Left Ventricular Border Recognition in Echocardiographic Images Using Modular Neural Networks and Sugeno Integral Measures

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Abstract The Echocardiography and the 2D ultrasound images are widely used to assess patients with heart diseases. The Observer (cardiologist) qualitatively deduces the heart morphology and left and right ventricular functions. In this paper we use the modular neural networks and Sugeno Measures to find patterns in echocardiogram images to recognize left ventricular borders of the heart and derive quantitative parameters. We studied 39 echocardiographic images that are used as an input to modular neural networks to find patterns and recognize the left ventricular border and also to a monolithic neural network to compare the results. We used the percentage of error recognition to evaluate the two neural networks, where modular neural networks offered better results with a 98 % of recognition versus 80 % recognition of monolithic Neural Network. Modular neural networks proved that they are an effective technique to recognize the left ventricular border of the heart.

1 Introduction

There have been many works with modular neural networks for pattern recognition, solving problems such as identification of face, fingerprints, voice, among many others [1, 4, 6, 8].

In this paper we use the modular neural network to find patterns in echocardiogram images to recognize the left ventricular border of the heart.

The 2D echocardiography is widely used technique to evaluate patients with heart diseases in medical hospitals [3, 7]. Ultrasound images allow a visual structure observation and motion observation of the heart. Observer qualitatively deduces the cardiac morphologic state and quantitatively measures the ventricular functions.

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Since cardiologists based on their experience provide a diagnosis of the heart using ultrasound imaging, it is recognized that new Physicians do not give an accurate diagnosis [7]. Quantification of LV parameters is important to provide accurate diagnosis [2, 3]. To obtain these parameters is necessary to recognize and draw the borders of the ventricle as show in Fig. 1. In Fig. 1a we show a typical gray scale 2D Left Ventricular (LV) ultrasound image and in Fig. 1b a 2D gray scale LV ultrasound image with traced border.

Left ventricle border recognition in echocardiographic images is limited by noise, gain-dependence and endocardial dropout [5, 7]. In the literature, the traditional methods to find edges such as Sobel, Prewitt, Canny, Roberts, do not provide favorable results in this particular problem. Instrumentation is recently available and can automatically identify and track the endocardial border of the left ventricle. The automatically tracker borders are then subject to calculation of volume using some methodology and the ejection fraction can be calculated from the maximal and minimal volumes [10, 11]. While manual manipulation of the contour is commonly needed to insure an accurate left ventricular cavity boundary, as the border detection algorithms. Neural networks on the other hand have the advantages of being able to work, learn and produce results in noisy environments [1, 4, 6, 8, 9]. We use this well documented soft computing technique to solve the issue of left ventricle border recognition in ultrasound images that could help us in the future to evaluate the mobility of each segment in the LV more precisely.
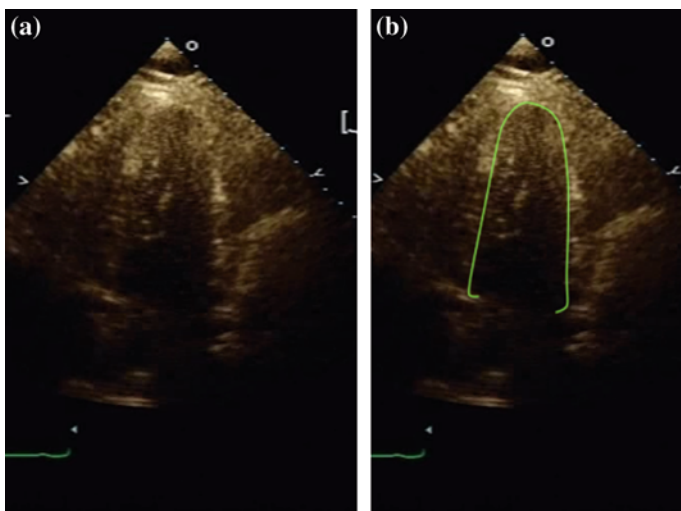

Fig. 1 **a** A typical gray scale 2D LV ultrasound image. **b** A 2D gray scale LV ultrasound image with traced border

1.1 Modular Neural Network

The main principle is simple, divide a task into less complex subtasks. Then, every subtask is assigned to an expert (Module), which generates a result. If a task can be separated into various subtasks, each subtask can be trained apart and then be integrated into an overall architecture for a solution [6, 8, 9].

1.2 Advantages of Modular Neural Network

- Learning abilities are better than monolithic networks abilities.
- Modularity may involve reducing the size of the parameters of neural networks that improves computation and generalization capabilities process.
- Helps to determine the activity that is taking place in every part of the system, identifying the function that performs each neural network in the whole system.
- If there are changes in the environment, editing is easier in modular system than a monolithic system, because modularity allows changes in a part of the system instead of change the whole entire system [8].

2 Methods

We worked with thirty-nine ultrasound images provided by Cardio-Diagnostic Center of Tijuana, Mexico. In these images we applied a pre-processing that consisted on segmenting the image to extract the region of interest, obtaining an image size of 51 pixels high by 46 pixels wide.

We worked with two neural networks, a modular and a monolithic to compare the results. We provided to the monolithic network, the complete image of 51×46 pixels as input and we provided to modular neural network the 51×46 image divided in three parts, where every part was given to an each expert module. Both networks used a number from 1 to 39 as a desired output. This number represents an indexed binary image with border traced. So the neural networks output is a number that represents an indexed image in a database. This database contains a set of traced border images. All networks are trained with two random samples of noise. Every pixel of the noisy samples is calculated according to Eq. (1). Where the new pixel (NP_i is the sum of the intensity of P_i plus a random variable taken from a normal distribution, with a media equal to 0 and standard deviation of 0.1 and 0.2 that represents a level of noise for every sample.

$$NP_i = P_i + u \tag{1}$$

where:

NP_i is the new valor of pixel i
P_i is the value of pixel i
u is random probability sample from a normal distribution with media equal to
      0 and standard equal to 0.2.

2.1 Modular Neural Network Architecture

Three modules (experts) for the modular neural network where taken in place, where each expert is responsible for recognizing a part of the image. Each module contains three monolithic networks. The result of each monolithic network is send to an integrator that used Sugeno Measures to provide a final result [6, 8]. Figure 2 illustrates the Modular Neural Network architecture used for recognition of LV borders.

The decision is made according to the Eq. (2).

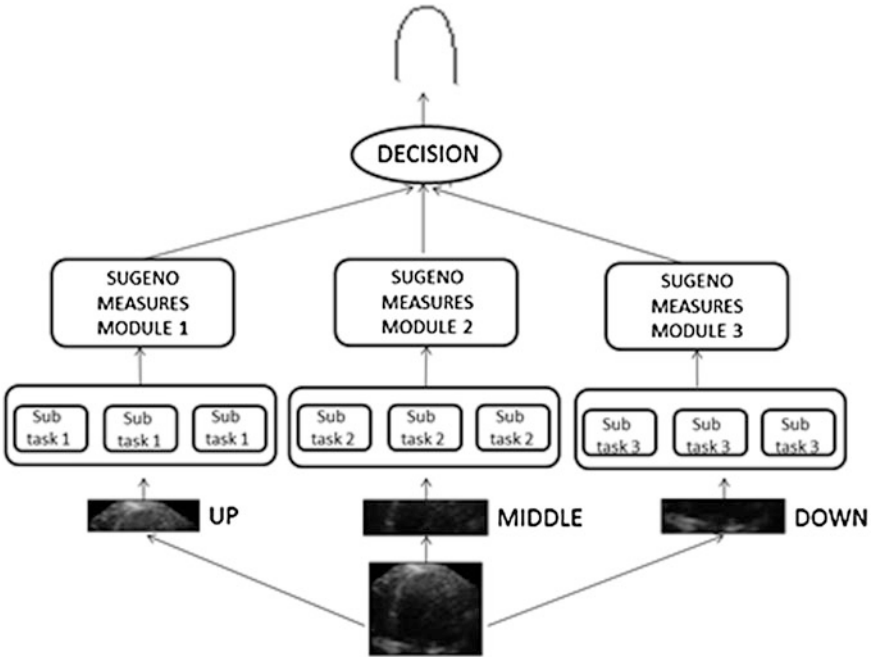$$g(M_i) = h(A) + h(B) + \lambda h(A)h(B) \tag{2}$$

Fig. 2 Modular neural network architecture

where:

g matrix that stores the results of each module
M_i module i
$h(A)$ best result of the module i
$h(B)$ second best result of the module i
λ is equal to 1.

3 Simulation Results

We describe in this section the simulation results that were obtained with the proposed approach.

3.1 Results and Experiments of the Monolithic Network

We performed 50 experiments for the monolithic network. Each experiment consisted of training the neural network and later performed a recognition rate test with 39 images. The monolithic network scored an average of 80 % of recognition.

3.2 Experiments and Results of Modular Neural Network

We performed 50 experiments for the modular neural network. Each experiment consisted on training the network with the 39 images. Each module was trained separately, and then we used the Sugeno Measures to integrate the results and make a final decision. After, a test is performed with the 39 images to obtain a percentage of recognition result. The 50 experiments produce an average of 98.1 % recognition.

3.3 Neural Networks Experiments with Noise

We performed 50 experiments with random noise levels of 0.1–1, with an increment of 0.1 for both neural networks and percentage recognition of error test was performed. Results are shown in Fig. 3.

Fig. 3 Test of noise level for
neural networks

Percentage of recognition errors
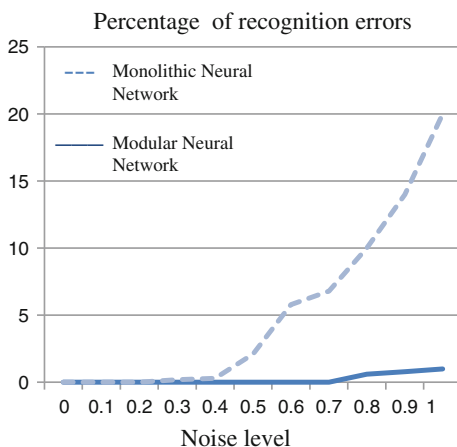
4 Conclusions

This study demonstrated the effectiveness of modular neural networks to find left
ventricular border patterns. We used only segmentation as pre-processing, with
routine adjustment settings in the input image from the capture.

Despite the difficulties like low contrast, speckle noise, and signal dropouts the
modular neural network scores well on gray scale routine images. The modular
neural network had a recognition rate of 98.1 %. Despite this success, the per-
centage declined with increasing levels of noise.

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