

Review

Segmentation Methods of Echocardiography Images for Left Ventricle Boundary Detection

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Abstract: Due to acoustic interferences and artifacts which are inherent in echocardiography images, automatic segmentation of anatomical structures in cardiac ultrasound images is a real challenge. This paper surveys state-of-the-art researches on echocardiography data segmentation methods, concentrating on methods techniques developed for clinical data. We present a classification of methodologies for echocardiography image segmentation. By choosing ten recent papers which have proposed innovative ideas that they proved certain clinical advantages or potential especial role to the echocardiography segmentation task. The contribution of the paper would be serving as a tutorial of the field for both clinicians and technologists, providing large number of segmentation techniques in a comprehensive and systematic manner and critically review recent approaches in terms of their performance and degree of clinical evaluation with respect to the final goal of cardiac functional analysis.

Keywords: Segmentation, Echocardiography, Active Contours Methods, Level Set (LS) Approaches, Deformable Templates

Introduction

The echocardiography and cardiac Computed Tomography (CT) are emerging diagnostic tools among modern imaging modalities for visualizing cardiac structure and diagnosing cardiovascular diseases. The echocardiography (Anderson, 2007) is real-time, non-invasive imaging modality which is less expensive than CT and Magnetic Resonance imaging (MR). Recently, the problem of automatic detection, segmentation and tracking of heart chambers in radiological imaging, such as ultrasound and CT, have received considerable attentions (Frangi *et al.*, 2001). Quality of echocardiography images influence directly on segmentation result. There are some artifacts such as attenuation, speckle, shadows and signal dropout which make the segmentation process difficult; because of orientation dependence for acquisition data, result can lead to missing borders. Since the contrast between areas of interest is usually low, segmentation task in ultrasound images turns to a challenging one (Noble and Boukerroui, 2006). Although, recently the quality of information from an ultrasound device has substantially improved, due to recent advances in transducer design,

spatial/temporal resolution, digital systems, portability, etc. (Bridal *et al.*, 2003). Due to these advances use of echocardiography has been increased in many ways; not only the traditional scope of application, CAD and diagnosis, but also new areas like therapy and image guided interventions. Therefore, currently, there is an urge in understanding how to do image segmentation, one of the oldest image processing tasks, to echocardiography data.

In ultrasound data, the LV appearance is mainly characterized by a dark region, representing the blood pool inside the chamber, enclosed by the endocardium, myocardium and epicardium, which are roughly depicted by a brighter region (Fig. 1). In ultrasonic devices, there is a great variability of the gray value distribution and the spatial texture in each of the above-mentioned regions (Santiago *et al.*, 2013). This happens among different ultrasound sequences and within the same sequence. This is due to the several reasons: Fast motion during systole phase, low signal-to-noise ratio, edge dropout (especially in the diastole phase) and the presence of shadows produced by the dense muscles, the specific properties and settings of the ultrasound machine and the anisotropy of the ultrasonic image formation (Bosch *et al.*, 2002).

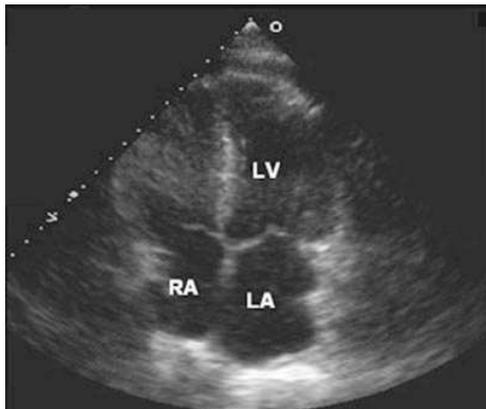


Fig 1. Echocardiography; apical four-chamber view (Chan and Veinot, 2011)

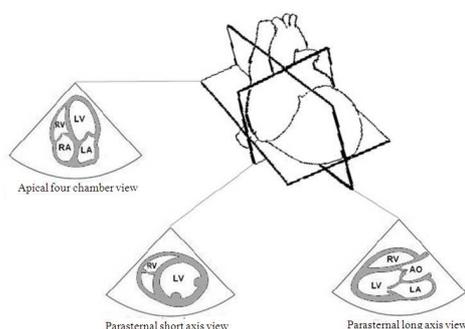


Fig 2. Explanation of different views in echocardiography (Lohr and Sivanandam, 2009)

Echocardiography images can be used for many different tests: Cardiac structure, heart development, function and also changes in normal physiologic states and pathologic conditions. For example, Left ventricular function can be obtained through 2 dimensional echocardiography images by calculating the ejection fraction. Depending on where on the chest the user positions the transducer, different views of the heart can be obtained. Some of the most common views are: Long axis view of the left atrium and the left ventricle, short axis views of the heart in planes from the base of the heart to the apex and the four chambers view; Fig. 2.

Previous works in our lab towards the goal of Cardiac Intervention Environment, Cardiovascular Information System, and Heart Diseases Diagnostic Systems has included an automatic coronary arterial tree extraction in angiograms (Moosavi Tayebi *et al.*, 2014), cardiac ultrasound fusion system development (Mazaheri *et al.*, 2014), Wavelet enhancement for x-ray angiography (Moosavi Tayebi *et al.*, 2015), 3D Multimodal Cardiac Data Reconstruction in CT Angiography (Moosavi Tayebi *et al.*, 2015), CT Angiography components categorization and coronary artery enhancement (Moosavi Tayebi *et al.*, 2014), and some surveys including review on segmentation approaches (Mazaheri *et al.*, 2013 and Moosavi Tayebi *et al.*, 2014), and review on registration of cardiac images Mazaheri *et al.* (2015).

The paper is organized as follows: In section II, we review the ideas in the field of segmentation methods; section III presents an overview of the proposed segmentation approaches for echocardiography images; section IV reviews the latest developments; and finally, section V concludes the paper with final remarks.

Segmentation Methods

Most considerations have been given to tracking the motion of the endocardium, e.g., blood pool or tissue border to allow for approximation of left ventricular volumes or areas and derived measures such as the ejection fraction and for regional wall motion analyzing. Especially, these measures are used in assessment and diagnosis of ischaemic heart disease. Most analysis is based on 2D acquisitions in which it is implicitly assumed that the principal component of motion is in the plane of the acquisition slice. Parasternal Short-Axis (SAX) is the standard 2D diagnostic views used for this and apical two-chamber (2C), Four-Chamber (4C) and Three-Chamber (3C) views. The latter three are also sometimes referred to as (apical) Long-Axis (LAX) views. The quality of data and therefore issues for segmentation, vary regarding to the view due to the anisotropy of ultrasound image acquisition, artifacts like attenuation and shadowing from the lungs which can be severe. Segmentation methods should also have strategies for avoiding the papillary muscles. Reliably finding the epicardial border, i.e., outer wall is more challenging, especially from apical views.

Lots of the preliminary works concentrated on one frame segmentation yet; considering maximum expansion or end diastole and maximum contraction or end systole frames to calculate some measurements like EF (the ejection fraction). Although, analysis should be done for the whole cardiac cycle for fully assess heart function. Cardiologists also use a movie of a heart in decision-making as the speckle pattern associated with de-forming tissue can be observed in a movie whereas in a still frame the speckle pattern is not always useful. As a result and in contrast to some other clinical application areas, in echocardiography it is perhaps more logical to view segmentation as a spatio-temporal problem. Lots of recent successful techniques have taken this point of view. A priori research of endocardial boundary detection is proposed in (Hammoude, 1998). In Fig. 3, there are some examples of segmentation results from (Bridal *et al.*, 2003).

Echocardiography images suffer from several specific drawbacks, which impede both human interpretation and automated analysis.

- There is no simple relation between pixel intensity and any physical property of the tissue visualized. Echocardiography images are formed as a combination of interference patterns (speckle) and reflections at tissue transitions.

Different tissues are mostly not distinguishable by their intensity values or texture

- Echocardiographic image information is highly anisotropic and position dependent, since reflection intensity, spatial resolution and signal to noise ratio depend on the depth and the angle of incidence of the echocardiography beam, as well as of user controlled depth gain settings
- Many imaging artifacts occur, resulting in local loss of anatomical information: Significant amounts of noise, dropouts (for structures parallel to the echocardiography beam), shadowing (behind acoustically dense structures), side lobes, reverberations and limited echo windows. Still-frame images, therefore, often only contain partial information

For these reasons, automated segmentation of echocardiographic image sequences has proven to be a challenging task. Many approaches to segmentation echocardiographic data have been proposed. They can be divided into the following classes: Level Set (LS) approaches, Deformable templates, Active Shape Models (ASM), Active contours methods, Active Appearance Models (AAM), Bottom-up approaches and Database-guided (DB-guided) segmentation (Santiago *et al.*, 2013).

Level Set Segmentation Approaches

The use of level sets for medical image segmentation aims at improving the performance of active contours due to the following. First, LS are able to increase robustness of the model by combining both region and boundary segmentation. Second, the texture and shape priors are jointly used with a continuous parametric function to model the implicit segmentation function (Bernard *et al.*, 2007; 2009; Cremers *et al.*, 2006; Lin *et al.*, 2003; Lynch *et al.*, 2008; Paragios and Deriche,

2002; Sarti *et al.*, 2005; Debreuve *et al.*, 2001; Paragios, 2003).

Deformable Templates

Alternatively, these issues can also be faced using deformable templates (Chen *et al.*, 2008; Duan *et al.*, 2010; Nascimento and Marques, 2008; Zagrodsky *et al.*, 2005) that use an unsupervised scheme for learning. However, deformable template-based methods require the knowledge of how the initialization is performed.

Both level-sets and deformable templates have demonstrated good results when dealing with medical images. Nonetheless, they also present some drawbacks regarding the prior knowledge included in the optimization function.

Active Shape Models (ASM) and Active Appearance Models (AAM)

The previously raised issues have also motivated the development of the supervised based models, in which the shape and appearance of the LV are learned from a manually annotated training set. This class of methods includes the Active Shape Model (ASM) (Cootes *et al.*, 1995; Parker *et al.*, 1994; Cootes *et al.*, 1994) and Active Appearance Model (AAM) (Bosch *et al.*, 2002; Cootes *et al.*, 1999; Mitchell *et al.*, 2001). However, both methods need a large set of annotated training images and the initialization must be close to a local optimum. Furthermore, these methods assume a Gaussian distribution of the shape and appearance derived from the training samples.

Active Contours Segmentation Methods

Active contours methods inspired the development of Level Set (LS) methods (Malladi *et al.*, 1995; Kass *et al.*, 1987; Chalana *et al.*, 1996; Hozumi *et al.*, 1997) which significantly reduce the sensitivity to initial conditions.

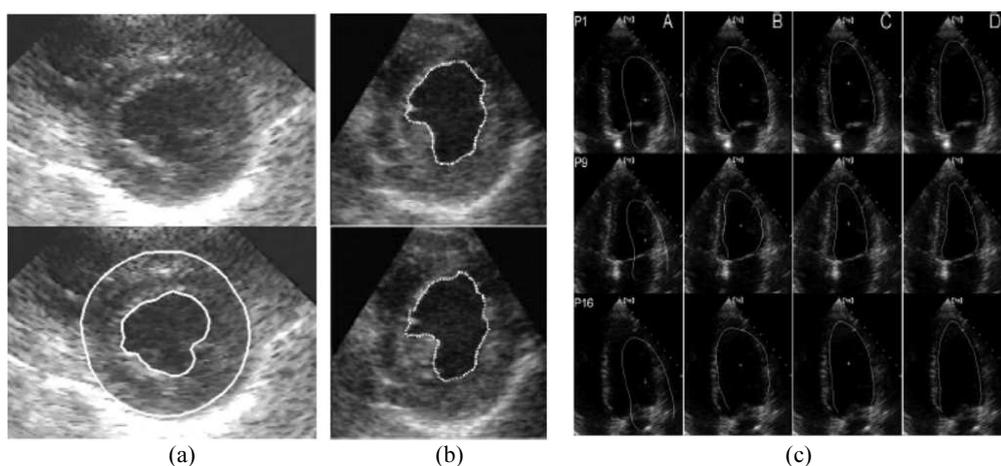


Fig 3. Some results of echocardiography image segmentation. Short Axis images (SAX) from (a) (Dias and Leitão, 1996) and from (b) (Mikic *et al.*, 1998) (c) Long Axis images (LAX) from (Bosch *et al.*, 2002)

Bottom-up Segmentation Approaches

Bottom-up approaches detect the LV boundary using edge detection that constitutes features to represent the object boundary. Although these methods have low computational complexity, they are sensitive to initial conditions and generally lack robustness to imaging conditions (Sonka *et al.*, 1995; Zhang and Geiser, 1984).

Database-Guided (DB-Guided) Segmentation

The above issues motivated the proposal of the DB-guided segmentation approaches that use supervised learning techniques (Georgescu *et al.*, 2005; Zhou *et al.*, 2005). Specifically, discriminative learning model based on boosting techniques (Freund and Schapire, 1997) is developed to segment LV from ultrasound images. Another important point in the DB-guided approach is its independence regarding an initial guess. Instead of that, a full search is conducted in the parameter space. However, these methods have several drawbacks. Besides the high complexity of the search process, super-vised learning methods face two main difficulties which are the large number of training images (in the order of hundreds) needed to estimate the parameters of the model and the robustness to imaging conditions absent from the training set (Carneiro and Nascimento, 2010; Carneiro *et al.*, 2008; Zhou *et al.*, 2005).

Though partially successful, three major problems are associated with many of the existing echocardiographic contour detection strategies.

- The current methods typically do not include information about the allowable range of shape and appearance variations of the segmented objects. Ultrasonic image information is often ill-defined or incomplete. Therefore, extensive model knowledge about the characteristic organ shape and appearance, its anatomical and pathological shape variations and spatial organ embedding should form an integral part of a robust segmentation approach
- Most existing methods use implicit, global and oversimplified models for the contour location. The location of strong local image features, however, does not always correspond to the desired contour as drawn by an expert human observer. The exact location of the contour cannot always be determined from the strongest image evidence, but should be modeled or learned from examples provided by expert observers. Moreover, contour characteristics vary for different parts of the local (and still unknown) anatomy
- Many automated techniques perform a static segmentation on single 2D frames or use

rudimentary continuity constraints and, therefore, often produce segmentation results that are inconsistent with the dynamics of the cardiac cycle. An expert observer, however, utilizes knowledge about cardiac contraction dynamics and temporal coherence of structures and texture to resolve ambiguities and to determine the exact LV boundary location, mostly after reviewing the image data in a cine loop. Recently, several methods have been reported that try to deal with the third problem in time sequences of either 2D or 3D echocardiograms

Nonetheless, 3D echocardiography has gained increasing interest and several methods to perform the 3D segmentation of the LV have become available in literature (Noble and Boukerroui, 2006). One approach to perform 3D segmentation is to consecutively applying 2D segmentations to each image plane and assembling them into a 3D structure (Nillesen *et al.*, 2006; Scowen *et al.*, 2000) as cardiologists manually do in such cases. However, such approaches require additional methods to pre-vent spatial inconsistencies in the surface. Other approaches have performed the 3D segmentation using 3D active contours such as level-set (Hang *et al.*, 2004; Yu *et al.*, 2006; Juang *et al.*, 2011). Furthermore, over the last decade some effort has been put into developing 3D+t LV tracking systems that are able to segment the LV over the course of the cardiac cycle, such as (Orderud *et al.*, 2007; Yang *et al.*, 2008).

Echocardiography Image Segmentation Approaches

2-Dimensional Endocardial Boundary Estimation

For echocardiography endocardial segmentation, finding contour method is the most common technique which has been considered. Since contrast surrounding the boundary of the left ventricle differs relating to the appropriate situation of the transducer orientation and also artifacts and attenuation, the boundary would not be clear. Therefore, conventional gradient intensity based techniques don't have success on common ultra-sound data.

Mishra *et al.* (2003) presented an active contour approach which for optimization used a genetic algorithm. Two experts have done manual descriptions on twenty frames and the usual amount compared with the automatic technique to indicate that the inter-variability among experts was resemble to the difference between the manual and automatic techniques. Mignotte and Meunier (2001) for the segmentation of short axis parasternal images, apply a statistical external energy in a discrete active contour and discussed this is work best for echocardiography

images which they have huge noise and disappeared borders. With this aim, a shifted Rayleigh distribution was applied to show the statistics of gray levels.

Mignotte *et al.* (2001) suggested a border detection algorithm, using Bayesian framework which used deformable templates for modeling the precedent information. This technique is unsupervised and fully automatic. The approximation problem which is formulated as a Maximum A Posteriori (MAP) optimization solved via a genetic algorithm. They also presented a comparison to manual descriptions which is done by two experts. Boukerroui *et al.* (2003) proposed the same Bayesian methodological method where the segmentation is region-based. They used level sets which they are usually considered as an alternative to active contours for echocardiography image segmentation.

Lin *et al.* (2002) proposed a different level set segmentation approach where fuses region and edge information with spatial scales. For this method they considered a closed curve as a border. They applied segmentation method to single 2D slices, while used their proposed method to rotational 3D echocardiography images. When the quality of echocardiography images is good, their method work well. Yan and Zhuang (2003) used an adaptation of the fast marching cube technique for applying the level set technique on echocardiography data. They used a mean gradient intensity based measure to deduct errors related to local feature measurements. They discussed the results only quantitatively, but applied their algorithm to an apical four chamber view and a SAX (parasternal short axis) view.

Boukerroui *et al.* (2003), proposed an accurate adaptive region segmentation which works in a Bayesian frame-work. The adaptive property for compensating existence inhomogeneity and non-uniformity of echocardiography data within the same tissue, considers a slow spatial variation and local class mean. They evaluated their method by manual description which is done by an observer on a LAX (long axis view) and compared with another segmentation which is also region based method, Xiao *et al.* (2002).

ANN-based (Artificial neural network) techniques also have been used for region based segmentation (Rekeczky *et al.*, 1999; Noble and Boukerroui, 2006). For example, Binder *et al.* (1999) applied a 2 layer back propagation network to end-systolic and end-diastolic SAX images (parasternal short axis view) from thirty-eight patients with different quality data which consist of 12 images with good quality, 13 images with moderate quality and 13 images with poor quality. This is one of the few researches that have done experience at data of different quality. Result of segmentation was successful in thirty-four of the thirty-eight database. The automatic technique was compared with manual tracking which is done by 2 experts.

Spatio-Temporal Methods (2D+T)

We can consider echocardiography image segmentation as a Spatio-temporal problem, as the Region Of Interest (ROI) changes in a non-rigid manner and it has inhomogeneity over the frames. Spatio-temporal examination gives a local approximate of image velocity along with segmentation and leads to more suitable localization of a boundary. For example, Mulet-Parada and Noble (2000) presented a local-phase-based approach for detection endocardial border with Spatio-temporal space. They showed that local phase would be a better basic for echocardiography feature detection and also segmentation; because local phase is fixed to intensity magnitude. They used a derived measure from phase, which is called feature asymmetry for identifying the endocardium in a 2D+T space (Spatio-temporal). Since then local phase approach has been used for feature identify in lots of ultrasound researches (Mulet-Parada, 2000; Ye *et al.*, 2002; Sanchez-Ortiz *et al.*, 2002).

Mikic and others presented an active contour technique, provided by the method of Singh and Allen (1992; Boukerroui *et al.*, 2003), which propagation of a contour from one single frame to another one was guided by optical flow approximates (Mikic *et al.*, 1998). This information can be used for determining the initialization of an active contour. Metrics in active contour empirically determined. The approach was evaluated on 3 long axis, 3 short axis and 2 aortic roots images; and compared with three to five manual delineations (Fig. 3a).

Dias and Leitão (1996), presented an approach for the both epicardial and endocardial boundary approximation like the former research of Friedland and Adam (1989) and also Teles de Figueiredo and Leitaa (1992). In (Friedland and Adam, 1989; Teles de Figueiredo and Leitaa, 1992), they used polar coordinates for contour description; although, as far as we know, this is the first method which considers noise statistics in border optimization. They modeled the estimation problem in a Bayesian frame-work as a MAP estimation problem with a Spatio-temporal MRF for the regularization term and Rayleigh statistics for the data term. For solving the optimization problem, they used a repetitive multi-grid dynamic programming algorithm. They presented results on one short axis view image and also on synthetic data. Figure 3(a) shows an example result from (Teles de Figueiredo and Leitaa, 1992).

Figueiredo *et al.* (2000), inside the same framework, proposed a parametric contour segmentation in an unsupervised way, based on B-spline descriptions. They applied a MDL (minimum description length) parameter to estimate B-spline knots' number.

Jacob *et al.* (1999; 2001; 2002) proposed a Kalman filter based epicardial and endocardial boundary

tracing technique based on contour tracking method of (Blake and Isard, 1998). They built a Spatio-temporal contour model where it has 2 sections; a shape model made from manual description of the left ventricle boundaries of a motion model and a training set.

Bosch *et al.* (2002) presented the Active Appearance Motion Model (AAMM) to represent the appearance and shape of the endocardium, also its motion by applying an adaption of the Active Appearance Model (AAM) technique; Fig. (3c) shows an example of this technique. Mitchell *et al.* (2002) proposed a 3D active appearance model for segmentation of 4 chamber cardiac ultrasound images (2D with the third dimension time, 2D+T). This technique adjusts itself in time and space; it means it is Spatio-temporal. They trained the model from manually segmented instances in a learning phase.

Endocardial Boundary Detection in 3D and 4D Images

In previous research on 3D endocardial boundary detection, Coppini *et al.* (1995) have taken into account reconstruction and segmentation of Left Ventricle (LV) from freehand echocardiography images which they are captured at 4 set angles regarding to the 4 chambers view.

Song and others considered the segmentation process in a Bayesian framework as a surface fitting problem which finding a 3D surface where has the largest previous probability is the aim (Song *et al.*, 2002). Wolf and others (Wolf, *et al.*, 2002) proposed the Restricted Optimal Path Exploring Segmentation (ROPES) method, where is a semi-automatic segmentation. They applied their method to 2D slices of 3D TEE (transesophageal echocardiography) data.

Angelini *et al.* (2001) considered segmentation of real time 3D echocardiographic images from a volumetric process. Montagnat *et al.* (2003) extended a 3D+T model based segmentation method for rotational 3D echocardiographic data. This research used a combined edge and region-based approach and for analysis it uses a cylindrical geometry. Especially, the orientation and intensity gradient magnitude are applied, together with a region-based on a local analysis of intensity values. The answers are set in a variational frame and some of their features make them well suited to 3D echocardiographic segmentation. Sarti *et al.* (1999) proposed a model for multiple scale analysis of space time echocardiography images which trying to solve a nonlinear (partial) differential equation fusing proposed methods of the Galilean invariant movie multi scale analysis of Guichard with anisotropic

diffusion model from Perona Malik (Guichard, 1998; 1994). In (Mikula *et al.*, 2000), authors extended spatial diffusion from Perona Malik and substituted it with a nonlinear anisotropic smoothing curvature driven level sets (Preußer and Rumpf, 2002). Then, Mikula and others proposed a truly-coupled Spatio-temporal anisotropic diffusion (Mikula *et al.*, 2004). In this research, time smoothing was curvature driven and they discussed, it resulted in better smoothing with velocity discontinuity preservation in compare with the last acceleration-based smoothing.

Corsi *et al.* (2002) applied a level-set based segmentation algorithm to real-time 3D echocardiographic data from a volumetric system. The level-set's initialization is defined by manual delineation on a few Short Axis frames (SAX). Sarti and others proposed a level set segmentation method for images, like echocardiographic data, that can have missing borders (Sarti *et al.*, 2000; 2002). This method differs completely with anterior level-set segmentation methods that consider just the zero level-set. Their research was later developed by (Corsaro *et al.*, 2004) and Mikula *et al.*, (2004); a robust and accurate semi-implicit numerical volume scheme was presented to solve the Riemannian mean curvature flow equation in 2D (Mikula *et al.*, 2004) and 3D (Corsaro *et al.*, 2004). Examples of segmentation from classical Kanizsa triangle were presented to show that the technique can find missing borders. They also presented some examples on 3D cardiac (Mikula *et al.*, 2004) and fetal echocardiography images (Sarti *et al.*, 2000).

Myocardium and Epicardium Segmentation

Eventually, for analysis and segmentation of myocardium, there is a very limited literature (Kerut *et al.*, 2000) and also for epicardial boundary estimation (Dias and Leitão, 1996; Feng *et al.*, 1991; Malassiotis and Strytzis, 1999). These two tasks are both difficult to do directly on B-mode images. Also it is done a little research for finding methods which work on general clinical data rather than data from subjects with a good acoustic window. We addressed to some of the few researches which have done so above (Bosch *et al.*, 2002; Binder *et al.*, 1999; Mitchell *et al.*, 2002). One further exception is the work of Boukerroui *et al.* (2001) which considers how to enhance B-mode images to reduce the effect of attenuation and enhance features. Although that meth-od was shown quantitatively to reduce attenuation, enhance features and not introduce artifacts after enhancement, that approach has not to date been fully tested in clinical practice.

Review the Latest Developments

Kucera and Martin (1997) presented an approach with an external force region based in their previous research for LV segmentation. In an active contour 3D model, they defined this force with time as one dimension. The proposed technique is relatively reliable on Short and Long Axis (SAX and LAX) views.

Sarti *et al.* (2005) applied a region based method in their proposed segmentation technique which they assemble a prior knowledge for statistical distribution of gray levels. They used a level set technique to drive the curve evolution to get a maximum likelihood segmentation of the target, regarding to the statistical distribution law of image pixels. When comparing the area enclosed by the resulting contours from this technique with manually outlined contours the correlation is excellent.

Sarti *et al.* (2005) also proposed a region-based segmentation in their adaptive segmentation approach. They use a weighting function that considers both global and local statistics during the segmentation process. The segmentation of the left ventricle shows good results when compared with manual outlines by a medical expert.

Mishra *et al.* (2003) use an active contour model when segmenting the left ventricle in Short Axis (SAX) view. They solve the optimization problem with using a Genetic Algorithm (GA) and the performance is com-parable with interobserver variations.

Mignotte and Meunier (2001) proposed a multi-scale approach to the contour optimization. Their external energy in the snake energy function is also region based. They demonstrated some segmentation results for Short Axis (SAX) views that are qualitatively good.

Chen *et al.* (2007) built an active contour algorithm in a geometric way with a prior intensity and shape. The results of applying the method to a 2 chamber view are promising.

Bosch *et al.* (2002) proposed an Active Appearance Motion Model (AAMM) that was used to do a segmentation of the left ventricle. This is an extension of Active Appearance Models (AAM) and they did an automated segmentation over the full heart cycle. Their results are comparable with inter-observer variations.

Mitchell *et al.* (2002) did a fully 3 dimensional Active Appearance Models (AAM) with time as one of the dimensions in echocardiography images. They obtained a correlation coefficient of 0.79 when comparing the area of the Left Ventricle (LV) defined by their method and an observer respectively.

Several other methods have also been evaluated for this segmentation problem, including a fuzzy multi-scale edge detector (Setarehdan and Soraghan, 1999), artificial neural Networks (Binder *et al.*, 1999; Rekeczky *et al.*, 1999) and a Kalman filter based tracking method (Jacob *et al.*, 2002).

All of these methods give acceptable segmentations of the Left Ventricle (LV) in Long Axis (LAX) and/or Short Axis (SAX) views.

Santiago *et al.* (2013) offered a bottom-up deformable-based model for the segmentation of the Left Ventricle (LV) in 3D ultrasound data. The presented methodology is based on Probabilistic Data Association Filter (PDAF). After a rough initialization given by the user, the following steps are performed: (1) low-level transition edge points are detected based on a prior model for the intensity of the LV, (2) middle-level features or patch formation is accomplished by linking the low-level information, (3) data interpretations are computed based on the reliability (belonging or not to the LV boundary) of the previously obtained patches, (4) a confidence degree is assigned to each data interpretation and the model is updated taking into account all data interpretations.

Landgren *et al.* (2013) presented a semi-automated segmentation method that used a region based snake. To avoid any unwanted concavities in the segmentations due to the cardiac valve they use two anchor points in the snake that are located to the left and to the right of the cardiac valve respectively. For the possibility of segmentations in different stages of the heart cycle these anchor points are tracked through the cycle. This tracking is based both on the resemblance of a region around the anchor points and a prior model of the movement in the y-direction of the anchor points. The tracking of the anchor points also seems to work well. The use of a prior model turned out to be necessary when testing the tracking algorithm without it. With no prior model the anchor points have a tendency to wander away or not follow the cardiac valve back when the heart relaxes.

McManigle *et al.* (2012) proposed a two-step Hough transform and introduced a myocardial segmentation technique based on the circular Hough transform. They developed a preliminary segmentation technique which takes advantage of both endocardial and epicardial image information. The segmentations generated are compared to expert manual segmentation of 3D+t echocardiogram data and evaluated for their appropriateness to initialize a subsequent segmentation step.

Skalski *et al.* (2012) presented an application of active contour without edges method to left ventricle

segmentation in ultrasound echocardiographic images. The proposed procedure consists of three basic modules: ROI calculation by means of Hough transform, image denoising by means of SRAD filtration and, finally, image segmentation by means of active contour without edges method. The proposed scheme can be modified and in conjugation with deformable image registration methods, e.g., B-Spline Free Form Deformation or Spring Mass system can be used for calculation of deformations of hearts structures like heart walls.

Pearlman *et al.* (2012) presented an algorithm for segmenting left ventricular endocardial boundaries from RF ultrasound. Their method incorporates a computationally efficient linear predictor that exploits short-term spatio-temporal coherence in the RF data. Segmentation is achieved jointly using an independent identically distributed spatial model for RF intensity and a multi-frame conditional model that relates neighboring frames in the image sequence. Segmentation using the RF data overcomes challenges due to image inhomogeneities often amplified in B-mode segmentation and provides geometric constraints for RF phase-based speckle tracking. The incorporation of multiple frames in the conditional model significantly increases the robustness and accuracy of the algorithm.

Dietenbeck *et al.* (2012) they proposed a method to segment the whole myocardium (endocardial and epicardial contours) in 2D echographic images. This is achieved using a level set model constrained by a new shape formulation that allows modeling both contours. Also their framework allows segmenting the whole myocardium for the four main views used in clinical routine. They approximated the heart boundaries by two hyper-quadrics that are then used as a shape prior for the evolving contour. The method is validated on a dataset of clinical images and compared with expert segmentation.

Robust and fast 3D tracking of deformable objects, such as heart, is a challenging task because of the relatively low image contrast and speed requirement. Many existing 2D algorithms might not be directly applied on the 3D tracking problem. The 3D tracking performance is limited due to dramatically increased data size, landmarks ambiguity, signal drop-out or complex non-rigid deformation. Yang *et al.* (2011) presented a 3D tracking algorithm, Prediction based Collaborative Trackers (PCT) and tested in both 3D ultrasound and CT. Compared with tracking by detection and 3D optical flow, PCT provides the best results. They demonstrated that PCT increases the

tracking accuracy and especially speed dramatically. Their tracker is tested on three clinical datasets for three 3D heart tracking problems with two different imaging modalities: endocardium tracking of the left ventricle, dense tracking in the myocardial regions between the epicardium and endocardium of the left ventricle and whole heart four chambers tracking.

Recently, introduced variant of the level set method called level set without edges. This variant takes advantage of the intensity value of area information instead of module of gradient which is typically used. Such approach guarantees stability and correctness of algorithm working on the border between object and background with small absolute value of image gradient.

Skalski and Turcza (2011) proposed an algorithm for heart shape estimation (segmentation) in ECHO images using this level set method without edge. They proceeded the image segmentation with automatic Region Of Interest (ROI) calculation. The main idea of ROI calculations is to receive a triangle-like part of the acquired ECHO image, using linear Hough transform, thresholding and simple mathematics. The described algorithm involves the following three steps: Removing multiplicative noise from an image by nonlinear diffusion filtration, determination of diagnostically relevant area by Hough image transformation and finally image segmentation with active contour algorithm. Erroneous situations with pixels representing background are classified as an object by an algorithm were excluded by the proper restriction of the segmented area and controlling contour evolution process using information other than image gradient magnitude.

Juang *et al.* (2011) proposed a method to automatically segment the left ventricle and atrium without any user input in 3D ultrasound volumes. Their method can segment volumes with open and closed mitral valves. They utilized the radial symmetry transform to determine a central axis along which the 3D volume is warped into a cylindrical coordinate space. A graph is constructed for the volume in this space and a min-cut algorithm is applied to segment the left ventricle and atrium from the background. The segmented results are transformed back to the Cartesian coordinate space. This method can be extended to other types of segmentation techniques, such as level sets and watershed. The method is generic enough to be applied to other imaging modalities such as MRI or CT (Table 1).

Table 1. Validation of echocardiography image segmentation

Ref	Year	Modality	Method	Dimension	Automation	Evaluation	Segmented part	Performance	
								Measure	Value
Santiago <i>et al.</i> , 2013	2013	4C	Contour method	3D	No	Quantitatively	LV	-The Hammoude metric (dHMD) -The average distance, dAV -Hausdorff metric, dHDF -Mean absolute distance, dMAD	0.15±0.1mm 2.5±1.1 mm 6.9±2.6 mm 3.6±0.9 mm
Landgren <i>et al.</i> , 2013	2013	SAX4C	Region based	3D	Semi-automated	Qualitatively	LV	-The computation time for performing segmentation in each frame in one cardiac cycle	40 s
McManigle <i>et al.</i> , 2012	2012	SAX	Modified Hough transform method	3D+t	Yes	Quantitatively	LV	-Distance between manual and Hough transform center points -RMSD between manual and Hough transform endocardial radii over 8 angles -RMSD between manual and Hough transform epicardial radii over 8 angles	3.31±2.65 mm 2.57±1.78 mm 3.04±2.10 mm
Skalski <i>et al.</i> , 2012	2012	4C	Active Contour (snake) Model -Hough transform	2D	Yes	Quantitatively	LV	-Dice's coefficient -Borders calculation -SRAD filtering -Initial contour calculation -Contour evolution	0.70±0.17 1.64 0.2 0.008 0.48
Pearlman <i>et al.</i> , 2012	2012	RF ultrasound	Spatio-temporal predictor	3D RF	Yes	Quantitatively	LV boundaries	-Dice coefficient -Mean absolute distance -Hausdorff distance	0.8-0.93 mm 1.5-2.7 mm 4.8-9.1 mm
Dietenbeck <i>et al.</i> , 2012	2012	SAX LAX 4C 2C	Geometrically constrained level-set method	2D	Yes	Quantitatively	Myocardium	-Hausdorff Distance (HD) -Mean Absolute Distance (MAD) -Dice's coefficient	1.23-2.96 mm 0.5-1.07 mm 0.96-0.01 mm
Yang <i>et al.</i> , 2011	2011	SAX 4C 3C 2C	Prediction based Collaborative Trackers (PCT)	3D	Yes	Quantitatively	LV tracking	-3D optical flow -Tracking by detection -PCT	0.94 - 10.38 0.59 - 9.89 0.38 - 9.80
Skalski and Turcza, 2011	2011	4C	Level set Method-active contour algorithm	3D	Yes	Quantitatively	Heart	-True Positive Fraction (TPF) -False Negative Fraction (FNF) -False Fraction (FF)	0.91 0.10 0.82
Juang <i>et al.</i> , 2011	2011	2C	Graph cuts and the radial symmetry transform	3D	Yes	Quantitatively	LV cavity and atrium	Mean Error ± StdDev on data A1 Mean Error ± StdDev on data A2 Mean Error ± StdDev on data B1 Mean Error ± StdDev on data B2	2.37 ± 3.59 mm 2.79 ± 3.36 mm 2.28 ± 3.49 mm 2.10 ± 2.37 mm

Table Explanations

Tables 1 summarize the evaluation which has been done on well-known techniques which explained in last Sections related to 6 common views echocardiography image for segmentation.

Key to table:

- Modality: SAX = Short Axis, LAX = Long Axis, XC = apical X Chamber (X= 2, 3, 4)
- Performance Metric: as mentioned, since researches are different in their measurements and naming, it is so difficult to set them through the studies
- Automation: (yes) full, (no) interactive guidance/correction

Conclusion

Usually, for examining medical image segmentation techniques in a quantitative way, we can use animal mod-el studies, phantom studies, simulation and manual delineation; one modality as a “reference” or “gold standard”, or some relation between clinical result. Mostly, clinical info is utilized in evaluation. However, there is some literature on echocardiography segmentation techniques shows that some phantom and simulation studies also have been done. This somehow indicates problems in defining real phantoms and simulations. The most popular metric of performance evaluation is manual delineation on clinical data; although regarding to

clinical area, there can be huge inter-expert and intra-expert variability; it is due to the fact that manual segmentation is not a routine task that they normally do. Therefore, delineation can be difficult to do. So, when manual delineation is applied as the gold standard, we should to take care in explaining results. Because there is no standardization of performance metrics, it is hard to compare techniques directly. That's why, in some researches, they use multiple experts to define the reference. We have made comparison between methods which proposed by research groups, since there is no standard database to compare results. Lacking of a standard dataset is confusing, since quality of echocardiography images varies a lot, in compare with other clinical imaging such as CT or MRI.

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Authors' Contributions

All authors have made substantial contributions to conception and design, data acquisition, analysis and interpretation of the data. All authors read and approved the final manuscript.

Ethics

The authors declare that *there are no conflicts of interest.*

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