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Deformable models with sparsity constraints for cardiac motion analysis

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ABSTRACT

Deformable models integrate bottom-up information derived from image appearance cues and top-down priori knowledge of the shape. They have been widely used with success in medical image analysis. One limitation of traditional deformable models is that the information extracted from the image data may contain gross errors, which adversely affect the deformation accuracy. To alleviate this issue, we introduce a new family of deformable models that are inspired from the compressed sensing, a technique for accurate signal reconstruction by harnessing some sparseness priors. In this paper, we employ sparsity constraints to handle the outliers or gross errors, and integrate them seamlessly with deformable models. The proposed new formulation is applied to the analysis of cardiac motion using tagged magnetic resonance imaging (tMRI), where the automated tagging line tracking results are very noisy due to the poor image quality. Our new deformable models track the heart motion robustly, and the resulting strains are consistent with those calculated from manual labels.

1. Introduction

Physics-based deformable models and their variations have been studied extensively in recent decades and widely used in computer vision, computer graphics and medical image analysis (Metaxas, 1992; McInerney and Terzopoulos, 1996; Metaxas, 1996; Nealen et al., 2006b). They are able to solve diverse types of problems, such as, but not limited to, image segmentation (Kass et al., 1988), image registration (Rueckert et al., 1999; Shen and Davatzikos, 2002), shape reconstruction (Terzopoulos et al., 1988; Metaxas and Terzopoulos, 1993), and motion analysis (Metaxas and Terzopoulos, 1991; Paragios and Deriche, 2000). The name "deformable models" is derived from the nonrigid body mechanics, which describes how elastic objects respond to applied forces. Starting from an initial shape, the model is usually deformed by two types of forces, i.e., internal and external forces. The external force drives the model to fit the observations, while the internal force constrains the geometric flexibility of the shape. For examples, in the image segmentation problem, the external force computed from the image intensity drives the model to the estimated boundary, while the internal force keeps the boundary smooth. In the motion analysis (e.g., cardiac motions (Park et al., 1996; Haber et al., 2000; Hu et al., 2003; Chen et al., 2008; Wang and Amini, 2012)) and the shape manipulation problems (Nealen et al., 2006b), *control points* are employed as the external force to drive the model, and the internal force maintains the smoothness and preserves shape details. The control points are tracked along a motion sequence, and then an initial model is deformed to fit the control points in each following frame. This is often measured by the distances between the control points and the corresponding points on the initial model. In fact, in the context of motion analysis and shape manipulation, many previous methods (Sorkine et al., 2004; Zhou et al., 2005; Yan et al., 2007; Wang et al., 2008a) use Euclidean distance or $L2$ norm as the distance metric for penalty functions. This assumes intrinsically that the errors of the target points follow a Gaussian distribution with small variances. Nevertheless, this is not always true in practice. Since the control points are usually from automated detections, they may contain not only Gaussian noise, but also some gross errors or outliers due to the erroneous detection. Therefore, the accuracy of the traditional deformable models depends heavily on the accuracy of the control point detection.

In this paper, we focus on improving the robustness of traditional deformable models, particularly for the problems of cardiac motion analysis. Inspired by the robust recovery power of the compressed sensing approach (Donoho, 2006; Candes et al., 2006), we propose a new class of deformable models using sparse regularization. Recent research in compressed sensing shows that using an $L1$ norm can dramatically increase the

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probability of accurate signal recovery, even when there are both sparse outliers and moderate Gaussian noise (Candes and Tao, 2006). Thus, we design a robust deformable model by integrating seamlessly an $L1$ norm regularization with a modified Laplacian deformable model (Sorkine et al., 2004; Yu et al., 2013). This new model is able to handle outliers or gross errors. In addition, it is designed as a convex optimization problem, and can be efficiently solved within a constrained solution space. However, when the variances of the Gaussian noise are large, solely using the $L1$ norm may cause overfitting problems due to its nature of pursuing the sparse structure (Candes et al., 2005). Therefore, we propose a deformable model using hybrid norm regularization that is able to handle both the Gaussian errors and gross errors. We also generalize these two models in a unified formulation, named as *sparse deformable models*.

In the following section, we discuss the relevant work of deformable models and compressed sensing. Our proposed sparse deformable models (SDM) are presented in detail in Section 3. In Section 4, we validate our models on a clinically important and challenging problem, i.e., the left ventricle (LV) motion analysis in mouse cardiac tagged MRI. Section 5 presents experimental results demonstrating the robustness of our models on mouse heart motion tracking even with inaccurate results of control point detection. The last section draws conclusions on model advantages, and discusses directions of future work.

2. Related work

2.1. Deformable models

With the success of active contour models (Kass et al., 1988), many methods have been proposed to improve deformable models. Most of the work focuses on either internal force or external force. In this section, we introduce some relevant papers in these two aspects.

Internal force usually enforces the smoothness characteristics of deformable models, such as the local deformation similarity. An unconstrained deformable model may easily result in unrealistic shapes due to the weak or misleading image cues. Therefore, the internal force is critical for the robustness. The global parametric models (e.g., deformable superquadratics) were proposed to build models based on a few global shape parameters (Terzopoulos and Metaxas, 1990; Bardinet et al., 1996). Although these models reduce the degree of freedom dramatically, they have difficulty to present the shape details. The local geometry properties can be used as constraints to solve these problems. For examples, splines were used on image deformation to constrain the smoothness of the deformation field (Tustison and Amini, 2006). Piecewise-smooth finite element model (FEM) was employed to present the deformable boundary (Duan et al., 2009b; Duan et al., 2010), which achieved real-time myocardial segmentation in both ultrasound and MRI data. The Laplacian coordinates (Sorkine et al., 2004) have been also a well-known measurement for the local similarity. Comparing with spline- and FEM-based methods, Laplacian coordinates allow more flexible shape representation. Sorkine et al. (2004) employed it to constrain the smoothness and local similarity of the 2D mesh deformation in shape editing. Shen et al. (2011) decomposed the Laplacian coordinates into components in the perpendicular and tangential directions, to formulate a detail-preserved internal force. In this paper, we adapt the traditional Laplacian coordinates in a new setting of *3D volumetric and meshless* deformable models to enforce the smoothness and local shape similarity.

External force matches the model to the observations derived from the image appearance. They are usually categorized as short-range and long-range forces. The short-range forces are defined based on the local information in a small neighborhood. For example, in segmentation problems, they drive the contour to the estimated boundary. The boundary may be defined by the intensity, gradient change, or high response of boundary detectors (Kass et al., 1988). In registration problems, the source image is deformed to match the target image according to the appearance similarity (Duan et al., 2009a). The pixels are matched based on textures in their neighborhoods. The long-range forces deform the model to match pre-calculated landmarks (Terzopoulos and Metaxas, 1991) or satisfy model priors (Cohen and Cohen, 1993). Region appearance features have also been used (Zhu and Yuille, 1996; Jehan-Besson et al., 2003; Huang and Metaxas, 2008) to augment the deformable models by leveraging the image intensity statistics. They discriminate the inside and outside region based on their intensities and textures. Recently, dictionary learning is also used to learn appearance characters (Huang et al., 2013a; Huang et al., 2013b). Each pixel is classified into different regions based on their reconstruction residues under different dictionaries. Our deformable model uses control points as the external force, which is a natural choice for cardiac motion analysis.

2.2. Robust shape priors

Most deformable models assume that there is no outlier or gross error on the detected landmarks, while such error are very common due to the image noise or weak appearance cues. Statistical shape models, such as active shape models (Cootes et al., 1995) and their variants, can effectively handle outliers using shape priors. Some of them detect and eliminate the outliers explicitly before the deformation. Duta and Sonka (1998) proposed a method to detect outliers by hypothesis testing based on the point distribution model. The detected outliers are removed or replaced based on the mean shape of the model. Prastawa et al. (2004) proposed to detect the abnormal regions by registering with a standard atlas. The regions largely different from the normal intensities are determined as outliers. Lekadir et al. (2007) used a local shape dissimilarity measure, which is invariant to scaling, rotation and translation, to detect the outliers, and then displaced them based on the local valid points. Other researchers aimed to reduce the effect of the outliers during the model deformation. Rogers and Graham (2006) evaluated M-estimator, least median of squares and random sample consensus (RANSAC) (Fischler and Bolles, 1981) to handle outliers in active shape models. RANSAC showed the best performance in the quantitative evaluation. Davatzikos et al. (2003) utilized wavelet transformation to build a hierarchical shape model to improve the local robustness. The low-frequency bands carry global shape information, and the high-frequency bands serve as local smoothness constraints. Besides shape priors, image atlas-based methods also naturally have the properties of handling segmentation errors (Shiee et al., 2011). Priors can also be based on data-specific properties, e.g., the relative positions of multiple components, which are modeled by formulating the relation explicitly (Paragios, 2002) or learning shape priors from examples (Paragios, 2003).

Recently, compressed sensing methods have been intensively investigated. These methods aim to reconstruct a signal that is known to be compressible with certain transformation based on sparse measurements. Such sparse methods have been widely used in computer vision and image processing communities to deal with gross errors or outliers. Particularly, the sparse constraints have been employed to model shape priors effectively (Zhang et al., 2012a; Zhang et al., 2012b) and register shapes robustly (Hontani et al., 2012). In their settings, most of the control points generated from point detectors are roughly accurate, while a small number of