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Review

ECG databases for biometric systems: A systematic review

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ABSTRACT

Computer-based biometric systems (CBBSs) individual recognition are expert and intelligent systems that are gaining increasing interest in many areas, such as securing financial systems, telecommunications and healthcare applications. The electrocardiogram (ECG) has been used as biometric feature for its low circumvention, large acceptability and uniqueness, thus being at the basis of several CBBSs. As ECG databases collected for clinical applications are not adequate for biometric applications, we have assisted to the development of other repositories of ECG, each one different from the others and highlighting certain issues of ECG-based biometric recognition. Through a systematic framework presented here, we quantitative analyse, evaluate and compare the acquisition hardware and the acquisition protocols of ECG databases available in literature and suited to develop CBBSs. Although the most recent ones, namely CYBHI and UofTDB, result the best for the acquisition hardware and the acquisition protocols, respectively, our survey shows that none is exhaustive for developing a robust and general enough CBBSs. The analysis also highlights the current lack of standardization in this field and the difficulty of performing an effective benchmarking activity. Since a publicly available database is essential for the research community in ECG-based CBBS to correctly assess the performance of existing algorithms or even commercial expert systems, we also discuss here the main features that an "optimal" repository for the intelligent application at hand.

1. Introduction

Computer-based biometric systems (CBBSs) for individual recognition are expert and intelligent systems that are gaining increasing interest in many areas, such as securing financial systems, telecommunications and healthcare applications.

They are generally part of either a *verification*[1] or an *identification* system. In the former case, an individual presents himself or herself as a specific individual. To find a match the system checks his or her biometric feature against a profile that already exists in the dataset linked to that individual's file, being usually named as a 1-to-1 matching system. In the latter case, the system seeks to identify an unknown individual, or unknown biometric. Hence, it checks the biometric presented against all others already in the dataset, being therefore described as a 1-to-n matching system (where n is the dataset cardinality).

The biometric recognition tasks are typically performed by means of physiological and/or behavioural characteristics that are unique to the individual (Da Silva, Fred, Lourenço, & Jain, 2013), such as the face, the fingerprint, the iris, the DNA, to name a few (Jain, Bolle, & Pankanti, 1999). Each of these traits satisfies the principles of universality, uniqueness, permanent, collectability, performance, acceptability, circumvention, while the user reports different levels of satisfaction (Jain et al., 1999). Biometric applications should carry out biometric verifications and identifications tasks through user-friendly systems: this need, in turn, has directed the recent research towards the development of CBBSs based on human characteristics with large uniqueness, collectability, and acceptability as well as with low circumvention. Among the various traits that can be employed (Chen, Zheng, & Dai, 2014; Zhao, Yang, Chen, & Luo, 2013), it is worth noting that Biel, Pettersson, Philipson, and Wide (2001) showed the suitability of the electrocardiogram (ECG) as biometric recognition methodology.

Researchers and practitioners interested in using ECG signal in CBBSs can find public databases very different each others. On the one side, the Physionet repository (Goldberger et al., 2000) makes available ECG signals collected for clinical purposes. On the other side, several repositories originally designed for CBBSs were conceived with breadth requirements reflecting in a wide variety of hardware and acquisition protocol used for signal registration

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[1] Some authors use the term *authentication* as a synonym for verification.

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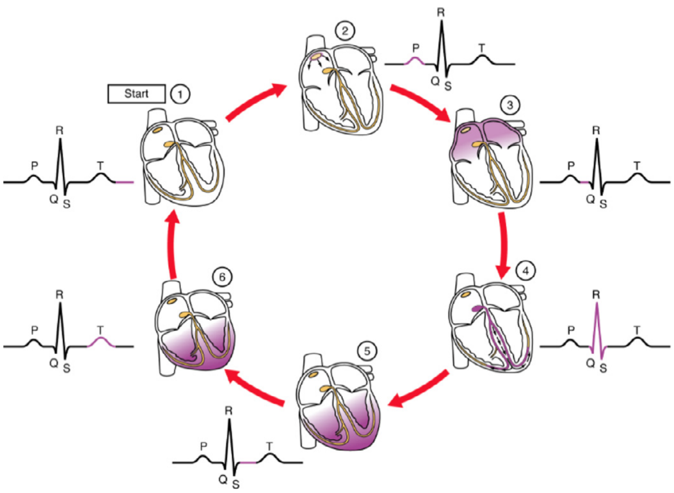


Fig. 1. A sketch of a common cardiac cycle with the associated waves of the ECG signal (one-lead).

(Agrafioti & Hatzinakos, 2010; Chan, Hamdy, Badre, & Badee, 2008; Da Silva, Lourenço, Fred, Raposo, & Aires-de Sousa, 2014; Irvine, Israel, Scruggs, & Worek, 2008; Israel, Irvine, Cheng, Wiederhold, & Wiederhold, 2005; Jang, Wendelken, & Irvine, 2010; Odinaka et al., 2010; Pouryayevali, Wahabi, Hari, & Hatzinakos, 2014; Shen, Tompkins, & Hu, 2010; Wübbeler, Stavridis, Kreiseler, Bousseljot, & Elster, 2007; Yao & Wan, 2010; Zhang & Wei, 2006).

The lack of a standardized hardware and measurement protocol for biometric application of ECG implicates the absence of an exhaustive ECG-database that not only prevents a robust validation of CBBSs, but also does not allow to develop expert systems robust to the variability given by different use cases. To the best of our knowledge, this article fills a void in biometric research presenting a detailed and systematic overview of available ECG databases. Its goal is the assessment of protocol and hardware used to identify the essential requirements and practical guidelines in the development of CBBSs. To this aim, we introduce here a framework to analyze the consistency between the methods used to collect the data in the various repositories, and a quantitative comparison of their acquisition hardware and protocols. Therefore, the focus is not on specific feature sets that could be extracted from the ECG recordings or on classification systems design, but instead on the ECG data and on the instrumentations employed. Our analysis reveals some lacks in existing databases and it discloses the requirements of a exhaustive ECG database for biometric research that could be useful to benchmark the ECG biometric systems proposed in the last decade.

This manuscript is organised as follows: Section 2 describes the background; Section 3 describes the selected databases, highlighting the main characteristics of their acquisition hardware and protocol; Section 4 details our framework for the systematic analysis and Section 5 discusses the results. Finally, Section 6 provides concluding remarks.

2. Background

The ECG records the different electrical potentials generated by the heart on the surface of the body, being an expression of its excitement and not of its contraction. While the interested reader can deepen the physiological principles of hearth electrophysiology in Horáček (2010); Malmivuo and Plonsey (1995), we now describe the one-lead waves of a common hearth cycle shown in Fig. 1 (Kligfield et al., 2007):

(2) P wave: this wave shows the status of activation of the atria. The contraction of atria (atrial systole) is not particularly powerful, so the P wave is small in size (amplitude equal to or less than 0.4 mV) and its duration ranges from 60 ms to 120 ms. It indicates the time taken by the pulse to propagate to both atria, being useful to precisely detect hearts diseases such as atrial flutter;

(3) PQ stretch: it is flat and free of waves; it measures the time that elapses from the time when the atria begin to be active until the moment in which the ventricles are activated. The length of a normal PQ interval ranges between 12 ms and 20 ms;

(4) QRS complex: it is composed of the Q, R and S waves. The first is short, downward and negative corresponding to the depolarization of the septum. The second wave is long and narrow, representing the depolarization of the left ventricle apex. The third wave is small, downward and negative corresponding to the depolarization of the basal and rear regions of the left ventricle. The duration of the QRS complex ranges from 60 ms to 90 ms. The alterations of this complex suggest the presence of heart diseases, such as arrhythmia, fibrillation, and heart attack;

(5) ST stretch: it is a long stretch starting after the S wave and ending with the T wave, which is described in the next item. This stretch corresponds to the time interval where the ventricles contract and return to rest and it is approximately in the baseline of ECG signal. The normal duration of ST stretch ranges from 230 ms to 460 ms. Its analysis can reveal ischemic problems;

(6) T wave: it represents the repolarization of the ventricles (the time when the ventricles have finished their activation stage and they are ready for a new contraction) and its duration ranges between 100 ms and 250 ms. The T wave gives information on cardiac hypertrophy, heart failure and ischemic heart disease.

Furthermore, the following are also significant for clinical analysis:

- QT interval: it represents the electrical systole, i.e., the period of time corresponding to the sequence of depolarization and repolarization of ventricles. The length of this interval varies with the heart rate and, usually, it ranges from 350 ms to 440 ms;
- U wave: it follows the T wave and it is a part of the process of ventricular repolarization; it is not always appreciable in an electrocardiogram. U wave duration ranges from 185 ms to 228 ms.

2.1. ECG in biometrics

The ECG signal is currently employed in a number of clinical applications based on the analysis of waveform morphological and temporal features, e.g., heart disease diagnosis follow-up (Martis, Acharya, Ray, & Chakraborty, 2011), home-care monitoring (Lobodzinski & Jadalla, 2010), telemedicine (Costa & Oliveira, 2012), arrhythmia detection (Wu et al., 2011; Zhang, Zhu, Thakor, & Wang, 1999), heart-rate monitoring (Malik et al., 1996), detection of congestive heart failure (Yu & Lee, 2012), monitoring of patients in intensive care units (Sayadi & Shamsollahi, 2011). They have been extensively analysed in the literature and their discussion is beyond the scope of this review. Further to the clinical applications reported so far, the ECG is also used for human biometric recognition, a non-clinical application receiving growing attention from the scientific community engaged in the development of expert and intelligent systems (Sansone, Fusco, Pepino, & Sansone, 2013). In this area, we identify three works demonstrating the usefulness of ECG. Biel et al. (2001) showed the uniqueness of electrocardiograph signal for each individual, presenting also the first proof of concept for the use of one-lead ECG configuration. This approach was then further explored by Shen, Tompkins, and Hu (2002), where the authors developed a neural network to identify a specific individual from a group of candidates by using a one-lead ECG. It is worth observing that the use of one-lead ECG configuration is suitable for biometrics since it simplifies and speeds up the preparation of the signal acquisition phase. Hoekema, Uijen, and van Oosterom (2001) demonstrated that some of the ECG signal characteristics might be utilised for biometrical applications, since they are related to the geometrical features of body. We would like to mention two other issues on using the ECG signal in CBBSs. First, the ECG can be used with other biometric features to strengthen the discrimination capability of the approach (Israel, Irvine, Cheng, Wiederhold, & Wiederhold, 2003). Second, there exists a wide literature on techniques using the electrocardiogram for biometric recognition: although their description is beyond the scope of this work, a recent work categorized and experimentally compared on a private database the methodologies for ECG-based identification and authentication (Odinaka et al., 2012). We would like to remark that Odinaka et al. (2012) adopted a different perspective from our contribution: while they surveyed the literature from a machine learning perspective, here we do not deal with any methodologies for biometrics but we would rather present a systematic overview of available ECG databases that can be used in CBBSs development.

2.2. Major sources of ECG variability

The ECG signals could be affected by three major sources of variability, namely artefacts and noise, intra-subject variability and inter-subject variability, that we now describe one by one.

2.2.1. Artefacts and noise

Electrode material. The most used electrodes are silver/silver-chloride coated electrodes with well known frequency-band characteristics and temperature stability. However, different materials can have different characteristics affecting the recording: temperature drift can cause variation of the baseline (low frequency oscillations) while frequency-band modification can cause attenuation of high frequencies (Webster, 1978).

Sensor locations. Standard (clinical) electrode locations (arms, legs, thorax) permit the acquisition of 12 ECG recordings: 3 (Einthoven leads I, II, III) + 3 (Wilson aVR, aVL, aVF) + 6 (precordial, v1 to v6); these locations have been in use since the early years of 1900 and they have produced a huge amount of literature for ECG clinical diagnosis. However, in the biometric scenario it is common the use of single ECG recording with only two electrodes placed in non standard locations that can lead to different morphology of the ECG recording with respect to the standard recordings (e.g. Einthoven's lead I); a preliminary study of this issue can be found in the paper by Israel et al. (2005).

Power-line interference. Capacitive coupling with power lines can induce a superimposed (distorted) harmonic signal whose amplitude can obscure the morphological characteristics of ECG: notch filtering is usually used to remove this interference since its frequency content is well known (Webster, 1978).

Baseline drift. Respiration causes changes in thorax volume/electrical impedance, causing therefore the isoelectric level to change slowly (in the low frequencies range): this artefact is usually removed via low pass filtering (Webster, 1978).

Movement artefacts. The contact interface between skin/electrode is subjected to electrochemical reactions of ionic chemical species under the electrode inducing half-cell potentials of the order of 1 *V* or less: these are usually removed via differential amplification under the hypothesis that they are quite similar between the electrodes. However, patient movements can change the electrode position and the chemical concentrations of these species can vary leading to different half-cell potential and therefore different isoelectrical (baseline) levels (Webster, 1978).

Instrumentation. As recalled above, ECG recordings should be acquired using a differential amplifier: for best performance this must have high input impedance and low bias current and high common mode rejection ratio (CMRR); these factors can mainly affect the quality of the recordings, but modern semiconductor technologies allow to have CMRR as high as 80 dB or more with bias currents as low as 1 nA, and input impedance as high as 1 GΩ which are quite satisfactory for this application.

2.2.2. Intra-subject variability

Health status of the subject. ECG from healthy subjects present some typical waves (PQRST) whose "normal" shape has been largely assessed in the literature. Deviations from these normal shapes and timing is an index of pathological conditions, for example, an infarction can induce ST elevation, an ischemia is associated to ST depression, a left/right bundle branch complete/intermittent block can alter QRS, an atrial flutter/fibrillation show several P waves before QRS, a ventricular fibrillation is revealed as an almost sinusoidal oscillation, a sinus block can produce no P-waves and enlarged RR intervals, an ectopic beats such as premature ventricular contractions show a different QRS shape and a peculiar timing relationship with the normal QRS and etc. As the list of heart diseases that can be detected analysing the shape and the timing of the ECG recording is really long, the interested reader is referred to a specific book such as Morris, Brady, and Camm (2009) and Vecht, Gatzoulis, and Peters (2009). It is worth to highlight that a preliminary study of the influence of a few irregular heart conditions on the biometric recognition can be found in Agrafioti and Hatzinakos (2009).

Heart rate (HR) variability. It is well known that heart rate reflects the variability of oxygen body-requirements because the pumping rate of the heart must increase or decrease to change the blood ejection fraction appropriately. In fact, heart rate is continuously varying in order to meet body needs: changes in HR affects the shape of the ECG recording and, specifically, of the QT segment (Foster, 2007).

Physical exercise. It is well known that during physical activity the ECG morphology (specifically baseline wandering and QT segment) can change both because of HR and respiration/movement of the thorax (Guyton & Hall, 2006).

Affective status. Emotion affects oxygen requirements and consequently HR; a preliminary study of the influence of emotion on the ECG can be found in Agrafioti, Hatzinakos, and Anderson (2012).

Drugs. It is well known that drugs can induce QT prolongation (Yap & Camm, 2003). A preliminary study on the influence of QT variations for ECG identification of individuals can be found in Gargiulo, Fratini, Sansone, and Sansone (2015).

Long-term stability. Wübbeler et al. (2007) have investigated the long-term stability of the individual ECG during time periods up to several years: they demonstrated that ECG remains sufficiently stable over years to allow recognition with an error rate of 3% on a population of 74 subjects.

2.2.3. Inter-subject variability

Thorax geometry and tissue characteristics. Main reason of inter-subject variability of ECG morphology is related to the specific electrical paths within the heart: different geometries and tissue characteristics lead to different recordings as demonstrated by Hoekema et al. (2001).

3. Survey of ECG databases for biometric scope

3.1. Study selection

This systematic review is structured according to Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Liberati et al., 2009). Our literature research were performed from February 2014 to December of 2014 in the medical databases Medline (1948–2014), Embase (1974–2014) and wide-ranging scientific databases Web of Science (1970–2014) via PubMed and Google Scholar online services. Search terms were based on a combination of the following keywords: identification, ECG, biometric, database, authentication, classification, recognition and one-lead derivation. This research returned twenty-eight papers. After duplicates removal and title, abstract and keyword screening, the full-text content of seventeen papers was deeply analysed. Twelve of them were included in this review Agrafioti and Hatzinakos (2010); Chan et al. (2008); Da Silva et al. (2014); Irvine et al. (2008); Israel et al. (2005); Jang et al. (2010); Odinaka et al. (2010); Pouryayevali et al. (2014); Shen et al. (2010); Wübbeler et al. (2007); Yao and Wan (2010); Zhang and Wei (2006) whereas Biel et al. (2001); Homer, Irvine, and Wendelken (2009); Kim, Yoon, Lee, Kim, and Koo (2006); Molina, Bruekers, Presura, Damstra, and van der Veen (2007) and Coutinho, Fred, and Figueiredo (2010) were excluded for two reasons. First, the corresponding databases contain few subjects; second, such papers do not present enough information for a detailed comparison.

3.2. Database categorisation

The growing interest in ECG-based biometric has motivated the collection of ECG signals specifically for this field. Existing databases are listed in Table 1, where several pieces of information are reported to facilitate the comparison. This information is organized as follows:

- *General information*: this section reports the year of publication, if the dataset is publicly available, and the purpose of the database, distinguishing whether the database is for clinical trials or biometric research.
- *Acquisition hardware information*: we report a set of information useful to analyse the characteristics of the acquisition systems. These data are: number of channels, type of electrodes, number of contact points, intrusiveness of the setup and acquisition frequencies. We distinguish the degree of intrusiveness into the following three categories (Da Silva et al., 2015; Da Silva et al., 2014):
  - *In-the-person* acquisition method refers to implantable devices, e.g., artificial cardiac pacemakers or implantable loop recorders;
  - *On-the-person* acquisition method refers to devices that need to be attached to the body of the subject, generally requiring conductive paste or gel;
  - *Off-the-person* acquisition method refers to devices that are integrated in objects or surfaces with which the subjects interact with (e.g. a computer keyboard), and do not require any special preparation of the subject.
- *Acquisition protocol information*: we report a set of information useful to analyse the characteristics of the adopted acquisition protocols. These data are: number of subjects, average number of ECG per person, average ECG length, gender distribution, condition o disorders, location of the electrodes. The item named as condition or disorders reports not only the mental and/or the physical activity carried out by the subjects during the ECG registration, but also if the database contains recordings of subjects with heart disease since these data data are useful to assess the recognition robustness (Da Silva et al., 2013).
- *Other information*: we report other useful information such as the resolution, the bandwidth of the pre-processing step and the sensor device used for the acquisition.

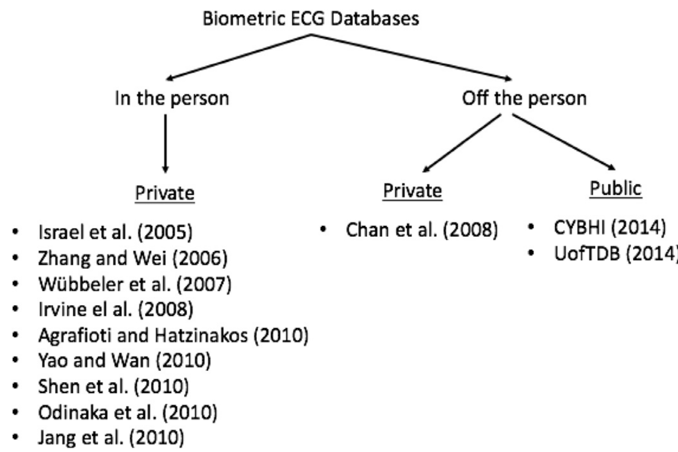


Fig. 2. A possible taxonomy of the databases developed for biometric purpose according to their availability and type of acquisition method.

For the sake of completeness, Table 1 reports also public databases available in the Physionet repository (Goldberger et al., 2000) that were originally collected for clinical trials rather than for biometric purposes. Among the six available there, we include American Heart Association database (AHA) (Hermes, Geselowitz, & Oliver, 1980), MIT-BIH Arrhythmia database (Moody & Mark, 1990) and PTB Diagnostic database (PTBD) (Goldberger et al., 2000), whose data were collected using the standard 12-lead ECG. Nevertheless, they are used to test biometric methods because they are publicly available and because they presented cases with health disorders that cause changes in the signals (Li & Narayanan, 2010; Venkatesh & Jayaraman, 2010). However, they were conceived for clinical applications and the acquisition procedure is highly intrusive for the subjects, limiting the potential practical applications of ECG-based biometrics (Da Silva et al., 2014). The other three databases available on Physionet, i.e., the QT, European ST-T and Long-Term ST databases, are discarded since their description does not contain enough information to be included in this survey (Goldberger et al., 2000).

In the rest of this section we provide a detailed description of the selected databases belonging both to the *On-the-person* and to the *Off-the-person* approaches, whereas we do not consider contributions adopting the *In-the-person* approach since it is not suited for CBBSs. Fig. 2 also graphically depicts a possible taxonomy of the databases according to the type of acquisition method. For each database, presented a following a chronological order, we provide information on the hardware used for signal acquisition, on the acquisition protocol as well as on the signal preprocessing stage.

Table 1
Summary of the existing database. Each column of the table reports data about the considered repositories, which are listed using the name of the database itself or, when this information is not available, they are listed with the name of the first author of the corresponding paper.

Info	Properties	Database/Paper														
		AHA (Hermes et al., 1980)	MIT-BIH (Moody & Mark, 1990)	PTBD (Goldberger et al., 2000)	Israel et al., 2005	Zhang & Wei, 2006	Wübbeler et al., 2007	Irvine et al., 2008	Chan et al., 2008	Agrafioti & Hatzinakos, 2010	Yao & Wan, 2010	Shen et al., 2010	Odinaka et al., 2010	Jang et al., 2010	CYBHI (Da Silva et al., 2014)	UofTDB (Pouryayevali et al., 2014)
General	Year	1980	1990	1995	2005	2006	2007	2008	2008	2010	2010	2010	2010	2010	2014	2014
	Publicly available	yes	yes	yes	no	no	no	no	no	no	no	no	no	no	yes	yes
	Purpose of the analysis	clinical	clinical	clinical	biometric	biometric	biometric	biometric	biometric	biometric	biometric	biometric	biometric	biometric	biometric	biometric
Hardware	Number of ECG channels	2	2	14	1	4	3	1	1	1	1	1	1	1	2	1
	Type of electrodes	wet Ag/ClAg	wet Ag/ClAg	wet Ag/ClAg	wet Ag/ClAg	wet Ag/ClAg	wet Ag/ClAg	wet Ag/ClAg	dry Ag/ClAg	wet Ag/ClAg	wet Ag/ClAg	wet Ag/ClAg	wet Ag/ClAg	wet Ag/ClAg	dry Ag/ClAg and electrolycra strips	dry Ag/ClAg
	Number of contact points	n.a.	n.a.	n.a.	3	4	3	3	2	3	3	3	2	3	4	2
	Intrusiveness of the setup	On-the-person	On-the-person	On-the-person	On-the-person	On-the-person	On-the-person	On-the-person	Off-the-person	On-the-person	On-the-person	On-the-person	On-the-person	On-the-person	Off-the-person	Off-the-person
	Acquisition frequency [kHz]	.25	.36	10	1	.50	.50	1	1	.26	.25	.50	1	.20	1	.20
Protocol	Number of subjects	155	48	290	29	502	73	43	50	52	30	168	269	65	128	1012
	Average number of ECG per person	n.a.	n.a.	n.a.	7	1	3	7	3	1.2	2	1	3	6	1.5	1.6
	Average ECG length [s]	n.a.	n.a.	n.a.	120	10	10	120	90	180	n.a.	90	n.a.	n.a.	120	180
	Gender distribution (%F,%M)	n.a.	n.a.	n.a.	(41.2,68.8)	n.a.	(45.9,54.1)	(39.6,60.4)	(10,90)	n.a.	(13.4,86.6)	(67.3,32.7)	(53.9,46.1)	(47.7,52.3)	(50.8,49.2)	(60.7,39.3)
	Condition or disorders	resting	resting	lying, cardiac disorder	resting, low or high level of stress tasks	resting	resting	resting, low or high level of stress tasks	resting	resting	resting	resting	resting, cardiac disorder	resting	resting, computer task	resting, physical exercise
	Location of electrodes	limbs, chest	limbs, chest	limbs, chest	neck-chest	limbs, chest	limbs	neck-chest	fingers	wrists	limbs	hand palms	lower rib cage	neck-chest	hand palms, fingers	fingers
Other	Resolution [bit]	12	11	16	12	n.a.	12	12	12	n.a.	n.a	12	n.a.	n.a.	12	12
	Bandwidth [Hz] (pre-processing)	n.a.	n.a.	n.a.	[2–40]	n.a.	[1–75]	[2–40]	[1–100]+notch filter (60 *Hz*)	[0.5–40]	[1.1–35]	[1–50]	[1–1000]+notch filter (60 *Hz*)	n.a.	[5–20]	[0.5–40]
	Sensor device	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	NI PCI-6071E	Vernier EKG sensor	n.a.	Biopac Student	n.a.	n.a.	bioPLUX research	Vernier EKG sensor

3.3. On-the-person

3.3.1. Israel et al. (2005)

This work presents one of the early database for biometric recognition purposes, which collects data from 29 volunteers, 17 male and 12 female (22–48 years old) (Israel et al., 2005).

With reference to the hardware, the authors used two electrodes Ag/AgCl placed at the base of the neck and fifth intercostal spacing (chest). The acquisition frequency and a resolution are equal to 1 kHz and 12 bit, respectively.

According to the acquisition protocol, each subject was required to perform two sessions. Each session is formed by seven tasks of two minutes, which were designed to stimulate different levels of anxiety and they were divided into high stress and low stress tasks. The low-stress tasks were: the subject's baseline state, the meditative and the recovery task. The high stress tasks were: reading aloud, mathematical manipulation, and driving in virtual reality.

With regard to the signal preprocessing stage, the authors eliminated the noise in the low and in the high frequencies using a frequency bandpass filter between 2 Hz and 40 Hz, which was written with the equivalent of a lower order polynomial so the filter is stable at the frequency limits.

3.3.2. Zhang and Wei (2006)

This database collects 502 ECG recordings and it represents the largest database with *On-the-person* approach that has been reported for biometric purpose (Zhang & Wei, 2006). The gender distribution and age range of the subjects are not specified in the paper.

The ECG recordings (10 s long) were acquired by a 12-lead ECG device with a sampling rate of 500 Hz, but no information on the used resolution is available.

The acquisition protocol required each subject to perform a single recording in resting condition.

With respect to the signal preprocessing stage, each ECG recording was divided into two segments: one is used to build the recognition model, whereas the other to test ECG segment for identification. The authors applied difference method to detection of the R-peak and of the QRS complex (Kohler, Hennig, & Orglmeister, 2002).

3.3.3. Wübbeler et al. (2007)

This database collects 234 ECG recordings from 40 Caucasian male and 34 Caucasian female (19–86 years old) (Wübbeler et al., 2007).

The hardware was built according to Einthoven's triangular scheme and the ECG traces (10 s length) were recorded from three channels (Leads I, II, III). The acquisition frequency and the resolution were was set to 0.5 kHz and to 12 bit, respectively. The electrodes were fixed to the left arm, to the right arm and left leg.

The acquisition protocol required each subject to participate in a variable number of sessions while he/she was seating, by a maximum of twelve to a minimum of two.

With regard to signal preprocessing, ECG traces were baseline corrected by subtracting a moving median of 1 s width. Additionally, a low-pass filter with a cut-off frequency of 75 Hz was applied to each channel, whereas the positions of the R-peaks were determined from the absolute value of the low-pass filtered temporal derivative of each ECG trace using a threshold procedure.

3.3.4. Irvine et al. (2008)

This database collects the ECG signal of 43 subjects, 26 male and 17 female (18–48 years old) (Irvine et al., 2008).

With reference to the hardware, the authors adopted the same hardware used by Israel et al. (2005) (Section 3.3.1).

According to the acquisition protocol, in each session the ECG signal was recorded while the subject performed seven tasks 2 min long. The tasks were designed to elicit different stress levels and to understand stress/recovery cycles.

With respect to signal preprocessing the raw data were analysed with adaptive filter structures to eliminate electrical, thermal, and A/D noise sources (Thakor & Zhu, 1991). The individual heartbeats were aligned by the peak of their R wave, computing the autocorrelation function of the ECG data stream and using that function to segment the heartbeats.

3.3.5. Agrafioti and Hatzinakos (2010)

This database collects ECG recordings from 52 healthy volunteers (21–40 years old), but data on the gender distribution of subjects are not specified (Agrafioti & Hatzinakos, 2010).

The acquired ECG signals consist of 3 min single channel recordings, obtained from the wrists using the Vernier ECG Sensor.[2] The acquisition frequency was set to 0.26 kHz, whereas the used resolution is not specified in the paper.

According to the acquisition protocol, all subjects were in resting position and they performed a single recording session. For 16 subjects the recording were repeated about a month later.

With regard to signal preprocessing, the ECG traces were filtered with a butterworth bandpass filter, whose cutoffs frequencies were set at 0.5 Hz and 40 Hz, to reduce the noise effects of baseline wander (low frequency), and of powerline interference (high frequency). The authors designed a periodicity transform (Sethares & Staley, 1999) to handle the detection and removal of ECG artefacts and they also introduced a measure to estimate if an ECG segment is free of major artefacts.

3.3.6. Yao and Wan (2010)

This database collects 121 ECG recordings from 30 subjects, 26 males and 4 females (18–51 years old) (Yao & Wan, 2010).

ECG data were collected by limbs with an acquisition frequency equal to 0.25 kHz. The authors used a wearable ECG sensor based on a low power precise instrumentation amplifier.[3] The analog signal amplified was acquired by a LabVIEW application through a National Instrument multifunction input/output card. The used resolution is not reported in the paper.

According to the acquisition protocol, each subject performed at least two sessions in resting condition. The time interval between different recording sessions varies from several hours to few weeks.

Signal preprocessing consists of a discrete wavelet transform applied to the raw ECG signal to eliminate the noise without appreciable signal degradation.

3.3.7. Shen et al. (2010)

This database is the most recent biometric database in the literature adopting the *On-the-person approach* (Shen et al., 2010). It is a further improvement of Shen et al. (2002). The authors collected a database with 168 subjects, 113 females and 55 males (19–52 years old).

The hardware was designed to acquire the ECG signal (90 s long) by the hand palms using Ag/AgCl electrodes. The acquisition frequency was set to 0.5 kHz, with a resolution of 12 bit.

According to the acquisition protocol, the subjects were in resting position and sitting upright during the recording. Furthermore, they were required to relax with their palms open and resting on their legs.

[2] Datasheet of EKG Sensor available at http://www.vernier.com/files/manuals/ekg-bta.pdf.

[3] Datasheet of LT1167 Single Resistor Gain Programmable, Precision Instrumentation Amplifier available at cds.linear.com/docs/en/datasheet/1167fc.pdf.

With respect to signal preprocessing, the authors calculated R-R intervals using Pan and Tompkins method (Pan & Tompkins, 1985), whereas the detection of PQRST fiducial points on raw ECG signals was achieved using digital filtering, first derivative ECG method (Kamath & Ananthapadmanabhayuyu, 2007), and the zero-crossing method.

3.3.8. Odinaka et al. (2010)

This database collects ECG signals of 269 subjects (145 females and 124 males), where 40% of the subjects had some heart disease while the 47% used drugs that may alter the ECG signal (Odinaka et al., 2010).

The ECG signal was recorded in all sessions with electrodes bilaterally placed on the lower rib cage of the subject. The acquisition frequency used was equal to 10 kHz, although successively the signal is down-sampled at 1 kHz and finally filtered with a digitally notch to 60 Hz to eliminate power-line interference. The authors did not report in the paper the resolution used.

The acquisition protocol demanded that all subjects perform three acquisition sessions in three different days. The time interval between different recording days varies from two weeks to six months.

With regard to signal preprocessing, the ECG signal was reduced to individual 700 ms segments aligned to the corresponding peak of the R-wave, starting 200 ms before the peak. To align the segments ECG to the peak R-wave, for each participant in the study the data were first filtered with an infinite impulse response elliptical filter (5 Hz cutoff frequency, 90 dB) and then an artefact-free calibration epoch of 15 s was selected. In this way, all the positive inflection points (peaks) within this epoch were determined. Only the peaks whose amplitude was at least 75% of the amplitude of the maximum detected peak were retained for subsequent analysis.

3.3.9. Jang et al. (2010)

This database collects ECG recordings from 65 subjects, 31 females and 34 males (22–48 years old) (Jang et al., 2010).

The authors used an unconventional ECG setup: the signal is acquired using a single channel with a frequency of 1 kHz and a resolution of 12 bit.

According to the acquisition protocol, the subjects were in resting condition and each carried out six recording sessions.

With respect to signal preprocessing the raw data were analysed with adaptive filter structures to eliminate electrical, thermal, and A/D noise sources (Thakor & Zhu, 1991). Then they were segmented to individual beats Clifford, Azuaje, McSharry (2006) and they were resampled to 100 Hz. Each heartbeat's amplitude were normalized to vary between zero and one. Finally, the authors discarded low quality signals after a quality screening.

3.4. Off-the-person

3.4.1. Chan et al. (2008)

This work presents one of the early databases whose signals were collected using the off-the-person approach (Chan et al., 2008). The authors recorded the ECG of 50 subjects, 45 males and 5 females (18–40 years old).

With regard to the acquisition hardware the ECG was recorded with a pair of 0.5-Ag/AgCl button electrodes, that were held on the pads of the subject's thumbs. In detail, the positive and negative terminals of a differential amplifier were connected to electrode leads of the left and right thumb pads, respectively.

Signals have been recorded connecting the electrode leads of left and right thumbs to the positive and negative terminals, respectively, of a differential amplifier. The acquisition frequency was equal to 1 kHz, whereas the resolution was 12 bit.

According to the acquisition protocol, all subjects participated in three sessions of acquisition in rest position (90 s long) with a minimum of one day between sessions.

With respect to the signal preprocessing stage, the authors set the bandwidth at 1–100 Hz and they reduce the power-line interference using a notch filter. The PQRST complexes are detected using the multiplication of backward differences algorithm (Suppappola & Sun, 1994); subsequently, the complexes were temporally aligned using a cross-correlation measurement. All the complexes with a correlation coefficient far from mean correlation coefficient were discarded, whereas the others were used in order to reduce additive noise and effect of low-frequency drifts through the computation of average ECG signal.

3.4.2. CYBHI database (Da Silva et al., 2014)

In this work (Da Silva et al., 2014) presented the CYBHI database which consists of 128 ECG recordings and the acquisitions were performed using the off-the-person approach. This work is the extension of Da Silva et al. (2013).

With respect to the acquisition hardware, the ECG signal (2 min long) was recorded by both wrists and fingers, using dry Ag/AgCl electrodes and electrolycra strips respectively. Both sensors were placed on custom hand-shaped support, guaranteeing data synchronization using the syncPLUX synchronization kit. The electrodermal activity data was simultaneously acquired to provide information about the arousal state of the subject, since their acquisition protocol included both neutral and emotional elicitation tasks. The acquisition frequency is equal to 1 kHz, and the resolution is 12 bit. It is worth observing that the paper of Da Silva et al. (2014) is the only one among all that reports the sensor bandwidth, which ranges in [1–30] Hz.

The acquisition protocol consisted of short-term and long-term sessions. Short-term sessions were held in two days with 65 participants, 49 males and 16 females (22–41 years old). The participants performed experimental procedure 5 min long, looking at a low arousal video and a high arousal video. The former video was an amusing video to stimulate low arousal (funny video); the latter video was a more intense video to stimulate high arousal such as a horror movie trailer. Long-term sessions consisted in two data acquisition moments separated by a 3 month with 63 participants, 14 males and 49 females (18–24 years old). In both phases only ECG signals at the fingers were recorded, and in each of the sessions the subjects were seated for 2 min in a resting position, with two fingers on the dry Ag/AgCl electrodes.

With regard to signal preprocessing, the authors respected the set of guidelines stipulated by in Lourenço, Silva, and Fred (2011). In additional, to enhance the ECG signal quality and increase the signal-to-noise, they used a 300 order band pass finite impulse response filter, with a Hamming window, and cutoff frequencies between 5 Hz and 20 Hz.

3.4.3. UofTDB (Pouryayevali et al., 2014)

Pouryayevali et al. (2014) collected the largest existing databases with 1012 ECG recordings of different people, 398 males and 622 females (18–52 years old).

Acquisition hardware was composed of a pad with dry electrodes Ag/AgCl positioned so that the left thumb was placed on the positive electrode, whereas the right thumb and right forefinger were placed on the negative and on the reference electrodes, respectively. The authors used an acquisition frequency of 0.2 kHz and a resolution of 12 bit.

According to the acquisition protocol, the ECG recordings were performed in the following conditions: supine, tripod, sit, physical exercise, and stand. The ECG signals were recored for all the subjects while sitting, but they were collected in supine, tripod, physical exercise, and standing conditions only for 63, 63, 71 and 81 participants out of the 1012 involved. As to the time interval, 72, 65, 54, 47, 43 out of 1012 subjects participated in two, three, four, five and six acquisition sessions, respectively. The length of each recording ranges from 2 min to 5 min.

As for preprocessing, to eliminate the corruption introduced by baseline distortion, by muscle movement and by power-line noise the raw ECG signals were digitally filtered using a fourth-order Butterworth bandpass filter with cutoff frequencies equal to 0.5 Hz and to 40 Hz. The QRS detection algorithm used is described in Pan and Tompkins (1985), whereas individual heartbeats are truncated to a length of 700 ms with 200 ms before the R peak.

4. Systematic analysis

In this section we present the framework to quantitatively compare the acquisition hardware and the acquisition protocol of the work presented in Sections 3.3 and 3.4.

4.1. Acquisition hardware

In order to compare the different acquisition hardware we first analyse the literature to determine which should be the preferable solutions. This analysis reveals that:

- A one-lead setup further to be appropriate for biometric applications (Shen et al., 2002), it is also the most practical solution;
- Reducing the number of contact points for data acquisition is of benefit to user acceptance;
- Signal quality of dry electrodes is comparable to the one provided by commercial Ag/AgCl gel-electrodes. Furthermore, the former electrodes permit faster data acquisition than the latter since skin preparation is not required (Searle & Kirkup, 2000; Silva et al., 2011);
- *Off-the-person* approach is preferable to *On-the-person* one. Indeed, off-the-person approach does away with time to locate the electrode on human body, being user-friendly and facilitating recording preparation. This allows one to collect data from many people in a short time (Da Silva et al., 2013).

On this ground, our comparison considers five variables: the number of ECG channels, the type of electrodes, the number of contacts points, the intrusiveness of the setup and the acquisition frequency. A graphical representation of the comparison is offered in Fig. 3, where we show radar plots whose axes represent the previous quantities, allowing to visually catch information on positive and negative aspects of each database. Indeed, the plots are conceived so that the larger the area in the plot, the better the acquisition hardware used. Consequently, the larger the value on each axis, the more positive the corresponding aspect of the database.

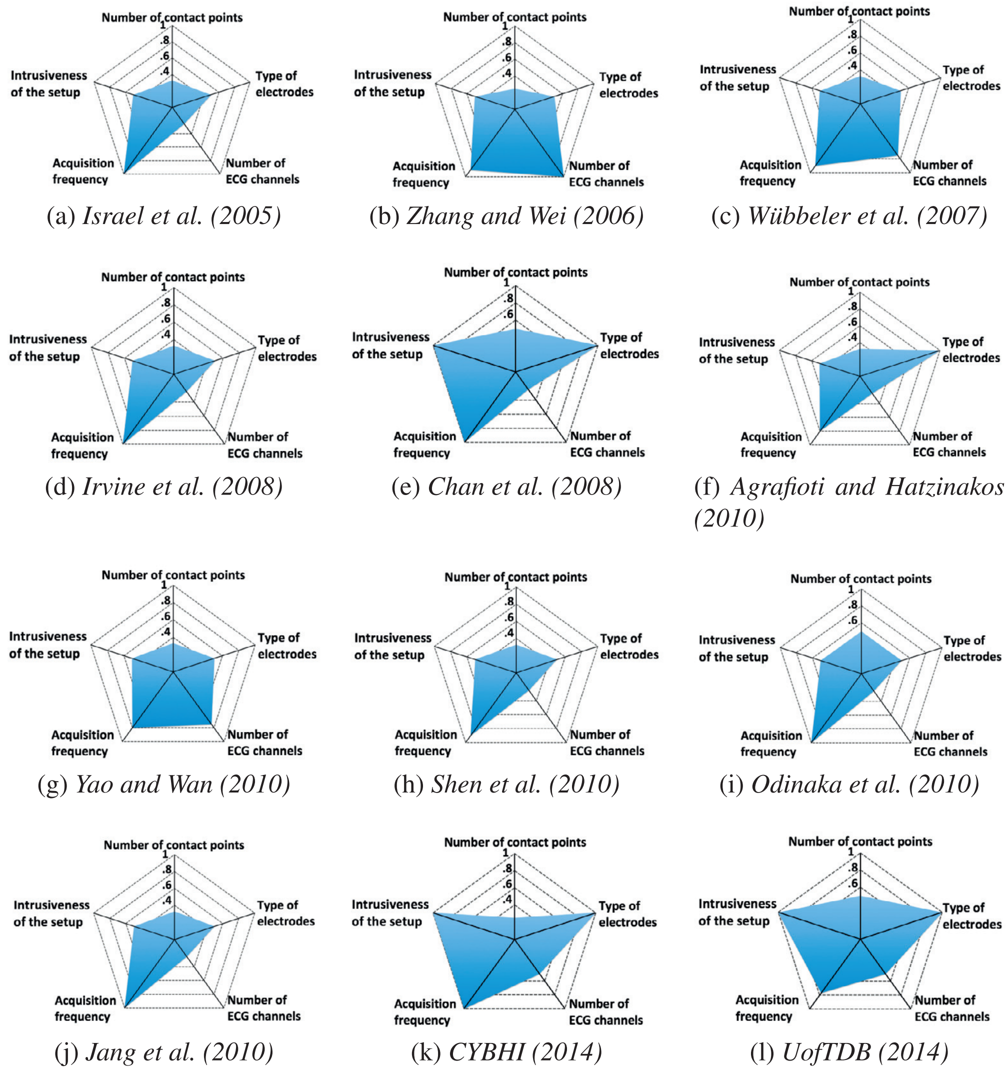
The five axes are defined as follows:

1. *Number of ECG channels*: it is an axis with increasing values that correspond to the number of ECG acquisition channels. To facilitate the comparison we normalize the values of this axis with respect to the largest value.
2. *Type of electrodes*: the ECG signals of the various databases are collected using, mostly, wet or dry electrodes. Although they provide similar acquisition performance (Searle & Kirkup, 2000), the latter permits a simpler user preparation to registration than the former. For this reason, we assign the 0.5 and 1 to the databases using wet and dry electrodes, respectively.
3. *Number of contact points*: the fewer the number of contact points, the simpler the acquisition setup, as mentioned before. We therefore applies a reciprocal proportion between the value reported on the axis and the number n of contact points, i.e., the axis value is equal to $1/n$.
4. *Intrusiveness of the setup*: the use of an acquisition hardware with low intrusiveness would allow to reduce the acquisition time as it ensures a high user acceptability and a simple setup. According to the categorization presented in Section 3.2 (Da Silva et al., 2015; Da Silva et al., 2014), it is straightforward to note that the in-, on- and off-the person approaches correspond to the highest intrusiveness, to an intermediate intrusiveness, and to the lowest intrusiveness, respectively. Since the lower the intrusiveness, the better the dataset, the in-, on- and off-the person approaches are scored by 0, 0.5 and 1, respectively.
5. *Acquisition frequency*: The determination of an adequate sampling frequency for ECG acquisition is still controversial. For example, Israel et al. (2005) used a frequency bandpass filter between 2 and 40 Hz. Indeed, there exist studies suggesting to use sampling frequencies higher than 250 Hz and up to 5000 Hz since some features derived from ECG for biometric purposes, e.g., maximum amplitude of QRS, heart rate variability, approximate entropy, might be affected by the sampling rate (Cysarz et al., 2008; Hejjel & Roth, 2004; Rijnbeek, Kors, & Witsenburg, 2001; Singh, Singh, & Banga, 2014). Although the Nyquist rate defines the minimum boundary above which a given analog signal can be reconstructed from its digital representation, sampling the ECG using a higher rate does favor an implicit reconstruction of the signal due to the larger number of samples available. The axis uses a logarithmic scale that reduces wide-ranging quantities to smaller scopes. In practice, we compute the base 10 logarithm of this value, and then we normalize the frequency axis to the largest value.

4.2. Acquisition protocol

We now compare the acquisition protocol used to collect the aforementioned databases. To this aim we consider six variables: the number of subjects involved in the study whose ECG is acquired once at least, the average number of ECG per person, the average length in second of ECGs, the gender distribution, the variability of conditions during ECG acquisition, and the location of electrodes. Again, positive and negative aspects of each database can be visually caught in the radar plot graphically representing these quantities (Fig. 4). When the data are not available, we appeal to the Dempster-Shafer theory (Dempster, 1968; Shafer et al., 1976), which is a general framework for reasoning with uncertainty that models the lack of information with a belief function measuring the strength of all the available evidence in favour of a proposition. In details, the six variables are:

1. *Number of subjects*: it is an axis with increasing values that correspond to the number of people whose ECGs were recorded at least once. This quantity represents the number of biometric recognition tests that can be performed on different subjects. To facilitate the comparison, we normalize the values with respect to the largest one.
2. *Average number of ECG per person*: the axis represents the average number of ECG per person stored in the database, which is normalized with respect to the maximum. A large number of tests repeated per person should permit to investigate how much a biometric methodology is robust to intra-subject variation over time.
3. *Average ECG length*: it is an axis with increasing values corresponding to the average length of ECG traces, whose value is normalized with respect to the maximum. It is straightforward to note that the larger the value, the larger the amount of data in the database that can be used in biometric research. Since this information is not available for Odinaka et al. (2010); Yao and Wan (2010) and Jang et al. (2010) we proceed as

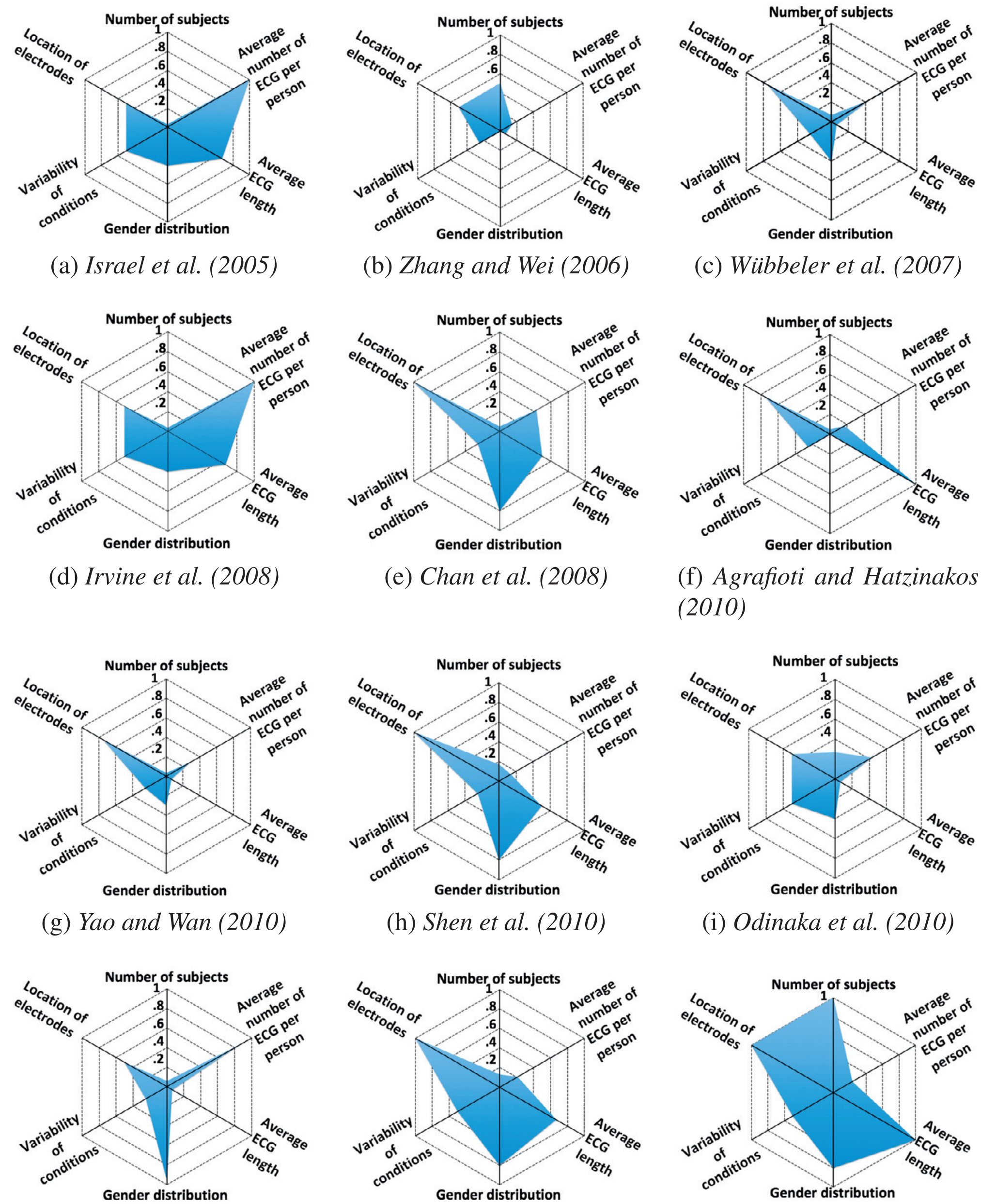


(a) *Israel et al. (2005)* (b) *Zhang and Wei (2006)* (c) *Wübbeler et al. (2007)*
(d) *Irvine et al. (2008)* (e) *Chan et al. (2008)* (f) *Agrafioti and Hatzinakos (2010)*
(g) *Yao and Wan (2010)* (h) *Shen et al. (2010)* (i) *Odinaka et al. (2010)*
(j) *Jang et al. (2010)* (k) *CYBHI (2014)* (l) *UofTDB (2014)*

Fig. 3. Radar graphs on the acquisition hardware. Each plot consists of five-axis: number of ECG channels, type of electrodes, number of contact points, intrusiveness of the setup, and acquisition frequency, described in detail in Section 4.1. The databases are shown following a chronological order.

follows to model this uncertainty. The shortest reasonable length of time to acquire an heart-beat usable for biometric purposes, which is 1 *s* (Zhao et al., 2013), represents the sure event in the Dempster-Shafer framework whose belief is one. As none other ECG length can exceed this value of the belief, we assign 1 s to such databases where the data is omitted.

4. *Gender distribution*: we introduce this axis since ECG patterns are significantly different between genders (Surawicz & Parikh, 2002). It is straightforward to note that a female gender distribution of 50% is the ideal case to avoid any bias. For this reason, the axis represent the quantity 2*f*, if $f \in [0, 0.5]$, or $2 * (1 - f)$, if $f \in]0.5, 1]$, where *f* denotes the relative frequency of female subjects who are in the considered repository. Data on gender distribution are not reported in Zhang and Wei (2006) and Agrafioti and Hatzinakos (2010): in this case we associate $f = 0$ since the Dempster–Shafer theory models the lack of information with a belief function equal to zero.
5. *Variability of conditions*: physical activities, mental stresses or heart disorders (disease- or drug-related) may introduce morphological changes in the ECG signal (Agrafioti & Hatzinakos, 2009; Wang & Zhang, 2014). This suggests that ECGs acquired with such three variability-inducing conditions would permit to assess the robustness of any biometric recognition method (Da Silva et al., 2013). To the best of our knowledge, we do not find in the literature on ECG biometric a reference defining the order of importance of these three conditions. We therefore define an increasing scale of values in arithmetic progression with common difference of 0.25 that, starting at 0.25 when the database contains only ECGs collected in the rest condition, adds the common difference for each variability-inducing condition added to the database. As a consequence, the four values in the radar plot axis are defined as follows: 0.25 (assigned as just mentioned); 0.50 (assigned to the database if the ECGs are collected in the presence of only one variability-inducing conditions); 0.75 (assigned to the database if the ECGs are collected in the presence of two out the three variability-inducing conditions); 1 (assigned to the database if the ECGs are collected in the presence of all the three conditions).
6. *Location of electrodes*: it gives clues about the user-acceptance and how long is the acquisition preparation phase. This axis has three increasing values: 0.5 (when the electrodes are put on the chest or on the lower rib cage); 0.75 (when the electrodes are put on the limbs); 1 (when the electrodes are put either on the fingers or on the palm).



(a) *Israel et al. (2005)* (b) *Zhang and Wei (2006)* (c) *Wübbeler et al. (2007)*
(d) *Irvine et al. (2008)* (e) *Chan et al. (2008)* (f) *Agrafioti and Hatzinakos (2010)*
(g) *Yao and Wan (2010)* (h) *Shen et al. (2010)* (i) *Odinaka et al. (2010)*
(j) *Jang et al. (2010)* (k) *CYBHI (2014)* (l) *UofTDB (2014)*

Fig. 4. Radar graphs on acquisition protocol. Each plot consists of 6-axis: number of subjects, average number of ECG per person, average ECG length, gender distribution, variability of conditions and location of electrodes. These quantities are described in detail in Section 4.2. The databases are shown according to a chronological order.

5. Discussion

On the basis of the data reported so far in this section we are going to discuss the following issues: (i) the shared features among the various biometric databases as well as the positive and negative aspects of each repository, (ii) the comparison of the acquisition hardware, (iii) the comparison of the acquisition protocol, (iv) the main features that a comprehensive and exhaustive database for developing CBBSs should have, (v) the link between these features, the application requirements and future research directions in CBBSs.

With respect to the first issue, Table 1 shows two key-points. First, the two most recent papers use the off-person approach, i.e., a non-intrusive acquisition method which is more suitable than others to acquire the ECG signal by many people since it does not require any subject preparation and it increases the acceptability. Second, the same recent papers collect the ECG data using a one-lead sensor-subject interface. Indeed, a low number of contact points makes easier the acquisition of a large database, reducing the amount of time needed to set-up the experiment. Furthermore, Table 2 shows a summary of positive and negative aspects of all the databases for each of the variables investigated in our systematic analysis. In particular, for each tabular we adopt the signs ↑ and ↓ to denote a positive and a negative feature of the database, respectively. The sign ↔ is used to denote a feature that cannot be considered either positive nor negative, whereas the sign × means that no information is available for the feature under consideration.

Let's now turn the attention to the second issue. Table 1 and Fig. 3 show that a variability between methods used to collect the various biometric databases exists. Indeed, we observe large differences to average ECG length, type of electrodes and number of

Table 2
Positive and negative aspects of the databases. For each tabular we adopt the signs ↑ and ↓ to denote a positive and a negative feature of the database, respectively. The sign ↔ is used to denote a feature that cannot be considered either positive nor negative, whereas the sign × means that no information is available for the feature under consideration.

Info	Properties	Israel et al., 2005	Zhang & Wei, 2006	Wübbeler et al., 2007	Irvine et al., 2008	Chan et al., 2008	Agrafioti & Hatzinakos, 2010	Yao & Wan, 2010	Shen et al., 2010	Odinaka et al., 2010	Jang et al., 2010	CYBHI (2014)	UofTDB (2014)
Hardware	Number of channels	↔	↑	↑	↔	↔	↔	↔	↔	↔	↔	↑	↔
	Type of electrodes	↔	↔	↔	↔	↔	↔	↔	↔	↔	↔	↑	↔
	Number of contact points.	↔	↓	↔	↔	↑	↔	↔	↔	↑	↔	↔	↑
	Intrusiveness of the setup	↔	↔	↔	↔	↑	↔	↔	↔	↔	↔	↑	↑
	Acquisition frequencies [kHz]	↑	↔	↔	↑	↑	↔	↓	↓	↑	↓	↑	↓
Protocol	Number of subjects	↓	↑	↔	↓	↓	↓	↓	↔	↑	↓	↔	↑
	Average number of ECG per person	↑	1	↑	↑	↑	↓	↑	↓	↓	↑	↑	↓
	Average ECG length [s]	↓	↓	↓	↑	↑	↑	×	↑	×	×	↑	↑
	Gender distribution (%F,%M)	↔	×	↑	↔	↓	×	↓	↔	↑	↑	↑	↔
	Condition or disorders	↑	↔	↔	↑	↔	↔	↔	↔	↑	↔	↑	↑
	Electrodes location	↓	↓	↔	↓	↑	↑	↔	↑	↓	↓	↑	↑

Table 3
Measures derived from Figs. 3 and 4. The second and the third columns report the areas of each radar plot in the two figures, whose values are normalized with respect to the maximum area of the plot. The last column shows the overall rank among the databases.

Database/Paper	Acquisition hardware	Acquisition protocol	Rank
Israel et al. (2005)	.34	.24	4
Zhang and Wei (2006)	.50	.08	4
Wübbeler et al. (2007)	.46	.07	8
Irvine et al. (2008)	.34	.24	4
Chan et al. (2008)	.69	.19	3
Agrafioti and Hatzinakos (2010)	.38	.07	10
Yao and Wan (2010)	.30	.05	12
Shen et al. (2010)	.32	.19	9
Odinaka et al. (2010)	.41	.13	7
Jang et al. (2010)	.34	.09	11
CYBHI (Da Silva et al., 2014)	.69	.29	2
UofTDB (Pouryayevali et al., 2014)	.64	.53	1

contact points. In order to facilitate a quantitative comparison between the databases we use the area of the plots as an aggregated score integrating all the metrics into a single number. The second column of Table 3 shows the radar plot area of each database normalized by the maximum area of the radar plot, which represents the score that would be assigned to a database winning against the others for all the variables of the acquisition hardware. Such score reveals that CYBHI (Chan et al., 2008; Da Silva et al., 2014) and UofTDB (Pouryayevali et al., 2014) are the three best databases, as also the visual inspection of Fig. 3 confirms. These databases adopt the off-the-person approach, confirming that it is suited for collecting data that have to be used for developing CBBSs. We notice that the databases presented by Da Silva et al. (2014) (CYBHI) and by Chan et al. (2008) obtain the same score because they have similar acquisition hardware, which appears to be the best one and the most user-friendly. In particular, their signals are acquired using an acquisition frequency higher than UofTDB: this choice provides more data that should be turned into features that can be exploited by the biometric expert systems when the features for the classification or the regression phase have to be used by a learning paradigm to take a decision. Furthermore, whilst hardware of Chan et al. (2008) allows one to acquire the ECG signal only by fingers, the CYBHI equipment can collect data also from the hand palm. The possibility to acquire the ECGs from fingers and palms allows one to compare the quality of the signals and to design a redundant and robust CBBSs taking advantage of both.

As far as the third issue, Table 1 and charts in Fig. 4 show a variability between protocols designed to collect the data of the various biometric databases. These differences, in conjunction with those of the acquisition hardware, may lead to a large inhomogeneity between ECG signals of different databases. The values of the single score reported in the third column of Table 3 show that the two best databases are again UofTDB (Pouryayevali et al., 2014) and CYBHI (Da Silva et al., 2014). However, they are now inversely ordered with respect to the results of the acquisition hardware and, also, the former almost doubles the latter. This happens because the CYBHI database consists of much lesser number of subjects than UofTDB, and it also has scores smaller for average number of ECG and average ECG length. Note that the UofTDB database, although it wins the comparison, it does not include signals collected while people are subjected to mental stresses or suffering from heart diseases. Furthermore, the value of its score, which is the largest, is only half of that maximum suggesting that further efforts are needed in this field. We also notice that Israel et al. (2005) and Irvine et al. (2008) get the same results since they adopts the same acquisition protocol. The only difference is the number of subjects, that is 29 for Israel et al. (2005) and 43 for

Irvine et al. (2008): this slight variation does not alter the results since these values are normalized with respect to the 1012 subjects enrolled by UofTDB.

We deepen now the comparison between the databases via a ranking analysis that contemporaneously considers both the acquisition hardware and protocol. To this aim, for each database we sum its area values, which are reported in the second and third column of the Table 3, and we assign a rank with respect to its place among the others. The largest rank is twelve (assigned to the worst database) and the lowest is one (assigned to the best database): the results are reported in the fourth column of the table. They show that UofTDB (Pouryayevali et al., 2014) and CYBHI (Da Silva et al., 2014) databases rank first and second, respectively. However, none of them outperform the other on both the acquisition protocol and hardware, suggesting that there is not a full predominance of one database over the others. We also observe that the sum over the two columns for the best database is equal to 1.17, a value corresponding to the 58.5% of the maximum representing the score that would be assigned to a database winning against the others for all the variables of the radar plots. To strengthen this ranking analysis we now discuss how much the different scores assigned to qualitative dataset information affect the database rank shown in Table 3. As widely described in Section 4, the axes of the radar plots where we assign quantitative scores to qualitative information are type of electrodes, intrusiveness of the setup, variability of conditions and location of electrodes. We ran a sensitivity analysis where we computed again the database rank when each of these scores varies $\pm 20\%$ of its values defined in Section 4. Note that we preserved the ordering between these scores when rescaling them; for instance, in case of the variable named as location of electrodes the value assigned when the electrodes are put on the limbs cannot exceed the value assigned when the electrodes are put on the hands. Interestingly, we found that the ranks are always equal to those shown in Table 3, suggesting that the quantitative claims derived from this table hold also if different scores are adopted.

The observations reported so far allow to introduce the fourth issue of the discussion as they suggest us that at the time of writing a comprehensive and exhaustive ECG database is not available for researchers and practitioners interested in developing CBBSs. Therefore, leveraging on our analysis of the literature, we deem that the collection of a database meeting the following requirements is a key future direction in this area:

- Large cardinality;
- Uniform gender distribution of subjects;
- Off-the-person acquisition method;
- High frequency recordings (>1 *kHz*);
- ECG signal acquisition through a single-lead setup;
- Records acquired under variability-inducing conditions, such as physical activities, mental stress and heard disorders (disease- or drugs-related);
- Repeated recordings of the same subject collected with a period of least six months between sessions;
- Raw ECG data to test different methods of pre-processing and ECG biometric recognition.

We deem that a database with these features allows one to perform more exhaustive studies than those developed until now, a need that should be fulfilled due to the growing interest on the ECG biometric research. This is more so true when there is no specific application that needs to be addressed, but we are interested in benchmarking CBBS ECG-based independently of the application requirements.

The final issue of this discussion focuses on future research directions in expert and intelligent systems for biometric applications. Currently, ECG biometrics is still in its infancy; in fact, the literature shows that good performance have been attained only on a small scale (tens of hundreds of individuals). Gathering a new (possibly multi-center) database having the characteristics underlined so far might boost the development of CBBSs, improving their performance and extending to a large scale population the use of ECG biometric. To this aim, the expert and intelligent systems should be able to satisfactory work in different and complex application scenarios that, on the other side, have to be represented within an ECG database.

For example, possible scenarios are:

- subject recognition in reserved areas, such as in the clinical environment at a local level (healthcare building) or at a national level (National Healthcare System identifier);
- subject recognition in forensic applications;
- multi-modal recognition: the use of ECG in addition to other biometrics such as face, fingerprint, iris, etc.;
- subject recognition within vehicles (Matsuda & Makikawa, 2008; Silva, Lourenço, & Fred, 2012): in this scenario [contactless] electrodes might be embedded within the seat or the steering wheel;

The possibility of effectively using ECG in such scenarios depends upon some considerations that must be taken into account. A first strong requirement in some of the above mentioned CBBS applications is the practical/easy feasibility and user friendliness of ECG recording. This requirement can be met by using off-the person acquisition methods and by performing signal acquisition through a single lead setup. Moreover, in some scenarios it is strongly required that recognition works in different stress conditions: it is well known that ECG characteristics such as QT interval and T shape might be affected by the heart rate, which in turn is strictly related to oxygenation requirements - both physical exercise and emotional stress can induce heart rate variation (Gargiulo et al., 2015). This implies that CBBSs have to use data acquired under variability-inducing conditions, as well as by considering repeated recordings of the same subject collected with a sufficient long period of time between sessions.

The availability of a new database having all the previously described features can also stimulate the development of new recognition algorithms and devices that, in turns, can rush the development of this research area. Algorithms and devices are not unlinked however: in fact, it might be expected that new devices (for example Sun and Yu (2016); Venugopalan, Savvides, Griofa, and Cohen (2014)), to which new kind of ECG waveform might correspond, will stimulate new processing algorithms.

6. Conclusions

The development and test of an intelligent system, as a CBBS, typically requires to have a database gathered from the domain of interest. In several cases, however, it seems that the habit of proposing new approaches is prevailing against the need of benchmarking the performance of the existing ones in an objective way (De Santo, Foggia, Sansone, & Vento, 2003). So, in order for the research community in the ECG-based CBBS to correctly assessing the performance of existing algorithms or even commercial intelligent systems (as the Nymi Band)[4] it is essential to have publicly available databases as well as standardized data in the operating environment of the specific application at hand. Our work is prominent from this perspective because it highlights the current lack of standardization in the considered field and then the difficulty of performing an effective benchmarking activity.

[4] Nymi Band is a wearable, multi-factor authenticator that can be used with any application, device or service for strong authentication (web site https://nymi.com/).

As a secondary result we have developed and presented a systematic framework that can be used for evaluating different type of databases gathered for a specific application, with the aim of individuating an "optimal" database for the intelligent application at hand. Of course, the specific features of the databases to be considered have to be chosen on the basis of the considered application; however, the comparison of different existing databases might be conducted using radar graphs, sensitivity analysis and ranking, as in our case.

Finally, it is worth noting that, in the field of benchmarking expert and intelligent systems, the proposed kind of database evaluation differ from the well-known meta-analysis method (Haidich, 2011), a statistical analysis that combines the results of multiple studies in order to increase the cardinality of the dataset as a whole. Our proposal, in fact, is also capable of pointing out the shortcomings of the data used in a specific study, given the considered application field.

Conflict of interests

None declared.

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