Echocardiogram Image Recognition Using Neural Networks

Beatriz González, Fevrier Valdez, Patricia Melin and German Prado-Arechiga

Abstract In this chapter we present a neural network architecture to recognize if the echocardiogram image corresponds to a person with a heart disease or is an image of a person with a normal heart, so that it can facilitate the medical diagnosis of the person that may hold an illness. One of the most used methods for the detection and analysis of diseases in the human body by doctors and specialists is the use of medical imaging. These images become one of the possible means to achieve a safe estimate of the severity of the injuries and thus to initiate treatment for the benefit of the patient.

1 Introduction

Research on medical imaging has been growing over the past few years as it is normally a non-invasive method of diagnosis and so its results may bring benefits to people's health. These research works cover many aspects of image processing and medicine, such as disease predicting and accurate diagnostics [12]. For this reason, we are considering in this chapter the application of neural networks for recognition of medical images.

Normally there are many kinds of noise in the ultrasound images. So the resulting images are contaminated with this noise that corrodes the borders of the cardiac structures [11]. This characteristic turns difficult the automatic image processing, and specially the pattern recognition. Besides this kind of noise, other factors influence the outcome of an ultrasound image. For instance in pregnancy

B. González · F. Valdez · P. Melin (✉)
Tijuana Institute of Technology, Calzada Tecnologico s/n, Tijuana, Mexico
e-mail: pmelin@tectijuana.mx

G. Prado-Arechiga
Excel Medical Center, Paseo de los Heroes No. 2507, Zona Rio, Tijuana, Mexico

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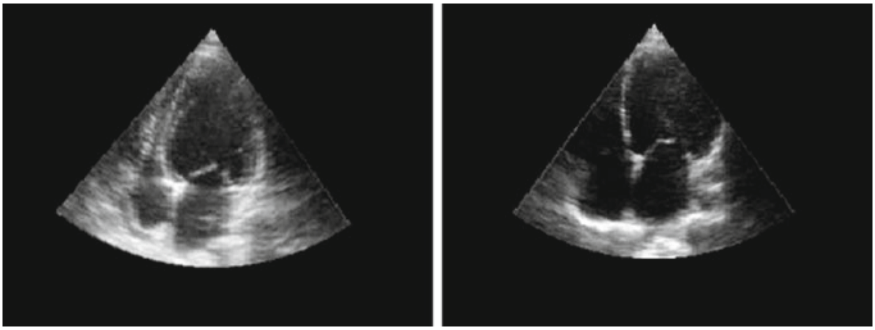

Fig. 1 (*left*) Echocardiographic frames from normal (apical 4 chamber view); (*right*) Motions of the heart for Hypokinesia patients [6]

tests, the transducer and the fetus position, the rotation and the scale variations in images of different patients and the composition of the tissue separating the fetus heart are issues that must be taken into account when dealing with heart images [23, 24].

However, the disease recognition problem is complicated by the heart's non-rigid motion (see Fig. 1). Furthermore, the poor imaging quality of 2D echo videos due to low contrast, speckle noise, and signal dropouts also cause problems in image interpretation [6, 7].

The rest of the chapter describes this approach in detail and is organized as follows. In Sect. 2, we describe some of the works related to image recognition echocardiography and basic concepts. In Sect. 3 we describe the methodology used for pattern recognition imaging echocardiography, and the database for this study, the pre-processing that is used, and the neural network that was designed. In Sect. 4 experimental results are presented. In Sect. 5 the conclusions are offered.

2 Background and Basic Concepts

2.1 Previous Work

In the first automatic cardiac view recognition system, Ebadollahi et al. [8] proposed a constellation-of-parts based method. They used a generic heart chamber detector [1] to locate heart chambers, and they represented the spatial arrangement of the chambers using a Markov Random Field (MRF) based relational graph. Final classification of a test image was performed using a Support Vector Machine on the MRF network output. This method suffers from sensitivity of the chamber detection method to frequently present noise in the echocardiogram images while demonstrating limited robustness to basic image transformations.

In another work of Ebadollani et al. an automatic identification of the views of the heart from the content of the echocardiogram videos is presented. In this approach the structure of the heart is represented by the constellation of its parts (chambers) under the different views. The statistical variations of the parts in the constellation and their spatial relationships are modeled using Markov Random Field models. A discriminative method is then used for view recognition which fuses the assessments of a test image by all the view-models [14].

Jacob et al. [2] and Sugioka et al. [19] developed research using patterns to detect cardiac structures using active contours (snakes) in echocardiographic images. In another work, Comaniciu [9] proposed a methodology to tracking cardiac edges in echocardiographic images using several information extracts of the images.

2.2 Echocardiography

Echocardiography is an important diagnostic aid in cardiology for the morphological and functional assessment of the heart. During an echocardiogram exam, sonographer images of the heart using ultrasound by placing a transducer against the patient's chest. Reflected sound waves reveal the inner structure of the heart walls and the velocities of blood flows. Since these measurements are typically made using 2D slices of the heart, the transducer position is varied during an echo exam to capture different anatomical sections of the heart from different viewpoints [4] (Fig. 2).

Echocardiography is often used to diagnose cardiac diseases related to regional and wall motion as well as valvular motion abnormalities. It provides images of cardiac structures and their movements giving detailed anatomical and functional information about the heart [5].

2.3 Noise in Ultrasound

Speckle is a characteristic phenomenon in laser, synthetic aperture radar images, or ultrasound images. Its effect is a granular aspect in the image. Speckle is caused by interference between coherent waves that, backscattered by natural surfaces, arrive out of phase at the sensor [3, 10]. Speckle can be described as random multiplicative noise. It hampers the perception and extraction of fine details in the image. Speckle reduction techniques can be applied to ultrasound images in order to reduce the noise level and improve the visual quality for better diagnoses [11].

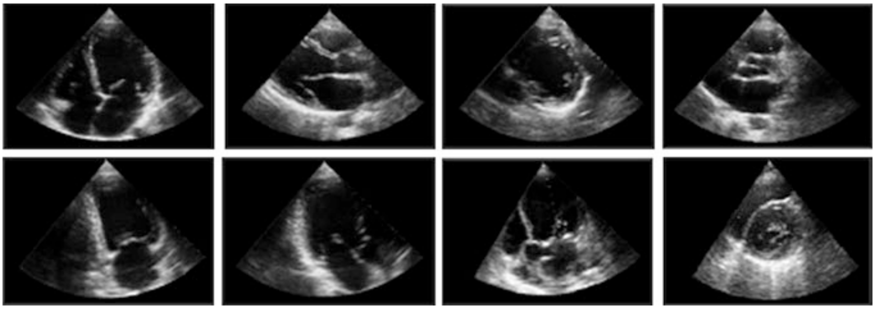

Fig. 2 Images from the eight echocardiogram viewpoints in this chapter. In clockwise order from top left, apical four chamber (a4c), parasternal long axis (pla), parasternal short axis—basal (psab), parasternal short axis—papillary (psap), apical two chambers (a2c), apical three chambers (a3c), apical five chambers (a5c), parasternal short axis—mitral (psam) [4]

3 Methodology

The methodology used for Echocardiography recognition in this chapter is described as follows:

- Database Acquisition
- Application of Preprocessing
- Neural Network Design
- Neural Network Training
  - Scaled Conjugate Gradient (SCG)
  - Gradient descent with adaptive learning rate backpropagation (GDA)
  - Gradient Descent with Momentum and Adaptive Learning Rate (GDX)

3.1 Data Acquisition

To create the database, we acquired videos of echocardiograms, of 30 patients, of which 18 echocardiograms are some heart in-disease patients and 12 echocardiograms from patients without any disease, in where each video is captured with 10 images. The size of the images is 200 × 125 pixels.

3.2 Preprocessing

For image preprocessing, we reduced the image size from 400 × 325 to 200 × 125 pixels taken the region of interest (ROI) to eliminate as much as possible the noise. The first thing we did was to clean up the image, then we apply a filter to the image

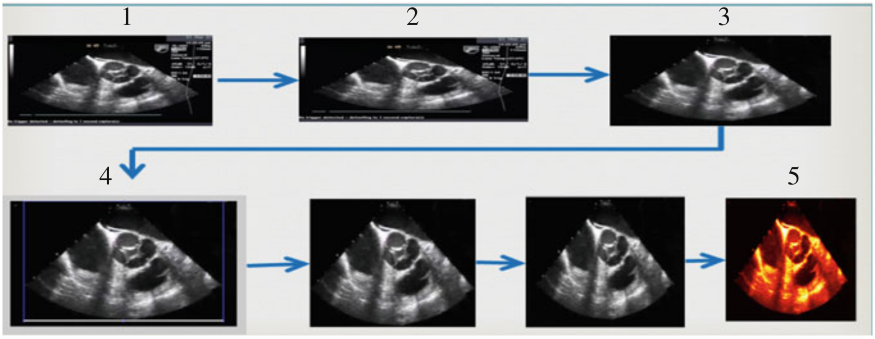

Fig. 3 In the above images *1* captured image, *2* clean image, *3* image filter to reduce the noise, *4* crop image, *5* color image

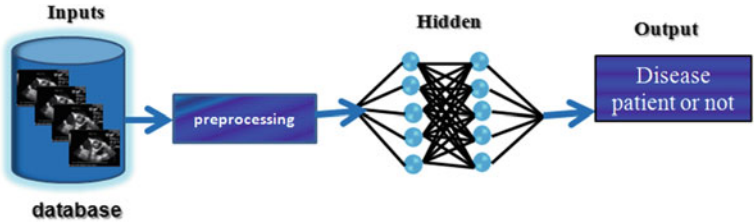

Fig. 4 Monolithic neural network architecture

to reduce noise, then we cut the image so that only the part of the image that is of interest remains, and finally we apply color to these images (Fig. 3).

3.3 Neural Network

We are considering a monolithic neural network in this chapter. Figure 4 shows the architecture used for this work and is described as follows: We have a data base, then we apply preprocessing to the images, then in the architecture of the neural network the output is if the image corresponds to a person with a cardiac illness or not.

4 Experimental Results

For the 30 patients in the study, we trained the neural network with the 2 available images of each patient. The size of the images is of 200 × 125 pixels.

Table 1 shows the experimental results with the "trainscg" training method, with 150 and 200 epochs and a goal error of 0.001.

Table 1 Experimental results with trainscg training method

	Training	Neuron by layer	Training time	Epoch	Recognition %
1	trainscg	60 55	01:26	143	59.1
2	trainscg	60 50	01:55	200	64.7
3	trainscg	50 55	04:04	200	57.3
4	trainscg	50 45	03:52	200	60.3
5	trainscg	42 40	03:27	200	58.5
6	trainscg	40 50	02:25	150	69.4
7	trainscg	70 60	07:13	250	58.6
8	trainscg	50 50	04:11	200	64.6
9	trainscg	65 65	01:52	200	70.3
10	trainscg	80 85	02:12	200	56.6

Table 2 Experimental results with traingda training method

	Training	Neuron by layer	Training time	Epoch	Recognition %
1	traingda	62 64	00:54	191	69.5
2	traingda	50 55	00:45	200	77.6
3	traingda	70 60	01:01	200	73.6
4	traingda	50 45	00:40	200	61.2
5	traingda	65 70	00:58	200	63.8
6	traingda	60 60	00:54	200	81.8
7	traingda	90 95	01:14	198	86.7
8	traingda	60 55	00:51	200	75
9	traingda	56 54	00:49	200	82.5
10	traingda	53 50	00:48	200	83.3

Table 3 Experimental results with traingdx training method

	Training	Neuron by layer	Training time	Epoch	Recognition %
1	traingdx	90 90	01:13	199	68.2
2	traingdx	60 60	00:47	200	60.1
3	traingdx	50 45	00:44	200	80.9
4	traingdx	88 72	02:41	200	59.1
5	traingdx	53 50	00:44	200	77.6
6	traingdx	56 54	00:56	200	60.4
7	traingdx	65 65	02:58	247	65.4
8	traingdx	75 75	03:29	200	60.7
9	traingdx	70 60	01:49	146	64.1
10	traingdx	64 64	01:27	144	60.5

Table 2 shows the experimental results with the “traingda” training method, with 200 epochs and a goal error of 0.001.

Table 3 shows the experimental results with the “traingd” training method, with 200 epochs and a goal error of 0.001.

Table 4 Learning algorithm comparison

Training	Neuron by layer	Training time	Epoch	Recognition %
trainscg	65 65	01:52	200	70.3
traingda	90 95	01:14	198	86.7
traingdx	53 50	00:44	200	77.6

Table 4 shows the learning algorithm comparison. The best learning algorithm in this case was Gradient descent with adaptive learning rate backpropagation (GDA). Comparing with scaled Conjugate Gradient (SCG) and gradient Descent with Momentum and Adaptive Learning Rate (GDX), GDA gets the best training time and recognition.

5 Conclusions

In this chapter we presented a monolithic neural network architecture to recognize if the image is of a person with a heart disease or is an image of a person with normal heart. Results obtained are good; the best learning algorithm in this case was gradient descent with adaptive learning rate backpropagation (GDA) with 86.7 % recognition rate. Comparing with scaled conjugate gradient (SCG) and gradient descent with momentum and adaptive learning rate (GDX), GDA gets the best training time and recognition.

Results obtained are good, however, other methods could be used to improve results, for example just to compare a modular neural network architecture can be used [18, 19, 20, 21, 22], or apply another kind of preprocessing, like in [13, 14, 15, 16, 17]. Other future work could include applying an optimization method to the design the neural network, like in [25, 26, 27].

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