Applications of Feature-Based Attribute Vectors for Improved Image Registration Towards Cardiac Motion Estimation in Cardiac Computed Tomography

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Abstract

As a result of technological advances in cardiac computed tomography (CCT), there is increased interest in investigating CCT's potential capabilities. Particular interest involves cardiac deformation estimation as it is useful for physicians to identify and quantify potential abnormally moving segments of the myocardium. Our contribution is a first step towards more accurate motion estimation in CCT. A major issue with motion estimation in CCT is the fact that within the myocardium the tissue appears quite homogeneous and therefore is difficult to track. In order to better characterize the myocardial tissue with CCT, we applied feature-based attribute vectors containing feature asymmetry information for image registration. Experimental results of attribute vectors on real clinical CCT data demonstrated reduction in registration error compare to registration done solely on intensity or feature asymmetry information.

1 Introduction

1.1 Regional cardiac function

Heart disease continues to be a major issue and new methods for quantifying severity of disease continue to be investigated. Currently, the most frequently used clinical measure of myocardial function is ejection fraction. However, in large scale population trials, global systolic ejection fraction has been recognized to lack predictive value in the subsequent development of cardiovascular events [3]. Given the premise of functional cardiac analysis that local/regional functional changes precede global changes, increased interest has arisen in investigating methods to estimate regional cardiac motion/strain.

1.2 Cardiac computed tomography (CCT)

The number of CCT studies has increased dramatically as a result of improvements in temporal resolution, spatial resolution, and radiation dose reduction [4]. Although cardiac deformation is well explored with cardiac MRI and echocardiography, currently there is no established method to obtain this information from CCT.

1.3 Different methods for cardiac motion estimation

There are a variety of different motion estimation methods developed to quantify the deformation of regional myocardial tissue in ultrasound and MRI that may be applicable to CCT. It is possible to classify these methods into three broad categories, specifically: marker based methods, boundary tracking methods, and dense tracking methods.

Marker based methods include both invasive markers such as sonomicrometry and non-invasive intensity-based tagged such as those found in tagged MRI or speckle tracking. A significant issue with invasive markers is that the marker themselves can alter myocardial motion. Existing clinical applications of non-invasive tagging include speckle tracking in echocardiography and tagged MRI. Currently, CCT is unable to fully replicate the methods used in tagged MRI because of the lack of embedded tags and speckle tracking because of the lack of speckles.

Boundary tracking methods involve edge detection and dense motion field estimation. However, only sparse displacement estimations along the boundaries can be produced due to the simplification of the problem to a surface model. In addition, boundary tracking methods can suffer from aperture problems making it difficult to distinguish different physical motions without additional information. These methods also strongly depend on accurate segmentation of the myocardium and in general perform poorly within the myocardium.

The last general category is dense tracking methods based on optical flow and non-rigid image registration techniques. The deformation of a whole 3D volume is tracked utilizing dense image information. Methods applying parametric basis splines produce reasonable motion estimations [2].

Using a nonrigid image registration framework [2], this work applies feature-based attribute vectors for robust correspondence between frames where the attributes vector uses both intensity information and feature asymmetry (FA) features to reduce ambiguity in image matching.

2 Methods

2.1 Feature-based attribute vectors at different scales

The attribute vector [7] is designed to be a morphological signature that minimizes the ambiguity in image matching and correspondence detection potentially towards a more accurate cardiac registration and subsequently motion estimations. If the attribute vector is rich enough to reflect the underlying anatomy, it is able to distinguish areas within the image.

In the current work, feature-based attribute vectors are defined to contain a FA measure $a^f(x,y)$ in addition to image intensity information, $a^i(x,y)$. A multi-resolution approach is used, with three different scales, to generate an attribute vector a(x,y) calculated on every

pixel (x,y) in image I(x,y) and represented by the equation,

$$a(x,y) = [[a_1^f(x,y)a_1^i(x,y)],[a_2^f(x,y)a_2^i(x,y)],[a_4^f(x,y)a_4^i(x,y)]] \quad (1)$$

where $[a_1^f(x,y)a_1^i(x,y)]$ represents fine-level attributes, $[a_2^f(x,y)a_2^i(x,y)]$ represents middle-level represents attributes and $[a_4^f(x,y)a_4^i(x,y)]$ represent coarse-level, global features.

2.2 Feature asymmetry

While image intensity is a good attribute for CT image registration, registration can be enhanced by using implicit structural features in a cardiac CT image such as endocardial and epicardial edges. Previous research suggests that local phase derived features such as FA can perform better than intensity based metrics. Therefore, we explored this in our research [6].

The general idea of local phase methods is to employ the monogenic signal to characterize each pixel in terms of its local amplitude, local phase, and local orientation. Structural information in images is principally contained in the local phase (LP). The 2D slice I^S is first convolved with a band-pass filter b(x,y) to obtain,

$$I^B = [I_j^B(x,y) = b(x,y) * I_j^S(x,y); j = 1,2,...n] \quad (2)$$

where I^B is the band-pass image, j is the slice number, n is the number of slices, and * denotes the convolution operator. The selection of the bandpass filter b(x,y) is an important aspect of the method, and in the proposed approach, an isotropic bandpass log-Gabor filter is chosen [6]. The monogenic signal image I^M of I^S is defined as $I^M = [I^B, h_1 * I^B, h_2 * I^B]$, where h_1 and h_2 are the convolution kernels of the Riesz transforms [17] defined as,

$$h_1(x,y) = \frac{x}{2\pi(x^2+y+2)^{3/2}} \quad (3) \qquad h_2(x,y) = \frac{y}{2\pi(x^2+y+2)^{3/2}} \quad (4)$$

From I^M, the corresponding local phase images I^φ are obtained. With the local phase information, the even and odd filter responses derived from the monogenic signal can be used to compute the feature asymmetry measure, $a^f(x,y)$, as described in [5].

2.3 Registration methodology using feature attributes

Based on the non-rigid registration methods established in [2] , we formulate the motion estimation problem as a hierarchal minimization of the energy function of images of M by N dimensions,

$$E = \sum_{x=1}^{M}\sum_{y=1}^{N} d(a_T(h(x,y)), a_R(x,y)) \quad (5)$$

where $a_R(x,y)$ represents the attribute vector of reference image, $a_T(h(x,y))$ represents the corresponding points in the transformed template image and $d(a_T(h(x,y)), a_R(x,y))$ represents the sum-of-squared difference between each attribute pair in the attribute vectors $a_R(x,y)$ and $a_T(h(x,y))$ summed over the entire image of M by N dimensions. This energy is minimized using a first derivative gradient descent optimization against each attribute class (i.e. feature asymmetry followed by intensity).

3 Results

We applied our methodology on CCT volumes obtained from a Toshiba Aquilion ONE CT scanner. The CT data was acquired on a 320 multi-row detector to facilitate the acquisition of isotropic volumes of an entire organ within a single rotation of the gantry. The imaging protocol included ECG triggering, split-bolus protocol with a dual-syringe injector and an initial bolus of contrast followed by saline, single heart-beat volumetric acquisition, detectors width of 0.4mm, voltage of 120 kV, and current from 150-500mA. Temporal resolution was 20 volumes/frames per cardiac cycle. The spatial resolution of the original image was 512 by 512 by 320 voxels. Focusing our analysis on the heart, we analysed a single cardiac dataset with a spatial resolution of 325 by 325 by 320 voxels examining specifically a clinically relevant cardiac four-chamber view.

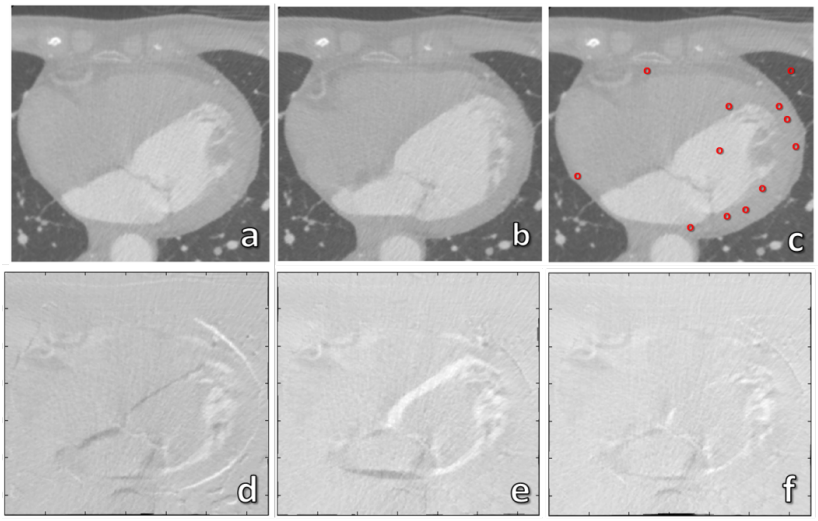

Figure 1: (a) Reference (fixed) image (b) Template (deformed) image (c) Clinically significant points manually selected for quantification in Table 1. Difference images between deformed template image and reference image based on (d) intensity information only (e) FA information only (f) attribute vector composed of both FA information and intensity information.

We compare registration using intensity information alone, FA information alone, and a combination of the two via feature-based attribute vectors. Visual inspection of the registration method is shown in Figure 1, d-f. A decrease in the difference between the deformed target image and reference image (i.e. a better registration) can be observed as a decrease in the visibility of the difference (i.e. a more homogeneous difference image). Note when the target image is deformed with attribute vectors (f) that the difference image is more homogeneous than when intensity information alone (d) or FA information alone (e) are used.

From these difference images we can quantify the registration error. In Table 1, we quantify the registration error for points located in the left ventricle (LV) wall (which are candidates for cardiac strain analysis) as well as additional clinically relevant points. As seen in Table 1, there is a general trend of lower quantified registration error [1] with feature-based attribute vectors compared registration error obtained from using solely intensity information

or solely FA information.

Location	Intensity only	FA only	Attribute Vector
LV wall	3.07	2.72	1.56
LV wall	2.51	2.76	1.95
LV wall	1.22	0.81	0.65
LV wall	4.73	9.50	3.41
LV wall	2.30	2.35	2.03
LV wall	3.65	5.29	3.06
LV wall	0.36	1.06	0.48
LA wall	1.53	1.29	1.1
RV wall	1.96	5.49	1.43
RA wall	0.36	1.06	0.48
LV cavity	0.22	0.81	0.65
lung	1.31	1.95	1.25

Table 1: Quantification of error metric, intensity difference d_I, of clinically relevant points. d_I is to the power of 10^{-2}. left ventricle (LV), right atria (RA), right ventricle (RV), left atria (LA).

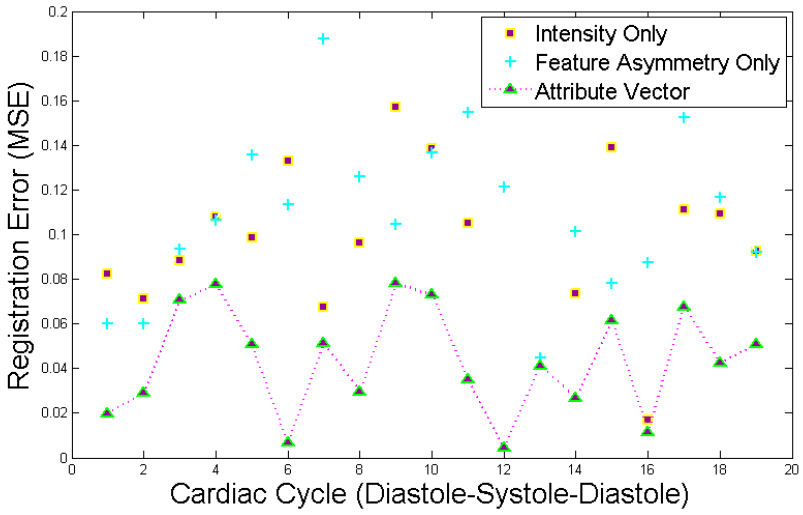

Figure 2: Demonstration of utility of feature-based attribute vector towards reducing registration error (MSE) across the cardiac cycle. Line indicates registration error obtained with feature-based attribute vectors.

In Figure 2, note how the registration errors, expressed as mean square error (MSE) [1], from the attribute vectors is lower than the registration error observed with the use of FA alone or image intensity alone across the cardiac cycle. Because of the number of temporal frame, small changes are noted from frame to frame, which helps explain the small registration errors noted with using FA alone, image intensity alone and attribute vectors. In

addition, our images were normalized for intensities from 0 to 1. Since our ultimate goal is to be able to quantify small local deformations, decreasing these registration errors can be considered valuable improvements.

4 Conclusion

The contribution of this work is the implementation of feature asymmetry (FA) within attribute vectors (feature-based attribute vectors) for improved image registration in cardiac computed tomography images. In our results, we can visually see an improvement in registration with the feature-based attribute vector when compared to registration using solely intensity information or FA information. Looking at clinically significant points, we can quantify an improvement in registration. Finally, looking across the cardiac cycle, we can see that feature-based attribute vectors consistently showed a lower registration error compared to using intensity information alone or FA information alone. Further research will includes expansion of our attribute vectors framework to better act as morphological signatures of cardiac tissues.

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