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Multipoint ECG Signal Extraction on Palms and Figures for Human Identification System

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Abstract: - The ECG signal contain vital information for cardiac disease which is one of main cause of catastrophic mortality. In conventional technique, the signals are extracted through different points located on the limbs and surface of the chest. The biological impedance of human body eliminates any practical means of making fake copies of the relevant physiological traits. Moreover, this method needs the complex data acquisition system and apparatus as well as inconvenience way of acquisition of signal at the chest. Hence, there is a demand to find out the promising alternative technique to extract the ECG signals in more convenient way with high accuracy. In this paper, the real-time ECG monitor has been developed to extract the signals from the multipoint on the hands and fingers. Placement of the electrodes are done based on the acupressure point on palms and fingers. A total of 120 volunteers were investigated to develop the ECG database as the development dataset. This work uses the template matching algorithm and distance classification method to analyze and to find the best similarities between the developed dataset of ECG biometric signals to improve the identification rate. In order to lessen the noise that was recorded with the ECG signals, signal averaging was used to create ECG databases and templates. The recognition rate rose to 98% accuracy on the development dataset when the prescreening procedure was introduced to create a combined system model. ECG biometric model was created by combining the two models and using the development dataset's results. The algorithm was applied on the entire developed ECG dataset and 96% of accuracy rate was achieved in identification.

Keywords: Bio-signal, electrocardiogram (ECG), hand fingers and palms, ECG features, template matching algorithm

I. INTRODUCTION

Modern living habits developed during the recent years created numerous health problems especially, heart/cardiovascular related disease. Around the world, about 32% of death causes by cardiac related diseases as per WHO-2019 report. The electrical activity of the heart is represented by an electrocardiogram (ECG) signal which is considered as golden standard for clinical diagnosis. The heart's electrical impulses are connected to the electrical activity such as polarization and depolarization of cardiac tissue. It provides details about the anatomy, rhythm, and heart rate. Normally, an electrode set is placed on the chest to record the ECG, the body's exterior, including the arms, legs, neck, and chest. The conventional machine interprets the data, and a graph is then produced. Multiple waves can be seen on the graph, which represents the various heart's activity such as heart rate, heart rhythm, size of the heart and heart damage [1]. The ECG signal shape varies depending on the type of cardiac disease, which aids the cardiologist in making a diagnosis. Various ECG characteristics are retrieved and evaluated using conventional methods. They include techniques based on time, frequency, and wavelet. A cardiac cycle can be seen on an ECG as a P wave, QRS complex, and T wave pattern. Figure 1 show the different segments and potential features for classification of ECG signal for common human being.

The isoelectric line is the term used to describe the electrocardiogram's reference voltage. The isoelectric line is typically defined as the section of the trace that comes after the T wave and before the subsequent P wave. By using the standard 12-leads conventional system can be used to simultaneously measure the electrical activity of the heart from frontal plane (Limb leads), horizontal plane (precordial leads), respectively, from different vectors, so 12 different shapes of P-wave, QRS complex, and T-wave are observed [2]. The ECG signal generated by each lead contains waves, intervals, segments, and one complex. Leads I, II, and III are the three limb leads in the standard 12-lead ECG. Leads aVR, aVL, and aVF are the three augmented limb leads using the Goldberger modification of the central terminal of Wilson as a derived indifferent electrode that is paired with the exploring electrode. Leads V1 through V6 are the six precordial leads using the central terminal of Wilson as a derived indifferent electrode that is paired with the exploring electrode. The precordial electrodes and the augmented limb leads have frequently been referred to as "unipolar" leads, whereas the three limb leads are "bipolar" leads [3, 4]. The electrical activity of the heart is reflected from various spatial angles in single-lead ECG signal data that was

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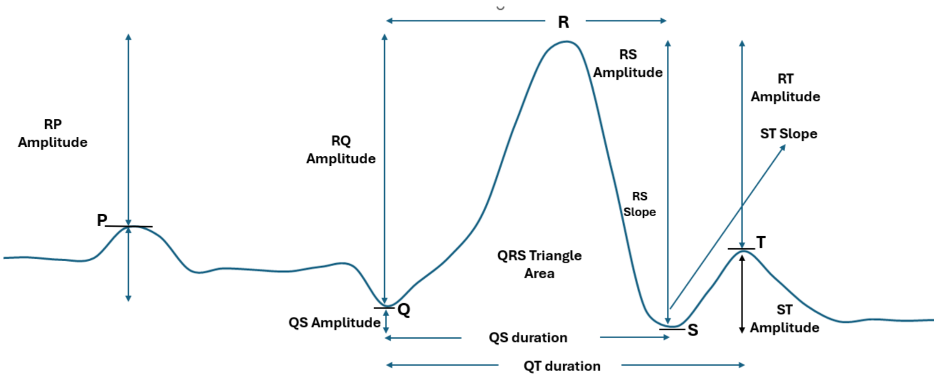


Figure 1. Segmentation and potential features for classification of ECG signal

recovered from the typical 12-lead ECG system. These leads are placed in three orthogonal directions such as superior to inferior, right to left, and anterior to posterior on human body.

The time between the beginning of the Q wave and the conclusion of the T wave in the heart's electrical cycle is known as the QT interval. The left and right ventricles' electrical depolarization and repolarization are represented by the QT interval. The duration and shape of each ECG characteristic are important to the doctor. The lead configuration is a major factor in the waveform, though [5]. To make his diagnosis, the cardiologist typically carefully considers the various time intervals, polarity, and amplitudes. Table 1 shows the morphological specification of common ECG signal. The standard 12-lead ECG signal offers the significant advantages in clinical interest such as, topographic form for higher diagnostically information, to detect cardiac conditions of the patients after surgical and after application of anesthesia etc. But still, this technique suffers from the major drawbacks of handling the data manually demands time, difficulties due to extensive steps, boring, and expensive when performing continuous ECG analysis [6]. Other ECG devices are readily available and uses recent technology which includes internet solutions, bluetooth, and wireless networks. However, it demands expensive instrumental setup and significant power usage. Although a wearable ECG system has been built with a PCB on a T-shirt which offers uncomfortable and needs to wear constantly for ECG monitoring.

In recent years, due to the rapid development of semiconductor technology newer and faster digital devices has been introduced in the market. They measure ECG signals in a way that is different from that of the conventional system used in hospital. To solve the problems with the existing methods, this paper proposes the extraction of ECG through the palms and fingers of the targeted patients. The self-adhesive, pre-gelled silver/silver chloride electrodes are used which provides optimal skin connection to ensure comfortable usage without an irritation. These sensors are plated in the acupressure point on palms and fingers. Totally, six electrodes are placed to extract the ECG signals from different acupressure points. This system uses AD8232 biopotential signal acquisition circuit, an Arduino Uno as signal processing unit and template matching algorithms used to identify and match the extracted signal with the signal obtained through the 12-lead conventional technique.

Table 1. Morphological specification of common ECG signal

Sl No	Waveform	Amplitude	Duration
1	P wave	0.25mV	0.11 sec
2	R wave	1.60 mV	--
3	Q wave	0.2-0.4mV	0.03 sec
4	S wave	1.8-3mV	--
5	T wave	0.1-.5mV	0.25sec
6	U wave	0.33mV	--
7	P-R interval	120mV	0.12 – 0.2 sec

8	Q-T interval	--	0.35 – 0.44 sec
9	S-T segment	0.2mV	0.05-0.15 sec
10	QRS interval	2.5 – 3 mV	0.09 sec

II. Experimental work

A collection of myogenic cells with the primary ability to periodically self-stimulate are at the center of the complex bioelectrical system that makes up the human heart. This capability is what eventually causes the cardiac cycle and rhythm. Both the heart cycle and the heart rhythm are currently well-known ideas that have been the subject of substantial research in the healthcare industry. The cycle is represented by the normal pulse waveform, whilst the rhythm is more often referred to as the heart rate. The proposed system uses fingers and palms of hands to extract the ECG signal for measurements, it will be able to overcome many of the limitations of current ECG measurement methods[7,8]. In fact, more than twelve silver/silver chloride electrodes are placed over patient skin, may aggravate patients who are prone to allergic reactions by causing pain, skin irritation, and inflammation. This can result in less precise measurements. Additionally, it is frequently impossible to apply electrodes directly to the body with skin injury. In search of an alternative approach to extract the precise ECG signals, the fingers and palm based technique quite impressive and accurate. There are totally 6-electrodes are placed in which one-electrode in right and five-electrodes in left hands fingers and palm, to extract the ECG signals.

Fig 2 shows the electrode placement position and system architecture. An integrated signal conditioning block AD8232 is used to extract, amplify and filter the small biopotential signals in high noisy conditions. The two-pole high-pass filter coupled with instrumentation amplifier eliminate the motion artifacts and the electrode half-cell potential. The flexibility to select the cutoff frequency of the filter makes this module to suit different types of application. The AD8232 automatically adjust the higher filter cutoff to fast restore function especially during leads off condition. This characteristic enables the AD8232 to quickly recover and, as a result, take accurate readings shortly after attaching the electrodes to the subject. This model cancels out 602Hz noise. The AD8232 ECG sensor module has nine connections, in which five pins needed are labeled as 3.3V, Gnd, LO+, LO- and OUT pins. On the one hand, it has a low power supply, making it possible for it to be powered by the Arduino uno development board, which will be used without posing any power supply issues. This ECG sensor's strong amplification enables for the augmentation of the signal while also allowing for the later filtering out of noise to remove its impacts. This sensor model has three input leads, RA(Right Arm), LA(Left Arm) and RL(Right Leg) attached with the pre-gelled silver/silver chloride electrodes pads to extract signals. Among these, the RA lead pasted below the index finger of right hand, the RL lead pasted at the top of the little finger of left hand. The LA lead placed at the different acupressure point on palms to extract the various cardiac signals. The output leads of the LAs are connected to the signal processing unit Arduino Uno through the analog multiplexer ADV3221. The ADV3221 is a 4:1 analog multiplexer with two address lines offers channel transition times of less than 20 ns with 1% settling and a signal bandwidth greater than 800 MHz by 3 dB are required.

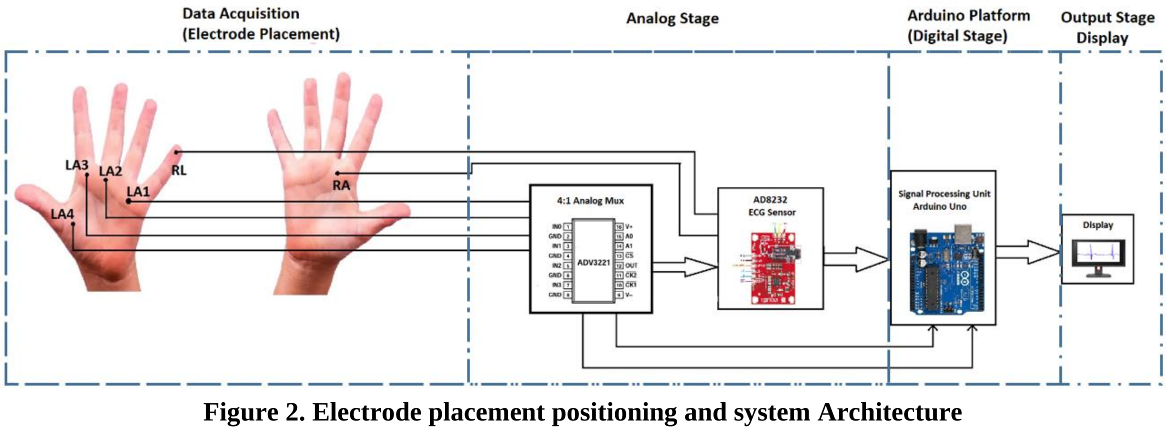


Figure 2. Electrode placement positioning and system Architecture

An output buffer is present in the multiplexer can be switched to a high impedance condition. As a result, many outputs can be linked together for cascading stages without the output bus becoming overloaded with off channels. The Arduino created an open-source microcontroller board based on the AT mega 328P microcontroller. Both analog and digital pins are included. It has 14 digital pins and 6 analog pins. It has a USB connection, a reset button, a power jack, a 16 MHZ clock, and 14 pins for input and output. It also has a 10-bit ADC (analog to digital converter) to process the analog data with built-in libraries for practically all applications. The AD8232 chip's analog ECG signal was digitally converted using the Arduino microcontroller (ATmega328), and the ADC converter was set up with a resolution of 10 bits, or 5V/1024 = 0.00488V of Lease Significant Bit (LSB). The extracted ECG signal can be viewed through the serial plotter. Figure 3 shows the extracted cardiac signal from various LA points (LA1 to LA4) from the palm of the left hand with RA and RL kept fixed [10].

For the development of ECG-based human identification, template matching, distance classification, and mixed models were studied. This technique is frequently employed in ECG analysis and has been utilized in the past to detect heartbeats, identify ventricular ectopy, and evaluate the quality of the ECG signal. This research focuses on normal, healthy individuals, in contrast to the ECG data from cardiology patients. To develop an ECG biometric database, 120 individuals (40 men and 80 women) had their short-term, resting Lead-I ECG signals measured. This research focuses on normal, healthy individuals, in contrast to the ECG data from cardiology patients [11].

To develop an ECG biometric database, 120 individuals (40 men and 80 women) had their short-term and resting ECG signals measured. These participants were instructed to unwind by opening their palms and resting on their thighs while sitting erect and in a relaxing position. The "template" or "kernel" acts as a computational blueprint for the representation of the shape of a heartbeat on an ECG. With a low CR and high reconstruction accuracy, the implemented template matching-based ECG compression approach requires fewer calculations. This technique does object searching coefficients and fixed template matching. The location of the objection is then determined using the coefficient value, which is subsequently utilized to justify whether there is matching or not. If the waveform shapes of two signals match, then the signals are said to be correlated [9]. The correlation coefficient offers a numerical assessment of how comparable the signals appear to be. It's crucial to remember that the correlation coefficient is unaffected by the amplitude discrepancies between two signals. The equation for the correlation coefficient is:

$$r_{xy} = \frac{\sum_{n=i}^{N}\{x(n)-\bar{x}\}\,\{y(n)-\bar{y}\}}{\sqrt{\sum_{n=1}^{N}\{x(n)-\bar{x}\}^{2}\sum_{n=1}^{N}\{y(n)-\bar{y}\}^{2}}} \ldots\ldots\ldots\ (1)$$

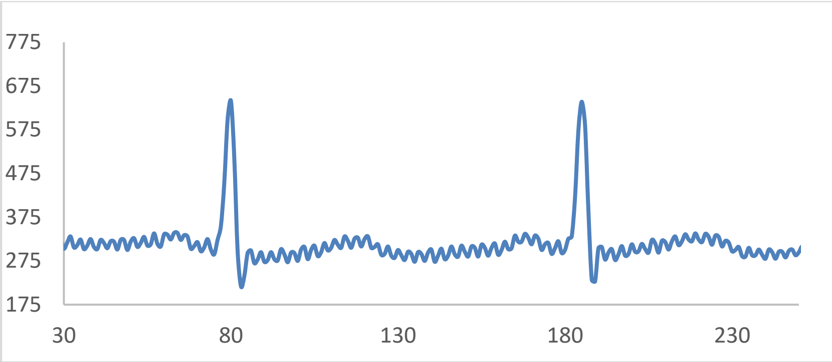
Where the value of rxy fluctuates between 1 and -1 according to the similar the forms of x and y values. Figure 4 shows the ECG patterns of two subjects extracted by proposed method have completely different pattern even though their age, gender, weight and height are same from the various LA points (LA1 to LA4). The similarity between feature vectors xp and xq in the Euclidean metric system can be used to represent the distance in R space as follows:

$$d(x^{p}, x^{q}) = \sqrt{\sum_{i=1}^{R}(x_{i}^{p} - x_{i}^{q})^{2}} \ldots\ldots(2)$$

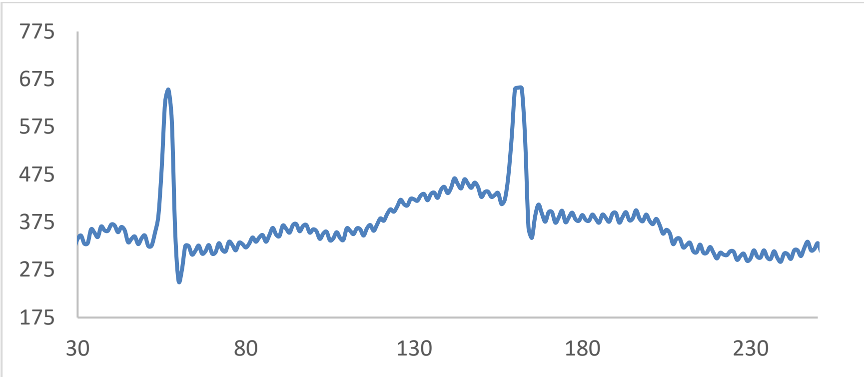
Not all features are equally weighted in the feature space, though. In order to change this relationship, a weight vector can be added w = [w1, w2, w3 ……wR]. The relationship between the distance between two classes known as SL and SK and the smaller value of d (xp, xq), can be expressed as follows:

$$\mathrm{D(SL, SK)} = \frac{1}{m_{L}\,.m_{K}} \sum_{x^{P}\in S_{L}} \sum_{x^{Q}\in S_{K}} d(x^{p}, x^{q}) \ldots\ldots(3)$$

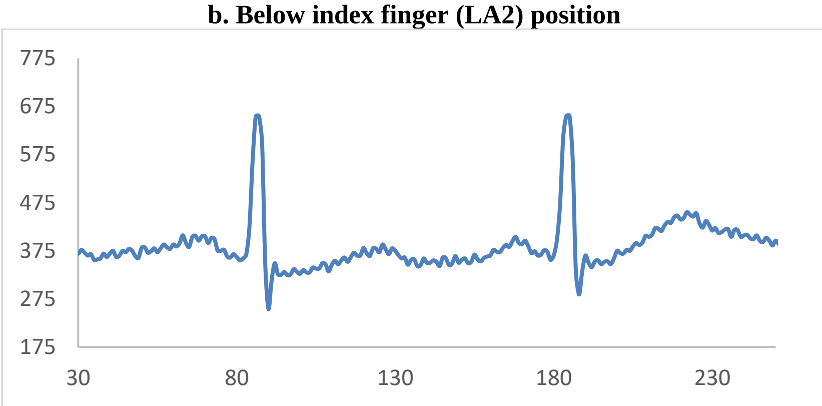
Where mL and mK are the numbers of feature vector in SL and SK.



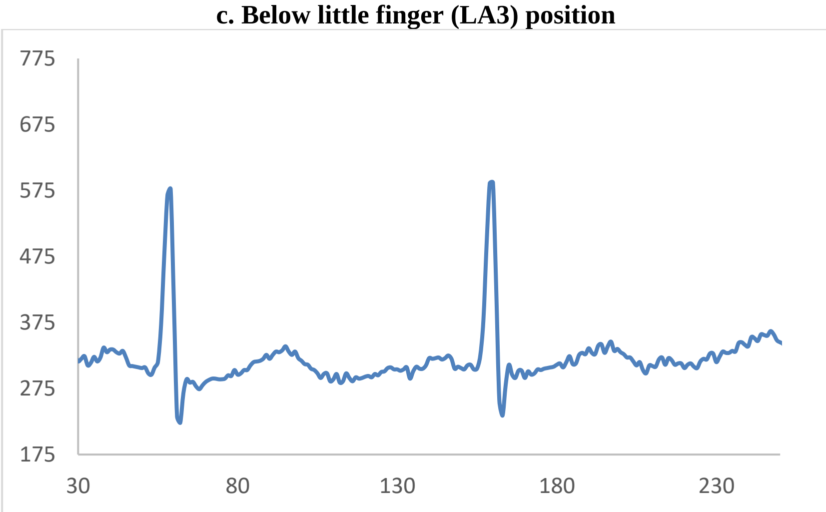
a. **Below middle finger (LA1) position**



b. Below index finger (LA2) position



c. Below little finger (LA3) position



d. Below thumb finger (LA4) position

Figure 3. Extracted ECG signal from various LA points from the palm of the left hand with RA and RL kept fixed

The heartbeat waveform usually compresses or expands in response to changes in heart rate. The segmented heartbeat signal's normalization will guarantee a decrease in each complex's latency variability. An example of an acquisition where the subject's computed heart rate varied from 133 to 70 beats per minute (BPM) from start to finish is shown in Figure 5. This example demonstrates the expansion/compression effect that variable heart rate values have on the waveform. After choosing the potential candidates using the template-matching prescreening, distance classifications were utilized in the identification procedure to prevent misidentification. There were seventeen features that were utilized to classify distance. The minimal distances between each pre-selected candidate and the feature vectors in an input template can be used to determine the class of the template. To improve identification accuracy, this technique was chosen for the identification process in a combined model and applied in tandem with the prescreening step.

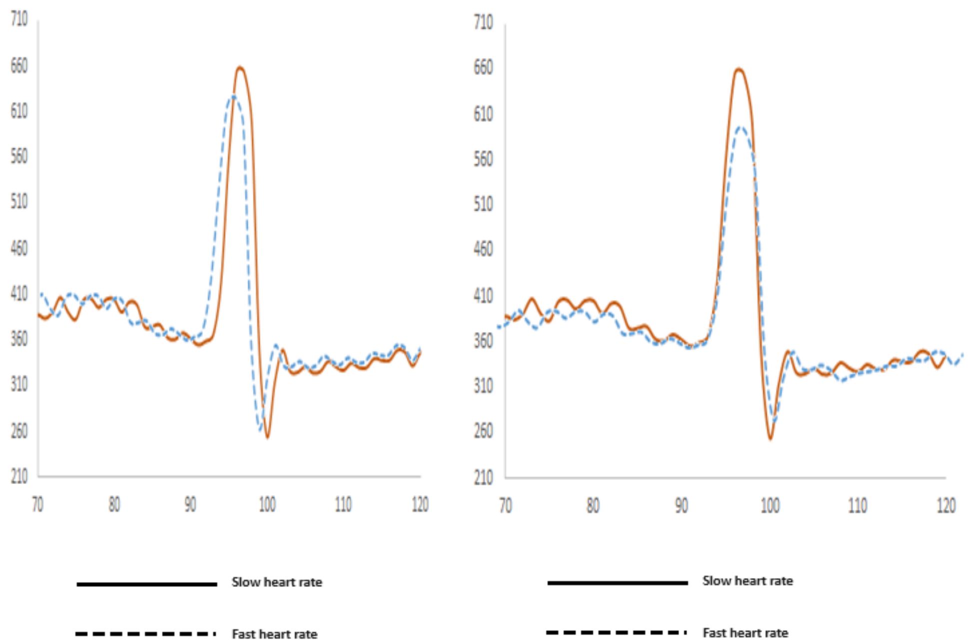


Figure 5. Waveform comparison of heartbeats at 70 (low) and 133 (high) BPM. The raw data are shown on the left, where a wave compression associated with a rapid heart rate is seen. The time-normalized signals are shown on the right.

Upon powering on, the microcontroller of the system navigates to the START memory location (h'0000'), resets all variable settings and aligns the ports. Software is developed in C++ language in open-source Arduino IDE, to initialize ports, to accept data from the microcontroller, to select analog channels for processing ECG data (LA1 to LA4), to choose UART mode, to adjust the 9600 baud rate for serial communication, to display data in serial monitor of Arduino IDE, and store data in a file.

III. Results and Discussion

In preprocessing, the ECG involved removing different artifacts and choosing suitable beats. High-frequency interference, power-line noise, baseline drift, and dc shift were eliminated. The bandwidth of typical ECG equipment is between 0.05 and 150 Hz. Nevertheless, the data was band limited to the frequency range of 1 to 50 Hz due to the noise, which was extremely high for a palm ECG. Prescreening was done using template matching. The degree of similarity between two signals between each template and the predefined database was displayed by correlation coefficients. Every manufacturer's ECG machine uses a standard bandwidth and amplitude calibration, thus the look and amplitude of the ECG for a given person should be the same regardless of the time or kind of ECG machine used. Table 2 shows the classification of selected seventeen features extracted from ECG waveforms. The amplitude normalization utilizing the average amplitude of the collected R peaks as a normalizing factor. By normalizing the intrasubject amplitude difference, this value lessens the possibility of amplitude variations within a single acquisition. There are seventeen ECG features were extracted and standardized using in order to compare them across features with various units using:

$$Normalized\ feature = \frac{feature - min}{\max - min}........(4)$$

The values of the highest and lowest among the seventeen features are represented by max and min. Since the QRS complex is the most widely recognized, detectable, vital to life, and stable at varying heart rates, the most of the features were derived from it. Normalization must be performed to ensure that the QT measurements are reliable because the QT time duration is dependent on heart rate. Furthermore, the amplitude from point R to the point following a 0.024-second delay is defined as the RS2 amplitude. To improve the recognition rate, a thorough test was done to remove the undesirable features or reduce their weights. During enrollment, three sets of ECG databases were created. Since a typical, healthy population was recruited for this study, all ECG signals came comparable backgrounds such as age, height, gender and weight. The fifty people (33 women and 17 men) were selected at random from the database to make up the system development dataset. Then, from each of the 50 participants in this study, the computer program randomly selected 20 consecutive normal heartbeats, creating a 1000-beat group that served as first ECG database. As our second and third databases, 50 mean average heartbeats and 50 median average heartbeats were then created by applying signal averaging to each 20-heartbeat group. Three different kinds of database sets were matched using five different kinds of template sets by the template matching technique. Table 3 shows the results of template matching method with different templates and/or database sets. The 15 matching results in Table 3 demonstrate that using a single pulse as a template is not a smart idea because the performance is erratic and heavily dependent on the selected heartbeat.

Table 2. Classification of selected seventeen features extracted from ECG waveforms

Selected Features					
Sl. No	Features	Sl. No	Features	Sl. No	Features
1	RP amplitude	8	QT duration	15	RS slope
2	QS amplitude	9	RT amplitude	16	TS amplitude
3	RQ amplitude	10	ST amplitude	17	PQ amplitude
4	QRS triangular area	11	Angle Q		
5	QS duration	12	Angle R		
6	ST Slope	13	Angle S		
7	RS amplitude	14	RS2 amplitude		

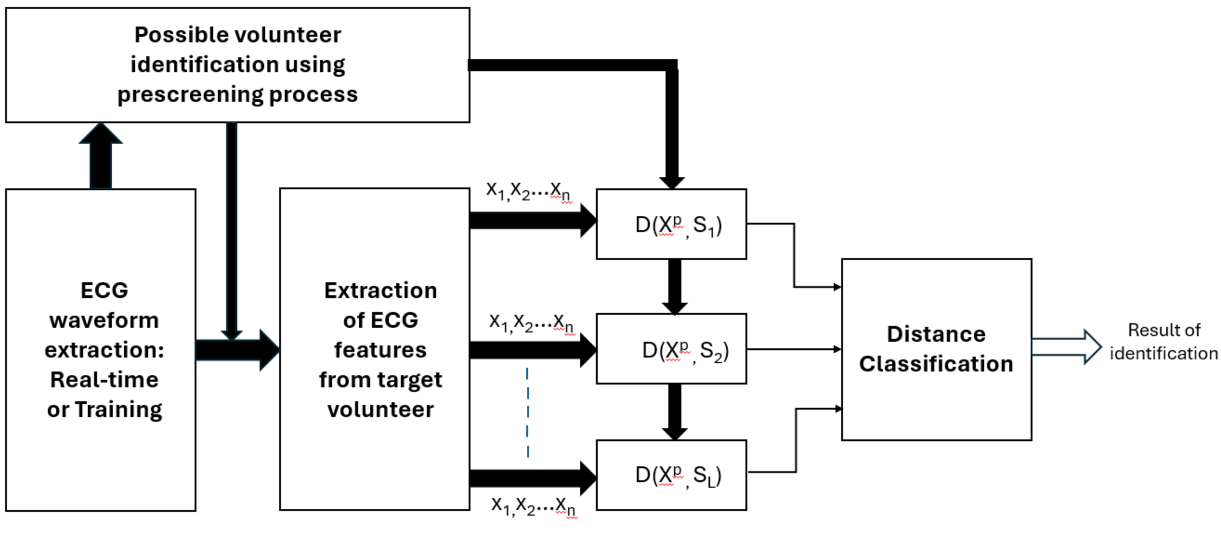


Figure 6. Combined template matching and distance classification model for ECG based human identification system

When the averaged heartbeats were applied to both templates and databases, the signal averaging produces significantly better template matching performance. Although they took longer to calculate, the templates with more averaged heartbeats performed better on the palm ECG biometric system. Equation (3) describes how the distance classification determines the separation between a template feature vector and database feature vectors. For seventeen features, four weight levels were applied. There are 0, 0.2, 1 and 2. By rating these traits, exhaustive tests were used to identify the proper weight vector w = [w1¬¬, w2….wR]. Utilizing distance categorization does not require any kind of training and the overall performance was found to be 97%, following the determination of the weight vector. Figure 6 shows combined model of template matching and distance classification for ECG based human identification system. The template matching and distance classification are combined and investigated on large population identification. This combined model requires less time, because no training processsss is required. Highest identification rate such as 98% was achieved in the pre-established group of 10, 20, and 50 individuals. Additionally, the predefined sample of 110 and 140 participants underwent additional testing of the combined system model, with identification rates of 95% and 94%, respectively.

Baseline wander, a low frequency artifact in the ECG signal, is typically caused by the patient moving, breathing, making poor electrode-to-skin contact, and other factors. In comparison with chest extraction of ECG signal, palms and fingers ECG signal having low baseline wander and higher signal-to-noise ratio (SNR). Moreover, the system performance was improved by increasing the SNR using signal averaging method which enable to detect low-amplitude and high-frequency signals. Further, the real-time identification process can be done because the combined model which does not require the pre-training process. The entire signal extraction done through the palm and finger using dry electrodes which makes the easy signal extraction and free from electromyogram interference.

Table 3: Results of template matching method with different templates and/or database sets

Database	Single Heartbeat** (%)	Five Heartbeat		Three Heartbeat	
		Mean (%)	Median (%)	Mean (%)	Median (%)
Twenty heartbeat	41-46/50(85-91)	44/50(90)	45/50(90)	44/50(86)	45/50(89)
Mean Heartbeat	47/50(91)	48/50(97)	48/50(98)	49/50(96)	49/50(96)
Median Heartbeat	43-46/50(86-90)	48/50(97)	48/50(98)	49/50(96)	49/50(96)

**The outcomes change depending on the selected heartbeat, when using a single heartbeat as an input template. Consequently, the outcomes are erratic and heavily reliant on the selected heartbeat.

IV. CONCLUSION

This works describes and findings shows, it is an alternative approach for identification based on ECG collected on palms and fingers, in comparison with conventional ECG recoding in 12-lead limb and thoracic signals. Because of its better features, such as its ability to change software quickly, its environment units, its ease of programmability, and its affordability, the microcontrollers have made experimental processes easier. This approach offers the necessary building block which can make a nonintrusive ECG biometric system. The signal extraction done through the slight contact with the subject palms and fingers without the conductive paste or pre-gelled electrodes. This make the signal acquisition setup simpler and effective to reduce electromyogram interference and baseline wander. The combine system model increases the accuracy to 98% on the development dataset and 96% of accuracy rate was achieved in identification process when applied to the entire dataset.

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