4D Sparse Landmark Cardiac Motion Tracking and Regional Function Analysis

Haiyan Wang

Wenzhe Shi

Wenjia Bai

Philip Edwards

Daniel Rueckert

Biomedical Image Analysis Group
Department of Computing
Imperial College London, UK

Abstract

Sparse landmark tracking can provide sparse, anatomy-specific constraints to help establish correspondences between images being tracked. We propose to identify the landmarks that are distinctive throughout the cardiac cycle and have a relatively large deformation by a method that analyses the entropy of the self-similarity through singular value decomposition (SVD). We then track this sparse set of landmarks simultaneously with a 4D two-stage multiple label Markov Random Field (MRF). The framework is evaluated on 47 cases, including data from normal volunteers and patients undergoing cardiac resynchronization therapy (CRT). Compared to conventional dense motion tracking (DMT), the tracking error of the proposed sparse motion tracking (SMT) and the DMT initialized with the result of SMT are both reduced by 15.7% and 4.2% respectively. The derived regional wall thickness systolic dyssynchrony index (SDI) for each of the 47 cases agrees well with the clinical measurements of regional volume SDI.

1 Introduction

The accurate estimation of cardiac motion aids the quantitative assessment of both global and regional wall deformation or strain, which is beneficial for the identification of the location and extent of diseases like cardiomyopathy and ischemic injury [2]. Approaches based on dense image registration and deformable model fitting techniques [6, 8] are very sensitive to the initialization and often computationally expensive. Alternatively, sparse landmarks can provide anatomy-specific constraints to establish correspondences between images being tracked or registered [3]. However, landmarks on the endocardium are often characterized by ambiguous appearance in cardiac MR images, which makes the extraction and tracking of landmarks problematic.

In this paper, we propose to identify a sparse set of cardiac landmarks that are distinctive throughout the cardiac cycle and have a relatively large deformation by an entropy-based

measure of self-similarity and singular value decomposition (SVD). We then track this sparse set of landmarks simultaneously by a 4D two-stage multiple label Markov Random Field (MRF), which enforces motion coherence across space and time.

The accuracy of the proposed sparse motion tracking is evaluated by tracking a group of manually marked landmarks on the endocardial border of the left ventricle (LV) in a dataset of 47 MR image sequences and comparing to their manually tracked positions. To study the clinical usefulness of the approach we assess the regional systolic dyssynchrony index (SDI). The derived regional wall thickness SDI for each of the 47 cases are compared with the clinical regional volume SDI measurements obtained using the TomTec system [5].

2 Detection and tracking of cardiac landmarks

2.1 Sparse Landmarks Identification

The motion of the heart is highly complex and is mostly characterized by the deformation of the endocardium. We initially identify a set of landmarks on the endocardial boundary and thereafter their counterpart on the epicardial border along the radial direction.

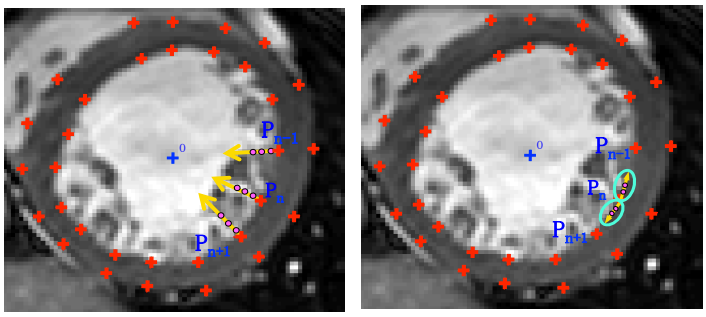
Many points on the endocardial boundary share similar appearance and shape features, which leads to ambiguities when these points are being tracked. We use an entropy-based landmark detector to identify landmarks that are recognizable in all frames throughout the cardiac cycle. For each point in the end diastolic phase, the detector defines a similarity at each location within a search region in all other frames. A low entropy of the distribution of these similarities corresponds to a more discriminative feature point.

Moreover, we are more interested in points that undergo relatively large deformation; by tracking them we are likely to capture the cardiac motion more accurately. A regional SVD based approach is applied to distinguish points with relatively large deformation from those which exhibit less complexity across frames. SVD seeks to find a low rank approximation. Different regions of a cine sequence may have different approximation levels due to the non-uniform complexity of the whole image and lower approximation ratios corresponding to regions with larger deformations, such as mitral valve point and apex. By combining the entropy and SVD based method, we select a set of sparse landmarks along the endocardial which best represent the myocardium. This part of work is same as that of Wang *et al*. [9].

2.2 Sparse Motion Tracking

After we have identified a set χ of distinctive landmarks in ED phase, our goal is to localize the corresponding landmarks in each frame of the cine sequence. Let the whole sequence of the image be modelled as a 4D MRF in which nodes are located pairwise at the endocardial and epicardial borders. The neighbourhood of each node in slice k and frame t includes not only the neighbouring nodes in the same slice, but also those in slices $k+1$ and $k-1$. In addition, the neighbourhood also includes temporal neighbours, i.e. the corresponding voxels at frame $t+1$ and $t-1$ respectively. We call these neighbouring edges as endo-endo, epi-epi, endo-epi, slice-slice and frame-frame edges. In our implementation, a total of seven neighbours are used for each landmark with the exceptions of landmarks in the first or last slice (or frame) of the short-axis image stack.

We associate each label of a node with displacements from its original position and formulate the multiple landmark tracking in a multi-label MRF framework in which we



(a) (b)

Figure 1: The tracking of a point P_n is modelled by a two-stage searching: a) towards centre O and b) towards/away from neighbouring points P_{n+1} and P_{n-1}.

minimise the following energy function:

$$E = \sum_{i \in \chi} V_i(x_i) + \sum_{(i,j) \in \chi} \omega_{ij} V_{ij}(x_i, x_j) \tag{1}$$

For the landmark tracking, the unary potential $V_i(\cdot)$ is defined by the patch-based similarity metric based on sums-of-squared differences (SSD) to compute the intensity similarity between the landmark under study and its candidate matching point:

$$V_i(x_i) = \sum_{\Omega_x, \Omega_y} \omega_i (x_i - y_i)^2 \tag{2}$$

Here Ω_x and Ω_y denote the local patches centred around point x_i and its candidate matching point y_i respectively. During the cardiac cycle, the myocardium may undergo thickening and the regions outside myocardium usually remain unchanged. To compensate for this myocardial thickening the SSD metric is spatially weighted and the weighting function ω_i is built to a) be zero outside the myocardium, b) increase the influence of the blood pool for the landmarks at the endocardial border and c) be zero inside the myocardium for the landmarks at the epicardial border to ignore the influence of the wall thickening.

The pairwise potential $V_{ij}(\cdot)$ of the energy function models the interaction between landmarks to enforce the smoothness, both spatially and temporally. $V_{ij}(\cdot)$ is defined as the Euclidean distance of the displacements $D(x)$ of a pair of neighbouring points.

$$V_{ij}(x_i, x_j) = |D(x_i) - D(x_j)| \tag{3}$$

The intuition of this term is to maintain a coherent motion between points close to each other. The magnitude of the constraints between neighbouring points is weighted by ω_{ij}, which varies according to the location of the point. For instance, the motion of a point at endocardial border correlates much stronger with that of its endocardial neighbours than that of its epidardial neighbours, hence the weight for the endo-endo edge is larger than that for the endo-epi edge.

The tracking is conducted in two stages: firstly along the direction towards the centre of the LV, and then along the direction towards or away from its two neighbouring points. The centre of the LV is defined as the intersection point of the middle slice of the short axis (SA) image and two LA images.

In the first stage of tracking, the main components of the deformations, i.e. the radial motion of the myocardium in the short axis slices, are best captured along the direction from the landmark towards the centre. The pairwise smoothness term is therefore defined as the Euclidean distance of the relative displacement along this direction of two neighbouring points. In the second stage of tracking, we track points in a 2D region along the direction towards or away from their neighbouring points in order to take into account the circumferential motion along the border. The penalty increases when two neighbouring points move towards or away from each other. Likewise the penalty decreases when the two points move in the same direction. The second stage of the tracking iterates several times to account for the large circumferential deformation in some cases, because the position of the search region needs to be updated after each iteration. At both stages, Fast-PD, a graph cut based algorithm is applied as the optimisation method to find the optimal solution for the MRF problem [4].

3 Evaluation and results

We have acquired SA sequences from 44 CRT patients and three normal volunteers using a 1.5T MR-scanner. Five landmarks are manually marked on the endocardial boundary in the middle slice at ED phase. In addition their corresponding positions are marked at the end systolic (ES) phase. The positions of these five landmarks at ES phase are also automatically tracked by the proposed sparse landmark motion tracking. Thereafter, the accuracy of the motion tracking is computed as the distance between the tracked position of the landmarks and their corresponding manually marked position at ES. For comparison we also tracked the landmarks using dense motion tracking (DMT) (using non-rigid registration [6]) with and without being initialised by the result from sparse motion tracking (SMT). The average tracking errors in terms of root mean square (RMS) using the two approaches are shown in Table 1. It can be seen that both SMT and DMT initialized by SMT outperform the DMT in this dataset. Figure 2 shows the case-by-case tracking errors of the three methods.

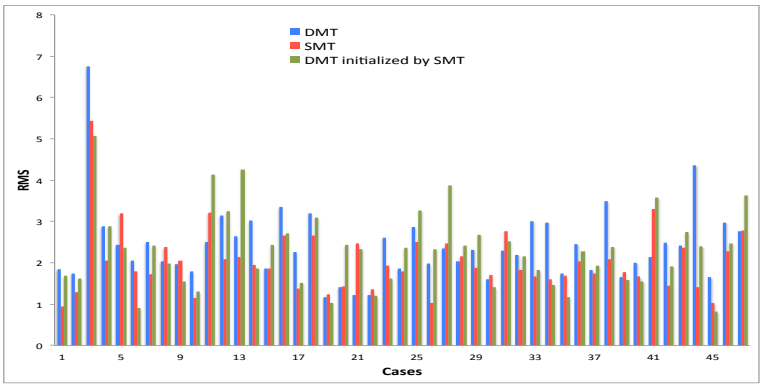
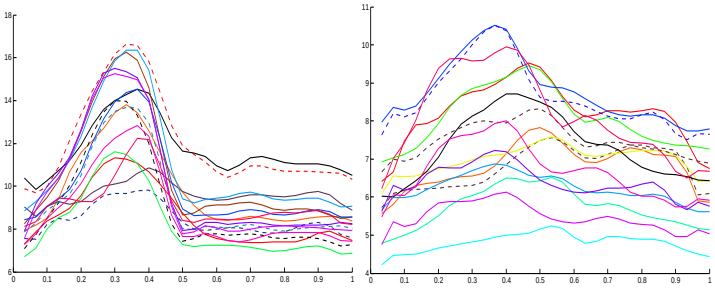


Figure 2: The landmark tracking errors (mm) for 47 cases, using DMT, SMT and DMT initialized with SMT

The LV contraction synchrony can be estimated via the change of wall thickness[7]. As the landmarks at the endocardial and epicardial boundaries are automatic selected in pairs along the radial line and tracked throughout the whole cardiac cycle, we can compute the change of the myocardium wall thickness as the Euclidean distance between pairs. For each

Table 1: Landmark Motion Tracking Error

	DMT	Sparse motion tracking	DMT initialized by SMT
RMS	$2.41 \pm 1.22mm$	$2.03 \pm 1.05mm$	$2.31 \pm 1.22mm$
Improvement	-	15.7%	4.2%



(a) (b)

Figure 3: This figure shows the wall thickness changing curves from (a) a normal subject and (b) a CRT candidate.

of the 16 segments of the left ventricular myocardium according to American Heart Association (AHA) model [2] there are around 2 to 8 endocardial-epicardial pairs of landmarks in our experiment. We average the distances at each of the 16 segments and view this as the wall thickness of that segment. Figure 3 demonstrates the change of the myocardium wall thickness of each of the 16 segments throughout the whole cardiac cycle from a normal volunteer and a patient respectively. As shown in the figure, the wall thickening for the normal volunteer is more synchronous across the segments.

The synchrony of the regional deformation can be represented by systolic dyssynchrony index (SDI), which has been previously reported to be a good indicator for selecting patients who respond to CRT [1]. The SDI is defined as the standard deviation of the time taken to reach the minimum systolic volume or maximum function for the 16 LV segments. We use a commercial software tool (TomTec 4D LV analysis tool V2.0 [5]) which relies on manual tracking within tri-plane projections and semi-automated border detection, to obtain

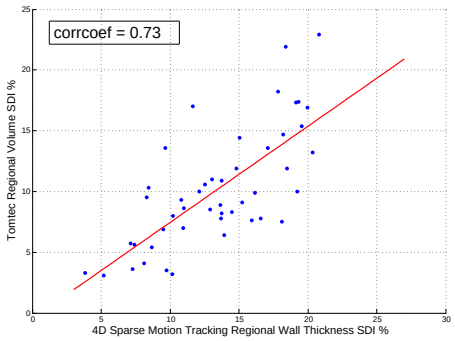


Figure 4: Evaluation of wall-thickness SDI against the Tomtec's regional volume SDI.

16 segments regional volume SDI for all the 47 cases. For comparison, we calculate the wall thickness SDI in a similar way: For the average wall thickness of the 16 segments throughout the cardiac cycle, the wall thickness SDI is defined as the standard deviation of the phases to reach the maximum wall thickness for each of the 16 segments, expressed as a percentage of the cardiac cycle. We also computed the Pearson correlation coefficient to measure the correlation with the regional volume SDI obtained by the TomTec software, which is $corrcoef = 0.73$. The comparison of the two SDI indexes, as shown in Figure 4, illustrates high correlation between them. It shows that it is plausible to use the proposed sparse motion tracking to estimate the dyssynchrony index for the regional deformation.

Acknowledgements. This work was funded in part by EPSRC grant EP/H019847/1.

References

[1] J. J. Bax, G.B. Bleeker, T. H. Marwick, S. G. Molhoek, E. Boersma, P. Steendijk, E. E. van der Wall, and M. J. Schalij. Left ventricular dyssynchrony predicts response and prognosis after cardiac resynchronization therapy. *J Am Coll Cardiol*, 44(9):1834–40, Nov 2004.

[2] MD Cerqueira, NJ Weissman, V Dilsizian, AK Jacobs, S Kaul, WK Laskey, DJ Pennell, JA Rumberger, TJ Ryan, and MS Verani. Standardized myocardial segmentation and nomenclature for tomographic imaging of the heart. *Journal of Cardiovascular Magnetic Resonance*, pages 203–210, 2002.

[3] S.C. Joshi and M.I. Miller. Landmark matching via large deformation diffeomorphisms. *IEEE Transactions on Image Processing*, 9(8):1357–1370, 2000.

[4] N Komodakis, G Tziritas, and N Paragios. Fast, approximately optimal solutions for single and dynamic mrfs. *IEEE Transactions on Image Processing*, 2007.

[5] H. P. Kühl, M. Schreckenberg, D. Rulands, M. Katoh, W. Schäfer, G. Schummers, A. Bücker, P. Hanrath, and A. Franke. High-resolution transthoracic real-time three-dimensional echocardiography: quantitation of cardiac volumes and function using semi-automatic border detection and comparison with cardiac magnetic resonance imaging. *J Am Coll Cardiol*, 43(11):2083–90, Jun 2004.

[6] D Rueckert, LI Sonoda, C Hayes, and et al. Nonrigid registration using free-form deformations: Application to breast MR images. *IEEE Tansactions on Medical Imaging*, pages 712–721, 1999.

[7] H. Sugihara, Y Yonekura, T Matsumoto, and Y Sasaki. Relationship between asynchronous myocardial contraction and left ventricular systolic and diastolic function–assessment using the ecg-gated polar map with 99mtc-methoxy-isobutyl isonitrile. *Circ J*, 69(2):183–7, Feb 2005.

[8] T. Vercauteren, X. Pennec, A. Perchant, and N. Ayache. Diffeomorphic demons: Efficient non-parametric image registration. *NeuroImage*, 45(1):S61–S72, 2009.

[9] H. Wang, W. Shi, X. Zhuang, X. Wu, K.P. Tung, S. Ourselln, P. Edwards, and D. Rueckert. Landmark detection and coupled patch registration for cardiac motion tracking. In *SPIE Medical Imaging*, pages 86690J–86690J. International Society for Optics and Photonics, 2013.