Review Article

Bioelectrical Signals as Emerging Biometrics: Issues and Challenges

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This paper presents the effectiveness of bioelectrical signals such as the electrocardiogram (ECG) and the electroencephalogram (EEG) for biometric applications. Studies show that the impulses of cardiac rhythm and electrical activity of the brain recorded in ECG and EEG, respectively; have unique features among individuals, therefore they can be suggested to be used as biometrics for identity verification. The favourable characteristics to use the ECG or EEG signals as biometric include universality, measurability, uniqueness and robustness. In addition, they have the inherent feature of vitality that signifies the life signs offering a strong protection against spoof attacks. Unlike conventional biometrics, the ECG or EEG is highly confidential and secure to an individual which is difficult to be forged. We present a review of methods used for the ECG and EEG as biometrics for individual authentication and compare their performance on the datasets and test conditions they have used. We illustrate the challenges involved in using the ECG or EEG as biometric primarily due to the presence of drastic acquisition variations and the lack of standardization of signal features. In order to determine the large-scale performance, individuality of the ECG or EEG is another challenge that remains to be addressed.

1. Introduction

1.1. Bioelectrical Signals. Bioelectrical signals are very low amplitude and low frequency electrical signals that can be measured from biological beings, for example, humans. Bioelectrical signals are generated from the complex self-regulatory system and can be measured through changes in electrical potential across a cell or an organ. The bioelectrical signals of our interest are in particular, the electrocardiogram (ECG) and the electroencephalogram (EEG). An ECG measures the electrical manifestation of the ionic potential of the heart while an EEG measures the electrical activity evoked along the scalp of the brain. The ECG and the EEG are recorded using standard equipments in the noninvasive fashion. The researchers of multiple disciplines have shown their greater interest in analyzing the ECG and the EEG to understand the high level features an individual is producing. However, the interdisciplinary analysis of bioelectrical signals not only helps in assessing the individuals state of health but also it suggests that the bioelectrical signals can be used as the candidate of biometrics for identity verification.

1.2. Characteristics of Bioelectrical Signals as Biometrics. Biometrics aim to facilitate an identity management system for achieving a higher level of accuracy while it uses the anatomical and behavioral characteristics of individuals which are unique and measurable. Anatomical parts of body and signaling methods include face, fingerprint, hands, eyes, ears, veins and voice while behavioural characteristics include handwritten signature, keystroke and gait [1]. The limitations using the conventional biometrics include that they are unique identifiers but they are not confidential and neither secret to an individual. For example, people leave their physical prints of finger on everything they touch, iris patterns can be observed anywhere they look, faces are visible, and voices
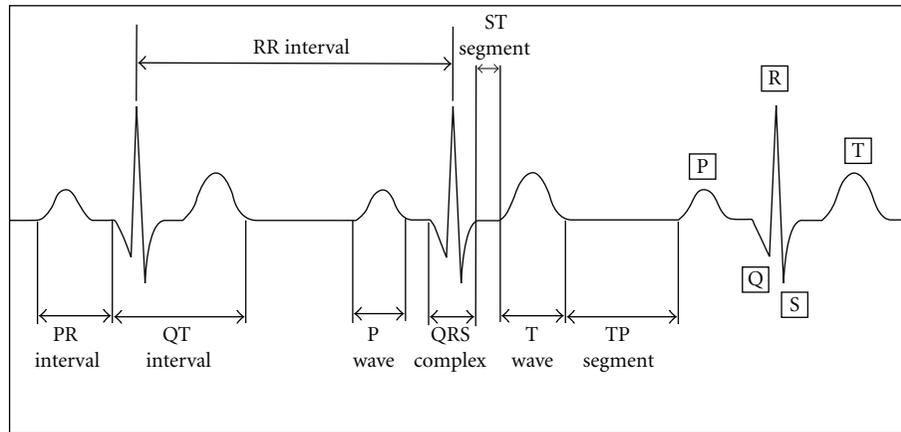
FIGURE 1: A typical ECG signal that includes three heartbeats and the information lying in the P, Q, R, S, and T waves.

are being recorded. The presence of biometric prints publicly, offering intruders to lift these prints and copy them as real, thus spoofs the system. Using bioelectrical signals as biometrics offers several advantages to an identity management system. Besides their uniqueness, the bioelectrical signals are confidential and secure to an individual. They are difficult to mimic and hard to be copied. Therefore, the identity of an individual is unlikely to be forged, thus preserving the secrecy and privacy of the users.

Bioelectrical signals especially, the ECG and the EEG are emerging biometric identities [2–17]. Unlike anatomical biometric identities that have two-dimensional data representation, the ECG or EEG is physiologically low-frequency signals that have one-dimensional data representation. Using the ECG or EEG signals as biometric may offer the following characteristics: universality, measurability, uniqueness, and robustness. Universality refers that each (live) individual must possess the ECG or EEG signals. Measurability refers that the ECG or EEG signals can be recorded using electrodes placed on the body surface near to the particular organ (e.g., chest, hands, and legs for the ECG and along the scalp for the EEG).

The biological information of a person genetically governed from deoxyribonucleic acid (DNA) or ribonucleic acid (RNA) proteins [18, 19]. Eventually, the proteins are responsible for the existence of uniqueness in the certain body parts [1]. Similarly, the organs like heart and brain are composed of protein tissues called myocardium and glial cells, respectively. Therefore, the electrical signals evoked from these organs show uniqueness among individuals [20]. Last but not the least, the replay or reproduction of the ECG or EEG signals is very difficult until the same individual is not called for the re-enrollment. Therefore, the proposed methods using the ECG or EEG as biometric are sufficiently nonvulnerable to spoof attacks. Consequently, the fact of using the ECG or EEG signals as biometric yields an assurance that the biometric data is coming from the legitimate individual who is indeed present during the enrollment. It is an essential condition for the perfect working of a practical biometric system.

1.3. Outline of Paper. In this paper we present a review on the effectiveness of the ECG and the ECG signals for biometric applications. Various methods that show the promiseness of the ECG or EEG as a candidate of biometric are critically analyzed. In addition, the issues and challenges of using the ECG or EEG as biometric are discussed. The paper is structured as follows. Section 2 describes the potential of the ECG signal as a biometric for individual authentication. An overview of the ECG signal and the factors supporting to use it as a biometric is given. A review of the existing methods that explore the feasibility of the ECG signal as a biometric and a new method in support of the promiseness of the ECG as a biometric is presented. The issues and challenges in designing the ECG-enabled biometric system that performs the authentication task across wide range of conditions are highlighted. Section 3 explores the potential of the EEG on biometric perspective where an overview of the EEG and the salient features favoring to use it as a biometric is presented. A review of the existing methods demonstrating laboratory results in support of the EEG as a candidate of biometric is given. The challenges from the perspective of an operational viability of the EEG as a biometric are summarized. Section 4 stipulates some of the promising directions of future research for a successful use of the ECG or EEG signals for biometric applications.

2. ECG as a Biometric

2.1. ECG Preamble. The ECG is a noninvasive tool used to record the electrical manifestation of the contractile and relaxation activity of the heart. Nobel laureate, Willem Einthoven, was the first who had recorded the ECG in 1903 [21]. It can be recorded with the surface electrodes placed on the limbs and chest. ECG devices use varying number of electrodes ranging from 3 to 12 for signal acquisition while the system using more electrodes exceeding 12 and up to 120 is also available [22]. Each normal cycle of an ECG signal contains P, QRS, and T waves (for instance see Figure 1). The P wave is a representation of contraction of the atrial muscle and has duration of 60–100 millisecond (ms).

It has low-amplitude morphology of 0.1–0.25 millivolt (mV) and usually found in the beginning of the heartbeat. The QRS complex is the result of depolarization of the messy ventricles. It is a sharp biphasic or triphasic wave of 80–120 ms duration and shows a significant amplitude deflection that varies from person to person. The time taken for ionic potential to spread from sinus node through the atrial muscle and enter the ventricles is 120–200 ms and known as PR interval. The ventricles have a relatively long ionic potential duration of 300–420 ms known as the QT interval. The plateau part of ionic potential is of 80–120 ms after the QRS and known as the ST segment. The return of the ventricular muscle to its resting ionic state causes the T wave that has an amplitude of 0.1–0.5 mV and duration of 120–180 ms. The duration from resting of ventricles to the beginning of the next cycle of atrial contraction is known as TP segment which is a long plateau part of negligible elevation.

The ECG signals acquired from different people show heterogeneous characteristics. The heterogeneity has been marked in the studies conducted for diagnosing arrhythmia present in the heart function [23]. The distinctiveness of ECG signals generally resulted due to the change of ionic potential, time of ionic potential to spread from different part of the heart muscles, plasma levels of electrolytes (e.g., potassium, calcium and magnesium, etc.), and rhythmic differences. These differences are reflected in various forms such as the change in morphology, difference in amplitudes and the variation in time intervals of the dominant fiducials of the heartbeats. The differences in the heart structure such as chest geometry, position, size, and physical condition among individuals also manifest unique characteristic in their heartbeat rhythm.

2.2. Supporting Factors. In the literature, different methods have been proposed in support of using the ECG signal as a candidate of biometric for identity verification [2–10]. Unlike other conventional biometrics (e.g., face and fingerprint), the ECG signal provides the real-time vitality feedback. The vitality-enabled biometric identity signifies the life signs. It ensures that the biometric sample is being collected from a live individual to be authenticated. Thus, it offers a strong argument against spoof attacks on a biometric security system. Furthermore, the ECG is often used by physicians in diagnosing cardiac and other related ailments. Through the deployment of ECG-enabled biometric system the identity of the persons can be verified online during ECG monitoring or offline through their medical records. It can be further supplemented by the existing state-of-art systems like mobile health monitoring or body area sensor network. This way of identity verification is much more useful for the protection of person identity and the protection of cardiovascular condition especially to the cardiovascular patients [24]. This private health information is strictly protected under the privacy regulation standardization of the Health Insurance Portability and Accountability Act (HIPAA) of 1996 [25].

Although, the methods using the ECG as a biometric may not offer adequate accuracy [26, 27], the ECG information can assist in improving the security of the system with other biometrics in a multibiometric framework. Singh et al. [27] have proposed a multibiometric system which is obtained from the fusion of the ECG signal with, the face and the fingerprint biometrics for robust persons authentication. The performance of the proposed system has reported optimum, and that the equal error rate (EER) of the fused system is found to be 0.2% as compared to an individual system of the ECG that has an ERR of 10.8% while the EER of the face and the fingerprint systems are 4.5% and 2.1%, respectively. They have concluded that the fused system may work in a user-perceived manner such that the ECG data of an individual can be acquired simultaneously with the other biometrics, that is, the fingerprints and the facial image acquisition.

Since, the DNA and the RNA proteins are eventually responsible for the existence of uniqueness in face, fingerprint, and other body marks identities. Therefore, it is imperative to note that the biometrics like facial geometry, texture of fingers, and the electrical manifestation evoked from the heart are orthogonal to each other. Eventually, there is a correlation between the heart function (ECG) and the characteristics of the other biometrics. While fusing the ECG with other biometrics, if ECG can narrow down the space of search to half (50%) then the chances of success to reach the right person from the remaining population would be doubled (using other biometrics). Therefore, a less-performed biometric can optimize the search space significantly, in order to supplement other biometrics for meeting the requirement of stringent security applications.

Besides genetic reasons, the ECG as a biometric is supported from the fact that the physiological and geometrical differences among individuals cause certain degree of uniqueness in their heartbeat features [28]. Although, the supporting factors discussed so far offer a choice of selecting the ECG as a biometric which are based on the laboratory demonstration, they are very promising. Therefore, it is the time to design an ECG-enabled biometric system, that can employ to the specific application of patient monitoring and thereafter the feasibility of system can be tested to an extended domain of applications.

2.3. Related Works. An analysis of the ECG and the interpretation of ECG patterns as a tool for clinical diagnosis are active fields of research. Taking the research advantage, several studies have been conducted in the recent past exploring the possibility of the ECG as a new candidate of biometric for identity verification.

Israel et al. [2] have shown that the ECG trace of an individual exhibits unique pattern. They have performed the ECG processing for quality check and a quantifiable metrics is proposed for classifying heartbeats among individuals. They have extracted stable features from each heartbeat that characterizing the uniqueness of an individual. The experiment has been tested on 29 individuals from males and females of 22 and 48 years of age where data is collected on different state of anxiety and at different sessions. A total of 15 intrabeat features based upon cardiac physiology have been extracted from each heartbeat and classification
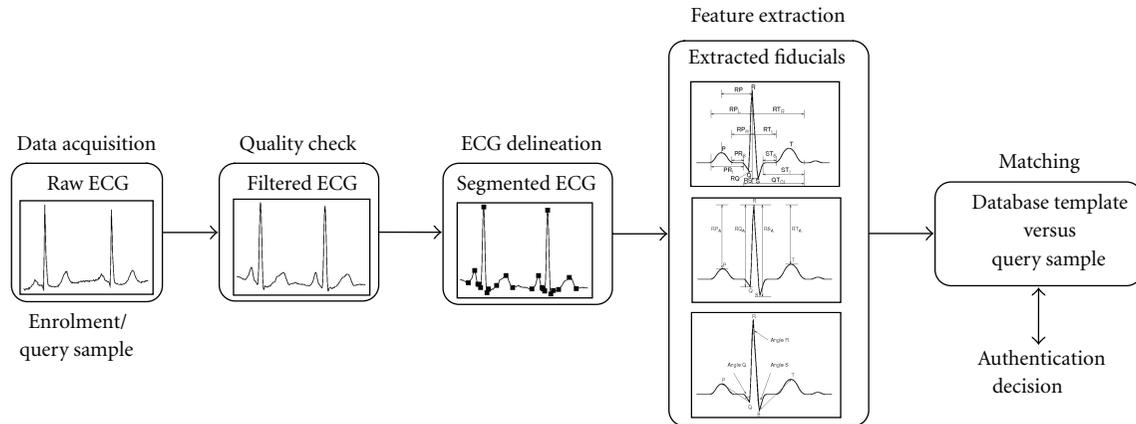
FIGURE 2: Schematic of ECG-enabled biometric authentication system.

is performed using linear discriminant analysis. They have shown that the extracted features are independent to electrode positions (e.g., around chest and neck), invariant to the individuals state of anxiety, and unique to an individual. The issues, for example, scalability of ECG features to authenticate a large population and the invariance of features over longer periods, are being examined on large dataset.

The Eigen space analysis to the ECG trace for human identification has been presented in [3]. Like traditional biometric methods (e.g., face, fingerprints and iris) have used principle component analysis (PCA) approach to exploit image samples, Eigen decomposition of heartbeat has yielded a more robust approach for human identification. A methodology for identity verification using ECG that quantifies the minimum number of heartbeats required to authenticate an individual has been discussed in [4]. The approach has rested on the statistical theory of sequential procedures that extracts the heartbeat features to compute the test statistics. The decision that the acquired ECG matches to the stored credential of the claimed identity has taken using continuous sampling of the heartbeats.

One of the earliest studies that demonstrated the possible use of the ECG signal to biometric application has been reported by Biel et al. [5]. They have conducted the biometric experiment on a group of 20 subjects including men and women where each subject belongs to 20–55 years of age. For each subject, the ECG data has been collected between a time period of six weeks and a total of 30 features have been extracted from each heartbeat. All these extracted features are normally used in helping clinical diagnosis of heart arrhythmia. In order to reduce the number of features, the features with a relatively high correlation with other features are discarded and finally, 12 features have been selected for classification. A multivariate analysis-based method has been used for classification; however principle component analysis (PCA) score plot has been utilized to interpret the similarities and differences of heartbeats among individuals.

The feasibility of using ECG as a new biometrics for individual identity verification has been shown by Shen et al. [6]. They have performed the experiment on appearance and time domain features of the heartbeat. However, most of the features have been extracted from QRS complex that is stable with change in heart rate. One feature, the QT interval that varies with the change in the heart rate, has normalized. Template-matching and decision-based neural network approaches have been used to quantify the identity verification rate that is reported to be 95% and 80%, respectively. After combining the classification approaches the result of identity verification has been found to be 100% from a group of 20 individuals.

Wang et al. [7] have introduced a two-step fiducial detection framework that incorporates analytic and appearance-based features from the heartbeat. The analytic features capture local information which combined temporal and amplitude features while the appearance-based features capture the holistic patterns of a heartbeat. To better utilize the complementary characteristics of analytic and appearance features, a hierarchical data integration scheme has presented. The method used for feature extraction has based on a combination of autocorrelation (AC) and discrete cosine transform (DCT). The AC/DCT method has performed on windowed ECG segments, and therefore does not need pulse synchronization. The recognition performance achieved by AC/DCT method is 94.47% and 97.8%, respectively, for PTB and MIT-BIH database [29].

Recently, the feasibility of the ECG signal to aid in human identification has been exploited by Singh and Gupta [8–10]. Signal-processing methods have been used to delineate the ECG waveforms. The delineation results have been found to be optimum and stable in comparison to other published results. These delineators have been used along with QRS complex to extract different features of classes: time interval, amplitude, and angle from clinically dominant fiducials on each heartbeat of the electrocardiogram. A test set of 250 ECG recordings prepared from PhysioNet [29] has evaluated on the proposed identification system, designed on template matching and adaptive thresholding. The matching decisions are taken on the basis of correlation between the stored credential and the test ECG data. As a result, individuals are classified with optimum performance.

2.4. ECG-Enabled Biometric System. The schematic description of ECG-enabled biometric authentication system is shown in Figure 2. First, the ECG signal is acquired from individuals; then for quality check the signal is preprocessed that it includes correction of signal from noise and artifacts. The ECG delineation includes detection of P, Q, R. S, and T waves and their dominant fiducials in each heartbeat. Feature extraction includes determination of different class features such as time interval, amplitude, and angle from the delineated waveforms. Finally, the matching is performed between the features of stored template and the query sample for identity verification.

The heartbeats from the ECG trace are detected using the technique [30] with some improvements. It employs digital analysis of slope, amplitude, and width information of the ECG waveforms. The fiducials of QRS complex are delineated according to the location and convexity of R peak. Once the heartbeat is detected, temporal time windows are defined before and after QRS complex fiducials to seek for P and T wave delineations from each beat of the ECG. The time-derivative and adaptive thresholding approach is used to delineate the P wave [31] while the T wave is determined using the analysis of its waveform curvature from each heartbeat [32].

In order to carry out the biometric experiment using the ECG signal, a feature set is prepared from the extracted fiducials of P, Q, R, S, and T waves for each heartbeat [10]. It contains the attributes of interval features, amplitude features, and angle features which are shown in Figures 3(a), 3(b), and 3(c), respectively. Further, the attributes related to atrium depolarization and ventricles repolarization are normalized [11] by dividing the beat length to vanquish from the changes occurring due to variation in the heart rate.

We adopt statistical framework approach to generate the match scores from the comparison of feature vectors between the query and the template samples. The computational procedure to generate the match scores from the comparison of query sample to the database template of ECG features is described as follows. First of all, the procedure to generate database templates of different individuals is illustrated. Consider, an individual i has an ECG data set of t unit of time. The m subdata sets of length s unit of time ($s < t$) are arbitrarily selected from the complete trace of an ECG. Then, a vector of d-features is extracted from each subdata set. Let $P^{(i)}$ be the pattern matrix consisting of m vectors of individual i of size $m \times d$ that can be defined as

$$P^{(i)} = \begin{pmatrix} f_{1,1} & f_{1,2} & \cdots & f_{1,d} \\ f_{2,1} & f_{2,2} & \cdots & f_{2,d} \\ \vdots & \vdots & & \vdots \\ f_{m,1} & f_{m,2} & \cdots & f_{m,d} \end{pmatrix}, \quad (1)$$

where element $f_{j,k}$ represents the kth feature of jth subdata set. The purpose of arbitrarily selection of subdata set is to statistically analyze the variations present in different heartbeats of an individual ECG. Consider, the population size is n, so there are n different ECG data sets. Thus, n different pattern matrices $P^{(i)}$ are generated in the database where $i = 1, 2, \ldots n$.
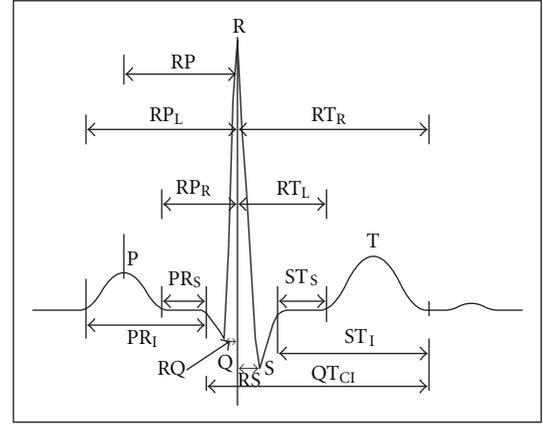
(a)
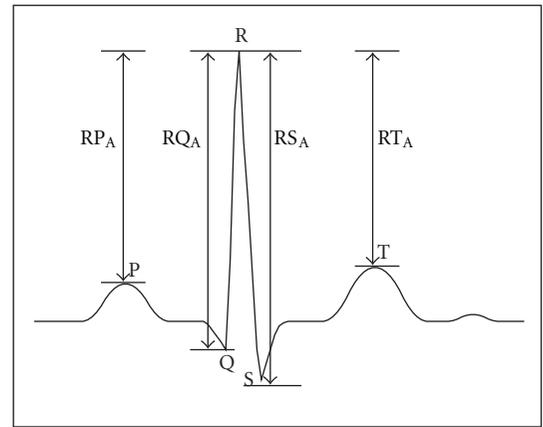
(b)
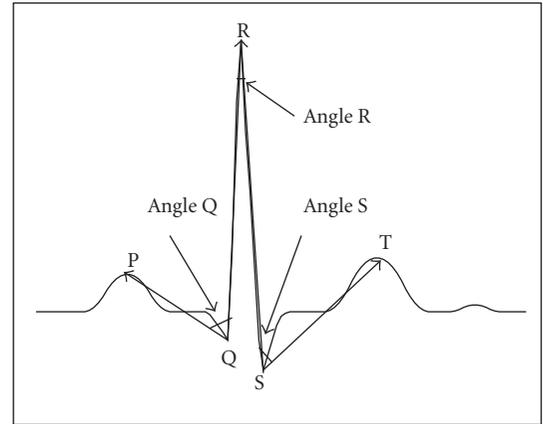
(c)

Figure 3: ECG features of classes: (a) interval, (b) amplitude, and (c) angle.

Let an individual have a query sample Q that generates the feature vector $f' = \langle f'_1, f'_2, \ldots, f'_d \rangle$. Statistically, the distance between the attributes of a query sample and feature vectors of a pattern matrix of an individual i is computed using Euclidean distance as follows:

$$d_j^{(i)} = \left(\left| f_{j,1} - f'_1 \right| \quad \left| f_{j,2} - f'_2 \right| \cdots \left| f_{j,d} - f'_d \right| \right), \quad (2)$$

where $j = 1, 2, \ldots m$. The sum of Euclidean distances between attributes of feature vectors gives the distance score measure for individual i, as

$$s_j^{(i)} = \sum_{k=1}^{d} \left| f_{j,k} - f_k' \right| \qquad (3)$$

for all subdata sets $j = 1, 2 \ldots m$. In order to acknowledge (incorporate) the variations present in the ECG data set of an individual i, the mean of the distance scores, denoted as $s^{(i)}$ can be computed and determined as follows

$$s^{(i)} = \frac{1}{m} \sum_{j=1}^{m} s_j^{(i)}. \qquad (4)$$

A genuine match score is obtained when two feature vectors corresponding to the same individual are compared, and an impostor match score is obtained when feature vectors from two different individuals are compared. A smaller value of distance score indicates a good match while a higher value of distance score indicates a poor match.

2.4.1. Experimental Results. We evaluated the performance of the ECG-enabled authentication system on the ECG database prepared from PhysioBank [29]. The database contains the ECG signals of 78 individuals acquired from European ST-T database, MIT-BIH normal sinus rhythm Database, MIT-BIH arrhythmia database and QT database of the PhysioBank. In the database each individual has only one ECG recording; so we partitioned each recording of ECG signal into two halves. The first half of the ECG recordings for each subject is labeled as target and the other half of the ECG recordings is labeled as query. The performance of the authentication system is analyzed through equal error rate (EER). The EER is the error rate where the frequency of fraudulent matches (FMR) and the frequency of nonmatches of individuals who should be correctly verified (FNMR) assume the same value. EER can be adopted as a unique measure for characterizing the security standard of a biometric system. The EER result of the ECG-enabled authentication system is reported to 10.8%. The EER result and the detection error trade-off (DET) curve show (see e.g., Figure 4) that the authentication performance of the ECG-enabled biometric system is low and hardly compete to conventional biometrics such as face and fingerprint.

However, the ECG signal can be combined with other biometric (e.g., face and fingerprint) and provide an excellent source of supplementary information in a multibiometric framework. Singh et al. [27] have proposed a multibiometric system that fuses the ECG signal with face and fingerprint biometrics, effectively. Transformation-based score fusion technique is used to evaluate the effectiveness of the aforementioned system. The EER results of the unimodal systems of face and fingerprint biometrics are 4.5% and 2.1%. The DET curve related to the better authentication rates, achievable using the multibiometric system that fuses the ECG signal with face and fingerprint biometrics, is shown in Figure 4. The aforementioned system achieved an EER of 0.2%. These results confirm that the ECG signal can be
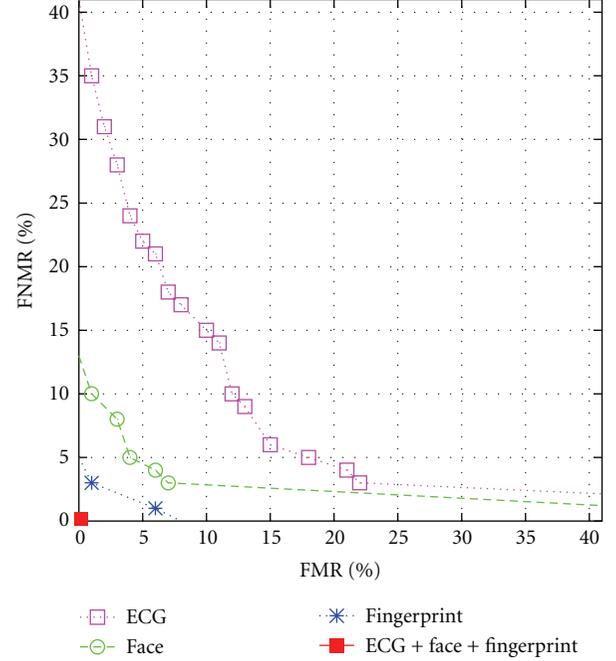

FIGURE 4: Performance of a multibiometric system fusing ECG signal with face and fingerprint biometrics.

effectively fused with the face and fingerprint biometrics for individual authentication. Although the EER result of the ECG signal as a biometric is slightly worse than the face and the fingerprint biometrics, the fused system shows a significant improvement in the EER result.

2.5. Performance Evaluation of Biometric Methods Using ECG. The methods that use the ECG signal as a biometric for identity verification are tested on different data sets and test conditions. The laboratory demonstration of the cited methods show that the classification accuracy is varying from one method to another while the performance of the methods is tested on a limited data size. The performance estimates of the different methods using ECG as a biometric under different validation and test conditions are given in Table 1. However, it is harder to ascertain any conclusion to the effectiveness of one method that uses the ECG as a biometric over other methods.

2.6. Issues and Challenges. ECG-enabled biometric methods accomplished individual authentication through statistical analysis of the ECG signal and perform quantitative comparison of the query signal to the enrolled signals. The performance of the proposed methods depends heavily on the task of data representation, that is how efficiently the ECG delineation and determination of its waveforms are performed. The results presented by most methods have shown the uniqueness of the ECG among humans and therefore can be considered as a candidate of biometric. But most experiments are done on modest data sets that are acquired under controlled conditions in laboratory demonstration. To

TABLE 1: Performance estimates of various methods using ECG as a biometric under different validation and test conditions. SIMCA: soft independent modeling of class analogy, NN: neural network, PCA: principle component analysis, LDA: linear discriminate analysis, EER: equal error rate, and N/R: not reported.

Methods	Data size	Data representation techniques	Classification techniques	Classification accuracy	Test conditions
Israel et al. [2]	29 subjects	Analysis of waveform curvature	Linear discriminant analysis	97-98%	Normal and different anxiety states
Irvine et al. [3]	43 subjects	Eigen pulse analysis, PCA	Correlation based analysis	∼100% enrollment rate	Varying stress levels
Biel et al. [5]	20 subjects	Siemens ECG using Siemens Megacart	Multivariate analysis SIMCA	N/R	Validated ECG data recorded in 6 weeks
Shen et al. [6]	20 subjects	Feature extracted from QRST fiducials	Template matching, decision-based NN	80–100%	MIT-BIH database [29]
Wang et al. [7]	31 subjects	Autocorrelation and discrete cosine transform	Nearest neighbor classifier (NN)	94.47%–97.8%	PTB and MIT-BIH database [29]
Singh and Gupta [9, 10]	50 subjects 250 ECG recordings	Time derivative and waveform curvature analysis	Correlation based classification	98.09% EER: 1.01%	Physionet database [29]
Multibiometric system using ECG signal Singh et al. [27]	78 subjects	Time derivative and waveform curvature analysis	Transformed based score fusion and classification	99.08% EER: 0.2%	Physionet database [29], face and fingerprint NIST [33]

be feasible, an ECG-enabled biometric system must perform the authentication task across wide range of conditions, while following issues are to be addressed:

(1) lack of standardization of the ECG features,

(2) variability of the ECG features,

(3) individuality of the ECG patterns,

(4) heritability of the ECG waves,

(5) customization of the ECG-enabled biometric system.

2.6.1. Lack of Standardization of ECG Features. Most methods described that the ECG as a biometric are based on temporal selection of wave boundaries, heuristically on time, and amplitude domain. Using the information of local maxima, minima and zero crossings at different scales, the methods identify the significant fiducials of the ECG waveforms. The effectiveness of these methods rely on the accuracy of the detected fiducials. This is an open challenge due to the lacking of any standardized definition of effective localization of the ECG wave boundaries.

Using ECG as a biometric, the knowledge utilized by researchers is based on medical findings of ECG information and they analyzed the ECG on approximate positions of medically dominant fiducials. Although the approximate localization of fiducials may be sufficient for clinical diagnosis, it could not be sufficient for biometric decision making. Because, application of using the ECG as a biometric expects the exact localization of its wave fiducials. A slight variation in the localization of its wave fiducials may cause a misclassification over a large data sets.

2.6.2. Variability of ECG Pattern. Another issue that challenges the use of the ECG as a potential candidate of

biometric is the variability of cardiac rhythm. Heart rate varies with individual's physiological and mental conditions. Stress, excitement, exercise, and other working activities may impact on the heart rate and it may elevate. It is to be noted that other than changes in the rhythm of a heartbeat, the morphology of an ECG remains unchanged. The changes in the heart rate consequently vary the heartbeat segments such as RR interval, PR interval, and QT interval. These features are carefully transformed and make them free from the impact of the varying heart rate before using them to biometric application [10].

Other factors like the presence of artifact and the emergence of irregular beats may cause changes in the morphology of the heartbeat. The dominant frequency of powerline interference 50–60 Hz can distort the ECG morphology while the presence of ectopic beats or premature beats can make an individual classification harder. Although the most methods are tested on a limited class of the ECG patterns it is, therefore, needed that the method could be extended to any number of morphologically distinct ECG waveforms for an operationally viable ECG-enabled biometric system.

2.6.3. Individuality of ECG Patterns. The issue of biometric individuality is a major concern to assess the performance of a biometric system. Individuality of a biometric refers to the likelihood of interclass variability and intraclass similarity of testing patterns observed in a target population. For example, individuality of the ECG refers that upto what extent the ECG patterns are scalable in a target population of sufficiently larger size. Statistically, the problem of individuality of ECG is yet to be addressed.

Unlike that, the feasibility of ECG as a candidate of biometric for individual authentication explored by most
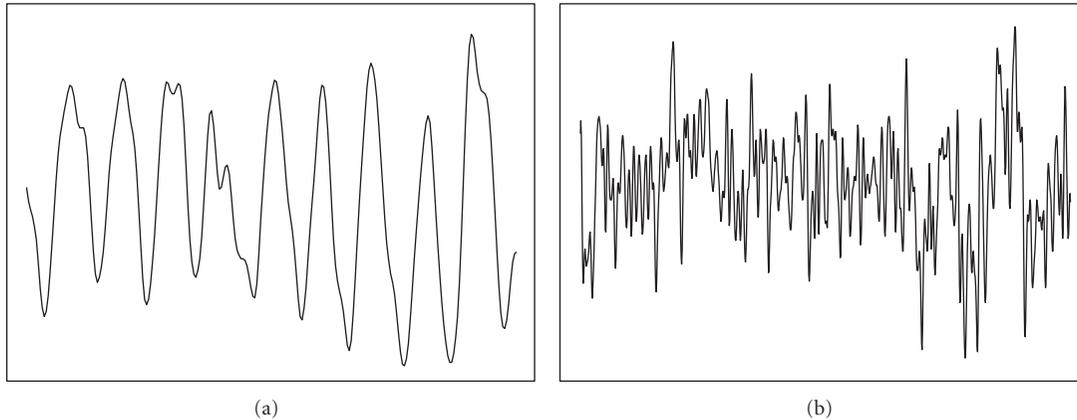
FIGURE 5: EEG signals of a real subject: (a) alpha waves and (b) beta waves.

methods has been tested on a limited data size. In order to assess large scale performance, the methods need to be tested on comparatively larger data size.

2.6.4. Heritability of ECG Waves. The heritability analysis of the ECG has shown intraclass correlation between adult male twins (monozygotic and dizygotic). In particular, ventricular repolarization (QT interval) and heart rate (RR interval) are significant heritable components while QRS complex does not show a significant heritable component [34].

2.6.5. Customization of ECG-Enabled Biometric System. A customized ECG-enabled biometric system similar to an ECG analyzer that diagnoses the cardiac ailments online is to be needed to perform the authentication task across a range of conditions. Such a device of size to a wrist watch or a mobile handset that can be fixed or holds on hands could be used for enrollment and perform the authentication task during an individual normal activity.

3. EEG as a Biometric

3.1. EEG Preamble. An electroencephalogram (EEG) is a recording of electrical activity of the brain that epoch spontaneously over a short period of time. Brain is made of two types of cells, neurons and glia cells [35]. Neurons are polarized protein molecules that transport charges across the membranes of the brain. The EEG measures the change in voltage resulting from ionic flow within the neurons. Hans Berger has shown that the electrical activity of brain can be recorded noninvasively through electrodes placed on the surface of the scalp [36] and named as alpha wave. The frequency range of alpha is 8–12 Hz. It emerges with closing of the eyes and with relaxation while it attenuates with opening of the eyes or mental exertion. The beta rhythms are low-amplitude waves with varying frequency between 12 and 30 Hz and often associated with active or anxious thinking. The wave patterns of alpha and beta rhythms are shown in Figures 5(a) and 5(b), respectively.

The automated analysis of an EEG has many applications in clinical neurophysiology. The EEG is a noninvasive tool used to measure the evoked potential and oscillatory features of the human brain function. The evoked potentials are transient waveforms, or brief perturbations in the ongoing activity. The oscillatory features in an EEG occur in response to the specific events that are typically studied through spectral analysis. Using the way to monitor the brain activity, it has applied in brain computer interfaces with an aim to enhance the communication and control abilities of motor-disabled people [37]. However, the extracted features of an EEG can be used to monitor the neurological status of the brain, in particular the identification of cerebral injury and management of patients with neurological trauma in critical care units.

3.2. Supporting Factors. The studies suggest that the brain electrical activity of an individual is unique and EEG can be used as a new biometric for people identity verification [12–17]. Although, the data acquisition of the EEG is somewhat cumbersome. The recorded signal is contaminated with noise and artifacts. Therefore, direct use of the signal for characteristic representation is difficult. In [16], authors have performed the experiment for people verification using their brain wave patterns. The authors have proposed a statistical framework based on Gaussian mixture models and maximum a posteriori model adaptation [38] that are used in other conventional biometric systems. They have shown that there are some mental tasks that are more appropriate for person identity verification than others.

The authors hold that the use of an EEG as biometric offers several advantages. First, it is confidential to an individual because the EEG waves correspond to his/her mental task. The EEG is very difficult to mimic and is almost impossible to be copied. An EEG is a reflection of individual dependent inner mental tasks and similar mental tasks are person dependent which cannot be reproduced by others. It is highly secure, so impossible to be stolen. The brain activities are sensitive to the stress and the mood of an individual, and one cannot force an individual to reproduce his/her mental passphrase.

3.3. Related Work. An earlier study that investigates the relationship between the EEG and the genetic uniqueness of individuals has been conducted by Poulos et al. [12]. They have employed autoregressive (AR) model to extract the parameters from the EEG and described the alpha rhythms. The parameters of the AR model have been later used as features in the classification process which is performed using linear vector quantizer and neural network adaption. The performance of the employed model to identify individuals has been tested on a set of 255 EEG recordings prepared from four persons. They have reported the classification accuracy of 72% to 80%. Paranjape et al. [13] have also examined 349 EEG epochs acquired from 40 subjects using AR model. Using discriminant analysis they have found the classification accuracy of about 80%.

Palaniappan and Mandic [14] have examined the energy of brain potentials evoked during processing of visual stimuli for individual identification. Following the study in [15], they have analyzed the potential of dominant frequency powers in gamma band visual evoked potential (VEP) signals as a biometric. The gamma band is a pattern of neural oscillation that may relate to the heightened brain activity, for example, consciousness and intellectual acuity. They have performed signal conditioning using sum and difference finite impulse response filter and that gamma band. VEP signals is extracted in the 3-db range of 32–48 Hz. In order to reduce the intraclass variance present in the signal, an average of the filtered VEP signals from all channels is computed using the following spatial averaging equation:

$$xx_{nT} = z_{nT} - \frac{1}{61}\sum_{i=1}^{61} z_{nTi}, \tag{5}$$

where x_{nT} represents the data sample of size n at discrete instance of time T and y_{nT} and z_{nT}, respectively, are the outputs of the sum and difference filters defined as follows:

$$y_{nT} = \sum_{j=0}^{M} \frac{M!}{j!(M-j)!} \cdot x_{(n-j)T},$$

$$z_{nT} = \sum_{j=0}^{M} (-1)^j \frac{N!}{j!(N-j)!} \cdot y_{(n-j)T}, \tag{6}$$

where M and N are filter length parameters that are set during the experiment.

After the preprocessing of VEP signals, features are extracted using a subspace technique called multiple signal classification. Finally, the extracted features are classified using the techniques based on k-nearest neighbors (kNN), Elman neural network (ENN) classifiers, and 10-fold cross-validation classification. The experiment has performed on a total of 3,560 VEP signals acquired from 102 subjects where there are a minimum of 10 and a maximum of 50 eye-blink-free VEP signals used for each subject. The classification accuracy of ENN classifier has reported to maximum and was found to be 98.12% ± 1.26% in comparison to the classification performance of kNN that has been found to be 96.13% ± 1.03%. They have argued that the proposed framework clearly indicates the potential of brain electrical activity as a biometric identity for persons identity verification.

Marcel and Millan [16] have proposed a statistical framework based on Gaussian mixture models (GMM) and maximum a posteriori model for identity verification of individuals using the EEG. They have argued that the potential of brain wave pattern for a individual resulted from strict validation and testing protocols. Let $\mathbf{x}^T = [x_1, x_2, \dots x_K]$ be a feature vector prepared from the EEG biometric data where $x_i \in \mathbb{R}^K$ and K is the number of features in each vector. Let $\psi^K(\mathbf{x}; \mu, \sum)$ be the K-variate Gaussian density function with mean μ and diagonl covariance matrix $\sum$ that is,

$$\psi^K\left(\mathbf{x}; \mu, \sum\right)$$
$$= \frac{1}{(2\pi)^{K/2}|\sum|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^T \sum^{-1} (x-\mu)\right). \tag{7}$$

Given the GMM parameter set (λ) and the mixture components (N), the estimates of density $P(x \mid \lambda)$ can be obtained as a mixture of Gaussian as follows:

$$P(x \mid \lambda) = \sum_{j=1}^{N} w_j \, \psi^K\left(x; \mu_j, \sum_j\right), \tag{8}$$

where $\lambda = (w_j, \mu_j, \sum_j)$ for all $j = 1, 2, \dots N$, w_j is the weight assigned to jth mixture components, $\sum_{j=1}^{N} w_j = 1$ and $w_j \geq 0$. The likelihood of a set of n feature vectors $X = [\mathbf{x}_i]_{i=1}^{n}$ can be obtained as

$$P(X\lambda) = \prod_{i=1}^{n} P(\mathbf{x}_i\lambda). \tag{9}$$

The maximum a posteriori training is used to estimate the model parameters (λ), λ_{MAP} as follows:

$$\lambda_{\text{MAP}} = \arg\max_{\lambda} P(X\lambda)P(\lambda), \tag{10}$$

where $P(\lambda)$ is the prior probability density of λ. Finally, the authentication decision $\Phi(X)$ is taken on the likelihood of claim coming from the genuine user $P(X \mid \lambda_G)$ or the likelihood of claim coming from an impostor $P(X \mid \lambda_I)$ as follows:

$$\Phi(X) = \begin{cases} 1, & \text{if } \log P(X \mid \lambda_G) - \log P(X \mid \lambda_I) \geq \tau \\ 0, & \text{otherwise} \end{cases} \tag{11}$$

for some threshold τ.

The performance of the authentication system has measured on half total error rate (HTER). It is defined as the average of false acceptance rate (FAR) and false rejection rate (FRR). In order to evaluate the potential of the proposed method the experiment has been conducted on the EEG data sets prepared from 9 normal subjects during 12 nonfeedback sessions over three days. The simulation results have been

obtained on distinct training or validation sets on different experimental protocols. The performance in terms of HTER has been found between 6.6%–36.2%. Finally, they have concluded that there are some mental tasks that are more appropriate for person authentication than others.

3.4. Performance Evaluation of Biometric Methods Using EEG.

Most proposed methods that used the EEG as biometric are in the stage of laboratory demonstration and their experiments are conducted mainly with the healthy subjects. The laboratory demonstration of the cited methods shows that the classification accuracy of individuals depends on their brain wave patterns such as alpha and beta waves. The performance estimates of the cited methods using EEG as a biometric under different validations and test scenarios are given in Table 2. Similar to the case of other bioelectrical signals, it is too early to ascertain any conclusion for using the EEG as a biometric for people authentication. The work is required to develop such a system that covers the population of clinically challenged persons in particular, the motor-disabled persons for their identity verification.

3.5. Issues and Challenges.

Summarizing the results obtained from the cited methods, it can be concluded that an EEG carries genetic information which offers a choice to use as a biometric for individual authentication. However, extensive analysis of the EEG is required to obtain statistically significant results for biometric applications. In order to work an operationally viable system using EEG as a biometric, the key issues that need to be addressed are as follows:

(1) placement of the scalp electrodes and the data acquisition,

(2) variability of the brain wave patterns,

(3) scalability to a larger population,

(4) heritability of the EEG patterns.

3.5.1. Placement of Scalp Electrodes and Data Acquisition.

An EEG usually involves recording from the scalp electrodes. The main source of an EEG is the synchronous activity of millions of neurons that have similar spatial orientation. In standard clinical practice, 19 electrodes are placed uniformly over the scalp; however the number of electrodes can be raised upto 256 to obtain detailed information about brain sources. Since the EEG has significantly lower spatial resolution; therefore, the choice of many electrodes and their placement needs special care to record highly spatial resolution data because an inappropriate spatial separation of electrodes causes distortion to the estimated potential on the brain surface. Further, any single electrode can be chosen as the reference and the potential at other location recorded with respect to this reference electrode. Therefore, inappropriate reference choice often leads to misinterpretation of brain source.

An EEG is characterized by small amplitude ($\sim \mu$V) noisy signal that falls in the range of 1–20 Hz. The EEG artifacts are mainly generated from the body such as, eye blinking, eye movements, cardiac activation and muscle activation. Movement of the subject and the placement of electrodes may cause electrode pops that originates spikes from a momentary change. The poor grounding of electrodes can result in a significantly high frequency (50–60 Hz) artifacts which are difficult to clean from the raw EEG data. As the artifact level increases the interclass variation increases (intraclass variation decreases) that results in a false nonmatch (false match). The total procedure of the EEG data acquisition requires absolute seriousness and complete participation of the subjects.

3.5.2. Variability of Brain Wave Patterns.

The EEG varies depending on the brain states. For example, different sleep stages such as rapid eye movement (REM) and nonrapid eye movement (NREM), walking, visualizing, and thinking result in a different EEG. The generated signals of visual evoked potential (VEP) that are known to be unique among individuals are related to consciousness and intellectual acuity which are controlled by motor activity of extraocular muscles. Therefore, people with severe neuromuscular disabilities who may lack extraocular muscle are inappropriate for identity verification using their EEG patterns.

A normal EEG varies with the age. The neonatal EEG is quite different from an adult EEG. The EEG in childhood generally shows slower frequency oscillations than an adult EEG [39]. The data analyzed by most proposed methods are lacking the information of time difference between the training and the test sets. Some of them are ranged from seconds to couple of days. But, no long term differences have been studied. Therefore, a periodic reenrollment of an individual EEG could be one strategy to monitor the long-term variations.

3.5.3. Scalability to a Larger Population.

The potential of brain electrical activity as a biometric explored by most methods is lacking the sample size needed to determine large-scale performance. Therefore, it is difficult to draw a definite conclusion about how to use the EEG as biometric for identity verification. However, the next step is to test the viability of the EEG as biometric over larger data sets where different mental states under different scenarios need to be investigated. Although, the study in [14] has experimented a total of 3,560 VEP signals collected from 102 subjects that are free from eye-induced artifacts, the feasibility of EEG data collected under multiple brain states including REM and NREM sleep to assess the performance for individual authentication over large data sets is yet to be addressed.

3.5.4. Heritability of EEG Patterns.

The spectral analysis of the EEG among twins has shown no significant differences [40]. However, the correlation of spectra of twins (monozygotic and dizygotic) has shown the intra-pair similarities that are significantly more than the inter-individual similarity between unrelated persons [41].

TABLE 2: Performance estimates of various methods using EEG as a biometrics under different validations and test conditions. EO: eye open and EC: eye closed, VEP: visual evoked potential, NN: neural network, MAP: maximum a posteriori model, and HTER: half total error rate defined as (FAR + FRR)/2.

Methods	Data size	Data representation techniques	Classification techniques	Classification accuracy	Test conditions
Poulos et al. [12]	4 subjects 255 EEG epochs	Autoregressive (AR) model	Linear vector quantizer (LVQ) NN	72%–80%	Resting with EO
Paranjape et al. [13]	40 subjects 349 EEG epochs	AR model	Discriminant analysis	80%	Resting with EO, resting with EC
Palaniappan and Mandic [14]	102 subjects 3,560 VEP signals	Multiple signal classification	k-Nearest neighbors (kNN), Elman NN	98.12% ± 1.26% 96.13% ± 1.03%	Eye-blink-free VEP signals
Marcel and Millan [16]	9 subjects	Power spectral density (PSD)	Gaussian mixture model and MAP	N/R HTER: 7.1%–36.0%	Evaluations of hand movements and words generation

4. Discussion and Future Work

This paper explores the effectiveness of bioelectrical signals especially, the ECG and EEG as biometrics for individual authentication. We have reported the research challenges incorporating the ECG or EEG in the domain of biometric applications. Incorporating the ECG or EEG signals to be used as a biometric offers several advantages. The ECG or EEG is confidential to an individual, therefore they are harder to mimic. They are highly secured, so almost impossible to be stolen. Using conventional biometric identities, it is indeed harder to design a secure and robust authentication system from the system components that are neither secrets nor revocable. The characteristics of the ECG or EEG signals create a difference from the conventional biometrics and offer an alternative to explore their feasibility in designing a secure identity verification system. As a countermeasure of spoof attacks, the ECG or EEG signals have the inherited feature of vitality. It signifies that the physiological features of the ECG or EEG can not be acquired unless the person is not alive.

Although the laboratory demonstration of using the ECG or EEG signals to authenticate individuals shows moderate performance, they can supplement to the other biometrics in a multibiometric framework for robust authentication. In particular, we have shown that the ECG signal can be combined with the face and fingerprint biometric information with an optimum system performance. In conclusion, the fruitful directions of further research may include the following.

(1) To be feasible, the system using bioelectrical signals as biometrics must perform the authentication task across a wide range of condition and over a larger population whereas the data is acquired at larger time intervals.

(2) The effectiveness of most methods using the ECG or EEG as biometric has been tested on normal healthy subjects. Therefore, efforts should be made to explore the extension of the proposed frameworks to the nonhealthy subjects.

(3) It is important to discover that up to what extent the ECG or EEG varies with emotions or different states of mind. Heart rate varies with a variety of stimuli. The brain wave pattern varies depending on neuron states. An investigation of robustness to the subjects of different mental and emotional states is needed to validate the results of most methods.

(4) The data acquisition of bioelectrical signals in particular the EEG, is a challenging activity. The placement of electrodes to right position such as the nonuniform or inappropriate spatial separation may cause distortion in the acquired signal. Therefore, the right placement of electrodes requires more knowledge and understanding of brain and heart physiology for EEG and ECG signals recording, respectively.

(5) The analysis methods of the ECG or EEG signals are still in its infancy. The exploration of alternative classification techniques that are robust enough to handle variations present in the features is needed. The specific efforts will be required to check the quality of the data acquired abruptly that may be due to noncooperation of the user or the presence of some artifacts. Data representation methods that would work in the nonstandardization features framework are further required.

(6) In order to categorize the ECG or EEG signals as lesser obtrusive biometrics, a customized system of size as small as a mobile phone handset is needed for enrollment and authentication. It will facilitate not only the authentication process but also the performing function during individuals normal activities.

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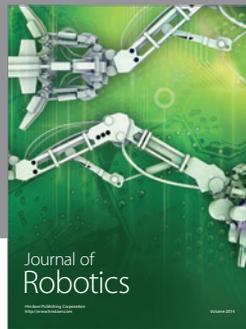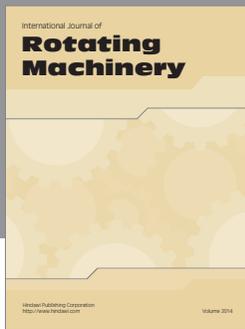
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