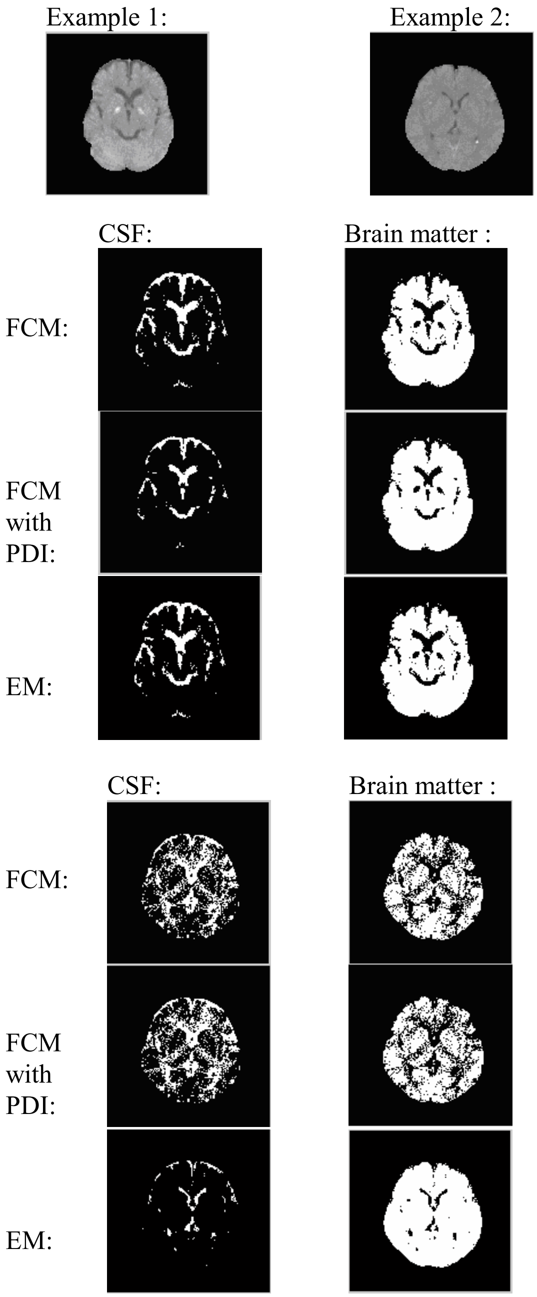


Fig. 11: Second stage segmentation results

From the obtained results from FCM method always encountered the problem of over-segmentation for CSF. This problem is contributed by the tendency of FCM method to form large clusters. On top of this, the obtained results always appear to be noisy. Therefore, FCM method is modified with PDI to solve the inclination to establish the large clusters and to reduce the noise.

However, the implementation of PDI does not solve the problem of FCM method for the images with the total CSF pixels is very low compare with brain matter as in Example 2. For these images, the segmented results of FCM method with or without PDI appear to be very noisy and inaccurate.

On the other hand, the results obtained from EM segmentation experience over-segmentation problem as shown in Example 1. However, for those images with the total CSF pixels is very low compared with brain matter as shown in Example 2, the obtained results from EM segmentation appear to be much more accurate compare with FCM with PDI method. In other words, whenever the unsatisfactory results are obtained by FCM with PDI segmentation, the satisfactory results can be obtained from EM segmentation.

8. CONCLUSION AND FUTURE WORK

The entire system as shown in Fig. 1 has been tested and the experimental results have shown that two-stage segmentation with four different unsupervised techniques has achieved satisfactory results.Our future work includes the implementation of the semantic retrieval and automatic annotation of the abnormal regions such as hemorrhage, calcification and lesion.

9. REFERENCES

[1] Petra Perner, "An Architecture for a CBR Image Segmentation System", In Proceedings of ICCBR, 1999, pp. 525-534.

[2] K.H. Hohne and W.A. Hanson, "Interactive 3D segmentation of MRI and CT volumes using morphological operations", J. Comp. Assist. Tomogr. 2, 1992, pp. 285-294.

[3] Qingmao Hu, Guoyu Qian, Aamer Aziz, Wieslaw L. Nowinsk, "Segmentation of brain from computed tomography head images", Proceedings of IEEE Engineering in Medicine and Biology 27th Annual conference, Sept. 2005, pp. 3375 – 3378.

[4] Wen-Nung Lie, Wen-Hung Peng, Cheng-Hung Chuang, "Efficient content-based CT brain image retrieval by using region shape features", ISCAS (4), 2002, pp. 157-160.

[5] Dubravko Cosic, Sven Loncaric, "Rule-Based Labeling of CT Head Image", 6th Conference on Artificial Intelligence in Medicine, 1997, pp. 453-456

[6] MATESIN Milan, LONCARIC Sven, PETRAVIC Damir, "A rule-based approach to stroke lesion analysis from CT brain images", 2nd international symposium on image and signal processing and analysis, June 2001, pp. 219-223.

[7] Tong Hau Lee, Mohammad Faizal Ahmad Fauzi and Ryoichi Komiya, "Segmentation of CT Brain Images Using K-means and EM Clustering", Fifth International Conference on Computer Graphics, Imaging and Visualization, 2008.

[8] Shihab AI, "Fuzzy Clustering Algorithms and Their Application to Medical Image Analysis", Ph.D. thesis, University of London, 2000.