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A comparison of left ventricular border detection techniques applied to 2D echocardiograms

Eduardo Jyh Herng Wu*, Denys E. Nicolosi

Abstract **Introduction:** *Cardiology has been one of the most important areas of medicine. For several applications to diagnose the heart functions diseases the measurement of left ventricular (LV) cavity area and LV fractional area change are of vital necessity. To achieve this task, it is necessary to trace the border of left ventricle, which manual tracing is a tedious and time-consuming work. To solve this problem, many techniques to automate this border detection have been developed using the specialist tracing as gold standard.* ***Methods:*** *The purpose of this approach is to analyze the features of the main techniques applied to left ventricle border detection in medical imaging. To facilitate understanding, the left ventricle border detection techniques are divided into three categories: image-based techniques, model-based techniques and pixel-based techniques. For each of the category, a literature review was made to get examples of the techniques applied to left ventricle border detection and to describe them. The result of this review is a comparative table where the main features of each technique is compared.* ***Conclusion:*** *From the comparative table we can conclude that the not mentioning of many features of the techniques by the authors and the lack of a standardization of the evaluation techniques hamper a more satisfactory comparison.*

Keywords *Border detection, Left ventricle, Medical imaging.*

*e-mail: wujyh@ig.com.br
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Introduction

Left ventricle size and LV ejection fraction (LVEF) are important for patient management, clinical decision-making and prognosis (Muraru *et al.*, 2010; Soliman *et al.*, 2008) that predicts a wide variety of cardiac diseases (Rahmouni *et al.*, 2008). Echocardiography has been widely used in the evaluation of cardiac systolic function because it is a noninvasive technique that causes minimal discomfort, besides its low cost and the absence of ionizing radiation. The quantification of cardiac structure or dynamics requires identification of borders. Manual tracing, however, is tedious and subjective especially on noisy ultrasound images (Sapra *et al.*, 1998; Sonka *et al.*, 1998; Spencer *et al.*, 2002; Vandenberg *et al.*, 1992). For this reason, many techniques have been developed to automate the left ventricle borders identification and simplify the subsequent area/volume assessment. To assess the efficiency the automatic techniques, it is necessary to compare their results with the specialist tracing as gold standard.

Some problems arise when we want to extract the contours of the left ventricle in 2D echocardiography image:

- Difference of size, shape and orientation of the ventricles between patients;
- Low contrast between the blood and the heart wall, which makes the edge of the left ventricle practically invisible in some regions;
- Presence of noise, especially in ultrasound images, whose size is equal to the contrast of edges;
- Presence of papillary muscle and organs overlapping the left ventricle that have the same order of magnitude as the wall of the left ventricle;
- Left ventricle out the window scanning problems due to cardiomegaly.

Depending on the extent of operator intervention, the border detection process can be manual, semi-automated or automated. The manual process (manual tracing done by the specialist) is used as gold standard to compare with others. In semi-automatic processes, the operator can intervene in various ways as determining points in the border (Di Bella *et al.*, 2010; Kuhl *et al.*, 2004), applying image processing tools (threshold, contrast adjustment, morphological filtering) to help the border detection (Reis *et al.*, 1998) or manually adjusting the border drawn by the system (Soliman *et al.*, 2007; Yu *et al.*, 2003). Most automatic processes need some operator help, based on 'a priori' knowledge, as gains adjustment (Chuang *et al.*; 1999; Kirkpatrick *et al.*, 2005; Mandarino *et al.*, 1998; Zhang *et al.*, 1998), determination of the region of interest (ROI) (Gorcsan *et al.*, 1993a; Morrissey *et al.*, 1994; Wilson and Rahko, 1995; Wu *et al.*, 2008) or determination of the center or any point inside de LV cavity (Binder *et al.*, 1999; Hozumi *et al.*, 1997).

With this article, we have the objective of comparing different techniques used in left ventricle borders detection which can be classified as image-based, model-based (active modeling) or pixel-based. Since the endocardial wall is the only contour required to compute ventricular volume (Petitjean and Dacher, 2011), we focused on endocardial border detection.

We have concentrated on 2D echocardiography and not included 3D echocardiography because the main goal of this review is the comparison of border detection techniques and these techniques applied on 2D echocardiography are similar to those applied on 3D echocardiography (Hung *et al.*, 2007).

Methods

A literature review based on SIBI/USP and PubMed databases was made to get the main publications about left ventricle border detection techniques applied to 2D echocardiography images. We conducted a systematic review searching for all publications that have comparisons of automatic tracing with manual tracing using correlations or area comparisons on which the authors presented at least five of the following features:

- Border detection technique – describes the technique used to detect the border;
- Pre-processing operations – describes the operations used to refine the image before the border detection technique;
- Pos-processing operations – describes the operations used to refine the image after the border detection technique;
- User interface – describes the interventions the user needs to do to help the process;
- Number of frames – describes the number of frames required by the system to process the border detection;
- Comparison technique – describes the technique used to evaluate the error compared with the gold standard;
- Results – describes the results (errors) obtained by the technique.

We classified the selected publications into three categories: image-based, model-based and pixel-based.

Image-based techniques

Image-based techniques are those that apply image processing tools to enhance features of interest on the image. Melton *et al.* (1983) applied a "rational gain compensation" approach to detect cardiac borders in real-time. Their technique corrected for differences in attenuation along individual lines-of-sight in the 2D echo image. Their instrument operates by determining from the "instantaneous" backscatter whether the ultrasound beam is traversing myocardial tissue or blood by comparing the amplitude of the backscatter to a preset threshold. The presence of an edge was detected by this signal transitions and from this signal, an edge signal and a composite edge signal were derived. The edge and composite edge signals for each line-of-sight were used to form edge image, that depicts only cardiac edges, and composit edge image, that distinguishes tissue from blood in addition to depicting the edges. Using six excised dog hearts, and comparing their results with manual tracing, they obtained a correlation coefficient of $r = 0.96$ and regression line of $y = 0.81x + 1.1$ [cm^2] for area and $r = 0.92$ and regression line $y = 0.84x + 0.78$ cm for perimeter. Maes *et al.* (1991) applied a dynamic programming technique (minimum cost algorithm with the following cost functions: radial gradient, tangent gradient, deviation from the resample line and gradient in texture) to detect the endocardial border in short axis view and long axis view on 2D echocardiograms after a noise reduction by sigma filter in a 15 × 15 window. The method requires the user to determine a region of interest (ROI): a circle for short axis view (center point and a radius) and a parabola for long axis view (annulus fibrosus of the mitral valve (2 points) and apex (1 point)). The algorithm for delineating the endocardium assumes a rough localization of the endocardial border, referred as 'resample line', in the first frame. Based on the slowly varying parameters (size, shape and displacement), the resample line was corrected to compensate for the larger deviations in the following frames that improved considerably the final result. To improve the raw contour, the applied a gaussian spatial smoothing and they executed a contour verification by comparing contours in the consecutives frames to reject contours whose difference exceeded a certain threshold and to call for manual corrections if the contour is rejected more than three times. To calculate the volume the authors applied a modified Simpson rule based on three short axis slices: one at the mitral valve, one at the papillary muscles and one close to the apex. They assessed the accuracy of the volume calculation and indirectly the delineation by comparing the actual and calculated volume of the LV of excised dog hearts filled with a known amount of water. They obtained a correlation coefficient R^2 significantly better with automatic delineated contours (0.99) than with hand drawn contours (0.97). Vandenberg *et al.* (1992) converted the received radiofrequency signal from echocardiography imaging into a power signal that was compared with a threshold for locating the tissue-blood interfaces along each scan line. Before the image acquisition, the operator adjusted the transmit power and time-gain compensation controls in order to approximate the automated borders to the visually apparent endocardial surface and selected the region of interest (ROI) with a track-ball. They used two training sets of images to establish optimal methods of gain setting and then evaluated in a test set of images. The comparison was performed by linear regression between the manually drawn areas and real-time areas. Timperley *et al.* (2006) applied a spatio-temporal boundary detection based on a phase-based method, which removes the spurious artifacts by a number of temporally orientated filters, to improve the reporting of regional left ventricular function using contrast echocardiographic images. The importance of spatial features was weighted according to their temporal significance. By a weighted Kappa test for agreement, they concluded that, for contrast images, the use of a semi-automatic boundary detection system which presents the reader with a moving endocardial border and a fixed end-diastolic border is an effective aid in the interpretation of regional function by inexperienced echocardiographers. Lacerda *et al.* (2008) applied watershed and radial-search-based algorithm to obtain the left ventricle contours in short-axis and long-axis images. They pre-processed the image with a high boost filter, followed by elevation filtering, thresholding and LoG filtering. For the short-axis images, the initial contour was obtained using watershed to identify and label regions in the pre-processed image and region filter to eliminate small regions in the left ventricle inner cavity, using empirically determined threshold values. From this initial contour, candidate points for the final contour were selected by the algorithm using radial search and shortest distance interpolation was used to trace a closed contour. Because the low contrast and dropouts in 2D echocardiography images, they proposed an extra step for segmenting long-axis images sequences, a sequential radial search. If no candidate points are found for a particular radius, the sequential algorithm searches for candidate points in the boundary extracted from a previous reference frame. The contours traced by this algorithm were compared to contours manually-prescribed by the specialist using three different metrics (Mean Pixel Deviation, Percentual Error and Sum Error) and

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showed very good agreement. Reis *et al.* (2008) applied the thresholding operation to obtain left ventricle border in 2D short axis echocardiographic images. Before the thresholding operation, they applied some pre-processing steps as rejection of frames with strong motion, denoise, increasing of contrast and morphological gray scale closing. To detect the frames with strong motion, they used sets of ten consecutive frames in a sliding window fashion and rejected five frames with stronger movement from each set. The noise reduction was obtained by averaging the remaining five (noisy) frames of each set of ten frames and a Laplacian of the Gaussian operator was applied to contrast enhancement. To obtain a uniform cardiac cavity, a morphological closing in gray scale is used and the value of threshold is chosen such that 72.7% of the pixels have gray scale level below it. Amorim *et al.* (2009) applied fusion of images from 3 cardiac cycles of 30 frames per cardiac cycle to obtain the left ventricle border in echocardiography images. As pre-processing step, the fusion of 9 images (3 consecutive images from each of the three cycles) produced a composite image and by moving the window of 3 neighboring frames (heuristically adopted), a set of 28 segmented images are obtained, covering a complete cardiac cycle. Gaussian filter was applied to smooth the image and to increase binarization tolerance. Otsu thresholding (Otsu, 1979; Suri, 2000), or dynamic thresholding, was applied to the smoothed image using the index calculated before applying the Gaussian filter. In the segmentation stage, after the identification of the ROI, successive erosions are applied to reduce image noise and distortion to avoid super-segmentation in the watershed step. The edges of eroded image are identified using the multiscale gradient (MG) operator (Gonzalez et Woods, 1992), which performs successive morphological gradient calculations with different structuring elements. The Euclidean distance between inner and outer border of the MG image is identified as the shortest distance from an inner boundary pixel *x* to the outer boundary of the filled region. Watershed transformation was applied to the images obtained from the Euclidean distance map to segment the image into two regions, background and object. Comparison with other methods showed equivalent or better accuracy.

Model-based techniques

Model-based techniques are those that use a preferred model to guide the border detection search. One of these techniques use the cost function to obtain the optimal contour as a path with the minimum total cost. Sonka *et al.* (1998) detected automatically the left ventricular epicardial and endocardial borders of intracardiac echocardiography (imaging technique that provides tomographic images of the heart wall without compromising on the image quality by interfering structures). Their first step was an interactive definition of the region of interest (ROI) where an ellipse was fitted through three points identified by the operator and the width of the ROI defined by one more interactive point definition. Their second step was an automated detection of the epicardial border by combining three sources of border information to form the border detection cost function (strength and direction of echo responses, expected epicardial border shape and larger sonolucent areas of the image). Their third step was an automated detection of the endocardial border, guided by the previously-determined epicardial border, that was used to derive the ROI for endocardial border detection (ROI_{endo}) whose outside limit was obtained by smoothing the epicardial border using a 20-point moving average filter followed by ists shrinking by 1.2 mm in the inside direction and inside limit obtained by shrinking the outside ROI_{endo} limit approximately to the position of the original inside ROI limit. The cost function for endocardium border detection differed from that of the epicardial border detection on that its edge detector size is 3 × 3 pixels while the edge detector size for epicardial border detection is 5 × 5 pixels and it´s allowed to its tracing to cut through the papillary muscles. Using this technique they obtained, without manual edition, a good correlation between computer-detected and observer-defined epicardial areas and LV cavity areas ($r = 0.99$, $y = 0.98x + 1.11$ [cm^2]; $r = 0.99$, $y = 0.98x + 0.43$ [cm^2]; respectively) and Bland-Altman analysis of agreement with very small bias (2%). For LV cavity volumes determined from the computer-detected borders and borders manually-identified in the same images, the correlation was excellent ($r = 0.99$, $y = 1.00x – 0.28$ [cm^3]). Other technique applies the active contours or snakes introduced by Kass *et al.* (1988), a deformable model that matches to an image by the minimization of an energy function composed of a data-driven term, which depends on the image data according to a chosen criterion, forcing the snake towards the object boundaries, and a regularization term, that impose a priori knowledge, usually smoothness of the region contour, on the segmentation result. The energy function is minimized by iterative technique using sparse matrix methods through implicit (internal energy) and explicit (image and external constraint energy) Euler steps. Cootes *et al.* (1994) introduced the Active Shape Model (ASM), similar to the snake of Kass *et al.* (1988) but applying global shape constraints, for locating structures in medical images. Their shape models rely on representing objects by sets of labeled points (each point placed on a particular part of an object and planted in the same way on every training example). After align the set of training shapes, they captured the statistics of a set of aligned shapes (mean, deviation and grey levels in regions around each of the labeled model points) and generated a flexible shape model and a description of the grey levels about each model point. Using this PDM (Point distribution model), their shape model gave a good fit after 50 iterations Cootes *et al.* (1995). Using the deformable model, Hozumi *et al.* (1997) developed an automated contour tracking (ACT) method that provides detection and tracking of the endocardial boundary using the energy minimization method without tracing a region of interest. The user points to only one point anywhere inside the left ventricular cavity and the initial contour model is automatically formed in the left ventricular cavity. This contour moves toward the endocardial border automatically and is used as initial contour to track the contour of next frame. In order to create a direct optimization approach which leads to an algorithm which is rapid, accurate, and robust, Cootes *et al.* (1998) proposed the Active Appearance Model (AAM), a method that exploits the fact the optimization problem is similar each time and these similarities can be learned off-line. While the ASM algorithm searches along profiles about the current model point positions to update the current estimate of the shape of the object, the AAM algorithm samples the image data under the current instance and uses de difference between model and sample to update the appearance model parameters. They found that the ASM is faster and achieves more accurate feature point location than the AAM, but the AAM gives a better match to the texture (Cootes *et al.*, 1999). Applying the AAM technique over an echocardiographic image sequence that represents the full heart cycle, Bosch *et al.* (2002) introduced the AAMM (Active Appearance Motion Models). They modeled the appearance of the heart for the entire cardiac cycle by considering the time sequence as a stack of 2-D images (time frames). All single-beat sequences are phase normalized into a fixed number of frames so that end-diastolic (ED) and end-systolic (ES) frames map to the same frame number. The other frames are found by nearest neighbor interpolation. In the training set, corresponding shape points on the LV endocardial contour are defined for each time frame based on expert drawn contours. The AAMM matching procedure resembles conventional 2-D AAM matching, but the rms error criterion and the parameter regression matrices for the appearance coefficients, pose, and global intensity are calculated for the full image sequences in AAMMs. Nandagopalan *et al.* (2010) developed a novel approach of combining a fast K-Means SQL clustering algorithm for segmentation and active contour model for boundary detection. For the segmentation, the echocardiographic images were preprocessed with a median filter and postprocessed with an average filter. The contour of the ventricular boundary was obtained by active contour (snakes) using a greedy algorithm to minimize a energy functional with three parameterized terms. The initial contour was marked by an operator over the segmented image and after 400 iterations boundary of any desired region was obtained. As result, they presented a table of comparison of automatic with manual calculations of area, volume, length and width.

Pixel-based techniques

In this category, each pixel of the image is assigned to a class or category on the image. The pixels that have close feature values are grouped into regions or classes using either unsupervised techniques or supervised ones. In unsupervised technique, the number of expected classes is provided, and the algorithm attempts to identify those classes. One of the unsupervised techniques is the Gaussian Mixture Model (GMM) that have a priori fixed number of gaussians which corresponds to the number of modes (tissue types) in the histogram (Petitjean and Dacher, 2011). The parameters of the mixture distributions can be estimated by the Expectation-Maximization (EM) algorithm that is a well established maximum likehood algorithm for fitting a mixture model to a set of training data. Other unsupervised technique is the clustering, which task is to assign a set of objects into groups (called clusters) based on some similarity that distinguished them from others clusters. The commonly used clustering algorithms are the K-means algorithm and the fuzzy c-means algorithm. The K-means clustering algorithm clusters data by iteratively computing a mean intensity for each class and segmenting the image by classifying each pixel in the class with the closest mean and the fuzzy c-means algorithm generalizes the K-means algorithm, allowing for soft segmentations based on fuzzy set theory (Dzung *et al.*, 2000). Binder *et al.* (1999) segmented regions of interest (ROI) of echocardiograms into areas of tissue and blood pool using a 2-layer artificial neural network (ANN) which input values for pixel classification are descriptors of the co-ocurrence matrix of grey values (mean grey value, variance, contrast, entropy and homogeneity). They used successive images and contour points were transposed from one image to the next using an Euclidean function (time-space transformation). They applied a polynomial function that assume a circular shape of the ventricle to link the detected contour points and trace the

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Table 1. Comparison between the main features of cited techniques.

IMAGE-BASED TECHNIQUE							
Author	**Border detection technique**	**Pre-processing**	**Post-processing**	**User interface**	**Number of frames**	**Comparison technique**	**Results**
Amorim *et al.* (2009).	Watershed.	Image fusion, smoothing and dynamic thresholding.		ROI definition.	Sequence.	Correlation and Sum Error.	R = 0.949; Mean sum error: 10,79 ± 2,95%
Lacerda *et al.* (2008).	Watershed, Radial-search-based algorithm.	High boost filter, elevation filter, thresholding, LoG filter.	Interpolation / Morphological close.	ROI definition.	Sequence.	Area percentil error and sum error with manual tracing, Mean pixel deviation.	Short-axis: Percentil error = 3.01 ± 1.5 (high) / 5.06 ± 3.0 (average); Sum error = 13.13 ± 2.07 (high) / 13.47 ± 1.99 (average). Long-axis: Percentil error = 10.65 ± 2.47 (high) / 18.06 ± 7.49 (average); Sum error = 18.51 ± 5.06 (high) / 24.62 ± 7.89 (average).
Maes *et al.* (1991).	Dynamic programming technique (Minimum cost algorithm).	Sigma filter.	Gaussian spatial smoothing.	ROI definition.	Sequence.	Correlation of calculated volume and measured volume.	R^2=0.99 (automatic delineated contours); R^2=0.97 (hand delineated contours).
Melton *et al.* (1983).	Rational gain compensation.			Threshold setting.		Correlation with manual tracing.	Area: r = 0.96, y = 0.81x + 1.1 [cm^2]; Perimeter: r = 0.92, y = 0.84x + 0.78 cm.
Reis *et al.* (2008).	Thresholding.	Frame rejection, denoise, contrast increasing, morphological closing in gray scale.		Frame select.	Sequence.	Area percentual and sum errors in comparison with manual tracing.	Percentil error = 2.49 ± 2.46; Sum error = 9.62±7.9; r = 0.98.
Timperley *et al.* (2006).	Spatio-temporal boundary detection based on phase-based method.	Artefacts filters.		apical views: three points placed at the margins of the mitral valve annulus and the apex. Short-axis view: one point at the junction of the inferior wall and inferior septum.	Sequence.	Kappa statistic.	Diagnosis comparation.
Vandenberg *et al.* (1992).	Thresholding.	transmit power and time-gain compensation controls.		ROI definition.	Sequence.	LV area with manual tracing.	High gain: y = 0.98x - 1.28, r = 0.92; Intermediate gain: y = 0.89x + 0.70, r = 0.91; Low gain: y = 0.65x + 7.46, r = 0.92;

ANN – Artificial Neural Network; bmp – beats per minute; EDV – End diastolic volume; ED – End diastole; ES – End systole; ESV – End systolic volume; LV – left ventricle; PC – Personal computer; r – Correlation; ROI – Region of interest; SEE – Standard error of the estimate.

Table 1. Continued...

Author	Border detection technique	Pre-processing	Post-processing	User interface	Number of frames	Comparison technique	Results
MODEL-BASED TECHNIQUE							
Bosch *et al.* (2002).	AAMM (Active Appearance Motion Model).			Manual corrections upon the border obtained by semi-automated detection.	Sequence.	Correlation with manual tracing.	PC = 0,9083Man + 1,7331 [cm^2], r = 0,873.
Hozumi *et al.* (1997).	Energy minimization.			The user points out only one point anywhere inside the left ventricular cavity.	1	Correlation and mean difference with manual tracing for cavity area and fractional area change.	Cavity: y = 0.83x + 2.6, r = 0.99; SEE = 15 cm^2. Fractional: y = 1.17x - 6.5, r = 0.95; SEE = 3.4%. Cavity mean differences: ED = -3.1 ± 5.1 cm^2; ES = -1.6 ± 2.4 cm^2. Fractional mean difference: -0.8% ± 7.1%.
Nandagopalan *et al.* (2010).	Fast K-Means SQL algorithm.	Median filter.		Initial contour.	1	area and volume with manual tracing.	Table.
Sonka *et al.* (1998).	Intracardiac Echocardiography.		Best route adjustment.	ROI definition and edition via elliptical contours.	Sequence.	Area and volume correlation and Bland-Altman.	y = 0.98x + 0.43 cm^2, r = 0.99; y = 1.00x - 0.28 cm^3, r = 0.99.
PIXEL-BASED TECHNIQUE							
Binder *et al.* (1999).	Neural Network Inputs: gray value, variance, contrast, entropy, homogeneity.	Segmentation.	Contour tracing by Euclidean function. Spatial/ temporal Transform.	Center determination.	2 successive.	Correlation and Bland-Altman with manual tracing.	ANN = 1.10Man + 0.84 cm^2, r = 0.99; Bland-Altman mean difference: -0,69 ± 1,7 cm^2.
Wu *et al.* (2008).	Neural network and pattern recognition.	Histogram adjust.	Contour smoothing.	ROI definition.	1	Percentil error and sum error with manual tracing, correlation and Bland-Altman.	y = 0.9299x + 689 px, r = 0.964; Average percentil error = 9.21%; Average sum error = 14.74%.

ANN – Artificial Neural Network; bmp – beats per minute; EDV – End diastolic volume; ED – End diastole; ES – End systole; ESV – End systolic volume; LV – left ventricle; PC – Personal computer; r – Correlation; ROI – Region of interest; SEE – Standard error of the estimate.

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complete endocardial border. Wu *et al.* (2008) trained a backpropagation neural network with samples from a matrix cursor which central pixel is on a border or out a border. The ANN tested every pixel inside de ROI and pointed out the points recognized as border's points. By radial sweeping, these points were linked and the contour was smoothed by an weighted average of the neighboring points.

Results

Although the review showed us a vast literature on left ventricle border detection techniques applied to 2D echocardiography images, only those articles containing at least five of the following features were selected and discussed in this article:

- Border detection technique – used to classify the technique;
- Pre-processing operations – the technique's ability to work with raw image;
- Pos-processing operations – the technique's efficiency;
- User interface – the technique's automation level;
- Number of frames – verifies if the technique uses the temporal variable as the tracking methods;
- Comparison technique – classifies the technique's evaluation method;
- Results – used to evaluate the technique's accuracy.

The classification on Table 1 is based on the border detection technique. For example, Nandagopalan *et al.* (2010) was classified as model-based technique, although they have used a Fast K-Means SQL algorithm to obtain the ventricle segmentation, because the border detection was obtained by active contours (snakes).

Discussion

We believe that the predominancy of image-based technique papers is because this is the oldest technique. Although the authors do not provide the processing time, due to the advances in the computers velocity, reducing the processing time, we can predict the trend towards the use of the model-based and pixel-based techniques because these techniques try to reduce operator intervention, but need more computer processing.

Although some authors claim their techniques are fully automatic, we consider the technique as semi-automatic if it depends on the intervention of the operator in helping ROI determination or setting gains or parameters based on prior knowledge.

Many other publications could be included in this review if they have mentioned the processing features or operator intervention since the objective is to compare the influence of these features on the results. We suggest that future papers on the area should try to complete this table items, because without some of them it is very difficult to compare the techniques or conclude about its performance.

Based on the Table 1, we can see that the results obtained by comparison with manual tracing, using correlation or area/volume comparison, of the cited techniques are very similar, regardless of their processing features. The main advantage of some more sophisticated techniques is the automatization to reduce the operator intervention.

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Author

Eduardo Jyh Herng Wu*, Denys E. Nicolosi
Instituto Dante Pazzanese de Cardiologia, Escola Paulista de Medicina, Universidade de São Paulo – USP,
Av. Dr. Dante Pazzanese, 500, Vila Mariana, CEP 04012-909, São Paulo, SP, Brasil.