Myocardial Motion Estimation Using Optical Flow with Multiple Constraint Equations

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Abstract—A new optical flow method is presented for estimating myocardial motion from MR image sequences. The concept of the local shape is introduced to generate four optical flow equations. Next, the interpolation operation is utilized to solve the four optical flow equations. Then a cost function is formulated from the intensity equation and gradient equations. The minimum method is considered to obtain an optimized position as the value of displacement. Finally, the optical flow method is tested with synthetic and experimental myocardial motion MRI data. There are two main contributions in this paper: the proposed estimation method can give a desired performance on both the cine and tagged MR image sequences, and for the simulation, we proposed synthesized cine and tagged sequences with the same ground truth motion field, which are used to evaluate the motion detection performances of the algorithms. Compared to classical methods, the results obtained improved displacement estimation and strain maps on cine and tagged images.

I. INTRODUCTION

Heart motion is usually considered an important element in coronary heart disease (CHD) diagnosis. It can be assessed from dynamic image acquisition in magnetic resonance imaging (MRI) and ultrasound imaging. In this domain, optical flow methods have been considered in the past. One of the difficulties of the optical flow method is that the brightness invariance equation is underconstrained in two and more space dimensions [1]. At the same time, the computation of image gradients presents an uncertainty error in the discrete case. Therefore, a local constrained scheme was proposed in the optical flow algorithm by Lucas and Kanade [2]. Recently, a monogenic signal-based optical flow approach to motion estimation has been proposed by Felsberg [3].

The image gradient is regarded as the coefficients of linear equations in optical flow methods [4]. The image gradient is used to estimate the displacement of the points in an adjacent area. If the gradient distribution is locally uniform, the linear optical flow equations are satisfied approximately under a first-order Taylor series. When the local curvature of image intensity pattern is not smooth, intensity and gradient must be computed on a smaller support. Interpolation is used for calculating the intensity or gradient of a non-node position by the four adjacent points.

In this paper, a motion estimation method is proposed to process both of the cine and tagged MR image sequences. We consider a geometric local shape model, in which the mean intensity and gradient are defined. In motion process, the local shape parameters are considered such that its values keep the rule in the conventional optical flow equation [1], i.e., the corresponding quantities are not changed. Four equations are derived to solve for the velocity field between two frames. A cost function is defined by an intensity equation and gradient equations with their interpolated values from the previous frame and the objective values in the next frame. The optimized value of the displacement results from the minimization of the cost function. Both the cine and tagged MR image sequences are taken into account to evaluate the proposed algorithm. Given a simulated cine sequence, we proposed a method to synthesize the tagged sequence from the same ground truth motion field of the cine sequence. The performance of the proposed algorithm is assessed on both simulated data and real acquisitions on patients.

The rest of this paper is organized as follows. In section II, optical flow equations are introduced. In section III, detailed implementation is described. The results obtained on synthetic and clinical data are given in sections IV and V, respectively. In the final section, we draw various conclusions from the study.

II. OPTICAL FLOW EQUATIONS

Let there be I1 and I2, two consecutive images in a sequence. The traditional optical flow equation is based on the intensity invariance assumption during motion, which can be formulated as:

\[ I_1(x - dx) = I_2(x), \]  \hspace{1cm} (1)

where \( x = (x, y) \). The vector \( dx = (u, v) \) represents the displacement for the time interval between the two frames. To solve for the two variables \( u \) and \( v \), and under the small motion assumption, a first-order Taylor expansion leads to the brightness invariance equation:

\[ \nabla I \cdot v + I_x = 0. \]  \hspace{1cm} (2)

Equation (2) is not sufficient to recover both components of velocity vector unambiguously \( v \).

At every pixel, the local shape is another intrinsic property in addition to intensity. In Fig. 1, four cylinders have the same intensity, but the local shape is different. By local shape, we...
Both the local gradient and intensity denote the local shape. According to (1) only, the three cylinders marked in white, or with lines and grids, can be regarded as the possible positions of the cylinder at time \( t_{n+1} \) of the cylinder marked in gray at time \( t_n \). The local shape, however, is not the same for all the cylinders. The grid-textured cylinder is the only valid solution as shown in Fig. 1. Both intensity and local shape constraints need to be satisfied before and after motion. The additional assumption:

\[
I_x I_y I_z = 0, \quad I_{xx} I_{yy} I_{zz} = 0
\]

where \( I_x, I_y \) are the \( x \) and \( y \) derivatives of \( I \), respectively. By combining (1) and (3), the displacement can be detected unambiguously. In this paper, two diagonal gradients \( I_a \) and \( I_b \) are introduced in addition to the horizontal and vertical gradients as illustrated in Fig. 2.

All the gradients are numerically estimated using five aligned adjacent points along each of the four directions (see Fig. 2) as:

\[
\begin{align*}
I_x(m, n) &= \frac{1}{12} [I(m-2, n) - 8I(m-1, n) + 8I(m+1, n) - I(m+2, n)] , \\
I_y(m, n) &= \frac{1}{12} [I(m, n-2) - 8I(m, n-1) + 8I(m, n+1) - I(m, n+2)] , \\
I_a(m, n) &= \frac{1}{12\sqrt{2}} [I(m-2, n-2) - 8I(m-1, n-1) + 8I(m+1, n+1) - I(m+2, n+2)] , \\
I_b(m, n) &= \frac{1}{12\sqrt{2}} [I(m+2, n-2) - 8I(m+1, n-1) + 8I(m-1, n+1) - I(m-2, n+2)] .
\end{align*}
\]

These gradients represent the local slope at location \((m, n)\). Both the local gradient and intensity denote the local shape. Gradients \( I_a \) and \( I_b \) are also required to respect the invariance assumption:

\[
\begin{align*}
I_{1,a}(x - dx) &= I_{2,a}(x) , \\
I_{1,b}(x - dx) &= I_{2,b}(x) .
\end{align*}
\]

### III. Optical Flow Scheme

In conventional optical flow methods based on the first-order Taylor expansion, the computation of gradients is needed, understanding the local configuration of the intensity pattern that can be reasonably approximated by the local intensity plane. As is the case for the Horn-Schunck [1] and Lucas-Kanade [2] methods. In our optical flow scheme however, the gradient is used to express the local shape via (4). The displacement will be solved by a random walk approach. The velocity magnitude is assumed to be bounded \( |v_x|, |v_y| \leq v_{max} \). For the velocity characteristic, the random walk model [5]–[7] is considered for obtaining a random velocity database in the range \( v_x, v_y \in [-v_{max}, v_{max}] \). Equations (1), (3) and (5) will be regarded as the criterion between the displacement database and the estimated result. The estimation of the optimal displacement fields in virtue of the intensity and local shape constraints ((1), (3) and (5)) is based on the cost function \( E_r(x) \) defined as:

\[
E_r(x) = \sum_{k} |J_{1,k}(x - dx) - I_{2,k}(x)|, \quad k = i, x, y, a, b
\]

where \( J_{1,k} \) is the result of a four-point interpolation operation with four adjacent points including the object point \( x - dx \) with the data \( I_{1,k} \). Here the displacement \( dx \) is fixed for all the pixels in a \( 3 \times 3 \) block (see Fig. 3). The variable \( dx \) is a random vector presenting the evaluated displacement in the unit time interval. Here the symbol “\( i \)” represents the intensity distribution of the images. In the discrete case, the equations \( J_{1,k} = I_{2,k} \) is unknown due to the expression of \( J_{1,k} \). When the function \( E_r \) is close to 0, \( J_{1,k} \approx I_{2,k} \), therefore, the minimum method is employed to obtain an optimized position \( x - dx \).

Considering that the myocardial motion field distribution in the local range is approximately continuous, an error function \( E_r(x_{m_0,n_0}) \) will be averaged in a \( 3 \times 3 \) pixel block as:

\[
E_r(x_{m_0,n_0}, dx) = \frac{1}{9} \sum_{m,n \in \Omega} w(x', m, n - x_{m_0,n_0}) E_r(x_{m,n}, dx),
\]

where \( \Omega \) represents the neighbor pixels. The variables \((m_0, n_0)\) are the center pixel index. \( w \) is a weighting function. Here an estimation of the velocity field \( dx \) is selected randomly in a
range to search for a minimum of the function $E_r$. While selecting the variable randomly, the optimized displacement is updated by checking the smaller value of function $E_r$.

The steps of the proposed estimation algorithm are detailed hereafter. The parameter $r_{max}$ is the possible random walk range, which is a square area. In this paper, the window filtering function $w$ is taken as:

$$w(\alpha) = \frac{4}{1 + \alpha} \begin{bmatrix} \frac{\alpha}{4} & \frac{1-\alpha}{4} \\ \frac{1-\alpha}{4} & \frac{1}{4} \end{bmatrix},$$  \hspace{1cm} (8)

The parameter $\alpha$ belongs in the interval $[0,1]$. The pseudo-code of the proposed method is given as below.

**Require:** two adjacent images $I_1, I_2$

window function: $w$

maximum possible displacement: $v_{max}$

region of interest: $roi$

**Step 1:** Initialize the displacement ($u$ and $v$) and the error function $E_r$ in (7).

**Step 2:** Compute the gradients $I_x, I_y, I_a$ and $I_b$ using (4). Calculate the values of the functions $J_k(x - dx)$ using an interpolation operation with random displacement $dx$.

**Step 3:** Search for an optimized displacement using the random walk model to minimize the value of the error function in (7) iteratively.

**Step 4:** Smooth the displacement field ($u$ and $v$) using a median filter.

**Ensure:** $u, v$: displacement between $I_1$ and $I_2$

IV. SYNTHETIC DATA RESULTS

Both synthetic and clinical cardiac cine and tagged MRI sequences are considered for testing the performance of the proposed optical flow scheme. The motion fields of the simulated image sequences serve as the theoretical displacement during the error analysis.

A. Cine sequence results

A group of synthetic cine sequences from ASSESS software [8] is used to estimate myocardial motion. The sequence name is 160D30R20P3F20, where the parameters are resolution (160), contraction/expansion (D), rotation (R), frame rate (F) and healthy (P0) or pathological (P3) state [9]. In Fig. 4, the first frame of the cine image sequence is given. The image has $160 \times 160$ pixels. The total frame number is equal to 21, in which the first seven frames are part of the systolic phase and the last 14 frames are part of the diastolic phase of the myocardium. Here the proposed optical flow method, Lucas-Kanade’s method [2] and Sun’s method [10] are employed to estimate the motion field of the cine image sequence.

In the proposed motion estimation procedure, the displacement $dx_k$ ($k=1,2,...,20$) between the two adjacent images $I_k$ and $I_{k+1}$ is obtained by optical an flow scheme. Figure 5 shows an example of the estimated displacement between frame 3 and frame 4 of the synthetic cine sequence. Subsequently, the Lagrange displacement $L_k$ between the first frame $I_1$ and current frame $I_{k+1}$ is derived using bilinear interpolation. To reduce the accumulation error of Lagrange displacement, the displacement $L_k$ is converted along two directions (see Fig. 6), namely forward and backward, which are marked by the black arrow and the red arrow, respectively. For three optical flow algorithms (the proposed scheme, Lucas-Kanade’s and Sun’s schemes), the motion estimation process is stopped at frames $I_{14}$ and $I_{15}$ forward and backward, respectively. The calculation parameters in the proposed optical flow scheme are: maximum possible displacement $v_{max} = 1.8$ pixels, window factor $\alpha = 0.01$, the interpolation method used is bilinear interpolation, and the maximum iteration number is 2000.

The estimation error is evaluated with the endpoint error (EPE) for each frame defined as [9], [11]. The EPE function is written as:

$$EPE = \sqrt{(u_e - u_c)^2 + (v_e - v_c)^2}, \hspace{1cm} (9)$$

where $(u_e, v_e)$ and $(u_c, v_c)$ are the estimated and ground truth velocities of one frame, respectively. The average of the EPE functions will be calculated for weighting the statistical quantitative error of the Lagrange displacement in this paper. In Fig. 7, the boxplot of Lagrange EPE for the
where $u$ along the radial direction. The Green-Lagrange strain tensor [13] is employed and expressed as:

$$ T = \frac{1}{2} \left( \nabla u + \nabla u^t + \nabla u^t \nabla u \right), \quad (10) $$

where $u$ is displacement. The normal strain along a direction $d$ can be calculated by $E = d^t E d$ [14]. Figure 8 shows an example of radial tensor on a healthy simulation. The myocardium region is presented by a non-zero value circular ring with its center around the position [80,80]. Along the radial direction, we observe there is a uniformity of the radial tensor value on the region with the same radius. Then, for our synthetic “160D30R20P3F20” cine sequence, the radial tensor is calculated by our method and two other methods, receptively. Figure 9(a) shows the ground truth. Compared with the other methods in Fig. 9(c) and Fig. 9(d), the proposed method in Fig. 9(b) gives a more precise location of the pathological region, indicated by a black dashed circle.

**B. Results on simulated tagged sequences**

A tagged MRI sequence is generated from the simulated cine sequence. A cosine-based modulation function is introduced:

$$ f(x) = \begin{cases} 
\cos(x), & \text{if } \cos(x) < T_v, \\
1, & \text{if } \cos(x) \geq T_v,
\end{cases} \quad (11) $$

where $f(x)$ is a truncated cosine function and is regarded as a basic function for constructing the 2D modulation data. The parameter $T_v$ is fixed at $-0.6$ from the experimental data. An example is displayed in Fig. 10, in which the blue line is considered as a modulator. In the truncated part, the information cine image is held. The 2D modulation function $f_m$ is addressed as:

$$ f_m(x, y) = f(k_x x + k_y y) f(k_y x - k_x y) \quad (12) $$

The function $f_m$ will be employed to convert the first cine image shown in Fig. 4. The first frame of the generated tagged sequence is given in Fig. 11; this tag sequence has the same reference truth displacement as the cine sequence. Here the parameters $k_x$ and $k_y$ are fixed at 160. The position variables $x$ and $y$ are limited to the range [0, 1]. In the discrete case, the sampling point $(x_k, y_k)$ is equal to $(\frac{2x}{N}, \frac{2y}{M})$, in which...
Fig. 11. The first frame of the tag image generated from the cine sequence.

Fig. 12. Boxplot of the Lagrange EPE for the “160D30R20P3F20TAG” tag sequence. Each box corresponds to the statistical distribution of all EPE values on one frame. The center bar of each box represents the median value, the circle indicates the mean value, and the box body extends from the 25th to the 75th percentile of one frame’s EPE values. The proposed method gives a better performance than the other two methods.

$N$ and $M$ represent the size of the image. Other tag images are obtained using the wrapping operation with the data of the theoretical displacement defined with the ASSESS software. In Fig. 12, the boxplot of the Lagrange EPE for the tag sequence generated is computed and shown for the three optical flow methods.

Similar to the cine case, the mean value of the EPE of the proposed method is smaller than the others from Fig. 12, and the overall performance of the proposed method is better than the other two methods.

Next, we make the same comparison as in the cine case for the radial tensor in Fig. 13. Hence, the result on frame 7 (maximum displacement frame) of the tag sequence is chosen to present the radial tensor. Seeing the pathological region in the black dashed circle, the proposed method in Fig. 13(b) has the most approximate result as the reference in Fig. 13(a), of the three methods.

V. CLINICAL DATA RESULT

In this section we present the results obtained on one patient with CHD. This clinical case illustrates an inferior AMI (acute myocardial infarction) in a 65 year-old male (right coronary occlusion - reperfusion H+5). Imaging was performed before discharge of the patient at day 5. A short axis cine and tagged MRI was performed on a Siemens Avento 1.5T with the following parameters: GRE (gradient echo) sequence, for the cine sequence, TR=38.3ms, TE=1.74ms, flip angle=70°, spatial resolution=1.48mm, 21 frames, temporal resolution=38.75ms, and for the tagged sequence, TR=36.4ms, TE=1.53ms, flip angle=20°, spatial resolution=1.09mm, 21 frames, temporal resolution=36.4ms, a 45° SPAMM (spatial modulation of magnetization) tagging pattern, tag spacing=6mm. Figure 14 shows the late gadolinium enhancement (LGE) image at the medium level of the left ventricle. The myocardium is divided into six segments according to the recommendation in [15]. The pathological areas concerns the inferoseptal (IS), inferior (I) and inferolateral (IL) segments. The proposed motion estimator is applied to both the cine and tagged MR images. In both sequence types, the pathologies can be highlighted from radial strain measurement.

Figure 15(a) and Fig. 15(c) show the myocardial region of interest within the red and yellow contours in the first frame of both the cine and tagged MRI sequences. Figure 15(b) and Fig. 15(d) display the radial strain at the end of systole.
(maximal contraction). One can clearly see the low radial strain values within anomalous territories in the IS, I and IL segments. Normal radial strain should present positive values. These detected pathological regions correspond to the clinical diagnosis result shown in Fig. 14.

VI. CONCLUSION

We present a new optical flow algorithm based on multiple constraint equations. Firstly, the intensity and four gradients are used to address the local shape of the image pixel. Then the optical flow equations are constructed by the local shape parameters. After that, the random walk model is introduced to solve the equations. Finally, the synthetic data from the ASSESS software is used for myocardial motion estimation of the cine sequence and tag sequence by the proposed method and other schemes (Lucas-Kanade’s and Sun’s methods). The result from our method is closer to ground truth displacement. The proposed method can correct the ground truth displacement. The proposed method provides a preferable motion estimation performance on the cine as well as the tagged sequences. The strain tensor is considered to measure the deformation of the myocardium. Finally, strain tensor distributions of clinical image sequences are analyzed using the proposed methods. From both of the cine and tagged sequence radial tensor results, the proposed method can correctly represent the pathologies. One of the probable future improvements of the proposed method is to improve the accuracy of the small displacement estimation result by an iteration method.

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