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ECG biometric in real-life settings: analysing different physiological conditions with wearable smart textiles shirts

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ABSTRACT

The adoption of biomedical signals such as the electrocardiogram (ECG) for biometric is rising in tandem with the increased attention to wearable devices. However, despite its potential benefits, ECG is rarely implemented as a biometric mechanism in real-life wearable applications. Therefore, this research aims to analyse the ECG signals extracted from wearable Hexoskin Proshirt for biometric authentication in different physiological conditions. A total of 11 subjects participated in this study, where the ECG signals were recorded while standing, sitting, walking, and uncontrolled activity. The raw ECG signal is first pre-processed using noise-removal butterworth filters in the time domain, followed by an efficient QRS segmented feature extraction approach. Finally, around 854 datasets were generated for training and validation, while the remaining 300 were used to test the proposed recognition method with a quadratic support vector machine (QSVM). The results show that the proposed method achieved a reliable accuracy above 98% with false acceptance rate (FAR) of 0.93%, false rejection rate (FRR) of 3.64%, and true positive rate (TPR) above 96% on the in-house datasets. This researchs findings confirm the possibility of using ECG biometrics for authentication purposes in various real-life settings with varying physiological parameters using a smart textile shirt.

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1. INTRODUCTION

In recent years, there has been a rise in the use of wearable electronics such as smart wristbands, smart socks, smart watches, and smart shirts. Progress in wearable devices has made it possible to use biomedical signals for different applications. This is made possible with the presence of a unique biomarker indicator in each individual, which is the electrocardiogram (ECG) signals [1]. Meanwhile, wearable devices that do not require any intrusive procedures to record human ECG over an extended period and do not interfere with the user's routine have attracted attention and sparked a demand in the consumer market for a shirt-like wearable ECG device with embedded measuring electrodes and lead cables [2], [3]. Besides that, the wearability of a smart textile shirt for a more extended time to obtain physiological parameters without experiencing any significant discomfort or limitations on mobility has outweighed all of the shortcomings of portable and wearable devices [3], and it has become an essential element for biometric recognition.

Furthermore, conventional recognition methods, including ID cards, passwords, and token-based verification, may make individuals uncomfortable since they must remember their passcodes [4]. They are also susceptible to spoofing caused by theft, squinting, and loss. On the other hand, biometric provide airtight security by recognising an individual based on physiological or behavioural characteristics. Apart from that, ECG as one of the biometrics modalities is becoming increasingly applicable to various products due to the advancement of real-time measuring equipment and the evolution of research into protecting authentication information in gadgets [5], [6]. Furthermore, ECG signals are unique, i.e. they differ between individuals and can only be captured through direct physical contact that is impenetrable from the outside and also carries a liveness indication at the point of detection [7]. Therefore, ECG-based biometric has a vast potential to replace other conventional biometrics completely, such as vein [8], [9] gait [10], face [11], [12], fingerprint [13], [14], and iris [15], [16].

Having said that, many existing methods for wearable ECG devices and algorithms are still at the infant stage and far from practical applications because of several drawbacks. For example, many current ECG signal classification methods were designed based on public ECG datasets. Furthermore, these ECG datasets are mainly recorded in clinical settings and under controlled setup [17]. Thus is unsuitable for wearable devices [18]. In addition, wearable devices for ECG biometric recognition have only been the subject of a small number of research [17], [19]–[21]. Despite this, wearable smart textiles shirts from VitalJacket were employed in pioneering biometric research [22], and followed seven years later [21], which utilised smart textiles from OMsignal for biometric recognition in their study. Research by Ye *et al.* [20], further showed that getting an ECG signal from a smart cloth may be a trustworthy biometric, and the work verified the theory of fiducial point data from ECG signals. Using a support vector machine (SVM) with a radius basis function, the study used data collected from five firefighters over six months to achieve an almost perfect recognition rate. In contrast to the work in [20], studies done by [21] show that noise, artefacts, and other disturbances make it difficult for the fiducial point detection approach to work. This study used ECG recorded from 33 female volunteers for six times over a week using a wearable smart textile from OMsignal and fed into a convolutional neural network (CNN) to obtain a biometric recognition rate of 95%.

It should be noted that most of the cited research does not consider contextual factors or foresee how various physiological conditions, such as standing, sitting, walking, and other conditions, might affect biometric performance for wearable ECG devices. In real life, authentication based on the ECG would typically be carried out across different physiological states. Therefore, to address the gap, this study aims to use wearable smart textile shirts to validate the performance of ECG authentication in various settings. In contrast to [20], [21], this work constructed an ECG dataset from 11 subjects across different physiological conditions with wearable Hexoskin Proshirts for biometric authentication in a real-life setting.

Section 2 of this article describes the approach used to acquire ECG in a real-life scenario while wearing wearable smart textile shirts, followed by the steps used to analyse and extract the raw ECG. This study's performance evaluation and findings for biometric authentication are then covered in section 3. Finally, section 4 concludes this study with several recommendations and outlines for potential future directions.

2. PROPOSED BIOMETRIC FRAMEWORK

The block diagram in Figure 1 illustrates the methodology framework that was adopted and re-constructed from studies in [22]–[30]. The authentication of identity framework comprises four stages: data acquisition, baseline correction, denoising in pre-processing, and fiducials detection in feature extraction, and parameter assessment in the classification block stage. The biometric operating system has two modes: recognition and enrolment [31]. In the recognition mode, the data will proceed directly to the classification stage after feature extraction has been completed. Following the feature extraction stage, the input data from enrolment mode will be saved as a template in the system's database for later usage in recognition mode. Subsequently, the matcher will compare the ECG data to the template data in the database to predict the verification decision. In the next part, we'll dive deeper into the proposed framework.

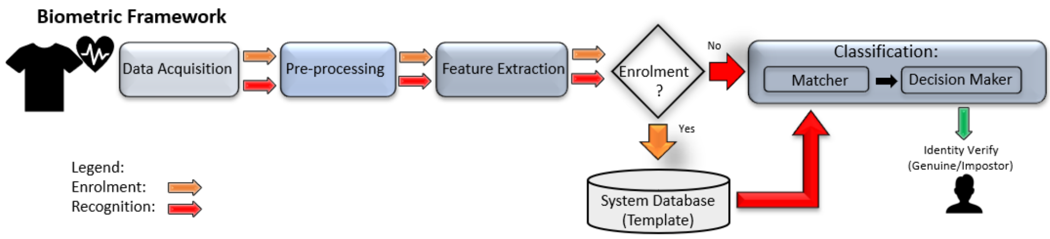

Figure 1. Biometric operation framework

2.1. Data acquisition

A total of 11 seemingly healthy male volunteers participated and selected in this study under the identification number International Islamic University Malaysia Research Ethics Committee (IREC) 2021-058 from the IREC in 2021. The selection of the participant was made as the smart wearable t-shirt consist of specific size and best wear by those within the size to ensure the location of textile sensor are always in contact with the body surface during the acquisition. Besides that, as this work consist of several active movement within one physiological condition to other continuously, all subjects were informed and advised of any possible risks and granted their consent. Furthermore, they were also required to wear the smart textile shirt for at least 15 minutes, which included 3 minutes of standing (condition 1), 3 minutes of sitting (condition 2), 3 minutes of typical walking (condition 3), and at least 6 minutes of simple, uncontrolled activities (condition 4) to simulate subjects casual real-life daily routine activities. Figures 2(a)-(c) shows the Hexoskin Proshirt smart textile shirts worn in a sequence of standing, sitting and walking positions by subjects through this study.

(a) (b) (c)

Figure 2. Subjects wearing smart textile shirts during (a) standing, (b) sitting, and (c) walking positions

2.2. Pre-processing

The presence of noise brought on by the wearer's movement while the data was being captured prevented the raw ECG signal from having a smooth waveform. This is because the body's movement generates motion artefacts, usually in high-frequency noises [27]. For the feature extraction step in the next part, a few data pre-processing techniques were used to process the raw ECG signal to meet the minimal acceptable features criteria.

The main goal of this study is to determine if smart textile shirts can conduct biometric authentication in various physiological conditions in a real-life environment for the participants. The raw ECG signal is subjected to some data pre-processing by adding a lowpass butterworth filter with a cut-off frequency of 30 Hz used to remove the undesirable noise that aid in lowering any high-frequency noise and interference noise from power lines. The filter also eliminated baseline wandering throughout the detrending procedure and returned the ECG signal to the isoelectric line using a direct fast fourier transform (FFT). Then, inverse FFT returns the ECG signal to its original state in the time domain, allowing for more precise signal analysis in the feature extraction stage.

2.3. Feature extraction

After the first two stages i.e., the acquisition and pre-processing stages are completed, feature extraction takes place. Steps like these are taken to improve the resulting signal's representation and aid decision-making by reducing residual noise and within-subject variability. The PQRST morphology of the ECG has been utilised extensively because it allows for the identification of wave differences in each individual's response from the overall ECG signal by excluding specific periods during the transition. The most widely used feature extractor in ECG for biometric is the signal of the QRS complex itself [19], [32], [33]. Similarly, this study relies on the QRS complex characteristic that aids in the classification stage.

To segment the QRS complex, the study used the notion of local maxima by using a windowed filter to locate the R-peaks. This filter ignores all other values and only displays the maximum value in its window. The work also took advantage of a default-sized window. Then, a threshold is used to remove the values of small peaks while maintaining the values of significant peaks. Later, to increase the filtration quality, the study further changed the window size and repeated the filtering procedure several times to ensure all of the R-peaks were present and correctly identified. After successfully marking the R-peaks of the ECG signal, 20 points around the marking peaks across the horizontal axis were segmented and stored in the database for classification stages.

2.4. Classification

Finally, the classification process in this study was established with an 80/20 split between training and testing datasets for each physiological condition of 11 participants. Furthermore, the ECG data was trained and tested with six concepts of a predefined scenario of different physiological conditions in scenarios A1, A2, A3, B1, B2, and C, as summarised in Figure 3. In scenario A, the study implemented the concepts of unseen data but in the same physiological condition set as testing data to the classifier that was previously trained with the same physiological state of the 11 participants. Scenario A1 is physiological condition 1; a trained classifier with standing physiological conditions was tested with each subject's exact condition of standing data. Followed by scenario A2 with physiological condition 2, a trained classifier with a sitting physiological position was tested with the precise condition of sitting ECG data across all participants. Lastly, in scenario A3, the walking physiology of condition 3. A trained classifier with walking condition ECG of the subject was then tested with the same physiological condition within the split ratio of training and testing of each participant's ECG data.

Meanwhile, in scenario B, the classifier was tested with unseen training data and an unknown physiological condition of condition 4. In this physiological condition, the subject was conducting simple unstructured daily routine activities of themselves, starting with scenario B1, where the classifier was trained with standing physiological condition ECG data and tested with physiological condition 4 for biometric verification. Secondly, in scenario B2, ECG data in physiological condition 4 of all subjects were tested in a previously trained classifier with a combination of all participants standing, sitting, and walking physiological condition ECG data.

Furthermore, in scenario C, the classifier was tested with unseen data during training but knew the physiological condition to the classifier. In this setting, the classifier was previously trained with the combination of standing, sitting, and walking ECG data across all subjects, then tested with each subject's ECG data in standing physiological conditions for biometric authentication. The training and testing strategies of all these six scenarios are illustrated in Figure 3.

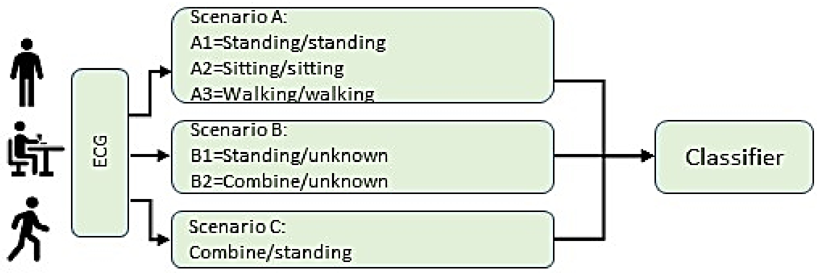

Figure 3. Training versus testing data feed to the classifier

In general, this study examines whether a system can discriminate between different persons based on recorded ECG data using standard biometrics evaluations. Intuitively, the study train classifiers to distinguish between one valid user and everyone else and then tests this system using data from that legitimate user data in scenarios A, B or C and the rest of the other subject data in the same scenario as the attacker or imposter to the model. Figure 4 illustrates this evaluation strategy implemented in the authentication process, and the basic concepts were in parallel with the study in [19]. The study formally designates participant u as the genuine user and participant *i* as the imposter for each pair of two subjects (*u, i*). The genuine user u, who is assigned the label 1, and all other users r, who is given the label -1, are separated into two groups using a classifier that the study train. The "rest of the subject," such as all other participants inside an enrolment database, is represented by all other participants, which r ∈ U\{u, i}. It should be noted that the study-designated participant *u* is trained based on the study condition and scenario set against the rest of the subjects in the same condition and scenario. Subsequently, next, the study put the classifier to the test by giving it two sets of data: set 1 (the test portion of *u*'s data), which it should ideally accept, and set 2 (the imposter portion of *i*'s data), which it should ideally reject (output -1). Furthermore, set 1 and set 2 data originate within the split ratio of train and test conditions of respected subjects.

Classifiers based on the quadratic support vector machine (QSVM) model are used to assess how well a classification scheme based on a set of predefined features performs. The selection recognition mode of QSVM as a machine learning approach was used as it supports binary classifications of the study model. Furthermore, six-fold cross-validation was also used to train and evaluate the classifiers; in this method, the entire dataset is divided into six parts; each portion acts as a test set. A training set is constructed from the remaining five parts. As will be seen and elaborated upon in the next section, this process is done six times, and the average results are then drawn. Meanwhile, the following section presents the evaluation results and discusses the implementation of different physiological conditions in wearable biometric authentication. Furthermore, in order to assess the performance of the classifier, several biometric authentication statistical performance metrics, including accuracy, hit rate or true positive rate (TPR), miss rate or false rejection rate (FRR), and false match or false acceptance rate (FAR), were generated with a confusion matrix and illustrated in next section.

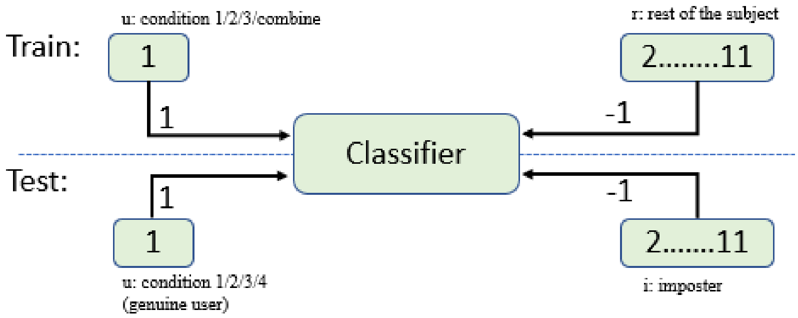

Figure 4. Classification study framework

3. RESULTS AND DISCUSSION

The performance evaluation of this study was supported with Intel(R) Core (TM) i5-10400F processors clocking in at 2.90 GHz and paired with 32 GB of RAM used for signal processing and data analysis. NVIDIA GeForce GTX 1050Ti 4GB graphics cards were also used to implement the recommended methods. The dataset was analysed using MATLAB R2021a software. It included data from 11 participants who wore smart textile shirts while doing various physical tasks, including standing, sitting, walking, and conducting simple, unstructured activities.

In order to reduce the unwanted noise, the raw ECG signal is subjected to some data pre-processing by adding a lowpass butterworth filter illustrated in Figure 5(a). Subsequently, Figure 5(b) shows how filtering help to reduce high-frequency noise as well as interference noise from power lines. Additionally, the filter eliminates baseline wander throughout the detrending process, which ensures the ECG signal returns to the isoelectric line as demonstrated in Figure 5(c) before the signal goes through the segmentation process.

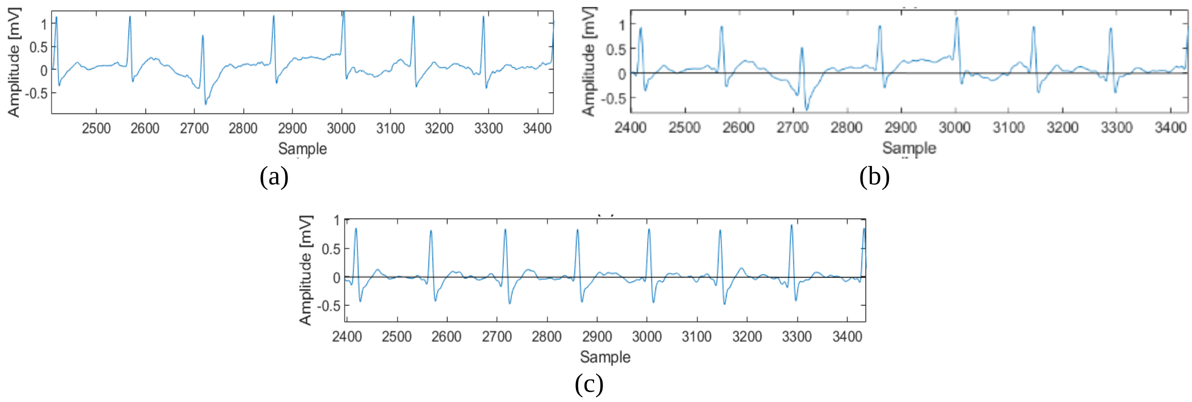

Figure 5. Pre-processing stages of ECG (a) after filtering, (b) ECG in baseline wandering, and (c) ECG in isoelectric line

Segmentation results were demonstrated in Figure 6(a), which shows the QRS of the ECG signal in standing physiological condition, followed by the signal in sitting condition Figure 6(b), and subsequently by the QRS in a waking state of the subject Figure 6(c) and finally the segmented ECG signal in simple, unstructured activities of physiological condition 4 in Figure 6(d). The MATLAB 2021a software's built-in classification learner app toolbox was utilised to carry out each test. The QSVM methods were used in the classification learner app, and the training and testing data for the model were created using 6-fold cross-validation with an 80/20 split between training and testing data. Values of 80/20 were utilised in this study as it was proven in Figure 7 of this study data to give the best combination for optimum accurancy results in testing. Whereas, Figure 7 also demonstrate that, if the ratio of training data only 10% of the entire data, the classifier performs moderately. However, when training to testing ration increase, the testing performance become better. Furthermore, it is noted that the training performance of any classifier mainly used to forecast the stability and possible performance outcome in testing and deployment stages. Hence, the results suggested that the split ratio of 50:50 and above are more promising in given 90% accuracy in training stages. However, the results faill to reach 90% in testing performance except for 80:20 split that give the optimum performance overall in reached 90% in both training and testing data. Admittedly, this result indicates the brighter hope for a better classifier performance.

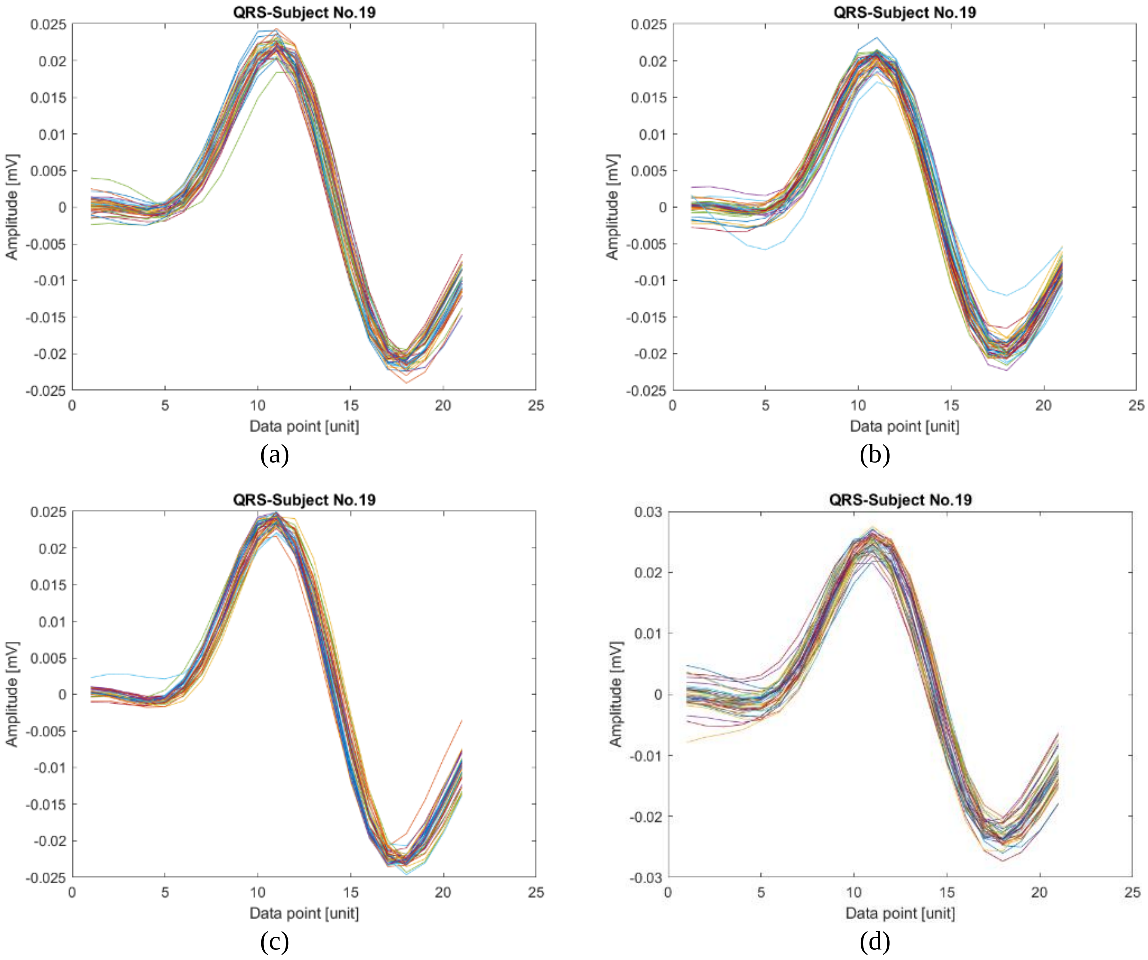

Figure 6. Segmented ECG in different physiological conditions (a) standing, (b) sitting, (c) walking, and (d) unstructured activities

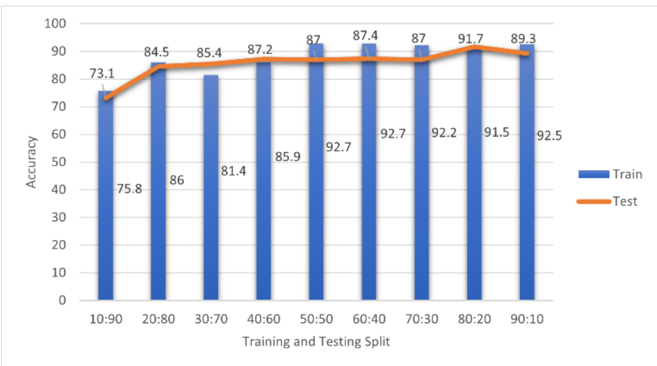

Figure 7. Training and testing split accuracy

It is noteable that, classification performance is a crucial component of evaluating any suggested models using several types of matrices, such example for biometric performance are shown in Table 1. Whereas, in scenario A, the classifier is never exposed to test data during training. The study found that even in different physiological conditions, the biometric authentication can still perform very well and almost comparable with more than 98% accuracy when training and testing in the same physiological conditions across all subjects. Walking was also found to produce the best biometric recognition performance among these physiological conditions of standing, sitting, and walking, with a remarkable average hit rate of 96.36%, the lowest miss rate of 3.64% in verified participants, and an acceptable value of 0.93% in false match rate across all subject authenticated.

The study also assessed the feasibility of generating biometric recognition judgments based on actions that include physiological conditions with which the classifier is unfamiliar, as in scenario B1. In this scenario, the classifier trained ECG data in one physiological condition and tested it in the instructed physiological condition, significantly reducing the biometric performance. However, what standout from the table is when the study applies the same approach for scenario B2 by letting the classifier experience the combination of three different physiological condition data in the training stage. The research found a notable improvement in its performance matrix, as seen in Table 1. For scenario C, where the decision using a combination of training data with the three different physiological condition and tested with one of the physiological conditions that the classifier had experienced before in biometric verification was observed in scenario C in Table 1 show interesting performance with accuracy above 98%, a lower FAR of 0.5 and acceptable value of TPR of 83.79% that almost comparable with A1 scenario of the study.

Furthermore, the data in Table 1 demonstrates the best situation of physiological conditions in performing biometric authentication for the smart textile shirt. Unexpectedly the observed results showed the most striking result to emerge from the data is from walking, followed by sitting and then standing in terms of its hit rate or true positive rate in verifying a person. Moreover, the factors that made walking physiological condition become the single most prominent observation to emerge from the data was because of the human factor itself that best matched the smart shirt technology used in this study, where the walking condition was the third activity engaged by the participants without pause between them. The continuous physiological condition activities undergone by the participant stimulated the participant to sweat; this wet body surface worked best with the textile electrodes used by the smart shirt as the effective medium between the body surface of the participant with the textile electrodes.

Table 1. Summary of classification performance in different physiological scenarios

Scenarios	Accuracy (%)	TPR (%)	FRR (%)	FAR (%)
A1=standing	98.66	80.00	20.00	0.51
A2=sitting	98.10	87.78	12.22	1.37
A3=walking	98.73	96.36	3.64	0.93
B1=unknown	88.16	38.79	61.21	7.10
B2=unknown	92.81	60.35	39.65	3.93
C=known	98.81	83.79	16.21	0.50

4. CONCLUSION

Most research on ECG biometrics has been conducted in a lab where the variables may be carefully controlled, and high-quality medical sensors are probably used. This means that the results may not be entirely applicable to real-life situations. Thus, the missing element on the effect of different physiological conditions on wearable ECG biometrics was not adequately addressed. Therefore, real-life field research was thus required by the prior literature. Moreover, this research aimed to fill that need by presenting comprehensive analyses of ECG biometric using a non-medical textile sensor incorporated in a smart shirt for various physiological conditions in a real-life setting.

The implementation of a smart shirt with textile electrodes as a biometric acquisition medium and the performance assessment of various physiological conditions for biometric authentication in a real-life scenario make up the critical contributions of this study. The ideal physiological conditions for ECG biometric verification of the in-house different physiological condition datasets were also highlighted by this research. Furthermore, this study demonstrates that, regardless of what activities humans engage in under various physiological conditions, it is feasible to differentiate individuals based on the ECG data captured by the textile sensor on the smart shirt.

The wearable Hexoskin Proshirt was worn by 11 participants as they engaged in a variety of physiological condition exercises in the comfort of the participant compound. The participant's choice of easy, unstructured daily routine tasks is included in those physiological conditions, along with standing, sitting, and walking. Using these four distinct physiological conditions, a six scenario was then generated and evaluated for biometric authentication. It's interesting to note that verification of walking physiological condition results in exceptional performance in every scenario shown. The positive results suggest that ECG from smart textile shirts is a trustworthy biometric authentication. Thus, the study inspires the interest of some specific questions for future research, such as whether the fusion of another classifier to the study classifier can improve its hit rate in different physiological conditions and whether times variability can affect the classifier performance in biometric recognition for the wearable ECG smart shirt in real-life.

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