Artificial Neural Networks Ensemble Applied to the Electrical Impedance Tomography Problem to Determine the Cardiac Ejection Fraction

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Abstract. Cardiac Ejection Fraction (EF) is a parameter that indicates how much blood the heart is pumping to the body. It is a very important clinical parameter since it is highly correlated to the functional status of the heart. To measure the EF, diverse non-invasive techniques have been applied such as Magnetic Resonance. The method studied in this work is the Electrical Impedance Tomography (EIT) which consists in generate an image of the inner body using measures of electrical potentials - some electrodes are attached to the body boundary and small currents are applied in the body, the potentials are then measured in these electrodes. This technique presents lower costs and a high portability compared to others. It can be done in the patient bed and does not use ionizing radiation. The EIT problem consists in define the electrical distribution of the inner parts that results in the potentials measured. Therefore, it is considered as a non-linear inverse problem. To solve that, this work propose the application of an Artificial Neural network (ANN) Ensemble since it is simple to understand and implement. Our results show that the ANN Ensemble presents fast and good results, which are crucial for the continuous monitoring of the heart.

Keywords: Cardiac mechanics · Medical applications · Cardiac ejection fraction · Electrical impedance tomography · Artificial neural networks

1 Introduction

The cardiac ejection fraction (EF) is a clinical parameter that determines the amount of blood pumped from the heart in each heart cycle. During each heart cycle, the ventricle relaxes, refilling with blood, and contracts, ejecting part of the blood out of the heart. The Ejection Fraction is the percentage of blood ejected from the heart in its contraction [1]. The left ventricle is the heart's main pumping chamber and is often used to determine the cardiac ejection fraction, because he is the one who ejects blood to the whole body, while the right ventricle pumps deoxygenated blood to the lungs. EF is calculated as follows:

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$$EF = \frac{PV}{EDV} = \frac{EDV - ESV}{EDV}, \tag{1}$$

where PV denotes the volume of blood pumped, given by the difference between the end-diastolic volume (EDV) and the end-systolic volume (ESV).

An EF outside of the considered normal range indicates that the heart is contracting abnormally (abnormalities in the heart wall moviments), which may indicate a malfunction of the heart. It is a relevant parameter because of its high correlation with the functional status of the heart - a low EF number may indicate a heart failure, where the heart doesn't pump enough blood to the body. Diverse non-invasive methods can be applied to measure EF, like Computer Tomography, Magnetic Resonance, and others. Nevertheless, these techniques cannot be used to the continuous monitoring of EF, once they require the movement of the patient to a scanner into another room. On the other hand, Electrical Impedance Tomography (EIT) may be applied in the patient's bed, obtaining continuous EF estimations of the heart. In addition, it doesn't use ionizing radiation, it has low costs and high portability, justifying researches for solutions involving this technique for monitoring EF.

The EIT consists in fixing a number of electrodes on the boundary of the tomography body and small electric currents are injected. The electrical potentials are then measured in the electrodes. By the measurements of the potentials and current injection taken on the boundary of the domain, an image of the inner body can be generated based on the already known resistivity and conductivity distribution of the body parts - lungs, torso and heart. This technique has been applied to many fields (e.g. industrial monitoring [2], geophysics [3], and biomedical engineering [4–7]), although recent works [8] and [9] have shown results in obtaining the cardiac EF, where the viability of EIT to continuos monitoring was also discussed. These works have generated a 2D image of the ventricles and the their areas are used instead of the volume for calculation the EF.

In our work, the goal is not to generate an image, instead we use the electrical potentials measured to straightforward determine the EF. The [10] used a single ANN to solve this same problem obtained good results compared to [9]. Moreover, the single ANN is simpler to implement than the method presented in [9] and it requires less computational complexity, since it is only necessary the measures of the electrical potentials obtained in the EIT. In this work, we used an Artificial Neural Networks (ANN) Ensemble.

The ANN Ensemble, after trained, presents fast and good results, since its parts also present fast results. Therefore, it is ideal to use them in the EIT problem, since it requires the result to be accurate and quickly computed, in order to keep the continuous monitoring of the patient.

The ANN Ensemble has been used in many problems to improve the performance and generalization error (see e.g. [11–13]). Our results show that it also helps in the EIT problem improving the stability and confidence of the single ANN, which is important in a medical environment [14,15].

The potential protocols taken by the EIT are used as the ANN Ensemble's inputs and the areas of both ventricles are the ANN Ensemble's output. Due to a lack of real data of EIT, a synthetic data set was generated as described in [10]. The electrical potentials were computationally simulated using a representation of the body. In order to represent the body parts, a segmentation is made based on a magnetic resonance image. This segmentation represents the curves approaching the boundaries of the body cavities using parameters defined by a mathematical method of spline. By changing the parameters of the spline, it is possible to generate new curves that represent new body cavities. Our interest is to generate new heart configurations. The generation of new synthetical hearts is made by creating new parameters settings. Each new setting is then passed to a function that compute the correspondent electrical potentials used as input of the ANN Ensemble.

This paper is organized as follows. The second section describes the ANN ensemble. The third section, a detailed explanation of how our dataset was done and its properties. In the fourth section, we present all the results obtained using ANN ensemble to the EIT problem, also a comparison with previous methods. Finally, a conclusion is made and some ideas for future works are presented.

2 ANN Ensemble

The idea of an ensemble is to use a finite number of a predictor and combine their predictions in one single prediction. The combination of these predictions can be done in several ways - averaging is one of them. An ANN ensemble consists of training some ANNs, usually it is done by changing the training set of each ANN. But different methods can be used, such as change the number of hidden neurons or use different training function in the ensemble parts. After all ANN's of the ensemble have been trained, a test set is used in all trained network and the outputs of each tested network are combined to generate one single prediction. This single prediction is said to be the output of the ANN ensemble and its error is calculated, which define the ensemble's generalization error.

The ANN ensemble have became very popular since the work by Hansen and Salamon [11], which concludes that using a combination of several ANNs performs better than using only one single model. The reason of it is that in order to performs well, each part of an ensemble has to be well trained - diverging in their predictions with different inputs in such a way that the inaccurate output of ones are the accurate output of others ([16,17]). The combination of these predictions converges to the target. Since ANNs are unstable predictors, small changes in the training process can produce very different results. Therefore, it is possible to train a number of ANNs in different ways that produce good, and at the same time, different results. The combination of these networks results in a prediction smoother and more stable than the one from its parts.

There are a few popular methods that ensure a good ensemble performance [12]. The technique used in this work for training the ANNs ensemble is the Bootstrap aggregating (bagging) [18]. The bagging algorithm consists in training each ANNs of the ensemble using bootstrapped samples of the training data set. The bootstrap method consists in resampling with replacement the data set into

N new samples, where N is the number of ANNs in our ensemble. 20% of the dataset is reserved as test set and used to measure the performance of the ANN Ensemble after the training phase. The other part of the data set is used for the bootstrap method to complete a training set, and a validation set is filled with data that was not used in the training set. The validation set on each ANN is used to apply the early stopping.

Firstly, part of the database is reserved to calculate the generalization error of the ensemble - the test set. After that, bootstrapped samples are generated from the remaining database, one for each ANN in the Ensemble. The bootstrap samples are used as the training set and the data of the remaining database that was not used in that training set is chosen as the validation set. In this work, after all ANN are trained, an averaged combination of their predictions is made to compute the ANN Ensemble's prediction. Its generalization error is then calculated in the test set.

As said before, the goal of this work is to use an ANN ensemble to determine the areas of the ventricles of a heart represented in a 2D-model. This area is then used to calculate the cardiac ejection fraction, which is a very important parameter to analyze the functional status of the heart. The ANN ensemble used in this work receive as input the electrical potentials that are measured by the electrodes attached to the body and the areas of both ventricules are calculated as output.

The implementation of the ANN ensemble is done using Matlab [19]. To determine the best ANN ensemble configuration, several previous test are made changing the number of neurons in the hidden layer of the ANNs, once the optimal number changes for different training sets. Two different training functions are used to train the ANNs - the Backpropagation Algorithm with the Levenberg-Marquardt (LM) optimization [20]; and the second also uses the LM optmization to update the weights and bias of the ANN, the difference is that it uses the Bayesian regulation in the determination of the weights and reduces the number of parameters after the training phase. The use of Bayesian regulation is inspired in a previous work that have shown good results when applied to an ANN ensemble [21]. The Mean Absolute Percent Error (MAPE) is used to measure the performance of each configuration and the results are shown in the conclusion section.

3 Results

In this work, an ANN Ensemble is used with 10 ANNs and the bagging technique, this choice was based on good results of previous tests. Also, as said before, we compare two training functions. In order to do this comparison, the ANN Ensembles for each training function received the same datasets for the training and test phases. The tests were made by changing the number of hidden neurons on each neural network from 1 to 20. Many different test sets were used in order to calculate the mean error. As the figure 1 suggests, the ANN Ensemble trained with the trainbr algorithm achieves better results than the other. The best configuration for the ANN Ensemble trained with the trainbr algorithm uses 11 neurons in the hidden layer of the ANNs parts and it obtained a MAPE of 0.7226. The best configuration for the ANN Ensemble trained with the trainlm algorithm uses 10 neurons in its hidden layer and obtained a MAPE of 0.7759. The ANN Ensemble training phase took 0.2 hours for the trainlm algorithm and 4.4 hours for the trainbr algorithm. After trained, both configurations take less than 0.07 seconds to compute their outputs. These tests were taken in a computer with Intel Core I5 2.4Ghz and 4GB of RAM.

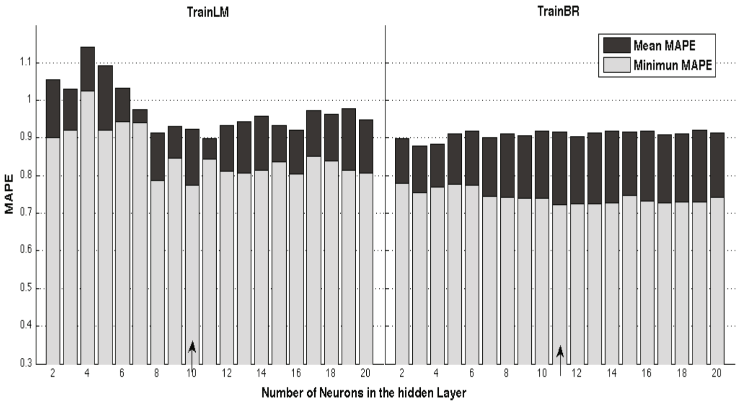

Fig. 1. Results for both training function

In [10] a single ANN was used to solve the EIT problem. Figure 2 makes a comparison between the best configuration achieved in that work and the ANN Ensemble trained with the trainbr algorithm. Both models use the test set that achieved a best result in [10]. The best MAPE achieved for the ANN Ensemble trained with the trainbr algorithm is 0.6551, while the best for the single ANN trained with the trainlm algorithm is 0.7253. Look at the figure 2 that the ensemble achieves a smaller error in majority configurations than the single ANN, following an error around 0.7%.

Until now, all results shown are in respect to the MAPE of the ANN Ensemble outputs that is related to the ventricules area of the heart. To show the errors in respect to the Cardiac ejection fraction, simulations are made and the results are compared with previous works.

In this work, we use a 2D representation of the body, therefore the following equation is used to calculate the EF:

$$EF = \frac{EDA - ESA}{EDA}, \tag{2}$$

where EDA and ESA are the area of the heart at the end of diastole and at the end of systole, respectively. Note that the area is now used instead of the volumes.

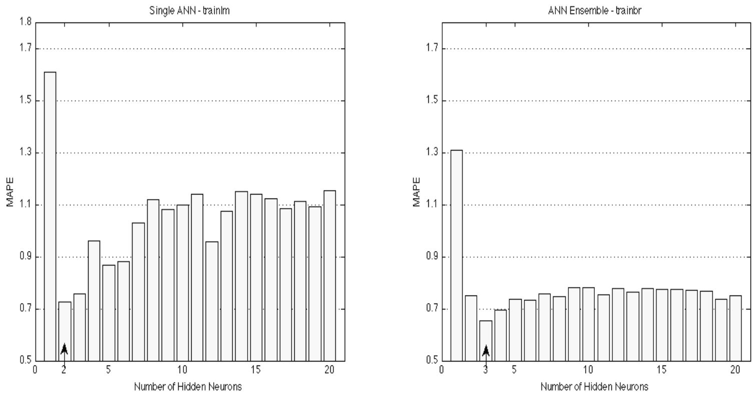

Fig. 2. Comparison between single ANN and ANN Ensemble

The table 1 shows the relative error obtained for three simulations compared in three methods - Levenberg-Marquardt Method [9], Single ANN [10], ANN Ensemble trainend with the trainbr algorithm, in both Right (RV) and Left Ventricle (LV). The simulations are done by the generation of an artificial cardiac malfunction where the first simulation expects the heart to have a normal diastole and only the systole is abnormal. The second one, expects the heart to have a normal systole and abnormal diastole. The last one does not represent a disease, instead it represents a heart that is pumping more efficiently and has a systolic area smaller than the one obtained in the resonance magnetic image (i.e. it is contracting more than expected).

Table 1. Comparison between LM Method [9], Single ANN [10] and ANN Ensemble

Relative Errors (%)						
	Bad Systole		**Bad Diastole**		**Efficient**	
Method	**RV**	**LV**	**RV**	**LV**	**RV**	**LV**
LM [9]	2.410	0.090	-	-	-	-
Single ANN	4.490	1.060	4.837	0.555	3.222	5.262
ANN Ensemble	3.210	0.046	1.995	0.009	1.289	4.79

4 Conclusions

The Cardiac Ejection Fraction (EF) indicates how much blood the heart is pumping to the body. It is a very important clinical parameter since it is highly correlated to the functional status of the heart and might indicate some malfunctions. Many techniques have been applied to measure the EF. One of the techniques used is the Electrical Impedance Tomography (EIT) which presents some advantages over another popular methods such as Magnetic Resonance.

The main advantage of EIT is its portability - the patient can stay in his bed the whole time. In order to maintain a continuos monitoring of the patient's heart, the EIT has to give online results. The solution proposed here is to use an Artificial Neural Network Ensemble, since it presents fast and accurate results.

The main goal of this work was to apply an ANN Ensemble to solve the EIT problem. In order to adjust the ANN Ensemble parameters, two training functions were compared - 'trainbr' and 'trainlm' algorithms. Altough the 'trainbr' algorithm took more time to train the ANN Ensemble, it presented better results than the 'trainlm' algorithm. Moreover, both algorithms showed online execution time results.

Another comparison is made with another method used to solve the EIT problem applied in the EF, which uses the Levenberg-Marquardt optimization [9].

As future work we plan to use a three-dimension model that can better represent the body and the heart cavities. We also plan to use multiple resonance magnetic images and generate the potentials based on that, in this process the usage of a spline is not necessary and the amount of parameters is reduced. Another plan is to use real EIT data.

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