Acute Stroke Brain Infarct Segmentation in DWI Images

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***Abstract*—Acute ischemic infarct can be quickly identified with Diffusion Weighted Imaging (DWI) method. This research proposes to segment infarct areas in DWI dataset by applying Chan-Vese active contour and localized region-based active contour algorithms. The knowledge about the infarct intensities of a particular problem dataset is gathered from the result in the first image slice and modified with some priori knowledge about the infarct in DWI images from an expert neurologist. The infarct segment areas from active contour algorithms in the consecutive slices that pass all three conditions: intensity, connectivity and size, are considered as infarct. Using an expert's manual segment areas as our gold standard, the experiments reveal that our proposed approach should be able to assist human in infarct segmentation in DWI images. The proposed approach achieved good results with 0.8548 ± 0.0384 sensitivity, 0.8787 ± 0.0860 precision and 0.8511 ± 0.0475 DSC respectively.**

***Index Terms*—acute ischemic infarct, diffusion weighted imaging, active contours, image segmentation**

I. Introduction

Acute ischemic infarction (acute stroke) is characterized by sudden impairment of brain function due to a reduced oxygen supply caused by an immediate vessel occlusion or embolism to the brain. Acute stroke is the second most common cause of death and a major cause of disability in developed countries after ischemic heart disease [1]. The incidence of stroke increases every year and is found in both genders at all ages.

Diffusion Weighted Imaging (DWI) is a standard protocol used for detection of ischemic changes in a brain. DWI is one type of diffusion magnetic resonance imaging (dMRI) methods that reflect the mobility of water molecules within a tissue. In the infarct area, the diffusion process is hindered resulting in a hyper-intense signal in the acquired scan. The ischemic changes can be detected with DWI within minutes after onset [2].

Therapeutic of acute stroke can be either to give intravenous tissue plasminogen activator within 3 hours or aspirin within 48 hours of stroke onset or intervention [3]. Neurologists must be very careful because those medicines can be harmful as they may cause bleeding in the brain.

Infarct area is one of many necessary factors for diagnosis and treatments. In clinical practice, imaging analysis and treatment decision are performed by neurologists [4]. Infarct segmentation is usually done manually or semi-manually by neurologists based on individual's experience and visual perception. Hence, the segmentation results are usually inaccurate because they can vary at times due to human's errors. Automatic segmentation can assist not only in making fast decision based on more detailed information neglected by visual analysis but also providing more accurate results.

Segmentation methods that are widely used in medical imaging can be divided into three categories: region-based methods, boundary based methods and hybrid methods. Firstly, region-based methods include thresholding, region growing, region splitting and merging and classification method. Secondly, boundary-based methods consist of parametric and non-parametric deformable models. Lastly, hybrid methods are such as level set method and graph cut method [5].

This research proposes to segment acute stroke brain infarct in DWI images by applying region-based active contour. Moreover, the system is trained with the most

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prospect infarct result from each individual problem dataset together with some priori knowledge from experienced neurologists in order to gain better infarct result areas in other slices of the same dataset.

In this research, region-based active contour is selected based on two main facts. Firstly, region-based active contour works efficiently in partition a given image into objects and background particularly in images that objects and background are homogeneous regions. Secondly, in DWI images, the areas of infarct and normal brain are rather homogeneous but their intensities are quite distinct. An example of brain DWI image of an acute stroke patient is shown in Fig. 1, the infarct area can be clearly identified with its higher intensity than normal brain area.

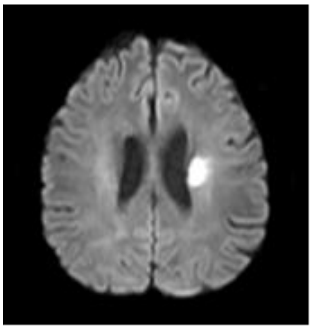


Figure 1. A brain DWI image of an acute stroke patient.

This paper is organized as follows: Section II includes the literature reviews about MRI image segmentation methods. Our proposed method is presented in section III. Section IV illustrates the experimental results. Finally, discussions, conclusions are presented in section V.

II. Literature Reviews

Norhashimah *et al*. [6] proposed brain lesion segmentation in DWI images based on thresholding technique. In this research, brain lesion includes solid tumor, acute infarction, haemorrhage and abscess. DWI images were normalized, background was removed and the images were enhanced with two different techniques: Gamma-law transformation and contrast stretching. The results revealed that thresholding with gamma-law transformation provided better segmentation results than that with contrast stretching.

Montiel *et al*. [7] proposed and applied nonparametric density method for estimating the segmentation of cerebral infarct lesion from DWI images. Edge confidence map was used to improve the quality of the boundaries in the merging adjacent regions. The outcome of infarct volume segmentation of this method compared with manually segmented volume by a neurologist showed a significant correlation.

Yiquan *et al*. [8] proposed a hybrid model which combined a kernel-base fuzzy c-mean (KFCM) algorithm and Chan-Vese (CV) model for segmentation and classification the region of interests (ROI) in MRI brain image. Firstly, the KFCM algorithm was used for initializing contour placement and making a coarse segmentation, which achieved the automatic selection of initial contour. Afterwards, ROI's fuzzy membership was extracted and CV model was used. The results showed that this proposed method could segment brain image better than fuzzy c-means (FCM) clustering, KFCM, and the hybrid model of FCM and CV in both accuracy and robustness to noise.

III. Our Proposed Method

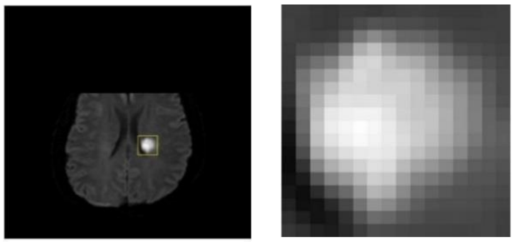
As mentioned earlier, this research proposes to segment brain infarct area in DWI images with region-based active contour. Chan-Vese region-based active contour algorithm [9] is applied to segment a target infarct area. Localized region-based active contour [10] is utilized to refine the result boundary. In our approach, the system is trained with the knowledge about the targeted infarct from the result in the starting image slice together with some priori knowledge of expert neurologists about the brain infarct in DWI images. More details are illustrated in section *B*.

A. Pre-processing

There are three pre-processing tasks to accomplish as follows: Firstly, the image slice with the largest infarct and its bounding box must be identified by a neurologist. Secondly, slices with artifacts are eliminated. Lastly, the data in the volume of interest are normalized.

(1) Initial infarct bounding box identification

In this research, an expert neurologist is asked to select an image slice with the largest infarct of a DWI dataset and mark a bounding box around it as shown in Fig. 2.



(a) (b)

Figure 2. (a) The largest infarct in a DWI dataset is marked with a bounding box by a neurologist. (b) The zoomed-in marked infarct area.

(2) Slices with artifacts elimination

One brain DWI dataset generally consists of several consecutive slices of the scanned brain. Fig. 3 illustrates an example of a brain DWI dataset.

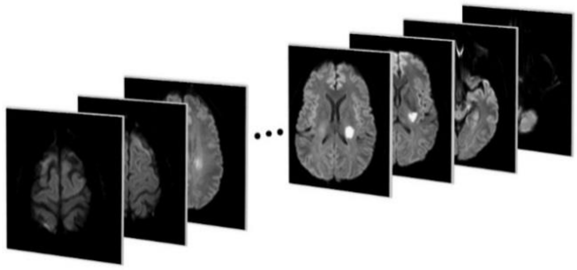


Figure 3. Example of one brain DWI dataset.

DWI images at high field (Philips Achieva 3.0T) are typically acquired using echo-planar imaging techniques. The single-shot images are inherently affected to susceptibility artifacts that can be found around the base of bony skull and air-filled paranasal sinuses [11]. These areas normally appear in several images at the beginning and the ending slices of the DWI dataset. Hence, this research chooses to avoid artifacts by eliminating those image slices. Fig. 4 shows a DWI image with artifacts around the paranasal sinuses.

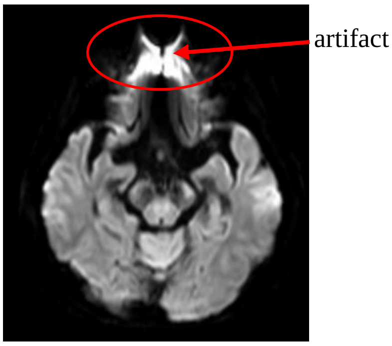


Figure 4. Artifact from DWI technique appears in paranasal sinuses.

(3) Volume of interest data normalization

Volume of interest is identified by expanding to some extent all sides of the infarct bounding box identified in (1) in all slices except those eliminated in (2). The data in the volume of interest are normalized by Equation (1).

$$Normalized(X_i) = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{1}$$

where X_i, $X_{\min}$ and $X_{\max}$ denote each data point, minimum and maximum values of all the data in the volume of interest respectively.

B. Brain Infarct Segmentation

This research adopts Chan-Vese region-based active contour [9] and localized region-based active contour [10] algorithms to extract targeted infarct areas in brain DWI images.

(1) Adopted active contour algorithms

Chan-Vese model [9] is a classical level set based active contour. The Chan-Vese algorithm relies on global information of homogeneous regions. The Chan-Vese model defines the segmentation particular partition of a given image $I(x,y)$ into two regions, objects to be detected and background. The Chan-Vese region-based active contour is formulated by minimizing the energy functional $F_{CV(c_1,c_2,C)}$ defined in Equation (2).

$$\begin{aligned} F_{CV}(c_1,c_2,C) &= \mu Length(C) + vArea(in(C)) \\ &+\lambda_1 \int_{in(C)} (I(x,y)-c_1)^2\, dxdy \\ &+\lambda_2 \int_{out(C)} (I(x,y)-c_2)^2\, dxdy \end{aligned} \tag{2}$$

where C represents the curve, the constants c_1 and c_2 denote the average intensities inside and outside the curve, and μ, v, λ_1 and λ_2 are positive parameters. In (2), the first and the second terms are called regularizing terms (or internal energy) that control the smoothness of the boundary and the last term is the external energy that pulls it towards the object boundary. The final energy functional representation of Chan-Vese active contour evolved with level set method is as shown in Equation (3).

$$\begin{aligned} F_{cv}(c_1,c_2,\phi) &= \mu \int_\Omega \delta(\phi(x,y)) |\nabla \phi(x,y)| dxdy \\ &+ v\int_\Omega H(\phi(x,y)) dxdy \\ &+\lambda_1 \int_\Omega (I(x,y)-c_1)^2 H(\phi(x,y)) dxdy \\ &+\lambda_2 \int_\Omega (I(x,y)-c_2)^2 (1-H(\phi(x,y))) dxdy \end{aligned} \tag{3}$$

where H and δ are the Heaviside function and the Dirac function. The constants c_1 and c_2 represent mean intensity values of the regions inside and outside C while ϕ denotes the curve's level set function. The final contour curve is obtained when the energy F_{cv} in Equation (3), is minimized at the zero level set.

Chan-Vese active contour works well for image segmentation in a large convergence range. It is also less sensitive to noise images. However, when the intensities inside or outside C are non-homogeneous, the constants c_1 and c_2 vary as C changes and hence, ϕ also varies and causes the active contour to evolve the wrong boundary. Consequently, this research adopts localized region-based active contour from [9] to improve the previously acquired object's boundary.

Localized region-based active contour proposed by S. Lankton and A. Tannenbaum [10] is a segmentation method described in terms of small local regions. Referring to Lankton and Tannenbaum [10] localized region-based active contour denotes x and y as independent spatial variables each representing a single point in Ω. We adopt $B(x, y)$ as a ball (or a circular) mask to define the local region as defined in Equation (4).

$$B(x,y) = \begin{cases} 1, & \|x-y\| < r \\ 0, & otherwise. \end{cases} \tag{4}$$

where x is a point on the contour, y is a point within the masked region and r is a radius parameter. This function is 1 when the point y is within a ball of radius r centered at x, and 0 otherwise.

The final energy function is added with regularlization term (the second term) as in Equation (5).

$$\begin{aligned} F(\phi) &= \int_{\Omega_x} \delta\phi(x) \int_{\Omega_y} B(x,y) \cdot F(I(y),\phi(y)) dydx \\ &+\lambda \int_{\Omega_x} \delta\phi(x) \|\nabla \phi(x)\| dx \end{aligned} \tag{5}$$

In terms of generic internal energy, Lankton and Tannenbaum [10] proposed three specific energies: uniform modeling energy, means separation energy and histogram separation energy. In this research, the uniform modeling energy (F_{UM}) is utilized with a constant intensity model (or the Chan-Vese energy [9]). The internal uniform modeling energy, F_{UM} is defined in Equation (6).

$$F_{UM} = H\phi(y)(I(y)-u_x)^2 + (1-H\phi(y))(I(y)-v_x)^2 \quad (6)$$

where u_x and v_x represent the intensity means of the inside and outside of the contour localized by $B(x, y)$ at a point x. The localized versions of the means, u_x and v_x are as shown in Equation (7) and Equation (8).

$$u_x = \frac{\int_{\Omega_y} B(x,y)\cdot H\phi(y)\cdot I(y)dy}{\int_{\Omega_y} B(x,y)\cdot H\phi(y)dy} \quad (7)$$

$$v_x = \frac{\int_{\Omega_y} B(x,y)\cdot(1-H\phi(y))\cdot I(y)dy}{\int_{\Omega_y} B(x,y)\cdot(1-H\phi(y))dy} \quad (8)$$

The F in Equation (5) is substituted by F_{UM} directly to form a complete localized energy.

(2) Brain segmentation by active contour

The process of segmentation by adopted region-based active contour methods is as follows:

1) A neurologist selects a DWI image slice that consists of the largest and most illuminance of the infarct area. He/She determines the extent of the most prospected infarct area and creates a bounding box to cover the infarct area. This bounding box is now called a region of interest (ROI).

2) Global active contour is utilized to segment the infarct area. The center of the ROI is used as the initial contour.

3) Localized region-based active contour is performed to achieve a more refine infarct result from the previous step.

4) For the next consecutive slice, a bounding box on this slice is redefined with the bounding box of the result contour of the preceding slice. Localized region-based active contour is processed using the morphological eroded contour from the previous slice as the initial contour. If there are two or more connected pixels of the result contour on either edge of the bounding box, the bounding box is expanded. Localized active contour reprocesses with the result infarct contour as the initial contour. This process is repeated until no infarct edge is adjacent to the bounding box edge.

5) Identify infarct by checking three conditions as illustrated in B (3).

6) Repeat steps 4 and 5 until no further infarct is founded.

7) Repeat steps 4 and 5 backwardly using the initial contour from step 3 until no more infarct is found.

(3) Infarct identification

In this research, the result from active contour is identified as infarct if it passes all three conditions that are intensity, pixel/voxel connectivity and size as follows:

1) The intensities of the result region in the slice under consideration must be within the intensity range.

In this research, a neurologist is asked to select the DWI image slice that contains the largest and most illuminance infarct area. The infarct intensity range is gathered corresponding to each individual problem dataset gathered from the segmented infarct in the slice selected by a neurologist. By virtue of the nature of infarct, high hyper-intense signal appears at the middle of infarct and the brightness reduces around the edge of the infarct. This research chooses to relax the minimum intensity by 10% from the gathered knowledge.

2) The result of segmented area in the present slice must have the pixel that is connected to the infarct in the previous slice.

3) The size of the infarct area at the present slice must be less than or equal to 125% of that in the previous slice.

IV. Experiments and Results

A. DWI Image Datasets

The DWI datasets in our experiments were acquired with Philips Achieva 3.0T MRI system from 6 ischemic acute stroke patients. One DWI dataset consists of 30 slices. Slices with expected artifacts, slices 1-14 and 26-30, are neglected; hence slices 15-25 are used in our experiments. Each slice is 4.0 mm slice thickness and 1.0 mm intersection gap. The matrix size is 224 mm × 224 mm and the FOV is 230 mm × 230 mm.

B. Evaluation Methods

In our experiments, the infarct areas that have been manually segmented by an expert neurologist are used as our gold standards. All 6 DWI datasets are segmented with our proposed approach. The experimental results are evaluated with three evaluation metrics: *sensitivity*, *precision* and *dice similarity coefficient (DSC)* in Equation (9), Equation (10) and Equation (11) respectively.

$$Sensitivity = \frac{TP}{(TP+FN)} \quad (9)$$

$$Precision = \frac{TP}{(TP+FP)} \quad (10)$$

where *TP* (or *true positive*) denotes to the number of pixels that our system correctly identified as the infarct. *FN* (or *false negative*) is the number of pixels that are infarct but our system incorrectly identified as non-infarct. Finally, the *FP* (or *false positive*) is the number of pixels that our system incorrectly identified as the infarct.

$$DSC = \frac{2\left|A_{\text{segment}} \cap A_{\text{gold}}\right|}{\left|A_{\text{segment}}\right| + \left|A_{\text{gold}}\right|} \quad (11)$$

where A_{segment} and A_{gold} denote the areas of an infarct as segmented by our proposed approach and by the expert neurologist respectively.

C. Experimental Results

Table I illustrates our experimental results. The table includes the image slice number, infarct areas from our proposed system and our gold standard of each patient. The mean sensitivity is 0.8548 with 0.0384 SD. The mean precision is 0.8787 with 0.0860 SD. The *DSC* equals 0.8511 with 0.0475 SD as shown in Table II.

TABLE I. COMPARISON SEGMENTATION OF AREA INFARCT FOR ADOPTED ACTIVE CONTOUR AND MANUAL SEGMENTATION. AND THE FIFTH , THE SIXTH AND THE SEVENTH COLUMNS SHOWS THE SEGMENTATION QUALITY OF EACH IMAGE

Patient	*Slice of infarcts*	*Adopted active contour Area (pixel)*	*Manual segmentation Area (pixel)*	*Sensitivity*	*Precision*	*Dice Similarity Coefficient (DSC)*
1	17	43	48	0.7679	1.0000	0.8687
	18	42	43	0.9302	0.9524	0.9412
	19	41	46	0.8000	0.9756	0.8791
	20	87	115	0.7565	1.0000	0.8614
	21	110	124	0.8661	1.0000	0.9283
2	17	63	28	0.8667	0.4000	0.5474
	18	110	141	0.8333	1.0000	0.9091
	19	177	208	0.8333	0.9887	0.9044
	20	132	181	0.7111	0.9697	0.8205
3	18	86	42	0.8500	0.3953	0.5397
	19	44	43	0.8511	0.9091	0.8791
	20	90	97	0.8776	0.9556	0.9149
	21	67	57	0.9649	0.8209	0.8871
4	19	36	24	0.9231	0.6667	0.7742
	20	57	68	0.8088	0.9649	0.8800
	21	96	106	0.8774	0.9688	0.9208
	22	71	38	1.0000	0.6197	0.7652
5	19	64	53	0.9259	0.7692	0.8403
	20	103	125	0.8110	1.0000	0.8957
	21	76	101	0.7451	1.0000	0.8539
6	15	57	0	-	0	0
	16	63	0	-	0	0
	17	82	87	0.8750	0.9390	0.9059
	18	99	101	0.8857	0.9394	0.9118
	19	92	101	0.8725	0.9674	0.9175

TABLE II. AVERAGE PERFORMANCE OF SENSITIVITY, PRECISION AND DICE SIMILARITY COEFFICIENT (DSC) RESPECTIVELY

Patient	*Sensitivity*	*Precision*	*Dice Similarity Coefficient (DSC)*
1	0.8241	0.9856	0.8957
2	0.8111	0.8396	0.7954
3	0.8859	0.7702	0.8052
4	0.9023	0.8050	0.8351
5	0.8273	0.9231	0.8633
6	0.8777	0.9486	0.9117
Average	0.8548	0.8787	0.8511
SD	0.0384	0.0860	0.0475

I. DISSCUSSIONS AND CONCLUSIONS

There are several discussions that should be noted. Firstly, the segmented infarct areas from an expert neurologist's manual segmentation or our gold standard are generally greater than those from our proposed approach. It is because of the fact that it is difficult for human to classify the infarct around the boundary with human's visual judgments. We have noticed that human tends to feel safer with over-segmenting the infarct area. Fig. 5 demonstrates an example of an infarct that the intensities around the boundary are not distinctly different and hard to define.

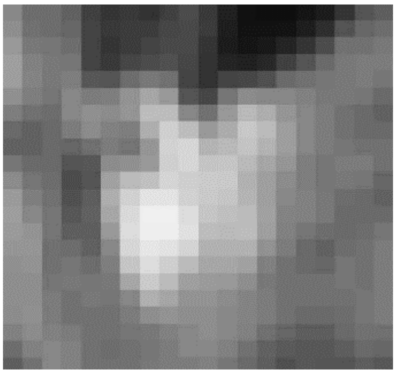
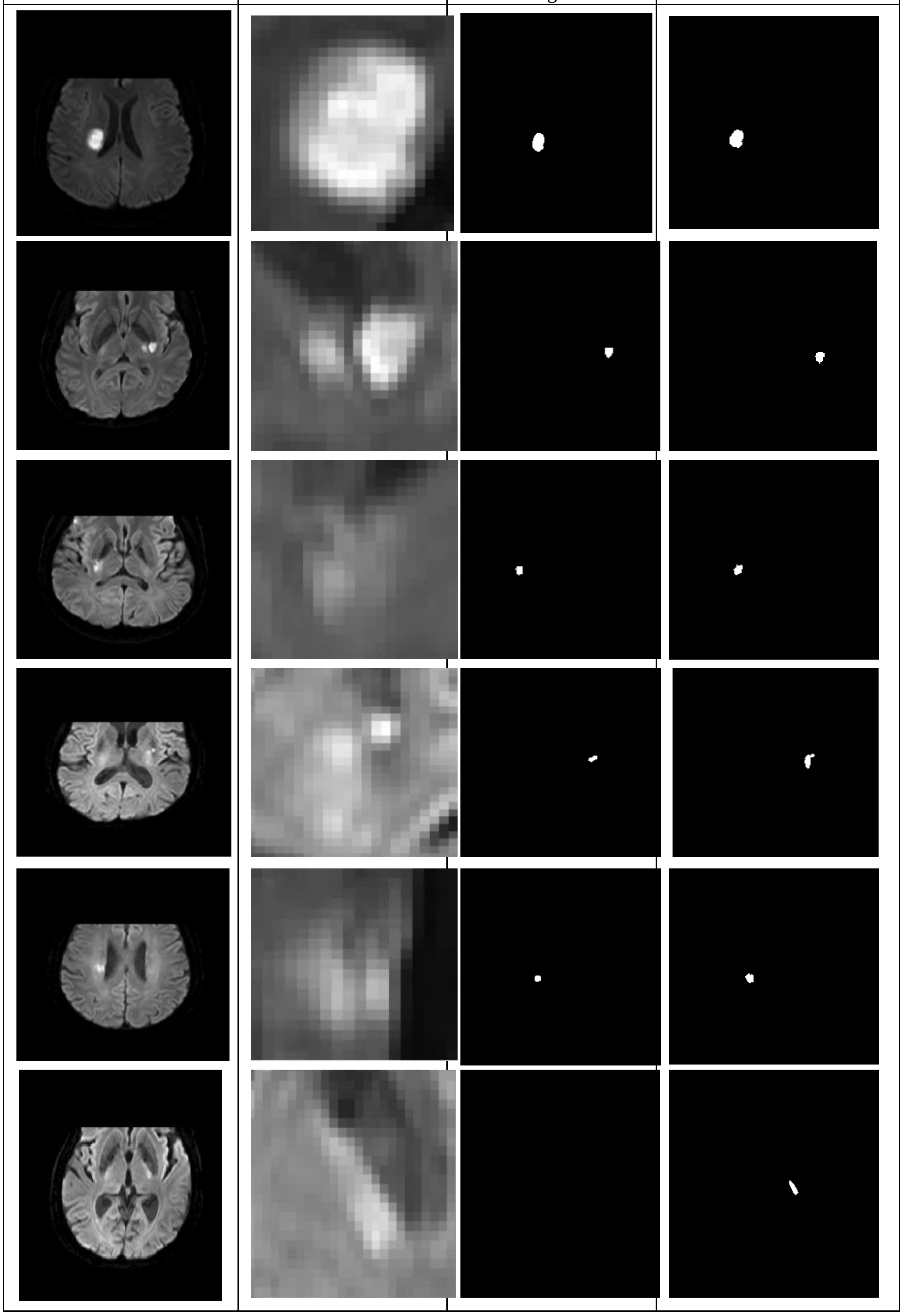


Figure 5. An example of a zoomed-in infarct area.

TABLE III. EXAMPLES OF INFARCT SEGMENTATION RESULTS FROM SIX PATIENTS. DWI IMAGES, ZOOMED-IN INFARCTS, AND THE RESULTS FROM MANUAL SEGMENTATION AND FROM OUR PROGRAM ARE ILLUSTRATED

DWI images	Zoomed-in infarcts	Infarcts from an expert neurologist's manual segmentation	Infarcts from our program



Secondly, the infarct segmentation results from our approach in some of the beginning and ending image slices of the volume of interest are greater than the gold standard. In these images, the infarct areas are small and not much different from the brain tissue area. Therefore, even the localized active contour algorithm evolves inaccurate infarct boundaries by including the brain tissues.

Thirdly, one comment from our expert neurologist is that it is hard to define the infarct boundary in many slices due to the indistinct different intensity of the infarct and brain tissue. Hence, it is noticed that the infarct areas from manual segmentation are usually over-segmented. On the other hand, our approach is able to find the infarct area based on the trained knowledge from individual dataset about the targeted infarct and an expert neurologist's selected slice which contains the largest and most illuminance infarct area. Consequently, the infarct's relaxed minimum-maximum intensity range from the selected slice can be used for determining an infarct in other slices.

Lastly, when a neurologist defined the bounding box, the adopted active contour algorithm considered only the bounding box area as shown in Fig. 6. Thus, program incorrectly detect infarct from some brain tissues which are not the infarct possess the intensity within the infarct's range. Some examples of segmentation results are shown in Table III.

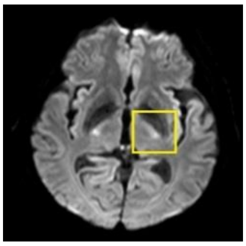


Figure 6. A posterior part of the internal capsule in left hemispheres which appears with high intensity in DWI image.

In this paper, it can be concluded that the adopted active contour methods, global active contour (Chan-Vese) and localized region-based active contour, are well capable in segmenting the DWI images which are non-homogenous. Moreover, training the system about the infarct from the individual problem dataset and the priori knowledge of a neurologist helps improving accuracy of the outcomes. For performance evaluation, the adopted active contour methods have high sensitivity (0.8548 ± 0.0384) to identify infarct areas. The program also precisely identified true infarct areas comparing with the gold standards. The average precision value is 0.8787 ± 0.0384. For the average of *DSC*, explaining the boundary of spatial overlap between segmented area and gold standard area, is 0.8511 ± 0.0384 which presents the high quality of segmentation.

In conclusion, the implementation of automatic segmentation by applying Chan-Vese and localized region-based active contour methods provides more accurate results, avoids human's error and human interaction and reduces the processing time of a neurologist.

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