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● *Original Contribution*

ARTIFICIAL NEURAL NETWORKS AND SPATIAL TEMPORAL CONTOUR LINKING FOR AUTOMATED ENDOCARDIAL CONTOUR DETECTION ON ECHOCARDIOGRAMS: A NOVEL APPROACH TO DETERMINE LEFT VENTRICULAR CONTRACTILE FUNCTION

THOMAS BINDER, MICHAEL SÜSSNER, DEDDO MOERTL, THOMAS STROHMER, HELMUT BAUMGARTNER, GERALD MAURER and GEROLD PORENTA
Department of Cardiology, University of Vienna, Vienna, Austria

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Abstract—This study investigated the use of artificial neural networks (ANN) for image segmentation and spatial temporal contour linking for the detection of endocardial contours on echocardiographic images. Using a backpropagation network, the system was trained with 279 sample regions obtained from eight training images to segment images into either tissue or blood pool region. The ANN system was then applied to parasternal short axis images of 38 patients. Spatial temporal contour linking was performed on the segmented images to extract endocardial boarders. Left ventricular areas (end-systolic and end-diastolic) determined with the automated system were calculated and compared to results obtained by manual contour tracing performed by two independent investigators. In addition, ejection fractions (EF) were derived using the area-length method and compared with radionuclide ventriculography. Image quality was classified as good in 12 (32%), moderate in 13 (34%) and poor in 13 (34%) patients. The ANN system provided estimates of end-diastolic and end-systolic areas in 36 (89%) of echocardiograms, which correlated well with those obtained by manual tracing ($R = 0.99$, SEE = 1.44). A good agreement was also found for the comparison of EF between the ANN system and Tc-radionuclide ventriculography (RNV, $R = 0.93$, SEE = 6.36). The ANN system also performed well in the subset of patients with poor image quality. Endocardial contour detection using artificial neural networks and spatial temporal contour linking allows accurate calculations of ventricular areas from transthoracic echocardiograms and performs well even in images with poor quality. This system could greatly enhance the feasibility, accuracy and reproducibility of calculating cardiac areas to derive left ventricular volumes and ejection fractions.

Key Words: **Echocardiography, Artificial neural networks, Left ventricular volume, Left ventricular ejection fraction.**

INTRODUCTION

Echocardiographic imaging is commonly applied noninvasively to determine and monitor left ventricular volume during the cardiac cycle and calculate parameters of ventricular function, such as ejection fractions. These parameters frequently provide critical diagnostic and prognostic information for patient management.

Recent advances in echocardiography, such as second harmonic imaging (Caidahl et al. 1998), left ventricular contrast opacification (Hundley et al. 1998) and 3D-dimensional echocardiography (Nosir et al. 1999; Lange et al. 1998), have improved the assessment of left ventricular function. For all these approaches, accurate tracing of endocardial boarders is a prerequisite to quantify left ventricular geometry. Various approaches to endocardial tracing have been reported (Geiser et al. 1988; Thomas et al. 1988; Conetta et al. 1985; Collins et al. 1984; Zwehl et al. 1983; Perez et al. 1992; Vandenberg et al. 1992). However, many of those require manual tracing and, thus, are operator-dependent, time-consuming and impractical for clinical use. Moreover, image quality is often a limiting factor for applying these techniques, and research has been directed to devising systems that are less limited by image quality (Lange et al. 1997).

An artificial neural network is a computer-based system that can be trained to analyze images. Computing

Address correspondence to: Thomas Binder, Klinik f. Innere Med II, Abt. f. Kardiologie, AKH Wien, Währingergürtel 18-20, A-1090 Vienna, Austria. E-mail: tbinder@pop3.akh-wien.ac.at

Table 1. Indications for echocardiography

Dilated cardiomyopathy	5 (13%)
Aortic stenosis	3 (8%)
Aortic regurgitation	2 (5%)
Mitral stenosis	2 (5%)
Mitral regurgitation	4 (10%)
Suspected coronary artery disease	5 (13%)
Heart transplantation	1 (3%)
Hypertension	7 (18%)
Arrhythmias	5 (13%)
Source of embolism	1 (3%)
Suspected endocarditis	1 (3%)
Chemotherapy	2 (5%)

texture information, an ANN can perform a segmentation process to differentiate between image regions with different image characteristics. ANN techniques have already been successfully applied for image analysis, including ultrasound, and could also allow delineation of blood pool regions from the surrounding myocardium on echocardiograms using the difference in their specular characteristics (Fujita et al 1992; Rinast et al. 1993; Prater and Richard 1992). Endocardial contours can then be derived from the segmented images by computing transitions between blood and tissue regions. To increase the accuracy of the system, it would, furthermore, be desirable to track the endocardial contour throughout the cardiac cycle (spatial/temporal contour linking) to increase the number of possible contour candidates. This process could be helpful to find contours also in image regions with poor image quality.

The purpose of this study was to detect endocardial contours on echocardiograms using an automated system that uses an ANN to segment echocardiographic images into regions of tissue and blood pool followed by spatial/temporal contour linking. The results obtained with this system were compared to manual tracing and to radionuclide ventriculography.

METHODS

Echocardiography was performed in 38 selected patients without regional wall motion abnormalities, regardless of image quality. The indication for echocardiography is depicted in Table 1. End-systolic and end-diastolic frames were defined according to the ECG. The areas of these frames were calculated using both the automated system and manual tracing by two independent experienced observers. The same end-systolic/end-diastolic frames were used for computation by the automated system and manual tracing. Manual tracing included tracing of the papillary muscle contours. Technetium radionuclide ventriculography (Tc-RNV) was performed in a subset of 12 patients within 24 h of the echocardiographic examination.

Image acquisition

A conventional echocardiographic scanner (Vingmed Sonotron CFM 800) was used to obtain and digitize transthoracic mid-ventricular short axis views of the left ventricle. The system delivers a sequence of 15–32 images of an entire heart cycle at a frame rate of 25–40 frames/s. The size of the extracted images is 179×179 pixels with a 6-bit grey-scale resolution.

Manual image analysis

Tracing of endocardial boarders was independently performed by two investigators experienced in echocardiography. Left ventricular end-systolic and end-diastolic areas were calculated using commercial software (EchoPac, Vingmed, Norway). In addition, the observers graded the overall image quality according to a 3-point scoring scheme ("good," "moderate" or "poor"). The end-diastolic and end-systolic length of the ventricle was measured from apical views.

Automated image analysis

The detailed description of the system has previously been reported (Strohmer 1995; Suessner et al. 1995a, b). In brief, image analysis included two steps: 1. image segmentation by the ANN followed by a radial search to identify possible contour points, and 2. time-space transformation of contour points and contour linking to generate smooth endocardial boarders.

Image segmentation was performed to classify echocardiograms into areas of tissue (myocardium) and blood pool using a 2-layer ANN that analyzes the specular reflection of the ultrasound image. The neighborhood of each pixel region (7×7 pixel) was analyzed to derive the following descriptors of the co-occurrence matrix of grey values: 1. mean grey values, 2. variance, 3. contrast, 4. entropy, and 5. homogeneity (Gonzales and Woods 1992).

These values were then used as input values for pixel classification by the net (Fig. 1). The network was trained using 279 sample regions obtained from training images. The training regions were identified by a human observer as either tissue ($n = 279$) or blood pool ($n = 90$) region. Segmentation was performed for all images of the cardiac cycle within a predefined rectangular region of interest (ROI). A contour detection algorithm was developed to extract contour points from the segmented images. This algorithm searches within the ROI for a cavity-tissue transition in a radial direction, starting at the user-defined center of the ventricle. After such a transition is detected, it is computed as a potential contour-point candidate. This analysis is performed for all images of the cardiac cycle. Previous experience with this system has shown that contour-point detection in a given image frame can be enhanced if contour informa-

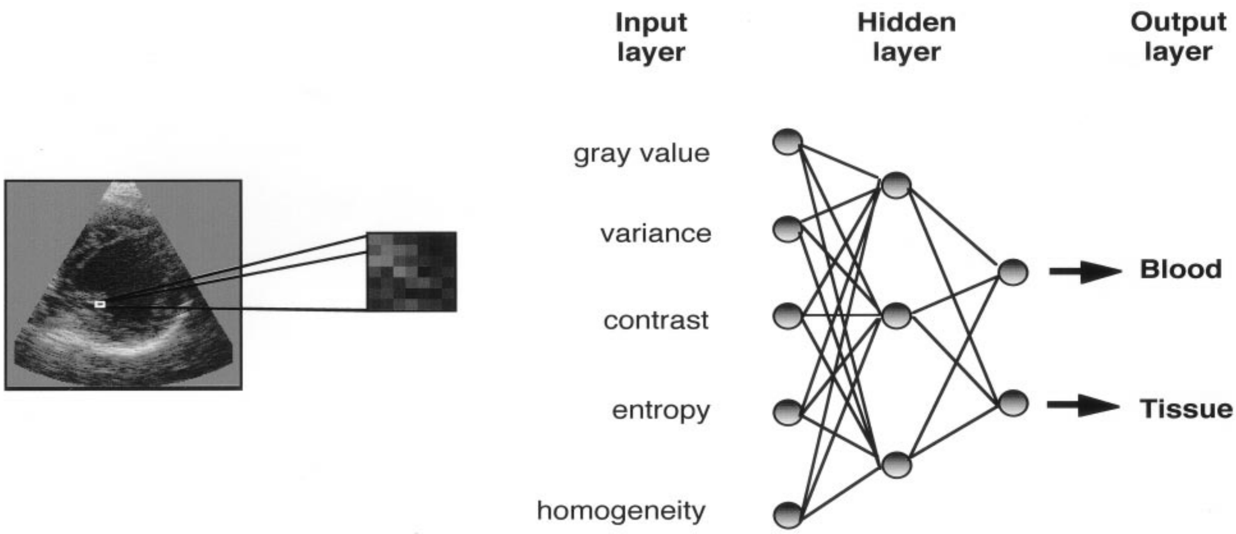


Fig. 1. Net architecture. The ANN decides the class-membership of each pixel by analyzing its local 7 × 7-pixel neighborhood. This pixel region is analyzed to derive the following texture parameters: mean grey value, variance, contrast, entropy and homogeneity. These values were then entered into a two-layer backpropagation net trained to segment images into blood pool and tissue regions.

tion of successive images is incorporated in the analysis. Thus, contour points are transposed from one image to the next using an Euclidean function (time-space transformation; Strohmer 1995; Suessner et al. 1995a). The results obtained after time-space transformation are applied as shown in Fig. 2. A complete endocardial border was derived by linking the detected contour points applying a polynomial function that assumes a circular shape of the ventricle (Stohmer 1995; Suessner et al. 1995a).

Figure 3 demonstrates the results obtained after the various steps of the analyzing procedure were applied.

Calculation of ejection fraction from echocardiograms

Left ventricular end-diastolic and end-systolic volumes were calculated by the formula (Folland 1979):

$$A \times L \times 5/6$$

where A is the left ventricular area at the mid papillary short axis plane (calculated by the ANN system) and L is the length of the left ventricle measured from an apical four chamber view.

Radionuclide ventriculography

Radionuclide ventriculography was performed in a subset of 12 patients according to a standard clinical protocol. Following *in vivo* labeling of red blood cells with pyrophosphate and ^{99m}Tc, ECG-gated acquisition was performed in the LAO 45° position for 10 min using 24 gates spanning the entire cardiac cycle. A semiautomated analysis was then utilized to derive on each of the 24 frames an ROI covering the left ventricle to quantify left ventricular counts, to detect the maximal and minimal number of total counts and to compute global left ventricular ejection fraction. All 12 patients were in normal sinus rhythm.

Statistical analysis

Regression analysis and Bland–Altman plots were used to compare the results between observers, the ANN system and Tc-RNV. The mean of two observers was used as the result of manual tracing. The Levene test was employed to test for difference in variance.

RESULTS

Segmentation, using the ANN system, could be performed in 35 (92%) of 38 patients. In 2 patients, segmentation failed due to poor image quality. In addition, in 1 patient with hyperkinetic left ventricle and almost complete cavity obliteration, the ANN system was not able to delineate the end-systolic area. The radial search algorithm failed in 1 patient due to misleading intracavitary structures (prominent papillary muscle). Thus, 34 (89%) of 38 images could be analyzed for end-diastolic and end-systolic areas.

Comparison between the ANN and manual tracing

Regression analysis showed a good correlation between left ventricular areas derived by the ANN system

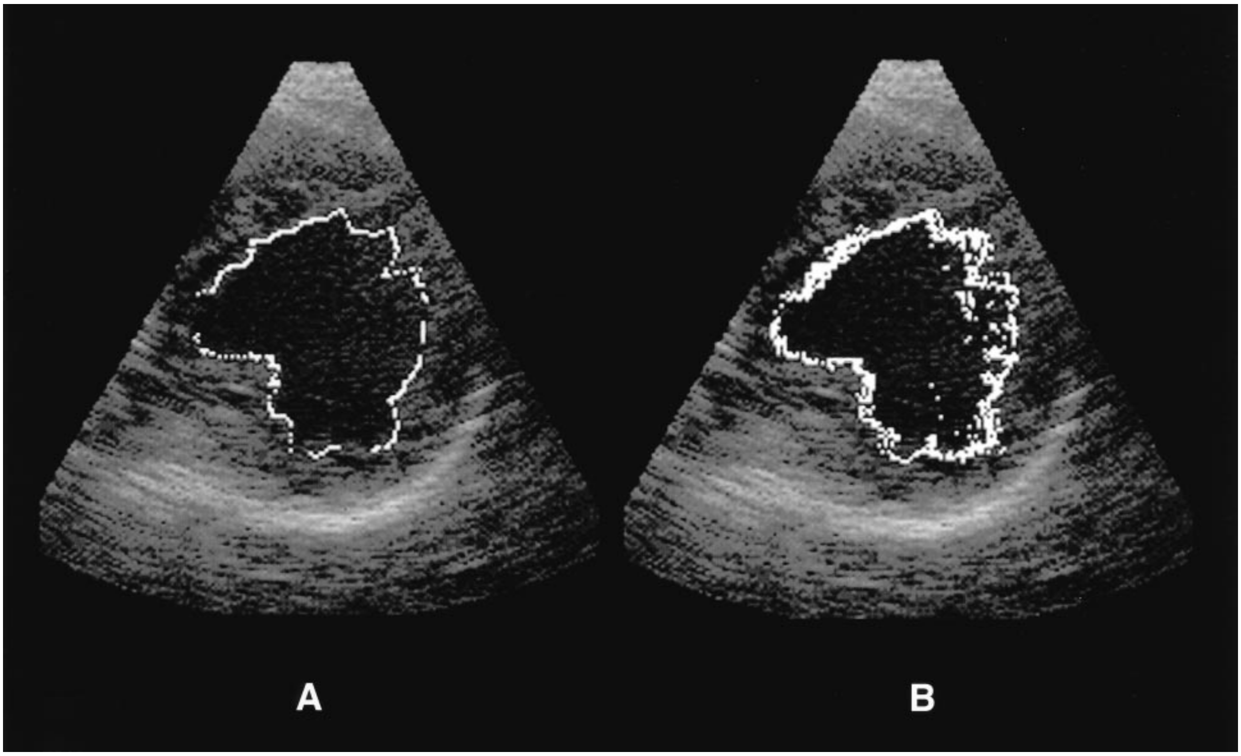


Fig. 2. Spatial/temporal contour linking. Short axis view at end-diastole (A) before and (B) after spatial/temporal contour linking was performed. The process of time-space transformation uses contour points from successive images to increase the number of contour points. This procedure is helpful in closing gaps in the endocardial boarder caused by poor regional image quality. Note how such a gap is closed in the posterior and septal region.

with manual contour detection (ANN = 0.84 + 1.10 Man, SEE = 1.44, R = 0.99, Fig. 4a). The corresponding Bland–Altman plot (mean difference = −0.69 ± 1.7 mm^2) demonstrates a tendency of the ANN to overestimate interventricular areas with increasing sizes of the left ventricle (Fig. 4b).

Interobserver variability

A similar agreement was found for the interobserver variability (Obs.1 = −0.67 + 1.04; Obs. 2, SEE 1.04, R = 0.99, mean difference = 0.07 ± 1.09 mm^2; Fig. 5a and b).

Comparison between the ANN and RNV

A good correlation was found between EF derived from Tc-RNV and the ANN system (ANN = 8.46 + 0.94RNV, SEE = 6.36, R =0.93, Fig. 6a), with a tendency of the ANN system to overestimate ejection fractions (mean difference of −7.01% ± 6.11). The corresponding Bland–Altman plot is shown in Fig 6b.

Image quality

Disagreements between the ANN and manual tracing were dependent on image quality. Figure 7 shows the differences between interventricular areas determined by manual contour detection and the ANN system, grouped by image quality. The best agreement was found for image loops with good quality (SD = 0.6 cm^2), followed by loops with moderate (SD = 1.3 cm^2) and poor image quality (SD = 2.5 cm^2). These differences were found to be statistically significant using the Levene test ($p <$ 0.05).

DISCUSSION

The presented paper describes a computer-based approach for the detection of endocardial borders for quantification of left ventricular volumes. The system is unique to previously reported methods because it performs a complex image segmentation process based on several texture parameters, using an artificial neural network. In addition, the system tracks the endocardial contour throughout the cardiac cycle, transposing image points from one image to the next (time-space transformation). This process increases the number of possible contour candidates and is, thus, helpful in image regions with poor image quality.

Endocardial tracing using the ANN system was

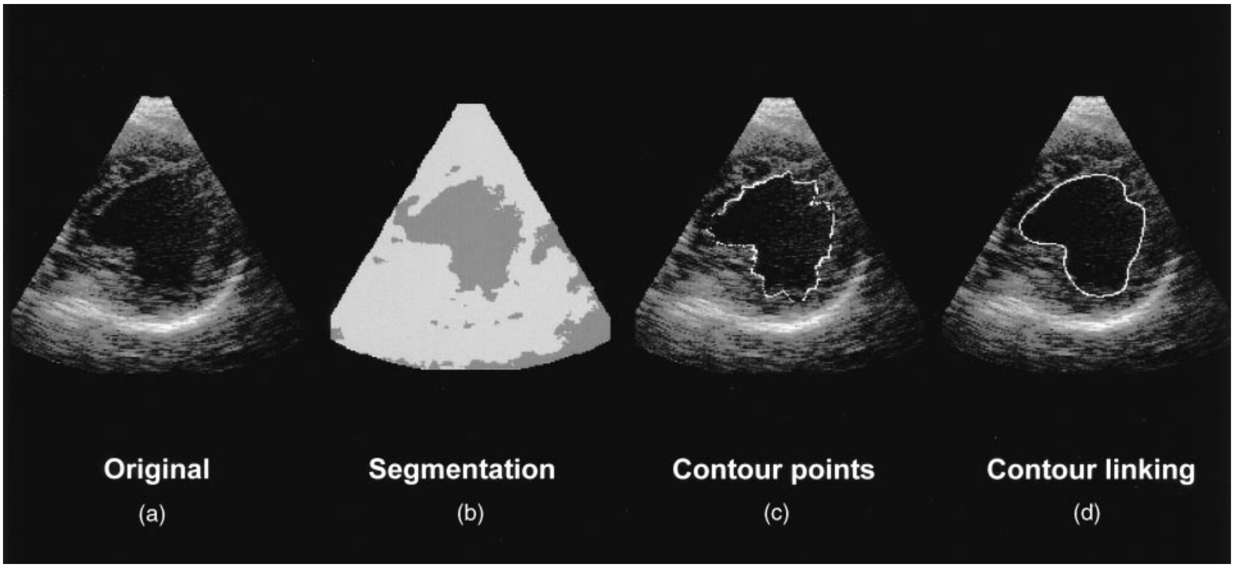


Fig. 3. Endocardial contour detection. Example of the results obtained with the ANN system during the different stages of contour detection. (a) Original image. (b) Results of image segmentation performed by the ANN (within the region of interest); light grey color corresponds to tissue (myocardium) and dark grey to the blood pool region. (c) Contour point detection after the radial search algorithm was applied and (d) final result with complete endocardial boundary detection after spatial/temporal contour linking.

feasible in a large proportion of the unselected patient population (89%). Failure of the system was either due to abnormal cardiac morphology (mesoventricular obstruction and prominent papillary muscle) that misled the radial search algorithm, or to poor image quality. However, these images were of very poor quality, with the entire lateral region displaying attenuation artifacts.

Comparison between the ANN system and manual tracing showed an excellent agreement. In addition, left ventricular ejection fractions derived from the ANN system compared well to ejection fractions measured with Tc RNV.

Less agreement was found between the ANN system and manual tracing for areas calculated from images with poor quality. However, this difference appears to be clinically insignificant. The ANN system tended to overestimate areas for increasing ventricular sizes. However, these differences were small, and are most likely caused by relative effects (the same magnitude of endocardial deviation results in a greater area change in large, compared to small, ventricles).

There is a need for a practical, yet accurate, method for quantification of left ventricular volumes from echocardiograms. Numerous different algorithms for automated calculation of areas and volumes have been proposed (Tsai et al. 1997; Detmer et al.1994; Zhang and Geiser 1994). Most of these algorithms depend on greyscale thresholding for image segmentation and do not account for grey-value disparities caused by instrument settings (*i.e.*, time-gain compensation) or physical phenomena of ultrasound, such as attenuation, poor lateral resolution and high speckle noise. Therefore, most of these algorithms require significant operator interference to correct for segmentation errors and have, thus, not become widely applied.

Other authors

Newer methods include acoustic quantification (AQ), a technique that uses the integrated ultrasound backscatter characteristics for online image segmentation. Even though this approach has a number of advantages, several limitations persist: end-diastolic and end-systolic volumes determined by AQ tend to underestimate volumes (Wilson and Rahko 1995), and AQ is gain-dependent (Vandenberg et al. 1992) and requires complete endocardial definition (optimal image quality). A comparison with TC-RNV showed that AQ overestimates ejection fraction with rather wide limits of agreement (Chandra et al. 1997). Other authors propose Doppler myocardial imaging that is relatively independent of attenuation artefacts that are often seen in low quality images (Lange et al. 1997). Although this technique holds promise for the future, there is presently little experience with this method in clinical practice.

In contrast to other approaches, the ANN system displays several unique features: because numerous parameters (grey-values, variance, contrast, entropy, homogeneity) are considered, the decision rule derived by the

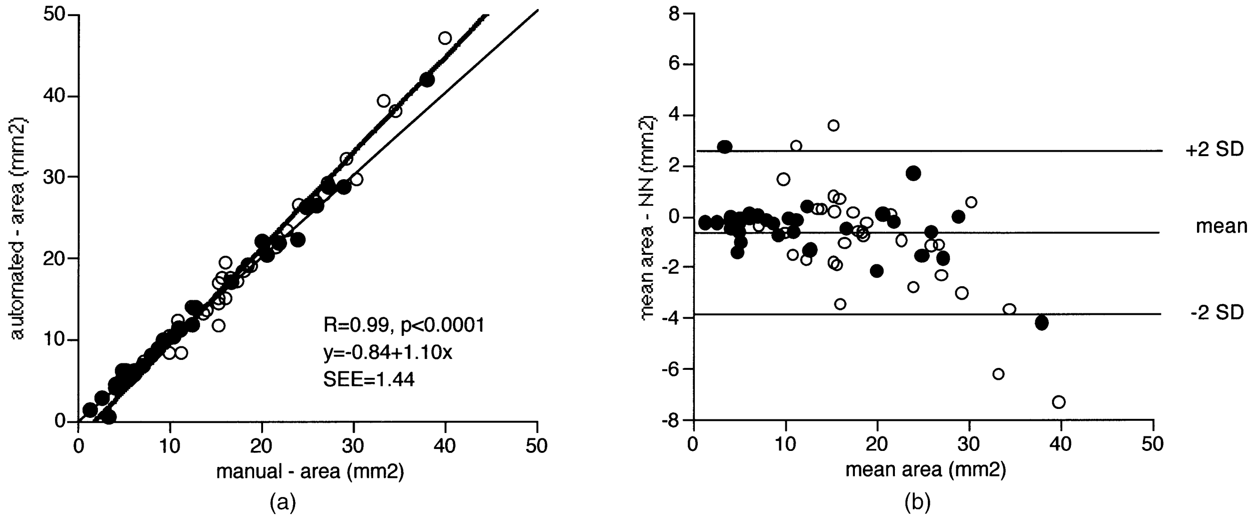


Fig. 4. Comparison between ANN and manual tracing. Regression analysis (a) comparing the results of manual tracing (mean of two observers) to the ANN system shows an excellent agreement. (b) The corresponding Bland–Altman plot demonstrates a small tendency of the ANN system to overestimate areas for increasing ventricular sizes. ○ = end-diastolic; ● = end-systolic frames.

net allows "fuzzy" logic is 1. robust and error tolerant, 2. the system is open to additional input values, which permits the system constantly to be adapted and expanded (*i.e.*, to include backscatter, tissue Doppler or contrast information), and 3. contour gaps are interconnected according to the most likely position of the endocardium using contour information of the entire cardiac cycle; thus, the ANN system produces meaningful segmentation results even in image regions with poor quality.

Limitations

In contrast to AQ, the analysis is performed off-line. However, processing time is in the range of 10 min per patient and future developments, which could include enhanced processing power and system integration, could allow near real-time analysis. The system was only tested using short axis views and in patients without regional wall motion abnormalities. Modifications both for the radial search process and the contour linking algorithm must be made to allow area computations from

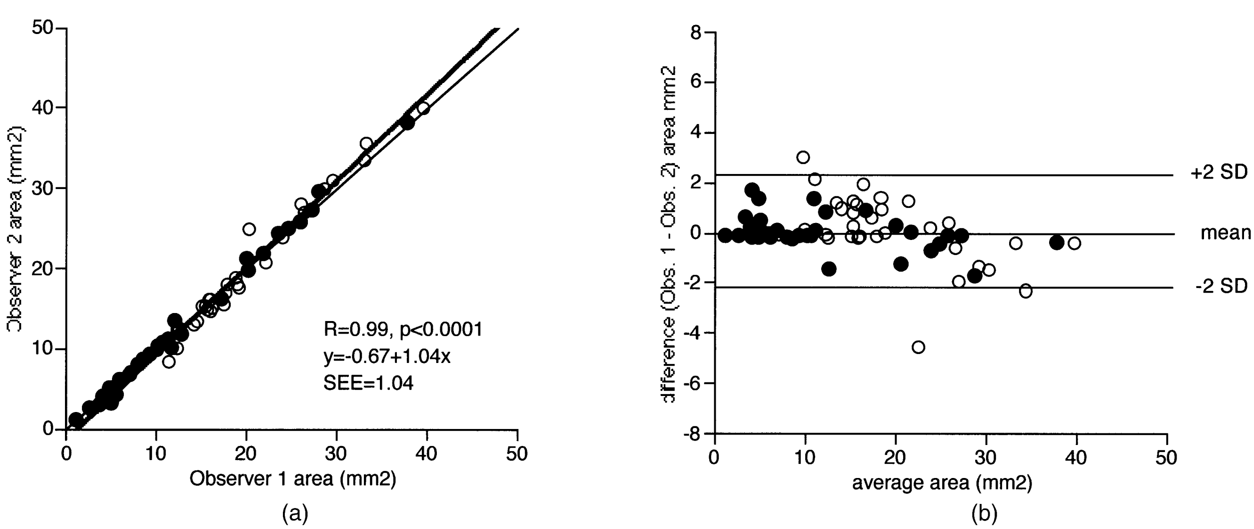
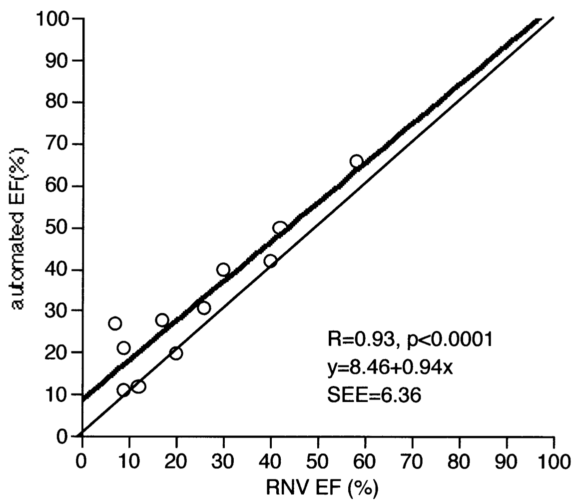
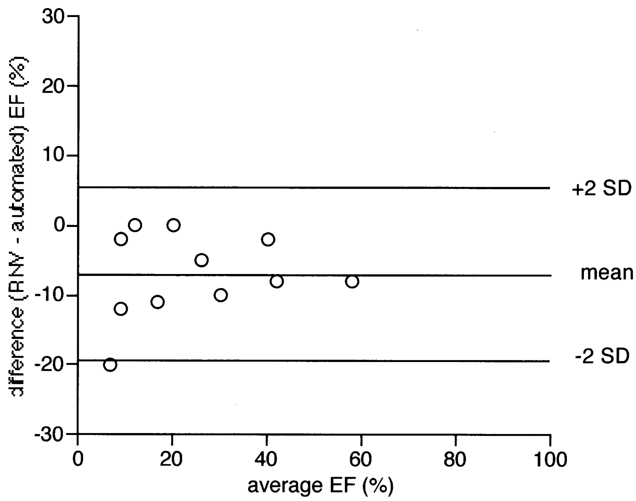


Fig. 5. Comparison between observers. (a) Regression analysis and (b) Bland–Altman plot, comparing the results of manual tracing between the two observers. ○ = end-diastolic; ● = end-systolic frames.



(a)



(b)

Fig. 6. Comparison between ANN and Tc-RNV. (a) Regression analysis and (b) Bland–Altman plot comparing EF derived with the ANN system to those determined with Tc-RNV.

apical views, and the system must still be validated for patients with regional wall motion abnormalities. Finally, image quality still plays a role in the accuracy of the system.

In conclusion, our results show that the implementation of artificial neural networks for automated border detection on echocardiograms is feasible, even in images with poor quality. Such a system provides an accurate estimate of left ventricular volumes and function and could greatly enhance the feasibility, accuracy and reliability with which such parameters can be obtained.

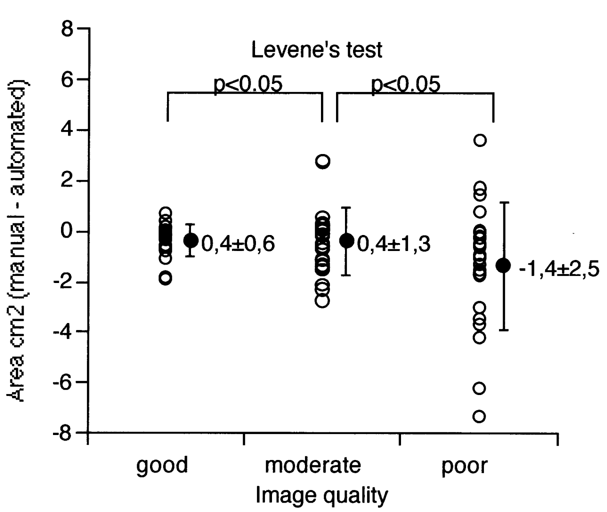


Fig. 7. Influence of image quality. Accuracy of the ANN system compared to manual tracing (mean of two investigators), grouped by image quality. The best agreement was found for images with good followed by moderate and poor image quality. Differences between groups were statistically significant (Levene test, $p \leq 0.05$). However, even in images with poor quality, the agreement between the ANN and manual tracing was high (mean difference -1.4 ± 2.5 cm^2).

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