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Left Ventricle Segmentation by Circular Shape Constrained Clustering Algorithm

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Abstract

This study presents a novel clustering algorithm for the automatic segmentation of the left ventricle (LV). A circular shape function is incorporated into the dissimilarity measure of the objective function of the well-known fuzzy c-means (FCM) clustering algorithm. In that way, the proposed circular shape constrained FCM (CS-FCM) algorithm integrates both intensity related feature and spatial shape information into the clustering procedure. As a result, pixels having similar intensity information but located in different regions (LV region and non-LV region) can be differentiated. A weighting parameter is introduced to adjust the weight of the spatial distance against the intensity feature, which increases the flexibility of the proposed CS-FCM algorithm. The experimental results on benchmark cardiac magnetic resonance (CMR) images show two obvious advantages of the proposed CS-FCM over the standard clustering algorithms: it successfully distinguishes the LV from other structures which have similar intensity as the LV. Also, it correctly segments the LV even when the papillary muscles are adjacent to or fall inside the LV region.

Keywords: Left Ventricle, Cardiac Image Segmentation, Fuzzy Clustering, Fuzzy C-Means, Circular Shape Function.

1. Introduction

Cardiovascular disease is the leading cause of death for both men and women in most developed countries. The early detection of cardiovascular diseases plays a very important role in the clinical management pathway. Cardiac Magnetic Resonance (CMR) is a popular non-invasive imaging modality used to diagnose cardiovascular diseases. The clinical CMR imaging modality produces 3D and 3D+time images of the heart. To diagnose cardiovascular diseases, doctors commonly assess the functionality of the left ventricle (LV) over the whole cardiac cycle. Quantitative indicators such as ejection fraction and cardiac output are used to assist in the assessment. To derive these metrics, the two boundaries describing the LV (i.e., the endocardial and epicardial borders) need to be extracted from a patient scan. Traditionally, this is done manually by doctors. However, manual analysis is no longer feasible due to the large quantity of data in 3D and 3D+time images. Moreover, manual annotation is prone to inter- and intra-observer variability which can affect the reliability and repeatability of cardiovascular diseases diagnosis. Therefore, an automatic segmentation solution is needed to address this practical problem.

A variety of segmentation techniques have been proposed for LV segmentation over the last few decades. While earlier approaches were often based on heuristics, recent studies employ more sophisticated and principled techniques. We refer the reader to the two recently published survey papers (Kang, 2012) and (Petitjean, 2011) for detailed review of this topic. Previously published automatic methods for this segmentation task have various disadvantages for routine clinical use (Cocosco, 2008): They are often computationally demanding, potentially unstable for subjects with pathology, require additional images to be acquired, or need complex shape and/or gray-level appearance models. Such models need to be constructed ("learned") from many manually segmented images, which is labour intensive, and are of limited use due to anatomical variability and image contrast variability. Moreover, most prior work has been devoted to segmenting cardiac data given a reasonable initialization, or an accurate manual segmentation of a subset of the image data. To achieve full automation and eliminate inter- and intra-observer variability, initialization should also be automatic. Despite several efforts, there is currently still a need for a fast and robust initialization procedure.

Many of the automatic medical image segmentation techniques rely on a combination of information directly derived from the image and information provided by prior models of anatomy and its appearance in the image. Due to the limitations and the construction cost of prior models, methods that rely primarily on image information have distinct advantages. In this study, we present a new CMR image segmentation method based on fuzzy image segmentation that is predominantly image-driven: it does not use any prior knowledge, and makes only plausible assumptions about the image and the imaged heart. In the last decade, fuzzy segmentation methods, especially the fuzzy c-means (FCM) algorithm (Bezdek, 1981), have been widely used in image segmentation. Its success is mainly attributed to the introduction of fuzziness for the "belongingness" of each image pixel. Unlike hard segmentation methods, such as K-means (Macqueen, 1967), which impose that pixels belong exclusively to one class, fuzzy segmentation methods allow pixels to belong to multiple classes with varying degrees of membership. This enables fuzzy segmentation methods to retain more information from the original image than hard segmentation methods (Pham, 2000). Some fuzzy clustering methods that have been used for LV segmentation in the literature are (Boudraa, 1997; Lynch, 2006; Cocosco, 2008).

In this study, a novel fuzzy clustering algorithm is proposed for the automatic segmentation of the LV endocardial border in CMR images. A circular shape function is incorporated into the dissimilarity measure of the objective function of the FCM clustering algorithm. In this way, the proposed circular shape constrained FCM (CS-FCM) algorithm integrates both intensity related feature and spatial shape information into the clustering procedure. As a result, pixels having similar intensity information but located in different regions (LV region and non-LV region) can be differentiated. A weighting parameter is introduced to adjust the weight of the spatial distance against the intensity feature, which increases the flexibility of the proposed CS-FCM algorithm. Experimental results on real CMR images show two obvious advantages of the proposed CS-FCM over the standard clustering algorithms like FCM: It successfully distinguishes the LV from other structures which have similar intensity as the LV; and it correctly segments the LV even when papillary muscles are adjacent to or fall inside the LV region.

The rest of this paper is organized as follows: Section 2 describes the proposed CS-FCM image segmentation algorithm. The experimental results of the proposed approach are reported in Section 3. Finally, the conclusion is given in Section 4.

2. Methodology

In this section, we provide a brief review of the fuzzy c-means (FCM) algorithm. This is followed by a description of the proposed circular shape constrained fuzzy c-means (CS-FCM) algorithm.

2.1 Standard Fuzzy C-Means (FCM)

Mathematically, the FCM algorithm [1] is used to minimize the objective function J_{fcm} with respect to the membership function $u_{k|ij}$ and the cluster centre v_k, such that

$$J_{fcm} = \sum_{x_{ij} \in I} \sum_{k=1}^{K} (u_{k|ij})^m \cdot d_{kij} \quad \text{subjected to} \quad \sum_{k=1}^{K} u_{k|ij} = 1, \forall x_{ij} \in I \tag{1}$$

where m is the weighting exponent on the fuzzy memberships. A value of m = 2 is known to give good results with the FCM algorithm. The parameter $u_{k|ij}$ is the membership of the $(i,j)th$ pixel x_{ij} in the $(k)th$ cluster, and d_{kij} is the squared Euclidean distance between the pixel x_{ij} and the cluster centre v_k where

$$d_{kij} = \left\| x_{ij} - v_k \right\|^2 \tag{2}$$

The minimization of (1) gives the updating equations for the membership $u_{k|ij}$ and cluster centre v_k, which are given by

$$u_{k|ij} = \frac{(x_{ij} - v_k)^{-2/(m-1)}}{\sum_{k=1}^{K} (x_{ij} - v_k)^{-2/(m-1)}} \quad \text{and} \quad v_k = \frac{\sum_{x_{ij} \in I} u_{k|ij}^m x_{ij}}{\sum_{x_{ij} \in I} u_{k|ij}^m} \tag{3}$$

The FCM algorithm is summarized as follows:

1) Fix the cluster number K; Initialize the cluster centres $\{v_k\}_{k=1}^{K}$ and set the threshold ε to a small positive value, e.g., $\varepsilon = 0.001$.
2) Alternatively update the membership function and cluster centre by using (3) until $\left\| v_{new} - v_{old} \right\| \le \varepsilon$.

2.2 Circular Shape Constrained FCM (CS-FCM)

Let $f(i,j,s)$ represents the geometric circular shape function. By incorporating it into (2), we have the new dissimilarity measure $\hat{d}_{kij}$, as shown below

$$\hat{d}_{kij} = d_{kij} + \alpha f(i, j, s) \tag{4}$$

where α is the weighting parameter used to adjust the weight of the spatial shape information against the intensity related feature. The circular shape function $f(i,j,s)$ is expressed as

$$f(i, j, s) = \left[\frac{(i - x_c)^2 + (j - y_c)^2}{r} \right]^{\beta_k} \tag{5}$$

where $s = \{x_c, y_c, r\}$ is a unique clique that denotes the circular shape, x_c and y_c denote the geometric x- and y-coordinates of the centre of circular shape, and r denotes the radius of the circular shape. The exponent parameter β ensures a small value for the pixels within the kth cluster and a large value for the pixels outside the cluster. In this study, we set $\beta = 2$ for the LV region, and $\beta = -2$ for the non-LV region.

The circular shape function $f(i,j,s)$ is an overall geometric information and its influence in the objective function is controlled by the weighting parameter α. The dissimilarity measure $\hat{d}_{kij}$ consists of a measure of the intensity dissimilarity between the $(i,j)th$ pixel x_{ij} and the $(k)th$ centre v_k in the intensity space as well as a distance dissimilarity in the spatial space. With the inclusion of the circular shape information, several advantages are achieved: 1) pixels with similar intensity but located in disjointed region can be differentiated; and 2) a large membership for the cluster associated with the LV region can be obtained.

By using the newly defined dissimilarity measure (4), the proposed CS-FCM algorithm is formulated as the minimization of the following objective function

$$J_{cs-fcm} = \sum_{x_{ij} \in I} \sum_{k=1}^{K} (u_{k|ij})^m \cdot \hat{d}_{kij} \tag{6}$$

The partial derivative of $J_{cs\text{-}fcm}$ with respect to membership $u_{k|ij}$ and cluster centre v_k yields the following updating equations

$$u_{k|ij} = \frac{\hat{d}_{kij}^{\,-1/(m-1)}}{\sum_{k=1}^{K} \hat{d}_{kij}^{\,-1/(m-1)}} \text{ and } v_k = \frac{\sum_{x_{ij} \in I} u_{k|ij}^m x_{ij}}{\sum_{x_{ij} \in I} u_{k|ij}^m} \tag{7}$$

The partial derivative of $J_{cs\text{-}fcm}$ with respect to s gives

$$x_c = \frac{\sum_{x_{ij} \in I} i \cdot u_{k|ij}^m}{\sum_{x_{ij} \in I} u_{k|ij}^m} \text{ and } y_c = \frac{\sum_{x_{ij} \in I} j \cdot u_{k|ij}^m}{\sum_{x_{ij} \in I} u_{k|ij}^m} \tag{8}$$

And

$$r = \sum_{x_{ij} \in LV} (i - x_c)^2 + (j - y_c)^2 \tag{9}$$

The CS-FCM algorithm is summarized as follows,

1) Fix the cluster number K. Initialize the cluster centres $\{v_k\}_{k=1}^{K}$ and set the threshold ε be a small positive value, e.g., $\varepsilon = 0.001$.
2) Update the membership function and cluster centre by using (7).
3) Update the circular shape by using (8) and (9).
4) Repeat Steps 2 to 3 until $\|v_{new} - v_{old}\| \le \varepsilon$.

3. Experimentation

To demonstrate and evaluate the performance of the proposed CS-FCM method on cardiac LV segmentation, we apply it to real CMR images obtained from the RV Challenge website (*http://www.litislab.eu/rvsc*). For the purpose of qualitative comparison, all the images are also subjected to the standard FCM algorithm. In all examples, we fix the cluster number as $K = 2$ (i.e., one cluster for LV region and the other for non-LV region) and the weighting parameter as $\alpha = 0.3$ for the CS-FCM.

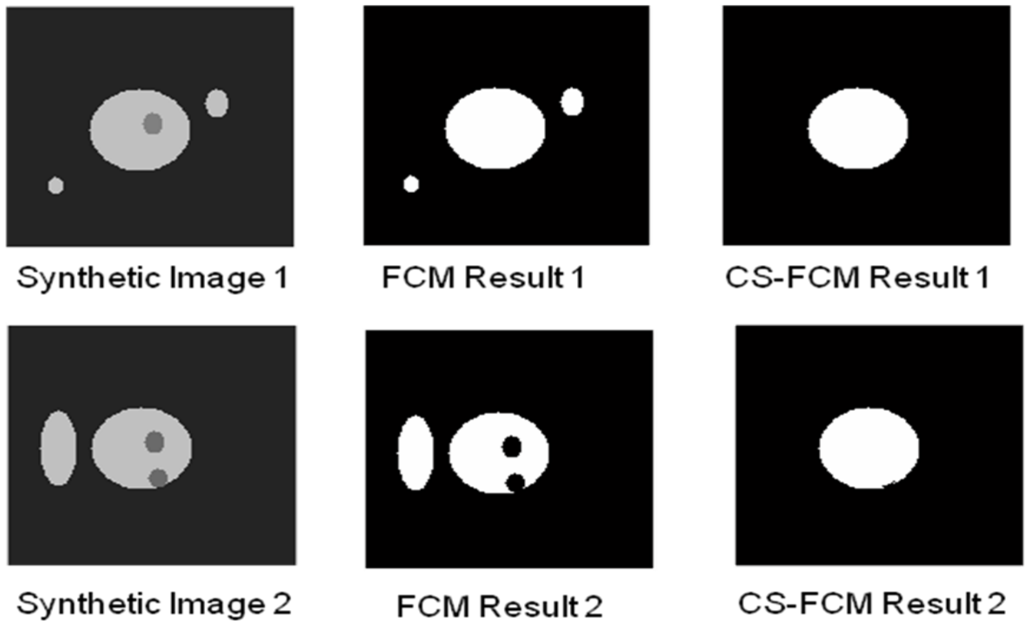

Fig.1 Segmentation results of the FCM and CS-FCM on two synthetic images.

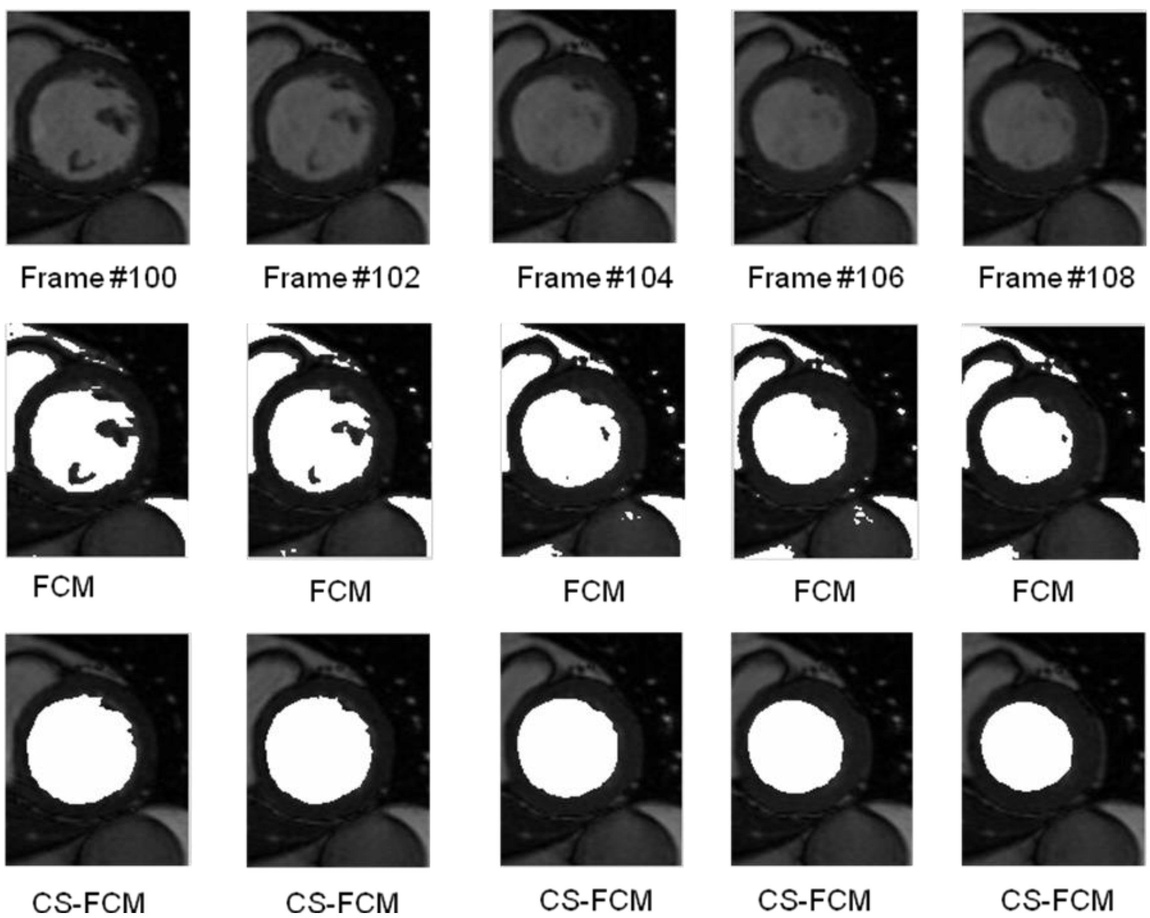

Fig.2 Segmentation results of the FCM and CS-FCM on real CMR images (Frames #100 to #119). Five frames are shown here.

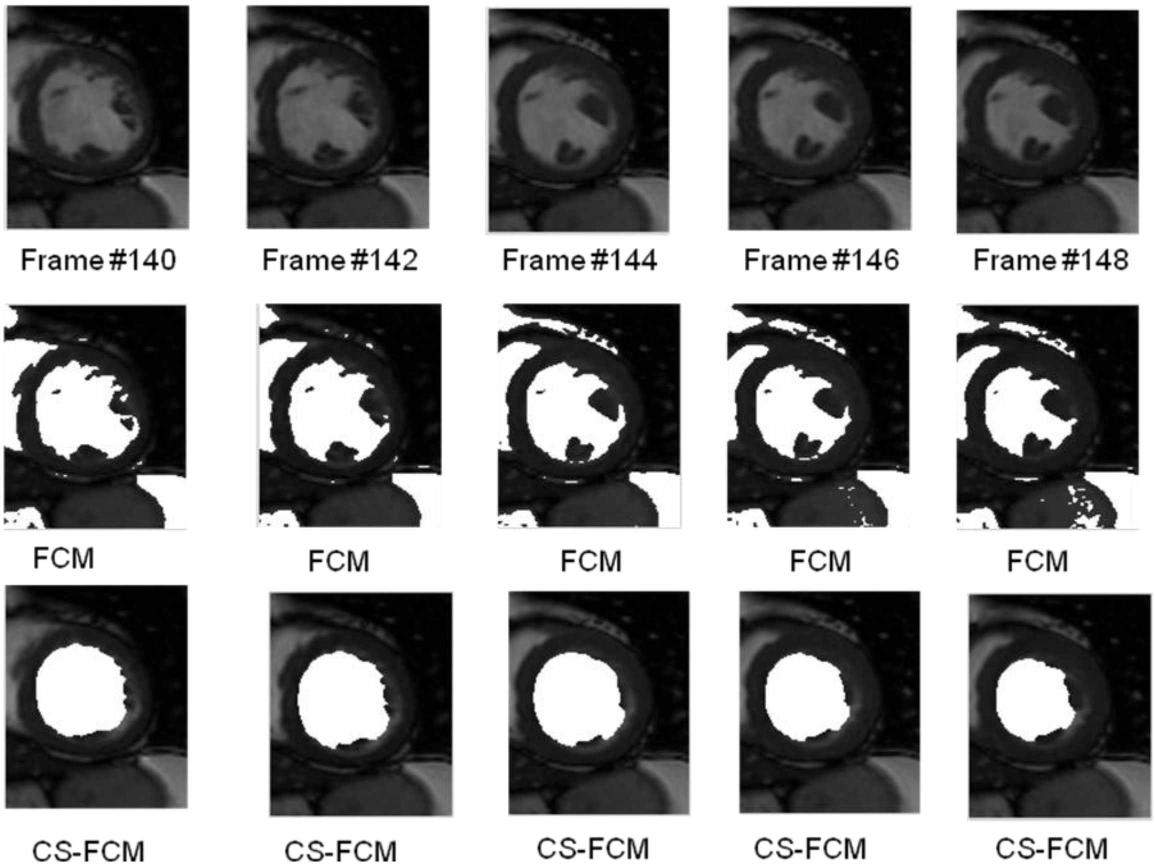

Fig.3 Segmentation results of the FCM and CS-FCM on real CMR images (Frames #140 to #159). Five frames are shown here.

Before performing the segmentation on the CMR images, we demonstrate the effectiveness of the proposed CS-FCM on some synthetic images. As shown in Fig.1, there are two synthetic images in the first column, the target is to separate the big bright ball from others. The segmentation results of FCM are shown in the second column, it can be seen that the FCM partitions several other bright objects with the ball into one cluster. In terms of intensity feature only, the FCM will cluster all the objects with similar intensity into one cluster regardless of their locations. In contrast, the proposed CS-FCM integrates the spatial shape information into the clustering procedure, such that objects with similar intensity but located in different regions can be differentiated. As shown in the third column, the proposed CS-FCM successfully partitions the bright ball with one cluster.

Fig.2 and Fig.3 show the segmentation results of the standard FCM and the proposed CS-FCM on the CMR images from the RV Challenge. The test is performed on data from Patient #1, Frames #100 to #119 (one cardiac cycle) in Fig.2 and Frames #140 to #159 (another cardiac cycle) in Fig.3. The segmentation results of the standard FCM are shown in the second row in Fig.2 and Fig.3. It can be observed from the figures that the standard FCM failed to separate the LV region from the image: The LV region is partitioned into one cluster together with other objects having bright intensities. In contrast, as shown in the last row, the proposed CS-FCM achieves much better results: it successfully distinguishes the LV from other structures which have similar intensity as the LV; and it correctly segments the LV even when papillary muscles are adjacent to or fall inside the LV region.

4. Conclusion

In this study, a novel clustering approach called the CS-FCM is proposed for cardiac LV endocardial border segmentation. The basic idea is to integrate the circular shape function into the standard FCM algorithm, such that pixels having similar intensity but located in different regions can be differentiated. The experimental results of the LV segmentation on real CMR images illustrate the superiority of the proposed approach over the standard FCM algorithm.

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