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# Sparse group composition for robust left ventricular epicardium segmentation

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ABSTRACT

Left ventricular (LV) epicardium segmentation in cardiac magnetic resonance images (MRIs) is still a challenging task, where the a-priori knowledge like those that incorporate the heart shape model is usually used to derive reasonable segmentation results. In this paper, we propose a sparse group composition (SGC) approach to model multiple shapes simultaneously, which extends conventional sparsity-based single shape prior modeling to incorporate a-priori spatial constraint information among multiple shapes on-the-fly. Multiple interrelated shapes (shapes of epi- and endo-cardium of myocardium in the case of LV epicardium segmentation) are regarded as a group, and sparse linear composition of training groups is computed to approximate the input group. A framework of iterative procedure of refinement based on SGC and segmentation based on deformation model is utilized for LV epicardium segmentation, in which an improved shape-constraint gradient Chan-Vese model (GCV) acted as deformation model. Compared with the standard sparsity-based single shape prior modeling, the refinement procedure has strong robust for relative gross and not much sparse errors in the input shape and the initial epicardium location can be estimated without complicated landmark detection due to modeling spatial constraint information among multiple shapes effectively. Proposed method was validated on 45 cardiac cine-MR clinical datasets and the results were compared with expert contours. The average perpendicular distance (APD) error of contours is $1.50 \pm 0.29$ mm, and the dice metric (DM) is $0.96 \pm 0.01$. Compared to the state-of-the-art methods, our proposed approach appealed competitive segmentation performance and improved robustness.



## 1. Introduction

Cardiovascular diseases (CVDs) are the number one cause of death globally [1]. An estimated 17.3 million people died from CVDs in 2008, representing 30% of all global deaths [1]. By 2030, the number of people who die from CVDs will increase to reach 23.3 million [1,2]. Non-invasive assessment of left ventricular function based on cardiac MRI is of great value for the diagnosis and treatment monitoring of these pathologies. For example, LV contractile function quantified through ejection fraction, myocardium mass and ventricle volume, are often used as a crucial indicator in the assessment of deficient blood supply to the cardiac tissue [3,4].Calculations of such measurements is dependent on accurate delineation of LV myocardial boundaries. However, reliable and accurate automatic delineation of cardiac inner wall and outer wall remains a difficult problem, due to intensity inhomogeneities of tissues outside myocardium, the poor contrast between these tissues and myocardium, papillary muscles connected to the inner myocardium wall, artifacts arising from flow and noise [3]. Some unreliable appearance cues in cardiac MRI images are demonstrated in Fig. 1.

Significant numbers of methods have been proposed for (semi-)automated LV segmentation, including approaches using no, weak, strong prior knowledge [3]. Methods that work with weak or

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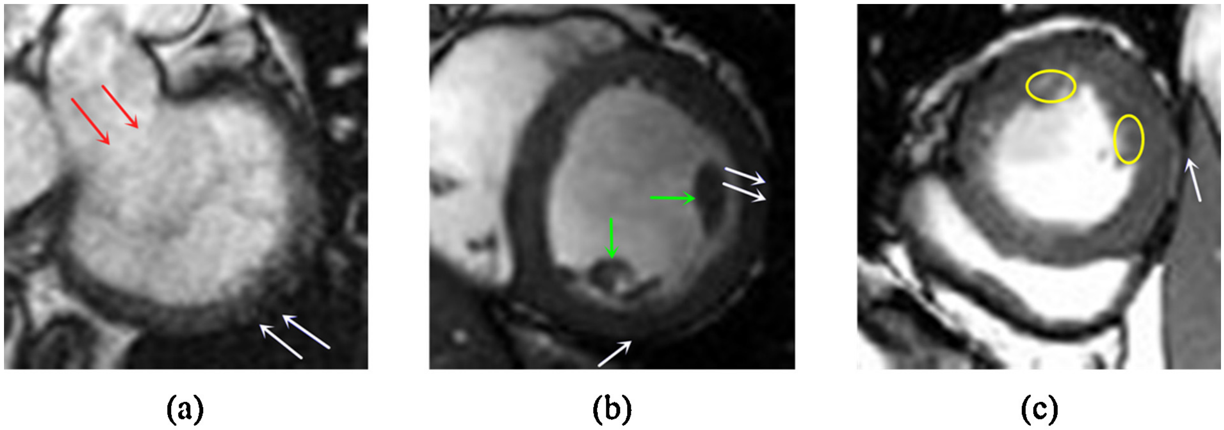

**Fig. 1.** Demonstration of several unreliable appearance cues in cardiac MRI images. (a) Missing border is pointed out by red arrows. Fuzzy borders are pointed out by white arrows. (b) Papillary muscles within the LV cavity are indicated by green arrows. (c) Muscles connected to the inner myocardium wall are surrounded by yellow ellipses. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

no prior knowledge, including methods based on thresholding [5], dynamic programming [6–9], clustering [10–12], and a combination of these [13–15], have been considered as general LV segmentation methods. Besides, graph-based methods, such as graph cut [16–18] and random walk [19], have been introduced that can achieve desired results with limited user-interaction. And, deformable model [20,21], such as active contour (or snake) model [22,23], level set [24], and their variants, have been prevalently applied in LV segmentation. However, almost all of these methods require manual intervention more or less.

In recent years, it has become widely recognized that integrate strong prior into aforementioned methods can be effective for medical image segmentation. Approaches that utilize strong prior knowledge have demonstrated great success in cardiac MRI and can be able to increase the final robustness and accuracy in the process of tackling LV segmentation tasks. Shape prior plays a significant role in these methods combining strong prior. Leventon et al. [25] defined a probability distribution over the variances of training shapes, and utilized it to constrain the flow of the geodesic active contour. Rousson et al. [47] introduced shape constraints to level set representations. Cremers et al. [26] incorporated statistical shape knowledge in the evolution process of a Mumford-Shah based segmentation [27]. In this area, Mahapatra et al. [28] use a single image from each dataset to get prior shape information and integrated prior shape constraints into a graph cuts framework for segmenting LV. Wu et al. [29] considered endocardium as a rough circle and applied a dynamic circle to constraint the snake model for its segmentation; and utilized its result as a prior shape of epicardium to constraint the segmentation through a shape-similarity based energy between evolution contour and endocardium. In recent years, active shape model (ASM) [30] and active appearance model (AAM) [31] have been proposed by Cootes et al. in 1995 and 1998, respectively, which are statistical shape models (SSMs) [43] of the distribution of a set of landmark points over a population of training samples. ASM is built up using a prior knowledge about the shape, usually hand-annotated segmentation from a training set of data. AAM is an extension of the ASM, except adding texture of the shape to the model. Hence, AAM represents both the shape and texture variability seen in a training set. Mitchell et al. [32] first presented AAM for the segmentation in 2D cardiac MR images. The method was later extended to a full 3D AAM [33]. Now, both ASM and AAM probably are two of the most popular methods in the segmentation of LV in 2D, 3D and 4D (3D + time) datasets. In [34], a combination of ASM and AAM was used to segment the left and right ventricles on 4D MR images. Atlas-based segmentation technique has also been used for heart segmentation, which can easily be propagated throughout the cardiac cycle using the same principle. Lorenzo-Valdes et al. [35] proposed an automatic atlas-based segmentation algorithm for 4D cardiac MR images. Zhang et al. [36] constructed an effective 3D shape atlas for LV from cardiac MRI data.

Sparsity theory was introduced into shape prior modeling by Zhang [37,38], named as sparse shape composition model (SSC). In their model, a sparse composition of training shapes is computed adaptively to infer/refine an input shape, which alleviates three problems in a unified framework, i.e., modeling complex shape variations, handling non-Gaussian errors and preserve local detail information of the input shape. Model assumes the given shape information may contain gross errors, but such errors are often very sparse. However, in the case of LV epicardium segmentation in cardiac MRIs, image noise or input shape errors might be gross and relatively dense, which degrades segmentation performance of these methods due to only modeling single prior shape. Considering the situation that epi- and endo-cardium are closely related two walls in myocardium, the spatial constraint in between them is supposed to be beneficial for the epicardium modeling. In this paper, we present an extension of SSC for epi- and endo-cardium modeling, that is, sparse group composition model (SGC), where epi- and endo-cardium are regarded as a group and modeled together. A framework of iterative procedure of refinement based on SGC and segmentation based deformation model is utilized for LV epicardium segmentation of cardiac MRI, in which an improved shape-constraint gradient Chan-Vese model (GCV) acted as deformation model [39–41,47]. The gradient vector energy acts as an effective image force to enhance the weak boundaries and partly inhibit overflow at fuzzy boundaries.

The main advantage of segmentation framework based on SGC is twofold: (1) for the given endocardial contour, a reasonable initial epicardial contour can be estimated solely from the endocardial contour based on SGC without complicated manual landmark detection; (2) it is capable of achieving more stable refinement result compared with conventional sparity-based single shape prior model even if image noise or input shape errors might be gross and relatively dense. Both properties of this extension have proven to be valuable in the epicardium segmentation process and can be merged into other segmentation methods conveniently.

## 2. Method

### 2.1. Sparse group composition model

Aiming at modeling multiple shapes simultaneously, SSC is improved into a coupled form to incorporate the prior spatial