Applying a Level Set Method for Resolving Physiologic Motions in Free-Breathing and Non-Gated Cardiac MRI

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Abstract. In cardiac MRI, ECG triggering is used or patients are required to hold their breath, to alleviate motion artifacts and deterioration of image quality. However, ECG signal quality is often suboptimal and patients may not be able to adequately hold their breath. Alternative solutions for tracking breathing and cardiac beating can open the way for robust free-breathing and ECG-less cardiac MRI. Herein, we present a novel approach that isolates the effect of breathing, as well as computes both the breathing and cardiac beating waveforms directly from real-time MRI sequences. It turns a challenge into an opportunity to guide the reconstruction of high temporal resolution images. The proposed method is based on a level-set method to segment the left ventricle from a real-time MR sequence collected with free breathing and without ECG triggering. The algorithm extracts an evolving surface area, which captures the heart's systolic contraction and diastolic expansion in real-time. The computed time series of the heart's dynamic area is subjected to wavelet analysis, where the breathing and pulsation components are separated. The method was investigated on 12 real-time cardiac MRI acquisitions. We demonstrate that the left ventricular area, as computed by the level set method, produces breathing and cardiac waveforms similar with those extracted by cardiac MR experts (ground-truth). This proof-of-concept work demonstrates the capabilities of the proposed methodology paving the way for incorporation into real-time or retrospective reconstruction of high resolution cardiac MR.

1 Introduction

Cardiac magnetic resonance imaging (MRI) is a widely used modality for evaluation of cardiac morphology and function. There are two major challenges which make MRI of the heart more difficult than MRI of other body structures, such as the brain and joints: First, the respiratory motion and second, the motion of the heart itself [1]. In general, the first challenge is typically overcome by simply asking the patient to suspend breathing (breath-hold) for a few seconds. While this is not a challenge in healthy volunteers, it can be quite problematic in patients with underlying cardiac disorders, many of whom have baseline

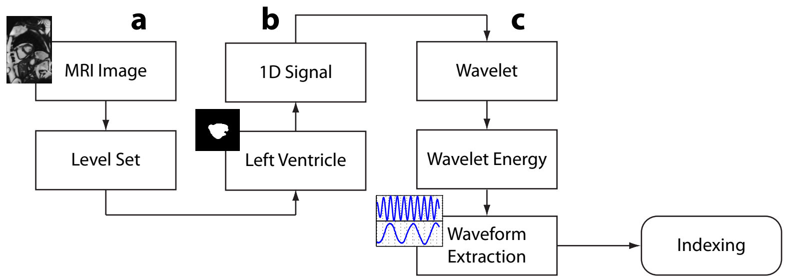

Fig. 1. Methodology framework: **a** Left ventricle segmentation. **b** Surface area evolution **c** Extraction of respiratory and cardiac signal waveforms.

dyspnea [2]. The second challenge of cardiac motion is typically addressed by timing the acquisition of MRI data with different points in the cardiac cycle using (electrocardiogram) ECG-gating. While this strategy frequently works, sometimes there is difficulty obtaining an adequate ECG signal due to strong electromagnetic noise from the MRI environment [3]. The consequence of these limitations is ghosting artifacts or blurriness that compromises image quality and renders clinical interpretation difficult.

To address suboptimal ECG signals and/or inability of patients to perform adequate breath-holding, MR methods have been introduced to track the two motions and provide gating. Such methods do not require ECG or breath-holding, by exploiting the inherent properties of the MR signal or using tailored MR pulse sequences. Notable, characteristic examples include the use of navigator-echo based MR to track both breathing and cardiac triggering [4], the analysis of the raw MR data on-the fly, as in the case of self-gated MRI [5], or using image processing methods, such as model-based approaches [6]. Ideally, clinical cardiac MR should be performed with free breathing and with real-time extraction of the cardiac beating waveform.

Despite groundbreaking efforts by numerous groups, such a robust MR protocol is not yet available. Motivated by the potential benefits of a free-breathing ECG-less cardiac MR protocol, we propose an approach to extract breathing and cardiac cycles. This method is based on processing on-the-fly the evolving surface area of the left ventricle (LV), which has been segmented by the means of the B-spline level-set method (Fig. 1a). In contrast to [7] we do not only use the level set method to segment the left ventricle, but we also follow the evolving 1D surface area signal of the left ventricle that captures the heart's contraction and expansion, while it is modulated by the superimposing breathing motion. We apply multi-resolution wavelet analysis (Fig. 1b) on the left ventricle surface area signal to localize the pulsation and breathing signals at different scales.

Knowing the free-breathing and cardiac beating waveforms, it is then possible to use the breathing and cardiac motion patterns to either perform on-the-fly reconstruction or retrospective reordering. In this work, we focused on the first aspect of such a cardiac MR imaging scheme: the accurate extraction of the

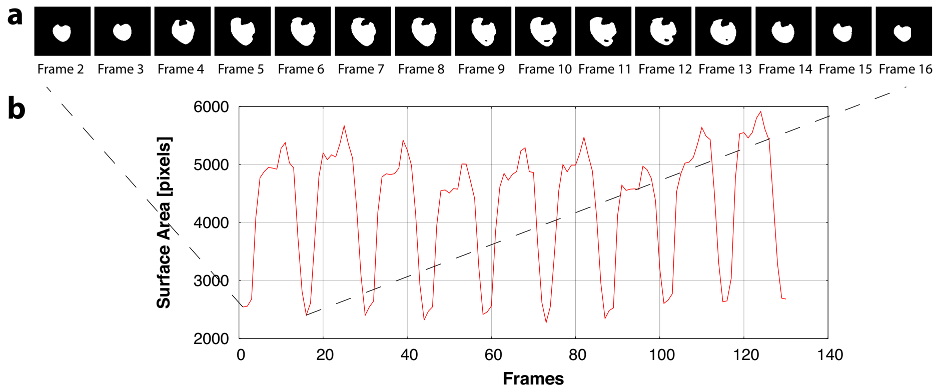

Fig. 2. Example of evolving surface area of left ventricle (Subject S001).

breathing and cardiac cycles. In section 2, we describe in detail the methodological framework and in section 3 we present and analyze experimental data from volunteers.

2 Methodology

2.1 Left Ventricle Segmentation

The left ventricle surface region contracts and expands periodically with the beating heart. Therefore, we first have to segment the left ventricle from its surrounding area. We choose a ROI around the left ventricle on the first frame of the MRI sequence and apply the B-Spline level set method [8]. We then select one coordinate point inside the left ventricle point to guide a connected component analysis which returns as a result only the segmented left ventricle. We examine the surface area of the left ventricle, which is computed as a polygon area covered by the level set (Figure 2a). After the first frame, the reference point for the selection of the left ventricle is updated by the centroid of the segmented area over time, and automatically updates itself in every frame. The level set method follows the heart surface while undergoing non-linear tissue deformations and the evolution of the left ventricle surface over time creates a 1D signal (Figure 2b).

2.2 Wavelet Analysis

Figure 2b shows the surface area plot for a set of MR image sequences consisting of 132 frames. The signal is a combination of the cardiac and respiratory signals. The cardiac signal is easy to observe, since the surface area of the heart changes with respect to the heart phase. The respiratory signal has a lower frequency than the cardiac signal. To separate the two sub-signals, we compute

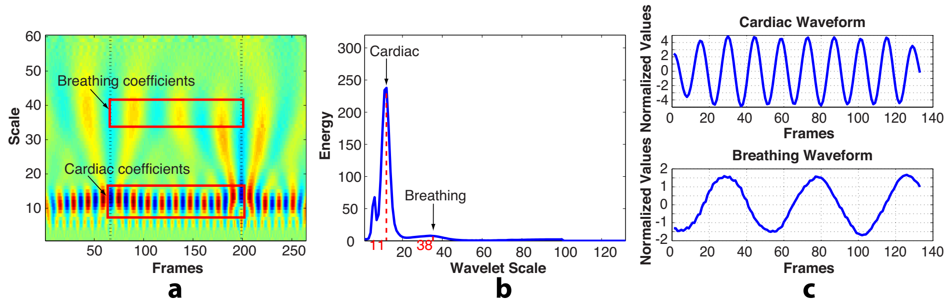

Fig. 3. Waveform Extraction: **a** Wavelet coefficients. **b** Computed wavelet coefficients. **c** Extracted pulse and breathing waveforms.

the wavelet energy of the left ventricle surface area signal for different frequency scales, ranging from 1 to 60 without losing time information. Since the signal is non-stationary in nature, signal analysis based on wavelet transformation is the method of choice. To quantify the contribution of pulse and breathing signals, we first normalize the signal because the wavelet energy computed on normalized signals exposes detailed information, specifically at the lower scales.

In order to avoid border discontinuity errors, we have to extend the signals beyond the boundary limits before computing wavelet coefficients. As our signals are non-stationary in nature, we select the symmetric extension technique. Since the selection of an appropriate signal extension length is very important in the wavelet energy computation, we apply three different extension lengths, 2N, N, and N/2. For each signal, we choose the one that has the minimal border discontinuity error in the wavelet energy computation. To quantify the contribution of pulse, and breathing in the preprocessed signals, we apply a continuous wavelet transform (CWT) with a Mexican Hat mother wavelet. Finally, we compute the energy of each signal in all scales (Figure 3a). Figure 3b shows the wavelet energy at different scales. There are two peaks on the plot, one corresponds to heartbeat (cardiac), the other corresponds to breathing. Corresponding peak waveforms are extracted from the wavelet coefficients as seen in Figure 3c-higher frequency represents the cardiac signal, lower frequency represents the breathing signal.

3 Experimental Results

3.1 Experimental Design

For the purpose of testing the performance of the level set method in the context of left ventricle segmentation, the authors used 12 real-time MRI sequences clips from 12 different subjects. Each sequence contains anywhere between 106 to 211 frames. Data were acquired with a 1.5T MAGNETOM Avanto Siemens MRI scanner. The collected real-time sets included short axis views of healthy

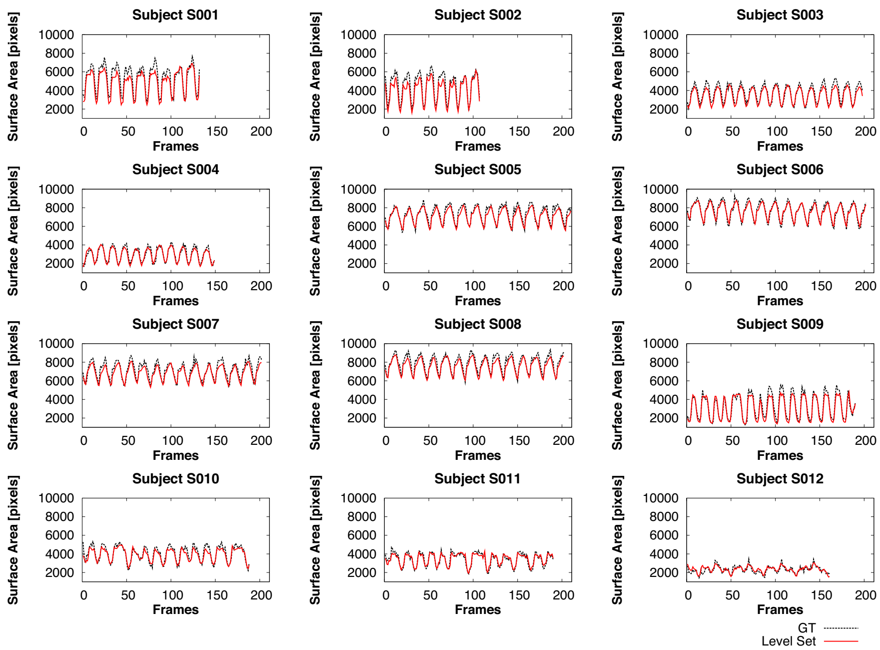

Fig. 4. Time series plot of the left ventricle surface area sizes as given by Ground-truth (GT) and level set (LS) method.

volunteers (N = 4), subjects with a diagnosis of low ejection fraction (N = 4) and fibrillation (N = 4).

To ascertain how well the segmentation performed, one needs to have the ground-truth location of the left ventricle area and compare the level set method output with the ground-truth throughout the timeline. Ground-truth (GT) was manually labeled by an expert. The labeled points were recorded as time series of the polygon area of the left ventricle. Then, the level set method (LS) was applied on the real-time sequences to obtain the 1D signal of the evolving left ventricle surface area.

3.2 Experimental Results

First of all we need to check whether the level set method is capable to track efficiently the periodic movement of the recorded surface. For this reason we provide the time series plot where at each frame the total number of pixels from the level set and ground truth surfaces are recorded. From Figure 4 we observe that there is a good agreement regarding the size of the surface as this is proposed by the level set and ground-truth data. The closer the level set time series to the corresponding ground-truth time series, the better. To quantify further the agreement between the two, we provide the scatterplot diagrams of the level set surface size versus the ground truth surface size for each of the 12 subjects (in

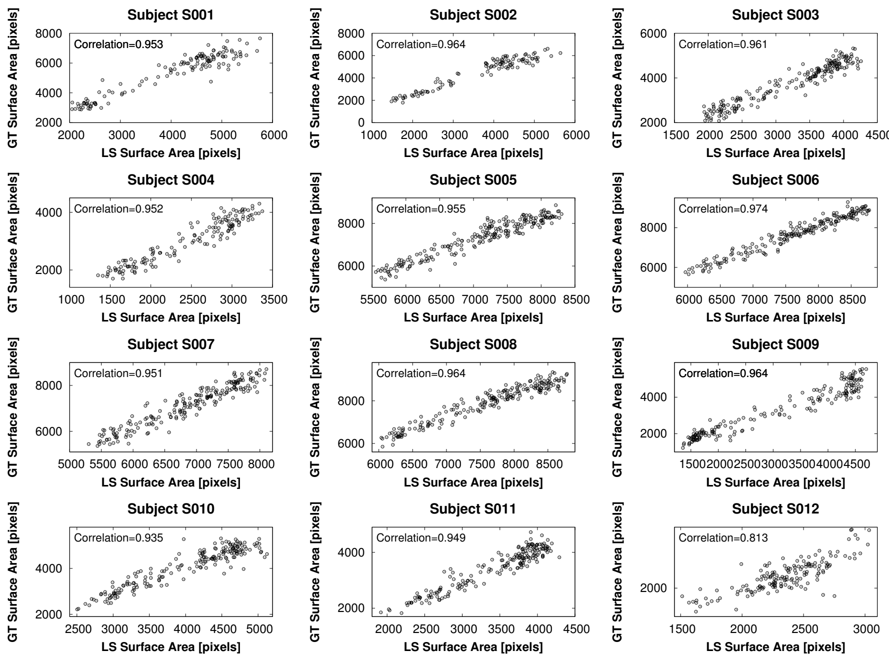

Fig. 5. Scatterplots (and correlation coefficients) for the surface area size given by the Level Set Method versus Ground-truth.

each plot every data point corresponds to the sizes given by LS and GT for the surface in a specific frame). In these plots linearity indicates good agreement in the periodic motion of the left ventricle. We further quantify the strength of the linear relationship by computing the correlation coefficient for each scatterplot. From Figure 5 we observe that there is strong linear relationship between the two time series (GT and LS) indicating that the LS method is capable of following efficiently the periodic change of the size of the ROI.

The agreement on the size of the surface between LS and GT will be valuable as long as the LS surface overlaps with the GT surface to an extensive degree (i.e, perfect agreement between GT and LS on the size of the ROI will be useless, if the two ROIs have as intersection the empty set). We therefore also computed the locations of the centroids of LS and GT output area for each frame in the data sequence of each subject and then calculated the Euclidean and Manhattan distances of each pair of (LS, GT). We provide the boxplots of Euclidean (Figure 6a) and Manhattan (Figure 6b) distances versus subject to have a better view of the distribution of the distances across subjects. From the figures we observe that in general the centroids are relatively close and there do not seem to be big discrepancies among the distributions of Euclidean/Manhattan distances across subjects. The reason we tried both Euclidean and Manhattan distances

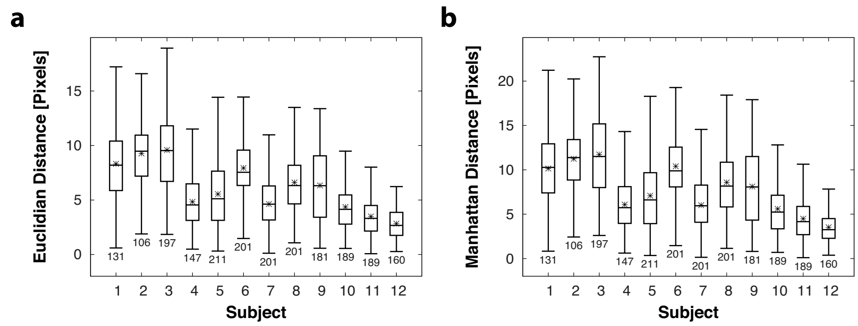

Fig. 6. Distribution of **a** Euclidian and **b** Manhattan distances between the level set (LS) and Ground-truth (GT) centroids for each of the 12 subjects. The mean Euclidean (Manhattan) distance ranges from 2.8 to 9.6 (3.5 to 11.7) for all subjects, with the standard deviations being relatively small indicating high concentration around the mean values. The '*' symbols in the box-plots indicate the mean values of the distributions. n is shown at the bottom of the corresponding column.

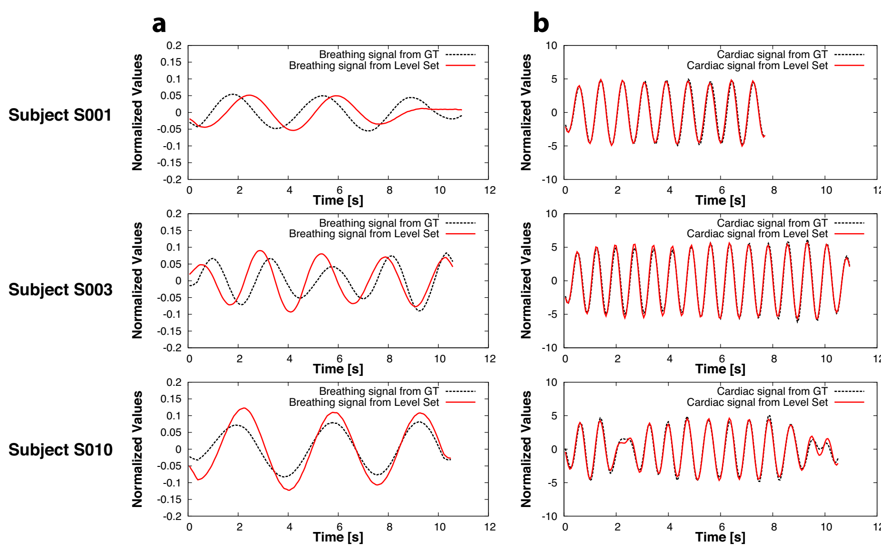

Fig. 7. Waveforms of **a** Breathing signals and **b** Cardiac signals extracted from the surface area signals.

was to provide some evidence that the results seem to be robust independently of the type of distance used.

Figure 7 shows results of the extracted cardiac and breathing waveforms produced using our automated tool. We observe that there is good agreement for the cardiac waveforms and some slight offset for the breathing waveforms. This is due to the automatic detection of the local wavelet energy peak point representing the breathing function, which was tuned towards fast processing so it can be applied on-the-fly.

4 Discussion

We described a method to compute physiological functions, namely, cardiac and breathing in real-time MR image sequences, which can be used to guide a reconstruction or retrospective reordering process. The method computes the surface of the evolving heart surface using a level set method to segment the left ventricle of the heart. The output of the level set method area forms a time signal, which when subjected to wavelet analysis reveals local energy maxima in high and low scales. We have implemented the proposed method into an automated tool. In the experimental analysis on real-time MR cardiac image sequences from breathing subjects, we demonstrated that the selected B-Spline level set method performs very well.

This method may find applicability in diagnostic cardiac MRI, by removing the breath-holding restriction on patients as well as the need for additional gating sensors. Indeed, the method's value is not only that it can effectively deal with breathing motion, but also that it can compute both breathing and cardiac function (in real-time), turning a challenge to an opportunity.

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