Estimation of Cardiac Motion Using Magnetic Resonance Imaging

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Abstract. This paper presents the application of the methods proposed in [1] to estimate displacements fields from two dimensional ultrasound sequences of the heart using spatio-temporal non-rigid registration. The main topic of our work is the application of these techniques to MR sequences, and validation of the obtained cardiac parameters: displacement, velocity and strain fields. The methods proposed are adjusted and validated on synthetic sequences that simulate the cardiac motion on MR sequences. These sequences provide a good framework to estimate the accuracy of the algorithms and to adjust the parameters to fulfil the problem requirements. Finally we applied the techniques to the regional analysis of the left ventricle on a set of MR sequences to illustrate the clinical applicability of the method proposed.

Keywords: Cardiac motion, registration, MR cine sequences, strain, displacement field.
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INTRODUCTION

Cardiovascular diseases are one of the primary causes of mortality in developed countries. The estimation of cardiac motion using medical imaging techniques constitutes an important aid for the quantification of the elasticity and contractility of the myocardium. Several cardiac pathologies create motion and contraction abnormalities especially in the left ventricle. In this way, the aim of many researches is to study the regional function of the left ventricle.

Conventionally, the evaluation of the ventricle regional function has been carried out by visual assessment, which may cause disagreements among different centres and specialists. For this reason, over the last years, several methods for automated detection of cardiac motion have arisen, with the aim of providing quantitative and objective information[2, 3].

Motion assessment is of special interest on Magnetic Resonance (MR) cardiac data [4]. Some characteristics make MR suitable for cardiac imaging: it provides good contrast among tissues, producing images with a high spatial resolution; it's possible to obtain images with multiple planes and different signal characteristics and does not use ionizing radiation. Different techniques have been proposed to compute motion

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fields on Tagged MR data, either using deformable models or registration algorithms [5, 6]. However, not much work has been done on conventional MR cine sequences. In this paper, we propose spatio-temporal non-rigid registration techniques based on pixel intensity to estimate the dense displacement field of the myocardium from 2D cine sequences.

METHODS

Two different algorithms are used to estimate the dense displacement field of the myocardium. They are described in [1, 7] and based in semi-local elastic registration. The solution of the problem is a deformation field, found using a multidimensional optimization strategy and gradient methods. Splines are used to obtain a continuous expression of the sequence:

$$f_{test}^{c}(\mathbf{x}) = \sum_{i \in I} b_i \beta_q(\mathbf{x} - \mathbf{i}) \tag{1}$$

Both algorithms are based on pixel intensity, and a similarity criterion based on the sum of squared differences.

Consecutive Registration

Consecutive registration allows us to estimate the displacement field by calculating the interframe displacement fields $\mathbf{g}_t(\mathbf{x})$, as it is described in [7]. The total deformation field $\mathbf{g}(t, \mathbf{x})$ is then obtained from the contribution of the partial fields, calculated by registering pairs of consecutive images.

The similarity criterion minimizes the differences between consecutive images, and it is expressed as follows:

$$E = \sum_{i \in I} e_i^2 = \sum_{i \in I} \left(f_{def}(\mathbf{i}) - f_{ref}(\mathbf{i}) \right)^2 = \sum_{i \in I} \left(f_{test}(\mathbf{i} + \mathbf{g}'(\mathbf{i})) - f_{ref}(\mathbf{i}) \right)^2 \tag{2}$$

where **I** represents the set of coordinates that define the region of interest.

The dense displacement field is represented by a linear combination of quadratic spline functions, placed on a uniform rectangular grid.

$$\mathbf{g}'(\mathbf{x}) = \sum_{j \in Z^N} \mathbf{c_j} \beta_r \left(\frac{\mathbf{x}}{h - \mathbf{j}} \right) \tag{3}$$

The parameter *h* determines the grid spacing, while coefficients $\mathbf{c_j}$ control the solution smoothness.

Spatio-Temporal Registration

In this case, we estimate $\mathbf{g}(t,\mathbf{x})$ working globally on all the images. The dense displacement field is represented as a continuous function, which applied to a sequence, compensates its movement.

Optimization criterion is defined as the mean along all the sequence of a criterion defined for each image E_t. We can choose between two different criteria:

- *A criterion* tries to minimize the quadratic difference between every frame with respect the first one in the sequence, which is used as reference image.

$$E_t = \frac{1}{N_I}\sum_{\mathbf{i}\in I}\left(f\left(t,g(t,\mathbf{i})\right)-f(0,\mathbf{i})\right)^2 \tag{4}$$

where N_I is the number of pixels in the selected area

- *B* criterion minimizes the difference between consecutive images. It may work better if each frame is similar to the previous one, but doesn't have resemblance with the first of the sequence. The expression of *Et* is:

$$E_t = \frac{1}{N_I}\sum_{\mathbf{i}\in I}\left(f\left(t,g(t,\mathbf{i})\right)-f\left(t-1,g(t-1,\mathbf{i})\right)\right)^2 \tag{5}$$

Using spatio-temporal registration, the deformation function is represented by a linear model, with parameters d_{ij}, separable in time and space:

$$g(t,x) = x + \sum_{l\in L}\sum_{\mathbf{j}\in\mathbf{J}}\mathbf{d}_{\mathbf{j},l}\,\phi_j(\mathbf{x})\psi_l(t) \tag{6}$$

$$\phi_{\mathbf{j}}(\mathbf{x}) = \beta^n(x_1/h-j_1)\cdot\beta^n(x_2/h-j_2), \text{ where } \boldsymbol{x}=(x_1,x_2) \text{ and } \boldsymbol{j}=(j_1,j_2) \tag{7}$$

$$\psi_l(t) = \beta^n(t/s-l) \tag{8}$$

In this case, splines are not only located in a spatial grid, determined by *h*, but also in a temporal one, governed by parameter *s*.

Cardiac parameters obtained

The aim of the register process is to obtain cardiac parameters which are useful to study regional ventricular function. For that reason, we calculate:

- *Displacement:* We estimate the displacement field along the three directions of the space (radial, longitudinal and circumferential)

$$u = \frac{1}{N_R}\sum_{\mathbf{i}\in R}\left(\mathbf{g}(t_c,\mathbf{i})-\mathbf{i}\right) \qquad u_{ax}=\mathbf{u}\cdot v_{ax}\,; \quad u_{long}=\mathbf{u}\cdot v_{long} \text{ y } u_{circ}=\mathbf{u}\cdot v_{circ} \tag{9}$$

- *Velocity*: Once we have obtained the displacement field, same components of the velocity vector can be computed as:

$$\mathbf{v}(t,\mathbf{x}) = \frac{d\mathbf{g}(t,\mathbf{x})}{dt} \tag{10}$$

- *Strain tensor:* The strain tensor is one of the most important parameters in the study of the cardiac function. The dense displacement field permits to calculate the deformation gradient **F**, and then Green-Lagrange strain tensor **E** is obtained as it is shown below:

$$\mathbf{F} = \nabla_{\mathbf{x}}\mathbf{g} + \mathbf{I} \qquad \mathbf{E} = \frac{1}{2}(\mathbf{C} - \mathbf{I}) = \frac{1}{2}(\mathbf{F}^T\mathbf{F} - \mathbf{I}) \tag{11}$$

EXPERIMENTS

Simulated data

The first experiments were done with simulated data, generated from a short axis end-diastole image, with a pixel size of 1.17x1.17 mm^2, a spatial resolution of 204x176 pixels and a slice thickness of 8 mm (Figure 1) .We deformed the image, using the function g_0 obtaining a sequence with 30 frames:

$$g_0(t,\mathbf{r}) = \chi(\mathbf{r}) \cdot \zeta(\mathrm{t})$$

$\chi(\mathbf{r})$ represents the spatial deformation. Its objective is to simulate the myocardial contraction, causing more radial movement in the pericardium wall than in the endocardium one. In this way, myocardium thickness changes when the temporal function is applied. It is also composed of a circumferential term that rotates the whole image to simulate circumferential movement of the heart, and only depends on the distance of each point to the centre of the ventricle

$$\chi(\mathbf{r}) = \begin{cases} \mathrm{k} \cdot sen\left(\frac{\pi}{2}\frac{r}{r_c}\right) & for \quad r < r_c \\ k \cdot sen\left(\frac{\pi}{2}\frac{r - r_1}{r_c - r_1}\right) & for \quad r_c < r < r_{ext} \\ k \cdot sen\left(\frac{\pi}{2}\frac{r_{ext} - r_1}{r_c - r_1}\right) & for \quad r_{ext} < r \end{cases} \tag{12}$$

where r_c is the endocardium radius, r_{ext} the pericardium radius, and k a constant whereby we can change the amplitude of the displacement.

$\zeta(\mathrm{t})$ simulates left ventricular contraction through the cardiac cycle (Figure 1):

$$\zeta(t) = sen^2\left(\frac{\pi \cdot t}{3 \cdot \frac{T}{4}}\right) \cdot e^{-3t} + \frac{1}{1000A} \cdot sen^2\left(\frac{\pi \cdot t}{\frac{T}{3}}\right) \cdot e^{5,8 \cdot t} \tag{13}$$

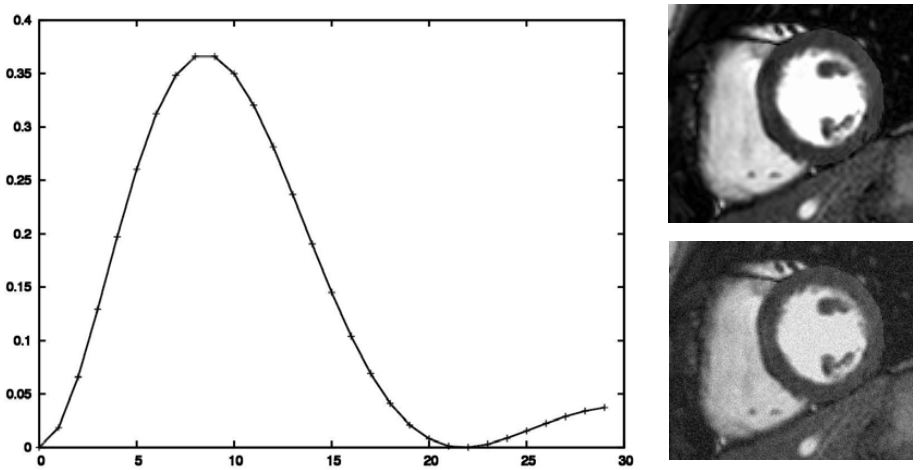

FIGURE 1. *Left*: curve representing temporal function ζ(t) .*Right*: First images of the phantom sequence, without noise (up) and with noise (down)

After generating the whole sequence, Gaussian noise was added in the K-space to make the simulated sequences more realistic (Figure 1), and to test the robustness of the algorithms with noise. The value of the noise is equal to the 5% of the image maximum.

Using this sequence, we have determined the optimal values of the registration parameters and the performance of the different algorithms.

Acquired Data

The evaluation also included real cardiac MR sequences from "Hospital Gregorio Marañon". 55 sequences from 15 different healthy volunteers were acquired (2C, 4C and short axis), with a Philips Intera, and with a wide range of time resolution values. The aims of these experiments were to determine:

- which method allows us to obtain a better estimation
- how many images are more appropriate to calculate cardiac parameters
- which view is the most appropriated to estimate myocardial movement

The method used to achieve the previous purposes was to compare the resulting curves of different regions, using a platform designed with IDL software. Displacement, velocities and strains have been calculated, as the mean values of each pixel within a region.

RESULTS

Simulated data

With simulated data, the accuracy of the motion estimation was measured using a *warping index*, as the mean geometric error between the true and the recovered deformation.

$$\varpi = \sqrt{\frac{1}{\|T\|\|R\|}\sum_{k\in T}\sum_{i\in R}\left\|\mathbf{g}(k,\mathbf{i})-\mathbf{g_0}(k,\mathbf{i})\right\|^2}$$

As we can see on table 1, the minimum error is produced by the spatio-temporal algorithm, using Criterion A as similitude criterion. Experiments were done using three different values of *h,* knot spacing where *splines* are placed. Best results were obtained with a grid spacing of 8 pixels, which is approximately equivalent to 1 cm

TABLE 1. Error (pixel)

Algorithm	**Consecutive Registration**			**Spatio-Temporal A**			**Spatio-Temporal B**		
Distance	4	8	16	4	8	16	4	8	16
Error	1.558	1.456	1.492	1.127	1.031	1.065	1.805	1.501	1.511

Next step was to add noise to the sequence. In this case, we can notice that the error committed estimating movement increases, but the values are acceptable, specially using the spatio-temporal algorithm with Criterion A.

TABLE 2. Error in sequences with noise (pixel)

Algorithm	**Consecutive reg**		**Spatio-Temporal A**		**Spatio-Temporal B**	
Distance	4	8	4	8	4	8
Error	3.726	2.413	1.859	1.353	4.524	2.653

Looking at Fig. 2, we can notice that the main cause of the error is the longitudinal movement estimation. That is because the lack of texture information within the myocardium wall, that makes difficult to find the correct transformation.

Acquired Data

With the post-processing tools, registered sequences were analyzed. ROIs (Regions Of Interest) were defined on the first frame of the sequence along the myocardium wall obtaining displacement, velocity and strain curves, as the mean of the value of each pixel within the ROI Assessing these graphics and the numerical values, of the parameters, we concluded:

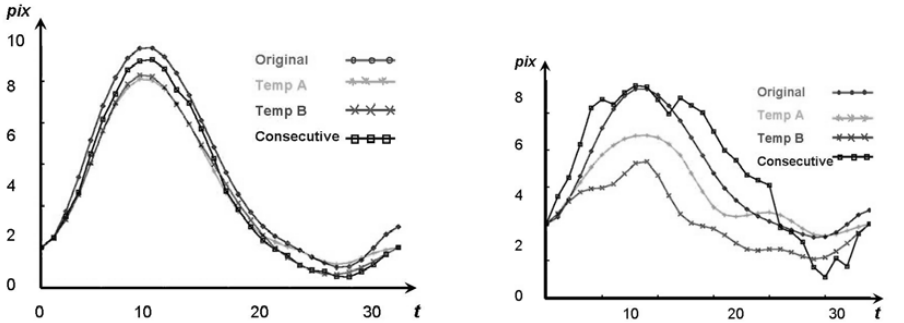

FIGURE 2. Original and recovered radial movement (*left)* and circumferential movement *(right)* using consecutive and spatio-temporal algorithms.

- The optimum number of frames per sequence to estimate cardiac movement is 60-70. If we had more images to represent cardiac cycle, SNR ratio would increase. That is because the sequences are acquired with the patient in apnea, so the acquisition time must not increase. This issue forces us to balance image quality and spatial resolution, making more difficult to find the correct transformation. On the other hand, if sequences with fewer frames were acquired, temporal resolution would decrease, so information would be insufficient to analyze movement.
- Results with spatio-temporal and consecutive registration were similar, providing the spatio-temporal method more temporal smoothness. In order to know which one works better on real sequences it will be necessary to compare them with a gold-standard technique, as HARP algorithms.
- Finally, the more appropriate sequences to estimate left ventricular movement are short-axis ones. The radial movement estimation is more accurate, as in previous experiments with synthetic data. The reason is also the similarity among myocardium textures.

Figure 3 shows the curves of the three parameters for a short axis sequence of 60 frames. Six ROIS were defined, covering the whole myocardium wall, resulting six different curves.

CONCLUSIONS

In this work two methods for cardiac movement estimation, based on non-rigid registration have been described. Two types of experiments have been done, ones with a generated synthetic sequence and others with real MR sequences, so we can conclude:

- MR cine sequences provide good movement estimation, but more accurate on radial than on circumferential and longitudinal direction, because the lack of details within myocardial wall
- With synthetic data, best results were obtained applying the spatio-temporal registration, and separating basis functions 8 pixel (1 cm)

- Further evaluation with gold-standard techniques will be necessary in real data, in order to determine which method provides better results

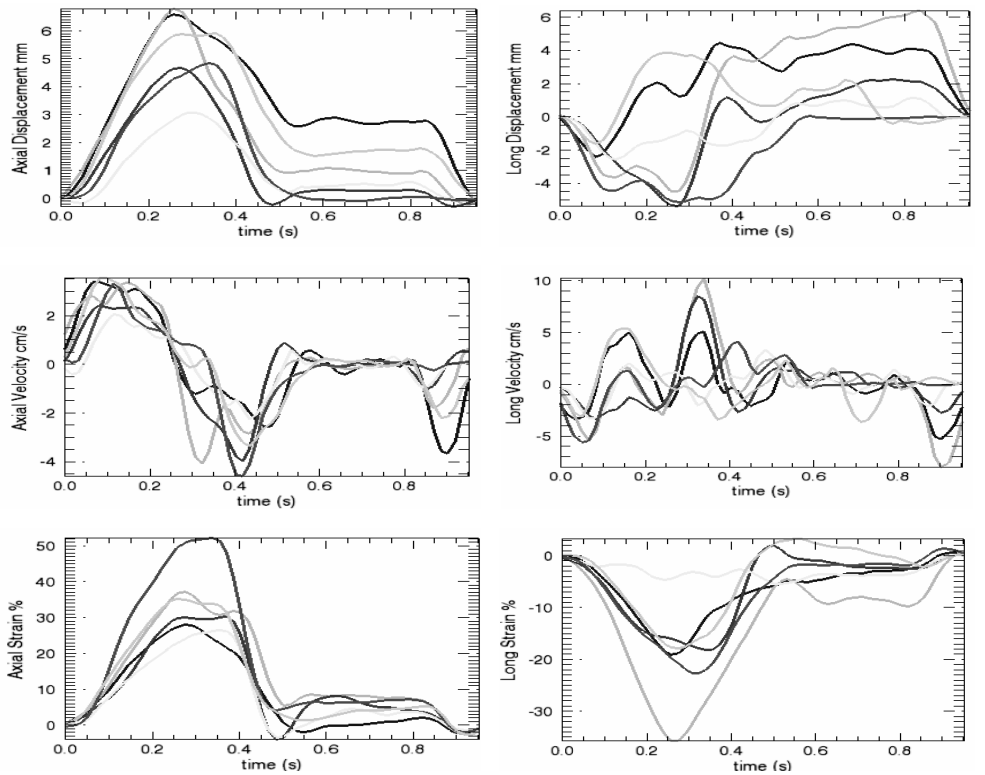

FIGURE 3. Displacement, velocity and strain of six different regions of the myocardium, on the radial axis (left) and the circumferential one (right)

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