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Algorithm for reconstruction of time signals and Artificial Neural Networks for taxonomy of thrombi in Ventricular Assist Devices

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Abstract

Affecting millions of people around the world, the cardiovascular diseases are responsible for the first cause of hospitalization and death in many countries. Cardiovascular diseases, like congestive failure, affect many patients, but some of them are not eligible to heart transplantation. Thus, they need to receive a circulatory device for their life support known as Ventricular Assist Devices. This kind of device still shows some problems in hemocompatibility, among of then the thrombogenesis, which is a kind of natural coagulation when blood comes in contact to any surface not fully covered by endothelium. The thrombus formation in Ventricular Assist Devices can result in its disablement or even cause patient death. To prevent this scenario, the thrombolytic therapy needs to start as soon as possible. However, a previous and not invasive diagnostic is relative complex. In order to avoid this problem, this work presents the use of Predictive Maintenance techniques concomitantly with Machine Learning Algorithms as an alternative to detect thrombus formation in its beginning or even, predict its formation before its occur. The objective of this work is to develop a Python language algorithm to reproduce time signals (from a previous work) that indicates presence and absence of thrombus, then use these signals to train Artificial Neural Networks to classify them. The Artificial Neural Networks obtained accuracy in test around 91% to classify thrombus absence, thrombus on pump base, rotor spiral and rotor vanes. As this algorithm enables simulate some situations, e.g. a transition state between no thrombus and thrombus presence, a predictive algorithm can be created in order to identify previously thrombus formation. As future work, we intend to test it in vitro, and the thrombus presence could be diagnosed and treated by Safety Instrumented System, which must be a safety system responsible for diagnosing and treating faults.

Ventricular assist device; thrombus; artificial neural network; predictive maintenance; taxonomy

1. Introduction

Affecting millions of people around the world, the cardiovascular diseases (CD), like heart attacks, coronary artery disease and etc. are responsible for the first cause of death and hospitalization around the world, being a serious public health problem [1]. Some patients affected by some CDs and not eligible for heart transplantation, receive a circulatory device for life support known as ventricular assist device (VAD) [2].

The VADs are established as a good therapy for patients with end-stage heart failure [3]. The function of VAD is to replace the mechanical work of left or right ventricles [4]. The VAD is basically a pump with motor, controller, outflow graft, drive line cable and batteries as shown in figure 1 [5]. The VADs still shows some problems in hemocompatibility, among of then the thrombogenesis, which is a kind of natural coagulation when blood is exposed to any surface not fully covered by endothelium, or some reaction with biomaterial [6]. One of the most common therapies to avoid thrombus formation on VAD is the prescription of anticoagulants that will dissolve thrombus [7]. However, this therapy will be effective only if patient start it on the first stages of thrombosis [8]. The thrombus formation on VAD can result in its disablement or even cause patient's death [2], [9]. An immediate action is necessary, and the current scenario is indecisive about which treatment needs to be carried out [10]. Figure 2 shows some examples of thrombus formation on HeartMate II VAD (Thoratec Corporation, Pleasanton, CA). In regions 0 and I conformal thrombus, partial occlusion in regions II and IV, and total occlusion in region III [11].

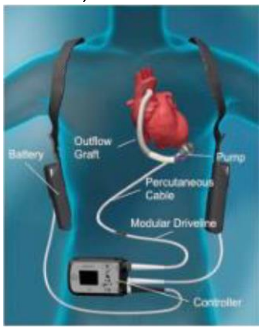

Figure 1. Ventricular Assist Device (VAD) with batteries, controller and peripheral systems

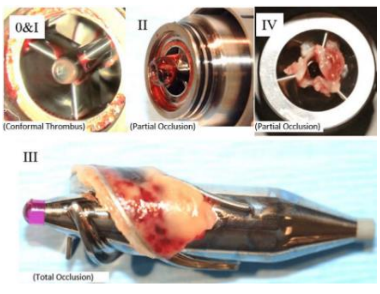

Figure 2. Examples of thrombus formation on VAD HeartMate II

The commercial VAD controllers use control techniques for maintaining of stable speed of VAD motor [12], however more sophisticated control techniques are being studied to increase the patient's survival rate [13]. The thrombus formation and its consequent release into patient's body is one of the main causes of death in patients implanted with VAD [14]. A VAD controller that diagnoses the appearance of thrombus before its release, can be vital to keep patient's life, and several studies are being conducted with this objective [8], [15].

Other studies have been made in order to detect thrombus formation on VAD using signal analysis. For instance, Hijikata presented an in vitro study where the thrombus formation was detected by measuring of phase difference between rotor frequency and electrical sinusoidal current inducted on magnet bearing. In this study, thrombus formation was simulated and they concluded that as thrombus get formed, the value of differences between phases increased [16]. In other study, Feldmann made an in vitro study where the thrombus was detected by acoustic method. In this study, they used a microphone connected to a stethoscope to get acoustic signals, and made a frequency spectrum analysis. The results indicate that this method is more sensible to indicate the thrombus presence than the other method, which uses power consumption [17]. Glitza presented a study where the thrombus could be detected by analysis of speed variation of VAD's rotor. In order to analyze this variation, they used data from electrocardiograms to calculate rotor's speed in presence and absence of thrombus. The proposed method showed accuracy around 99.8% on speed calculation. In addition, this study showed that the rotor's speed changes also according to the patient's posture when the data is being collected [2]. Neto presented an in vitro study where the vibrational signal analysis, obtained with Micro-ElectroMechanical Systems (MEMS) accelerometers, was used to identify disturbances or stimulations that indicate dynamics changes on pump's rotor when thrombi adheres or if there is wear on rotate elements. As the used system for signals acquisition receive the signal on time function, the Fast Fourier Transform (FFT) is used to characterization of signal components in the frequency domain [18].

2. Objectives

Based on data of an experimental study of [18] that performed tests with artificial thrombus on pumps prototype, the objective of this work is to develop a Python language algorithm to reproduce simulated signals that indicates the disturbances caused by presence of artificial thrombus adhered in three different regions of pump, then use these signals to train an Artificial Neural Network (ANN) to taxonomy them.

3. Methodology

This work was divided in two main methodologies: Creation of an algorithm to reproduce the time signals and creation of an ANN algorithm to taxonomy them.

3.1. Creation of time signals

Using the results from [18], a dataset in language Python of voltage in time domain was created. The graphs shown in that work provide data as maximum voltage amplitude for determinate frequency, noise and sampling rate. With these data, cosine signals with same amplitudes were created. After creation of "clean signal", a background noise was added with Gaussian distribution with goal to get simulated signal similar to the real one.

The FFT was applied to each one of the created signals, then the results were squared to get power spectrum value, and these results were plotted. This methodology was applied to all results of the work referenced in this section. Figure 3 shows a functional flowchart of the created algorithm.

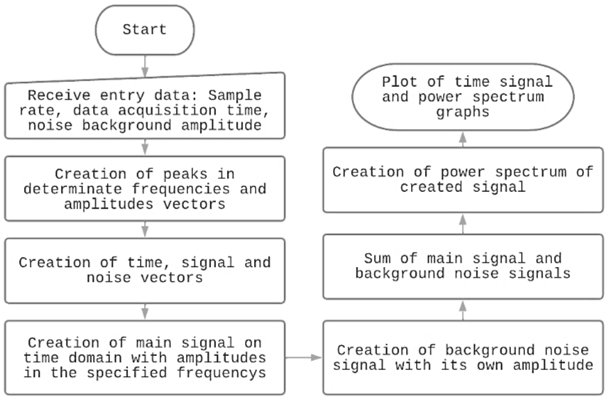

Figure 3. Functional flowchart of algorithm

3.2. Artificial Neural Network

The dataset obtained was processed. Four classes and four labels to classify the data (Table 1) was chosen. To train and test the ANN, the dataset was divided as follow: 70% of dataset to train and 30% used to validation. The ANN created is the Feed Forward (FF) type, has 3 layers, and the characteristics of each one are:

•Layer 1 – Type dense, number of neurons = 26, activation function = "relu";

•Layer 2 – Type dense, number of neurons = 128, activation function – "relu";

•Layer 3 – Type dense, number of neurons = 10, activation function – "softmax".

The number of epochs were 4000 and the optimizer used to reduce overall loss was Adam [19] . The metric used to check the performance was accuracy. The signal of 1800 rpm was the only one used to be classified by the ANN. Figure 4 shows an example how the ANN algorithm works. The ANN was tested and trained also with time signals with background noise being increased.

Table 1 Dataset created to classify different VAD working scenarios

Label	Class
0	Thrombus absence
1	Thrombus on rotor's base
2	Thrombus on rotor's vanes
3	Thrombus on rotor's spiral

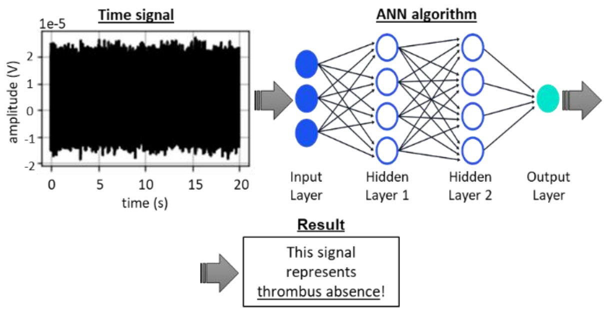

Figure 4. Example of how the ANN works

4. Results

Figure 5 shows the results for 1800 rpm rotor speed obtained by the algorithm. The time signals created are shown in this figure with respective signal in the power spectrum. Figure 6 shows a comparison between the graph extracted from Neto *et al.* [18] and the simulated signals graphs from the algorithm. They show information about thrombus absence and presence in the rotor for 1800 rpm speed. In that work is informed that the presence or absence of thrombus is characterized by occurrence of peaks in determinate frequencies. The red arrows in the graphs at bottom section of Figure 6 indicates an imbalance caused by thrombus presence. For example, on graph "Thrombus at pump's base" the peak next to 145Hz frequency indicates an unbalance on rotor caused by thrombus presence. The ANN obtained an average accuracy around 91% to classify each one of these signals. Was observed that the accuracy decreases as background noise increases (Figure 7).

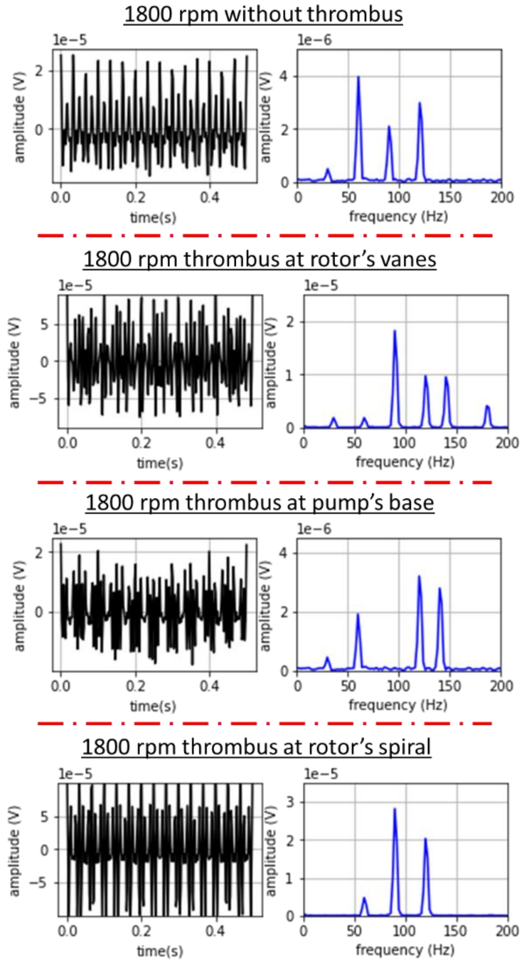

Figure 5. Results for spectra of 1800 rpm speed plotted

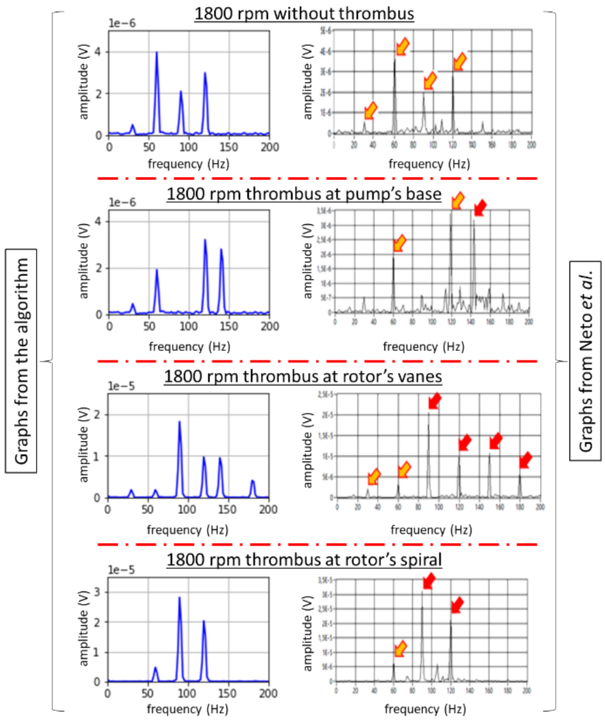

Figure 6. Comparison of results for 1800 rpm pump speed

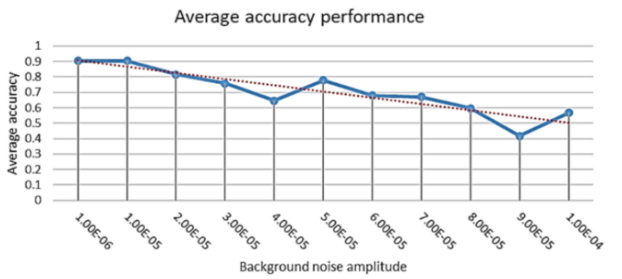

Figure 7. Accuracy performance with different background noise amplitudes

5. Conclusions

It was found that with the algorithm was possible to reproduce the same signals with certain similarity that Nero et al. [18] obtained in their work. Thereby, new time signals can be easily "synthesized", e.g., a mix of time signals of presence and absence of one or more thrombus, signals with amplitude and any spectral noise distribution or other interesting characteristics. Using only accuracy as metric, the ANN showed satisfactory performance to classify the signals, however its performance decreases with high values of background noise. Thus, the proposed taxonomy methodology was considered satisfactory in terms of its performance evaluated by ANN accuracy.

As this algorithm enables the simulation of some situations, e.g. a transition state between no thrombus and thrombus presence, a predictive algorithm can be created to be able to identify previously thrombus formation before it occurs.

The application of ANNs and algorithms within the logic of VAD controllers to make them more secure is becoming a reality. As future work, we intend to test it in vitro, and the fault (thrombus presence) could be diagnosed and treated by Safety Instrumented System (SIS), which, according to the IEC61508 standard, must be the safety system responsible for diagnosing and treating faults [20].

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