ROI EXTRACTION FROM MOTION AFFECTED MRI IMAGES BASED ON FUZZY AND ACTIVE CONTOUR MODELS

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ABSTRACT

A new method for extracting the boundary of the region of interest (ROI) from motion affected magnetic resonance images (MRI) is presented. An image pre-processing stage is included to suppress prominent ghost artifacts and excessive blurring in the background, in order to facilitate the contour extraction algorithm. The pre-processing stage consists of a novel fuzzy model, incorporating a technique of hierarchical view by view image reconstruction. The contour extraction is performed using an intelligent, *attractable* active contour model (snakes), which is capable of driving any initial guess in the area of the evolving estimate towards the desired contour, and fitting in to the object without any overrun. The proposed method has been applied to spin echo MRI images affected by rotational motion, producing good results.

1. INTRODUCTION

The popularity of MRI over other imaging disciplines depends predominantly on its high spatial resolution and soft tissue contrast. In order to obtain such high quality, diagnostically interpretable images, relatively long image acquisition times are required, which makes it vulnerable to artifacts caused by physiological motion or voluntary patient motion. In two-dimensional (2D) Fourier imaging, such artifacts appear as blurring or ghost repetitions of the moving structures along the phase encoded direction [1]. Post-processing methods have been proved to be effective in suppressing such motion artifacts during the image reconstruction stage. These methods either use navigator echo information on the nature of the motion [2] or estimate motion parameters directly using the acquired data [3]-[6]. Projection onto convex sets (POCS) [7] is often used in motion estimation and correction [3][8]. The success of POCS largely depends on the convex sets, defined by the constraints imposed via available *priori* knowledge. Finite support constraint [7] is one of the most popular convex sets employed in past literature. However, no convincing methods have been proposed as to how the finite support, marked by the outer boundary of the region of interest (ROI), is extracted from the motion affected image. Minimization of pixel energy outside the ROI has also been widely used in acquiring useful motion information [3]-[6]. Therefore, it is imperative to extract the ROI boundary with high accuracy, for the success of post-processing methods.

There are two methods of ROI boundary extraction, proposed in the past literature. Zoroofi et. al. [7] propose that simple thresholding would produce an estimate for the ROI. This method seems impractical due to two reasons. Firstly, the resulting ROI entirely depends on the thresholding value, which is chosen arbitrarily. Secondly, in the presence of strong ghost artifacts outside ROI, thresholding will not be capable of eliminating these high intensity ghosts without seriously compromising the edges of the original object. The result will be an erroneous estimate for the boundary of ROI. Hedley et. al. [2] propose a method of manually fitting a boundary by an expert. This technique may be successful in some cases where the corrupted image warrant edge estimation by a trained eye, in spite of the presence of artifacts. However, such a method is shown to produce unacceptable results in the midst of severe rotational motion, where the spurious ghost edges conceal the real boundary of the object. Manual curve fitting also demands a considerable time and concentration on the part of the expert, rendering this method to be inefficient.

This research is motivated by the need for a robust, efficient, reliable and automatic algorithm for the purpose of ROI contour extraction from the motion affected MRI images. Since the nature of the motion artifacts differ according to the motion itself, conventional techniques such as dedicated filters (e.g. Gaussian) are ineffective in suppressing artifacts in the image background. Therefore, in this paper, we present a novel pre-processing stage consisting of a fuzzy model incorporating a technique of hierarchical view by view image reconstruction, in order to suppress strong ghosts and blurring in the background of the image, and to refine the edges of the object. Then, a robust *attractable* active contour (snakes) model is employed to extract the ROI boundary. The new snakes model features enhanced capabilities compared to the conventional model, such as, driving *any* initial guess towards a desired contour, working against a constant image background, overcoming spurious edge points and flowing into the object without overrun. Using additional control parameters, it is also possible to control the convergent properties of the active contour, which provide a high degree of flexibility and adaptability.

2. PRE-PROCESSING

In order to formulate the pre-processing algorithm, we observe the following properties of the acquired MRI signal space, which is also known as the k-space:

- Each view provides, in part, the spatial frequency information of the object in a particular location and orientation. For rigid in plane motion, the imaged object is constant over the scanned views. However, its location and orientation may differ from view to view;
- If N views of data are acquired, ranging from $V = -\frac{N}{2}$ to $V = \frac{N}{2} - 1$, the views in the middle of the k-space (i.e. near $V = 0$) contain the intensity information, whereas the views towards the top and bottom ends of the k-space contain the edge information. Therefore, in the event of motion, strong ghost edges are produced by the views that provide edge information; and
- The effect of including view information for $V = \pm i$ $\left(\text{where } i = 1, 2, \ldots, \frac{N}{2} - 1\right)$ in the reconstruction stage, is twofold. Firstly, it improves stationary edge information, but secondly it also introduces motion-induced blur and ghosting artifacts.

According to the above properties of k-space, it is possible to form a blurry image of the object undergoing rigid in-plane motion, using only the low frequency information given by the views in the vicinity of view $V = 0$. The resulting image exhibits the orientation and location of the object at view $V = 0$.

Since the low frequency image exhibit blurred object edges, the pre-processing algorithm is required to incorporate additional high frequency information obtained from the views in the top and bottom parts of the k-space. The algorithm should be capable of extracting view information corresponding to the orientation and location of the low frequency image, while discarding the view information that lead to ghost artifacts. This is a non-trivial task since the motion information is unavailable at each view. The following section proposes a fuzzy algorithm, which is capable of enhancing the object boundary edges while suppressing the ghost artifacts in the image background.

2.1 Fuzzy Model

Let the whole set X be defined by each pixel location $\vec{x} = (x, y)$ in the reconstructed $N \times N$ MR image. We define a range of fuzzy sets in X, mapping the intensity information of each progressive image m_i reconstructed from views $V = -i$ to $V = +i$ $\left(\text{where } i = 1, 2, \ldots, \frac{N}{2} - 1\right)$, in to *membership functions* [9]. If the intensity distribution of the image m_i is given by $I_i(\vec{x})$, the membership function for the fuzzy set $\tilde{E}_i$ is given by

$$\mu_{\tilde{E}_i}(\vec{x}) = \frac{I_i(\vec{x})}{255} \tag{1}$$

The fuzzy set $\tilde{E}_p$ that represents the pre-processed image m_p is now defined as the intersection [9] of the fuzzy sets $\tilde{E}_i$, as given by the following equation:

$$\tilde{E}_p = \bigwedge_{i=0}^{\frac{N}{2}-1} \tilde{E}_i \tag{2}$$

where N is the number of acquired views [1].

3. CONTOUR EXTRACTION

The overall goal of this paper is to find a smooth contour, which describes the boundary of the ROI most accurately. Hence, we use a method based on the active contour model proposed by Kass [10], since it has been proved successful in many such applications. However, in order to overcome the drawbacks of the original snake model, we use an *attractable* contour model with enhanced features. Our *attractable* Snake model is defined as follows:

$$E_{snake}[V(s)] = \int_{\Omega} \{E_{\text{int}}[V(s)] + P_{image}[V(s)] + E_{feedback}[V(s)]\} ds \tag{3}$$

where $V(s)$ is the deformable contour and arc length $s \in \Omega$. $E_{\text{int}}[V(s)]$ and $P_{image}[V(s)]$ are as given in the original snake model [10]. $E_{feedback}[V(s)]$ is defined by the following equation:

$$E_{feedback}[V(s)] = -f_{db}(s) \cdot \nabla P_{voltage}[V(s)] \cdot \vec{n}(s) \tag{4}$$

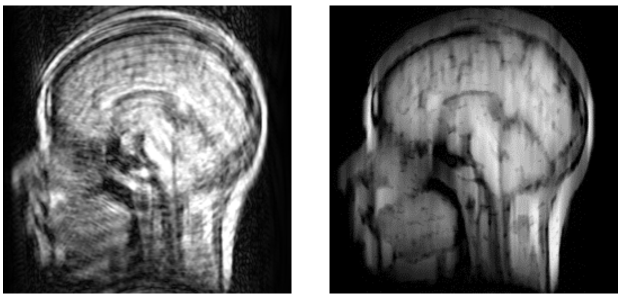
where $\vec{n}(s)$ is a unit vector, which represents the direction of normal to deformable contour and the prime $f_{db}(s)$ controls feedback pulling (for expansion) or pushing (for contraction) on snake. $E_{feedback}[V(s)]$ is designed to directly reflect the potential energy variation $\nabla P_{voltage}[V(s)]$ of image features (i.e. edges). If the attraction from the desired image feature is large enough to overcome the internal mechanical resistance (due to bending and stretching) of the contour, and with the condition that there is no external energy influencing, the snake can then be attracted to the attraction source and adhere to it. $E_{feedback}[V(s)]$ responds to the variation of potential energy of the snake while it is driven close to the desired contour and will disappear automatically when the snake reaches the object. Hence, the improved model can achieve the equilibrium of the original snake. We solve the minimization process of snake based on the fast greedy algorithm [11] because it reasonably combines speed, flexibility and simplicity compared to dynamic programming. In order to avoid inherent numerical instability, we use a synthetic convergent criterion based on the characteristic parameters of snakes approaching equilibrium, which allows the snake to converge either oscillatingly or normally to the usual contour or a subjective contour.

An overall optimal edge detection scheme was developed to handle low contrast and noisy pre-processed MR images. We first split a 2-D Gaussian smoothing filter into two directions (i.e. x and y), then implement a smoothing operator with the opposite sequence of Sobel edge detecting. This approach presents stronger edge strength, more competitive noise suppression, higher efficiency in weaker edge detection and lower time cost compared to the Canny detector [12].

In addition, a method of dynamic, linear interpolation was employed to sense the local shape of the desired contour accurately or to flow into the complicated shape of the object contour properly. To avoid re-parametering after each interpolation and to maintain the continuity of optimizing iteration, we retain the original parameter setting at each contour point and give the neighboring point's setting to each new contour point. The threshold for average length of the contours (*GAP*) can reflect the basic geometric property of snake. Therefore in order to avoid clustering or even looping we remove those snake points much closer to their previous points according to *GAP*, during each interpolation.

4. RESULTS

The proposed algorithm has been applied to spin echo MRI images subjected to severe rotational motion. Even a slight rotation during the data acquisition can cause strong ghost artifacts and spurious edges. We regard such motion as the worst case scenario, for testing our algorithm. The motion involved continuous rotations with maximum angular span of 40 degrees. The total number of acquired views is 256, and the resultant image size is 256×256 pixels, as shown in Fig. 1(a).

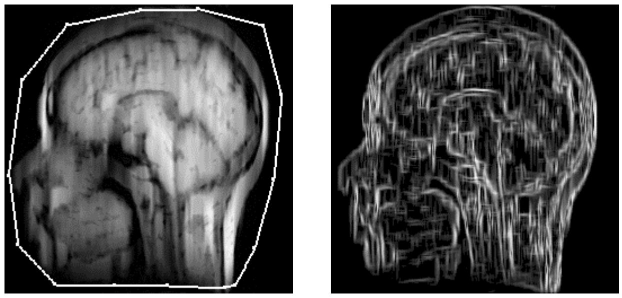


(a) (b)

Figure 1. (a) Image with rotational motion artifacts; (b) Pre-processed image.

The pre-processed image of Fig. 1(a) is shown in Fig. 1(b). Notice that the image background has been cleared of ghost artifacts, while reducing the motion induced blur, producing a better-defined object area.

Since our snake model is less sensitive to the shape and position of the initial contour, it can be any closed initial guess in the image background. Due to the interpolation scheme described in Section 3, which re-sampled each initial contour before starting minimization process of a snake, our algorithm can start from very simple, automatically placed initials as shown in Fig. 2(a).

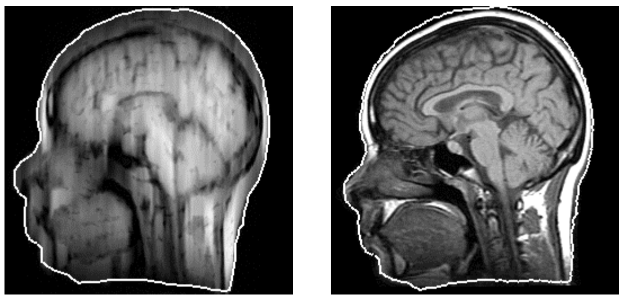


(a) (b)

Figure 2. (a) Initial guess for ROI; (b) Edge image

The overall optimal edge detection scheme described in Section 3 was employed, which picked up low contrast edges and provided more than one pixel edge strength, as shown by the edge image in Fig. 2(b). The final contour after the convergence of the snake is shown in Fig. 3(a). The parameters used for the iterations are $\alpha = 0.8$, $\beta = 1.2$, $\gamma = 1.5$, $f_{db} = 1.2$ and $GAP = 7$, where α, β, γ are the original snake parameters [10].

To illustrate the quality of our estimated ROI boundary, we overlaid the extracted contour on the same image slice without motion artifacts (Fig. 3(b)). The orientation of the estimated contour is matched to fit the object with best possible fit. Notice that, the estimated ROI boundary does not invade the object. Such an invasion can affect both the motion correction and motion parameter estimation stages. Since both these stages heavily rely on minimizing the pixel energy outside ROI [3]-[6], an invasion can remove parts of the object from the reconstructed image by forcing the pixel energy to zero. However, allowing significantly larger estimate for the boundary of ROI will result in ambiguous estimation of motion parameters [3] and slow convergence of reconstruction algorithms that use POCS [8]. Therefore, it is important to ensure that the ROI boundary is on or outside but adjacent to the outer boundary of the object, as shown in Fig. 3(b).



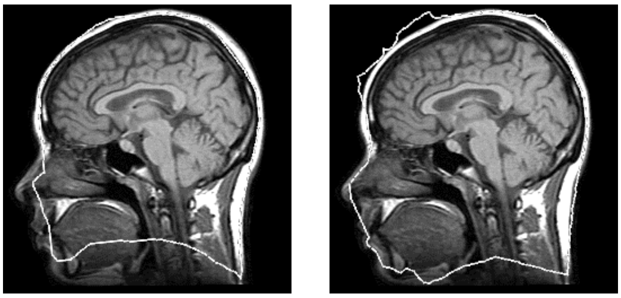
(a) (b)

Figure 3. (a) Extracted contour; (b) Extracted ROI boundary overlaid on the motion artifact free image in the best fitting orientation.

In order to compare our results with that of thresholding, we obtained two images with threshold values 150 and 95 as shown in Fig. 4(a) and Fig. 4(b). The value 150 was chosen so that most of the ghost artifacts outside ROI were eliminated. However, this resulted in ROI boundary invading the object, due to the loss of edges (Fig. 5(a)). In order to preserve the object edges, the threshold value was reduced to 95. However, this resulted in residual ghost edges that mislead the Snakes algorithm, resulting in an erroneous ROI boundary as shown in Fig. 5(b). It is obvious from the comparative results that our algorithm produces higher quality ROI boundary compared to thresholding.

(a) (b)

Figure 4. Threshold images of Fig. 1(a), using threshold value: (a) 150; (b) 95.



(a) (b)

Figure 5. Extracted ROI boundaries from the threshold images in Fig. 4, overlaid on the motion artifact free image in the best fitting orientation. The threshold values are: (a) 150; (b) 95.

5. CONCLUSIONS

The preliminary tests involving spin echo MR images indicate that the proposed algorithm is capable of extracting the ROI boundary from motion affected MR images, with high accuracy and reliability without invading the object area. Compared to the previously proposed techniques, our model is robust, less subjective and can be applied in wide variety of motion including severe rotations. In the future, the method can be tested with many other types of motion such as expansion and out of plane rotations. We believe that the proposed technique can be combined with intelligent motion parameter estimation schemes and POCS based motion correction algorithms to effectively suppress motion artifacts in MR images.

6. REFERENCES

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