Automatic Detection of Brain Tumor using Novel Segmentation Method

Hema Rajini N

Department of Computer Science and Engineering, Annamalai University, Annamalai Nagar – 608002, Tamilnadu, India.
auhemasmith@yahoo.co.in

Abstract— *A new brain tumor detection system has been designed and developed. This work presents a new approach to the automated detection of brain tumor based on hybrid segmentation, which separate brain tumor from healthy tissues in magnetic resonance images. The magnetic resonance imaging has become a widely used method of high-quality medical imaging, especially in brain imaging where the soft-tissue contrast and non-invasiveness is a clear advantage. The magnetic resonance feature image used for the tumor detection consists of T2-weighted magnetic resonance images for each axial slice through the head. To remove the unwanted noises in the magnetic resonance image, bilateral filtering is used. Fast bounding box-based watershed segmentation algorithm is used to segment the images. The application of the proposed method for tracking tumor is demonstrated to help pathologists distinguish exactly tumor region. The results are quantitatively evaluated by a human expert. The average overlap metric, average precision and the average recall between the results obtained using the proposed approach and ground truth are 0.85, 0.80 and 0.97, respectively.*

Keywords— *Bilateral filter; Fast bounding box; Watershed segmentation.*

I. INTRODUCTION

The brain is the nervous system's main organ. It regulates most of the body's activities; stores, incorporates and coordinates the sensory organ information it receives [1]. Magnetic Resonance Imaging (MRI) technique provides more accurate results than Computed Tomography (CT), ultrasound and X-ray clinical methods. Brain tumor is the most hazardous thus its identification ought to be quick and more precise. This can be achieved by processing of automated tumor detection methods on MR brain images. Noise and delay for detection of tumor will affect the image accuracy. More than 1,900,000 people worldwide are diagnosed with primary or metastatic brain tumor (secondary) every year. Several experiments were investigating the causes of brain tumor, but the findings were not definitive. Normally the magnetic resonance imaging techniques are used for detecting the brain tumor. Magnetic Resonance (MR) images generally contain many artifacts; including homogeneity frequency, extra cranial images.

In the literature, various research works have been reported to minimize the effects of artifacts in MR images. Jaya et al. proposed a technique consists of four processing stages. In the first stage, the MRI brain image is acquired from MRI brain data set to MATLAB 7.1 [2]. After acquisition the MRI is given to the pre-processing stage, here the film artifacts (labels) are removed. In the third stage, the high frequency components and noise are removed from MRI using the median filter, weighted median and adaptive filter. Finally, the performance of above filters is measured and evaluated. Shyam Anand et al. developed a wavelet-based bilateral filtering scheme for noise reduction in MRI [3]. Undecimated wavelet transform is employed to provide effective representation of the noisy coefficients. Bilateral filtering of the approximate coefficients improves the denoising efficiency and effectively preserves the edge features. Denoising is done in the square magnitude domain, where the noise tends to be signal independent and is additive. The visual and the diagnostic quality of the denoised image is well preserved. The quantitative and the qualitative measures used as the quality metrics to demonstrate the ability of the proposed method for noise suppression.

Ben George et al. designed a novel approach for the MRI image enhancement, which is based on the modified tracking algorithm, histogram equalization and Center Weighted Median (CWM) filter [4]. This method consists of two approaches. The first approach is applying the modified tracking algorithm to remove the film artifacts, labels and skull region and then applying the histogram equalization and CWM filter techniques separately to enhance the images. Alyaa et al. has developed a new brain tumor segmentation using an enhanced thresholding algorithm [5]. In this method high pass filter is applied for noise removal and median filter is applied to enhance the quality of image.

There are many computer-aided detection systems for MR brain images in the literature, most of them are used to detect and classify abnormalities. Yongxin Zhou et al. proposed a framework that combines atlas registration, fuzzy connectedness (FC) segmentation and parametric bias field correction for the automatic segmentation of brain MRI [6]. Experiments on both simulated and real MRI images demonstrate the validity of the method, as well as the limitation of the method. Sathya et al. designed a multilevel thresholding that depends on Adaptive Bacterial Foraging (ABF) algorithm for MR brain image segmentation [7]. Kaur Jaskirat et al. proposed a thresholding and an edge detection method, which is one of the most significant concepts of brain image segmentation prior to feature extraction and image recognition system [8]. This technique is applied to geo satellite images, medical images and architectural images. Kannan et al. proposed an effective kernelized fuzzy c-means with weighted bias field information for robust automatic segmentation of MRI [9]. Further, the proposed method initialized the initial cluster centers by using center initialization which consumes more time period for completion of clustering process was avoided. Segmentation accuracy of the proposed method was 86%. Ahmed et al. proposed a method using wavelet-based texture features [10]. The optimum features are selected using genetic algorithm and given to support vector machine for efficient classification of brain MRI with high sensitivity 94%, specificity 100% and accuracy 96%.

In medical imaging, manual segmentation and analysis of MR brain images by radiologists is time-consuming and impractical. A large number of images taken for a single patient and most of them are used in current brain tumor testing. Systems collect compound brain data and do not provide accurate results on the presence of a tumor. A formal consultation with a radiologist is therefore necessary.

The challenge here is therefore to develop a system that offers an automated indication of the presence or absence of tumor from the images of a brain MR. Thus, there is a need to develop a new and reliable, smart algorithm to enhance, segment and identify the images of brain MR with less time.

The main objective of this research work is to remove noise in MR brain image using bilateral filtering and a hybrid segmentation technique is used to segment the brain tumour.

The rest of this paper is organized as follows. Introduction part is given in Section 1 as well as the studies of several research papers are portrayed, the Section 2 describes the proposed methodology following Section 3 signifies the experimental results and the work are concluded in Section 4.

II. METHODOLOGY

This proposed research aims at improving brain tumor identification in brain MR images. In this work imaging techniques such as bilateral filter, Fast Bounding Box (FBB) based watershed segmentation, have paved the way to make it suitable for the medical field, which lets medical experts analyze various diseases in a non-intrusive system. The methodology of proposed work is shown in Figure 1.

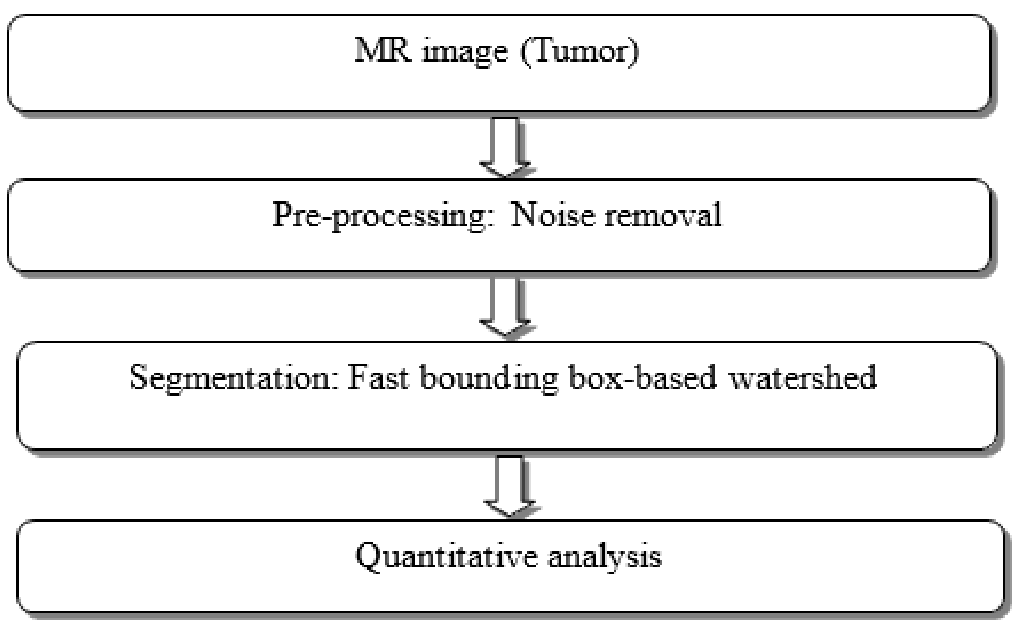


Fig.1: Methodology of the Proposed Technique

2.1. Preprocessing

The pre-processing step focuses on specifically removing the outliers present in the captured image without affecting the subtleties that play key role in the general procedure. It is done to improve the visual look and characteristic of an image. The key activities of pre-processing of done by bilateral filtering.

Bilateral filtering is a kind of scheme for smoothing images, thus retaining edges at the same time [11]. The use of bilateral filtering has grown rapidly and is commonly used in applications for image processing, such as image de-noising, image enhancement. Numerous bilateral filter qualities are formulation of this is uncomplicated, each pixel is replaced by a weighted average of its neighbours, basically it relies on the two parameters that point to the size and contrast of the features to be retained, and it is a kind of non-iterative scheme. This makes the parameters easy to maintain in view of the fact that their influence over quite a few iterations is not cumulative.

In the case of traditional low pass filtering, the pixel of any point is assumed to be equal to that of the nearby points:

$$h(x) = k_d^{-1}(x)|| \int_{-\infty}^{\infty} f(\delta)c(\delta, x)d\delta \qquad (1)$$

where $(c(\delta, x))$ determines the geometric closeness among the neighborhood center x and a nearby point δ . Both input (f) and output (h) images might be multiband. In addition,

$$k_d(x) = || \int_{-\infty}^{\infty} c(\delta, x)d\delta \qquad (2)$$

Bilateral filter combines gray levels based on both geometric closeness and photometric similarity, and it requires values in both domain and range nearby. Similarly, the range filtering is given as:

$$h(x) = k_r^{-1}(x)|| \int_{-\infty}^{\infty} f(\delta)s(f(\delta), f(x))d\delta \qquad (3)$$

Where $s(f(\delta), f(x))$ computes the photographic resemblance among the pixel at the neighborhood center x and that of close by point δ. In this scenario, the kernel computes the photometric similarity among pixels. The normalization constant in this scenario is,

$$k_r^{-1}(x) = || \int_{-\infty}^{\infty} s(f(\delta), f(x))d\delta$$
(4)

The bilateral filtering described as given below:

$$h(x) = k^{-1}(x)|| \int_{-\infty}^{\infty} f(\delta)c(\delta, x)s(f(\delta), f(x))d\delta$$
(5)

where, $k(x) = \int_{-\infty}^{\infty} c(\delta, x)f(f(\delta), f(x))d\delta$ combines domain and range filtration will be described as bilateral filtering.

Bilateral filtering is something of a non-iterative process. This removes noise and preserves the edge information, unlike traditional filters.

2.2. Segmentation

The segmentation objective is to simplify the representation of an image in various segments, which is more meaningful and easier to analyze. Segmentation of images is usually used to identify points and borders in images It is also the method of assigning each pixel to a label in an image in such a way that pixels with the same label share those visual properties. Hybrid method is used in this proposed research work, FBB based watershed segmentation technique is used.

2.2.1. Fast Bounding Box Algorithm:

Bounding box is a simple segmentation algorithm in which the local tumor is separated by denoting a box and further segmenting this part of the tumor. In this approach the tumors will be segmented by the watershed algorithm while FBB will define the tumor region and position in a 2D image. With the bounding box approach, the segmented tumor region is obtained and that is superimposed with watershed procedure. This strategy places the MR brain portioned tumor box around the tumor area. The fractured tumor from the watershed technique involves the tumor division, as well as misclassification of some sound tissues. These cells are wiped out by using the watershed procedure which expands the edge of an incentive until the tissues that are misclassified are wiped out to acquire fine tumor. At that point, in the light of the shape characteristics of the recognized tumor, at long last bounding box will be put around the tumor portion.

The basic principle of FBB is the concept of change detection, where a region of change (D) is detected on a test image (I) compared to a reference image (R). The left image is taken as a test image and the right is taken as the reference image. Mostly shift identification is associated with local pixel changes to pixel but here the change is associated with a region-based global change. A score function E(l) is used to detect the shift region (D) by searching in two directions-horizontal and vertical.

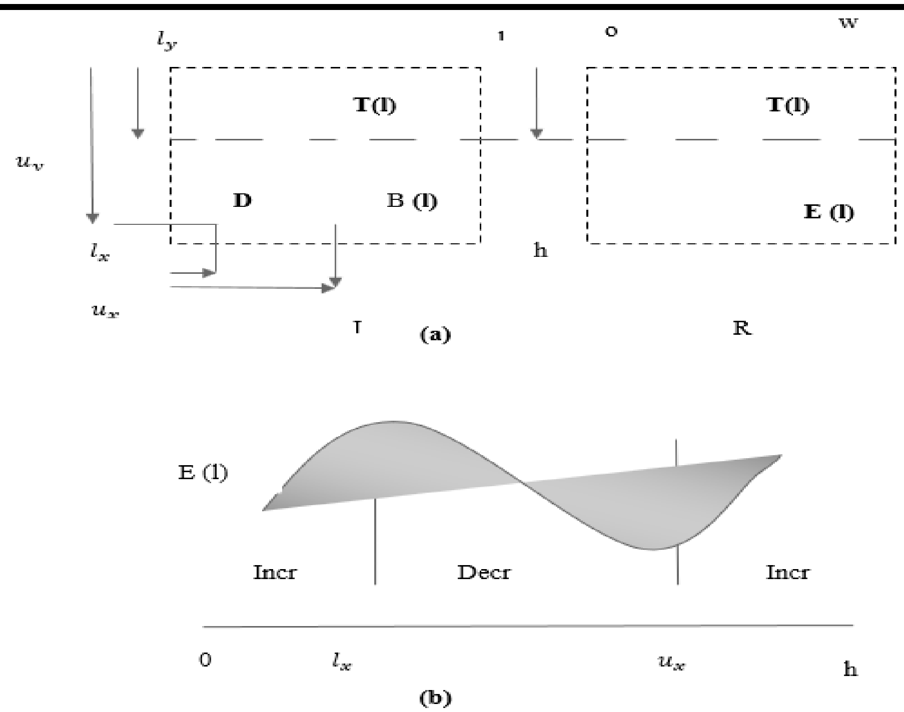


Fig.2: (a) Finding Anomaly D from Test Image I using Reference Image R. (b) Energy Function Plot

Figure 2 represents the test and the reference images, having the same height h and the same width w. The rectangular region represents the region of change / region of interest (D) between images I and R. FBB algorithm finds rectangle D, i.e. the four unknown parameters l_x , u_x , l_y and u_y are identified in two linear image flows. Next, in a vertical sweep, it finds the best l_y and u_y values and then finds l_x , $u_x$in a horizontal sweep over the image pair. As the score function for the horizontal is the same as that of transposing the same picture from the vertical score function. Here, to find the vertical ranking vertical score function is defined as

$$E(I)= BC(P_I^{T(I)}, P_R^{T(I)}) - BC(P_I^{BI)}, P_R^{B(I)}) \quad (6)$$

Where $P_I^{T(I)}$ denotes the normalized intensity histogram of image I within the region T(l). $P_R^{T(I)} P_R^{B(I)}$ are defined respectively. $BC(a\,,b\,) = \Sigma i\sqrt{a(i)b(i)}\ \varepsilon[0,1]$ denotes the Bhattacharya Coefficient (BC) between two normalized histograms a(i) and b(i), with i indicating the histogram group.

The similarity between two normalized histograms of strength is calculated using the BC. When two standardized histograms are the same, the BC value between them is 1 and if two standardized histograms are not the same the BC value is 0.

$$P(x)=\left\{\frac{\Sigma_{x'\in c_{j(x\to x')}} dist(x,x')}{|c_i-1|}\right\} \quad (7)$$

$$q(x)=\min_{x\,\in\,Ci\ (1\le i\le m)}\left\{\frac{\Sigma_{x'\in c_{j(x\to x')}} dist(x,x')}{|c_i-1|}\right\} \quad (8)$$

The silhouette coefficient of x is then defined as

$$r(x) = \frac{q(x)-p(x)}{\max(p(x).q(x))} \quad (9)$$

2.2.2. Watershed Segmentation:

It is based on gradient and used for grouping higher intensity pixels [12]. It is used to distinguish image discrepancy. It breaks an image for tumor extraction. Watershed used a gray image flooding procedure carried out by the morphological operator. Watershed notices ridges lines in images where light pixels are high and dark pixels are small. This is useful for identifying or marking foreground points and position of the background.

FBB based watershed segmentation

- *First the outer regions are marked*
- *On each input MR slice, FBB first locates the length-right of symmetry of the brain*
- *The algorithm searches for an axis-parallel rectangle on the left side that is very dissimilar from its reflection about the axis of symmetry on the right side.*

- *FBB finds the rectangle D i.e. the four unknown parameters $\boldsymbol{l_x}$, $\boldsymbol{u_x}$, $\boldsymbol{l_y}$ and $\boldsymbol{u_y}$ are identified in two linear image flows. Next, in a vertical sweep, it finds the best $\boldsymbol{l_y}$ and $\boldsymbol{u_y}$ values*

watershed transformation

- *Read the image*
- *Compute foreground markers*
- *Compute the watershed transform of the image*

Watershed segmentation is a segmentation technique based on gradients. It regards the image's gradient map as a relief map. The operator Sobel is suitable for detection of edges. Sobel operator is used in marker operated watershed segmentation to discern the edge of the object

The sobel masks in matrix form are as follow:

$$M_x = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \qquad M_y = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$M = \sqrt{{M_x}^2 + {M_y}^2} \qquad (10)$$

$$\text{angle } \theta = tan^{-1}\frac{M_x}{M_y} \qquad (11)$$

2.3 Quantitative Analysis

The automatic segmentation results are compared to the manual results. The results are quantitatively evaluated by a human expert. A region of tumor which is identified by an experienced radiologist is the ground truth. Each pixel belongs to one of the four classes accordingly: true positive (TP) is correctly classified as positive pixels; false positive (FP) is incorrectly classified as negative pixels; true negative (TN) is correctly classified as negative pixels and false negative (FN) is incorrectly classified as positive pixels. Three quantitative measures are employed to evaluate the segmentation result: precision, recall and overlap metric. They are defined in the following eqs. (12)-(14).

$$Precision = \frac{TP}{TP + FP} \qquad (12)$$

$$Recall\ or\ Sensitivity = \frac{TP}{TP + FN} \qquad (13)$$

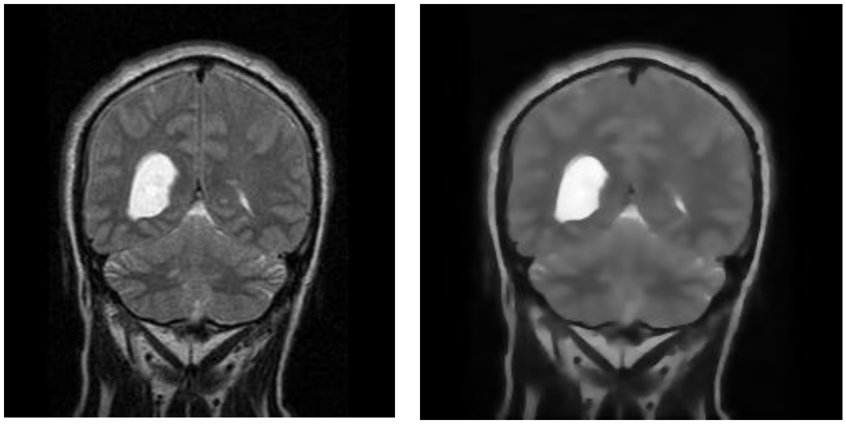
$$Overlap\ metric = \frac{2 \times TP}{2 \times TP + FP + FN} \qquad (14)$$

The average overlap metric, average precision and the average recall between the results obtained using the proposed approach and ground truth are 0.85, 0.80 and 0.97, respectively.

III. RESULTS AND DISCUSSION

Five brain tumor cases are collected of from the Department of Radiology, Rajah Muthiah Medical College Hospital (RMMCH), Chidambaram. All the input data set used for tumor detection consisted of T2-weighted of 512×512 MR brain images. The MR brain images collected from the patients were acquired on 1.5 Telsa, Intera MR Scanners. This section portrays some experimental results on real data on brain MRI. The number of MR brain images in the input data set is 40 abnormal brain images. The abnormal brain image set consists of images of brain affected by a brain lesion.

In the first stage, noise is suppressed using an image filtering. Preprocessing techniques is applied on the images to remove the noise and enhance the quality of images. In this method initially the bilateral filter is used for de-noising. It effectively sharpens the edges and enhances the image. The results of the input and preprocessed images are given in Figure 3. After the preprocessing, the brain image is free from noise and this smoothed image is ready to be used in further processing.



(a) **(b)**

Fig.3: Input (a) and Preprocessed Images (b)

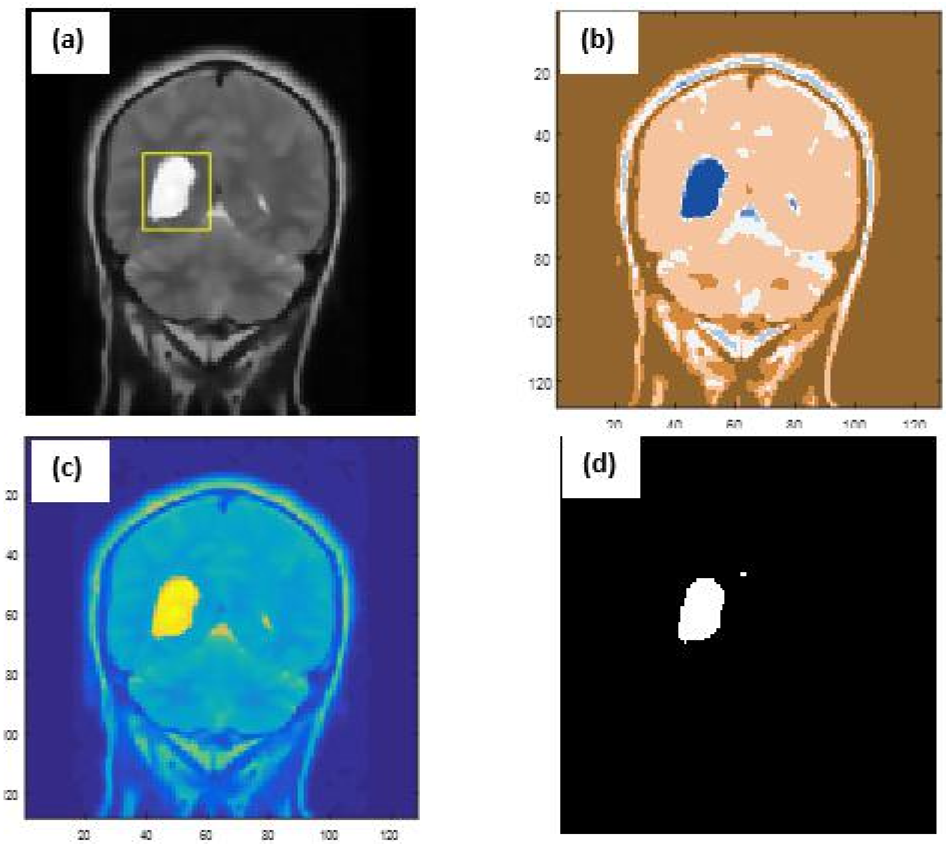


Fig.4 (a-d): Segmentation Result of Fast Bounding Box-Based Watershed Segmentation

Segmentation techniques are used to detect the region of brain tumor. In the second stage, segmentation is computed using fast bounding box-based watershed segmentation algorithm. After the preprocessing the segmentation is performed on the preprocessed image. Here fast bounding box-based watershed segmentation is used for segmentation. The exact brain tumour region is extracted using this method. The segmentation results of fast bounding box-based watershed segmentation are shown in figure 4(a-d). Thus, it is an accurate and robust brain segmentation method. It does not require any user interaction. It reduces over segmentation and under segmentation. Finally, the results are quantitatively evaluated by a human expert. The proposed method has been evaluated on a data set of 5 patients. The average overlap metric, average precision and the average recall between the results obtained using the proposed approach and ground truth are 0.85, 0.80 and 0.97, respectively. The performance of the algorithm is excellent. The application of the proposed method for early detection of tumor is demonstrated to improve efficiency and accuracy of clinical practice.

IV. CONCLUSIONS

An automatic method has been developed for the detection of tumor in brain MR images using fast bounding box-based watershed segmentation algorithm.

To remove the unwanted noises in the magnetic resonance image, bilateral filtering is used. Fast bounding box-based watershed segmentation algorithm is used to segment the images. This system has been successfully tested on large brain images causing brain tumor. The brain region related to a lesion is exactly separated from the brain image. The proposed system helps the physicians to know the brain tumor region, for further treatment. The average overlap metric, average precision and the average recall between the results obtained using the proposed approach and ground truth are 0.85, 0.80 and 0.97, respectively.

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