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Real-time Atrial Fibrillation Detection Using Artificial Neural Network on a Wearable Electrocardiogram

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Abstract: Providing equal healthcare quality on heart diseases are an issue in developing countries, especially in Indonesia, due to is wide-spread areas. It is founded that the heart diseases occur not only in big cities but also in rural areas, that is caused by unhealthy lifestyle and foods. Heart disease itself is a disease with gradually symptoms changes that can be seen based on the hearts' electrical activity or electrocardiogram signals. Now, wearable medical devices are capable to be worn daily, so that, it can monitor our heart condition and alert if there is an abnormality. An embedded device worn on the chest can be used to perform a real-time data acquisition and processing of the electrocardiogram, that consists of a 1-lead ECG, an ARM processor, a Bluetooth module, an SD card, and rechargeable batteries. Also, by performing a digital filter and Tompkins algorithm, we obtain the P-wave presences and the heart rate variability values (heartbeat, average heartbeat, standard deviation, and root mean square) then by using an artificial neural network with 4 input, 6 hidden, and 1 output layers that has multi-layer perceptrons and backpropagation. We are able to perform a pre-diagnosis of atrial fibrillation, that is one of the common arrhythmias, from 41 recorded training samples (Physionet MIT/BIH AFDB and NSRDB) and 6 healthy subjects as test samples. The neural network has 0.1% error rate and needed 31548 epochs to train itself for classification the heart disease. Based on the results, this prototype can be used as a medical-grade wearable device that can help cardiologist in giving an early warning on the user's heart condition, so that it can prevent sudden death due to heart diseases in rural areas.

Keywords: Heart disease, atrial fibrillation, wearable device, artificial neural network, real-time data analysis.

1. Introduction

Atrial Fibrillation (AF) is a common heart disease that is prevalence as increased age > 65 years old. Now, wearable medical devices are capable to be worn daily, so that, it can monitor our heart condition and alert if there is an abnormality. By connecting our medical devices to the smartphone that is commonly named mHealth, it is one example of digitalization in healthcare that can be done easily using wireless technology, such as Bluetooth, Wi-Fi, etc.

So, to implement mHealth to the real-world application, we need to find new measurement techniques in our daily activities, to digitalize standard clinical medical device for data analysis, and to adapt the device to the ongoing regulations in clinical usage (Bhavnani *et al.*, 2016). Another example is by using the iPhone with a single-lead ECG to perform a rapid AF screening by using an algorithm to detect the absence of the P-wave and manually interpret by the cardiologist (Lau *et al.*, 2013).

Usually, to identify the AF, we can use the R-to-R interval analysis by calculating the absolute deviation and the difference between successive R-to-R intervals (Ghodrati, Murray and Marinello, 2008). This method is commonly used by the smart-watch or wrist-band heart rate measurement device that is normally a fitness device.

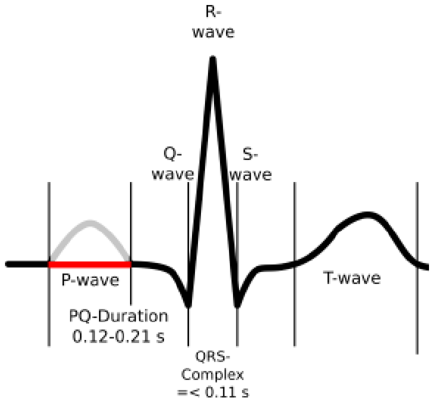

Figure 1. The ECG Signals Intervals and P-wave conditions: normal (color: grey) and Atrial Fibrillation (color: red).

Also, artificial intelligence has entered the healthcare sector in aiding or suggestions on the patients' heart conditions. By combining artificial neural networks algorithm with these fitness devices on the wrist has great results by analyzing the beat-to-beat (Rezaei Yousefi *et al.*, 2019).

As shown in Figure 1, it is the Electrocardiogram (ECG) signal with intervals and normal duration that can differentiate from normal and abnormal with the PQRST-wave characteristics. In AF detection, the P-wave shape-form reflect the phase of the cardiac cycle when the stimulus transmitted from the SA node to the AV node at the heart's atrium. In the condition of AF, the heart's atrium will fibrillate due to the spread of the electric stimulus so that the P-waveform is rippled or flat. Beside the absences of the P-wave (Figure 1 red), the irregular heart rate is another parameter that shows AF. Also, there is a guidelines for AF (Camm *et al.*, 2010) that considered the AF from irregular heart beat, the absence of the P-waves, and the atrial length cycle > 300 bpm. Those characteristics can be seen in the ECG results by measuring the 30 seconds of 12-lead ECG or 24 hours to 7 days ambulatory ECG for stroke survivors (Hodgson-Zingman *et al.*, 2008).

In this research, we implement both methods (P-wave presences and irregular heart rate) by extracting those parameters from the ECG signals using digital filters and peak detection algorithms. Later, the ANN is used to classify between normal and AF.

2. Methods

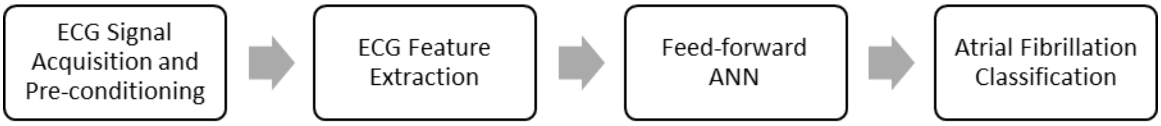

Figure 2. General Flow Diagram of the ECG Signals to classify AF.

The first step to analyze the AF is by acquiring and pre-conditioning the ECG signals using the single-lead ECG from the AD8232 with analog filters and amplifiers, then, the signals are acquired using a microcontroller ARM Cortex M4 on the Teensy 3.2 development board as shown in Figure 2. The feature extraction is implemented using the Tompkins algorithm (Pan and Tompkins, 1985) as digital filters and peak detection algorithm to receive the R-to-R interval for heart rate, average N-to-N interval (ANN), standard deviation ANN, and root mean square ANN. Also, the P-wave presences are calculated from the P-wave peak detection.

After four ECG signal parameters are retrieved, those parameters are then inputted to the multi-layer perceptron neural networks with back-propagation to train the neural network so that it can classify AF. The training sets are taken from the Physionet Atrial Fibrillation Database (AFDB) and the Normal Sinus Rhythm Database (NSRDB) (Goldberger *et al.*, 2000) that consists of 41 records. Also, we used 6 records normal healthy subjects as the tests sets.

As shown in Figure 3 is the configuration of the neural networks that consists of 4 input parameters (ANN, SDANN, rMSSD, P-wave presences), 6 hidden layers, and 1 output that is implemented in an embedded device in the form of a wearable chest-strap for daily usage. The neural network is trained until the error is 0.1% in classifying between normal and AF.

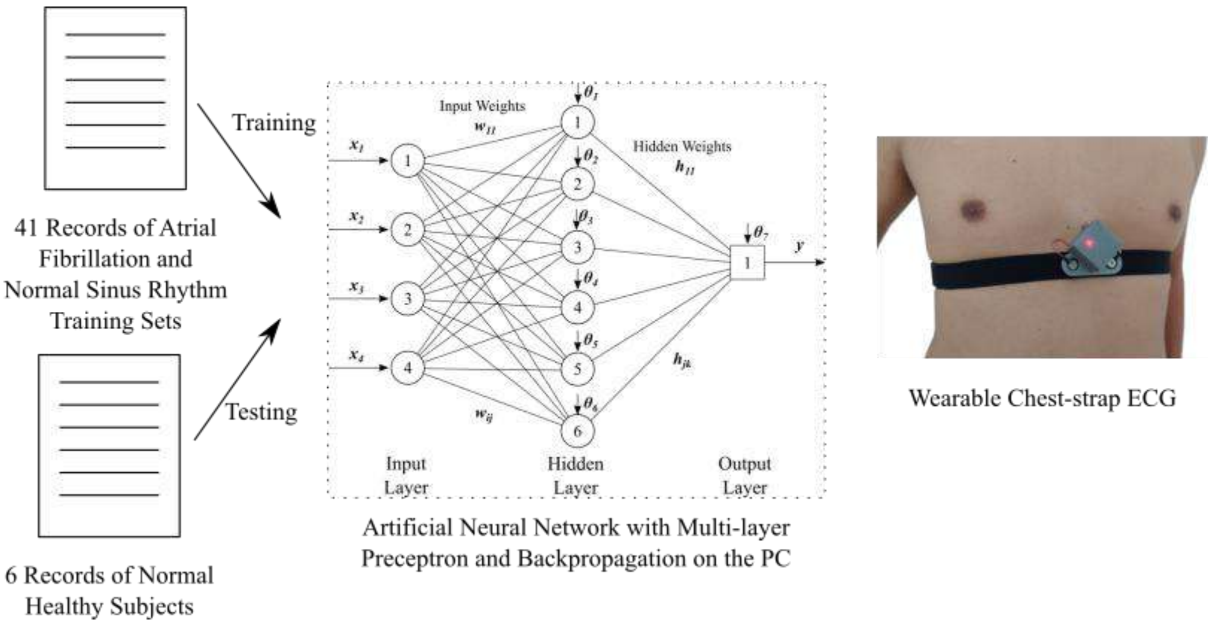

Figure 3. The Artificial Neural Network Configuration with Training Sets of 41 records and Test Sets from 6 Normal Healthy Subjects that will be transferred to the Wearable Chest-strap ECG.

The embedded device worn on the chest can be used to perform a real-time data acquisition and processing of the electrocardiogram, that consists of a single lead ECG, an ARM Cortex M4 microprocessor at 24 MHz clock frequency, a Bluetooth Low Energy 4.0 module, a micro-SD card, and 3.7 V 220 mAh Li-ion rechargeable batteries. The chest-strap itself is a typical fitness tracker form with 2 poles as the dry electrodes measurement points that is like the standard ECG position lead-I left arm-to-right arm. The device can be worn continuously for 21 hours in a single charge that need 20 minutes to charge until full. So, all the algorithms to classify AF is computed in this chest-strap device in real-time.

Table 1. Processed ECG Parameters of the 41 Records of Normalize Data of AFDB and NSRDB as the Training Sets.

ANN	SDANN	RMSSD	P-wave Presence	Output AF (1) or Normal (0)
x_1	x_2	x_3	x_4	y
0.40	0.64	0.15	0.68	1.00
1.00	0.05	0.12	0.87	1.00
0.27	0.78	0.09	0.96	1.00
0.35	0.77	0.27	0.94	1.00
…	…	…	…	…
0.32	0.07	0.05	0.97	0.00
0.16	0.07	0.05	0.97	0.00
0.53	0.07	0.05	0.97	0.00
0.65	0.07	0.05	0.97	0.00

In Table 1, we can see the normalized training sets data that consists of four extracted ECG signal parameters: ANN, SDANN, RMSSD, and P-wave presence from 41 records AFDB and NSRDB, each record has more than 24 hours of recorded data. The ECG signal extraction algorithm had calculated the ANN, SDANN, RMSSD and the P-wave presences was calculated from the P-wave peak algorithm. The parameters are normalized to a value range from 0 until 1, so that the neural network can classify the AF. Also, the output node has a value from 0 until 1, whereas 0 is normal and 1 is AF.

3. Results

After configuring the neural network's input, hidden, and output layer, we train the neural network with the desired training sets and record the epochs needed to achieve 0.1% error in classifying AF. The hidden layer nodes were the variable that we change to achieve the same error value with the lowest hidden layer nodes, so that, we can implement it on an embedded system with limited memory for the matrix.

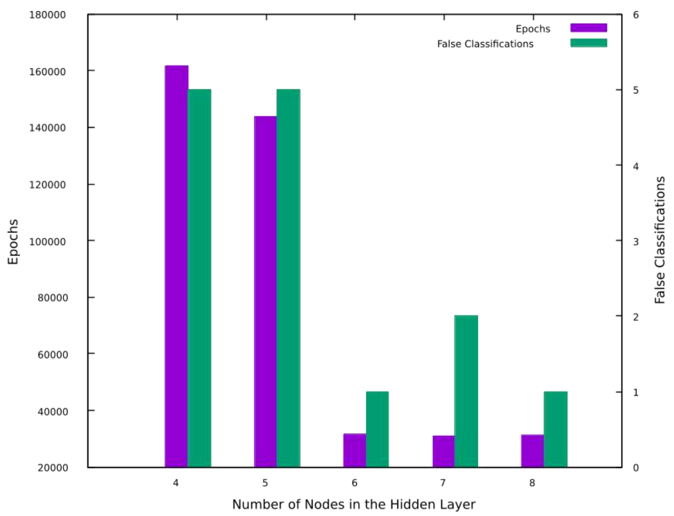

Figure 3. The Results of the ANN Epochs and False Classifications with different Hidden Layer Nodes from 4 until 8 Nodes.

Table 2. Results of the 31548 Epochs AF Classification Weights and Thresholds with Supervised Training Process using Back-propagation with 4 Input, 6 Hidden, and 1 Output.

Input Weights (w_{ij})		*J*						
		1	2	3	4	5	6	
i	1	4.1523	2.6107	-5.2214	2.2574	3.9854	2.5748	
	2	4.1854	2.8748	-5.0966	2.485	1.9937	1.5094	
	3	2.0437	1.4594	-2.4432	1.4068	-2.3246	-1.8103	
	4	-2.5246	-1.5103	3.1774	-1.4105	-0.1393	-0.203	
Hidden Weights (h_{jk})		*K*						
		1	2	3	4	5	6	
j	1	6.8769	4.3342	-9.2277	3.7552	-0.8606	-0.8818	
Theta (θ_j)		*J*						
		1	2	3	4	5	6	7
		1.315	0.9214	-1.6332	0.6927	0.1855	0.0038	1.2175

The results of different hidden layer node values can be seen in Figure 3. The initial hidden layer node value is 4 that is same as the input layer node, then we increase the value until we see the false classification of the AF is starting to be stable. In the training processes, the neural network back-propagation will adjust the weights and threshold of the perceptron with sigmoid activation in every loop until it achieves the 0.1% error value, that is usually called epochs. We consider the lowest epochs and lowest false classification value at the lowest number of nodes to be implemented in the firmware of the embedded system.

In Table 2, we can see the computed results on the PC of the classification of the AF using 4 nodes input, 6 nodes hidden, and 1 node output layer from 31548 epochs to achieve 0.1% error rate. The weights consist of input weights ($\boldsymbol{w_{ij}}$) with matrix of 4 x 6 values and hidden weights ($\boldsymbol{h_{jk}}$) with matrix of 1 x 6 values, also the threshold theta ($\boldsymbol{\theta_j}$) has 7 values. These values are the knowledge in determining the AF from the normal sinus rhythm or normal heart condition.

Table 3. Test Sets from Healthy Subjects

ANN x_1	SDANN x_2	RMSSD x_3	P-wave Presence x_4	Test Results y
0.00	0.86	0.12	0.97	0.60
0.58	0.15	0.02	1.00	0.00
0.09	0.72	0.09	0.91	0.40
0.58	0.16	0.12	1.00	0.00
0.22	0.53	0.16	0.87	0.40
0.27	0.47	0.09	0.93	0.10

Based on the findings of the minimum nodes needed to classify the AF, we perform a test sets that consists of 6 normal healthy subjects to the feed-forward neural network with the knowledge to classify the AF. In Table 3 are the results from 6 test subjects with the output value y varied from 0 until 1, where 0 is classified as normal and 1 is AF. Some of the values are in between the given range but there are two subjects that is positively normal with the value 0.

4. Discussions and Conclusions

In this research, we had developed a real-time ECG signal acquisition and processing by using the artificial neural network to classify the AF in an embedded device worn on the chest. The embedded device has a single-lead ECG with analog filters to pass only the ECG signal and to be acquired by a 10-bit analog-to-digital converter on the ARM Cortex-M4 microprocessor at 200 samples/sec, then the ECG signals will be extracted every 3 seconds to retrieve the heart rate and P-wave presences. Next, the heart rate variability values are computed to result the ANN, SDANN, and RMSSD that is related to the irregularity of the heart rate as one of the AF parameters. Also, the P-wave presences is calculated every 3 seconds to find the percentage of the P-wave appearance that is related with the fibrillation at the heart's atrial. Both, of these parameters are used to determine AF.

Previously, artificial intelligence has been used for arrhythmias with artificial neural network (Modarressi *et al.*, 2016) and convolution neural network (Rajpurkar *et al.*, 2017), however, deep learning (Yuan *et al.*, 2016; Shashikumar *et al.*, 2017; Gotlibovych *et al.*, 2018) has been used to for AF classification from the heart rate.

However, in this research we have implemented an artificial neural network on an embedded device to classify AF from irregular heart rate and P-wave presences percentage. So, this prototype can be used as a medical-grade wearable device that can assist or even give help to the cardiologist by providing the AF knowledge to the embedded device and pre-diagnose the user's heart condition.

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Carbon Nanotube-Coated Thread for Wearable Proprioception Sensing

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Abstract: This paper focuses on the development of thread-based sensor for proprioception sensing in finger and knee. The thread sensor is made by dipping cotton thread into carbon nanotube (CNT) dispersion. The electrical and electromechanical properties of the thread change depending on the dipping parameters. The resistance of the CNT-Coated threads changes due to in-plane force, exhibiting a piezoresistive-like mechanism. The CNT-coated thread functioning as strain gage is sewn into hand glove and yoga pants. The thread sensor will stretch upon finger or knee bending, and its resistance will change accordingly. Using this wearable sensor, proprioception detection is conducted for finger bending and sit-to-stand movement.

Keywords: Carbon Nanotube, Cotton Thread, Proprioception, Wearable Sensor

5. Introduction

Proprioception is the sense of the effort to make movement of one's parts of the body (Elsevier, 2013). The loss of proprioceptive sense may affect muscular control. Many neurological and orthopedic conditions are related to proprioception such as stroke (Kenzie et al., 2014). Therapies have been applied and proven to be effective (Aman, Elangovan, Yeh, & Konczak, 2015). Therapies can be assisted by using orthosis, or prosthesis in the case of missing body part. In order that an assessment can be done during the therapy, there is a need to detect and sense the relative position of one's part of the body to the others, hence proprioception sensing.

For therapy assessment purposes, this can be carried out using camera and image recognition system, called as visual proprioception monitor (Pauwels & Kragic, 2015). However, such system is complex and cumbersome. Furthermore, it cannot be made portable, let alone wearable by the person undergoing the treatment. Previously, silver nanoparticles (AgNP) have been patterned on cotton fabrics to develop stretchable sensor for finger's proprioception sensing (Yuen et al., 2014). While the sensor performs quite well, AgNP is a rather expensive nanomaterial with potential toxicity towards human's body. In 1991, Carbon Nanotube (CNT) was discovered by Iijima (Iijima, 1991). CNT has fascinating electronic, and mechanical properties. The atoms bonding on CNT is very strong and CNT has high electrical conductivity. CNT has been applied in several applications. CNT has also been used to coat thread for finger proprioception sensing (Shafi & Wicaksono, 2017). CNT-coated thread offers a lower cost, stretchable and wearable sensor for proprioception sensing.