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THE DEVELOPMENT OF HUMAN BIOMETRIC IDENTIFICATION USING ACCELERATION PLETHYSMOGRAM

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ABSTRACT

This study explicates the practicability of using acceleration plethysmogram (APG) signal in biometric identification. The introduction of APG signal is initiated from the congenital of photoplethysmogram (PPG) signal since APG signal has been widely known as the second derivative of PPG signal. Previous researchers claimed that APG signal elucidates more information as compared to PPG signal. For this reason, the robustness and reliability of APG signal as biometric recognition is demonstrated. A total of 10 subjects obtained from MIMIC II WAFEFORM Database (MIMIC2WDB) which provides PPG signals with a 125 Hz sampling frequency are used as test samples. The signals are then differentiated twice to obtain the APG signals. Then, discriminative features are extracted from the APG morphology. Finally, these APG samples were classified using commonly known classification techniques to identify individuals. Based on the experimentation results, APG signal when using Multilayer Perceptron gives an identification rate of 98% as compared to PPG signal of 76% for the same waveform. This outcome suggests the feasibility and robustness of APG signals as a biometric modality as an alternative to current techniques.

Keywords: APG, biometric, multilayer perceptron, MIMIC2WDB, PPG.

INTRODUCTION

Personal credentials are important and a valuable asset of an individual. Once compromised, the identity of a person maybe illegally misused which causes confidential and valuable possessions to be in jeopardy. In the year 2014, UNISYS Security performed a survey which suggest that security fear is a disturbing issue worldwide. The investigation pointed out that 85% of Malaysians are extremely concerned about their personal safety. In addition, 51% of Australian and British people are apprehensive when it comes to personal credentials [1]. Furthermore, nearly 15 million residents in the United States have become the victims of identity theft where 7% of all the adults have their identity been misused with approximately $3500 losses for each individual [2]. One of the main approach to counter identity misuse is to apply biometric system.

Common body characteristics or biometric modalities that can be adapted in the biometric recognition system are fingerprint, iris, gait, keystroke, ear, face and palm. Recently, biomedical signals such as photoplethysmogram (PPG) signals have gain the attention in the biometric domain [3]. This type of signal has its own criteria and attributes that represents a person's identity by the systolic and diastolic regions as shown in Figure-1.

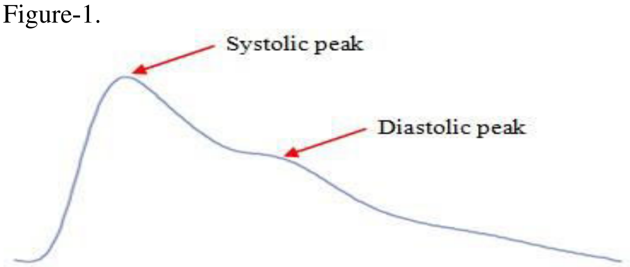

Figure-1. A typical PPG waveform [4].

However, the morphological shape of PPG are difficult to analyse as the phases change and sometimes are not prevalent which could lead to classification errors. Hence, other alternative mechanisms to aid the interpretation of PPG waveform is required. Elgendi in [4] proposed the second derivative of PPG signal that could possibly assist the analysis of the actual PPG signal which is called acceleration plethysmogram (APG) signal as depicted in Figure-2.

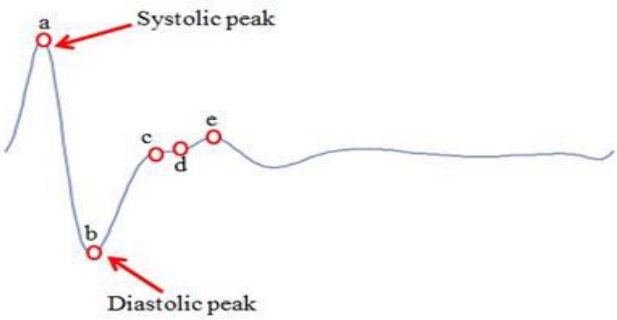

Figure-2. A typical APG waveform [4]

APG signal derived from the second derivative of the PPG signal represents the acceleration of blood in the finger. The waveform consists of four systolic waves and one diastolic wave which are the a-wave (early systolic wave), b-wave (early systolic negative wave), c-wave (late systolic reincreasing wave), d-wave (late systolic redecresing wave) and e-wave (early diastolic positive wave). Each wave location reflects the closure of aortic valve and blood flow which can be used to determine and monitor cardiac function. As can observed from the waveform of the APG signal, it can be seen that the morphological wave shapes are distinguishable as

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compared to a PPG signal. It would be difficult to discriminate the peaks in a PPG signal specifically the diastolic peak as it would resemble the diastolic slope as shown in Figure-1. However, the systolic and diastolic peaks are prevalent and obvious in an APG signal as shown in Figure-3. The clear waveform obtained from the second derivation of PPG signal enables the visualization of individual features to be detected and analyzed easily.

However, previous researches on APG signal were commonly used to analyze the heart rate variability and detect the condition and stiffness of peripheral artery located in the heart using different techniques. Due to the waveform which contains visible phase changes, little has been said about the probability of APG to be used for person identification. Thus, this study will be focusing on the implementation of APG signal for biometric identification purposes.

LITERATURE REVIEW

PPG signal is commonly used in measuring the concentration of oxygen in blood. Many researches related to PPG signal usually describe the methods used to facilitate the reading and measurement of PPG waveform. One of the methods used to ease the analyzation of PPG signal is by using APG signal which is also known as the second derivative of PPG. In this study, we will focus on identifying individuals via APG signal. Based on our knowledge, the APG biometric is an under-researched area of study where little has been said about APG based recognition system. Thus, in this section, related literatures pertaining to other aspects of non-biometric characteristics of the APG signal are briefly discussed.

Singh and Nagpal in [5] explained the shape of APG signal consisting of seven different types which are A, B, C, D, E, F and G. Each type represents different condition of a person's heart. Type A indicates a good circulation of blood in healthy subject. Type B and C indicate the impairing and poor circulation respectively, whereas, type D to G is often obtained in patients with cerebrovascular, ischemic and uterine heart diseases. The changes from D to G also reflect the disease development.

Nousou et. al. in [6] developed a diagnosis assistance system that used a signal of APG acquired from the fingertip of a person which can be measured and diagnosed in a short period of time. The signal generated upon the change of blood capacity in capillary is called as APG signal. The researchers applied the technique of self-organizing map (SOM) to classify the 1500 collected data of APG signals. As a result, comparison of the wave shapes became possible and classification by SOM gave out a similar diagnosis as what had been obtained by the physician.

Baek et. al in [7] implemented second derivative of PPG to monitor arterial condition in their study. They collected samples of finger PPG signals that have no history of coronary artery disease (CAD) from 30 volunteers which were divided into groups according to their ages. They used second derivative method to perform their analysis on evaluating the vascular aging. The calculation of second derivative PPG aging index (SDPTG-AI) was used to measure the aging index where SDPTG-AI = (b - c - d - e)/a. The result showed that the ratio of b/a increased with age, whereas, c/a, d/a and e/a ratio decreased with age.

Nishimura *et al*. in [r] presented the study assessing the peripheral circulatory function of women by measuring APG and then investigated it relationship to target maximum oxygen intake levels. Peripheral circulatory function was measured at the tip of the right index finger using a precaregraph or a blood circulation checker. The results showed a significant positive correlation between APG index and the other parameters such as height, percentage body fat and maximal oxygen consumption with the significant negative correlation of the parameters of age, weight, body mass index, systolic blood pressure and diastolic blood pressure.

Fujimoto and Yamaguchi in [8] investigated the possibility to diagnose a stress quantitatively using APG which applied the criterion based on chaos theory. They calculated the time-series data of APG measured from forty-tester using the proposed evaluations. The method of chaos analysis is used to determine the mental condition of the persons involved in the experimentation. As the result, the researches confirmed by experiment that the proposed method has high potential for evaluating mental stress.

However, based on these previous studies, person identification based on APG signal has never been reported. Thus, this will be the focus of our study and we will propose of applying APG signals for biometric means.

METHODOLOGY

In this study, five steps are required to develop an APG signal based biometric system. These steps consist of data acquisition, signal differentiation, pre-processing, feature extraction and classification as summarized in Figure-3.

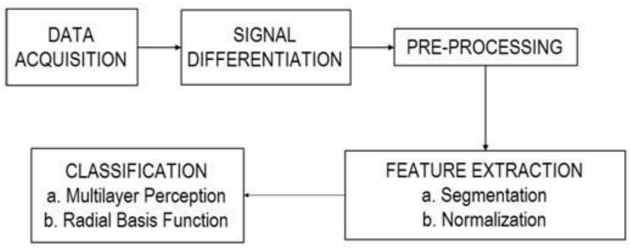

Figure-3. The proposed APG based biometric identification system.

Data acquisition

In this work, PPG signals were acquired from 10 different subjects with duration of ten seconds each. These datasets were obtained from an online and publicly available biosignal repository called the Multiparameter Intelligent Monitoring in Intensive Care II Waveform Database (MIMIC2WDB) [9, 10]. The database consist of multiple physiologic signals collected from bedside patient monitors in adult and neonatal intensive care units (ICUs).

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The PPG signals which were sampled at 125 Hz with 8-bit resolution.

Signal differentiation

The second order differentiation is computed to produce the APG signal prior to data collection stage. In the earlier stage, the PPG data, which is denoted as x is differentiated to produce the differentiated output represented as y in Equation. (1).

$$y(m) = x(n-1) - x(n) \tag{1}$$

where m = 1, 2, 3, . . . , (N − 1) and $y(m)$ is the differentiated PPG signals.

$$\frac{\partial^2 y}{dx^2} = \frac{\partial}{\partial x}\left(\frac{\partial y}{dx}\right) \tag{2}$$

These differentiated values are again differentiated to obtain the second order derivative as in Equation. (2). As a result of the process, the APG signal will be produced.

Pre-processing

Even though APG signal has been produced, commonly, the signal is not clean from additional noise in the waveform which causes misinterpretation of the outcome. This is due to various surrounding factors such as the body movement, equipment discrepancies and etc. Thus, a Butterworth low pass filter is used to reduce the noise factor.

Feature extraction

Then, salient features are extracted to become the input for the classification algorithm. This step is categorized into two important phases which are segmentation and normalization.

i. Segmentation

APG signals are segmented based on the amplitude criteria of the waveform. This step starts by identifying the **a-**wave and marking it the reference pivot since it represents to the highest and most prevalent peak in an APG signal. From the peak of the **a**-wave, equidistant numbers of points are chosen to the right and left of the reference. We iterate the steps in different time period to acquire more APG signals to represent enrolment and recognition samples.

ii. Normalization

Next, normalization is implemented to mitigate inherited noise due to baseline wanders from the PPG signal by levelling it to a common scale. As a result, it would be much easier to analyse resemblances of PPG waveforms. This method is denoted in Equation. (3).

$$Normalization, N = \frac{x - \mu_x}{n_x} \tag{3}$$

where x is the PPG data, μ_x is the mean value of x and n_x is the data points in x. The normalized PPG dataset then becomes the input for the induction algorithm.

Classification

Classification is a part of pattern recognition that includes the construction of a classification algorithm. In this study, two commonly applied classifiers were used to identify the class attributes and instances, each typically described by a set of features (attributes) for the APG signals. The classifiers are Multilayer Perceptron and Radial Basis Function Network. These classification algorithms are briefly described in the following sub-sections.

i. Multilayer perceptron (MLP)

MLP is a feed-forward structure with a several layers. It has an error based training mechanism. MLP is derived by an input layer that consists of the extracted features, one or more hidden layers, and an output layer. Each of these layers consists of at least one neuron. The number of hidden neurons was determined by comparing the performance of different cross-validated networks, with some numbers of hidden neurons, and choosing the number that produced the greatest network performance. This resulted in a network with single input neuron, five hidden neurons and a single output neuron. Figure-4. illustrates the structure of MLP.

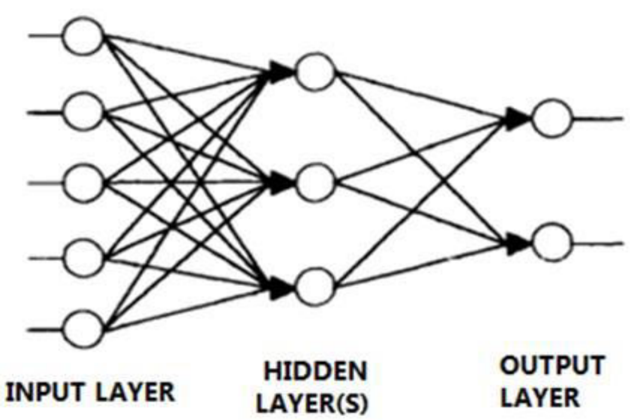

Figure-4. A multilayer perceptron network.

i. Radial basis function

Radial Basis Function (RBF) network comprises of three layer feed-forward network with single hidden layer of basic functions, or neurons. Figure-5. illustrates an RBF network. At the input of each neuron, the distance between the neuron centre and the input vector is calculated. The outputs of the neuron whose are inversely proportional to the distance from the centre of the neuron is then formed by applying the basis function to this distance. The further a neuron is from the point being evaluated, the less the influence [12].

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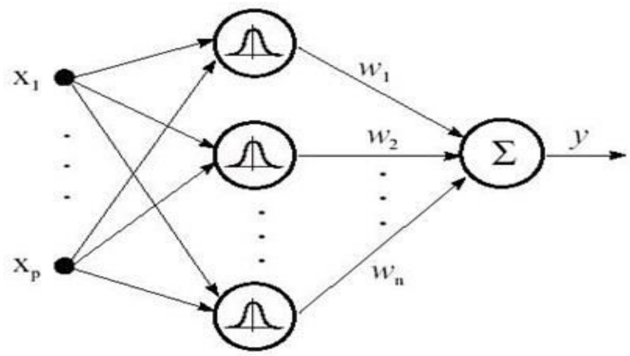


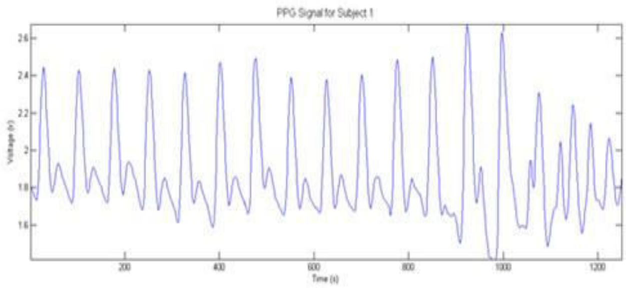
Figure-5. A radial basis function network [13].

EXPERIMENTATION AND RESULTS

In this study, ten samples of raw PPG signals were taken from MIMIC2WDB. However, we only discuss four random samples which are subjects 1, 3, 4 and 7 for example purposes. The experimentation was performed using MATLAB R2008a. These four random samples of the filtered PPG signals are shown in Figure-6.

Based on the observation, the PPG morphologies are different for each individual. After obtaining these PPG waveforms, the signals were then undergoes segmentation procedure whereby these signals were overlapped with each other that were obtained in different time instances. The result of the segmentation for Subject 1, 3, 4 and 7 are shown in Figure-7.

Later, the signals were transformed into APG waveforms by the second derivative. However, these signals have not yet been filtered and there were some unwanted signals (noises) present. In order to remove these noises, a low pass Butterworth filter with the second order and normalized cut off frequency of 0.01Hz was used and the resultant signals are illustrated in Figure-8.



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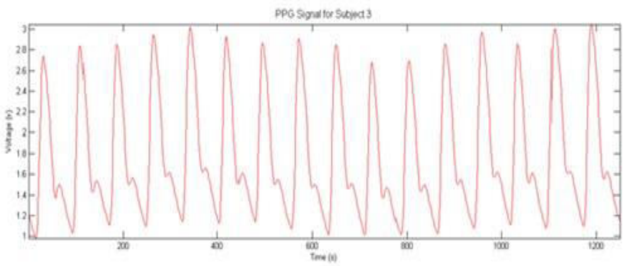

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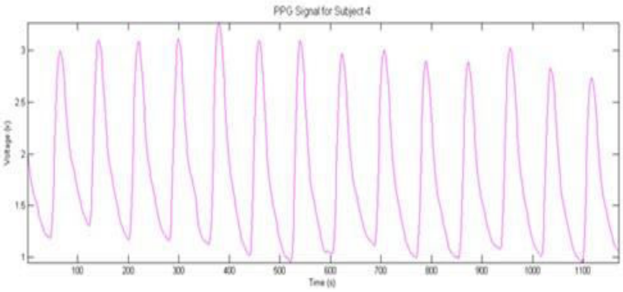

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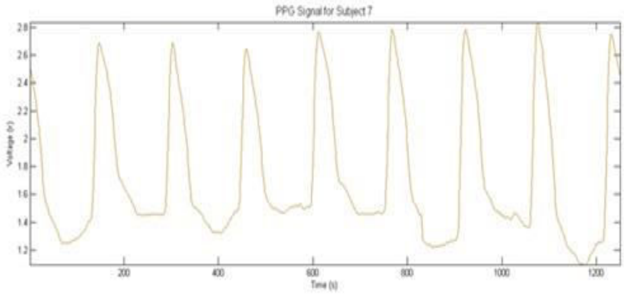
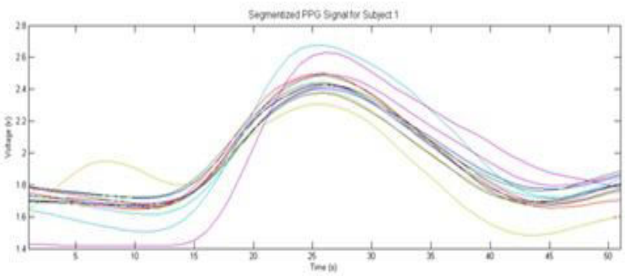


(d)

Figure-6. (a) PPG signal for Subject 1. (b) PPG signal for Subject 3. (c) PPG signal for Subject 4. (d) PPG signal for Subject 7.



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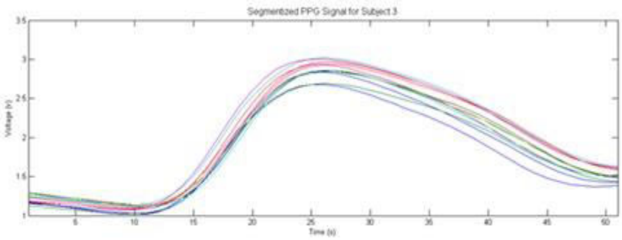

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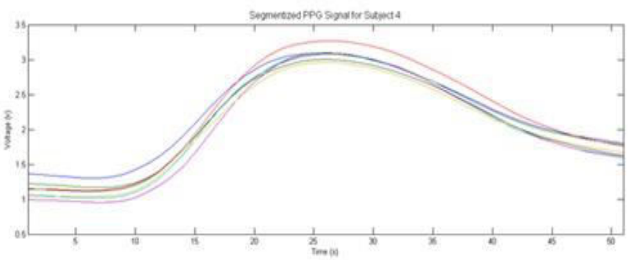

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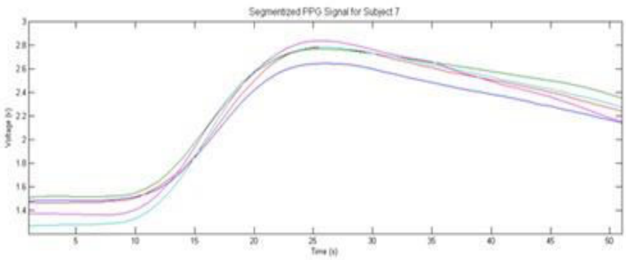
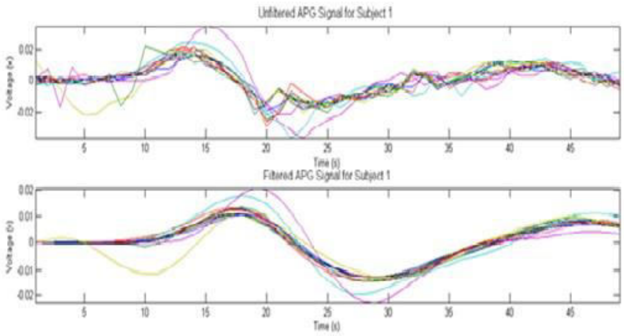


(d)

Figure-7. (a) Segmentized PPG signal for Subject 1. (b) Segmentized PPG signal for Subject 3.(c) Segmentized PPG signal for Subject 4. (d) Segmentized PPG signal for Subject 7.



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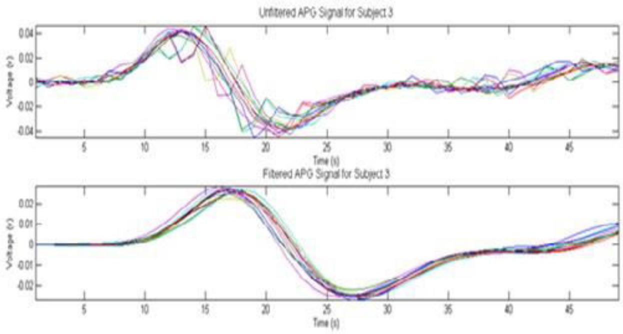

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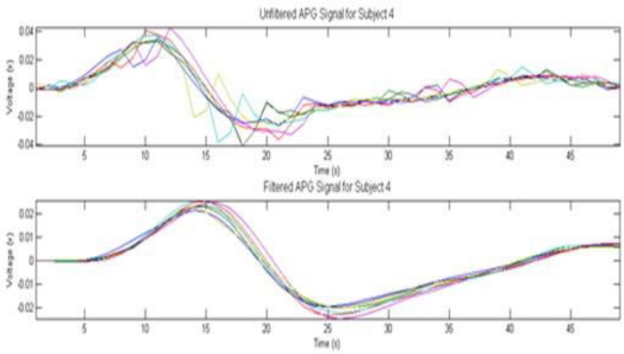

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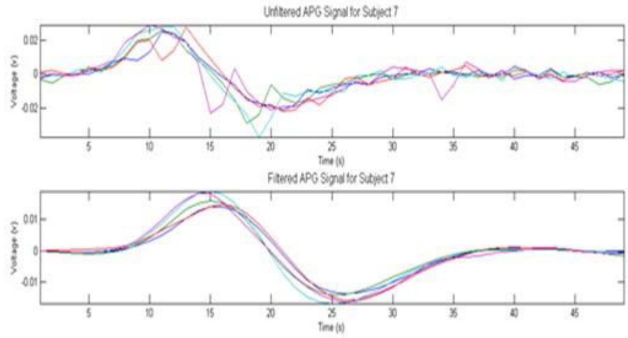

(d)

Figure-8. (a) Unfiltered and filtered APG signal for Subject 1. (b) Unfiltered and filtered APG signal for Subject 3. (c) Unfiltered and filtered APG signal for Subject 4. (d) Unfiltered and filtered APG signal for Subject 7.

Lastly, using the filtered APG signals the classification procedure was implemented on 50 instances in total whereby each subject have five instances. Later, a ten-fold cross validation method which assesses the generalization accuracy of the classification algorithms was implemented on the attributes to classify the subjects.

For the result analysis, classification accuracy was used as the performance metrics as it evaluates on how efficient a classifier correctly recognizes subjects. To show the feasibility of APG signals in comparison to PPG signals, the classification accuracy for both biosignals were computed by applying MLP and RBF Network. These signals were obtained from similar subject in the same time instance. For instance, the PPG signals were collected for ten second duration. Therefore, the APG signal was converted using the same ten second period from the same PPG signal.

Based on the experimentation, the classification accuracies of APG signal when implementing MLP and RBF Network outperformed the outcomes of PPG signal achieving identification rates of 98% and 96% as compared to 76% and 84% respectively. These classification accuracies are summarized as in Table-1. The result shows an intense rise of the classification accuracy when converted from PPG to APG waveform. These outcome supports the ability of APG signal to display clear systolic and diastolic peaks in its morphological waveform and obtained improved classification effects.

Table-1. Classification accuracies when comparing APG and PPG signals applying two classification algorithms.

CLASSIFIER	CLASSIFICATION ACCURACY	
	APG SIGNAL	PPG SIGNAL
MLP	98 %	76 %
RBF	96 %	84 %

Both classifiers obtained high classification accuracy for APG signal with only slight difference of 2%. This indicates that the use of neural network for classification of APG results in high classification accuracies. In addition, the implementation of APG signal produces better outcome as compared to PPG signal which justifies the visibility of the APG morphologies wave shape to differentiate individuals. In another aspect, APG signal resembles the electrocardiogram (ECG) signal which is a well-known biological signal known for person identification and heart abnormalities detection. Being closely alike to ECG signal enable a promising results.

CONCLUSIONS

As a summary, the feasibility study of human biometric identification using APG signal has been presented. Biometric recognition using APG signal has never been reported in previous literatures. Based on the experimentation results, the high identification rate when using APG signals as compared to PPG signals proves the capability of APG signal to classify individuals better in comparison to PPG signals. The result is substantial as it suggests the viability and robustness of APG signals as a biometric modality. The proof-of-concept of applying APG signal for biometric identification purposes has met the objective. In addition, APG based biometric identification is capable to become an alternative method for currently present biometric schemes.

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