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DEVELOPMENT OF THE 'HEALTHCOR' SYSTEM AS A CARDIAC DISORDERS SYMPTOMS DETECTOR USING AN EXPERT SYSTEM BASED ON ARDUINO UNO

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ABSTRACT

In the modern era, our lifestyles are very fast-moving; this makes us highly susceptible to diseases, especially those associated with heart problems. In this research, we developed a portable early detection system for cardiac disorders. This system consists of passive electrodes, named SHIELD-EKG-EMG-PA; a shield which allows Arduino-like boards to capture electrocardiography (ECG) and electromyography (EMG) signals, named SHIELD-EKG-EMG, both devices produced by Olimex; a microcontroller, based on Arduino Uno; and an expert system which is implemented by a personal computer. This system detects time intervals of various segments in ECG signals which are captured by the devices; it then analyzes the signals in order to determine whether the patient has cardiac disorders. We call our detecting system the HEALTHCOR system. A database was established, containing various possible values of parameters in ECG signals. The types of diseases that can be detected are heart rhythm disorders including sinus bradycardia, sinus tachycardia, sinus arrhythmia, and cardiac symptoms associated with intervals and the wave height, such as myocardial infarction. From our tests, the accuracy of our system is 96%. The resultant diagnoses of four patients are all appropriate, and used a commercial 12-lead electrocardiograph.

Keywords: Cardiac disorders detection system; Expert system; Electrocardiograph; HEALTHCOR

1. INTRODUCTION

A lifestyle in which people often consume unhealthy food and rarely undertake exercise leads to the emergence of diseases such as cancers and cardiac disorders, as experienced by the current generation. The number of people with these diseases continues to increase year on year. The patients are no longer just older people, but are also teenagers with unhealthy lifestyles. Cardiac disorders can appear more easily and quickly than cancers, and therefore can also be detected earlier. Routine heart examination in a hospital, using a commercial electrocardiograph (ECG), is one solution for predicting the development of chronic heart problems. An ECG generates a graph of the heart's electrical activities, known as an electrocardiogram (EKG), which can show abnormalities in the heart's function. An EKG can only be read by a cardiologist; that is, a doctor who specializes in heart diseases. Although ECG technology has existed for a long time, and cardiologists have emphasized the importance of

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early examinations, public awareness is still very low. However, a simple, low cost, and portable ECG with an acceptable level of accuracy could well offer a solution to this problem.

A cardiologist can also perform medical diagnostics using computer-based analysis and classification techniques (Acharya et al., 2002). Several algorithms have been proposed for classifying ECG heartbeat patterns, based on the feature extraction of ECG signals. Some researchers have analyzed the frequency spectra of signals using Fourier Transform; unfortunately, this transform provides only the spectral information, and their temporal relationships are not included in the analysis. A representation that relates to time versus frequency information of the signal can be achieved using wavelets; this works well on non-stationary data (de Chazal et al., 2000; Minami et al., 1999; Romero & Serrano, 2001, Sarkaleh & Shahbahrami, 2012). Some algorithms have utilized heartbeat temporal intervals (Alexakis et al., 2003), morphological features (de Chazal et al., 2004), frequency domain features, and multi-fractal analysis (Ivanov et al., 2009). In order to best classify the various types of ECG signals, algorithms in biomedical signal processing require appropriate classifiers. An early computer-aided diagnostic system was proposed by Shortliffe in 1976. This system was implemented for the diagnosis and treatment of symptoms of bacterial infections (Mahmoodabadi et al., 2010). Some techniques have been proposed for classification of the patterns of ECG signals; for example, statistical Markov models (Andreao et al., 2006; Coast et al., 1990), artificial neural networks (Ameneiro et al., 1998; Fernández-Delgado & Ameneiro, 1998; Hu et al., 1994; Hu et al., 1997; Linh et al., 2003), mixture-of-experts algorithms (Hu et al., 1997), support vector machines (Osowski et al., 2004), and linear discriminant analysis (Minami et al., 1999). In addition, self-organizing maps have been applied in unsupervised clustering of ECG signals (Lagerholm et al., 2000).

The main focus of computer-based classification is the wide variability of the structures of beats that are owned by the same class, as well as those of beats with similar structures but that are owned by different classes (Osowski & Linh, 2001; Shyu & Hu, 2008). In general, algorithms for computer-based diagnosis include three steps: detection of ECG beat, extraction of the useful features from beats, and classification of the beats based on the features extracted.

The QRS complex is detected for heart rate computation by many algorithms. Heart rate is usually calculated from the distance between two adjacent QRS complexes. Some algorithms used to detect QRS complexes are genetic algorithm, wavelet transform or filter banks, artificial neural networks (Köhler et al., 2002), zero crossing counts (Köhler et al., 2003), and adaptive threshold (Christov, 2004). Direct methods of detecting heart rate include spectral analyses of ECG signals (Surda et al., 2007) and the short-term autocorrelation method (Piotrowskia & Rozanowski, 2010). All of the above mentioned algorithms or methods are complicated when implemented in the detection of real-time heart rate frequency in a microprocessor unit.

Our idea was to integrate these devices in an expert system to achieve a simple, low cost, portable, and convenient method of detection of heart disorders (known as 'HEALTHCOR') that can be used by a patient at home. This system not only records signals from one's heart, but also provides an initial evaluation of whether the person shows symptoms of heart problems through the integrated expert system. With this system, a patient will be able to assess the health of his or her heart independently from an early age, without the need to visit a hospital. In developing the evaluation system for the detection of heart disorders, we followed the method proposed by Afonso and Tompkins (2000). This system consists of passive electrodes, named SHIELD-EKG-EMG-PA; a shield which allows Arduino-like boards to capture electrocardiography (ECG) and electromyography (EMG) signals, named SHIELD-EKG-EMG, both devices produced by Olimex; a microcontroller, based on Arduino Uno; and an expert system which is implemented by a personal computer.

2. ALGORITHM OVERVIEW

The scheme of signal processing, which is used in the systematic analysis and interpretation of ECG signals, can be seen in Figure 1. Signals obtained from the intercepts are first processed to remove noise such as electrical signals from lungs, muscle, or other body parts, and then further refined through QRS detection and wave delineation.

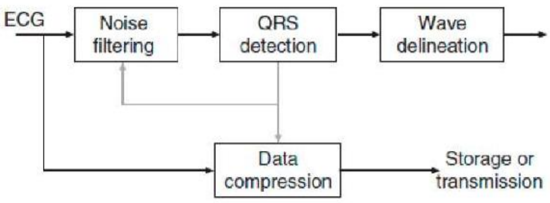


Figure 1 ECG signal processing scheme

2.1. ECG Pre-processing

Electrocardiogram (EKG) is a record produced by a process known as electrocardiography. This records the electrical activity of the heart over a period of time, using electrodes placed on a patient's body. These electrodes detect the tiny electrical changes on the skin caused by the heart muscle depolarizing during each heartbeat. EKG is also known as ECG signal. Figure 2 shows an EKG for one typical normal heartbeat, with typical amplitudes and time durations for the P, QRS, T, and U waves.

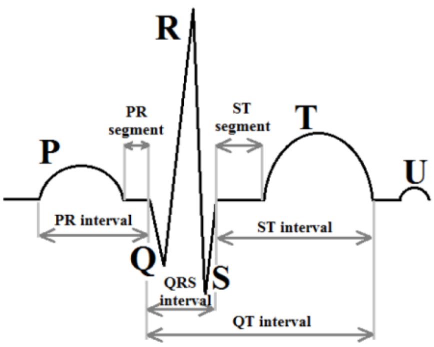


Figure 2 Typical ECG signal with specified waves, intervals, and segments

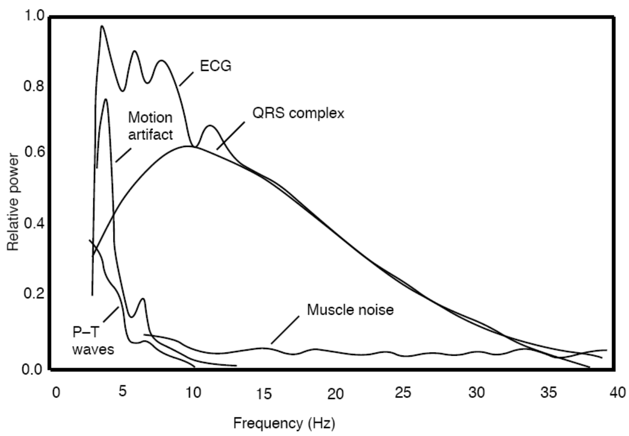


Figure 3 Relative power spectra of ECG and EMG waves (Afonso & Tompkins, 2000)

In essence, pre-processing is performed to eliminate noise from signals captured directly from the use of electrodes, in order to attain pure ECG signals. Noise arises naturally from the activities of other muscles in the neighborhood of the heart, such as electromyogram (EMG) signals. Therefore, pre-processing should be able to separate pure heart signals from others that occur at the same time. ECG signals have a frequency range between 5-100 Hz, but their significant frequency components are generally between 5-15 Hz, while EMG signals are significant at frequencies below 5 Hz, as shown in Figure 3. This figure summarizes the relative power spectra of the ECG, QRS complexes, P and T waves, motion artifact, and muscle noise based on an average of 150 beats. Each spectrum in Figure 3 was obtained from the corresponding wave in Figure 1, using fast Fourier Transform (FFT).

In addition to the noise that arises from the activities of the muscles around the heart, monitoring of the heart also suffers in Indonesia from power line interference caused by electrical equipment with a frequency of 50 Hz. Harmonic waves of the power line may also appear at frequencies that are multiples of the value of the power source frequency; for example, 100 Hz, 150 Hz, 200 Hz, and so on.

In our study, pre-processing is performed by applying a bandpass filter (BPF) with a passband of 5-15 Hz. This BPF was designed by merging a low pass filter (LPF) and a high pass filter (HPF) to obtain the heart activity signal in a frequency range of 5-15 Hz. Meanwhile, to overcome the interference from the power source and the effects of harmonics, we implemented an LPF with a frequency cut-off of 50 Hz (Afonso & Tompkins, 2000).

2.2. QRS Complex Detection

The presence of the heartbeat signal and the time of its appearance constitute highly important data in the analysis of the ECG signal. In the process of heartbeat detection, it is much easier to detect the QRS complex than other signals because its morphology is more visible. Through detection, early analysis can be conducted for heart disorders associated with the presence of rate and rhythm.

Certain techniques are used in detecting the location of the QRS complex; these are moving-window integration, fiducial marks, and thresholding. Moving-window integration relates to the appropriate use of the time window width of the QRS wave as a diagnostic marker area. The use of a window that is too wide will result in the QRS complex and T wave being detected as a temporary window that is too small. This will result in an error in marking the beginning and end of the wave and the QRS peak detection of the multiple sequential. Fiducial marks are used to mark the peak of the QRS complex. The appearance of the QRS wave is characterized by the presence of the highest peaks and the largest tilt angle. After the peak of the wave is determined, the next step is to examine the threshold height of the QRS complex. Through this process, the peak of the QRS wave can be distinguished from the crest of another, lower, wave, such as P and T waves (Pan & Tompkins, 1985).

2.3. Wave Delineation

After the QRS complex is detected, the P and Q signals will be more easily determined. At this stage, the algorithm should be able to define the time window for signals PQRSTU, where all signals are included in a complete EKG. The algorithm must be able to read some of the backward interval for P and T, adjacent to where the window should be aligned with the positions where P starts and T ends. An illustration of each signal in this subsection can be seen in Figure 2.

2.4. Heartbeat Morphology Classification

From the processed signal, the next step is to determine the signal grouping. This process allows us to discover any interruption to a patient through the interpretation of the signal shape. The grouping is based on the amplitude, interval, and shape of each signal section.

3. SYSTEM IMPLEMENTATION

SHIELD-EKG-EMG actually has an analog filter circuit to discard the muscles signals received by the electrodes that are under 0.16 Hz and above 40 Hz. However, in the process of data transmission between SHIELD-EKG-EMG, Arduino Uno, and the personal computer, the data is affected by noise from the power source. Such noise has high-frequency components caused by the source's harmonic effects, as seen in Figure 4 below.

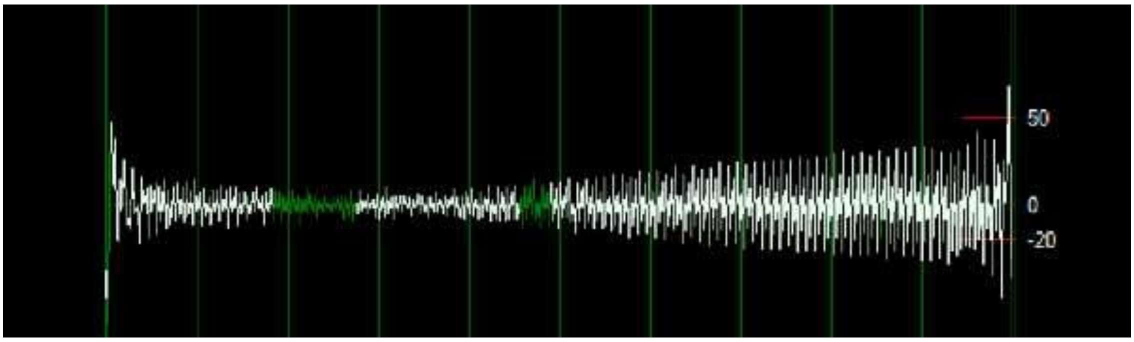


Figure 4 Heartbeat signal exposed to the effects of power line noise and harmonics

There are three types of digital filters that are often used in similar cases: Butterworth, Chebyshev, and the elliptical filter. In our system, we use the Butterworth LPF. This filter was selected because it generates smooth output and, most importantly, has a high value of constant reinforcement. The first step in implementing the Butterworth filter is feeding an input signal to a FFT in order to convert the signal from time domain to frequency domain, as the filtering process will be carried out in the latter. The frequency response of a Butterworth LPF can be written as follows:

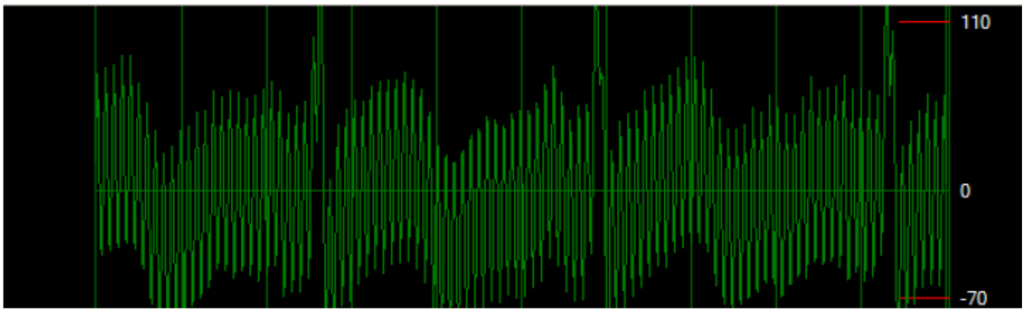
$$G(\omega) = \sqrt{\frac{G_0^2}{1+\left(\frac{f}{f_c}\right)^{2n}}} \tag{1}$$

where G_0, f_c, and n are gain, cut-off frequency, and order of the Butterworth LPF, respectively. The signal that passes through the FFT process has a symmetrical shape at N/2 positive frequencies and N/2 negative frequencies. Due to this, filtering can be performed by looping N/2 times. To set the scale of the FFT signal with a gain of Butterworth filter, we require the frequency value at each point of:

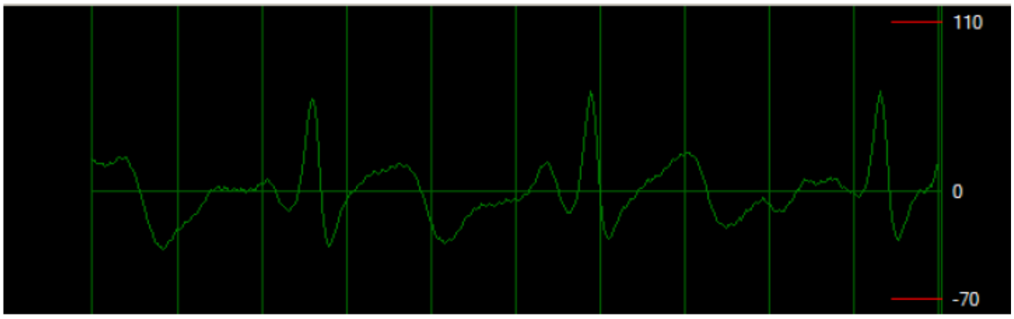
$$f = i\left(\frac{f_s}{2I}\right) \tag{2}$$

where i is the sequence in the data, I is the total amount of data, and f_s is the sampling frequency of the SHIELD-EKG-EMG (i.e. 256 Hz).

After the filtering process is complete, the next step is to restore the signal from the frequency domain back into the time domain; this requires the inverse of the FFT. To determine the cut-off frequency, we used experimental methods to look for the most appropriate level of frequency as seen from the results of the filter. Tests performed on frequencies of 50 Hz, 100 Hz, and 150 Hz found that the best cut-off frequency was 50Hz, as seen in Figure 4. The order of the LPF used in this system was 3.



a) Signal captured from the heartbeat before filtering



b) Signal of heartbeat after filtering

Figure 5 Result of filtering of the heartbeat signal using Butterworth filter (f_c = 50 Hz and n = 3)

After preprocessing is complete, the next step is to determine the position of the QRS signal, which can be found by using moving-window integration to look for signals with a high waveform. However, in this system, the signal runs in real time, so it is easier to use a passive window. Such a window is governed by the general characteristics of the QRS signal, in which the average width of the signal is 0.12 seconds. It can thus be determined that the pixel size of the window used is 32. The height of the window can be adjusted as needed depending on the characteristics of each patient, as each signal's height is dependent on the strength of the electrical signal of one's body.

Each incoming signal in this window will be measured if its highest amplitude exceeds the maximum threshold of the window and its lowest amplitude exceeds the minimum threshold. The highest value in the interval is stored as an R peak for the checking process, then moved forward to seek the lowest point as S and moved backward to seek the lowest point as Q. Each signal that has these characteristics will be suspected as a beat, and then validated using the up and down gradient calculation to show that the shape of a closed curve signal/wave is positive. Checks are also carried out to determine whether QRS is in position above or below the baseline, by calculating the average value of the QRS interval.

To count the number of beats per minute (BPM), the time of each emergence rate is recorded in an array. The next step is to calculate the interval between the occurrences of two consecutive heartbeats. The intervals of heartbeat pairs are then averaged. The value of BPM is obtained in milliseconds by dividing the average interval by 60,000.

The next stage is to implement wave delineation techniques to discover the existence of the P wave on the back of the QRS and T waves, after the QRS. As with the QRS signal, the processing of the P and T waves is done by finding the position of the peak point and the start and end point of each wave. Once the position of each wave is obtained, we can calculate the length of each segment, such as the PR interval, QT, ST, and other wave characters. From the values of such information, the system searches the database for types of diseases that have similar symptoms. The database is a text file that is stored in the same folder as the system. The types of diseases that can be detected are heart rhythm disorders including sinus bradycardia, sinus tachycardia, sinus arrhythmia, and cardiac symptoms associated with intervals and wave height such as myocardial infarction.

4. RESULTS AND DISCUSSION

The system was first tested on a patient with normal cardiac condition; it correctly detected the patient's heart condition as a normal sinus rhythm. The result can be seen in Table 1. As stated in the third column of this table, the values of parameters of interest obtained from the system are within the interval values for a normal patient.

Table 1 Result of tests on a patient with normal heartbeat

Parameter	Normal Value	Value from System	Status
BPM	60–100	90	Normal
P-Width	< 0.11 sec	0.0980 sec	Normal
QRS Width	< 0.12 sec	0.1058 sec	Normal
PR Interval	0.12–0.2 sec	0.1333 sec	Normal
QT Interval	< 0.42 sec	0.3229 sec	Normal

Further analysis was conducted on the cardiac signal characteristics of seven patients (subjects A-G). This was performed by comparing the diagnosis given by a cardiologist and the diagnosis of the system. This analysis aimed to determine the accuracy of the developed expert system, using the integrated database within it. Table 2 shows the results of the conducted tests in diagnosing the cardiac signal characteristics of subjects A to G.

The results in Table 2 show an outcome that is inconsistent with the cardiologist's analysis, that of test number 14. To further validate the result of this test, diagnoses from further cardiologists are required. Therefore, from a total of 26 indications found, there are 25 indications that are in accordance with the results of the cardiologist's diagnoses. This tells us that the accuracy of the developed expert system is about 96%.

The final validation technique was to compare the results of the HEALTHCOR indication with the actual outcome of a cardiologist's diagnosis, using a commercial 12-lead ECG GE MAC1200. Tests were conducted at Bethsaida Hospital, Tangerang, Indonesia, on July 2nd, July 21st, and July 25th 2014, on subjects C, D, F, and G at resting condition. From the validation, it was found that these subjects had diagnoses that matched the results of HEALTHCOR. The other subjects were patients of the cardiologist (anonym). The cardiologist only provided data for these patients. However, further tests are needed to more precisely determine the accuracy of our system's diagnoses.

Table 2 Comparison between diagnoses from the system and those from a cardiologist

No.	Subject	Result from System	Result from Cardiologist	Amount of Result	Correct Result
1.	A (sample 1)	Sinus arrhythmia and (hyperkalemia, hyperacute myocardial infarction, left bundle branch block)	Sinus arrhythmia and (hyperkalemia, hyperacute myocardial infarction, left bundle branch block)	2	2
2.	A (sample 2)	Sinus arrhythmia and (hyperkalemia, hyperacute myocardial infarction, left bundle branch block)	Sinus arrhythmia and (hyperkalemia, hyperacute myocardial infarction, left bundle branch block)	2	2
3.	A (sample 3)	Sinus arrhythmia and (hyperkalemia, hyperacute myocardial infarction, left bundle branch block)	Sinus arrhythmia and (hyperkalemia, hyperacute myocardial infarction, left bundle branch block)	2	2
4.	B (sample 1)	Normal	Normal	1	1
5.	B (sample 2)	Normal	Normal	1	1
6.	B (sample 3)	Normal	Normal	1	1
7.	C (sample 1)	Sinus bradycardia	Sinus bradycardia	1	1
8.	C (sample 2)	Sinus bradycardia and sinus arrhythmia	Sinus bradycardia and sinus arrhythmia	2	2
9.	C (sample 3)	Sinus bradycardia	Sinus bradycardia	1	1
10.	D (sample 1)	Sinus arrhythmia	Sinus arrhythmia	1	1
11.	D (sample 2)	Normal	Normal	1	1
12.	D (sample 3)	Sinus arrhythmia	Sinus arrhythmia	1	1
13.	E (sample 1)	Normal	Normal	1	1
14.	E (sample 2)	(Right/left bundle branch block, ventricular rhythm, hyperkalemia)	Normal	1	0
15.	E (sample 3)	Normal	Normal	1	1
16.	F resting (sample 1)	Normal	Normal	1	1
17.	F resting (sample 2)	Normal	Normal	1	1
18.	F after exercise (sample 3)	Sinus tachycardia	Sinus tachycardia	1	1
19.	F after exercise (sample 4)	Sinus tachycardia	Sinus tachycardia	1	1
20.	G (sample 1)	Normal	Normal	1	1
21.	G (sample 2)	Normal	Normal	1	1
22.	G (sample 3)	Sinus arrhythmia	Sinus arrhythmia	1	1
		Total Diagnosis		26	25

5. CONCLUSION

From the implementation and tests conducted, it can be concluded that our system of portable early detection of heart disorders can be used as a simple, low cost, and portable ECG; in other words, an early detection system for cardiac disorders that can be used by people at home or anywhere. Our system can perform the filtering process so well that its use would not interfere with power lines. In addition, our system is also highly capable of detecting various waves in ECG signals and calculating intervals of each segment in these signals. Our system provided diagnostic results from 25 tests that were in accordance with diagnoses from a cardiologist, out of 26 tests. Therefore, the accuracy of the expert system, based on the developed database, is 96%. Our system also provided diagnoses that were well matched to those of the cardiologist by using a commercial 12-lead ECG GE MAC1200 on all four patients tested.

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