ECG Biometric Recognition: A Comparative Analysis

Ikenna Odinaka, *Student Member, IEEE*, Po-Hsiang Lai, *Student Member, IEEE*, Alan D. Kaplan, *Member, IEEE*, Joseph A. O'Sullivan, *Fellow, IEEE*, Erik J. Sirevaag, and John W. Rohrbaugh

***Abstract*—The electrocardiogram (ECG) is an emerging biometric modality that has seen about 13 years of development in peer-reviewed literature, and as such deserves a systematic review and discussion of the associated methods and findings. In this paper, we review most of the techniques that have been applied to the use of the electrocardiogram for biometric recognition. In particular, we categorize the methodologies based on the features and the classification schemes. Finally, a comparative analysis of the authentication performance of a few of the ECG biometric systems is presented, using our inhouse database. The comparative study includes the cases where training and testing data come from the same and different sessions (days). The authentication results show that most of the algorithms that have been proposed for ECG-based biometrics perform well when the training and testing data come from the same session. However, when training and testing data come from different sessions, a performance degradation occurs. Multiple training sessions were incorporated to diminish the loss in performance. That notwithstanding, only a few of the proposed ECG recognition algorithms appear to be able to support performance improvement due to multiple training sessions. Only three of these algorithms produced equal error rates (EERs) in the single digits, including an EER of 5.5% using a method proposed by us.**

***Index Terms*—Authentication, biometrics, classification, ECG, EKG, electrocardiogram, fusion, identification, recognition, verification.**

I. Introduction

INHERENT in the concept of identity is both the permanence and uniqueness of every individual. Biometric systems that perform identity recognition on the basis of informative data collected from an individual are vital for security. Such systems may take many forms, varying with respect to the type and quantity of data collected, specific algorithms used, and operational modes. Biometric identity recognition is attractive because data are measured from the body itself, and are ubiquitous (or nearly so). Various biometrics have been proposed for use in identity recognition, such as fingerprint, iris, face, and speech. These biometrics each have operational trade-offs in terms of performance, measurability (ease of collecting data), and circumvention (ease of replication), and acceptability [1]–[4].

Recently, cardiovascular signals have been studied for use in identity recognition problems, using electrocardiography [5]–[7] and carotid laser Doppler vibrometry (LDV) [8]–[10]. These signals differ from the signals mentioned above in that they are intrinsically connected to critical biological function. Circumvention is significantly more difficult with these biometrics, and measurability is nearly always guaranteed. Significant challenges remain to incorporate this information into successful recognition systems.

An ECG is a recording of the electrical activity of the heart. Electrodes placed on the surface of the body are used to measure the electrical signals originating from the myocardium, the heart muscle. The ECG consists of three main components: P wave, QRS complex, and T wave. The P wave occurs due to atrial depolarization, the QRS complex, due to ventricular depolarization, and the T wave, due to ventricular repolarization.

Identity recognition based on the ECG dates back to the pioneering work of Biel *et al.* [5], Irvine *et al.* [7], Kyoso and Uchiyama [6]. The premise of these and other studies is that the ECG contains sufficiently detailed information pertaining to the electrical operation of the heart, and that the nature of this activity is highly personalized. The ECG signal will be highly individualized, insofar as it depends on functional and structural properties including conductivity of the heart and other tissue. The main hypothesis shared by these studies is that *the detailed electrical activity of the heart, as captured by the ECG, is of sufficient quality to be used in high performance identity recognition systems*.

In this review paper, we summarize existing methods from the literature on identity recognition systems based on the ECG. The use of the ECG in this setting has three key properties [11]:

- ECG signals are difficult to counterfeit, in supervised conditions.
- The ECG signal is present in all living individuals.
- ECG signals provide additional information related to psychological states, and physiological and clinical status, which may be of interest.

An identity recognition system typically operates in either the identification or authentication mode. In the identification mode, the system outputs the identity of an individual using the input data. In the authentication mode, the system accepts or rejects a claimed identity associated with the input data. When

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I. Odinaka and J. A. O'Sullivan are with the Preston M. Green Department of Electrical and Systems Engineering, Washington University in Saint Louis, St. Louis, MO 63130 USA (e-mail: iodinaka@ese.wustl.edu).

P.-H. Lai is with Samsung Dallas Technology Laboratories, Dallas, TX 75082 USA.

A. D. Kaplan is with Exponent, Inc., New York, NY 10170 USA.

E. J. Sirevaag and J. W. Rohrbaugh are with the Department of Psychiatry, Washington University School of Medicine, St. Louis, MO 63110 USA.

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the claimed identity is wrongly rejected, the system is said to have incurred a false rejection error. When the claimed identity is wrongly accepted, a false acceptance error occurs.

The methods that have been proposed for ECG biometrics can be grouped based on the number of ECG data channels used, the operational setting, the method for generating desirable features, and the type of classifier adopted.

All the studies on ECG biometrics are based on one-channel, two-channel, three-channel, or 12-lead ECG signals. These are by far the most common lead configurations employed in clinical practice. Of these, ECG as a biometric based on a single channel is the most studied; simplicity plays a major role in this, since one does not have to worry about effective channel combination schemes. However, in this context, it is not clear that simpler is necessarily better. Many of the single-channel studies use the data from one of the channels of a standard 12-lead ECG recording. However, there are studies that use nonstandard electrode placement techniques; Chan *et al.* [12] studied the biometric performance of one-channel ECG signals recorded from the pads of individuals' thumbs, Shen *et al.* [13] used single-channel ECG signals obtained from the palms, while Odinaka *et al.* [11] used single-channel ECG signals obtained from electrodes placed bilaterally across the lower rib cage. Wübbeler *et al.* [14] used data from three channels, while Agrafioti *et al.* [15] fused data from all 12 ECG channels for recognition purposes.

Most studies of ECG biometrics require the segmentation of an ECG recording into single heartbeat signals. One of the reasons for this is the ease of signal alignment, which leads to coherent feature extraction. Another reason for segmenting ECG recordings into single heartbeat signals is that the variations across individuals within one cardiac cycle is thought to be sufficient in discriminating amongst them. Exceptions include the works of Plataniotis *et al.* [16], Agrafioti *et al.* [17], Li and Narayanan [18], and Loong *et al.* [19]. Plataniotis *et al.* and Agrafioti *et al.* used features based on the autocorrelation of nonoverlapping segments of the ECG recording, while Li and Narayanan, and Loong *et al.* used linear frequency cepstral coefficients (LFCC) and linear predictive coding (LPC) spectral coefficients of overlapping segments of the ECG recording, respectively.

ECG signals obtained during normal resting conditions have been investigated by most studies [5], [11], [20]. In addition, there have been studies designed to test the feasibility of ECG biometrics during changes in emotional and mental states [21], exercise [22], and benign cardiovascular conditions [23].

Based on the features that are extracted from ECG signals, we can classify ECG biometric methods as either fiducial-based, non fiducial-based, or a hybrid. The fiducial-based methods extract temporal, amplitude, area, angle, or dynamic (across heartbeats) features from characteristic points on the ECG signal. The features include but are not limited to the amplitudes of the P, R, and T waves, the temporal distance between wave boundaries (onset and offset of the P, Q, R, S, and T waves), the area of the waves, and slope information [5], [6], [20], [21], [24]. The non fiducial-based methods do not use the characteristic points as features. Instead, features like wavelet coefficients [12] and autocorrelation coefficients [16] are utilized. The hybrid methods combine both fiducial-based features and non fiducial-based features [25], [26].

There have been several choices of classifiers in the literature, ranging from simple nearest neighbor/center classifiers [17] to neural networks [27] and support vector machines [18]. Previous literature reviews of some of the methods that have been applied to ECG based identification can be found in the reports of Nasri *et al.* [28], Sufi *et al.* [29], Chauhan *et al.* [30], and Israel and Irvine [31].

The rest of this paper is organized as follows: In Section II, we review the ECG biometric methodologies; in Section III, we provide a comparative analysis of a few of the methods using our inhouse multisession database. Section IV is devoted to open issues in ECG recognition, while Section V provides a summary and conclusion. The final section serves as an Appendix, were we describe some of the databases that have been utilized in the literature.

II. Survey of ECG Recognition Methods

Most studies in ECG biometrics have employed single-channel ECG signals following the work of Biel *et al.* [5], who showed that a single channel contains sufficient information to support biometric recognition. However, some studies have adopted multiple channels in an effort to improve performance. Such studies include those that utilized two channels [32], three channels [14], [33], and 12 channels [5], [15].

There are a host of feature extraction and reduction techniques that have been proposed for use in ECG recognition. Moreover, different types of classifiers have been utilized for placing test feature vectors into predefined classes. Table I shows most of the methodologies that have been proposed for ECG recognition, in chronological order of publication. Within a year, the studies are arranged in lexicographical order based on the first author's last name. Similarly, the abbreviation descriptors are ordered in lexicographical order.

A. Categorization Based on Features

1) Algorithms Based on Fiducial Features: Algorithms based on fiducial features use the characteristic points—wave onset, peak (minima or maxima), and offset, extracted from an ECG trace to generate the feature set. We define characteristic points to be the actual points located on an ECG trace and fiducial features to be the features that are derived from these characteristic points. For example, the peak of the R wave is a characteristic point, while the time difference between the peaks of the R and T waves, the RT interval, is a fiducial feature. There are four types of fiducial features [61] that have been used for ECG based recognition: temporal, amplitude, angle, and dynamic (R-R intervals). Several subsets of these fiducial features have been used in the literature [5]–[7], [21], [22], [24], [34], [36], [38], [42], [45], [46], [56], [62].

2) Algorithms Based on Nonfiducial Features: Algorithms based on nonfiducial features do not use the characteristic points for generating the feature set. Instead, some of the algorithms use one or more of the characteristic points for heartbeat segmentation [12], [41], while others do not use the characteristic points at all, but segment the ECG recording into segments that may be overlapping [18] or nonoverlapping [15], [16].

TABLE I
SUMMARY OF EXISTING LITERATURE ON ECG RECOGNITION
FT = FEATURE TYPE; CT = CLASSIFIER TYPE; AP = AUTHENTICATION PERFORMANCE; IP = IDENTIFICATION PERFORMANCE

Study	Sample Size n	Technique	FT	CT	Session Type	AP (%)	IP (%)
Biel *et al.* [5]	20	10 fiducials + PCA + GMC	F	GMC	Multiple days	-	100
Irvine *et al.* [7]	5	3 temporal fiducials + MD	F	LDAC	Multiple states	-	-
Kyoso and Uchiyama [6]	9	4 temporal fiducials + GMD	F	LDAC	Single day	-	>90
Shen *et al.* [20]	20	7 fiducials and HB + TMCC + DBNN (HC)	H	NN	Single day	-	100
Irvine *et al.* [34]	104 (WS), 95(AS)	15 temporal fiducials + WLFS + LDAC	F	LDAC	Multiple states	-	91(WS), 88(AS)
Kyoso[35]	21	9 fiducials + GMD	F	LDAC	Single day	-	-
Palaniappan and Krishnan [36]	10	6 fiducials + MLP-BP or SFA	F	NN	Single day	-	97.6(MLP-BP)
Israel *et al.* [21]	29	15 temporal fiducials + WLFS + LDAC	F	LDAC	Multiple states	-	97-98(AST), 100(AEL)
Kim *et al.* [22]	10	4 RHBTF + GMD	F	LDAC	Multiple states	-	-
Saechia *et al.* [37]	35	FTF + MLP-BP	NF	NN	-	-	97.15
Shen [13]	168	17 fiducials and HB + NNC,WED (HC)	H	*k*NN	Single day	-	95.3
Chan *et al.* [12]	60	SAECG + WDIST and CCORR	NF	NC	Multiple days	-	90.8
Plataniotis *et al.* [16]	14	AC/DCT + NNC,ED or GLLC	NF	*k*NN	Single day	-	92.9(NNC), 100(GLLC)
Zhang and Wei [38]	520	14 fiducials + PCA + BC	F	GMC	Single day	-	97.4
Molina *et al.* [39]	10	MSRRS + ED	NF	NC	Multiple days	2(EER)	-
Silva *et al.* [26]	168	8 fiducials and SSMW + FSC + NNC,ED	H	*k*NN	Multiple states	-	99.63, 99.97(FSC)
Wübbeler *et al.* [14]	74	WHVD + NC	NF	NC	Multiple days	2.8(EER, 3 channels)	98.1(3 channels)
Agrafioti and Hatzinakos [15]	14	AC/LDA + NNC,ED	NF	*k*NN	Single day	-	100(12 leads)
Agrafioti and Hatzinakos [17]	27	TMAC + AC/LDA or AC/DCT + NNC,ED (HC)	NF	*k*NN	Single day	<1(EER)	96.3(AC/DCT), 100(AC/LDA)
Agrafioti and Hatzinakos [23]	56	APC and PVC Screening + AC/LDA + NNC,ED	NF	*k*NN	Single day	∼5(EER)	96.42
Chiu *et al.* [40]	45	DWTMSS + NC,ED	NF	NC	Single day	12.50(FAR), 5.11(FRR)	95.71(PHBIA)
Fatemian and Hatzinakos [41]	27	MRHB + CC	NF	HMS	Single day	-	99.63
Gahi *et al.* [42]	16	24 fiducials + IGRFS + NC,MD	F	LDAC	Single day	-	100
Irvine *et al.* [43]	39	EigenPulse + NC,ED	NF	NC	Single day	-	100
Khalil and Sufi [44]	15	LPE of QRS wave	NF	LMS	Single day	-	-
Singh and Gupta [45], [46]	25, 50	19 fiducials	F	LMS, HMS	Single day	-	99
Sufi *et al.* [47]	15	PDM of P, QRS, T waves, NC	NF	NC	Single day	0(EER)	100
Wan and Yao [27]	23	DWTMRRS + MLP-BP	NF	NN	Multiple days	-	100 (n = 15)
Wang *et al.* [25]	13, 13	21 fiducials and RDHB + WLFS + LDAC or *k*NN (HC)	H	LDAC or *k*NN	Single day	-	100
Yao and Wan [48]	20	DWTMRRS + PCA	NF	LMS	Mixed	-	91.5
Agrafioti *et al.* [49]	10	Template Updating	NF	*k*NN	Multiple states	3.4(EER,HFU), 6.3(EER, MFU), 14.7(EER, LFU)	-
Boumbarov *et al.* [50]	9	HMMHS + PCA or LDA + RBFNN	NF	NN	-	-	∼86

Most of the methods based on nonfiducial features require the detection of the R peaks for heartbeat segmentation and alignment [11], [12], [14], [18], [27], [32], [33], [37], [39], [40], [43], [48], [50], [51], [53], [55], [57].

There are a few methods that not only require the detection of the R peaks, but also some other characteristic points such as the onset and peak of the P wave, the onset and end of the QRS complex, the peak and end of the T wave [41], [58]–[60]. Some methods require the detection of all or a subset of the three major components of each heartbeat (P wave, QRS complex, and T wave) for feature extraction [37], [44], [47].

However, there are other methodologies that do not extract any characteristic points, but rather segment the entire ECG trace into nonoverlapping or overlapping windows, and extract

TABLE I
SUMMARY OF EXISTING LITERATURE ON ECG RECOGNITION (CONTINUED)
FT = FEATURE TYPE; CT = CLASSIFIER TYPE; AP = AUTHENTICATION PERFORMANCE; IP = IDENTIFICATION PERFORMANCE

Study	Sample Size n	Technique	FT	CT	Session Type	AP (%)	IP (%)
Fang and Chan [33]	100	ECGPSR + SC or MNPD	NF	HMS or LMS	Single day	-	93(1 channel, MNPD), 99(3 channels, MNPD)
Homer *et al.* [51]	12	GF and RARMA + NNC,ED	NF	*k*NN	Multiple states	-	∼85.2
Irvine and Israel [24]	29, 75	WSPR	F	GMC	Multiple states	∼0.01(EER, n = 29), >0.05(EER, n = 75)	-
Agrafioti and Hatzinakos [52]	52	AC/LDA, PT + NNC,ED	NF	*k*NN	Mixed	>10	92.3
Coutinho *et al.* [53]	26	QHB + ZMCP + MDL	NF	NC	Multiple states	-	100
Ghofrani and Bostani [54]	12	ARC, MPSD, HD, LE, AE + *k*NN or MLP-BP or PNN	NF	*k*NN or NN	Mixed	-	100
Jang *et al.* [55]	65	EigenPulse + Heartbeat Screening	NF	NC	Multiple states	-	>96.92
Li and Narayanan [18]	18	HPE + SVMLK	NF	SVM	Single day	0.55(EER)	98.11
Li and Narayanan [18]	18	LFCC + HLDA + GMM + LLRC or SVMGSV	NF	GMC or SVM	Single day	4.05(EER, LLRC), 2.5(EER, SVMGSV)	94.78(LLRC), 95.9(SVMGSV)
Li and Narayanan [18]	18	SLF [SVMGSV + (HPE + SVMLK)]	NF	SVM	Single day	0.5(EER)	98.26
Loong *et al.* [19]	15	LPCS + MLP-BP	NF	NN	Single day	-	100
Odinaka *et al.* [11]	269	log-Normal spectrogram	NF	GMC	Multiple days	0.37(EER, WS), 5.58(EER, ASWF)	99(WS), 76.9(ASWF)
Venkatesh and Srinivasan [56]	15	6 fiducials + FLDA,*k*NN + NNC,DTW	F	*k*NN	Single day	-	100
Yao and Wan [57]	30	DWTMRRS + BMS + WDIST	NF	NC	Mixed	-	>80
Ye *et al.* [32]	18, 18, 47, 65	DWT and ICA + SVMRBK	NF	SVM	Single day	-	99.6 (2 channels, PHBIA, n = 47)
Lourenço *et al.* [58]	16	MANRHB + NC,ED	NF	NC	Single day	13(EER)	94.3
Safie *et al.* [59]	112	PAR + NC,ED	NF	NC	Mixed	9.89	-
Tawfik *et al.* [60]	22	DCT of QRS + MLP-BP	NF	NN	Multiple days	-	99.09

AC/DCT = Autocorrelation/Discrete Cosine Transform; AC/LDA = Autocorrelation/Linear Discriminant Analysis; AE = Approximation Entropy; AEL = Across Electrode Locations; APC = Atrial Premature Contraction; ARC = Autoregression Coefficients; AS = Across Sessions; AST = Across Stress Tasks; ASWF = Across Sessions With Fusion; BC = Bayes' Classifier; BMS = Birge–Massart Strategy; CC = Cross Correlation; CCORR = Cross CORRelation measure; DBNN = Decision-Based Neural Network; DTW = Dynamic Time Warping; DWT = Discrete Wavelet Transform; DWTMRRS = DWT of Mean R-R Segments; DWTMSS = DWT of Mean Synthetic Signal; ECGPSR = ECG Phase Space Reconstruction; ED = Euclidean Distance; EER = Equal Error Rate; F = Fiducial; FAR = False Accept Rate; FLDA = Fisher's LDA; FRR = False Reject Rate; FSC = Feature Selection Context; FTF = Fourier Transform Features; GF = Gaussian Fit; GLLC = Gaussian Log-Likelihood Classifier; GMC = Generative Model Classifier; GMD = Generalized Mahalanobis Distance; GMM = Gaussian Mixture Model; H = Hybrid; HB = Heart Beat; HC = Hierarchical Classification; HD = Higuchi Dimension; HFU = High Frequency Updating; HLDA = Heteroscedastic LDA; HMMHS = Hidden Markov Model Heartbeat Segmentation; HMS = High Match Score; HPE = Hermite Polynomial Expansion; ICA = Independent Component Analysis; IGRFS = Information Gain Ratio Feature Selection; k NN = k Nearest Neighbors; LDA = Linear Discriminant Analysis; LDAC = LDA Classifier; LE = Lyapunov Exponent; LFCC = Linear Frequency Cepstral Coefficient; LFU = Low Frequency Updating; LLRC = Log-Likelihood Ratio Classifier; LMS = Low Match Score; LPCS = Linear Predictive Coding Spectrum; LPE = Legendre Polynomial Expansion; MANRHB = Mean of Amplitude-Normalized Resampled Heart Beats; MD = Mahalanobis Distance; MDL = Minimum Description Length; MFU = Medium Frequency Updating; MITDB = MIT Database; MLP-BP = Multilayer Perceptron Back-Propagation neural network; MNPD = Mutual Nearest-Point Distance; MPSD = Mean Power Spectral Density; MRHB = Median of Resampled Heart Beats; MSRRS = Morphological Synthesis of R-R Segments; NC = Nearest Center; NF = Nonfiducial; NN = Neural Network; NNC = Nearest Neighbor Classifier; PAR = Pulse Active Ratio; PCA = Principal Component Analysis; PDM = Polynomial Distance Measurement; PHBIA = Per Heart Beat Identification Accuracy; PNN = Probabilistic Neural Network; PT = Periodicity Transform; PVC = Premature Ventricular Contraction; QHB = Quantization of Heart Beat; RARMA = Residual Auto-Regressive Moving Average; RBFNN = Radial Basis Function Neural Network; RDHB = Reduced-Dimension Heart Beat (via PCA or LDA); RHBTF = Resampled Heart Beats; SAECG = Signal-Averaged ECG; SC = Spatial Correlation; SF = Score Function; SFA = Simplified Fuzzy ARTMAP; SIMCA = Soft Independent Modeling of Class Analogy; SLF = Score Level Fusion; SSMW = Subsampled Mean Wave; SVM = Support Vector Machine; SVMGSV = SVM GMM Super Vector; SVMLK = SVM Linear Kernel; SVMRBK = SVM Radial Basis Kernel; TMAC = Template Matching based on Autocorrelation coefficients; TMCC = Template Matching based on Cross Correlation; WDIST = Wavelet DISTance; WED = Weighted Euclidean Distance; WHVD = Wübbeler's Heart Vector Distance; WLFS = Wilks' Lambda Feature Selection; WS = Within Session; WSPR = Wald's Sequential Probability Ratio; ZMCP = Ziv-Merhav Cross Parsing

features from those windows [15]–[19], [23], [49], [52], [54], [63], [64].

3) Algorithms Based on Hybrid Features: There are a few algorithms that use nonfiducial features for pruning the match space and fiducial features for the final classification [13], [20], while there are others that combine fiducial features with nonfiducial features to create the feature set [25], [26], [65].

B. Categorization Based on Classifier

Based on the type of classifier utilized, one can divide ECG recognition methodologies into seven groups: k nearest neighbors, nearest center, LDA, neural networks (NNs), generative model classifiers (GMCs), support vector machines (SVMs), and others. Of these groups, the most frequently used in the ECG recognition literature are nearest neighbor, nearest center, and LDA.

1) kNN Classifiers: k nearest neighbors (kNN) classifiers, which include the nearest neighbor classifier (NNC) as a special case ($k = 1$), is the most frequently used classifier type in the ECG recognition literature [13], [15]–[17], [23], [25], [26], [51], [54], [56]. It involves comparing a feature vector to a collection of feature vectors, and selecting the top k vectors that produce the best match.

2) Nearest Center Classifiers: A nearest center classifier can be seen as a special kind of nearest neighbor classifier, where a representative training feature vector is created during training, as opposed to using the entire training feature vector set [12], [14], [39], [40], [43], [47], [53], [55], [57]–[59].

3) LDA Classifiers: Classification based on linear discriminant analysis, a special case of generative model classifiers (GMCs), has been used by several studies in the ECG biometrics literature [6], [7], [21], [22], [25], [34], [35], [42].

4) Neural Network Classifiers: Neural network classifiers have been used extensively for classification, because of their ability to learn complex relationships between the feature vectors in the training set. The most commonly used neural network for ECG biometric recognition is the multilayer feedforward (perceptron) neural network [19], [27], [36], [37], [54], [60]. Other neural networks that have been used in the literature include decision-based neural network (DBNN) [20] and radial basis function neural network (RBFNN) [50].

5) Generative Model Classifiers: Generative model classifiers depend on modeling the distribution of the feature vectors. The estimated models are later used for classification. These classifiers include the log-likelihood ratio (LLR) [11], [16], [18], [24], Bayes' classifier [38], SIMCA [5].

6) SVM Classifiers: Support vector machines have also been used in a few studies to find the linear boundaries between classes, after projecting the feature vectors in the training set to a high (possibly infinite) dimensional space. Ye *et al.* [32] used an SVM based on a Gaussian radial basis kernel. Also, Li and Narayanan [18] used SVMs based on a linear kernel for classification.

7) Match Score Classifiers: This category of algorithms include those that cannot be strictly put into any of the six groups above. Most of the algorithms in this category depend on the computation of match scores based on the similarity (cross correlation [41], spatial correlation [33]) or the dissimilarity (MNPD [33]) between a feature vector and a stored template/model.

When similarity is sought, during identification, the template that gives the highest match score is associated with the test (probe) signal; during authentication, the score is compared to a threshold and the claimed identity is accepted, if the score is greater. On the other hand, when dissimilarity is desired, during identification, the template that gives the lowest match score is associated with the test (probe) signal; during authentication, the score is compared to a threshold and the claimed identity is accepted, if the score is smaller.

Examples of classifiers that seek a similarity between the feature vector and the stored template include template matching algorithms [17], [20], [33], [41], [46]. Some classifiers find the dissimilarity between the feature vector and the stored template [33], [44], [45], [48].

C. ECG in a Multimodal Framework

The ECG has been used in combination with other modalities (biometric or nonbiometric) in multimodal systems, either as a means of liveness detection, to prevent replacement attacks in a continuous monitoring setting, or to improve overall biometric performance.

ECG has been used in combination with other modalities for human recognition. Israel *et al.* [66] combined ECG features with those from the face to enhance identification performance. Fatemian *et al.* [67] combined the ECG and phonocardiogram (PCG) at the decision level, to obtain an improvement in recognition performance. Moreover, ECG has been combined with electroencephalogram (EEG) [68] for human recognition purposes. ECG has also been combined with accelerometer readings for continuous authentication in a remote health monitoring setting [65]. Damousis *et al.* [69] looked at ECG as part of a larger framework of multiple biometrics including face and voice.

Agrafioti *et al.* [70] proposed an identity management system based on the ECG signals recorded as part of a body area sensor network (BAN). To avoid misclassifications, which can have drastic impacts on the routing and storing of health information, a two-stage identification scheme was implemented, where the AC/LDA system [17] was used in the first stage to obtain a ranked list of the top matching individuals to the probe ECG signal. In the second stage, a fuzzy commitment scheme (a key-binding authentication method) was used for validation—to select the best matching individual from the ranked list of individuals.

III. Comparative Analyses and Results

Using our inhouse database [11], we studied the authentication performance of some of the methodologies that have appeared in the ECG recognition literature. The criteria for selecting the algorithms include: uses nonfiducial features, and requires reasonable amount of training and testing times. There are several reasons for not implementing methodologies that use fiducial features including [43]:

- Variability among standards for detection of some characteristic points, such as the onset and offset of the component waves of the ECG.
- Location of some characteristic points are disproportionately affected by the presence of noise, even using a fixed fiducial detector.
- Difficulty in defining the boundaries and peaks of atypical heartbeats usually leads to an increased failure to enroll.
- Problems with generalizability to larger databases, when the number of features are limited.

We studied the effect of variability across different measurement times on the performance of the biometric system, and how to improve the performance by fusing information from multiple sessions. Although considerable variation can occur in an ECG recording over the course of a day, nonetheless, we define multiple sessions as data collected on different days.

The authentication performance of the ECG biometric systems was evaluated using equal error rate (EER) and the detection error trade-off (DET) curve. A DET curve is a plot of the error rates on each axis [71]; EER is a point on the DET curve where the false acceptance (match) rate (FAR) equals the false rejection (nonmatch) rate (FRR) [72]. We consider three operational scenarios using ECG recordings obtained on three different days [11]:

- Training and testing on session 1 (within-session analysis).
- Training on session 1 and testing on session 3 (across-session analysis without fusion).
- Training on sessions 1 and 2, and testing on session 3 (across-session analysis with fusion). In this scenario, the training data from both sessions are simply pooled.

For each of the scenarios, we consider using a varying number of heartbeats (or chronological time equivalent) for training and testing. For the top performing (in terms of EERs) algorithms, we also present the DET curves, for across-session (with fusion) analysis.

All the methodologies were implemented to follow the descriptions provided by the authors. Exceptions are the works of Fatemian and Hatzinakos [41], and Yao and Wan [27], [48]. Fatemian and Hatzinakos used a stationary wavelet transform (SWT) to reconstruct the signal part of the raw ECG recording after which a moving window was used to smooth the signal. As implemented by us, a 1–40 Hz band-pass filter was used because there was significant baseline wander uncorrected by the SWT preprocessing. Yao and Wan used a wavelet-based denoising approach, using hard thresholding, for preprocessing. We employed a 1–40 Hz band-pass filter for preprocessing, in the place of wavelet-based denoising, because the denoising approach led to a noticeable distortion of the ECG recording. Also, in addition to implementing the algorithm proposed by Molina *et al.* [39], we also implemented a slight modification of the algorithm, where band-pass filtering, using a 1–40 Hz frequency band, supplanted the morphological baseline wander removal technique. In the tables that follow, "Molina (M)" will be used to represent this modified version. Fang and Chan [33] implemented an algorithm that creates a three-dimensional ECG portrait, and finds the similarity or dissimilarity between the ECG portraits during authentication. In particular, we implemented the algorithm that finds the similarity between portraits via spatial correlation (SC), which is suboptimal to the one which finds the dissimilarity between portraits through the mutual nearest point distance (MNPD). MNPD was not utilized because it does not satisfy the timing constraint.

Moreover, the algorithm proposed by Wübbeler *et al.* [14] uses three channels, but is adapted here to use a single channel.

A. ECG Dataset

We used the same database from previous work [11], with the exclusion of data from four individuals for whom the ECG signal was technically flawed. The current database has 265 individuals (121 males and 144 females). The ages of the individuals varied from 18 to 66 years, with mean and standard deviation of 38.9 and 14.1 years respectively. As is typical in a community sample of this sort, 40.4% of the individuals self-reported some heart-related disease, including hypertension. 46.8% of the individuals reported using medicines or other substances that may affect the ECG signal. 28.3% of the individuals were healthy and did not use substances that may affect the ECG signal. 72.1% of the individuals were Caucasians.

The ECG signals were obtained from a single channel, with the electrodes placed bilaterally on the lower rib cage. This differs from that of the X channel, in the standard orthogonal (Frank) lead configuration, where the electrodes are located at the mid axillary lines in the fourth intercostal space [73]. The ECG signal acquired at this location has strong R and P wave components and is less affected by movement artifact than some of the conventional ECG channels. Additionally, these electrode sites have an advantage over standard electrode sites in terms of test subject acceptability; the individual does not have to disrobe before the signal can be acquired.

The signals were recorded with a Biopac TEL-100 system, using a 0.5 Hz high-pass filter and 500 Hz low-pass filter. The signals were further filtered to match the frequency range stipulated by each author whose method(s) we implemented. The individuals were asked to sit for five minutes as the recording took place. Each individual had three ECG recordings, each taken on a different day. We will call these three recordings, sessions 1, 2, and 3, where the separation between two consecutive sessions ranged from one week to six months. The mean and standard deviation of the time interval between sessions 1 and 2 were 15.4 and 14.4 days, respectively; for sessions 2 and 3, they were 47.2 and 79.4 days, respectively.

B. Results

The results presented here were obtained based on implementing the methodologies as described in the literature. The within-session analysis results are given in Table II, which shows each algorithm, the authentication performance reported in the cited paper (if any), and its performance using our database. In the table, FS and NFS stand for "feature selection" and "no feature selection" respectively [11]; FS and NFS correspond to the cases where relative entropy based feature selection is or is not used, respectively. Moreover, "train 8, test 8" represents using 8 heartbeats (or 8 s, for the cases of Agrafioti *et al.* and Wang *et al.*) for training and the same number for testing. From the table, we can see that most algorithms do a decent job in modeling the ties within a class (individual) and discriminating between individuals. However, for some algorithms there are noticeable differences between the authentication performance reported in the literature and what we obtained using our database.

The original algorithm proposed by Molina *et al.* [39] uses a morphological baseline wander removal technique during preprocessing, which introduces distortions in the ECG recording; when band-pass filtering was used for preprocessing instead, the authentication performance improved. Also, the polynomial-

TABLE II
AUTHENTICATION PERFORMANCE FOR WITHIN-SESSION ANALYSIS

Researchers	Equal Error Rates (%)				
	Literature	Train 8, Test 8	Train 16, Test 16	Train 32, Test 32	Train 64, Test 64
Agrafioti *et al.* [17]	0.6	3.88	0.85	0.57	0.38
Chan *et al.* [12]	-	5.82	3.84	3.02	2.26
Chiu *et al.* [40]	0.83 - 0.86	4.15	2.64	1.76	1.01
Coutinho *et al.* [53]	-	42.54	38.92	35.14	33.34
Fang and Chan (SC) [33]	-	19.81	19.1	19.03	18.82
Fatemian and Hatzinakos [41]	-	8.69	5.99	4.37	2.26
Irvine *et al.* [43]	-	2.25	1.74	1.26	0.69
Khalil and Sufi [44]	-	5.28	2.64	1.56	1.13
Li and Narayanan (HPE+SVM) [18]	0.55	2.19	1.24	1.17	0.96
Lourenço *et al.* [58]	13	12.01	9.3	6.56	5.25
Molina *et al.* [39]	2	19.99	16.31	16.27	15.98
Molina (M) [39]	-	13.71	7.53	6.16	5.57
Odinaka *et al.* (FS) [11]	0.02	1.89	0.93	0.38	0.03
Odinaka *et al.* (NFS)[11]	-	1.93	1.04	0.51	0.06
Sufi *et al.* [47]	-	27.39	21.97	17.14	13.42
Wan and Yao *et al.* [27]	-	7.98	2.15	0.75	0.27
Wang *et al.* (DCT) [25]	-	3.9	2.22	1.74	1.36
Wübbeler *et al.* [14]	-	1.08	0.57	0.57	0.38
Yao and Wan [48]	-	24.46	22.32	20.63	18.49
Ye *et al.* [32]	-	5.11	2.84	1.64	1.13

"Train 8, Test 8" represents training on 8 heartbeats (or 8 s) and testing on 8 heartbeats (or 8 s) from the same session. "Molina (M)" represents a modified Molina algorithm. DCT = Discrete Cosine Transform; FS = Feature Selection; HPE = Hermite Polynomial Expansion; NFS = No Feature Selection; SC = Spatial Correlation; SVM = Support Vector Machine.

TABLE III
AUTHENTICATION PERFORMANCE FOR ACROSS-SESSION (WITHOUT FUSION) ANALYSIS

Researchers	Equal Error Rates (%)				
	Train 8, Test 8	Train 16, Test 16	Train 16, Test 32	Train 32, Test 16	Train 32, Test 32
Agrafioti *et al.* [17]	17.95	11.73	11.64	10.48	10.36
Chan *et al.* [12]	16.83	15.37	14.99	14.91	14.64
Chiu *et al.* [40]	26.56	26.28	26.20	26.38	26.36
Coutinho *et al.* [53]	47.14	45.77	44.67	44.59	43.93
Fang and Chan (SC) [33]	29.53	29.54	29.59	29.57	29.71
Fatemian and Hatzinakos [41]	20.40	20.30	20.18	19.42	19.31
Irvine *et al.* [43]	22.25	21.93	21.87	21.66	21.57
Khalil and Sufi [44]	24.16	22.89	22.13	21.94	21.13
Li and Narayanan (HPE+SVM) [18]	19.94	19.20	19.16	18.33	18.16
Lourenço *et al.* [58]	26.11	25.29	25.33	24.85	24.58
Molina *et al.* [39]	37.07	31.75	30.77	30.20	29.42
Molina (M) [39]	34.61	28.65	27.13	25.92	24.67
Odinaka *et al.* (FS) [11]	12.30	11.29	11.13	11.11	11.30
Odinaka *et al.* (NFS)[11]	21.46	20.66	20.37	19.80	20
Sufi *et al.* [47]	35.34	33.17	31.98	32.23	31.64
Wan and Yao [27]	16.93	18.44	16.82	21.65	19.22
Wang *et al.* (DCT) [25]	17.94	17.69	17.63	17.72	17.61
Wübbeler *et al.* [14]	16	15.6	15.79	15.59	15.77
Yao and Wan [48]	33.33	31.79	31.38	30.92	30.13
Ye *et al.* [32]	22.98	19.19	20.17	20.17	18.55

"Train 32, Test 16" represents training on 32 heartbeats (or 32 s) from session 1 and testing on 16 heartbeats (or 16 s) from session 3. "Molina (M)" represents a modified Molina algorithm. DCT = Discrete Cosine Transform; FS = Feature Selection; HPE = Hermite Polynomial Expansion; NFS = No Feature Selection; SC = Spatial Correlation; SVM = Support Vector Machine.

based algorithm proposed by Sufi *et al.* [47] suffers from performance deficiencies compared to what was reported in the literature. This is likely due to the large sample size we used for this study; only 15 individuals were used in the original study performed by the authors. When the first 15 individuals from our database were used for the biometric study, an equal error rate of 0.95% was obtained.

The same phenomenon holds true for the algorithm proposed by Coutinho *et al.* [53]. The original study performed by the authors used ECG data obtained from 26 individuals. When the first 26 individuals from our database were used for the biometric study, an equal error rate of 0% was obtained, in comparison to the much higher rates (in the range of 35%) observed when applied to our full database of 265 individuals. The algorithm proposed by Yao and Wan [48] doesn't perform as well as some of the other methodologies. One possible reason for this is that only a single principal component was used for classification. The principal component may not be adequate to completely separate overlapping classes in the feature space. In general, when training and testing data come from the same session, most algorithms are good at accepting a true identity and rejecting a false one, as evidenced by their within-session authentication performance.

However, when training and testing are on different days, all the algorithms suffer deterioration in performance, as is reflected in Table III. In the table, "train 32, test 16" represents using 32 heartbeats (or 32 s) from session 1 for training and using 16 heartbeats (or 16 s) from session 3 for testing.

TABLE IV
AUTHENTICATION PERFORMANCE FOR ACROSS-SESSION (WITH FUSION) ANALYSIS

Researchers	Equal Error Rates (%)			
	Train(8+8), Test 8	Train(8+8), Test 16	Train(16+16), Test 16	Train(16+16), Test 32
Agrafioti *et al.* [17]	10.68	10.53	9.56	9.51
Chan *et al.* [12]	12.30	11.91	11.57	11.22
Chiu *et al.* [40]	21.34	21.18	21	20.97
Coutinho *et al.* [53]	46.17	45.64	44.41	43.77
Fang and Chan (SC) [33]	30.18	29.85	30.22	30.18
Fatemian and Hatzinakos [41]	17.13	16.66	16.92	16.35
Irvine *et al.* [43]	19.65	19.43	19.35	19.22
Khalil and Sufi [44]	18.91	18.58	18.87	18.53
Li and Narayanan (HPE+SVM) [18]	17.40	17.38	17.06	17.09
Lourenço *et al.* [58]	23.22	22.48	22.46	21.97
Molina *et al.* [39]	27.62	27.21	26.12	26.19
Molina (M) [39]	22.24	21.46	20.89	20.48
Odinaka *et al.* (FS) [11]	6.12	6.04	5.64	5.47
Odinaka *et al.* (NFS)[11]	16.08	15.85	14.91	14.73
Sufi *et al.* [47]	33.49	31.03	31.35	29.95
Wan and Yao [27]	9.31	9.45	6.23	6.28
Wang *et al.* (DCT) [25]	16.16	15.92	15.85	15.93
Wübbeler *et al.* [14]	14.62	14.29	14.11	13.98
Yao and Wan [48]	30.99	30.69	30.15	29.84
Ye *et al.* [32]	16.74	17.06	14.32	13.67

"Train (8 + 8), Test 16" represents training on 8 heartbeats (or 8 s) each from sessions 1 and 2, and testing on 16 heartbeats (or 16 s) from session 3. "Molina (M)" represents a modified Molina algorithm. DCT = Discrete Cosine Transform; FS = Feature Selection; HPE = Hermite Polynomial Expansion; NFS = No Feature Selection; SC = Spatial Correlation; SVM = Support Vector Machine.

The results for across-session testing, when the training data are obtained from two different days is given in Table IV. In the table, "train (8 + 8), test 16" represents using 8 heartbeats (or 8 s) each from sessions 1 and 2 for training and using 16 heartbeats (or 16 s) from session 3 for testing. Cross-session training is vital to the improvement of biometric performance as it accommodates variability across different measurement times in the model.

Comparing the last columns in Table III and Table IV, where a total of 32 heartbeats (or 32 s) are used for training, and 16 heartbeats (or 16 s) are used for testing, we can see the effect of fusing data from more than one session during training, on the authentication performance. With the exception of the algorithm by Fang and Chan [33], all the algorithms show a varied degree of improvement in performance, which can be attributed to data fusion. The most remarkable improvement in performance can be seen in the algorithm by Odinaka *et al.* [11] and Wan and Yao [27], where data fusion accounts for about a 52% and 67% change in EER, respectively.

Based on the across-session performance when fusion is used, we can see that a few of the methodologies provide the framework to capture the variability across time during training and provide for a significant improvement in authentication performance. It seems that most of the methods under review do not directly extend to across-session scenarios. However, with further research on how to extend them to include across-session variability, many of the methods may perform well.

A precise explanation as to why some of the algorithms benefit greatly from fusion approaches, while others do not, would constitute an important contribution to the field. Unfortunately, such explanations are not always readily apparent. For example, the Wan and Yao [27] neural networking approach involves self-organizing networks. It is extremely difficult to deconstruct the inner workings of this type of algorithm. However, we suspect that the way the feature vectors are processed prior to passing them through the network may explain the improved performance of the neural network algorithm; Wan and Yao [27] concatenated feature vectors obtained from different individuals, alongside the concatenated feature vectors from the same individual, in training a neural network to learn the contrast between the concatenated feature vectors. Providing the neural network with examples from multiple training sessions makes it better able to discriminate future test data. Moreover, the algorithm by Odinaka *et al.* [11] uses a generative model which was selected in large part because of its ability to capture the variability across sessions. That is, the model is inherently robust. As a result of the robustness, multiple training sessions lead to better estimates of the model parameters.

Fig. 1 shows the detection error trade-off curves, plotted using a normal deviate scale as prescribed by Martin *et al.* [71], for the top performing (based on EERs) methodologies in the across-session (with fusion) analysis, when 16 heartbeats each from sessions 1 and 2 are used for training, and 32 heartbeats from session 3 are used for testing. The DET curves are plotted this way to spread out the curves that would otherwise be bunched up by receiver operating characteristic (ROC) curves [71].

IV. OPEN ISSUES IN ECG RECOGNITION

Irvine and Israel [24] raised several issues that need to be resolved before biometric systems based on the ECG can be used in practice. These include heart rate variability due to mental, emotional, and physical changes, issues relating to sensor placement, scalability to larger populations, and the time-varying nature of the ECG signal.

The results we presented above are for ECG recordings obtained during a calm, seated resting condition, where heart rate changes during the signal measurement can be expected to be minimal. We should add that the database, in an albeit uncontrolled fashion, allows for substantial variability in factors

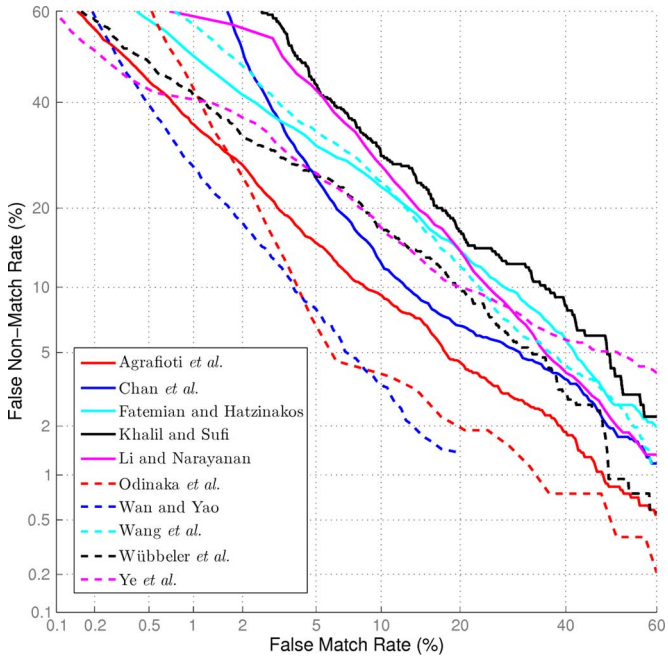

Fig. 1. Detection error trade-off (DET) curves for the top performing methodologies in the across-session (with fusion) analysis. Training was performed using 16 heartbeats each from sessions 1 and 2, while testing was based on 32 heartbeats from session 3.

which could significantly impact the state of the individual. For instance, we do not restrict the individuals' daily activities, food or substance consumption and medicinal use. Indeed, heart rate varied considerably across sessions for some individuals. In a real world setting, individuals will usually not be in a normal resting condition. As such, if ECG recognition is to become a reality, extensive studies have to be designed to assess the effects of heart diseases, mental and physical stressors, exercise [22], [74], and other factors including common drugs, medications, and diet. To our knowledge, the work by Agrafioti *et al.* [23], is the only one that examines the use of the ECG for biometric recognition in a cardiac irregularity condition.

Heart rate variability due to physical, mental or other stressful activities can have the effect of changing the morphology of the ECG. A few methods have been proposed to compensate for such changes, such as resampling the entire heartbeat [22] or ST segment [41], [60] and normalizing fiducial features using the length of the heartbeat [21], [34]. Agrafioti *et al.* [17] proposed that the autocorrelation sequence obtained in the AC/LDA methodology has the potential of reducing the effect of heart rate variability on the recognition process. Moreover, Safie *et al.* [59] stated that pulse active ratio features can adapt to changes in heart rate. That notwithstanding, an extensive study is yet to be performed; one that would put the compensation techniques to the test. If the techniques are found short of success, other ideas would need to be investigated.

The ECG signal undergoes both short-term and long-term changes. Short-term changes can be attributed to short-lived (impulsive) activities such as physical or mental activities or the consumption of substances like caffeine. However, long-term changes are mainly due to changes in lifestyle, like the use of medication. Based on the across-session results, we can see that the performance of all the biometric systems degrades over time between training and testing. However, some of the systems were able to regain some of the performance loss by pooling data from multiple sessions.

Perhaps, increased emphasis should be placed upon across-session effects when developing methodologies for ECG biometric recognition, since simply pooling the data from multiple days for the purpose of training does not seem to considerably improve the across-session performance of most of the methods. More data collection efforts will be required to show definitively that such fusion of data from multiple sessions will improve system performance as the number of sessions increases.

Some reports in the literature [14], [60] have proposed the use of only the QRS complex for biometric recognition because it is the most invariant amongst the other wave components of an ECG heartbeat to heart rate changes and changes over time. However, it is uncertain whether its sole use can support ECG biometric recognition over a large database.

An equally important issue is the database size. Most studies have used a database size below 50 individuals. Based on previous results [11] it is known that ECG identification performance tends to decrease as the number of individuals in the database increases. As such, it is necessary to test the methodologies that have been proposed in literature, to see if they can carry over to larger databases.

In addition to issues that may compromise the performance of the ECG system, other issues have raised some concerns, including privacy issues. ECG signals have health information embedded in them. Such critical information in the wrong hands can be very devastating. As such there is an interest in methods for template protection or obfuscating such information prior to the use of the ECG for biometric recognition.

V. Conclusion

The inability to fool ECG sensors, in a supervised setting, is one of the reasons why ECG based biometric offers an attractive alternative to other traditional biometrics. Although Tsao *et al.* [75] showed that, in theory, it is possible to fool an ECG biometric system by synthesizing an ECG recording using measured features, in practice it may be difficult to replicate an ECG signal at the sensor level.

Despite the considerable effort aimed at developing the ECG as a biometric modality, several important issues remain. These include factors associated with heart rate variability, ECG signal changes over time, and privacy concerns.

We took a closer look at some of the methodologies that have been proposed in the literature using our inhouse multisession database. From that study, we observed that time between training and testing has a drastic impact on system performance, and that some systems have the ability to capitalize on multiple training sessions to achieve improved performance. However, there clearly remains a need for further research involving multisession protocols. We suspect that robust generative models perform better with multiple training sessions because of their ability to capture the variability across sessions and lead to better model parameter estimates.

APPENDIX

There are six public ECG databases and many more inhouse private databases that have been used for evaluating the recognition performance of an ECG biometric system.

A. Public Databases

The public databases that have been used for evaluating the performance of ECG recognition systems include the MIT-BIH Arrhythmia (MITDB), MIT-BIH Normal Sinus Rhythm (NSRDB), PTB Diagnostic (PTBDB), QT (QTDB), European ST-T (EDB), and Long-Term ST (LTSTDB) databases. All six databases are hosted in the Physionet website [76].

MITDB and NSRDB are ECG collections that were obtained in the Arrhythmia Laboratory at Boston's Beth Israel Hospital. MITDB is a collection of 48 fully annotated 30-min excerpts of two-channel ambulatory ECG recordings, obtained from 47 individuals suffering from some form of arrhythmia.

NSRDB is a collection of 18 long-term (about a day) two-channel ECG recordings. The individuals included in the database were found to have had no significant arrhythmias.

PTBDB (Physikalisch Technische Bundesanstalt Database) is an ECG collection that was provided by the National Metrology Institute of Germany for teaching and research purposes, and for algorithm evaluation. The database contains 549 recordings from 290 individuals. Each individual has between one and seven recordings. Although the subject number runs from one to 294, there are no individuals numbered 124, 132, 134, or 161. Each recording has 15 data channels; the standard 12 leads and the three Frank leads. 52 of the 290 individuals are healthy, while the others suffer from a variety of cardiac disorders.

There appears to be some confusion in the literature about the number of healthy individuals from the PTB database with recordings from multiple days. Seven (patient numbers 174, 180, 198, 233, 245, 251, and 284) of the 52 healthy individuals have recordings from at least two different days, while only one individual (patient number 180) apparently has recordings from three or more different days.

QTDB is a collection of 105 15-min excerpts of two-channel ECG recordings, selected to avoid significant baseline wander or other artifacts [77]. The recordings were obtained from five MIT-BIH ECG databases (including MITDB and NSRDB), the European ST-T database (EDB), and an inhouse database containing Holter recordings of patients who experienced sudden cardiac death during the recordings.

EDB is a collection of 90 two-channel recordings from 79 individuals suffering from myocardial ischemia, intended for use in evaluating algorithms that analyze changes in the ST segment and T wave.

LTSTDB contains 86 long-term two- or three-channel ECG recordings from 80 individuals, chosen to represent a variety of changes in the ST segment [78]. The database is mainly intended for use in evaluating algorithms that can differentiate between ischemic and nonischemic ST events.

B. Private Databases

In addition to the public databases, several researchers have utilized recordings obtained in their laboratories for evaluating the biometric capability of their proposed ECG recognition system.

The database used by Biel *et al.* [5] consisted of four to 10 recordings obtained from 20 individuals. The standard 12-lead recordings were taken over a span of about six weeks, during normal resting conditions.

The database used by Irvine *et al.* [7], [24], [34], [43], Israel *et al.* [21], Homer *et al.* [51], and Jang *et al.* [55] were from data collection protocols designed to elicit different states of anxiety in the individuals. Single-channel recordings were obtained from a total of 126 individuals.

The database used by Shen *et al.* [13] consisted of lead I recordings obtained from the palms of 168 healthy individuals during normal resting conditions.

The database used by Kim *et al.* [22] consisted of single-channel ECG recording obtained from 10 healthy males, both during normal resting condition and a physical activity (running up and down a flight of stairs).

The database used by Zhang and Wei [38] consisted of 10 s standard 12-lead ECG recordings from 520 individuals. This database represents the largest that has been reported for the development of ECG biometrics algorithms.

The database used by Silva *et al.* [26] and Coutinho *et al.* [53] consisted of 26 individuals. Within a session, each individual performed a series of cognitive tasks.

The database used by Molina *et al.* [39] consisted of ECG recordings obtained from 10 individuals, obtained during normal resting conditions. Each individual participated in five 5-min sessions over the course of four weeks.

The database used by Wübbeler *et al.* [14] consisted of 234 three-channel (leads I, II, and III) 10-s ECG recordings obtained from 74 healthy individuals. Each individual had between two and 20 recordings, with an average time of about 500 days between each recording.

The database used by Chan *et al.* [12] consisted of 90 s ECG recordings obtained from 60 healthy individuals. There were three recordings for each individual, corresponding to three sessions, with a minimum of one day between sessions. The button electrodes were held between the thumb and index finger.

The database used by Yao and Wan [27], [48], [57] consisted of 121 two-minute ECG recordings taken from 30 individuals, during normal resting condition. Each individual participated in at least two sessions, with the time interval between two sessions ranging from several hours to a few weeks.

The database used by Agrafioti and Hatzinakos [52] and Gao *et al.* [64] consisted of three-minute single-channel wrist recordings from 52 healthy individuals. The recordings were repeated about a month later, for 16 of the individuals [64].

The database used by Lourenço *et al.* [58] consisted of two-minute single-channel finger recordings from 16 individuals within a single session.

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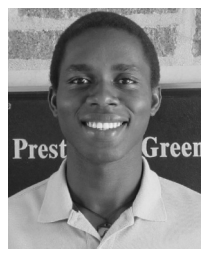

Ikenna Odinaka (S'10) received the B.S. degree in physics and mathematics from Illinois Wesleyan University, Bloomington, in 2008. He is currently working toward the Ph.D. degree in electrical engineering at Washington University in Saint Louis, St. Louis, MO. His research interests include biometrics, pattern recognition, machine learning, and imaging.

Po-Hsiang Lai (S'06) received the B.S. degree in applied science and the D.Sc. degree in electrical engineering from Washington University in Saint Louis, St. Louis, MO, in 2006 and 2012, respectively.

He is currently a senior engineer at Samsung Dallas Technology Laboratories. His research focuses on nonintrusive load monitoring, green home systems, machine learning, biometrics, and computational stemmatology.

Alan D. Kaplan (M'11) received the B.S. degree in electrical engineering from the University of Illinois, Urbana-Champaign, in 2005, and the M.S. and Ph.D. degrees in electrical engineering from Washington University in Saint Louis, St. Louis, MO, in 2007 and 2011, respectively.

He is currently with Exponent, Inc. His research interests include biometrics, information processing, and pattern recognition.

Joseph A. O'Sullivan (F'03) joined the Department of Electrical Engineering at Washington University in 1986, and is now the Samuel C. Sachs Professor of Electrical Engineering. He has joint appointments in the Departments of Radiology and of Biomedical Engineering. He is Dean of the University of Missouri-Saint Louis/Washington University Joint Undergraduate Engineering Program; in this capacity, he sits on the Provost Council at the University of Missouri-Saint Louis. He was Chair of the Faculty Senate Council and Faculty Representative to the Board of Trustees at Washington University 2002–2004. His research

interests include information theory, information-theoretic imaging, recognition theory and systems, CT imaging, optical imaging, information hiding, and hyperspectral imaging.

Prof. O'Sullivan was the Publications Editor for the IEEE TRANSACTIONS ON INFORMATION THEORY, 1992–1995, was the Associate Editor for Detection and Estimation, and was a Guest Associate Editor for the 2000 SPECIAL ISSUE ON INFORMATION THEORETIC IMAGING. He was cochair of the 1999 Information Theory Workshop on Detection, Estimation, Classification, and Imaging. He was local arrangements chair for the IEEE 2003 Statistical Signal Processing Workshop. He was cochair of the IEEE 2006 International Symposium on Information Theory. He was chair of the Saint Louis Section of the IEEE in 1994. He is a member of Eta Kappa Nu, SPIE, SIAM, AAAS, and ASEE. He was awarded an IEEE Third Millennium Medal.

Erik J. Sirevaag received the Ph.D. degree in biological psychology from the University of Illinois, Urbana-Champaign, in 1992.

He is currently a Research Assistant Professor in the Department of Psychiatry, Washington University School of Medicine, St. Louis, MO. Trained as a Psychophysiologist, his current research interests center upon the exploration and application of physiological processes and measures related to stress, emotion, biometrics, and human factors.

John W. Rohrbaugh received the Ph.D. degree in psychology from the University of Illinois, Urbana-Champaign, in 1973.

This was followed by postdoctoral studies in the Departments of Psychology and Anatomy at the University of California Los Angeles (1972–1979), and positions at the University of Nebraska College of Medicine (1979–1983) and the National Institutes of Health (1983–1990). He is currently Professor in the Department of Psychiatry at Washington University School of Medicine, Saint Louis, MO, which he joined in 1990. His interests lie in general psychophysiological studies of cognition, stress, and emotion, with an emphasis over the past decade on laser-based methods.