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An unsupervised clustering framework for automatic segmentation of left ventricle cavity in human heart angiograms

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Abstract

Cardiac function is routinely assessed from X-rays angiograms acquired at the cardiac catheterization rooms. Currently, the evaluation of cardiac function involves the global measurement of volumes and ejection fraction (EF). This evaluation requires the segmentation of the left ventricle (LV) contour. Several automatic segmentation methods have been reported, however, they are not yet fully validated and accepted in the clinical work. This paper reports on an automatic segmentation method for the ventricular cavity in mono-plane and bi-plane ventriculographic image sequences. The first step is the preprocessing, where a linear regression model is applied to exploit the functional relationship between the original input image and its smoothed version. A two stage clustering algorithm is used for segmenting the left ventricle cavity. First, an approximate initial segmentation is achieved by using a simple linkage region growing algorithm on the preprocessed version of the input image. The second stage is based on a region growing method by multiple linkage. This second stage is intended for refining the initial approximate segmentation. A validation is performed by comparing the estimated contours with respect to contours traced manually by several cardiologists. The average positioning error considering 15 mono-plane and 3 bi-plane angiographic sequences is 0.72 mm at end-diastole (ED) and 0.91 mm at end-systole (ES). The average contour error is 6.67% at ED and 12.44% at ES. The average area error is 8.58% at ED and 3.32% at ES. The left ventricle volume and the ejection fraction are estimated from manual contours and from the estimated contours showing an excellent correlation: 0.999 for ED volume, 0.998 for ES volume, and 0.952 for EF.

Keywords: Segmentation; Unsupervised clustering; Cardiac function; Cardiac images; Human heart; Left ventricle

1. Introduction

A clustering approach for image segmentation consists in determining the regions containing pixels that have similar properties [1]. In general, clustering is the division of a dataset into groups of similar objects. Clustering methods have been used for recognition of shapes [2,3]. In this context, the segmentation problem consists in detecting an object or several objects of interest in an image or a sequence of images. Clustering-based segmentation considers features such as pixel values and their location, topological relations and contour features. Examples of these techniques are the methods for classification [4] and clustering by region growing [5].

Region growing methods have been used for performing the segmentation of several medical imaging modalities [6]. The region growing is usually based on simple linkage, on multiple connections or centroid-based linkage [7]. An alternative classification method is clustering based on graph theory [8]. According to this method, data is initially represented by adjacent graphs [9]. Where a spatially connected region in the image is represented by the union of several subgraph sets. The fuzzy C—means classification algorithms have also provided good results for image segmentation [10,11]. These methods require a high computational cost, they are sensitive to initialization and they are not able to attain a global minimum [12]. Split and merge techniques have also been used for image segmentation. The idea is to start with an initial segmentation which is split according to a given condition and then, the appropriate subregions can be merged into a single new region [13]. These clustering approaches are identified in pattern recognition problems as unsupervised learning or learning without a teacher.

Classifiers designed using machine learning algorithms such as artificial neural networks, decision trees, support vector machines have proven to be efficient tools for image segmenta-

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tion. The machine learning algorithms enable the extraction of rules and patterns representing the objects of interest in an image through a training process [14]. These algorithms are considered as supervised learning methods because they require a training set of classified samples for constructing a general function that enables classification of input data images.

1.1. Left ventricle angiograms

Ventriculograms are images acquired using X-rays. These images are recorded after injection of a contrast medium in the heart cavities aiming at enhancing their contrast with respect to other tissues. Such examination enables the assessment of morphology and function of the heart. Ventriculographic image analysis requires a precise description of ventricular shape in order to quantify the parameters associated with the cardiovascular function [15,16]. Alternatively, image analysis techniques are also useful for performing the visualization of this anatomical structure [17]. The accurate description of ventricular shape and their quantitative analysis are important, since cardiovascular disease (CVD) accounts for one third of the deaths in the world [18].

1.2. Left ventricle cavity identification

Several left ventricular (LV) cavity detection methods are based on tracing a curve that delimits this heart structure and enables the quantification of this image region [19]. Other methods are based on pattern recognition techniques where clustering methods are applied. These methods allow splitting the image into a non-overlapped set of regions whose union is the complete image [11]. Additionally, there are methods that consider the contour features and region information for extracting the ventricular contours [20].

Several robust methods for ventriculographic image segmentation have been proposed. Sui et al. [21] developed a left ventricle boundary delineation system based on anatomical knowledge about the cardiac cavity. The proposed method consists of three stages: (1) a nonparametric Bayesian classification; (2) a shape regression; and (3) a rejection classification. A first LV boundary was estimated using a Bayesian classifier and three points are selected, by the user, from end-diastole (ED) and end-systole (ES) images. The shape regression approach was used to normalize the shape bias error introduced by the classifier. Left ventricle volumes, ejection fraction (EF) and areas in ED and ES phases were calculated from boundaries obtained using a Bayesian classifier and corrected boundaries after the regression shape process. These parameters were used to construct the rejection feature vectors. A boundary was rejected when the difference between two feature vectors is lower than a decision threshold. Comparisons between estimated contours and its corresponding ground truth contours provided a mean absolute contour error of 3 mm. A total of 375 clinical cases were processed.

Suzuki et al. [22] have developed a ventricular contour detector based on neural networks (NN). The detector was implemented using a multilayer neural network which was trained through a back-propagation algorithm. The training set includes LV images and ventricular contours traced by a cardiologist. Validation was performed by comparison of the area enclosed by the estimated contour with respect to the reference contour traced by the cardiologist. The average contour error obtained at end-diastole was 6.2%.

Oost et al. [20] have proposed a ventricular cavity automatic segmentation method based on active appearance models (AAMs) and dynamic programming (DP). The active appearance model is used to exploit the existing correlations in shape and texture between end-diastole and end-systole images. A dynamic programming algorithm was used to incorporate cardiac motion features to the method. The method was evaluated by using 140 images. The average border positioning error was smaller than 1.45 mm.

The methods reported in the last 5 years provided an accurate representation of ventricular borders, however, they are not yet accepted in the clinical world.

1.3. Purpose

The objective of this research is developing a left ventricle automatic segmentation method based on unsupervised clustering. This is an extended version of the clustering-based approach for automatic image segmentation presented in Ref. [23]. The performance of the proposed method is quantified by estimating the difference between contours obtained by our approach with respect to contours traced by two cardiologists (expert 1 and expert 2). The segmentation error is quantified by using a set of metrics that has been proposed and used in the literature [22,24,20].

2. Method

An overview of the proposed method is shown on flowchart in Fig. 1: first, a preprocessing stage is used to enhance the image data by means of the logarithmic subtraction and a linear regression model. In the second stage, an unsupervised clustering approach based on a region growing technique is used for classifying the left ventricle and background regions. This clustering approach uses a feature vector including the gray-level intensity of each pixel and the gray-level average of pixels included in a neighborhood around each pixel.

2.1. Image preprocessing

The images in a ventriculogram sequence acquired before injecting the contrast agent are averaged to obtain a mask image ($\mathbf{I}_{\mathrm{mask}}$). Each image in the ventriculographic sequence acquired after injecting the contrast agent (the contrasted image is denoted as $\mathbf{I}_{\mathrm{contrast}}$) is processed by logarithmically subtracting the mask image according to Eq. (1), for obtaining an image where the opacified cavity ($\mathbf{I}_{\mathrm{O}}$) is enhanced:

$$\mathbf{I}_{\mathrm{O}} = \log(\mathbf{I}_{\mathrm{contrast}}) - \log(\mathbf{I}_{\mathrm{mask}}) \tag{1}$$