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Deformable regions of interest with multiple points for tissue tracking in echocardiography

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ABSTRACT

By tracking echocardiography images more accurately and stably, we can better assess myocardial functions. In this paper, we propose a new tracking method with deformable Regions of Interest (ROIs) aiming at rational pattern matching. For this purpose we defined multiple tracking points for an ROI and regarded these points as nodes in the Meshfree Method to interpolate displacement fields. To avoid unreasonable distortion of the ROI caused by noise and perturbation in echo images, we introduced a stabilization technique based on a nonlinear strain energy function. Examples showed that the combination of our new tracking method and stabilization technique provides competitive and stable tracking.

1. Introduction

The quality of echocardiography images is progressively improving because of recent advances in ultrasound sensors and data processing technologies. Furthermore, the performance of accompanying computer systems has also advanced rapidly because of multicore CPU and GPU technologies, which enable us to run more extensive software for image analysis, than previously, to obtain more accurate and clinically informative results. In any image analysis, however, the performance of myocardial motion tracking is essential in echocardiography. In clinical practice, the strains in the distinct layers across the myocardial wall are generally considered for evaluating cardiac functions (Voigt et al., 2015). In a recent study, the mid layer strain of myocardium was measured by spatial smoothing of the displacement field (Michael et al., 2012). Tracking of arbitrarily-positioned points in the intramyocardium will be required for more detailed analysis.

Various tracking methods have been proposed so far (Smeulders et al., 2014). The Block Matching (BM) method is one of the most classical tracking methods. This approach involves searching in a small window to match a target block in consecutive images, and thus obtain the displacement vector **d**. In this framework Bohs et al. (1999) proposed a system to measure 2D velocities in real time using a Sum-Absolute-Difference (SAD) algorithm. Efforts have also been made to improve the accuracy of the BM method. Yeung et al. (1998) applied a Coarse-to-Fine strategy aiming to improve the robustness against the noise and capture the motion field details at the same time. Behar et al. (2004) proposed an algorithm which incorporates the SAD algorithm, optical flow method and an affine motion model to take account of the deformation of the myocardial wall. Duan et al. (2006) extended BM method to 3D echocardiography. In another approach, the gradient-based Optical Flow (OF) methods have been widely used. The basic premise is that the intensity of a material point does not change with time. Because this assumption is not adequate to give a unique solution of displacements, Horn and Schunck (1981) introduced a constraint to minimize the sum of the squares of the Laplacians of the two velocity components. Lucas and Kanade (1981) localized the computation of the OF in a small window in which the motion field is assumed to be constant. The Horn and Schunck method and the Lucas-Kanade method were assessed by Baraldi et al. (1996). The Lucas-Kanade method was fully developed by Tomasi and Kanade (1991) and was verified by Shi and Tomasi (1994). The Lucas-Kanade method

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together with the work by Tomasi and Kanade is called the "KLT" method. Based on these OF methods, various techniques have been proposed to improve the tracking accuracy such as the introduction of Smoothness Constraints to reduce the discontinuity of the motion field (Nagel and Enkelmann, 1986; Weickert and Schnörr, 2001), Coarse-to-Fine strategies to track large displacements (Anandan, 1989; Black and Anandan, 1996), affine motion to incorporate the deformation and rotation (Maurice and Bertrand, 1999; Behar et al., 2004; Sühling et al., 2005), preprocessing filters to reduce the noise (Kusunose et al., 2014). Additional interesting work on the OF method can be found in (Duan et al., 2005; Mukherjee et al., 2012).

In the field of image processing, many image registration methods have been proposed for overlapping two images (Brown, 1992). Image registration methods have been divided into a "rigid" registration method (only rotation and translation are considered) (Maintz and Viergever, 1998; Hill et al., 2001) and a "non-rigid" registration method (besides the rotation and translation, deformation is also considered) (Zitová and Flusser, 2003; Modersitzki, 2004; Crum et al., 2004). The non-rigid image registration techniques first introduced by Broit (1981) and Bajcsy and Kovačič (1989) have been widely applied to the analysis of myocardial motion. In non-rigid registration methods, by introducing a set of control points and a deformation model, a reference image is deformed to match a target image. Because the expression of the motion model is a key for non-rigid registration methods, studies have used various basis functions (Holden, 2008), such as polynomials, B-splines (Unser, 1999; Ledesma-Carbayo et al., 2005), thin-plate splines (Goshtasby, 1988), radial basis functions (Fornefett et al., 1999), and wavelets (Amit, 1994; Yoshida, 1998; Wu et al., 2000). Kybic and Unser (2003) showed that B-spline deformation is computationally more efficient than the other basis functions. Heyde et al. (2013) compared the BM method and non-rigid registration methods. Other comparative studies can be found in (Zagorchev and Goshtasby, 2006; Craene et al., 2013; Jasaityte et al., 2013).

Regardless of whether the method belongs to the tracking family or the image registration family, the deformation of the image is taken into account by a motion model. In this study, instead of pursuing a new motion model, we introduce a technique developed in so-called computational mechanics. The most common technique is the finite element method (FEM) and we explored this method to find that the Meshfree Method (MFM) is more flexible and robust for this application. MFM is one of the latest computational mechanics methods that approximates a displacement field by the superposition of the interpolation functions of nearby nodes without dividing the analysis domain into finite elements. By distributing multiple MFM nodes in a ROI as tracking points, the displacement field in the ROI is determined according to the movements of the tracking points. The ROI can thus translate, rotate and deform within the ability of the given freedoms, i.e., twice the number of tracking points. By minimizing the dissimilarity between two consecutive images, we can then obtain the movements of tracking points as the solution of the MFM nodal displacements. The resultant deformed ROI is used for further tracking.

It is also noted that we are readily able to introduce stabilization into the deformation of the ROI by adding strain energy to the dissimilarity energy, aiming at better tracking of echo images including noise and perturbation. This process is nothing but the original function of the MFM and the constitutive equations developed in Continuum Mechanics can be fully utilized. Namely, unlike conventional regularization techniques such as spatial averages, bending energy penalty (Rueckert et al., 1999), Jacobian based constraint (Kybic et al., 2000; Rohlfing et al., 2003), curvature penalty term (Fischer and Modersitzki, 2004) and some other non-derivative based methods (Holden, 2008), the strain energy based stabilization term can suppress only abnormal strains by properly selecting a nonlinear potential function. To the best of our knowledge, this is the first paper that has introduced Computational Mechanics based nonlinear strain energy for stabilization. We will see the effectiveness later in this paper.

This paper focuses on the investigation of the basic characteristics of the proposed method and for this purpose two numerical phantoms are introduced firstly. These are both donut-shaped, but the first simply consists of randomly distributed scatterers, while the second is its simulated ultrasound B-mode image including artificial noise. Under such controlled circumstances the proposed method is closely compared with other methods. Secondly, to examine the potential of our method in more practical situation, we applied the method to real ultrasound images of a physical phantom in a benchmark database (Tobon-Gomez et al., 2013).

Section 2 describes the proposed method, and the performance is examined in Section 3. Section 4 discusses the tracking results, and Section 5 concludes the work. The detailed formulae and protocols are placed in Appendices.

2. Method

2.1. The RMTP method

The optical flow methods estimate the myocardial motion by minimizing dissimilarities of a sequence of images. Here, it is assumed that the intensity of a material point remains the same during the motion to the next frame. Denoting the intensity functions of two consecutive frames by $I(\mathbf{x})$ and $J(\mathbf{x})$, the assumption can be written as:

$$J(\mathbf{x} + \mathbf{d}(\mathbf{x})) - I(\mathbf{x}) = 0, \tag{1}$$

where $\mathbf{x}$ is a 2D position vector, and $\mathbf{d}(\mathbf{x})$ is a 2D displacement vector of a material point $\mathbf{x}$. The KLT method further assumes the displacement vector $\mathbf{d}(\mathbf{x})$ to be constant within a small square region of the ROI, and tries to minimize the following residual to solve for $\mathbf{d}$:

$$\varepsilon(\mathbf{d}) = \sum_{\mathbf{x}\in W} (J(\mathbf{x} + \mathbf{d}) - I(\mathbf{x}))^2, \tag{2}$$

where W denotes all the pixels in the ROI. This equation may be interpreted as reflecting a tracking point at the center of the ROI which represents the translational movement of the whole ROI for the minimization.

In Fig. 1, the middle row schematically shows a square ROI boundary which rotates and deforms with the tissue and therefore with the image. The upper row depicts the notion of pattern matching in the KLT method where only parallel translations are allowed. The difference between the two images in the middle row is made intentionally large to obtain a perspective on the limitations of the KLT method; in practice the difference for a single step is much smaller. However, the same type of error in pattern matching always occurs even if the difference is small, and accumulates from step to step resulting in a significant error as shown later. The limitation of the above pattern matching in the KLT method stems from the fact that there is only one tracking point to represent the ROI. However, if we allow multiple tracking points for an ROI, we can introduce controllable displacement fields including parallel translations, rotations and deformations as follows. Note that affine transformations have already been applied to the KLT method as mentioned earlier (Maurice and Bertrand, 1999; Sühling et al., 2005), but the gradient of the resultant displacement field is limited to being constant by its nature. We will discuss this point together with the image registration methods later.

In the Finite Element Method (FEM), which has been widely used in structural analysis, the displacement field is interpolated