

## CHAPTER 2 – LITERATURE REVIEW

### 2.1 ECG Signal Introduction

Recently, various lifestyle-related health issues are propagated enormously. Surprisingly with cardiovascular diseases becoming the leading cause of mortality in the United States of America, with 43.8% deaths by cardiovascular heart disease, followed with 16.8% deaths by stroke and 9.4% deaths by high blood pressure (Benjamin et al., 2018). The electrical activity of the heart comes from the nerve stimulation for the heart muscle, due to depolarisation and repolarisation of  $\text{Na}^+$  and  $\text{K}^-$  ions in the blood. An electrocardiogram is a diagnostic device that records and characterised this electrical activity of the heart by skin electrode. This diagnosis method is a non-invasive technique. The ECG signal provides below information of a human heart:

- Heart position and its relative chamber size
- Impulse origin and propagation
- Heart rhythm and conduction disturbances
- Extent and location of myocardial ischemia
- Changes in electrolyte concentrations
- Drug effects on the heart

Unfortunately, ECG does not provide information on cardiac contraction and pumping function (Sanamdikar, Hamde, & Asutkar, 2015), but the measurement can be done during blood pressure measurements (Lowe, Oh, & Stewart, 2018).

Further ECG waveform signal analysis can point out if there is any disorder of heart rate, rhythm, or change in the morphological pattern as an indicator of cardiac arrhythmia. The main idea is to analyse the amplitude and duration of the P-QRS-T wave in which contained useful and unique information about the characteristics of each heart diseases.

The presence of abnormal rhythms of the heart indicates problems in the electrical conduction system of the heart. All of these arrhythmias are life-threatening problems,

which have a high risk of sudden cardiac arrest and even death. Thus, the appropriate therapy is critically needed within a few minutes since the arrhythmia happens.

### 2.1.1 ECG Segments

ECG signal is segmented based on the heartbeats. Each heartbeat is composed of five standard waves labelled with the letters P, Q, R, S and T in the time domain, as shown below in Figure 1.

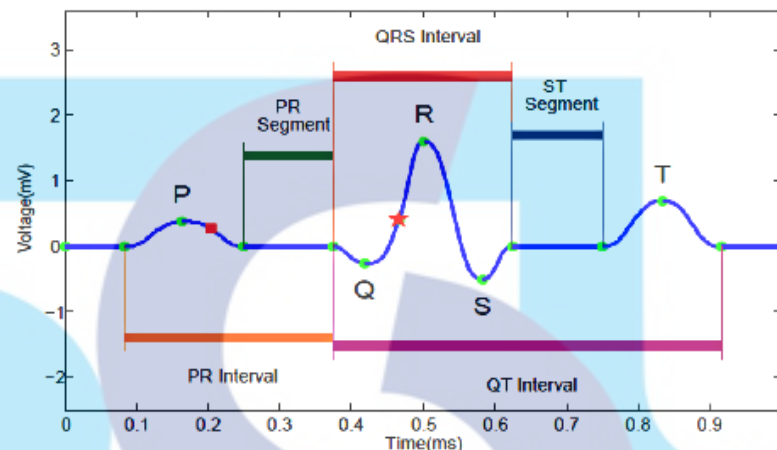


Figure 1. Main characteristics of an ECG signal curve (Oweis & O. Al-Tabbaa, 2014).

- P-wave represents the depolarisation of the atriums before atrial contraction. This feature is hard to detect due to low amplitude but necessary to distinguish various cardiac arrhythmias.
- QRS-complex reflects the depolarisation of the ventricles. It is the most significant wave of the ECG due to the large muscle mass of the ventricles. The QRS-complex can be easily detected and often used to determine the heart rate (Lee, Park, Dong, & Youn, 2018).
- T-wave represents the repolarisation of the ventricles when the cardiac muscle undergoes recovery phase. Analysing the shape of this wave is essential to obtain information about cardiac abnormalities. Its geometrical properties include symmetry, asymmetry, and slope.

- PR-interval is the period between the beginning of the P-wave and the beginning of the next QRS-complex. It reflects the electric conduction over the atrioventricular (AV) node.
- PR-segment is the flat, usually isoelectric segment, between the end of the P-wave and the beginning of the QRS-complex. The delay in the PR-segment mostly occurs in the AV node.
- ST-segment represents the period from the end of ventricular depolarisation to the beginning of ventricular repolarisation. The shifts in ST-level are essential markers of cardiac abnormalities.
- QT-interval represents the time elapsed between the beginning of ventricular depolarisation and the end of ventricular repolarisation. The QT-interval is inversely proportional to heart rate. It shortens at faster heart rates and lengthens at slower heart rates.

### 2.1.2 ECG Database

The recommended standardisation requires the use of databases. Below are various databases worldwide available on Physionet (Goldberger et al., 2000), composed of various cardiac arrhythmias.

#### 1. MIT-BIH Normal Sinus Rhythm Database (nsrdb)

This database includes 18 ECG recordings of subjects referred to the Arrhythmia Laboratory at Boston's Beth Israel Hospital. The hospital is now Beth Israel Deaconess Medical Center. Subjects included in this database consist of five men and 13 women, who were found to have had no significant arrhythmias. Each record was digitised at 128 samples per second.

#### 2. MIT-BIH Arrhythmia Database (mitdb)

The Massachusetts Institute of Technology – Beth Israel Hospital Arrhythmia Database is commonly used in the study for performance evaluation. The database contains 48 records of two-channel ECG signals with a duration of 30 minutes each, selected from 24-hour recordings of 47 individuals. All 48 records are completed with reference annotation files. The recordings were digitised at 360 samples per

second per channel with 11-bit resolution over a  $10\text{ mV}$  input range (Moody & Mark, 2001).

### 3. MIT-BIH Supraventricular Arrhythmia Database (svdb)

This database includes 78 ECG recordings, chosen to supplement the examples of supraventricular arrhythmias in the MIT-BIH Arrhythmia Database. Each record is 30 minutes in duration with 128 samples per second.

### 4. Creighton University Ventricular Tachyarrhythmia Database (cudb)

This database includes 35 ECG recordings, each of eight minutes, from human subjects who experienced episodes of ventricular tachyarrhythmias, such as sustained ventricular tachycardia, ventricular flutter, and ventricular fibrillation. Each record is sampled at 250 samples per second with 12-bit resolution over a  $10\text{ mV}$  input range (Nolle, Badura, Catlett, Bowser, & Sketch, 1986). There are 127,232 samples per record, which is slightly less than 8.5 minutes.

## 2.2 ECG Signal Acquisition

The electrical signal of the heart starts with the polarisation of the Sino-Atrial (SA) node, then the atrio-ventricular (AV) node, and through the rest of the muscle. The electrical signal propagation follows a pattern. As a result, electrical currents are transmitted to the surface of the body, so that electrical potential can be picked up on the skin surface. These electrical signals can be captured by using electrodes with appropriate equipment on the skin surface.

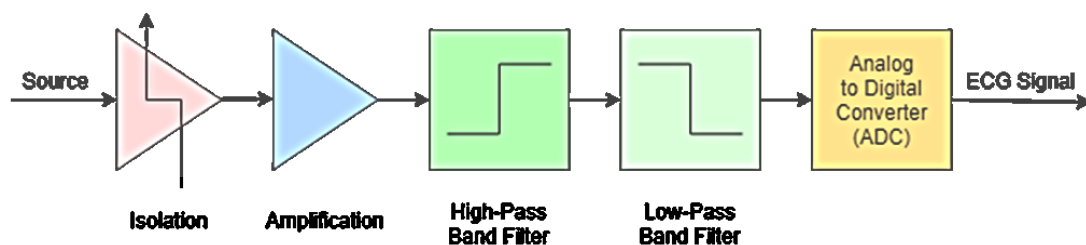


*Figure 2. Architecture for the acquisition of an ECG.*

The ECG signals belong to bipolar low-frequency weak signals (Wang et al., 2012). Figure 2. represents the series of processes in acquiring clean ECG signal from the

source. The preamplifier amplifies the ECG signal about ten times, and the main amplifier amplifies them about 100 times. Normal sinus ECG signal frequencies vary in the range of 0.05-100 *Hz* with the critical region of 0.05-35 *Hz* and amplitude range of 10  $\mu V$  to 4 *mV* with an average of 1 *mV*. A band-pass filter circuit composed of a second-order active high-pass filter and a second-order active low-pass filter isolates the ECG transmission band with cut-off frequencies at 0.05 *Hz* and 100 *Hz*, respectively. Additionally, a 50 *Hz* notch filter (band-stop filter) restrain the 50 *Hz* power frequency interference. The output data is then converted into digital data and ready for further digital filtering or signal processing.

## 2.3 ECG Signal Conditioning

### 2.3.1. Fast Fourier Transform

Fast Fourier transform (FFT) is an algorithm that analyses and converts a signal from the time domain to the frequency domain. FFT is useful to analyse the spectrum of a signal and to determine at which frequency a noise signal interferes with the desired ECG signal. After acquiring the ECG signal, through the filters and amplifier, some noises still can be found, which commonly is electrical noise of 50 *Hz* in Indonesia.

SWISS GERMAN UNIVERSITY

### 2.3.2. IIR Notch Filter

Cleaner ECG signals can be obtained by adding an infinite impulse response (IIR) notch filter to filter electrical noise. This type of recursive digital filter is widely used due to its quick and easy application of reject band filter (Mei Wang & Cai Xiao, 2013; Ramesh, Satyanarayana, & Sailaja). For the digital signal processing (DSP) realisation, the transfer function of a two-order digital filter can be expressed as shown here in Equation ( 1 ),

$$H(z) = \frac{Y(z)}{X(z)} = \frac{b_0 + b_1z^{-1} + b_2z^{-2}}{1 + a_1z^{-1} + a_2z^{-2}} \quad (1)$$

whereas the linear difference equation is as shown here in Equation ( 2 ).

$$y(n) = a_1y(n-1) + a_2y(n-2) + b_0x(n) + b_1x(n-1) + b_2x(n-2) \quad (2)$$

The ST segment measures are usually affected by baseline wandering noise. This artefact comes from respiration rate and electrode impedance changes due to perspiration. The baseline wander is usually filtered at 0.5 Hz with the sleeping condition as the baseline consideration.

SWISS GERMAN UNIVERSITY

## 2.4 ECG Signal Feature Extraction

### 2.4.1 QRS-complex Recognition

The algorithm developed in the previous study (Pan & Tompkins, 1985) has been able to detect QRS-complex of ECG signal in real-time. The algorithm is then named after them, called the Pan-Tompkins algorithm. The Pan-Tompkins algorithm has been the most prominent algorithm to detect QRS-complexes in real-time. The signal processing steps of the Pan-Tompkins algorithm is shown in Figure 3.

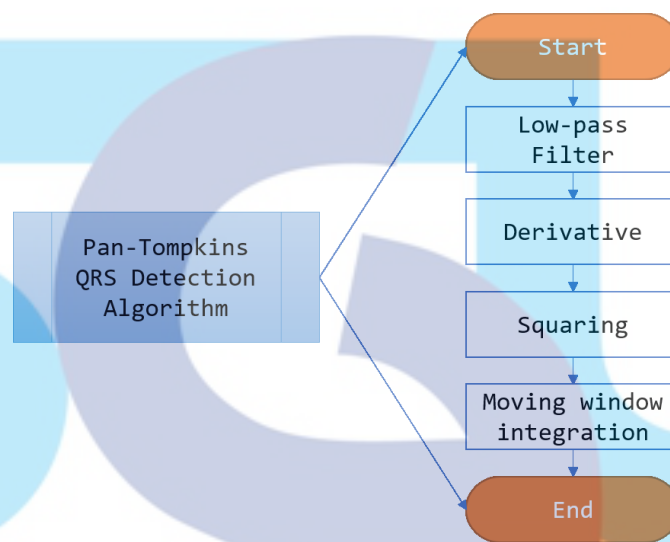


Figure 3. Pan-Tompkins Algorithm flowchart for QRS-complex detection.

Firstly, ECG signals pass through a digital band-pass filter composed of cascaded high-pass and low-pass filters (LPF) to attenuate noise. Since filters have delays, only the low-pass filter is applied in this research to minimise the delay. Then, the process is followed by differentiation to obtain the slope of the QRS-complex. The next process is squaring to intensify the slope of the frequency response curve and help restrict false positives caused by high T-wave spectral energy. Afterwards, the moving window integration generates information about both the slope and the width of the QRS-complex. Thus, the R-peak decisions are made, as shown in Figure 4. After extracting the R-peaks, a backward search down the R-peak produces the QRS-onset and offset. If there is no zero crossing, the Q or S-wave is absent. The detection of P- and T-waves includes backward and forward-searching to find the maximum and minimum value of the slope. The detection of T-wave is based on a window defined by heart rate.

Pan-Tompkins algorithm recognises QRS-complexes by its slope amplitude, and width. Several signal processing steps consist of an LPF, derivative function, squaring function, and moving window integration are applied to the raw ADC signal with a 200 Hz sampling rate to do the analysis.

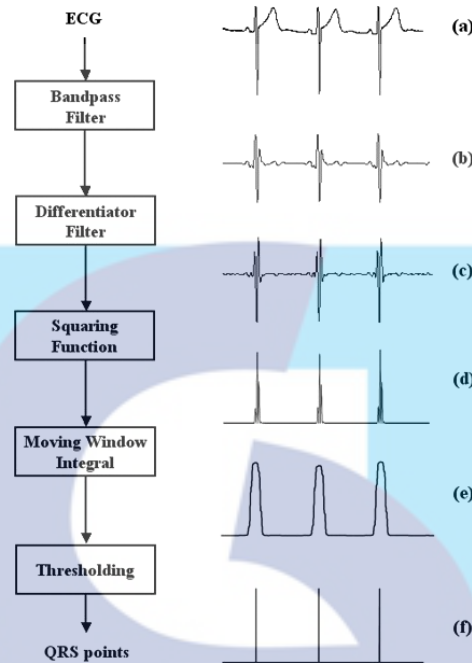


Figure 4. Pan-Tompkins algorithm signal output for every stage (Laciar & Valentinuzzi, 2010).

SWISS GERMAN UNIVERSITY

The second-order low-pass filter in the Pan-Tompkins algorithm has a transfer function shown in Equation ( 3 ),

$$H(z) = \frac{(1 - z^{-6})^2}{(1 - z^{-1})^2} \quad (3)$$

with the amplitude response shown in Equation ( 4 ) below,

$$|H(\omega T)| = \frac{\sin^2(3\omega T)}{\sin^2(\frac{1}{2}\omega T)} \quad (4)$$

where  $T$  is the sampling period. The difference equation would be the Equation ( 5 ) so that the cutoff frequency of the filter is around 11 Hz, and the gain is 36.

$$y(nT) = 2y(nT - T) - y(nT - 2T) + x(nT) - 2x(nT - 6T) + x(nT - 12T) \quad (5)$$

This filtering process has a delay of about six samples. Subsequently, a five-point derivative function shown in Equation ( 6 ) is implemented to determine the slope of the QRS-complex.

$$y(nT) = \left(\frac{1}{8}T\right) [-x(nT - 2T) - 2x(nT - T) + 2x(nT + T) + x(nT + 2T)] \quad (6)$$

Moreover, later, a squaring function shown in Equation ( 7 ) is implemented to provide a positive signal curve (no negative value) thus emphasising the QRS-complex. The negative value from the previous step is made possible to be converted into positive value by the squaring function.

$$y(nT) = [x(nT)]^2 \quad (7)$$

As the method of the algorithm is to analyse the QRS-complex slope and width, the last step is to implement the moving window integration in Equation ( 8 ).

$$y(nT) = \left(\frac{1}{N}\right) [x(nT - (N - 1)T) + x(nT - (N - 2)T) + \dots + x(nT)] \quad (8)$$

The final result of this algorithm is the markings of every R-peak in the ECG signals, based on the sample number.

## 2.4.2 R-peak Detection

To this point, the peak of the QRS-complex, or the R-peak, is the peak of the ECG signal that corresponds with the peak marked by the moving window integrator. The algorithm developed by Iskandar has the ability to perform the peak detection of the ECG signal, even the signal with artefact noises. The peak detection algorithm is as follows.

*Algorithm 1. Peak detection algorithm.*

```

Result: Numbers of  $R_{peak}$  detected.
Load buffer with QRS algorithm signals;
Let  $Y_{threshold} = \frac{1}{2} Y_{max}$ ;
Let  $t_{max} = 240 \text{ bpm} = \frac{240}{60} \times 250 \text{ Hz} = 62.5$ ;
for every buffer QRS do
| find QRS peak that represent  $R_{peak}$ ;
| if  $buffer_n - buffer_{n-4} < 7$  AND  $buffer_{n+10} > Y_{threshold}$  AND  $buffer_n > Y_{threshold}$ 
| then
| | if  $R_n - R_{n+1} > t_{max}$  then
| | | Peak has been found and position is stored;
| | else
| | | Record sample for tracing;
| end
end

```

Algorithm 1 begins with loading an array of buffer with the QRS algorithm signal in it. Then, the threshold is set to half of the maximum amplitude, which is the possible minimum QRS peak. The minimum duration of RR-interval is determined by the maximum heart rate possible in human body daily life, which 240 bpm. Thus, multiplied by the sampling rate of 250 Hz, the minimum RR-interval is 62.5 ms. Next, for every QRS buffer value, the algorithm traces for a peak of the signal by its turning point when the peak amplitude value is higher than the threshold. The peaks found are stored in another array of buffer, ready for further data processing, such as heart rate calculation (Subsection 2.4.4).

### 2.4.3 P-wave Detection

The presence of P-wave holds a vital role in cardiac arrhythmia detection. The absence of P-wave often leads to several cardiovascular disease diagnosis. If cardiac arrhythmia detection can also be done using another LED-based sensor, the P-wave detection can only be done by analysing the ECG signal.

The normal PQ-interval is between 0.12 s and 0.21 s, meaning the recognised P-peak is located in the middle of that range. Algorithm 2 begins by setting the recognised Q-wave position by going backwards several samples according to the QRS-interval and the sampling rate. Then, the P-peak range is determined by the PQ-interval and the sampling rate. The isoline also influences the recognition. The P-wave locations are stored and calculated, then compared to the R-peaks found using the previous algorithm. If the ratio is not 1:1, some of the P-wave might be absent and thus help to recognise the possibility of cardiac arrhythmias.

*Algorithm 2. P-wave detection algorithm.*

```

Result:  $P_{wave}$  locations and occurrence.
Let  $Q_{wave} = R_{peak}position - (\frac{1}{2} \times QRS_{duration} \times samplingrate)$ ;
Let  $P_{range} = \frac{1}{2} \times PQ_{duration} \times samplingrate$ ;
for every  $R_{peak}$  search  $P_{range}$  do
| if signal direction is downwards AND  $P_{peak} - P_0 \leq 0.2mV$  then
| |  $P_{wave}$  found and stored;
| end
| Keep on tracing;
end

```

#### 2.4.4 Q-wave and S-wave Recognition

The location of Q-wave and S-wave determine the QRS-onset and offset, which are essential for the arrhythmia analysis. Kim-Lee developed a novel formula to better recognise the QRS-onset and offset in 2015. The algorithm consists of four steps, which are baseline correction, R-peak detection, search for the junctions of Q-wave and S-wave, and QRS-onset and offset detection.

There are four major noises to be removed in the noise cancellation process. The noises are power line interference, baseline drift, muscle contraction, and motion artefact. Erosion and dilation, the two basic morphological operators, are performed for combining the opening and closing operators for baseline correction and noise suppression.

Next, the R-peak detection follows the Pan-Tompkins algorithm and the signal proceed to the next step, which is the highlight of this research. RR-intervals are obtained using the detected R-peak locations. The location of the Q-wave and S-wave would then be determined by the distance ( $D_i$ ) from the imaginary aid line between R-peaks (coloured orange line in Figure 5) to sample points ( $p_i$ ) of ECG signal in RR interval using Equation (9).

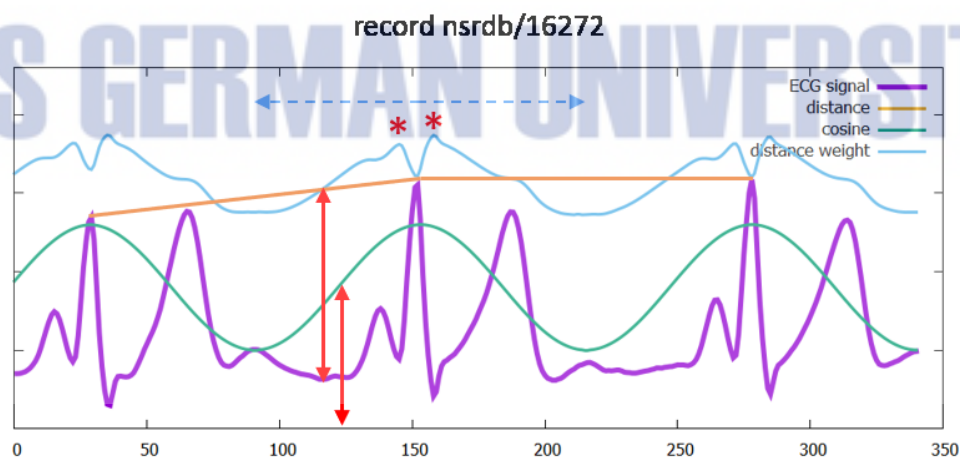


Figure 5. The implementation of QRS-onset and offset detection using the distance weight method, adapted from Kim-Lee formula.

$$D(p_i) = \frac{|(y_R - y_L)x_i - (x_R - x_L)y_i + x_R y_L - y_R x_L|}{\sqrt{(y_R - y_L)^2 + (x_R - x_L)^2}} \quad (9)$$

$$p_i = (x_i, y_i) \quad ; \quad R_R = (x_R, y_R) \quad ; \quad R_L = (x_L, y_L)$$

$$i = x_L + 1, x_L + 2, \dots, x_R - 2, x_R - 1$$

Every sample point ( $p_i$ ) has a location ( $x_i$ ) and an amplitude ( $y_i$ ) in RR-interval. Every R-peak has a location ( $x_R, x_L$ ) and an amplitude ( $y_R, y_L$ ), which in this case, two R-peaks would be sandwiching a set of sample points. The weight function is defined as Equation ( 10 ) below, and its curve is coloured green in Figure 5.

$$W(p_i) = \cos\left(2\pi \frac{x_i - x_L}{x_R - x_L}\right) \quad (10)$$

When the distance value is adjusted according to its cosine value, as shown in this formula in Equation ( 11 ), the distance weight  $WD$  could be determined, creating a new curve coloured blue in Figure 5.

$$WD(p_i) = W(p_i)D(p_i) \quad (11)$$

The Q-wave location would be found in the location, from the distance weight line (coloured blue in Figure 5), that has the maximum value  $WD(p_i)$  on the left side of the R-peak while S-wave on the right side of the R-peak (shown as red stars in Figure 5). Further analysis can be performed by removing the R-peak, which covered by the imaginary aid area. However, this step is not further explained in this section, as it would not be adopted for this research.

## 2.4.5 Heart Rate Calculation and Outlier Removal

The R-peak detection algorithm in Subsection 2.4.2 results in an array of RR buffer. The calculation of RR-interval is highly essential for calculating the heart rate and its variability. Algorithm 3 results in validated heart rates. The outlier removal is based on the normal range of heart rate, usually between 30 *bpm* and 200 *bpm*. Firstly, a series of calculation is done to calculate the duration of in-between R-peaks. Then, heart rate is defined by the sample numbers in one minute divided by the RR-interval.

*Algorithm 3. Heart rate calculation and outlier removal.*

```
Result: Validated heart rates.
Let  $RR = RR_{n+1} - RR_n$ ;
if 30 bpm <  $RR \leq 200$  bpm then
| RR-interval is valid;
| Store valid RR-interval;
|  $HR = \frac{60 \times \text{sample-per-second}}{RR}$ ;
else
| Record sample for tracing;
end
```

## 2.4.6 Heart Rate Variability in Time Domain

The most typical indication of most CVDs is the irregular heart rate over time. By calculating the average heartbeat complete with its variance and standard deviation based on Algorithm 3 above, Algorithm 4 provides a computer-aided method to detect irregular rhythms. The calculation of *SDANN* also leads to *RMSSD* calculation, which also similarly based on the heart rate variance.

*Algorithm 4. Heart rate variability calculation.*

```
Result: Standard deviation of the heart rates (SDANN).
Let  $\mu = \frac{\sum RR_{valid}}{RR_{valid}-1}$ ;
for every valid RR until N do
| Calculate the variance;
|  $\sum var = (RR_n - \mu)^2$ ;
end
 $var = \frac{var}{N}$ ;
 $SDANN = \sqrt{var}$ ;
```

## 2.5 Cardiac Arrhythmias

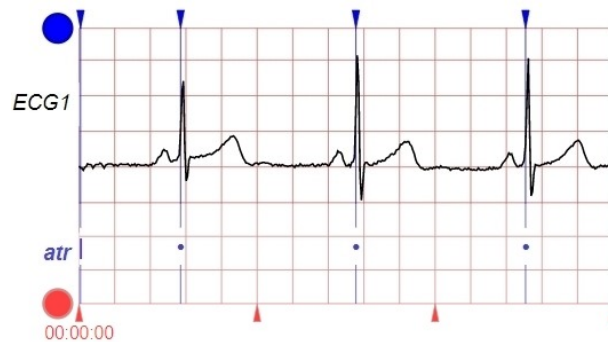


Figure 6. Normal sinus rhythm (NSR), from nsrdb/16272 (Goldberger et al., 2000).

The normal rhythm in the morphology of the ECG signal is called Normal Sinus Rhythm (NSR), with a regular heart rate of 60 to 100 beats per minute. An ECG recording example of NSR is shown in Figure 6. Irregular heartbeats indicate cardiac arrhythmia: too fast (tachycardia, above 100 beats per minute) or too slow (bradycardia, below 60 beats per minute) (Adabag, Luepker, Roger, & Gersh, 2010). There are four main types of arrhythmia: extra beats, supraventricular tachycardia, ventricular arrhythmias, bradyarrhythmia.

Extra beats include premature atrial contractions (PAC), premature ventricular contractions (PVC), and premature junctional contractions (PJC). Supraventricular tachycardia includes atrial fibrillation (AFib), atrial flutter (AFL), and paroxysmal supraventricular tachycardia (PSVT). Ventricular arrhythmias include ventricular fibrillation (VFib) and ventricular tachycardia (VT). The detection system in this study is based on the Lead I ECG signal strip.

Every cardiac arrhythmia has several distinctive characteristics, on which cardiologists usually base their decision. However, without proper acquisition and timing, these ECG signals might not be captured.

### 2.5.1 Premature Ventricular Contraction (PVC)

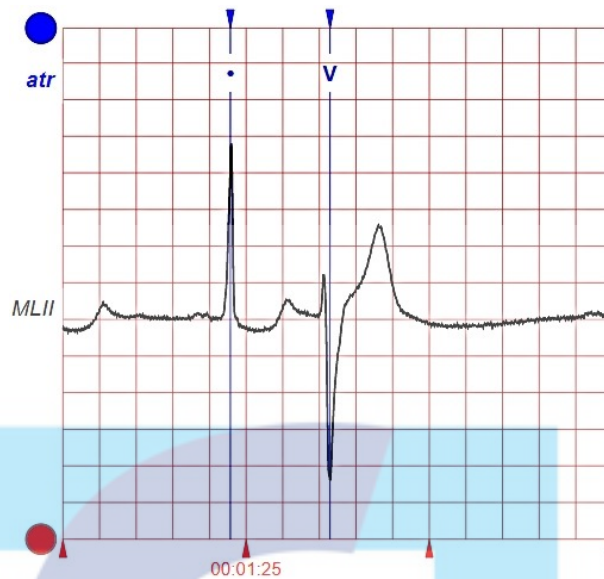


*Figure 7. Premature ventricular contraction (V), from mitdb/114 (Goldberger et al., 2000).*

The synonym of this arrhythmia is Ventricular Extra Systole (VES). PVC is an extra heartbeat begins with a single electrical pulse originates at one of the ventricles. PVC is indicated by broad QRS-complexes, more than 0.10 ms, as shown in Figure 7. This type of arrhythmia is common and does not cause a severe health threat, but if it frequently occurs, such as six times per minutes, treatment might be needed.

## 2.5.2 Supraventricular Tachycardia (SVT)

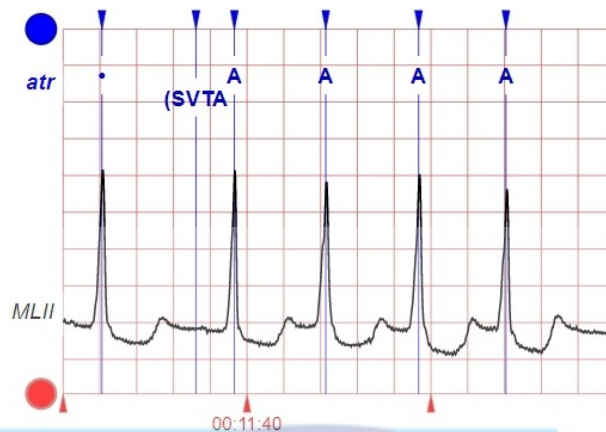


*Figure 8. Supraventricular tachyarrhythmia (SVTA) and premature atrial contractions (A), mitdb/114 (Goldberger et al., 2000).*

SVT happens when the heart beats fast (more than 100 *bpm*) caused by abnormal electrical activity in the atria. There are four main types of SVT: AFib (as described in Subsection 2.5.4), paroxysmal SVT, atrial flutter, and Wolff-Parkinson-White syndrome. The P-wave appears indiscernible or hidden within the QRS-complex. The QRS-complex width is usually less than 0.1 s with either narrow or broad shape, as shown in Figure 8, except when aberration occurs.

SWISS GERMAN UNIVERSITY

### 2.5.3 Premature Atrial Contraction (PAC)

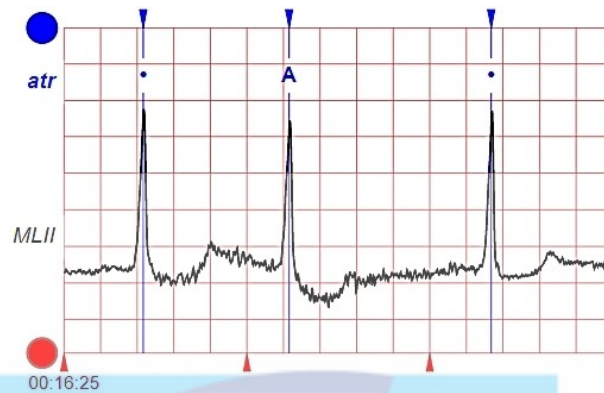


*Figure 9. Premature atrial contraction (A), mitdb/114 (Goldberger et al., 2000).*

The synonym of this arrhythmia is Supraventricular Extra Systole (SVES) (Radhwane, 2013). PAC is an extra heartbeat begins with electrical impulses originating in the atria. This arrhythmia is somewhat tricky to be seen by analysing solely based on the ECG Lead I. Usually, PAC has no apparent cause and no health risks. It happens naturally without followed by heart disease symptoms. PAC is indicated by very narrow QRS-complexes, far less than  $0.10\text{ ms}$ , as shown in Figure 9.

SWISS GERMAN UNIVERSITY

### 2.5.4 Atrial Fibrillation (AFib)

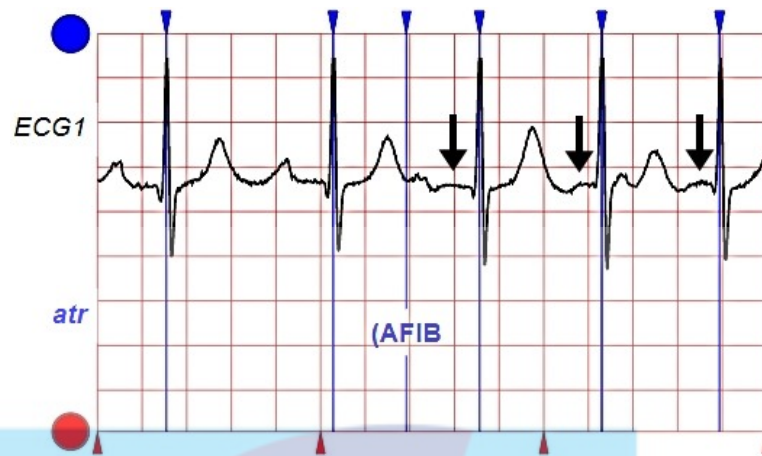


Figure 10. Atrial fibrillation (AFIB), afdB/06995 (Goldberger et al., 2000).

AFib is the most common cardiac arrhythmia, happens when electrical impulses fire off in random pathways in the atria, causing the atria to twitch and beat irregularly. The P-wave appears unclear, as shown in Figure 10. The QRS-complex width is usually less than 0.1 s, except in AFib with aberration cases.

SWISS GERMAN UNIVERSITY

### 2.5.5 Ventricular Tachycardia (VT)

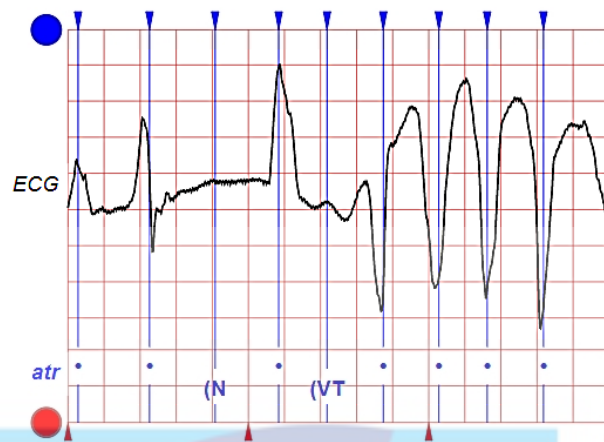


Figure 11. Ventricular tachycardia (VT), cudb/cu02 (Goldberger et al., 2000).

The electrical impulses in ventricular tachycardia originate at ventricular pacemaker. There are many types of VT: monomorphic, polymorphic, sustained, non-sustained, bidirectional, and so forth. The heart rate regularly goes with more than 100 *bpm*. The P-wave is hard to detect with either narrow or broad QRS-complexes, as shown in Figure 11.

SWISS GERMAN UNIVERSITY

## 2.6 Bluetooth Communication Introduction

The two most common version of Bluetooth in this twenty-first century is Bluetooth 4.0 and Bluetooth 5.0. The Bluetooth 5.0 enables connectivity with several devices, while Bluetooth 4.0 only allows one device connectivity. Bluetooth 4.0 can be in the form of Bluetooth Classic, or traditional Bluetooth, and Bluetooth Low Energy (BLE). BLE is designed to have a low power usage for its communication, thus enabling operation with a small power source, such as lithium coin cell batteries.

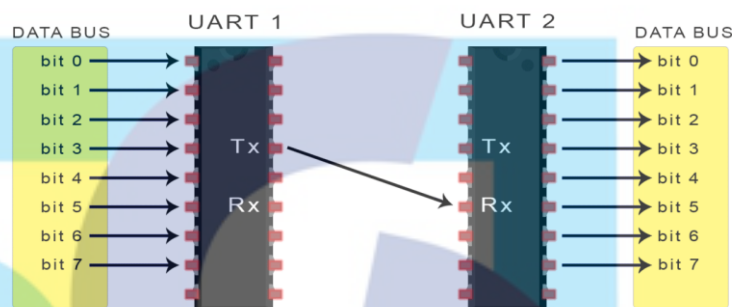


Figure 12. Basic of UART communication (CircuitBasics).

There are two types of communication discussed in this research. The first one is UART or Universal Asynchronous Receiver/Transmitter, whose concept is depicted in Figure 12. The second one is GATT or Generic Attribute Profile, whose concept is depicted in Figure 14. Their principle of works differs, which also influence the power usage. Bluetooth Classic uses UART for communication, but the downside of this system is that the channel of communications is usually kept open and connected, even if there is no data being transferred. Even so, the data from the transmitter is erased from the queue/communication channel once the data reach the receiver. This principle of work, in an analogy, might be similar with Serial Peripheral Interface (SPI), where one device acts as a master when it is transmitting, and a slave when it is receiving. The concept of SPI is shown in Figure 13. These SPI communications happen through a serial communication port.

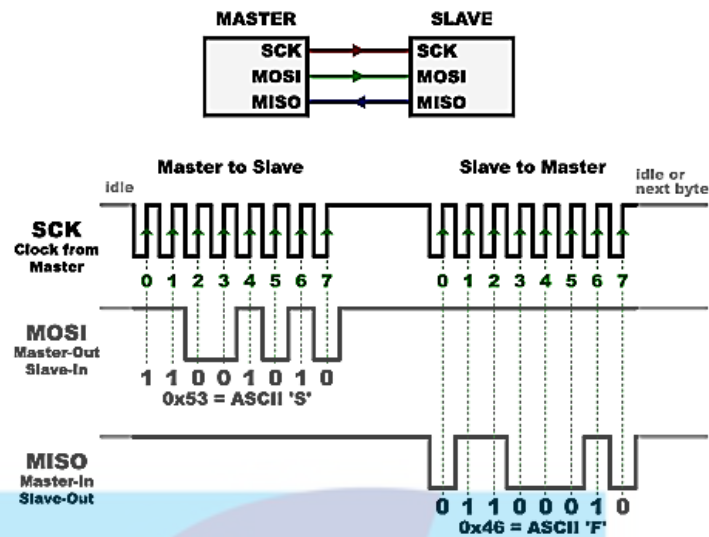


Figure 13. Basic SPI communication (Grusin).

On the other hand, GATT is the way of communication between two Bluetooth Low Energy devices (Beach et al., 2018) that enable them to transfer data back and forth using a set of protocols/concepts named Services and Characteristics. The concept of GATT is depicted in Figure 14. Rather than a single communication channel, this communication is more similar to an announcement board. A peripheral device, the one transmitting information, posts all data and information for all other radios/devices. It indeed contains much information, but the central device, the one receiving information, can only care about specific information that suits its characteristics. In conclusion, central devices are the clients to the Bluetooth Low Energy that read available information from the peripherals, which are the servers or usually called publish-and-subscribe.

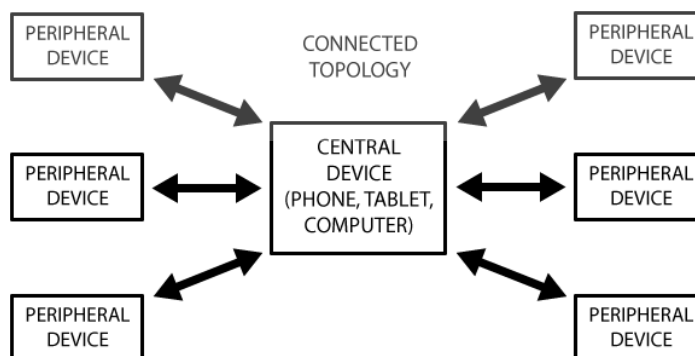


Figure 14. Basic GATT communication (Townsend, 2014).

The BLE peripherals provide services, which in turn also provide characteristics. An example of a standard service is the heart rate measurement. Custom services are also available to be modified independently. The services are identified by unique combinations, known as UUIDs. Standard services have a 16-bit UUID (hexadecimal), and custom services have a 12-bit UUID. A characteristic has a value that can be up to 20 bytes long. A central device can read, write, or indicate and notify the characteristics.



## 2.7 Previous Studies

In this section, some notable previous studies or commercial products towards wearable ECG and its arrhythmia identification capability is briefly described in terms of detecting ability and/or software.

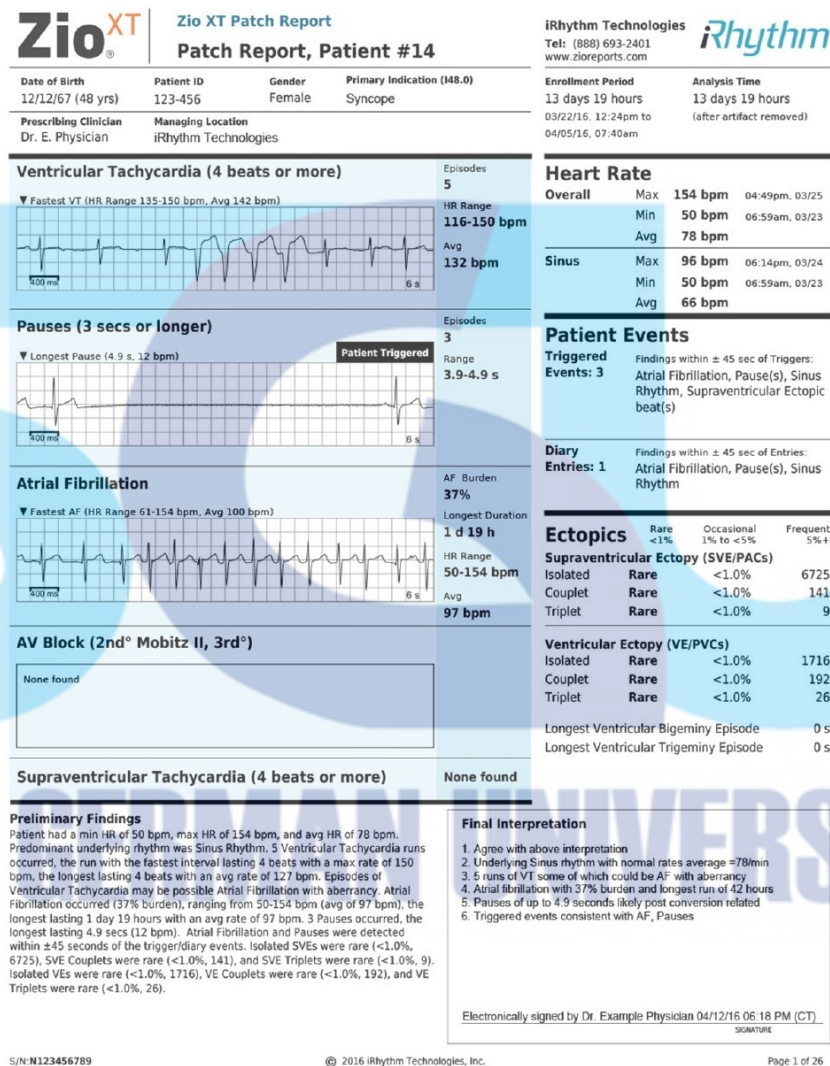


Figure 15. iRhythm Zio Patch sample report (M. Barrett et al., 2014).

The disposable Zio Patch is a novel adhesive patch that can monitor ECG and claims to have 14 days of product life after its application. It reads single-lead ECG, is lightweight, and Food and Drug Administration-cleared. The device is usually worn by patients with the need for ambulatory ECG monitoring. Zio newest XT Patch provides ECG information, especially regarding the occurrence of arrhythmias, in real-time from

device to doctors. The sample report of iRhythm Zio Patch is shown in Figure 15. The report claims to be comprehensive and contains much information regarding the current condition of the patient.

Qardiacore develops a wire-free and patch-free reusable ECG monitoring device. Similar to the device used in this research, the wearable ECG is chest-worn. The processing is not in real-time, but it is still considered fast since it takes 30 seconds to process the data. The processing unit does not process the data, but only records and sends it to the smartphone application. The electrode provides single-lead reading (Lead I).



Figure 16. AliveCor's KardiaMobile 6L (Abudan et al., 2019).

AliveCor is a technology company that enables the use of artificial intelligence to detect atrial fibrillation in real-time using a device called KardiaMobile. The latest version of KardiaMobile 6L in Figure 16 has two handheld electrodes and already employs six-lead readings: Lead I, II, III, aVL, aVR, and aVF. The readings are in real-time, but not continuous since the device is only detecting ECG signal as long as it is held.

EPI mini handheld ECG is a smartphone-like device produced in Singapore, priced at about 10 million rupiahs can detect heart problems early. Even more, in case of detected abnormality, this device will also provide a reference to which hospital you should go. It is based on ECG reading of Lead I.

AfibAlert is the oldest and the simplest atrial fibrillation detector. The device is handheld, and its accuracy of detection is often compared to Qardiacore in numerous studies. It has two electrodes to read the single-lead ECG signal (Lead I).