Volumetric Analysis and Modeling of the Heart Using Active Appearance Model

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INTRODUCTION

Echocardiography is the fastest, least expensive, and least invasive heart imaging method. Accordingly, it is one of the most commonly used techniques to quantify the ventricular systolic function in patients. The examination is based on visual analysis of myocardial wall motion and deformation by an experienced and trained physiologist. This investigation is subjective, experience dependent, and the obtained results are only partially quantitative. The segmentation of the measured image sequences focuses on finding the exact boundaries of particular objects of interest, but it usually requires manual assistance.

Besides their several advantages, ultrasound images have the following drawbacks:

- They include not only the reflections from tissue transitions, but also several interference patterns (speckle noise). Consequently, tissues can hardly be distinguished by the intensity of their representing pixels.
- Image data highly depend on the position and angle of incidence of the ultrasound beam.
- A wide scale of imaging artifacts are frequently present, so still-frame images might contain only partial information.

In order to deal with these kinds of deficiencies, several automated segmentation techniques have been developed and reported. Geiser, Wilson, Wang, Conetta, Murphy, and Hutson (1998) proposed arc filtering for boundary detection, while Brotherton, Pollard, Simpson, and DeMaria (1994) gave a hierarchical fuzzy neural network solution. Dias and Leitão (1996) introduced an iterative multigrid dynamic programming technique based on Rayleigh distributed random variables and a probabilistic model formulated within Bayesian framework. Belohlavek, Manduca, Behrenbeck, Seward, and Greenleaf (1996) proposed the automated segmentation using a modified self-organizing map. Chalana, Linker, Haynor, and Kim (1996) traced the epi- and endocardial border using active contour models. In spite of their significant merits, these methods still neglect the following aspects:

- Sought boundaries are not always represented by the strongest edges.
- They use no a priori information concerning the allowable shapes and ranges of the segmented object.
- Segmented boundaries should be consistent with the cardiac cycle.

In the last decade, advances have been made in the content-based retrieval of medical images, such as extraction of boundaries of cardiac objects from echocardiography image sequences (Duncan & Ayache, 2000). Montagnat, Delingette, and Malandain (1999) used a two simplex mesh-based cylindrical deformable surface to produce time-continuous segmentation of 3-D sequences. Angelini, Laine, Takuma, Holmes, and Homma (2001) proposed a feature enhancement and noise suppression using a wavelet-like decomposition of the spatial frequency domain. A snake-based segmentation is carried out later on the denoised data.

Active appearance models (AAM), introduced by Cootes, Edwards, and Taylor (2001), are promising image segmentation tools that may provide solutions to most pending problems of echocardiography, as they rely on both shape and appearance (intensity and/or texture) information. Bosch et al. (2002) proposed a robust and time-continuous delineation of 2-D endocardial contours along a full cardiac cycle, using an extended AAM, trained on phase-normalized four-chamber sequences.

To understand the physiology and patho-physiology of the heart, not only the electrical activity and spatial distribution of its structures are important, but also their movement during normal and abnormal cardiac cycles. The ECG signal is measured simultaneously with echocardiography sequence recording in order to localize the investigated events. We developed an algorithm that reconstructs the heart wall boundaries and motion in order to determine the spatial and temporal cardiac activity.

In this article we present our algorithm that reconstructs the heart wall boundaries and motion in order to determine the spatial and temporal cardiac activity.

Several papers in the literature have already reported the usage of spatial AAM (Mitchell, Lelieveldt, Bosch, van der Geest, Reiber, & Sonka, 2002; Stegmann & Pedersen, 2005). The present work has the following contributions:

- Reported techniques classify ultrasound images only as belonging to systolic or diastolic interval. Our approach distinguishes normal and extra beats, and processes the corresponding images accordingly.
- ECG event classification makes possible the investigation of several pathological cases (e.g., volumetric effect of a given extra beat). Comparisons were made between normal and pathological cardiac cycles of the same patient.

MATERIALS AND METHODS

The echocardiography measurements were carried out as presented in the article with title "Echocardiographic Image Sequence Compression Based On Spatial Active Appearance Model" (see Figure 1).

The necessary minimal duration of the recorded image sequences was restricted by the semi-periodic behavior of the ECG signal. The spatial movement of the heart is constrained by the course of the depolarization repolarization cycle (Szilágyi, Benyó, & Szilágyi, 2005). For example, normal and ectopic beats imply different spatial heart movements. The studied ECG parameters, as presented in Figure 2, were: shape of QRS beat, QT, and RR distances. These parameters characterize the nature of a QRS complex, and were determined as presented in (Szilágyi, Benyó, & Szilágyi, 2003).

As the measurements were made with known spatial coordinates x, y, z, time t, and direction represented by angle α, the selected image sequences could be concomitantly processed with the measured ECG signal. All selected images that correspond to the same depolarization-repolarization phase and had almost the same ECG pattern (same QRS class, low QT, and RR difference) were included into calculations. Let $c(cl,t)$ be the clustering function that determines the appertainity coefficient to a cluster cl of a given ECG period measured at moment t. These clusters were determined with hermitage functions and self-organizing maps as presented in Lagerholm, Peterson, Braccini, Edenbrandt, and Sörnmo (2000).

The strength of the relation between a given wall segment and cluster cl is determined by function f with form:

$$f\left(x,y,z,cl,t\right)=\frac{c\left(cl,t\right)}{dist\left(x,y,z,t\right)}$$

where Box 1 represents the spatial distance at moment t of the sensor s from the studied wall piece w. The angle α of the sensor and the wall place at the image measured at moment t determinates the spatial coordinates of the muscle segment. In this way, each wall

Box 1.

$$dist(x,y,z,t)=\sqrt{\left(x_s\left(t\right)-x_w\left(t\right)\right)^2+\left(y_s\left(t\right)-y_w\left(t\right)\right)^2+\left(z_s\left(t\right)-z_w\left(t\right)\right)^2}$$