Detection of cardiac arrhythmias using simple artificial neural network

Espindola M. F., Iano Y, Leite R. B., Lino F.

Abstract — **Cardiopathy, a heart disease or inadequate functioning of the heart, is the third largest "cause mortis" in Brazil and worldwide. Detect and diagnose cardiac arrhythmias, promptly and properly, can drastically reduce rates of premature death. Some arrhythmias, when detected, must be resolved in a timely manner because they are lethal to the heart. The objective of this work is to develop a system of acquisition, storage and visualization of 4 cardiac rhythms: normal rhythm, ventricular tachycardia, ventricular fibrillation and atrial fibrillation. For this, we first collected several electrocardiograms (ECG) samples obtained from a simulator. The output of this simulator will produce a database that is used as input in a Hamming window to produce the necessary frequencies that can represent the 4 cardiac rhythms. The output of this windowing is passed to a Fast Fourier Transform (FFT) algorithm, resulting in a frequency spectrum for each one of the cardiac rhythms. Otherwise, using a simple neural network, in a next step work, are intended to implement in real time and on low cost embedded hardware as a wearable solution for cardiac healthcare.**

Keywords— **Neural Networks, FFT, Cardiopathy, Wearable Health.**

I. INTRODUCTION

Detecting and diagnosing cardiac arrhythmias promptly and properly can dramatically reduce premature death rates [3]. Among the potentially most dangerous are: ventricular fibrillation, ventricular tachycardia and atrial fibrillation. However, other arrhythmias can occur throughout a lifetime without major consequences for the proper functioning of the heart. Therefore, the development of computer equipment or programs to properly detect a restricted set of arrhythmias is of great importance in clinical life.

Several techniques have been developed over time to solve this problem.

Changes in frequency can be easily detected by measuring your heart rate, such as a reduction in rhythm (bradycardia) or elevation (tachycardia). However, the most lethal arrhythmias cannot be identified solely by the analysis of the beat, but by the shape of the generated rhythm. In this context, one of the most commonly used forms is that employing neural network techniques to identify a restricted set of arrhythmias [1].

Figure 1 shows the representation of the heart in the various places of heartbeat generation. Under normal conditions, the sinoatrial node (AS node) spontaneously generates action potentials. These signals propagate through the Purkinje fibers until they reach the ventricles to excite / relax the heart and thus pump blood to the various tissues of the human body. The electrical voltage captured at any two points on the heart is called electrocardiogram (ECG), as shown in Figure 2.

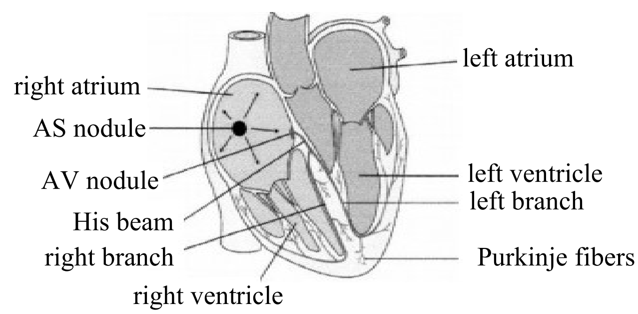

Figure 1. Inside heart view.

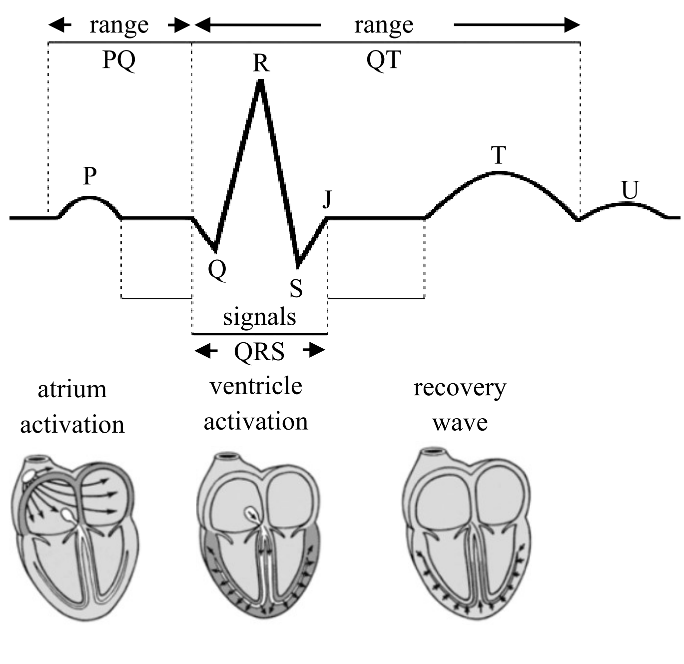

Figure 2. P, T waves e QRS signals complex [2].

Espindola M. F., Laboratory of Visual Communications – LCV, Faculdade de Engenharia Elétrica e de Computação da Universidade Estadual de Campinas / Instituto Federal de Educação, Ciência e Tecnologia de São Paulo – IFSP, marcos.espindola@ifsp.edu.br.

Iano Y., Laboratory of Visual Communications – LCV, Faculdade de Engenharia Elétrica e de Computação da Universidade Estadual de Campinas, yuzo@decom.fee.unicamp.br.

Leite R. B., Instituto Federal de Educação, Ciência e Tecnologia de São Paulo – IFSP, ricardo.leite@ifsp.edu.br.

Lino F., Instituto Federal de Educação, Ciência e Tecnologia de São Paulo – IFSP, flino@ifsp.edu.br.

.

The P wave is the record of action potentials when propagating in the atria; The potentials then spread to the ventricles, giving rise to the QRS complex, and the T wave is the result of ventricular relaxation after arousal. Normally the ECG is generated at the sinoatrial node; However, due to various genetic or physiological factors, other parts of the heart may control the beat, for instance, in ventricular tachycardia, the ventricles assume this role. The consequence is a different signal than that shown in Figure 2. In Figure 3, shown below, the first ECGs are from a ventricular tachycardia, then the rhythm normalizes. The shape of the ECG signal is of fundamental importance in identifying an abnormal rhythm, making the arrhythmia detection task a very complex analysis [2], [3].

Figure 3 Heart rhythm example [3].

II. OBJECTIVES

Given the computational tools and mathematical methods, the detection process can be separated into three groups: preprocessing, extraction and classification [11]. Among the groups, this paper demonstrates the use of an artificial neural network-based classifier for four cardiac conditions: normal, ventricular fibrillation, atrial fibrillation, and ventricular tachycardia. It is approached as a case study of application and implementation exercise of artificial neural networks. The unfolding of this work is envisaged for the implementation of a product or use model in health-related Wearables devices and solutions [13].

The theme ANN (Artificial Neural Networks), despite having its first works published more than 50 years ago, only began to be researched strongly from the 1990s [5].

ANNs, as one of the techniques in artificial intelligence, are of great value when we have a large mass of data, without knowing the mathematical model of a particular problem in science or engineering [7].

The implementation involves a system for acquisition, storage, visualization and training of the four cardiac conditions to be classified. This system should provide ease and mobility through its small size for cardiac monitoring.

III. MATERIALS E METHODS

The signals of the 4 types of heart rate will be generated by a heart rate simulator, as shown in Figure 4, which will be previously processed and stored in a personal computer as per [9]. Using the simulator facilitates repeatability of the test and the ethical issue of using patient information.

With the collected heart rhythms, we make use of an application [10], where we enter the starting frequency, the final frequency, the frequency increment and the desired rhythm type, as shown in figure 5.

Figure 4. Heart rate simulator [9].

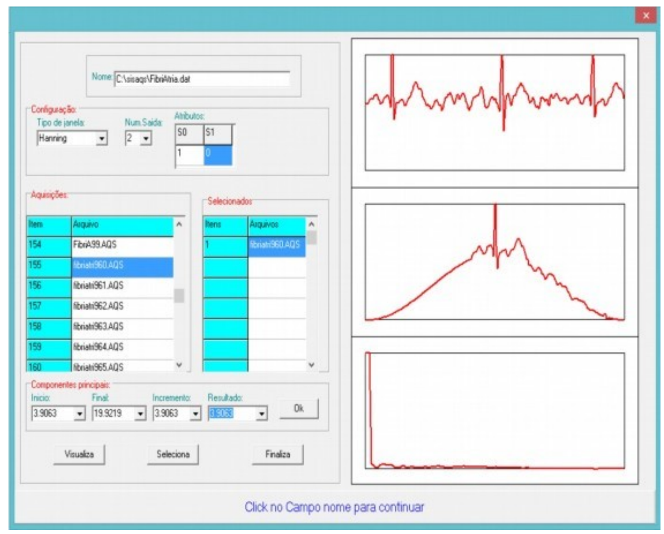

Figure 5. Acquisition of signals (heart rhythms).

With the data entered, the system generates an output signal at the desired rate continuously.

In the study, our initial and final frequencies were 3.9 Hz and 19.9 Hz, respectively, with 3.9 Hz increments, values suggested according to [4] and [8].

In the following figures. from 6a to 6d we have the four rhythms that will be of interest for this work: (a) normal, (b) ventricular tachycardia, (c) atrial fibrillation, (d) ventricular fibrillation.

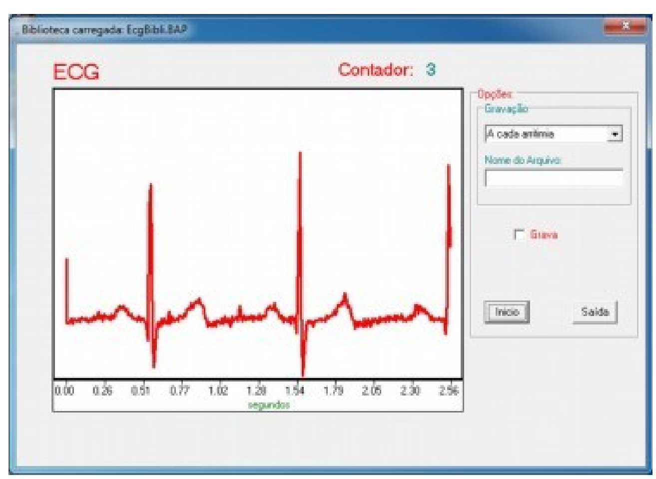

Figure 6a. Normal.

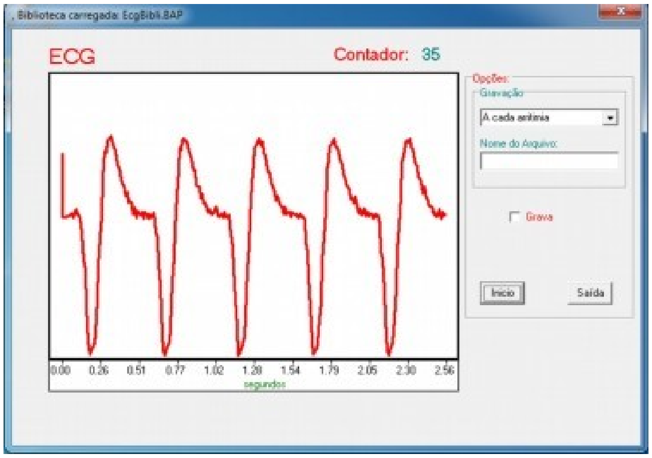

Figure 6b. Ventricular tachycardia

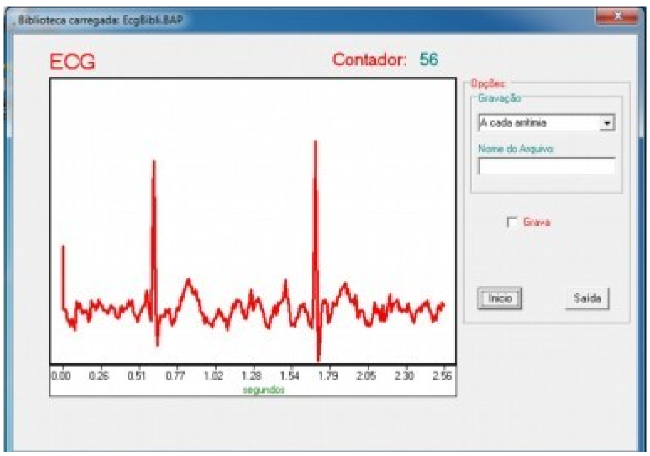

Figure 6c. Atrial fibrillation.

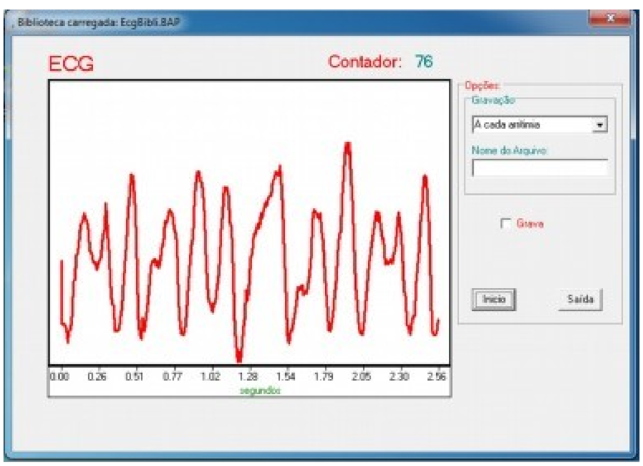

Figure 6d. Ventricular fibrillation.

Once each of these rhythms is collected, only the interval comprised by the P, T waves and the QRS complex is taken, applying the FFT algorithm [6] to obtain the results shown in Figure 7.

Note that it is possible to identify characteristics of the various rhythms in their spectral representations. The normal rhythm presents the largest modules at the frequencies of 15 and 19 Hz, which is in agreement with the presence of the QRS, whose frequency is in this range. Ventricular tachycardia arrhythmia concentrates the FFT modulus at 4 Hz, as well as Ventricular Fibrillation at 4 and 8 Hz, and Atrial Fibrillation has a more dispersed spectrum. In short, through this analysis it is possible to identify these four types of signals by using the FFT modules at these respective frequencies.

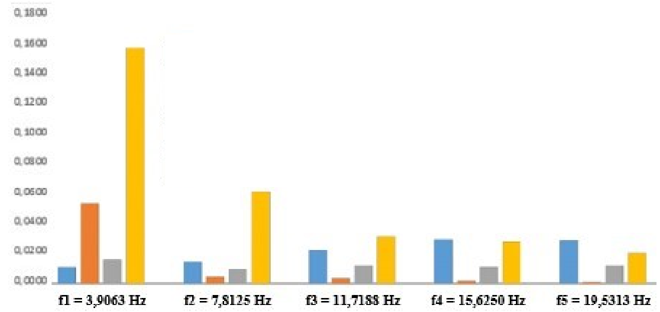

Figure 7. ECG's FFT's [10], respectively left to right: normal, ventricular tachycardia, atrial fibrillation, ventricular fibrillation.

IV. RESULTS

With the data provided by the apparatus shown, the cardiac rhythms were classified through the use of an artificial neural network. A simple network was defined for this work only for conceptual validation. The network model chosen was the Perceptron type, developed in the 1950s and 1960s [12] and was implemented using MATLAB®.

The result was not satisfactory for single-layer Percepton as many errors were detected and heart rate classification could not be performed. From then on, we used the MLP (Multilayer Perceptron) network, initially working with two layers, the first with five, eight, ten and twelve neurons. Simulations also with three-layer networks were performed.

Among two- and three-layer simulations it was observed that the best results were obtained using a two-layer MLP network, ten first-layer neurons and two outputs (S0 and S1), whose values were defined for the four types. rhythms according to table 1.

Figure 8 shows the MLP network used in the simulations and as a block diagram of the input and output data in that network.

For each of the five frequencies shown in Figure 7, fifty samples were collected from each rhythm, where 80% were applied, forty samples of each frequency, as values for network learning and the rest, ten samples, as simulation.

For forty samples: 5x160 matrices for input data and 2x160 matrices for output or expected training values.

For simulation: 5x40 arrays for input data and arrays and 2x40 for simulation output.

Figures 9 and 10 show the results of MATLAB® simulation using the *nntool* tool.

TABLE I

S0	S1	Classification
0	0	Normal
0	1	Ventricular fibrillation
1	0	Atrial fibrillation
1	1	Ventricular tachycardia

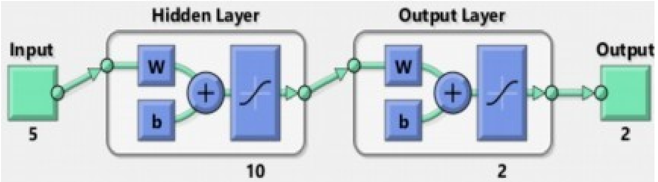

Figure 8. MLP network used in simulation.

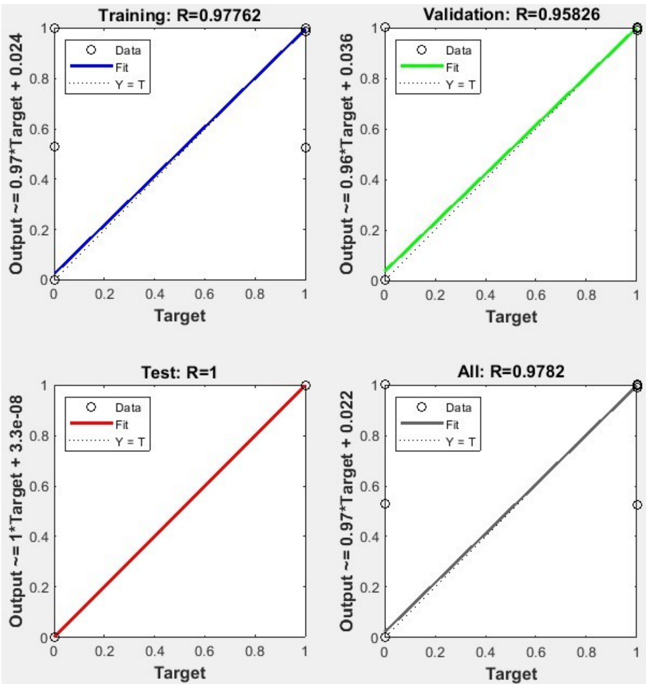

Figure 9. Simulation results (regression).

V. CONCLUSION

With the tools used it was possible to validate the concept of detection of four commonly known heart diseases [3]. The results are intended to implement the implementation of the MLP network in real time and on embedded hardware as a wearable solution [13] for cardiac healthcare. Also as a consequence for future work, the implementation of other neural network models must considered in the comparative analysis of performance, hardware implementation cost and power consumption.

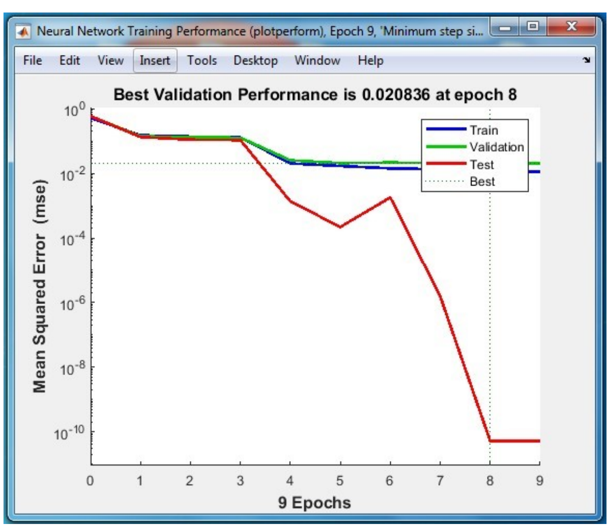

Figure 10. Simulation results (performance).

REFERENCES

[1] Ribeiro A. A. B., Sistema para simulação de ECG e arritmias cardíacas para ensino e treinamento de pessoal. Dissertação de Mestrado FEEC/UNICAMP, 1991.

[2] Eletrocardiograma de um coração normal. Web link: http://empendium.com/manualmibe/chapter/B34.V.25.1.1. Access: April 29 2019.

[3] Barbosa M. P. T. Arritmias cardíacas e morte súbita. XXXII Congresso Brasileiro de Arritmias Cardíacas SOBRAC https://sobrac.org, november 2015.

[4] Gothwal H., Kedawat S., Kumar R. Cardiac arrhythmias detection in an ECG beat signal using fast fourier transform and artificial neural network. J. Biomedical Science and Engineering, 2011, 4, 289-296.

[5] Silva I.; Spatti, D; Flauzino, R. Redes Neurais Artificiais para engenharia e ciências aplicadas. São Paulo: Artliber, 2010.

[6] Oppenheim A., Schafer R. DISCRETE-TIME SIGNAL PROCESSING. Prentice-Hall, 1989.

[7] Santos R Inteligência Artificial. Redes Neurais Artificiais: Aulas 1 e 2, 2019.1. Notas de aula.

[8] Minami K., Ohkuma Y., Nakajima H., Toyoshima, T. Real-time Ventricular Arrhythmia Detection with Fourier Analysis and Neural Network. Computers in Cardiology, 1996, 545 – 548.

[9] Lucena, S. E. UM SIMULADOR DE ECG/ARRITMIAS CARDÍACAS. Tese apresentada à Faculdade de Engenharia Elétrica da UNICAMP, 1989.

[10] Ribeiro A. A. B. IFSP - Instituto Federal de Educação, Ciência e Tecnologia de São Paulo. Aplicativo de aquisição de sinais com geração do espectro de frequências de ritmos cardíacos, 2010.

[11] Sogari, Diego. Análise comparativa de métodos de detecção automática de isquemias cardíacas. Monografia apresentada ao Instituto de Informática – UFRS, 2014

[12] Deep Learning Book, Data Science Academy - http://deeplearningbook.com.br/

[13] Cicek M. - Wearable technologies and its future applications, International Journal of Electrical, Electronics and Data Communication, ISSN: 2320-2084 Volume-3, Issue-4, April-2015.