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ECG Biometric Authentication: A Comparative Analysis

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ABSTRACT Robust authentication and identification methods become an indispensable urgent task to protect the integrity of the devices and the sensitive data. Passwords have provided access control and authentication, but have shown their inherent vulnerabilities. The speed and convenience factor are what makes biometrics the ideal authentication solution as they could have a low probability of circumvention. To overcome the limitations of the traditional biometric systems, electrocardiogram (ECG) has received the most attention from the biometrics community due to the highly individualized nature of the ECG signals and the fact that they are ubiquitous and difficult to counterfeit. However, one of the main challenges in ECG-based biometric development is the lack of large ECG databases. In this paper, we contribute to creating a new large gallery off-the-person ECG datasets that can provide new opportunities for the ECG biometric research community. We explore the impact of filtering type, segmentation, feature extraction, and health status on ECG biometric by using the evaluation metrics. Our results have shown that our ECG biometric authentication outperforms existing methods lacking the ability to efficiently extract features, filtering, segmentation, and matching. This is evident by obtaining 100% accuracy for PTB, MIT-BHI, CEBSDB, CYBHI, ECG-ID, and in-house ECG-BG database in spite of noisy, unhealthy ECG signals while performing five-fold cross-validation. In addition, an average of 2.11% EER among 1,694 subjects is obtained.

INDEX TERMS ECG biometric, authentication, segment, off-the-person, on-the-person, Kalman Filter, feature extraction, ECG datasets

I. INTRODUCTION

BIOMETRIC systems are increasingly being adopted to improve security, convenience, and inclusion in society and to provide potential applications in various research and industrial fields. Notable biometric traits that have been successfully used in practical applications include the face, fingerprint, and iris. Furthermore, the recent advancement of artificial intelligent technologies makes them vulnerable to spoofing attacks (or presentation) through their inherent weakness. A common spoofing attack on faces or fingerprints was explored and discussed in [1]–[4]. In order to combat against presentation attacks and illegitimate user access to the systems, liveness detection or continuous biometric authentication approaches should be taken into account [5]–[7]. Continuous biometric authentication continuously check the identity of the user by using non-invasive measurable sensor that can collect users' biometric data. Thus, continuous biometric authentication has gained a lot of attention as a next-generation promising technique due to unique characteristics of the electrocardiogram (ECG) signals, it may be very promising trait mechanism for continuous biometric authentication. Since the liveness nature of ECG signals is not only ubiquitous and easy to use, but also difficult to counterfeit, the ECG-based technology is popularly used for continuous authentication to grant certain access privilege for users to identify a specific person [8]. In addition, there are other various applications that can be integrated with a continuously monitor for user's ECG and derive a quantitative measurement of their current stress state, fatigue, and disease, enabling users to understand their body's true state and take appropriate actions [9], [10]. In other words, since ECG signals will be recorded anyway for health application purposes, they can also be used for biometric based authentication and considering the advanced wearable technologies such as Apple watches, recording real-time ECG signals has been also dominated in our life to monitor user's health.

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Despite the substantial effort that has been made for developing the ECG as a biometric modality, it has yet to reach a sufficient level of technological maturity and acceptance. The immaturity of ECG development is caused by a lack of real ECG data. Furthermore, the research community depends on the small ECG gallery, which leads to good performance, but high error rates. On top of that, most of the existing methods often fail to report standard metrics for analyzing the results of ECG data evaluation in order to balance several important evaluation metrics, such as false acceptance rate, false reject rate, and equal error rate. In addition, most approaches have not even intensively evaluated the effectiveness of filtering, segmentation, feature extraction, and matching, which are the main steps to develop the right algorithm for any application.

In this paper, not only the biggest off-the-person ECG datasets will be incorporated for the first time, but also, we will discover and evaluate the effectiveness of different techniques in different steps in ECG biometric systems. This paper proposes a new filtering technique to create a bio template for biometric authentication while providing a comprehensive evaluation result for other popular techniques with diverse ECG data sets including our large new data set. We provide our insights to the ECG-based research community through intensive literature reviews and all-inclusive experiments in ECG biometric systems field.

Our main contributions are described as follows:

- We summarize existing techniques from the literature on identity recognition systems based on the ECG by conducting a deep overview and discussion based on the type of databases, number of subjects, health status, metrics, and methodology.
- We present a comprehensive study on ECG by investigating different feature extraction, filtering, segmentation, and matching. Each of these methods of performance is provided on various ECG databases with different health states on the data. We also provide comprehensive metrics such as false accept rate (FAR), false reject rate (FRR), equal error rate (EER), and identification rate for the important evaluation metrics.
- The large off-the-person ECG database is introduced for the first time. The new ECG database contains 68,274 samples ECG recordings that were collected from 1,119 subjects.
- Various experiments with ECGs from 1,119 different subjects were conducted to illustrate the efficacy of the proposed scheme. The result shows that we were able to achieve 100% accuracy with respect to 1.2%, 1.48%, and 0%, for EER, FAR, and FRR respectively.
- The impact of segmentation on ECG biometric authentication is discovered. We found that the optimal segment and the number of sample per cycle while obtaining high accuracy.

In addition to this introduction, the background of ECG signal along with data acquisition is presented in section II; Section III briefly summarizes recent works on different modules of an ECG biometric verification and identification; Section IV describes pipelines on ECG biometric system and challenges in signal denoising, segmentation, feature extraction and matching; Section V demonstrates experimental results; We discuss the advantages, drawbacks and future work in Section VI. Finally, we conclude with a summary and final remarks in section VII.

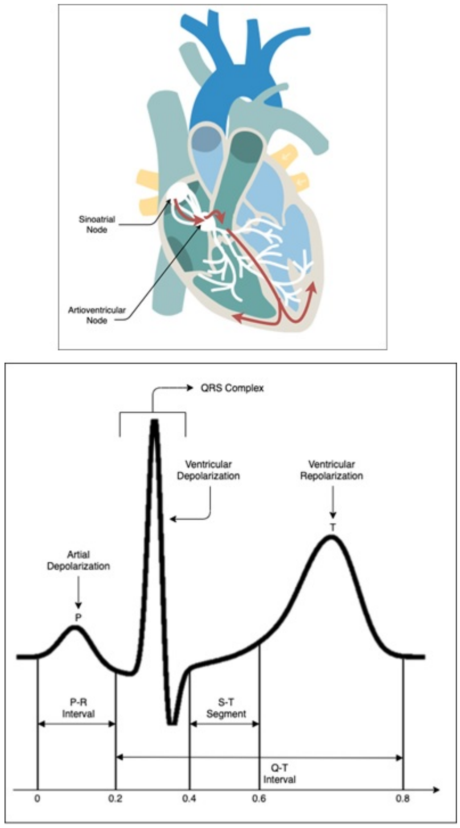

FIGURE 1. An electrocardiogram (ECG) waveform. The labels identify the three normally recognizable deflections (waves) and the important intervals.

II. BACKGROUND ON ECG

The electrocardiogram (ECG) is a graphic tracing of the heart activity that is generated in the heart and spread throughout the body and can be detected with a pair of electrodes external to the heart called an electrocardiograph. An ECG is a composite of several action potential generated by sinoatrial (SA) and atrioventricular (AV) node at a given time. The five distinguishable major deflections on a normal ECG are designated by the letters P, Q, R, S, and T waves – which make up the PQRST complex. As can be seen in Fig. 1, the P wave is smallest, lasts about 0.08s and results from movement of the depolarization wave from the SA node through the atria node (The large QRS complex results from ventricular depolarization and precedes ventricular contraction. The T wave, caused by ventricular repolarization, typically lasts about 0.16s. ECG waveform varies due to a range of factors including the size and shape of the heart, the position within the chest, and the conductive properties of the torso that provide a unique pattern per person.

Recording ECG signals can be classified into two recording configurations, including *"on-the-person"* and *"off-the-person"*. On-the-person recording refers to direct measurements by using body sensors that need to be attached to the person's body surface (e.g. the electrode leads), generally requiring conductive paste or gel. This method is primarily used in medical equipment at the chest to collect ECG signals. Moreover, it has been almost exclusively used in the medical industry due to its strength as a diagnostic tool, in which the capture method can be highly controlled. Examples of such devices range from bedside monitors integrated in medical diagnostics systems used in a hospital setting, to personal devices for self-monitoring of 1-lead ECG data, such as chest straps or attachable patches for heart rate monitoring. In addition, most of the biometric research has shown broad evidence regarding the applicability of ECG signals collected in an "on-the-person" approach. Despite its advantages, this approach is highly intrusive for the subjects, thus limiting the potential industrial applications of ECG-based biometrics. On the other hand, the "off-the-person" recording utilizes devices to measure ECG signals and does not require any special preparation of the subject with objects or surfaces. Examples of such devices range from fingertips or wearable devices that have dry electrodes. A major benefit of this technique is the fact that the sensor placement does not require a corporation from the user [11]. These novel approaches are actually well aligned with potential industrial applications of ECG-based biometrics. However, it is noteworthy that this type of ECG database contains more noise and variability than "on-the-person" databases.

III. LITERATURE REVIEW OF ECG-BASED BIOMETRIC METHODS

In this section, we discuss several recent works on ECG verification and identification. For better visualization, we summarized the most relevant aspects of ECG biometrics, such as the number of subjects, ECG data (on-the-person vs off-the-person databases), filtering types, segmentation techniques, feature extraction (handcrafted vs non-handcrafted extraction. More importantly, we summarized specific evaluative metrics such as an EER, an identification rate, a false accept rate, and a false reject rate in Table 1 and 2, to contribute to the biometric research community for a better understanding of ECG analysis results and the best selection of methods for their applications. Over the past decade, various handcrafted feature extraction techniques, such as fiducial feature extraction, discrete cosine transform (DCT), autocorrelation (AC), and wavelet transform, have been developed for ECG biometric authentication and identification. In addition, various public databases including off-the-person, on-the-person with healthy and no-healthy ECG have been investigated. From Table 1 and Table 2, the UofTDB is one of the largest databases among the existing off-the-person ECG database with 1019 subjects, while PTB is one of the largest on-the-person ECG databases that consists of 290 subjects. As shown in these tables, most studies in ECG biometrics have employed the bandpass (BF) filter for denoising ECG signal to remove intra-class variation. Moreover, fixed-length segments for capturing one heartbeat or one cycle of ECG are a common technique to segment continuous ECG signals. Furthermore, what is common to the literature shown in the tables is that single-channel ECG (one lead of sensor) contains sufficient information to be discriminated between different subjects for the support of biometric recognition. There are different types of feature extraction modalities [8], [15], [18], [19], [27] and various classifiers [12], [21], [23], [24], [28] have been utilized for ECG-based recognition. In the following section, we summarize the methodologies based on the features and classification schemes.

A. FEATURE EXTRACTION CATEGORY

Algorithms Based on handcrafted Features: Handcrafted feature extraction can be classified into two categories: fiducial and non-fiducial. Algorithms based on fiducial features use the characteristic local features of ECG beats such as temporal or amplitude onset, peak (minimum or maximum), and offset, extracted from single ECG beat or segment. For example, the P, Q, R, S, and T peak wave, the time difference between the peaks of the Q and T waves, and the QT interval are considered as fiducial features. Several subsets of these fiducial features have been used in the literature [15], [45], [49]. On the other hand, non-fiducial feature extraction does not rely on characteristic points for generating the feature set. Instead, some of the algorithms rely on holistically analyzing an ECG, typically by applying time or frequency analysis to obtain other statistical features. This method aims to extract discriminative information from the ECG waveform without having to localize fiducial points. Several subsets of these non-fiducial features have been used in the literature such as autocorrelation [19], [27], discrete cosine transform [18], [44], [46], [47], NCN [8], [28], [35], and wavelet transform [8], [22], [40], [47].

Algorithms Based on Non-handcrafted Fiducial Features: Most handcrafted feature extraction approaches involve a pre-processing phase for preparing the ECG (e.g., a statistical analysis such as fiducial or non-fiducial features extraction). With the advent of deep learning, researchers have started to explore non-handcrafted features based on the use of deep learning methodologies to achieve better performance and robustness. The reason is that the handcrafted approach relies on separate steps and preparation such as feature transforms and/or noise removal along with its optimization task, which leads to low performance. Thus, deep learning helps to boost performance by bypassing the aforementioned restrictions. Hong et.al [12] uses a 2D convolutional neural network (CNN) model in which the ECG signal is converted to an image using spatial correlation-based, temporal correlation-based, and raw signal as an input of CNN model. Specifically, the author uses the Inception-v3 model and transfers learning for the implementation. The drawback of this work is that, not only are 90 subjects excluded from experimental setup,

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Authors	Database		NS	Filter	Segmentation	Feature extraction		Matching	EER	Accuracy	FAR	FRR	SE
	OFP	ONP				HC	NHC						
Hong et.al [12]	–	PTB	200	–	Fixed length	–	CNN (Inception)	Softmax	–	98.1%	–	–	Y
Labati et.al [13]	–	PTB	52	BW	Fixed length	–	CNN	Softmax	2.90%	100	–	–	Y
Kim et.al [14]	–	PTB MIT-BIH	52 18	BP	Fixed length	–	CNN	Softmax	–	98.45% 99.2%	–	–	Y
Choi et al [15]	–	MIT-BIH PTB	175	BP	Fixed length	8 Fiducial	–	SVM	4.46%	95.9%	2.8%	8.5%	Y
Kim et.al [16]	–	ECG-ID	89	BP	Fixed length	CS	–	GLRT	3.80%	–	–	–	N
Salloum et.al [17]	–	ECG-ID MITDB	89 47	–	Fixed length	Raw ECG	–	LSTM GRUs	3.5%	100% 96%	–	–	N
Pinto et.al [18]	private	–	6	SG	Fixed length	DCT	–	SVM	2.66%	94.9%	–	–	N
Komeili et.al [19]	TEOAE	–	82	BP	Fixed length	AC/LDA	–	SVM	6.9%	–	–	–	N
Iulian et.al [20]	UofTDB	–	20	BP	Fixed length	–	CNN	–	0.2%	90.4%	–	–	N
Chu et.al [21]	–	ECG-ID PTB MIT-BIH	90 290 48	–	Raw ECG	–	CNN	SVM	2% 0.59% 4.74%	98.24% 100% 95.99%	–	–	Y
Zhang et.al [22]	–	CEBSDB STDB MITDB NSRDB AFDB WECG VFDB FANTASIA	20 28 47 18 23 22 22 20	BP	Fixed length	CWT	CNN	Softmax	–	99% 90.3% 91.1% 95.1% 93.9% 95.5% 86.6% 97.2%	–	–	N
Hammad et.al [23]	CYBHi	PTB	126 100	–	–	–	CNN VGG-Net	QG-MSVM	3.2%	96.83%	3.1%	–	Y
Wang et.al [24]	UofTDB	MITDB ECG-ID PTB	1019 47 90 290	BP	Fixed length	MSDF-1DMRLBP	–	Euclidean distance	2.17% 5.03% 3.3% 3.1%	100% 94.68% 100% 98.19%	–	–	N
Li et.al [25]	–	CEBSDB NSRDB STDB AFDB FANTASIA	20 18 28 23 20	BP	Fixed length	–	Cascaded CNN	Softmax	–	93.1% 91.4% 92.7% 89.7% 99.9%	–	–	N
Luz et.al [26]	CYBHi UofTDB	–	126 1019	BP	Raw ECG	–	CNN	Softmax	13.93% 14.27%	–	–	–	Y
Wahabi et.al [27]	UofTDB	–	1019	BP	windows of 6 seconds length	AC/LDA	–	Euclidean distance	5%	–	–	–	Y
Sidek et.al [28]	–	DiSciRi MITDB SVDB	39 47 78	–	QRS	NCN	–	MLP BN kNN RBF	–	99.3% 96.7% 96.4%	–	–	Y

TABLE 1. Summary of the state-of-the-art approaches for ECG biometrics. OFP - off-the-person, ONP - on-the-person, NS - number of subject, HC - handcrafted, NHC - non-handcrafted, SE - subject exclusive, Y - Yes, N - No, SG - Savitzky-Golay, DCT- discrete cosine transform, CWT - continuous wavelet transform, CNN - convolutional neural network, AC - normalized autocorrelation, LDA - linear discriminant analysis, BP - band pass filter, BN - Bayes networ, MLP - multilayer perceptron, RBF - radial basis function, kNN - k nearest neighbor, SVM - support vector machine, and NCN - normalized convoluted normalized.

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Authors	Database		NS	Filter	Segmentation	Feature extraction		Matching	EER	Accuracy	FAR	FRR	SE
	OFP	ONP				HC	NHC						
Agrafioti et.al [29]	–	PTB MIT-BHI	13 30	BW	Fixed window	AC coefficients	–	NN	–	87%	1%	–	Y
Safie et.al [30]	–	PTB	112	IIR	P peak to T peak	PAR	–	Euclidean distance	19.15%	86.70%	–	–	Y
Shen et.al [31]	–	NSRDB	14	BW	Fixed window	PLR	–	DTW	5%	92.3%	–	–	Y
Mai et.al [32]	–	NSRDB	18	–	QRS	QRS complex	–	MLP RBF	–	98% 97%	2%	–	N
Kim et.al [33], [34]	–	ESTTD	79	–	RR-interval	Shannon entropy	–	DT	–	95%	–	–	N
Karimian et.al [35]	–	ECG-ID PTB	90 290	IIR	Fixed window	NCN	–	Hamming distance	1.25%	98.4%	–	–	N
lynn et.al [36]	–	ECG-ID MITDB	90 47	BW	Fixed window	–	LSTM CNN	Softmax	–	98.60% 98.40%	–	–	N
Karimian et.al [8]	UofTDB	PTB	52 290	BW	Fixed window	DWT DCT NCN	–	Hamming distance	–	99.9% 97.4% 94.7%	–	–	Y
Liu et.al [37]	SIAT-ECG private	PTB	140 50	BW	RR-interval	Fiducial	–	SVM	–	93.15%	11.58%	1.2%	Y
Zhao et.al [38]	–	ECG-ID	90	–	Fixed window	S-transformation	CNN	Softmax	–	96.63%	–	–	N
Hejazi et.al [39]	BioSec.Lab	–	52	wavelet	–	KPCA	–	SVM	–	99%	–	–	Y
Tan et.al [40]	–	MITDB NSRDB ECGID	47 18 90	BP	Fixed window	Fiducial DWT	–	Random Forest	–	98% 99% 91%	–	–	N
Pinto et.al [41]	UofTDB CYBHi	PTB	1019 126 290	–	Fixed window	–	CNN	Euclidean distance	7.86% 15.37% 9.03%	–	–	–	Y
Ranjan [42]	Private	–	800	BW	Fixed window	–	CNN	Softmax	2.0%	–	–	–	N
Li et.al [43]	–	MITDB ECG-ID	47 90	BP	Fixed window	GNMF	–	residuals	10.44% 4.26%	98.03% 100%	–	–	N
Zaghouani et.al [44]	–	ECG-ID	90	BP	Fixed window	AC/DCT	–	Hamming distance	15%	–	–	–	N
Krasteva et.al [45]	–	PTB	290	BP	–	Fiducial	–	LDA	–	91.6%	–	–	N
Plataniotis et.al [46]	–	PTB	50	BP	Fixed window	AC/DCT	–	Euclidean distance	–	100%	–	–	Y
Pathoumvanha et.al [47]	Private	–	20	IIR	Fixed window	CWT AC/DCT	–	FLDA	–	97%	–	–	N
Labati et.al [48]	–	IDEAL	202	IIR	Fixed window	QRS	–	Cross correlation	5.36%	–	6.11%	5%	N
Paiva et.al [49]	–	PTB	10	BW	RR-interval	Fiducial	–	SVM	–	97.45%	5.71%	3.44%	Y
Hammad et.al [50], [51]	MWM-HIT	MIT-BHI	20	MD	–	Fiducial	–	CNN, NN	–	99%	–	–	Y

TABLE 2. Summary of the state-of-the-art approaches for ECG biometrics. Here are the symbols for each: OFP - off-the-person, ONP - on-the-person, NS - number of subject, Y - Yes, N - No, HC - handcrafted, NHC - non-handcrafted, SE - subject exclusive, DCT- discrete cosine transform, CWT - continuous wavelet transform, CNN - convolutional neural network, AC - normalized autocorrelation, MLP - multilayer perceptron, RBF - radial basis function, kNN - k nearest neighbor, SVM - support vector machine, NN - neural network, PAR - pulse active ratio, IIR - infinite impulse response, MD - Median Filter, DTW - Dynamic Time Warping, PLR - Piecewise Linear Representation, DT - decision tree, NCN - NormalizeConvoluted Normalize, IIR - finite impulse response, LSTM - Long short-term memory, KPCA - kernel principal component analysis, GNMF - graph regularization non-negative matrix factorization decomposition, FLDA - Fisher linear discriminant analysis, and RRN - Recurrent Neural Networks.

but also the metric is not comprehensive and the accuracy of only 98% has been reported. Labati et.al [13] also used 2D CNN where raw ECG signal is segmented and fed as an input. The author reported 100% accuracy with a 2.90% equal error rate (EER) while only healthy ECG from the PTB database has been studied. More work on deep learning can be found in [14], [20]–[23], [25], [26], [38], [41], [42] which the detail has been described in Table 1, and Table 2. The heavy computational and large size of database requirements for deep learning models still restrain it from being realistic.

B. CLASSIFICATION CATEGORY

Since ECG biometric systems can be considered either as identification or verification, and we discuss the ECG biometric systems into two categories: verification and identification.

ECG verification Most of the algorithms in this category depend on the computation of matching scores based on the similarity and dissimilarity between a query feature vector and a template. During authentication, the score is compared to a predefined threshold, and the claimed identity is accepted, if the score is greater. There are different types of classifiers such as Euclidean distance, support vector machines (SVMs), dynamic time warping (DTW), and hamming distance utilized in the literature [8], [15], [18], [19], [21], [23], [24], [27], [35], [41], [44], [46].

ECG identification Most of the deep learning approaches for ECG biometric systems have been studied in the literature review used a fully connected layer and softmax for a classifier. During identification, the template that gives the highest matching score is associated with the query signal. A neural network is especially applied in non-linear classification problems. Various types of these classifiers were used in ECG identification, especially the Multilayer Perceptron (MLP) [12]–[14], [20]–[23], [25]–[28], [32], [36], [38], [42], but also the Long short-term memory (LSTM) [17], the Dynamic Time Warping (DTW) [31], the Radial Basis Function Neural Network (RBFNN) [28], [32], and k nearest neighbor (KNN) [28]. Most of the aforementioned classifiers used a similar approach for the loss function, optimization with a different node activation function. In addition, there has been a few research that investigates decision-based on discriminant and component analysis which can be found in [45], [47].

It can be clearly seen in literature that there is no standard technique to demonstrate and evaluate the effectiveness of each approach and algorithm in the ECG biometric system, such as the impact of filtering, segmentation, feature extraction, and matching and type of database. In this paper, we will discuss and evaluate each of the aforementioned problems.

IV. OUR APPROACH: ECG BIOMETRIC

ECG based biometric systems, in general, are comprised of five major components: *sensing, filtering, segmentation, feature extraction,* and *matching*. Fig. 2 provides a high-level overview and flow of the ECG based biometric authentication process, which constitutes of the *enrollment* and *authentication* phases. In the enrollment phase, the user's ECG signal is registered to generate the template, and in the authentication phase, raw data from a user is provided and compared to the previously stored template to determine the access permissions. In what follows, we explain our approach to implement the ECG-based biometric authentication algorithm while describing the various steps of the authentication algorithm.

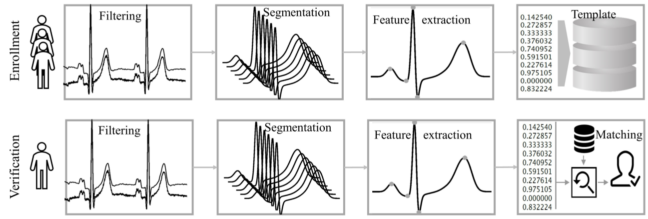

FIGURE 2. High-level overview of an ECG biometric authentication system. It contains of filtering, segmentation, feature extraction, template and matching module.

A. PRE-PROCESSING

The goal of pre-processing is to separate the required biometric trait from the background noise. In the context of ECG, both low and high-frequency noise components are combined, commonly referred to as baseline drift and power-line interference respectively. High-frequency noise contains muscle artifacts and external interference. Electromyogram (EMG) is generated from the electrical activity of the muscles and appears as rapid fluctuations which are much faster than the ECG waves. Low-pass filters on the ECG are used to remove high-frequency noise. A high pass filter can remove low-frequency components such as motion artifacts, respiratory variation, and baseline wander noise. In the pre-processing stage, ECG signals are filtered to remove noise which can impact the biometric signal. In this study, we have employed two filters, namely Kalman and IIR. Details are discussed below.

Kalman Filter: The Extended Kalman Filter (EKF) is used for a nonlinear problem for many applications which is the extension of the standard Kalman Filter. Since ECG signal is non-stationary discrete-time series signal, thereby it can be model with unobserved underlying state vector (original ECG signal) z_t and observation vector (filtred ECG) y_t at time instant t. Thus, the model can be represented as follows:

$$\begin{aligned} z_{t+1} &= f(z_t, w_t, t) \\ y &= g(z_t, v_t, t) \end{aligned} \tag{1}$$

where $f()$ is the state evolution function and $g()$represents the relationship between the state vector and the observations. w_t and v_t are measured noise vectors with covariance matrices $Q_t = E\{w_t w_t^T\}$ and $R_t = E\{v_t v_t^T\}$. In order to transfer into a linear equation for using the KF formalism, it is necessary to derive a linear approximation of 1 near a desired reference point $(\hat{z}_t,\ \hat{w}_t,\ \hat{v}_t)$ [52], [53]. Thus, the following linear approximate model is derived:

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$$
\begin{aligned}
z_{t+1} &\approx f(\hat{z}_t, \hat{w}_t, t) + A_t(z_t - \hat{z}_t) + F_t(w_t - \hat{w}_t) \\
y_t &\approx g(\hat{z}_t, \hat{v}_t, t) + C_t(z_t - \hat{z}_t) + G_t(v_t - \hat{v}_t)
\end{aligned} \tag{2}
$$

where

$$
\begin{aligned}
A_t &= \left.\frac{\partial f(z, \hat{w}, t)}{\partial z}\right|_{z=\hat{z}} \\
F_t &= \left.\frac{\partial f(O\hat{ECG}, w, t)}{\partial w}\right|_{w=\hat{w}_t} \\
C_t &= \left.\frac{\partial g(z, \hat{v}, t)}{\partial z}\right|_{z=\hat{z}} \\
G_t &= \left.\frac{\partial g(\hat{z}, v, t)}{\partial v}\right|_{v=\hat{v}_t}
\end{aligned} \tag{3}
$$

furthermore, to shorten the matrix notations, the F_t and G_t matrices are usually smeared into the noise covariance matrices as follows:

$$
F_t Q_t F t^T \longrightarrow Q_t, \quad G_t R_t G t^T \longrightarrow R_t \tag{4}
$$

With these notations, the EKF algorithm may be summarized as follows:

$$
\begin{aligned}
&\hat{z_{t+1}^{-}} = f(\hat{z_t^{+}}, w, t)\Big|_{w=\hat{\bar{w}}_t}, r_t = y_t - g(\hat{z_t^{-}}, v, t)\Big|_{v=\hat{\bar{v}}_t} \\
&K_t = P_t^- C_t^T [C_t P_t^- C_t^T + R_t]^-, \hat{z_t^{+}} = \hat{z_t^{-}} + K_t r_t \\
&P_{t+1}^- = A_t P_t^+ A_t^T + Q_t \quad P_{t+1}^+ = P_t^- - K_t C_k P_t^-
\end{aligned} \tag{5}
$$

where by definition r_t is the innovation signal, $\bar{w_t} = E\{w_t\}$, $\bar{v_t} = E\{v_t\}$, $z_t^- = \hat{E}\{z_k | y_{t-1}, ..., y_1\}$ is the a priori estimate of the state vector in the t^n stage using the observations y_1 to y_{t-1}, and $z_t^+ = \hat{E}\{z_k | y_{t-1}, ..., y_1\}$ is the a posteriori estimate of this state vector after using the kth observation y_t.

Infinite Impulse Response (IIR) Filter: The infinite impulse response (IIR) filter is a recursive filter in that the output from the filter is computed by using the current and previous inputs and previous outputs. The transfer function of the IIR filter is defined as follows:

$$
H(z) = \frac{Y(z)}{X(z)} = \frac{b_0 + b_1 z^{-1} + \cdots + b_M z^{-M}}{1 + a_1 z^{-1} + \cdots + a_N z^{-N}} \tag{6}
$$

where is can be described using the difference equation as follows:

$$
\begin{aligned}
y(n) = b_0 x(n) + b_1 x(n-1) + \cdots + b_M x(n-M) \\
- a_1 y(n-1) - \cdots - a_N y(n-N)
\end{aligned} \tag{7}
$$

where b_i and a_i are the (M + 1) numerator and N denominator coefficients, respectively. Y(z) and X(z) are the z-transform functions of the input x(n) and output y(n). In this paper, we employed IIR butterworth filter with cut of frequency of 1-40Hz.

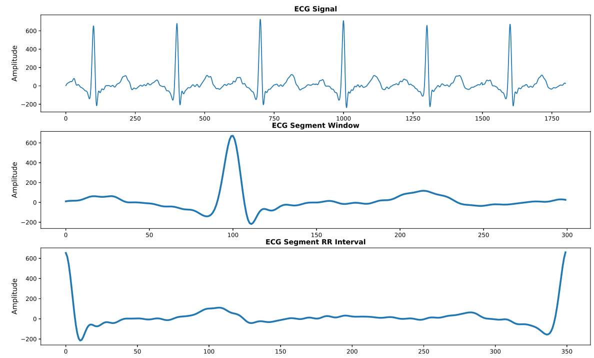

FIGURE 3. Show the ECG signal along with fixed window and RR interval segmentation.

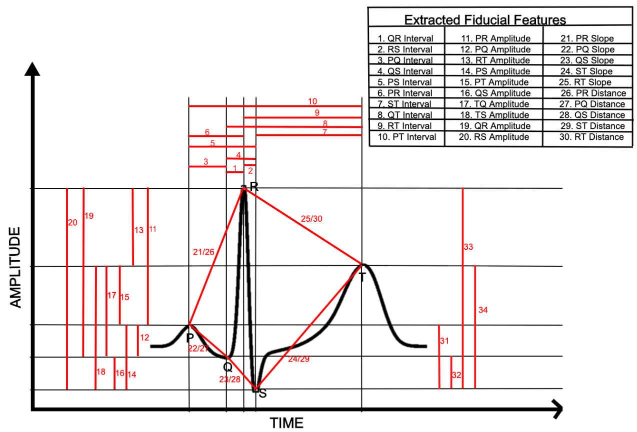

FIGURE 4. Show single ECG beat with fiducial features that has been studied in this paper.

B. SEGMENTATION

ECG waveforms occurring in a repetitive order that are comprised of five major peaks such as P, QRS, and T. Since each ECG heartbeat contains the same information it is not efficient to repetitive heartbeat heartbeats that has a correlation. ECG segmentation is the most popularly used signal preparation method for limiting the signal size for feature extraction. In other words, the segmentation goal is to find repeating patterns in the ECG signal known as P, QRS, and T waves. Thus, it helps to reduce the template size significantly in order to simplify template matching. In ECG biometric, the segmentation follows the reference point (identifying a R-peak) and fixed distances before and after the identified R-peaks. Taking the partial ECG signal $(R - t,\ R + t')$ instead of the entire signal called *Fixed Length Segmentation* where the t and t' are a pre-defined fixed time that covering the majority of P-QRS-T fragment. On the other hand, taking whole waveform of ECG signal (R_i, R_{i+1} called *RR segmentation* where, the R_i is the ECG R peak at cycle t and R_{i+1} is the ECG R peak at cycle $t+1$. Fig. 3 demonstrates our technique for segmenting ECG signals using sliding windows into the different heartbeats.

C. FEATURE EXTRACTION

The feature extraction stage translates the segmented ECG into a representation that further reduces the effects of intra-subject variability while emphasizing discriminative and intra-class variations to obtain better performance. ECG handcrafted feature extraction can be categorized as a *fiducial point* or *non-fiducial point*.

Fiducial feature extraction: In the fiducial feature extraction technique, the features of focus are the local features of heartbeats such as temporal or amplitude difference between consecutive fiducial points [8]. Fiducial methods rely on accurate detection of the main ECG characteristic points such as P, Q, R, S, and T waves as shown in Fig. 4, to obtain their relative amplitude, temporal intervals, and morphological features. In fact, each temporal and amplitude of each waveform are distinctive from each individual user. However, fiducial feature extraction relies on accurate detection of each waveform, which is a very challenging task in ECG since they are very sensitive to noise. Moreover, it may not be considered as a universal characteristic due to a lack of fiducial points in abnormal signals, resulting in significant errors. Thus, non-fiducial methods have become preferred in ECG based biometrics systems. Therefore, we also study and evaluate non-fiducial feature extraction for comparison.

Non-fiducial feature extraction: In the non-fiducial feature extraction technique, the features of focus are the holistic analysis of an ECG, typically consisting of applying time or frequency analysis to obtain other statistical features. In this paper, we used different wavelet families, such as Symmlet and Daubechies. The reason for using Symmlet and Daubechies mother wavelet is that the function is similar to the ECG signal. In order to evaluate the effectiveness of the aforementioned mother wavelet transformations, different levels of decomposition have been examined, however, we only report a level of four decompositions.

D. MATCHING

In the matching stage, identification and verification functions can be performed. The purpose of matching is to compare the query ECG feature sets against stored templates to generate match scores. The matching score is a quantitative measurement that checks the similarity between template and query ECG feature sets. A Higher match score indicates that the template and query have a high correlation. In this paper, two different matching methods are studied.

Euclidean Distance: In this part, we focus on authentication and employ Euclidean distance as a matching technique between the features' vectors to decide whether to accept or reject the identity claim. Given claimed identity I and a query feature set X^q, we need to determine if (I, X^q) belongs to genuine or imposter user. The Euclidean distance D between two feature vectors T_j and q_j is defined as

$$D(\{\mathbf{X_I^T}\},\{\mathbf{X^q}\}) = \sqrt{\sum_{j=1}^{K}(\mathbf{X_I^T}[j] - \mathbf{X^q}[j])^2} \qquad (8)$$

in which X_I^T is a stored template corresponding to identity I. So, we compare X_I^T and X^q to measure similarity for verification. If the distance D or score above a predefined threshold (t), the claimed identity is accepted as a genuine user, otherwise, it is rejected and considered an imposter.

Dynamic Time Warping (DTW): Dynamic Time Warping (DTW) is a technique that compares two sequences that do not necessarily need to be the same lengths [54], [55]. The DTW algorithm finds the optimal alignment between two sequences with different lengths, such that the sum of the differences between each pair of aligned points is minimal. This method appears to be able to handle comparison between template and query specifically if they are not aligned such as fingerprint or they have a different length such as ECG. This paper shows the RR segmentation technique depending on the heart rate variability. In short, each segment of RR is different from each other. Thus, DTW plays an important role in our case study. The DTW measures the similarity between template and query of ECG feature sets after aligning them.

V. EXPERIMENTAL SETUP

A. DATABASE

In our study, we utilized five on-the-person public ECG databases plus an in-house off-the-person ECG database. We examined the authentication performance of some of the techniques that have appeared in the ECG biometric literature. We used only a single ECG lead from collecting ECG for realistic scenarios. The databases used are summarized in Table 3, where the maximum duration utilized for both training is 5 minutes. For example, if the ECG signal duration is less than 5 minutes, we took the whole signal; otherwise, we use only 5 minutes. The databases utilized for these experiments in this paper can be listed as follow based on public one-the-person and in-house off-the-person ECG:

On-the-Person:

- Combined measurement of ECG, breathing and seismocardiograms Database (CEBSDB): The cohort in this database [56] involves 20 healthy subjects, and the ECG records were collected in a supine position on a comfortable single bed, while the subjects were awake. The ECG was collected in the basal state of the subjects by measuring for 5 minutes and after that, the subjects started to listening to classical music for approximately 50 minutes. Channel 1 and 2 of the system (lead I and II) were devoted to recording the ECG at a sampling frequency of 5 kHz. In our work, we used 5 minutes of phase 1 for training our recognition system while the rest of the data for testing.
- Arrhythmia Database (MITDB): The MITDB [57] is an ECG database that was collected in the laboratories at Boston's Beth Israel Hospital and MIT. It contains 48 half-hour ECG recordings from 47 subjects. Out of 47 subjects, twenty-three recordings were selected from a mixed population of inpatients (about 60%) and outpatients (about 40%), and the remaining 25 recordings were selected from the same set to include less common

Dataset off-the-person	Dataset On-the-person	Sample rate	# of subjects	Electrode type	Health state
	PTB	1000Hz	290	Gel	Myocardial infarction
	MIT-BHI	360Hz	47	Gel	Arrhythmia
	CEBSDB	5000Hz	20	Gel	Healthy
CYBHi		1000Hz	125	Dry Ag/AgC	Healthy
ECG-ID		500Hz	90	Gel	Healthy
ECG-BG		1000Hz	1119	AD8232	Healthy/hyperglycemia

TABLE 3. The summary of the four data sets adopted in our experiments.

Dataset	Seg.	Filtering	Feature Extraction																			
			Fiducial				Non-Fiducial															
							FAR				FRR				ERR				Accuracy			
			FAR	FRR	ERR	Accuracy	ED		DTW		ED		DTW		ED		DTW		ED		DTW	
							SYM4	DB4	SYM4	DB4	SYM4	DB4	SYM4	DB4	SYM4	DB4	SYM4	DB4	SYM4	DB4	SYM4	DB4
ECG-ID (90 Users)	FW	IIR	**1.86**	**0**	**2**	**100**	10.4	9.89	8.14	7.77	0	0	0	0	10	10	8	8	100	100	100	100
		Kalman	**2.6**	**0**	**2.5**	**100**	8.67	8.1	4.98	5.04	0	0	0	0	9	8	5	5	100	100	100	100
	RR	IIR	2.49	0	2.5	100	12.2	11.38	4.87	4.86	0	0	0	0	12	11	5	5	100	100	100	100
		Kalman	4.54	0	4.5	100	8.46	7.92	4.074	4.086	0	0	0	0	9	8	4	4	100	100	100	100
MIT-BIH (47 Users)	FW	IIR	**4.1**	**0**	**4**	**100**	9.13	10.7	5.34	3.53	0	0	0	0	9	10	5	4	100	100	100	100
		Kalman	**7.06**	**0**	**7**	**100**	10.73	8.22	9.95	6.11	0	0	0	0	10	9	10	6	100	100	100	100
	RR	IIR	4.84	0	5	100	8.98	9.2	6.11	6.74	0	0	0	0	8	9	6	7	100	100	100	100
		Kalman	8.103	0	8	100	10.94	9.36	9.31	9.09	0	0	0	0	10	9	9	9	100	100	100	100
CEBSDB (20 Users)	FW	IIR	3.6	0	3	100	2.7	1.8	**0**	**0**	0	0	**0**	**0**	2	2	**0**	**0**	100	100	**100**	**100**
		Kalman	1.108	0	1	100	3.6	3.7	**0.55**	**1**	0	0	**0**	**0**	3	4	**1**	**1**	100	100	**100**	**100**
	RR	IIR	3.32	0	3	100	2.34	2.98	1.66	1.93	0	0	0	0	2	3	2	2	100	100	100	100
		Kalman	1.93	0	2	100	5.8	6.2	4.15	3.36	0	0	0	0	6	6	4	4	100	100	100	100
PTB (294 Users)	FW	IIR	3.5	0	3.5	100	1.98	1.9	0.75	0.5	0	0	0	0	2	2	0.75	0.5	100	100	100	100
		Kalman	1.473	0.69	1.4	99.31	2.1	1.7	0.95	0.25	0.34	0	0.34	0	2	2	1	0.25	99.66	100	99.66	100
	RR	IIR	**0.59**	**0**	**0.5**	**100**	3.4	2.9	0.6	0.25	0	0	0	0	3	3	0.6	0.25	100	100	100	100
		Kalman	**0.475**	**0**	**0.5**	**100**	2.95	2.3	0.95	0.78	0	0	0	0	3	2	1	0.7	100	100	100	100
CYBHi (126 Users)	FW	IIR	4.09	0	4	100	8.4	6.67	6.25	4.487	0	0	0	0	8	7	6.5	4	100	100	100	100
		Kalman	4.95	0.8	5	99.2	5.9	7.84	4.28	5.25	3.85	0.91	3.85	0.91	6	8	4.5	4.5	96.15	99.09	96.15	99.09
	RR	IIR	3.61	2.38	4	97.62	3.87	6.2	**2.25**	**3.84**	5	3.37	**5**	**3.37**	4	6	**3**	**3**	95	96.63	**95**	**96.63**
		Kalman	4.15	3.97	4	96.03	5.32	8.9	**2.5**	**4.59**	5	3.34	**5**	**3.34**	5	9	**2.5**	**2.3**	95	96.66	**95**	**96.66**
ECG-BG (1117 Users)	FW	IIR	**1.288**	**0**	**1.2**	**100**	3.96	2.89	2.01	1.57	0	0	0	0	4	3	2	1.5	100	100	100	100
		Kalman	**1.48**	**0**	**1.4**	**100**	5.2	4.66	2.25	2.95	0	0	0	0	5	5	2.2	3	100	100	100	100
	RR	IIR	1.5	0	1.5	100	4.1	3.1	1.84	1.57	0	0	0	0	4	4	1.8	1.5	100	100	100	100
		Kalman	1.39	0	1.4	100	5.3	5.2	2.25	2.64	0	0	0	0	5	5	2.2	2.5	100	100	100	100

TABLE 4. A performance comparison of ECG biometric authentication using different segmentation, filtering, feature extraction. Seg. - segmentation, FW - Fixed window, DWT - Dynamic Time Warped, ED - Euclidean distance.

but clinically significant arrhythmias. The recordings were digitized at 360 samples per second per channel with an 11-bit resolution over a 10 mV range. This database is unknown as abnormal ECG data, which would be ideal to test it for the ECG recognition system for universality characteristics.

- PTB Diagnostic ECG Database (PTDB): This database is obtained by the Physikalisch-Technische Bundesanstalt (PTB), National Metrology Institute of Germany [58]. The database contains 549 records with diverse profile information such as gender, age, health information, and different lengths of ECG obtained from 290 subjects sampled at 1 kHz, which mimics real-world scenarios. Among the 290 subjects, 148 subjects suffering from myocardial infarction, and 18 have cardiomyopathy or heart failure, whereas it has only 52 healthy subjects. All channels were involved, where only 14 are for ECG. However, in this work, we only used lead 1 as our experimental setup.

Off-the-Person:

- ECG identification database (ECG-ID) were recorded for biometric identification purpose [59]. Each raw ECG record was acquired for about 20 seconds with a sampling rate of 500 Hz and a 12-bit resolution. The first two records acquired from the same day were used for each subject. The database consists of 310 one-lead ECG recording sessions obtained from 90 volunteers during a resting state. The number of sessions for each volunteer varied from 2 to 20 with a time span of 1-day to 6-months between the initial and last recordings. The challenges in this database are the number of noisy environment condition in which two records such as filtered and noisy ECG signal mimics real-world scenarios.
- Check Your Biosignals Here initiative (CYBHi) belongs to the off-the-person category and is publicly available, which makes them most suitable for ECG recognition. Data was recorded using two differential lead electrodes at hand palms with dry Ag/AgCl electrodes and at the fingers with Electrolycras [60]. The acquisition was digitized at 1K Hz samples per second per channel with a 12-bit resolution using the biosignalsPLUX device. The database (128 subjects) is divided into two types of experimental protocol namely short-term and long-term. The short-term was recorded from 65 people at intervals of two days. The demographics of 65 subjects from short-term 49 males and 16 females, with an average age of 31.1 ± 9.46 years old. The long-term dataset was collected over a period of several days and different settings which acquired from a total of 63 healthy subjects. The demographics of 63 subjects from the long-term are 14 males and 49 females, with an average age of 20.68 ± 2.83 years.

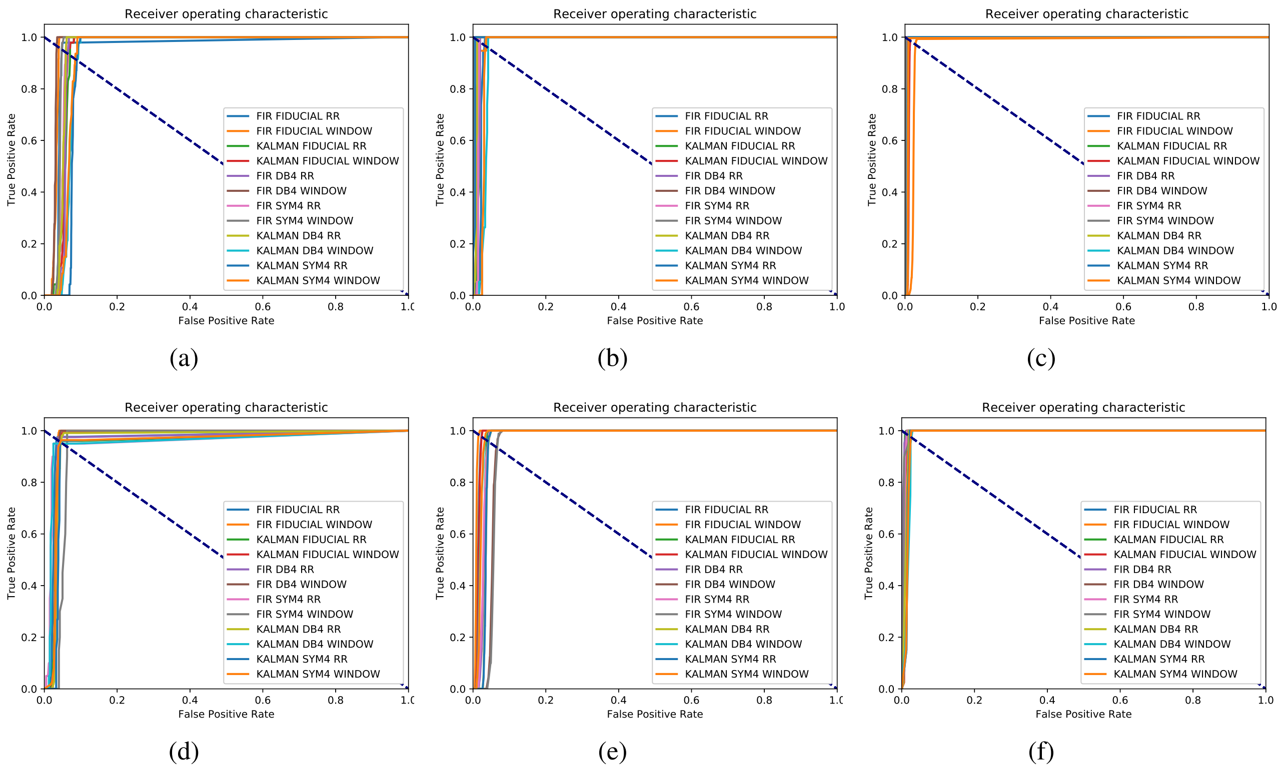

FIGURE 5. ROC curves for different hand-crafted features extraction such as fiducial features, non-fiducial features; filter including Kalman filter, IIR filter; segmentation such as fixed window and RR interval. (a) on-the-person MITDB, (b) on-the-person PTB, (c) on-the-person CEBSDB, (d) off-the-person CYBHi, (e) off-the-person ECG-ID, and (f) off-the-person ECG-BG respectively.

- In addition to the public off-the-person dataset, we also studied the largest off-the-person database called ECG-BG, containing data collected from 1,119 individuals, with 386 females and 733 males of 38 to 80 years of age. The database was collected by the Research Center for Applied Sciences, Academia Sinica, Taiwan based on the following protocol. Each subject participated in two sequential recording sessions, both taken in the morning. ECG was acquired using Analog AD-8232 with a sampling rate of 1K Hz. This off-the-person ECG database beside other off-the-person ECG databases contains healthy and unhealthy which makes it suitable for real-world scenarios.

B. EVALUATION METRICS

Since our primary focus is verification, comprehensive metrics such as accuracy, false accept rate (FAR), false reject rate (FRR), and equal error rate (EER) have been evaluated with the various databases. FPR is the percentage of genuine users who were denied access to the ECG recognition system whereas FAR is the percentage of an imposter who has successfully gained access to ECG recognition. The two error rates FRR and FAR can be traded-off with each other in order to find the optimal and desired EER. EER is the location on the receiver operator characteristic (ROC) curve where the FAR and FRR are equal. We also calculate the accuracy for each subject as the number of successful attempts (segments) by the genuine user divided by the total number of attempts.

Moreover, in order to assess the effectiveness and estimate how the model is expected to perform in general, 5-fold cross validation was used, so the 5 blocks from each task were split into 4 training blocks and 1 test block. Each block contains 10 segments of feature sets from each user. For each training block, we used average segments from each block. This was repeated 5 times with non-overlapping windows to obtain 50 results per task, per subject.

1) Experimental Results

The results presented were obtained based on implementing the methodologies as described in Section IV. Table 4 shows the experimental results obtained from different databases using different techniques. In this work, our template is constructed using a single ECG beat (segment). In fact, we collected 10 segments of ECG signal from each user and calculated the average to make a template for authentication. A single ECG segment (average of multiple ECG segments) as a template provides advantages for storage size and computational cost to match a new input with the template. In a verification process, the number of ECG segments varies and depends on the database. Thus, unless otherwise stated, one can assume the presented results represent an average in Table 4. *Unlike most of the work in the literature, we did not exclude any subjects in our evaluation process for fair*

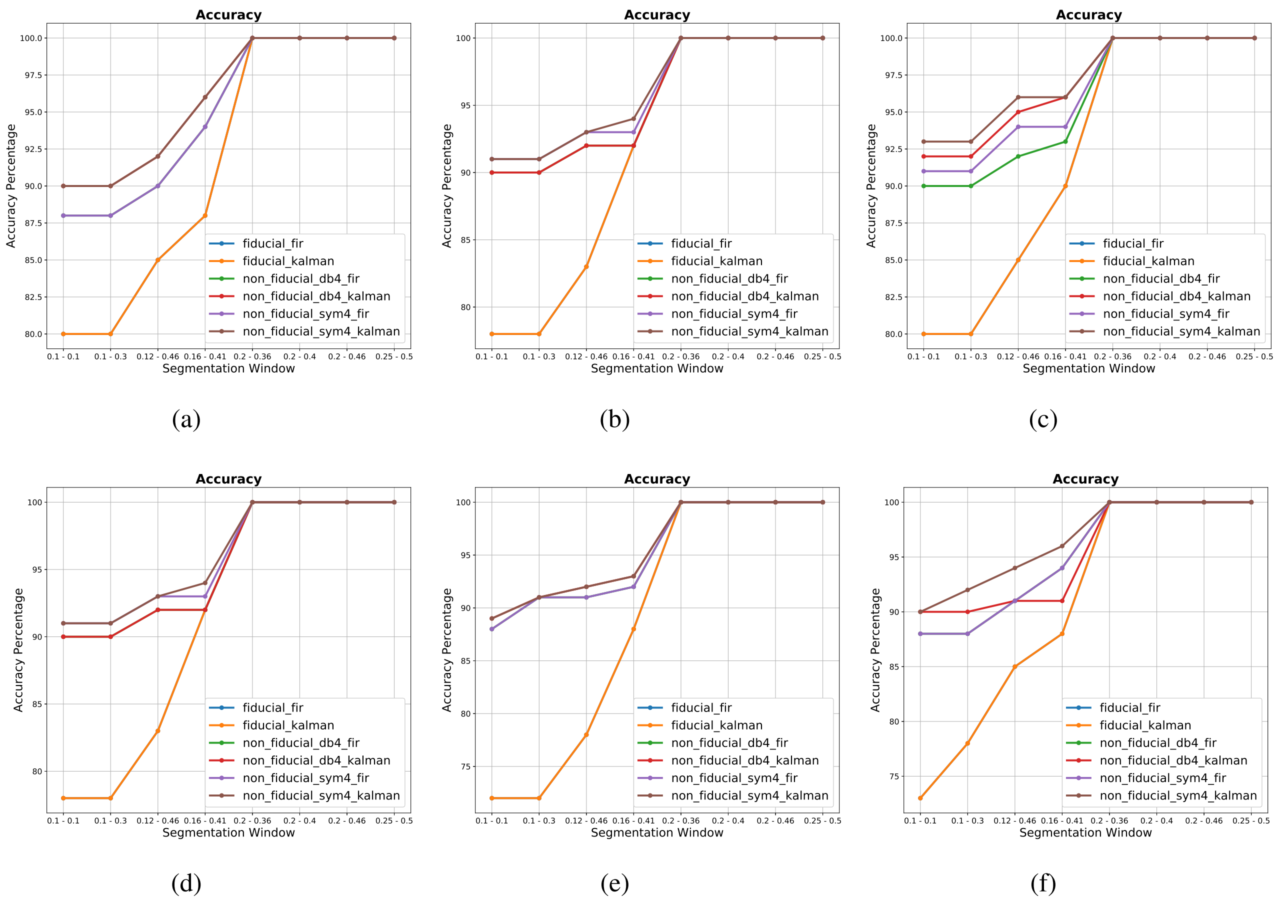

FIGURE 6. The average accuracy under different segmentation. (a) on-the-person MITDB, (b) on-the-person PTB, (c) on-the-person CEBSDB, (d) off-the-person CYBHi, (e) off-the-person ECG-ID, and (f) off-the-person ECG-BG respectively.

and realistic evaluation even though the data includes noises and uncertain values. One of the reasons the subjects are excluded in the literature work is that their filtering, segmentation, and feature extraction techniques were not performed very well and as a result, they had to eliminate some of the users. We have conducted our experiments over different filtering, segmentation, feature extraction, and matching. In particular, we have tested different ECG database on fixed window segmentation, RR interval segmentation, FIR filter, Kalman filter, fiducial, non-fiducial feature extraction, Euclidean distance, and dynamic time warping. It should be noted that the results of DTW are superior to Euclidean distance for matching and the FAR and FRR is lower than Euclidean distance. In the Euclidean distance as a matching, one should be assumed is the i^{th} point in the template feature vector is aligned with the i^{th} point in the query feature vector, will produce a pessimistic dissimilarity measure. In contrast, the non-linear DTW alignment allows a more intuitive distance measure to be calculated in which every index from the template feature vector must be matched with one or more indices from the query feature vector and vice versa. As shown in Table 4, from the ECG-ID database, fixed window segmentation along with FIR filter achieved 100% accuracy with 1.86% FAR based on fiducial feature extraction. While non-fiducial feature extraction, the FAR 4 times higher than the fiducial. Note that the reason FAR of non-fiducial features is higher than fiducial is because non-fiducial feature extraction relies on the entire ECG waveform which may contain more noise than fiducial features where temporal and fiducial points (a small number of features) are extracted. Moreover, for the MITDB database which has arrhythmia ECG, we were able to obtain 100% with 4.1% FAR. For the sake of clarity, it should be noted, fixed window segmentation methods showed a good performance for most of the databases except the PTB database. The reason is that the PTB database has various diagnostic classes including Myocardial infarction, Cardiomyopathy/Heart failure, Bundle branch block, Dysrhythmia, Myocardial hypertrophy, Valvular heart disease, and Myocarditis. Therefore, it should be expected changes/loss on the ECG waveform while sensing the ECG signal. Thus, the fixed window may not capture all the ECG waveforms such as P, QRS, and T waveforms. As a result, RR interval segmentation accomplished better performance compare to fixed interval segmentation in the PTB database. In addition, we can observe that the CYBHI database also derives a benefit from RR interval segmentation since most of the ECG waveform has been captured during RR segmentation. Unlike the PTB database, the CYBHI database has only a normal ECG signal but the sample rate is much higher than the PTB database which has 1000Hz. Hence, a fixed window may not be an appropriate technique to cover the entire important ECG waveform such as P, QRS, and T waves. Compared to the work in the literature [12]–[14] which excludes some subjects from the original PTB database for their experiments, we achieved 100% accuracy with 0.5% EER, 0% FRR and 0.47% FAR without excluding any subject from the original database. The extensive experimental results on the three on-the-subject and three off-the-subjects datasets demonstrated that our method outperforms several state-of-the-art methods. In addition, our features extraction methods provided a lower EER, FAR, FRR, and high accuracy for ECG biometric systems. We also implemented our several new methodologies and evaluated them using a new large scale off-the-person ECG database (ECG-BG) based on 1,119 subjects with healthy and unhealthy status as a significant contribution in this research community. The proposed methods demonstrated a 100% recognition rate with 1.2% EER, 1.28% FAR, and 0% FRR for authentication. Moreover, it can be seen in Table 4, for most of the cases, the fiducial feature extraction outperforms comparing to non-fiducial techniques. We also presented the receiver operating characteristic (ROC) curve for each database along with different ECG biometric algorithms in Fig. 5.

We also evaluated the performance of our algorithm over different databases for various fixed window segmentation ($R - t$, $R + t'$) using different combinations of t and t', the time periods before and after the R peak: (1) $t = 0.1s$ and $t' = 0.1s$, (2) $t = 0.1s$ and $t' = 0.3s$, (3) $t = 0.12s$ and $t' = 0.46s$, (4) $t = 0.16s$ and $t' = 0.41s$, (5) $t = 0.2s$ and $t' = 0.36s$, (6) $t = 0.2s$ and $t' = 0.4s$, (7) $t = 0.2s$ and $t' = 0.46s$. Fig. 6 shows the accuracy of various algorithms averaged for six different databases.

As can be seen from Fig. 6 for the above seven cases, the consequence of the larger windows such as cases (5), (6) and (7) are neutral in terms of accuracy, since most of ECG waveforms such as P, QRS, and T waves are included. The remaining cases such as (1), (2), and (3), where partially ECG waveforms have been discarded, the accuracy rate is degraded. Even though the majority parts of ECG waveforms like the QRS complex were captured, the performance was finally degraded because of discarding the P and T waveforms. From the results demonstrated in Fig. 6, it can be noticed that cases (1) and (2), the $t = 0.1s$, while t' changes, the accuracy does not change. Therefore, we can cautiously conclude that the effect of the t where the P wave is included is higher than the t' where the T wave is included. We can draw the conclusion from a test result that, the best segmentation for ECG among all the database is the case (4) where $t = 0.16s$ and $t' = 0.41s$. In other words, the accuracy is already saturated from these window segments. Thus, not only we can reduce the time for enrollment/authentication phase, but also the memory space for storing the template will be decreased.

VI. DISCUSSION

In this section, we are discussing the advantage and drawbacks of the proposed system. Besides most of the proposed ECG-biometric authentication system used multiple segments in the template, in this work, only a single ECG segment for each user is stored in the template for comparison in the authentication phase. Moreover, most of the previous work reported, evaluation metrics are not comprehensive. However, in this work, all the metrics such as FAR, FRR, and EER has been reported. Our proposed work has been evaluated under both on-the-person and off-the-person ECG databases from diverse poll without any subject exclusion. While other works limited diverse database along with subject exclusion has been examined. As can be seen in the result, the DTW matching algorithm achieved the best performance for different types of feature extraction and segmentation. Nevertheless, the authentication process is slower than Euclidean distance and it requires more power consumption. Although the ECG-based biometric system has long been deemed as unclonable, the vulnerabilities of the ECG biometric systems have been studied by Karimian et al. [61]. While, The ECG biometrics spoofing area has not received much attention in the existing work, but it serves as a warning to researchers to develop a countermeasure for prevention. Recently, Karimian et al. [62] proposed countermeasure by using heart rate variability and photoplethysmogram (PPG) to combat against spoofing. This paper can incorporate countermeasures suggested in [62] for anti-spoofing.

VII. CONCLUSION

Despite the considerable effort for developing ECG-based biometric modality, several important issues have not been properly addressed in the efforts to make a new algorithm. First, the database for ECG is limited and includes unhealthy data with noises. Second, the previous developed algorithms have not been intensively investigated for each of the well-known main techniques: filtering types, segmentation, and feature extraction and ECG data quality. In this paper, we completely evaluate the impact of filtering type, segmentation, feature extraction and health status on ECG biometric by using the evaluation metrics: accuracy, FAR, FRR, and ERR. In other words, several experimental results were conducted to evaluate the impact of such important techniques for ECG biometric systems. In addition, we created large gallery off-the-person ECG data-sets, that opens up a state-of-the-art of challenges and opportunities for the ECG biometric research community. The large datasets will significantly contribute to other ECG research areas in the future. We have also provided a comparative analysis of the authentication performance of existing on-the-person ECG databases and new off-the-person ECG. While discussing the limitations of the previous works, this paper presents that our new proposed approach shows better performance in terms of FAR, FRR, EER, and identification rate.

VIII. ACKNOWLEGEMENTS

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