Active Contours: An Overview with Applications to Motion Artifact Cancellation in MRI

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Abstract

Motion can be estimated by detecting the edges of a moving object using Active Contours, and registering them together to obtain the motion model parameters. This idea can be applied to patient motion during the acquisition of an MRI to eliminate motion artifacts in the image. The data obtained during the MRI acquistion, the k-space, can be divided into several subbands such that each subband is acquired in a small fraction of the full imaging time. These subbands create invariant tissue feature maps called subband images. Using Active Contours, the relative motion is analyzed across the different subband images to determine the motion parameters. Using these motion parameters it is possible to correct the subbands, thus correcting the k-space. This has the potential to yield clear, noise-free MR images.

Keywords: Active Contours, Motion Estimation, Motion Artifacts

1 An Overview of Active Contours

An Active Contour is an energy-minimizing spline that detects specified features within an image. It consists of a set of *control points* connected by straight lines. The Active Contour is defined by the number of control points as well as the coordinates of each control point, shown in Figure 1. It is held together by internal forces and is guided toward image features, such as an object's boundary, by external forces. This can be useful for edge detection, object recognition, and object tracking[2][3][4].

The energy function that describes Active Contours is composed of two components, the internal energy and the external energy. The internal energy deals with intrinsic properties of the contour and is a smoothness constraint which keeps the points contained within the contour. The external energy guides the contour toward image features. The internal energy is the summation of an elastic energy and a bending energy. The elastic energy allows the Active Contour to shrink or expand. To shrink (expand) the contour, the elastic energy can be defined to increase (decrease) as the length increases. The elastic energy is defined as:

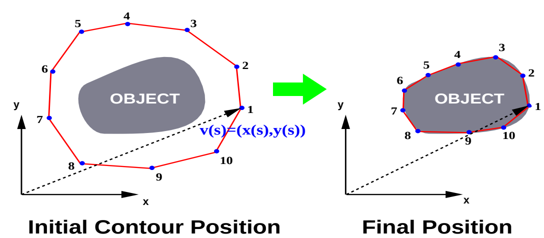

Figure 1: *The structure of an Active Contour.*

$$E_{elastic} = \int_s \alpha(\vec{v}(s) - \vec{v}(s-1))^2 ds, \qquad (1)$$

where s is the normalized index of the control points on the contour, $\vec{v}(s) = (\vec{x}(s), \vec{y}(s))$ is an array of the coordinates of all the control points on the contour, and α is an adjustable constant that determines the extent to which the contour is able to expand or contract. The second part of the internal energy is the bending energy. The bending energy causes the Active Contour to be a smooth curve or a straight line. To smooth the contour, the bending energy needs to be defined such that it increases as the curvature increases. Summing the squares of the curvature at each control point defines a smoothing contour, i.e.,

$$E_{bend} = \int_s \beta(\vec{v}(s-1) - \vec{v}(s) + \vec{v}(s+1))^2 ds, \qquad (2)$$

where β is an adjustable constant that determines the extent to which the contour is allowed to bend.

The energies defined so far have been intrinsic energies that deal with the Active Contour itself. The

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desired behavior for the Active Contour is to respond to image features within the image. Although any image feature can be included, only lines and edges are considered in our case. The line energy is used to attract the Active Contours to either bright or dark lines within the image. Thus, for detection of bright (dark) lines, one can define an energy that increases with decreasing (increasing) grayscale values. The image Energy is defined in terms of the image intensity as follows [2]:

$$E_{image} = \int_s w_{line} E_{line} ds = \int_s -w_{line} I(\vec{v}(s)) ds, \quad (3)$$

where $I(\cdot)$ is the image intensity and w_{line} is a constant determining the strength of attraction. The edge energy allows the contour to evolve toward the edges. Since an edge is defined where a large grayscale gradient exists, the energy should decrease as the gradient increases.

$$E_{image} = \int_s w_{edge} E_{edge} ds = \int_s -w_{edge} |\nabla I(\vec{v}(s))|^2 ds \quad (4)$$

where $\nabla I(\cdot)$ is the image gradient and w_{edge} is a constant to adjust the strength of attraction. Other types of external energy can also be defined [2][3][4].

The total energy of the Active Contour is the sum of the internal energies and the external energies. The Active Contour minimizes this total energy in order to converge as desired. Through the calculus of variations it is possible to obtain an optimal $\vec{v}(s)$ such that the following equation is minimized:

$$\begin{aligned} E &= \int_s \alpha(\vec{v}(s) - \vec{v}(s-1))^2 \\ &+ \beta(\vec{v}(s-1) - 2\vec{v}(s) + \vec{v}(s+1))^2 \\ &+ w_{line} I(\vec{v}(s)) + w_{edge} |\nabla I(\vec{v}(s))|^2 ds. \quad (5) \end{aligned}$$

This can be rewritten in the following form:

$$\begin{aligned} E &= \int_s \frac{1}{2}(\alpha|\vec{v}'|^2 + \beta|\vec{v}''|^2) + E_{ext}(\vec{v}) ds \\ &= \int_s F(s, \vec{v}, \vec{v}', \vec{v}'') ds, \quad (6) \end{aligned}$$

where $\vec{v}'$ and $\vec{v}''$ denote the first and second derivatives of $\vec{v}$, and $E_{ext}(\cdot)$ is the external energy function. From the calculus of variations, the solution to this optimization problem must satisfy the following Euler's differential equation[2]:

$$F_v - \frac{d}{ds} F_{v'} + \frac{d^s}{ds^2} F_{v''} = 0. \quad (7)$$

Substituting (6) into (7), the following Euler equation is obtained:

$$-\alpha' \vec{v}' - (\alpha + \beta'')\vec{v}'' + 2\beta' \vec{v}''' + \beta \vec{v}'''' + \frac{\partial E_{ext}}{\partial \vec{v}} = 0. \quad (8)$$

The discrete form of this equation produces two independent linear equations for $x(s)$ and $y(s)$ in the form $\mathbf{A}\ \vec{x} = \vec{f_x}$ and $\mathbf{A}\vec{y} = \vec{f_y}$, where $\mathbf{A}$ is a circulant pentadiagonal matrix consisting of several combinations of α and β [2][3][4].

A number of approaches have been used to implement Active Contours, e.g., dynamic programming [4], the Greedy algorithm [3], and the Kass method [2].

In this paper, we extend the Kass method in order to develop a technique to suppress motion induced noises in MRI. The equation for the Kass method is as follows:

$$\begin{aligned} \mathbf{A}\vec{x}_t + f_x(\vec{x}_{t-1}, \vec{y}_{t-1}) &= -\gamma(\vec{x}_t - \vec{x}_{t-1}) \\ \mathbf{A}\vec{y}_t + f_y(\vec{x}_{t-1}, \vec{y}_{t-1}) &= -\gamma(\vec{y}_t - \vec{y}_{t-1}), \quad (9) \end{aligned}$$

where $\mathbf{A}\vec{x}_t$ is the internal forces, $f_x(\vec{x}_{t-1}, \vec{y}_{t-1})$ represents the external forces, and the right side of the equation is a constant γ multiplied by the step size. Solving for the position update, (9) becomes:

$$\begin{aligned} (\mathbf{A} + \gamma\mathbf{I})\vec{x}_t &= \gamma\vec{x}_{t-1} - \vec{f}_x(\vec{x}_{t-1}, \vec{y}_{t-1}) \\ (\mathbf{A} + \gamma\mathbf{I})\vec{y}_t &= \gamma\vec{y}_{t-1} - \vec{f}_y(\vec{x}_{t-1}, \vec{y}_{t-1}). \quad (10) \end{aligned}$$

Because taking the inverse of the matrix $(\mathbf{A} + \gamma\mathbf{I})$ can cause problems, the LU decomposition is taken instead. This allows forward and backward substitution to solve for the new position of the Active Contour.

Figure 2 illustrates the effects of the elastic and bending energies when applied independently. If an elastic energy is applied to an initial contour (Figure 2 (left)), it will pull the Active Contour into a smooth circle which keeps contracting. The outlying points get pulled in the fastest while the innermost points are pulled outward until they are aligned with their neighbors. This is shown in Figure 2 (middle). If a bending energy is applied, it pulls the Active Contour into a smooth circle where the outer points get pulled in while the inner points get pushed out. A simulation of this is shown in Figure 2(right).

The Kass method [2] is applied to three simple objects to show the relative effects of the internal forces and external forces. The results are shown in Figure 3. The Active Contour conforms easily to objects with smooth contours while corners are more difficult to detect. This is because these results where obtained using constant β. If β were variable the contour would be more apt to detect corners.

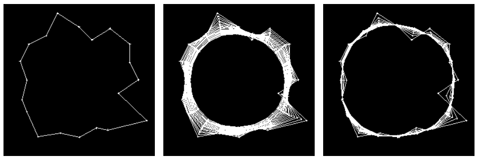

Figure 2: *An example of Elastic and Bending Energy: (left) initial contour, (middle) 20 iterations of elastic, (right)20 iterations of bending*

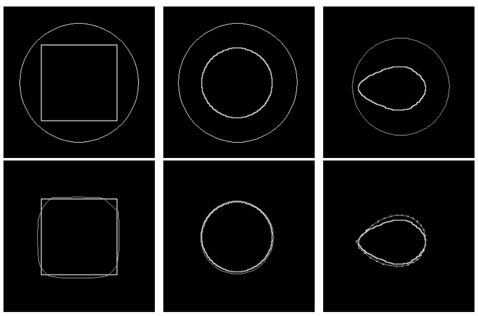

Figure 3: *An example of Active Contours after 150 iterations of the Kass, et al. method*

2 Motion Estimation using Active Contours

To estimate motion of an object, the contours of the object can be detected at each time interval using the methods described. The relative motion of the Active Contours throughout the full-time duration is estimated using elastic registration assuming an affine transformation model [5].

An advantage of using Active Contours for motion estimation is that they can reduce computation time of motion estimation because the number of points to track is reduced to the number of control points on the contour. One problem with Active Contours is its tremendous dependence on the values of α and β for the desired convergence. Also, points can move along the contour as well as perpendicular to it which tends to guide points toward stronger features allowing them to bunch up [3][4].

An application of motion estimation using Active Contours, which will be discussed in the following section, is the reduction of motion artifacts in MRI data. Motion Artifacts in MRI is the result of patient motion during the data acquisition time. To simulate the effect of motion artifacts, the motion must first be assumed. Once the motion is determined, the position of the object can be found at any moment. Because the data in MRI is not acquired simultaneously, the data is obtained at different time intervals. Thus, for each time interval, t_i, the new position of the object is found. We transform the data with the object in its new position by taking the FFT. The new data acquired by the FFT replaces the artifact free data corresponding to that particular time interval. After repeating this procedure for each time interval, the inverse FFT of all the data creates an image with motion artifacts. An example of simulated motion artifact is shown in Figure 4.

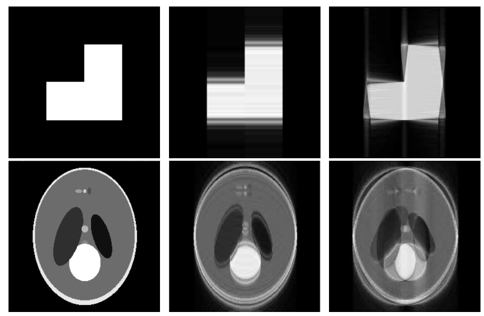

Figure 4: *An example of Simulated Motion Artifacts: (left) Images without Motion artifacts (middle) Images containing translation motion (right) Images containing rotational motion*

3 Applications to Motion-Artifact Reduction in MRI

Since motion can be estimated using Active Contours, it is possible to estimate the motion of a patient during MRI acquisition using this method. Patient motion causes blurring and ringing in MR images which alters the accuracy of the MRI. Estimating the motion of the patient and correcting for it would eliminate the possibility of repeating the long MRI procedure to obtain clear artifact-free images.

To track the patient's motion, we must consider the data obtained throughout the acquisition time, the k-space. The k-space is the data in the frequency domain that the MRI machine acquires. The inverse Fourier Transform of this data is the actual image of the object. Because the MRI k-space is not acquired simultaneously, it can be divided into N subbands where each subband is obtained within a fraction of the time the total data is acquired. Within each subband of time the motion is assumed to be negligible. If the boundaries are found in each subband image, it is possible to track the motion throughout the subband images.

Active Contours are used to detect features, such as boundaries, in each subband image. Thus, the contours can be registered together to obtain the motion model parameters of the object[7]. A block diagram of this motion estimation procedure is shown in Figure 5.

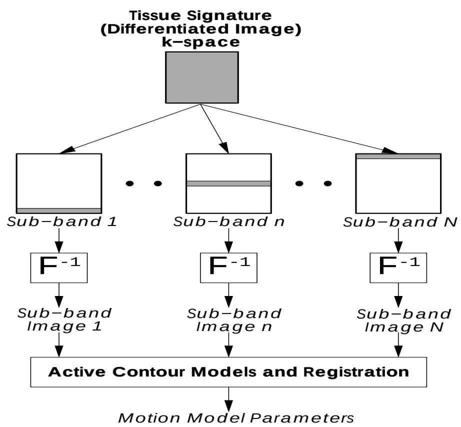

Figure 5: *Block Diagram of the proposed method of motion estimation using Active Contours.*

Basically, after detecting the edges of the subbands, the registration determines the motion between each subband. Once the motion is determined the subband is repositioned to correct for the motion. For example, if we would like to determine the motion between the first subband image and the second, we would detect the edges using Active Contours. Registration of these contours would tell us the motion between the first and second subband images. Suppose the motion is a rotation of 5 degrees, then the second image would be rotated by -5 degrees to align the second image with the first. An example of image correction is shown in Figure 6.

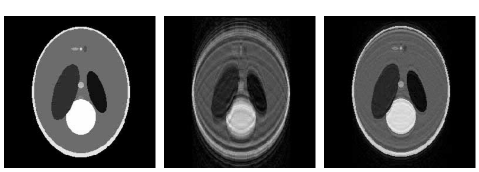

Figure 6: *Image correction from translational motion artifact. (left) Original image without motion (middle) Image containing Translational Rigid Body Motion (right) Corrected image*

Our current work aims at implementing the approach described above to real MRI data and at comparing it with other approaches in the literature, such as navigator-echos, projection onto complex sets, auto-focus algorithms, and the approaches described in [1].

4 Summary and Conclusions

The theory and implementation for the proposed method for motion artifact reduction in magnetic resonance imaging were developed. This method divides the k-space into subbands that are individually collected in much shorter time intervals than the whole image. Using Active Contours, the motion is tracked throughout the subband images, which allows patient motion to be estimated during the data acquisition period. The estimated motion allows reconstruction of an artifact-free image. The results of applying this method demonstrate the potential to free MRI from one of the fundamental problems due to motion sensitivity.

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