Medical Evaluation of Improved Label Fusion Based Haematoma Segmentation in Traumatic Brain Injury Images

P. Manimegalai, U. S. Ragupathy

Abstract: ***Atlas based segmentation is a well-known method of automatically computing the segmentation. When multiple atlases are available, then each atlas can be used to compute a 'label', which is an estimation of the ground truth segmentation of a target image. By combining these labels, a more accurate approximation of the ground truth segmentation can be made. In the proposed work, the axial view of brain CT image for target and prelabelled images are taken for haematoma segmentation. The canny edge detection is performed to detect the wide range of edges in the images. The edge detected images are registered by using the rigid transformation method to spatially align one image to fit into another. The atlas images are selected based on the fixed threshold value and all the selected atlases are combined by using Selective and Iterative Method of Performance Level Estimation (SIMPLE) algorithm in label fusion process for the accurate segmentation of haematoma. The label fusion process is performed for a set of 6 labelled images and 10 target images and from the results it is observed that the error is reduced by 3% and similarity coefficient is increased by 16%, which indicates that the proposed method performs better when compared to the existing method.***

Index Terms: Multi Atlas based segmentation, Registration, Edge Detection, label fusion, Brain Images, SIMPLE

I. INTRODUCTION

Traumatic brain injury (TBI) also known as intracranial injury, occurs due to the external force which injures the brain. The injury is caused by various factors which includes fall from workplace, road accidents, and due to blast injury, etc. The brain function is temporarily or permanently impaired when there is a consequence of a sudden acceleration or deceleration within the cranium or by a complex combination of both movement and sudden impact to the brain by injuries. Based on Glassgow Coma Scale (GCS) and Loss of Consciousness (LOC), the brain injury is categorized as mild, moderate or severe injury. Data from National Health Interview Survey (2016) estimated that only 89% persons with head injury were consulting the physician in which 16% were admitted in hospital. More than 80% of all TBIs are considered to be mild in nature and the average length of hospital stay was 2–3 days.

The segmentation of medical images is often required to diagnosis and treatment planning. However, manual segmentation is a tedious and time-consuming task, and for this reason automatic image segmentation is currently one of the main challenges of medical image analysis.

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One of the alternatives to manual segmentation is atlas-based segmentation in which the segmentation of a target image is derived from already segmented atlas images.

Many researches are in progress to fuse the pre-labelled images to obtain the complementary information from multiple images into a single image to make it better for analysis and detection of haematoma. In the proposed work, the occurrence of haematoma in the various regions of brain image is identified by using mutiatlas based segmentation. From the literature review, it is inferred that the mutiatlas based segmentation is very effective for Label fusion applications. The CT image of target image is registered to make spatial alignment with respect to pre-labelled images.

In this paper, Multi-atlas based segmentation is a segmentation method that allows fully automatic segmentation of image populations that exhibit a large variability in shape and image quality. The improved label fusion method .This paper proposes a new method, called Selective and Iterative Method for Performance Level Estimation (SIMPLE) that aims to improve the label fusion process. The atlas-based approaches are similar to classifier methods, except that it is implemented in the spatial domain rather than in the feature space [2].

In Section II, a short introduction to atlas-based segmentation and to review existing work is given. In Section III, proposed method will be outlined. In Section IV, describes the improved label fusion method based multiatlas based segmentation for haematoma segmentation in traumatic brain injury images. The results of these experiments are given in Sections V and VI will discuss our work and draw conclusions.

II. ATLAS-BASED SEGMENTATION

The atlas based segmentation method is used where the objects of the same structure need to be segmented automatically (i.e. have the same texture). Atlas-based approaches uses pre-labeled images, called atlases which is given by experts in medical field. If an atlas image of the human brain for a specific population of interest is available, then atlas-based methods can be a powerful tool for brain CT segmentation. Some atlas-based segmentation methods use a single atlas, which is either a representative reference image constructed by experts [5] or a computed average of multiple reference images where the process of label fusion is unnecessary but it leads to non systematic local errors in the labels. In order to avoid the errors, the multiple atlases are used to compute a 'label',

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Which provides the estimation of the ground truth segmentation of a target image [9]. By combining these labels, a more accurate approximation of the ground truth segmentation can be obtained.

In [1], Chengwen Chu et al., proposed the Multi-atlas pancreas segmentation that allows the automatic segmentation of pancreas by using the vessel structure for atlas selection strategy. This paper concludes that vessel structure around the pancreas is used to select the atlases with high pancreatic resemblance to the unlabeled volume.

In [8], Christian Ledig et al., proposed the Multi-Atlas Label Propagation with Expectation–Maximisation based refinement (MALP-EM) algorithm for the segmentation of haematoma in brain MRI images. This paper concludes that MALP-EM is superior to joint label fusion.

In [2], T.R. Langerak et al., proposed the Multi-atlas based segmentation that allows fully automatic segmentation of image populations that exhibit a large variability in shape and image quality. This paper concluded that the SIMPLE algorithm for label fusion process provides accurate results by utilizing the local information which is present in propagated segmentations of pancreatic cancer, otherwise the labels are discarded. In [15], M.Vulpen et al., proposed the Performance Estimation by Iterative Label Selection (PEILS) method for estimating the true segmentation. This paper conclude that the poorly performing labels are discarded for obtaining the true segmentation of prostate cancer in MRI images.

In [6], Xabier Artaechevarria et al., proposed the generalized local weighting voting method to improve the segmentation accuracy. This paper conclude that the accurate segmentation is not obtained in images with low contrast borders.

In [14], Simon K. Warfield et al., proposed the expectation-maximization method for Simultaneous Truth and Performance Level Estimation (STAPLE) algorithm for estimating the ground truth segmentation. A disadvantage of STAPLE is that its computational complexity is linear in the number of atlases, its computation time can be large due to the fact that it depends on the degree of agreement between observers, which is typically small in multi-atlas based segmentation.

III. METHOD

In this paper, the Selective and Iterative Method for Performance Level Estimation (SIMPLE) algorithm for haematoma segmentation is proposed. This method, like STAPLE, uses an iterative strategy in which the performance of the input segmentations and the ground truth segmentation are alternately estimated. The main difference with STAPLE is that in each iteration badly performing segmentations are discarded. These segmentations no longer contribute to the estimate of the ground truth segmentation. The formulation of our method is much simpler than that of STAPLE because it does not use an expectation-maximization approach. Finally, it is considerably faster, as it does not depend on the degree of agreement between atlases.

The block diagram of improved label fusion based multiatlas based segmentation is shown in Fig 1.

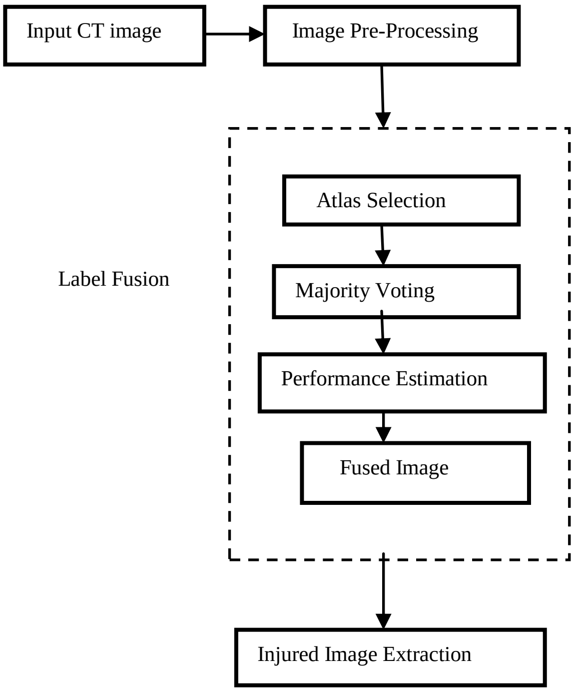


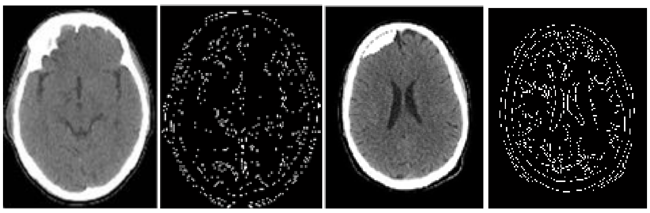
Fig 1: Block Diagram of Proposed Method

A. Edge Detection

Edge detection is an important image processing task, both as a process itself, and as a component in other process. The purpose of edge detection in medical images is to identify the areas of image where the large change in intensity occurs.

The canny edge detector is one of the standard edge detection method used to find out the real edge points by maximizing the signal to noise ratio in medical images. This is an edge detection operator that uses a multi-stage algorithm to detect a wide range of edges with noise suppressed which gets at the same time. This technique is used to obtain useful structural information from different vision objects and dramatically reduce the amount of data to be processed.

Fig 2. Shows the output of Canny edge detection for target image (IMG001) and the reference image(IMG013) which is collected from Johnsons MRI and Maruti Hospital in Erode.



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

Fig 2. Results for the Canny Edge Detection (a) Target Image (IMG001), (b) Canny Edge Detection Image (IMG001), (c) Reference Image (IMG013), (d) Canny Edge Detected Reference Image (IMG013).

B. Registration

Image registration is an image processing technique used to align multiple scenes into a single integrated image. It helps overcome issues such as image rotation, scale and skew that are common when overlaying images.The purpose of registration is to find a spatial relation between the atlas and target image in the form of a transformation T that aligns the two images.

Under Rigid registration, the Mutual Information (MI) and Normalized Mutual Information (NMI) are the most commonly used similarity measures in medical images. The Normalized Mutual Information between the target and reference image is determined by the mutual information of pixel intensity with respect to the joint entropy Based on the pixel intensity obtained after edge detection, the matching of target and reference images are obtained. The NMI method improves the robustness of MI by avoiding some misregistrations.
The formula for MI and NMI to calculate the similarity measurements

$$I(X,Y) = \sum_{y \in Y} \sum_{x \in X} P(x,y) \log * \left(\frac{P(x,y)}{P(x)p(y)} \right)$$

$$NMI(X,Y) = \frac{H(X)+H(Y)}{H(X,Y)} = 1 + \frac{I(X,Y)}{H(X,Y)}$$

where,

$$H(X) = I(X,Y) + H(X \mid Y)$$

$$H(Y) = I(X,Y) + H(Y \mid X)$$

C. Performance Analysis of NMI Matching

The proper alignment between the prelabelled images and target images is obtained by calculating the Normalized Mutual information (NMI). Table 1 shows the performance analysis of NMI matching for target image (IMG001).

Table 1. Performance Analysis of NMI Matching

S. No	Label No	NMI Matching (%)
1	IMG011	9.7232
2	IMG012	9.9558
3	IMG013	100
4	IMG014	86.4154
5	IMG015	9.6069
6	IMG016	88.8811
7	IMG017	9.8628

From the table 1, it is inferred that the target image (IMG001) is perfectly matched with the label image (IMG013) which indicates that similarity measurements between the two images which is used in further segmentation of haematoma in traumatic brain injury images.

IV. IMPROVED LABEL FUSION METHOD FOR HAEMATOMA SEGMENTATION

Label fusion is a method which is used in medical image segmentation. The unknown ground truth segmentation of target image is obtained by combining several different labels of the same entity into a single label by label fusion. In a multiatlas based segmentation, the SIMPLE algorithm is preferred for label fusion in order to the obtain accurate segmentation of haematoma. In this algorithm, the poorly performing labels are discarded, because these labels provide no longer contribution for the estimation of ground truth segmentation. The SIMPLE algorithm improves the label fusion process by the combination of atlas selection and performance estimation to obtain true segmentation of haematoma in brain CT scan.

A. Atlas Selection

The selection of labels is important for accurate estimation of ground truth segmentation. For the selection of atlases, the mutual information between the target image and registered prelabelled image is calculated. One of the registered label image (L) whose mutual information with target image (T) is greater when compared with the median values of all other mutual information registered label image.
The formula of atlas selection for i-th registered label

MI (Ii,T) >median {MIj(Ij,Tj), where j=1,…,11}

In the atlas fusion process, the usage of adaptive threshold method to pick up the appropriate registered labels for label majority voting. The thresholding value is set to be high in order to obtain good performing labels.

B. Majority Voting Procedure for Label Fusion

In a label fusion process, the labels are combine by per-voxel basis. The pixel based fusion is preferable in majority voting method because it uses the original (pixel values) information of images and can be performed both in spatial and transform domains.

There are two basic requirements for image fusion. First, fused image represents all possible relevant information which is contained in the source images. Second, fusion process should not introduce any artifacts, noise or unexpected feature in the fused image. The spatial domain fusion techniques uses pixel Average Method for estimating the ground truth segmentation. In the Average method, regions of images which are in focus are of higher pixel level intensity as compare to other regions of images.
Fig 3. Shows the block diagram of spatial domain image fusion scheme to fuse the input image.

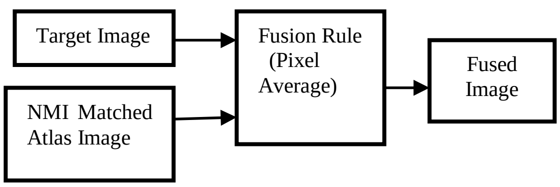


Fig 3. Block Diagram of Spatial Domain Image Fusion Scheme

Average method of fusion is a method to obtain an output image in which all regions are in focus. Sum of values of pixel.

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(i, j) of each image is done and then divided by total number of input images which results in average value. The average value obtained is given to the correspondingly pixel of the output image. In medical image processing there are only two states are available that are min and max. The formula for pixel average fusion rule is

$$\text{whitepixel} = \sum_{i,j=0}^{n} \min[A(i,j), B(i,j)]$$

$$\text{blackpixel} = \sum_{i,j=0}^{n} \max[A(i,j), B(i,j)]$$

Let $V_i^K \in [0,1]$ be the k-th voxel in segmentation in registered atlases (Li)'.The weighted majority voting rule is used to combine the different labels. The formula for majority voting is

$$f(V_1^K ....., V_n^K) = \sum_{i=0}^{n} \frac{W_i V_i^K}{n} - 0.5$$

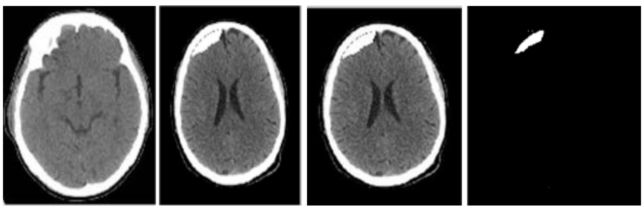
C. Segmentation of Haematoma

The segmentation of Haematoma from the fused output is important for the efficient treatment plan in medical field. The Sum of Absolute Difference (SAD) method is used for the haematoma segmentation.

The SAD is a measure of similarity between the target and reference (Normal) image. It is calculated by taking the absolute difference between each pixel in the reference block and compared with the corresponding pixel in the target (fused) image block. These differences are summed to create a simple metric of block similarity which is used to obtain the segmentation of haematoma.

To find the similarity between the two images, there are exactly three unique locations within the target image where the reference image gets fitted. The locations to be considered are the left side, the centre and the right side of the image. The absolute value of the difference between each corresponding pair of pixels is used to calculate the SAD values.

Fig 4. Shows the output of multiatlas segmentation for target image (IMG001) with atlas image (IMG013) for haematoma segmentation inorder to make the treatment plan more effective.



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

Fig 4. Results for the Multiatlas Segmentation (a) Target Image (IMG001), (b) Atlas Segmented Reference Image (IMG013), (c) Fused Image, (d) Segmented Image

V. RESULTS AND DISCUSSION

The performance analysis is used to find the quality of final segmented image by performing the improved label fusion algorithm. The computation of true performance with estimated performance is done by Single Segmentation Estimation Error (SSEE) and Combined Segmentation Estimation Error (CSEE).

A. Evaluation Criteria

To evaluate the segmentation performance over the entire atlas set, the Single Segmentation Estimation Error (SSEE) is calculated between the target and pre-labelled images. The evaluation of each propagated atlas segmentation with target image is estimated by comparing the estimated performance of reference pre-labelled images.

The formula for the Single Segmentation Estimation Error (SSEE) equation is

$$\varphi_i = f(L_i^1, L_T)$$

The smaller the estimated error, the more accurate the estimate of the true performance. The performance estimation is small for badly performing segmentations, while it is large for well performing labels.

B. Performance Analysis of Estimated Error

The Mean Square Error (MSE) and Peak Signal to Noise Error (PSNR) are calculated in order to estimate the performance between prelabelled and target CT brain images. The performance estimation of SSEE for the target image (IMG001) is shown in Table 2.

Table 2. Performance Estimation of SSEE

S. No	Label No	Mean Square Error (MSE)	Peak Signal to Noise Ratio (PSNR) (dB)
1	IMG011	23.8829	34.3839
2	IMG012	24.4049	34.2901
3	IMG013	0	INF
4	IMG014	8.3259	38.9605
5	IMG015	29.4476	33.4743
6	IMG016	4.4062	41.7241
7	IMG017	25.6969	34.066

C. Performance Comparison of Fusion Algorithm

The Average SSEE and Dice Similarity Coefficient (DSC) are calculated to analyse the performance comparison of STAPLE and SIMPLE fusion algorithm.

Table 3. Performance Comparison of Fusion Algorithm

PERFORMANCE METRICS	VALUE (%) (Existing Method)	VALUE (%) (Proposed Method)
Average SSEE	19	16
DSC	83	94

Table 3. Shows the performance comparison of fusion algorithm. Based on the results obtained, it is observed that the error is reduced by 3% and similarity coefficient is increased by 16%, which indicates that the proposed method performs better when compared to existing method.

VI. CONCLUSION AND FUTURE SCOPE

Brain abnormalities are one of the leading causes of death among all over the world. Hence accurate localization and segmentation is necessary. Thus the proposed method using label fusion based Multiatlas segmentation helps to improve the visualization of medical image and localize the abnormalities accurately.

In this report, a new approach of improved label fusion based haematoma segmentation in traumatic brain injury images for approximate and detail band is proposed. The Label fusion in multiatlas based segmentation using (SIMPLE) algorithm gives effective result when compared to the existing techniques. This fusion algorithm has the advantages of estimating the performance of segmentations in an iterative procedure, in which badly performing segmentations in each iteration step get discarded. The remaining segmentations are used to compute the accurate segmentation of the ground truth segmentation. The proposed algorithm is tested using 6 reference (label) images with 10 target brain CT images.

In future, the localization and segmentation of abnormalities can be done effectively with more number of training data set and also classification using Neuro-Fuzzy method will be implemented.

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