
Heartbeat biometrics: a sensing system perspective

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Abstract: This paper reviews the emerging research into exploitation of heartbeat data as a biometric for human identification. A variety of methods have been proposed for acquiring heartbeat signatures and a range of processing methods has been examined. We approach the biometric identification and verification problem by characterising the three major factors affecting performance: individual variants, environmental variants, and sensor variants. The ability to collect and process the signal, exploit the data for individual identification or verification, and disseminate the information depends on all three of these factors. Within each component, we have identified the relevant research. Where possible, we have tied these research papers to practical examples using high resolution ECG data. The research indicates that the heartbeat contains rich information about the individual, their level of anxiety, and the cardiac state.

Keywords: biometrics; heartbeat; ECG; sensing system; cardiovascular function; human identification.

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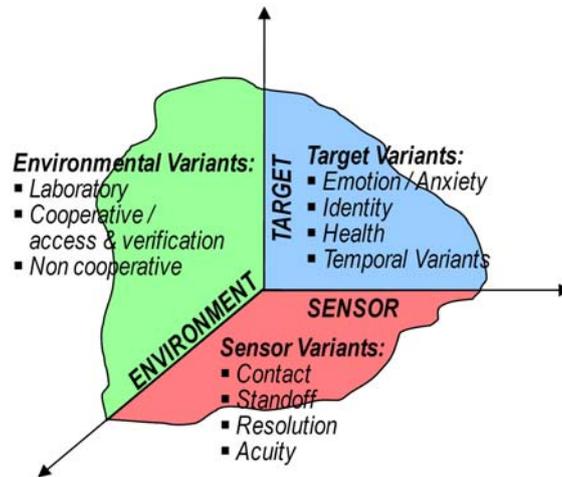
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1 Introduction

Human identification based on cardiac performance involves acquisition, processing, and exploitation of heartbeat measurements. The sensing arrays are either in contact or close proximity to the target, and the consumer has direct access to the signal formation and the storage elements. However, isolating the signal does contain its challenges for characterising the individual with respect to their identity, emotional state, or normal cardiac state. The challenges lie in three fundamental domains and are highly dependent upon applications: the collection environment, the target variations, and the sensor effectiveness (Figure 1). The recorded heartbeat is a convolution of these factors: sensor, environment, and target. By setting the heartbeat recognition problem as a signal processing problem, we will identify the issues to solve for operational utility.

Figure 1 Noise sources for a sensing system (see online version for colours)



The biggest question to answer is, why use heartbeat data as a biometric? The signal is persistent, repetitive, and dependent on fundamental physiological processes, which makes it difficult to spoof or mask (Hawkins, 2002). This makes the heartbeat data valuable for characterising non-cooperative and un-cooperative individuals. Heartbeats

are orthogonal information to traditional biometrics of iris, face, and fingerprint. Heartbeats are collected using non-imaging techniques, which makes long theoretical standoff distance collection possible. Cardiac maladies are readily observable in nearly all collection modalities, which could segment those individuals to a reduced candidate population (Clifford, 2006). Heartbeats are the ultimate liveness metric and the inability to collect the cardiac information from a targeted individual is in itself an indicator.

However, heartbeat data have several dramatic limitations that must be overcome before operational employment occurs. The data contain a relative low information content to identify a reasonably size population using the current collection and feature extraction techniques (Israel et al., 2009). Long dwell times on target are needed to collect a sufficient number of samples to identify an individual. The expression of environmental variables and stressors on the heartbeat data is fairly unique to the individual. Compensation for emotional state requires an intra-individual normalisation. Contact measurements vary with position of the sensors on the body and the sensing technique. Although recognition and verification processing appear to be tolerant to normal changes over short time spans of months to a couple of years, no systematic study has examined biometric performance over multiple years. Cardiac events and health have dramatic impacts on the resulting data signatures, even across short time lines.

The digital exploitation of the heartbeat began with Bayly (1968). Even then, the digital filters were mechanical impedance devices rather than computational algorithms. The majority of the work has occurred for medical applications. The greatest volume of work occurs with the assessment of heart rate variability (HRV) (Malik, 1996; Tiller et al., 1996; Dekker et al., 1997; Liao et al., 1997). The basic HRV processing is to compute the beat-to-beat interval statistics over long durations. Low variance is a strong indicator for sudden cardiac failure. The second common digital signal processing medical application is classifying heartbeats as either normal or associated with a cardiac malady (Kundu et al., 2000; Vila et al., 2000; Carlson et al., 2001). This latter process is an application of supervised classification.

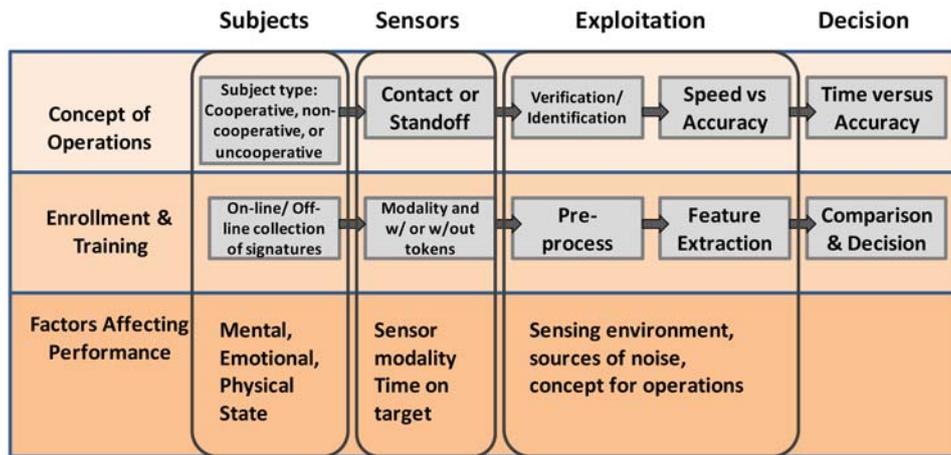
One of the real breakthroughs for HRV processing is for sleep apnoea (de Chazal et al., 2003). The transmission of digital heartbeats allows remote monitoring and the determination of the sleep state of the subject. This allows the subjects to be monitored in their own home which drastically improves the diagnostic impact, while reducing the data acquisition costs. The earliest focused biometric studies appear with van Oosterom et al. (2000) who noticed that the inter-individual differences for electrocardiogram (ECG) traces were significant. This was followed by Irvine (2001) and Biel (2001) who devised experiments for a human identification proof of concept.

As with any biometric system, the heartbeat processing methods encompass an enrolment and operational process. Each stage of the signal acquisition, processing, and decision depends on the factors identified above: the subject, the sensing method, and the environment. Figure 2 illustrates this relationship.

The remainder of this paper is organised in the following manner. The next section covers the data collection and processing to create the heartbeat trace. The following section identifies the information exploitation required and their performance measures to characterise three specific applications: human identification, heartbeat classification, and mental state. The final section covers the dissemination issues that must be solved

when deploying a heartbeat identification or verification system. This paper covers the technical issues associated with signal and information processing. Any policy or societal reference is only for illustrating engineering constraints.

Figure 2 Biometric system design (see online version for colours)



2 Signal acquisition and processing

Unlike many sensing systems, the heartbeat mechanics are widely understood as are the noise sources. A detailed review for the biophysics of a heartbeat appears in Marieb (2003).

2.1 Signal acquisition

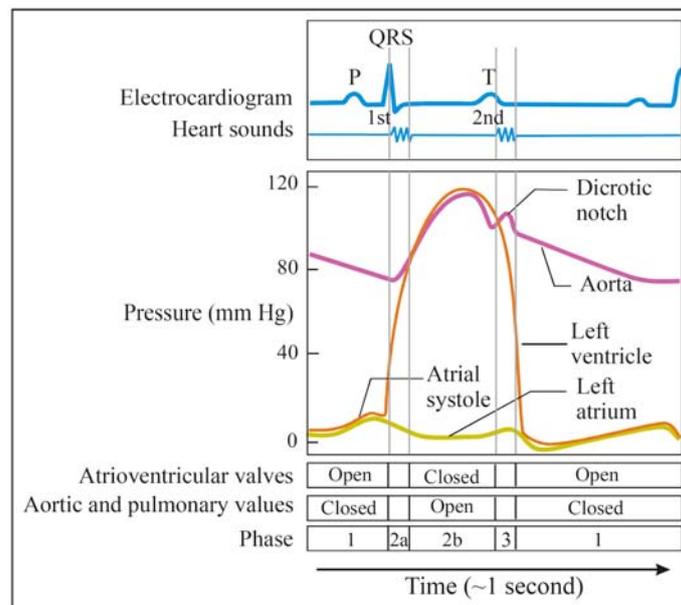
The heartbeat produces signals that can be observed using a variety of sensors. First, the heart's contraction is triggered by an electromagnetic pulse. The body is sufficiently conductive to transmit electrical signals. Second, the heart physically contracts. The heart contraction circulates blood through the vascular network of veins and arteries. Much of the vascular network is near the human skin. The veins and arteries themselves are sufficiently elastic to produce a deflection during changes in blood pressure. Blood oxygenation and therefore light absorbance is highly correlated to blood pressure. The deflection changes of the heart also produce sounds.

Sensing of the heartbeat can be realised through a variety of phenomena: electric, optical, pressure and acoustic (Table 1).

Contact measurements of cooperative subjects provide the highest fidelity measurement, but non-contact, non-invasive sensing techniques have also been explored. Figure 3 shows the mechanics of a single heartbeat. The ECG and blood pressure data overlay the opening and closing of the heart valves to highlight the sensing phenomenology. The blood pressure lags the electrical firing mechanisms of the heartbeat. The contrast in the two metrics indicates the state of the heartbeat.

Table 1 Summary of sensing methods

<i>Method</i>	<i>Phenomenology</i>	<i>Signal acquisition</i>	<i>Comments</i>
ECG	Electrical	Contact	Very rich signal
Pulse Oximeter	Optical	Contact	Easy to acquire
Blood pressure	Pressure	Contact	Easy to acquire
Heart sounds	Acoustic	Contact or non-contact	Affected by environmental noise
Laser Doppler Vibrometry	Surface displacement	Non-contact	Subject motion is an issue
Radar	Doppler	Non-contact	Subject motion is an issue
Motion imagery	Skin colour fluctuations	Non-contact	Experimental method

Figure 3 Heartbeat electrical, acoustical, and mechanical (see online version for colours)

Source: Adapted from Marieb (2003)

2.1.1 Contact measurements

Auscultation is the science of listening to body sounds; i.e. a physician characterising patient health by using a stethoscope. Modern microphones and recording techniques have improved sufficiently that digital heartbeat data can even support training medical students (Barrett et al., 2004). Recently, heart sounds have been exploited to classify medical maladies and as a biometric (Nigam and Priemer, 2004; Beritelli and Serrano, 2007; Phua et al., 2008). Scanlon (2001) mapped the body sound changes as a function of macro movements.

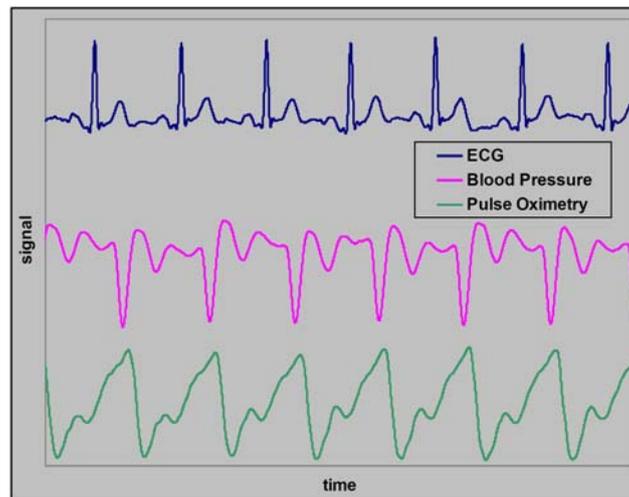
Blood pressure has also been collected to characterise cardiac performance. The blood pressure information is based upon the expansion of the blood vessels with changing pressure during the heart's contraction. Classically, the sphygmomanometer is used to record the peak and low points on the pressure curve. Baselli (2002) digitally collected dynamic blood pressure measurements across multiple heartbeats.

Similarly, the pulse oximeter was developed to exploit the changes in blood flow through the blood vessels. The device uses the absorption of light to characterise differences in the heartbeat sequence. Specifically, the difference between the absorption in the red and near infrared spectra of visible light provides a measure of blood oxygenation (Yoshiya et al., 1980). Tai (2006) exploited pulse oximetry data for liveness metrics.

The earliest mechanical sensing of the heartbeat used a magnet (Bazett, 1920) to deflect a sewing needle connected to two pieces of wire and affixed to the body. The needle was later attached to a pen to form the electrocardiograph. The first ECG data processing occurred later in the 20th century (Golden Jr et al., 1973; Huhta and Webster, 1973).

By far the most common contact measurement of cardiac performance is the electrocardiogram. The ECG measures the changes in electrical potential over time. The relative sensor positions to the plane of zero electrical potential provide additional information about the cardiac performance (Dubin, 2000). The resultant expression of the heartbeat mechanics is captured in the synchronised electrocardiograph, blood pressure, and pulse oximetry data show in Figure 4.

Figure 4 Simultaneous ECG, blood pressure, and pulse oximetry (see online version for colours)



More generalised electrical recordings can be obtained using a charged sensitive bed. The process is called ballistocardiography. The subject is in contact with two sheets that are sensitive to electrical potential differences brought about by the depolarisation of the heart. The advantage is that these measuring procedures are more tolerant to the subject's movement during sleep studies (Jansen et al., 1991).

2.1.2 Non-contact measurements

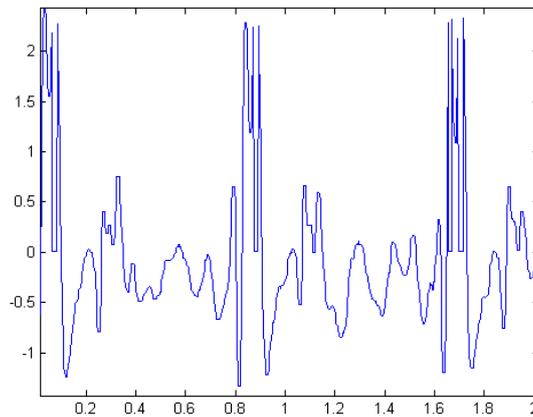
Notionally each of the above contact sensing modalities has a surrogate standoff sensing modality. However, the strength of signal and noise environments makes standoff cardiac biometric signatures difficult to acquire. This section contains information about those sensing modalities currently feasible.

Researchers at Georgia Technology Research Institute (GTRI) used an active radar to note the changes heart volume over time (Greneker, 1997; Geisheimer and Greneker III, 1999). The physical deformation provides extensive information about the individual and the relative health of the heart itself along with respiration and other body movements and muscle flexor noises. This work for human identification is impressive because the potential standoff ranges are in excess of 1 km.

The GTRI work formed the basis for Mazlouman et al. (2009) to characterise cardiac performance using microwave Doppler radar. Instead of attempting to provide surrogate ECG information, these researchers looked in the infrasonic range, i.e. < 20 Hz through ultra-wide band radar > 2 MHz. The researchers continually were able to collect reliable data between 2 and 10 metres. The group was able to overcome the problem of separating macro-body movement from cardiac pulsing by reducing the pulsing dwell times and characterising only the heart rate variability rather than heartbeat identification.

Another measure of standoff cardiac measure was provided by (Parra and Da Costa, 2001). Interferometric data were collected from the pulsing of the carotid artery over time. The measurements were collected with an eye-safe laser. The technique uses laser Doppler vibrometry at high speeds to capture of impulse of the deflection (example in Figure 5). Chen et al. (2010) observed a 0.5% equal error rate across a population of approximately 300 individuals, but concede that the separation of macro-body movement is not currently a solved problem.

Figure 5 Sample interferometric data collected from 10 metres at the carotid artery (see online version for colours)



Standoff range can be estimated using the following scenario. A moderately stable laser has a spot stability of ± 80 radians. The carotid artery deflects across 5 mm minor axis. Therefore, the standoff range can be computed as:

$$\text{standoff distance} = \frac{\text{cross-sectional area}}{\tan \theta} = \frac{0.005 \text{ m}}{\tan 80e^{-6}} = 62 \text{ metres}$$

This improves the standoff range to 1000 metres with a highly stabilised laser that accrues only a 5 μ -radian deflection. Lasers with a spot stability of 5 radians are commercially available. However, no filtering techniques exist to effectively remove the macro body movement noise from the carotid artery interferometry.

2.1.3 Absorption coefficient

The absorption of light in the red and near infrared domain could also be used as a standoff biometric (Sun et al., 2005). A passive system does not contain the combination of cardiac function and macro-body motion signals of active systems. Therefore, the theoretical standoff distance more closely matches the idealised computational distance. If the target is the human face, the sensor would only need 6 pixels to cover a 10 cm \times 10 cm area. For visible light, a 5 μ m pixel pitch focal plane array is available. Given those constraints, a remote pulse oximeter could collect signals from a 640 \times 480 standard format focal plane array digital camera can easily focus on 5 degree field-of-view. The camera would require filters to capture the red and near infrared spectral components (Figure 6). However, standard visible light sensors are sensitive to these bandpasses. To perform this analysis, only a 4 \times 4 pixel array on the face is required which equates to a

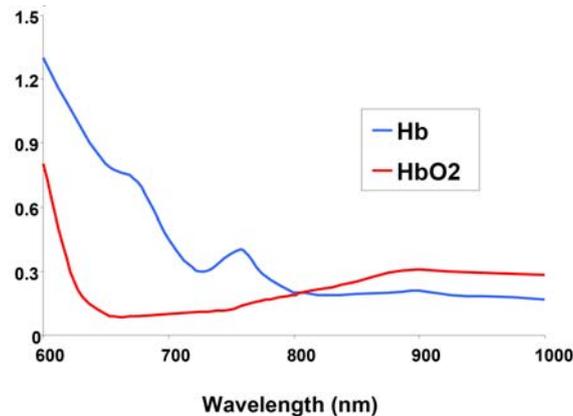
$$\text{facial extent FOV} = \frac{4 \text{ pixels} * 5 \text{ degrees}}{480 \text{ pixels}} = 0.04 \text{ degrees}$$

and a

$$\text{standoff distance} = \frac{\text{cross-sectional area}}{\tan \theta} = \frac{0.01 \text{ m}}{\tan .04} = 138 \text{ metres}$$

Early experiments have confirmed the viability of this technique (Poh et al., 2010; Farley et al., 2011; Poh et al., 2011).

Figure 6 Absorption of light by wavelength by the blood (see online version for colours)



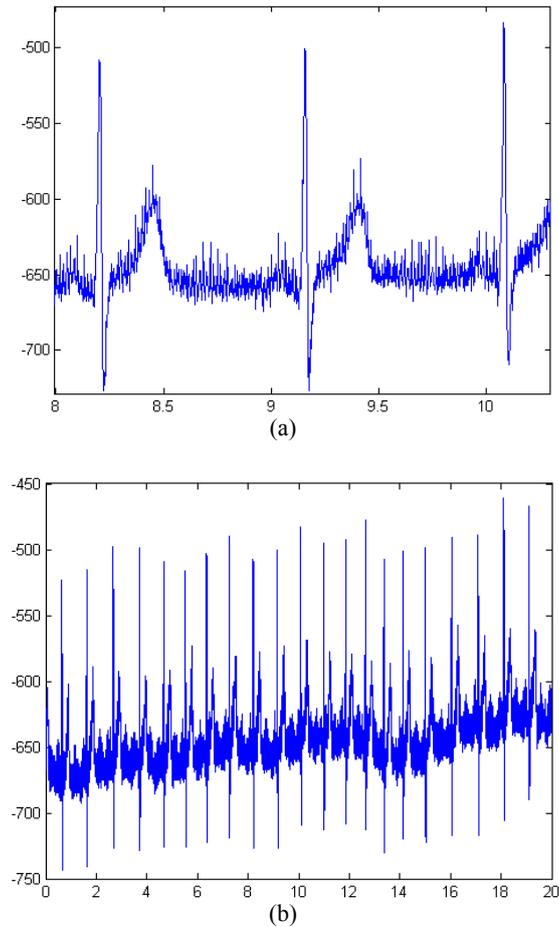
2.2 Signal processing

2.2.1 Noise removal

Both contact and non-contact heartbeat signals contain noise. These sources were characterised by Clifford (2006) and Friesen et al. (1990) for contact ECG data. These authors have characterised these noise sources effects on data exploitation. The noise sources are defined as powerline interference (Huhta and Webster, 1973), electrode contact noise (Oster, 2000), motion artefacts (Garcia et al., 2003), muscle flexor, baseline drift/ sensor thermal noise (Barros et al., 1995) and ECG amplitude drift with respiration (Lindberg and Oberg, 1991; Cysarz et al., 2008), instrumentation noise (Fernandez and Pallas-Arney, 2000), and electrosurgical noise, which is not relevant to biometrics.

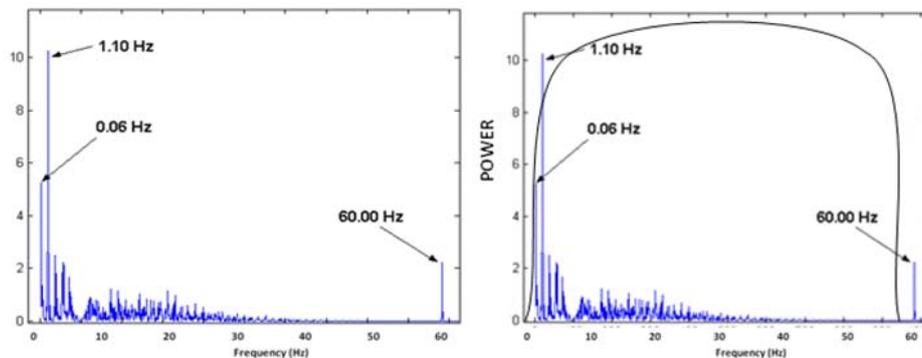
The noise sources are expressed in the heartbeat trace as high frequency (intra-beat) and low frequency (inter-beat) components. The most significant high frequency noise is the power line interference (Figure 7a), which in North America occurs at 60 Hz and elsewhere at 50 Hz. The lower frequency components, such as thermal drift and muscle flexor noise, are expressed in Figure 7b.

Figure 7 Noise sources: (a) powerline and (b) thermal drift (see online version for colours)



Powerline removal was surveyed by Hamilton (1996). There exist three basic strategies: 60 Hz notch filtering (Pei and Tseng, 1995), non-adaptive (Kaur and Arora, 2010), and adaptive filters (Thakor et al., 1984; Thakor and Zhu, 1991). The 60 Hz notch filter, sometimes called spectral differencing, focuses on one specific frequency band and is removed by frequency convolution. Most signal processing techniques apply a more general bandpass approach to extract both the low frequency and high frequency components at the same time (Figure 8). In Figure 8, we can see the heart rate at 1.10 Hz and thermal or sensor baseline noise at 0.06 Hz in addition to the powerline noise.

Figure 8 Fourier bandpass filtering: 0.06 Hz peak = thermal noise; 1.1 Hz peak is the subject's heart rate; and 60 Hz peak is the powerline noise. The arch over the graph is the equivalent bandpass acceptance region (see online version for colours)



Other effective low computation cost filtering includes regression spline reconstruction (Stegle et al., 2008) and local temporal averaging. Researchers have also proposed methods for evaluating the noise source relative to the known ECG trace (Laguna et al., 1992; Olmos and Laguna, 2000). However, these latter techniques provide limited improvement over bandpass filtering because the noise environment is nearly constant.

For moving subjects, the macro body movement becomes a significant noise source. This has been observed in simple cases for ambulatory clinical patients (Hayes and Smith, 2001). In these cases, an additional factor for understanding body movement must be characterised using an instantaneous movement model.

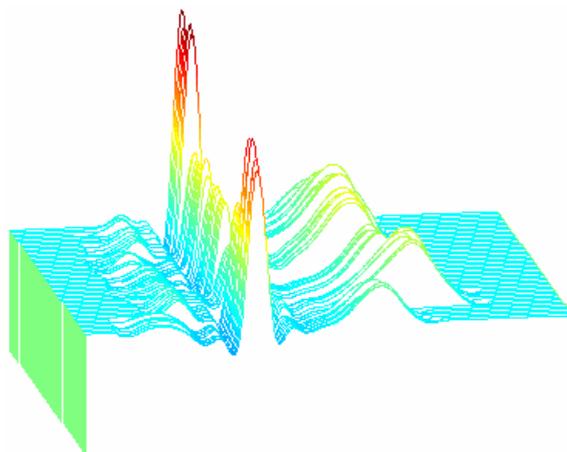
The above methods have focused on ECG data. However, Israel (2009) applied them to blood pressure and pulse oximetry data with similar improvements to signal quality. Jimenez-Gonzalez and James (2009) showed the process can be applied to foetal heart sounds. However, the recovery of the signals using independent component analysis (ICA) employs a more adaptive strategy to separate the macro body movements of both the mother and child. In addition to powerline noise, Khamene and Negahdaripour (2000) and De Lathauwer et al. (2000) proposed a deconvolution between the maternal and foetal ECG trace with varying success. Husoy et al. (2002) offered a method to remove CPR effects from the ECG trace using signal processing. Boucheham (2008) identified a pattern matching noise removal technique using forward prediction and backward interpolation of the repetitive time series data.

2.2.2 Heartbeat alignment

After the signals are cleaned, the next step is to align the heartbeats for human identification and heartbeat classification. Although some researchers have proposed methods that do not require heartbeat alignment (e.g. Phua et al., 2008), most approaches include this step. The reason for alignment is that most techniques rely on features derived from the morphology, amplitude, and timing of the heartbeat, thus requiring segmentation of individual beats. For the ECG, alignment is performed for two reasons: (1) orient the P, R, and T complexes for fiducial segmentation; (2) remove spurious heartbeats that broaden the individual's expected template. The most obvious method is to extract the heartbeats using an autocorrelation approach. Figure 8 shows that the strongest frequency occurs at the mean heart rate, 1.1 Hz. The problem is just as obvious because any individual beat-to-beat interval has the potential of being dramatically different from the mean. Therefore, each heartbeat must be segmented using an adaptive approach (Jane et al., 1991). For the ECG, the process is straightforward because the trace contains a number of high frequency components to match.

Most commonly, the R complex is used for peak-to-peak alignment (Afonso et al., 1999; Al-Khalidi et al., 2001). The R complex is nearly invariant to heart rate and is readily observable, which makes ideal for registration. The basic process is to use moving windows (Kohler et al., 2002) or a multi-scale approach (Laciar et al., 2003). A less efficient approach is to employ a Fourier correlation approach, but this has limitations of performance based upon the coarseness of the power spectral density attributes (Laguna et al., 1992). Alignment output can be visualised as a waterfall diagram (Figure 9).

Figure 9 Waterfall diagram: Registered heartbeats for multiple intra-subject ECG traces for multiple subjects (see online version for colours)



2.2.3 Sources of variance

To transition any system, the sensor and target must be characterised within a specific operating environment. For most of the heartbeat studies, the environment has been optimised to a clinical setting. These studies shine light on the requirements for data

processing. Palova et al. (2010) showed that even with contact measurements, subjects with autonomic neuropathy generated traces with low signal-to-noise ratios. Pullan et al. (2001) oversampled the ECG to generate an individualised 3D heart models within a conductive environment. However, for human identification this is just impractical.

In addition to the physical sources of variance such as CPR and foetal traces, there exist changes in a subject's emotive state expressed in the heartbeat data. Usanova et al. (2009) identified changes in the ECG caused by music. Pina et al. (1995) collected subject data under varying stress levels. They concluded that a large amount of metadata is required to characterise the subject during their experiments.

Sharpley et al. (2000) identified the changes in the heartbeat pattern as an individual transitioned from exercise to recovery. Chemical issues will alter a subject's ECG trace. Benatar et al. (2000) showed the significant effects of a gastrointestinal drug on the QT interval compared to those drug-free subjects. The heartbeat is also affected by nature and pollution (Liao et al., 2010). Each subject's reaction to stress is different (Steinbrook, 1992) and that is expressed in their heartbeat traces.

Finally, the most obvious variations from the norm are those individuals with cardiac maladies. Their heartbeat traces differ dramatically from normal. Extracting standard features or using principal components analysis with this small section of the population greatly weakens the performance of any identification or verification application (Sahu et al., 2000). Chauhan et al. (2002) and van Oosterom et al. (2000) noticed gender difference, but did not collect sufficient amounts of data to understand if this was due to body size or level of fitness. Hoekema et al. (2001) and Peng et al. (1993) showed that beat-to-beat correlations exist locally and break down over time.

Heart rate varies with a person's mental or emotional state. Excitement or arousal from any number of stimuli can elevate the heart rate. Irvine et al. (2001) and Israel et al. (2005) developed an experimental protocol where subjects performed a series of tasks designed to elicit varying mental and emotional states (Irvine et al., 2001; Irvine et al., 2002; Irvine et al., 2003; Israel et al., 2005). The subjects exhibited changes in heart rate associated with these tasks. A set of fiducial features, designed to represent heartbeat morphology, show relatively small differences due to the variation in heart rate. To illustrate, Figure 10 presents 6 heartbeats from a single subject and the baseline task, where the subject is seated at rest. In addition, 6 heartbeats from a high stress task were aligned, temporally re-scaled, and overlaid on the same graph. For this particular subject, the mean R-R interval for the baseline task was 0.715 seconds and for the high stress task it was 0.580 seconds. The high-stress heartbeats align well with the baseline heartbeats. A difference in the height of the T wave is evident, but the fiducial features depend on the relative temporal positions of the peaks, not the electrical potential (heights).

We characterised the sources of variance in the fiducial features using a multivariate analysis of variance (MANOVA). The 29 subjects performed seven tasks in the experimental protocol eliciting a range of stimulation (Irvine et al., 2001; Israel et al., 2005). The MANOVA (Figure 11) shows that there are small, but statistically significant, differences in the fiducials across the various tasks, indicating that there are subtle differences in the ECG signal that are more complex than a linear rescaling. This source of variance, however, is typically one or two orders of magnitude smaller than the variance across subjects. This relationship is why the fiducial-based features are likely to provide good information about a subject's identity across a range of mental and emotional conditions.

Figure 10 Aligned heartbeats from high stress and low stress tasks.

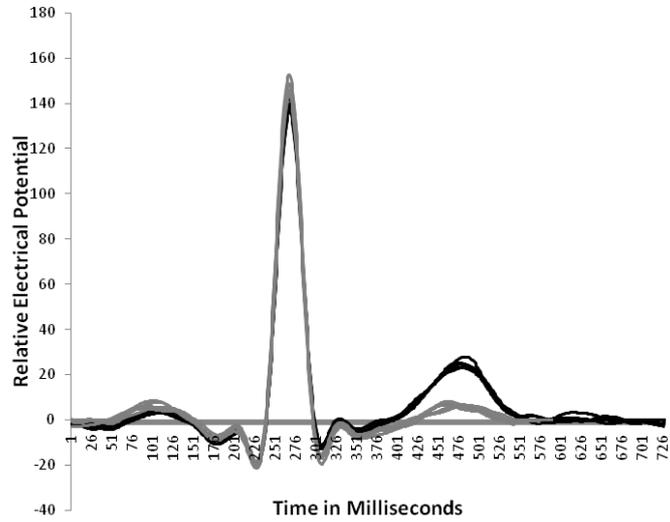
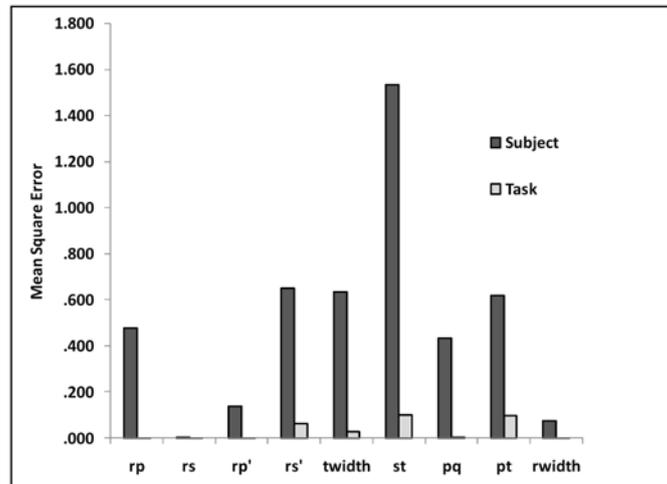


Figure 11 Comparison of attribute variance to subject vs. task



3 Experimental data

To characterise subjects in the operational environment, we need to generate a more diverse dataset data at higher levels than simple proof-of-concepts. Israel et al. (2005) collected data across multiple levels of mental and emotional stimulation. The assay was organised to observe each subject within each session through meditative, stressor, and recovery periods.

The protocol enrolled 104 individuals: 68 males and 36 females. Individuals were required to be in good health without known cardiac anomalies. The fiducial method was unable to enrol approximately an additional 30 individuals based upon excessive noise in their ECG trace or heartbeat irregularities. Ages range from 8–84. Males skewed younger and females skewed older. The exact demographics are not available for all subjects since some of the data were collected with a proprietary system that encrypted the ‘interesting’ metadata. A total of 350 subject sessions were acquired. Using the fiducial method identified 88.25 of the individuals.

Other experiments approached operational issues for human identification based upon heartbeat information. Wubbeler et al. (2007) identified 74 individuals using 234 sessions. Zonios et al. (2004) characterised the pulse oximetry trace as a function of subject’s state of anxiety. Irvine and Israel (2009) identified the number of heartbeats required for a classifier to make a decision for each subject in a verification system. Chellakumar et al. (2005) showed no significant difference between heart rate variability calculations for data with temporal resolutions greater than 100 Hz. Information below 100 Hz could only be inferred.

The most complete repository for ECG data is the MIT BIH database (Goldberger et al., 2000). However, it was generated without concern for the operational environment and there are very few cases of individuals under stress. The amount of metadata is limited to the state of the individual and the condition of their heart. Jager et al. (2003) described their ST database for development of algorithms to detect myocardial ischemia. Taddei et al. (1992) offered a database and standards with metadata for evaluating ST-T for ambulatory ECG patients. Chronaki et al. (2002) provided a common sensor collection and exploitation system message format. However, these systems have not incorporated the variety of environmental conditions essential for developers to commercialise a heartbeat biometric system.

4 Exploitation

Despite the limitations identified above, many researchers have developed systems to exploit heartbeat information. In this section, we identify the features from the cleaned heartbeat data. Then, we describe the algorithms used to characterise the subjects. Many of these sources are focused to medical diagnostics, but their data handling techniques are important.

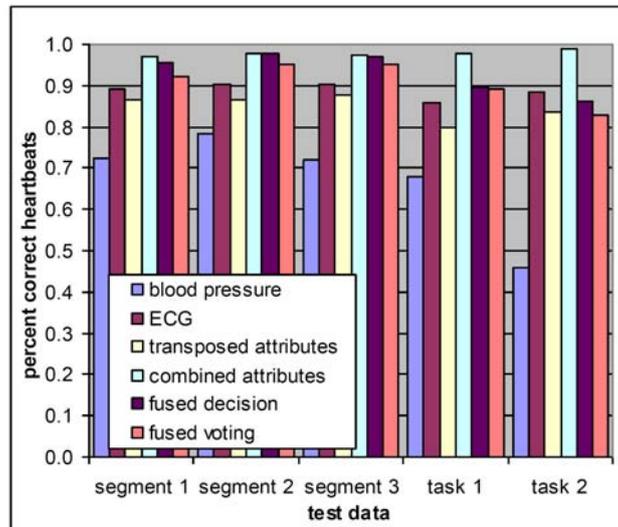
4.1 Feature extraction

Heartbeat features have been extracted from multiple domains: temporal (Koski et al., 1995; Molina et al., 2007), Fourier (Berger et al., 1986), and discrete cosine transform (Plataniotis et al., 2006). Within a domain, features are extracted as either raw (Israel et al., 2005), texture (Porta et al., 2001), power spectrum (Barros and Ohnishi, 2001; Stridh et al., 2004), and PCA/ICA (Garcia et al., 1998; Barros et al., 2000). Afonso et al. (1999) integrated the noise reduction and feature extraction by using filterbanks. This estimates the heartbeat trace with a polynomial spine and uses the polynomial coefficients as features themselves. The most common medical application is HRV. This can be performed by analysing the heart rate using statistics.

Feature extraction from the heartbeat traces has become more focused for human identification pattern recognition problems. The experiments can be broken into two basic classes: (1) raw features; and (2) eigen features. Irvine et al. (2001) used raw temporal features based upon an additional set of fiducials not commonly identified by the medical community.

The problem with fiducial based feature extraction is exception handling. Only 75% of the candidate subjects from the Irvine et al. (2001) experiment were successfully enrolled. However, those enrolled were identified over 95% of the time. Kim (2001) used Fourier features to identify 10 individuals using 20 attributes. The over specification, of attributes to output classes, does not provide any level confidence on the extrapolation of these results into the operational environment. Dokur et al. (1999) found that wavelet measures were significantly better able to classify heartbeats than Fourier features. Israel et al. (2008) fused ECG, Pulse Oximetry, and blood pressure data for human identification (Figure 12). The results showed a significant improvement in performance and reduction in false alarms, particularly when fusion is performed at the feature/attribute level.

Figure 12 Fused cardiac performance biometrics for human identification (see online version for colours)



Biel et al. (2001) used temporal and electrical potential amplitude features and combined them using principal components analysis. Similar experiments were performed by Shen et al. (2002) and Wang et al. (2008). Van Oosterom et al. (2000) performed similar experiments using multiple lead ECG data, extracting features from the individual leads, and then performing the PCA analysis. No corresponding enrolment rates or data handling issues were provided by these authors.

An eigenPulse method was developed by Israel et al. (2003) and refined by Irvine et al. (2008). For eigenPulse, the processing follows that commonly used for face recognition (Turk and Pentland, 1991). The raw temporal values from the individual

segmented heartbeats are temporally normalised to a specific attribute length. The normalised heartbeats are then put into a PCA and the highest eigen features are used as attributes for the classifier. Although performance is lower than for the attribute based systems (number identified/number enrolled), all 130 subjects were capable of being enrolled (number identified/total population). Therefore, the overall performance for the eigenPulse technique was higher (number enrolled < total population). The downside with eigen features is that the researcher does not know the physical mechanics behind the individual attributes that explains the significance of the attributes.

The next level of feature extraction is converting the data into attributes through a mathematical process. Chiu et al. (2009) used energy attributes of ECGs computed from wavelets to classify heartbeats between normal patients and those with cardiac maladies. Palaniappan and Krishnan (2004) moved a window across the segmented heartbeats and generated textures for each window position. These were placed into a classifier for human identification. Plataniotis et al. (2006) generated a cosine transform from the temporal data.

4.2 Algorithms and decision rules

As in the early stages of other datasets, researchers have applied multiple pattern recognition algorithms and fusion strategies to the heartbeat data. The supervised classification articles focused on statistical and neural network approaches (Tatara and Cinar, 2002). Irvine et al. (2003) used linear discriminant analysis (LDA) to separate among the individuals. The LDA statistically models the hypersurfaces that best separate the subjects' attributes in the feature space. This is different from a neural network approach that performs a similar function through a stochastic optimisation. The latter separator is not required to be linear (Guler and Ubeyli, 2005). Neural network attributes themselves can be fuzzified (FNN) to improve their sensitivity (Israel, 1999). FNNs have been used (Osowski and Linh, 2001; Acharya et al., 2003; Arif et al., 2010) to classify normal heartbeats from cardiac maladies.

Data and information fusion have been performed for heartbeat data. At the lowest data fusion level, Agrafioti and Hatzinakos (2008) integrated multiple ECG leads for human identification. The attributes extracted from the data were combined using PCA. A limited number of features were used to classify a small number of individuals. Finlay et al. (2010) performed a similar experiment by oversampling the torso with 117 sensors. Then, using the raw electrode signals, the researchers generated synthetic traces or eigenleads. The authors were rewarded by a dramatic improvement in SNR. Operationally this is impractical for biometric applications, but interesting nonetheless.

5 Performance evaluation

At this stage, the data used during different parts of the process must be defined. Training data are examples used by the developer to generate their classifiers. Labels may or may not be important for the training data depending upon the classification algorithm used. The gallery data are those examples used for matching by the verification or identification. Gallery data examples have known labels. Test data are those examples

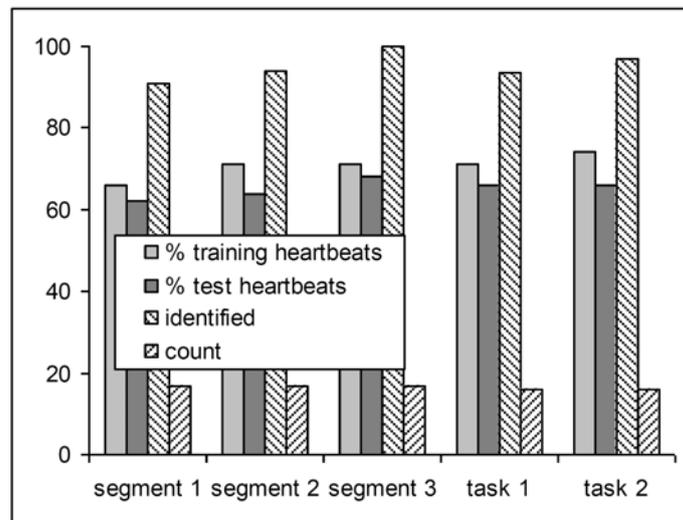
used by the system to evaluate performance or in the operational environment. For evaluation, the test labels are used to confirm whether the system performed correctly or not. In the operational environment, the test examples have no confirmed labels.

Verification and identification are two different functions (Israel, 2006). Verification is a 1-to-1 match. For verification, the differences between the test and gallery data are compared to a distance or acceptance threshold. Verification is evaluated using ROC curves to characterise detection performance versus false alarm rate (FAR). Tilbury et al. (2000) and Theofanos et al. (2007) explored the role of confidence intervals in biometric verification.

5.1 Blood pressure identification

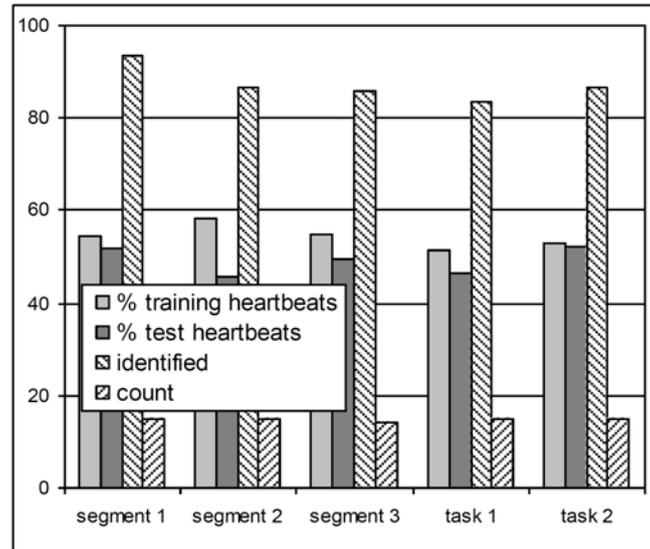
Irvine (2003) collected blood pressure measurements from 17 adults: males and females. Data consisted of baseline and meditative tasks alone. The heartbeats were normalised and power spectrum attributes were extracted. Six trials were performed; across segments and across tasks. Independent training and testing produced a 65% correct heartbeat classification and 93% of the individuals based on voting across heartbeats (Figure 13).

Figure 13 Blood pressure classification



5.2 Pulse oximetry identification

Irvine (2003) collected pulse oximetry signals from 17 adults: males and females. Data consisted of baseline and meditative tasks alone. The heartbeats were normalised and power spectrum attributes were extracted. Six trials were performed; across session and across tasks. Independent training and testing produced a 51% correct heartbeat classification and 87% of the individuals. Due to the relatively poor performance, human identification using blood pressure and pulse oximetry is limited.

Figure 14 Pulse oximetry classification

5.3 ECG identification

To use ECG as a biometric, individuals will enrol their information into the security system. After enrolment, the user's ECG will be interrogated by the system. Unlike the traditional static biometrics, the heartbeat varies with stress. The state of anxiety and the relative orientation of the ECG electrodes with respect to their heart's potential centre are unknown. As the number of access controllers and individuals within a facility increases, the number of interrogations grows rapidly. To mitigate data handling issues, the number of descriptors for a given individual must be minimised. The results show a high degree of agreement of generalisation across the tasks, except for the VR driving. VR driving is the highest stressed task. Upon review of the VR driving data, many of the subjects' data still contained muscle flexor noise that was not removed with the current filter (Figure 15).

Identification is a higher function in the detection, classification, recognition, and identification (DCRI) hierarchy. Identification occurs after an individual is detected. The contingency matrix, Figure 16, is a visualisation for classification performance (Congalton and Green, 1993). The columns represent the known input classes. The rows indicate how the discriminant function(s) classified or assigned the data. The correctly identified samples (heartbeats) lie along the major diagonal, i.e. the known input labels equal the assigned labels. If the maximum number of heartbeats within a row or column occurs along the major diagonal, then the subject is correctly identified; i.e. voting. Errors occurring along the column are errors of omission. For a verification system, these are false negative errors where an authorised user cannot gain access. Errors along the row are errors of commission. Commission errors are false acceptance errors, where an unauthorised user gains accesses the system, intruders. The identification error rate cited here is the average of the omission and commission values.

Figure 15 Classification performance for heartbeats and identification. Labels indicate training data. Test data was the remainder of the database. The ‘all data’ was an average of segments across all tasks (i.e. train segment 1 – test segments 2, 3, 4, 5, and 6) (see online version for colours)

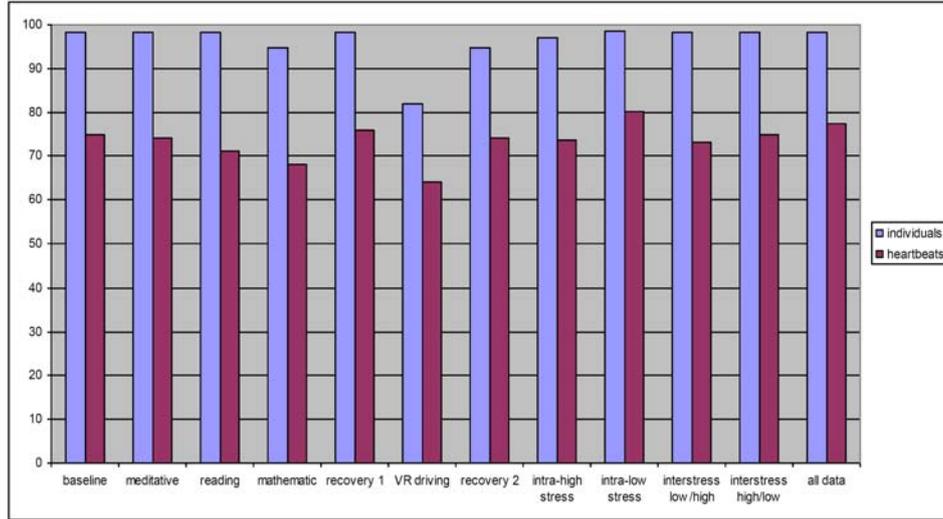


Figure 16 highlights a number of interpretation issues. First, the contingency matrix is not symmetrical. So, the rate of false acceptance between individuals is not the same. The number of heartbeats acquired is not the same for all individuals. The variable number of examples percolates through the contingency matrix. For Subject B, approximately 30% of the heartbeats have a commission error with Subject J. These heartbeats are over 50% of the total assigned to Subject J. If the two subjects contained the same number of heartbeats, then no confusion or false acceptance of Subject B to Subject J would occur.

Figure 16 Sample contingency matrix (see online version for colours)

		known inputs													
		A	B	C	D	E	F	G	H	I	J	K	sum	1-comiss	identified
computational outputs	A	52	15				10					1	78	67	1
	B	15	165										180	92	1
	C			69		6							75	92	1
	D			1	125								135	93	1
	E					76							83	92	1
	F	7					77						88	88	1
	G				5			65					68	96	1
	H								154	12			166	93	1
	I								11	50			61	82	1
	J		85								76		161	47	0
	K				35		3	2				49	89	55	1
	sum	74	265	70	165	92	80	67	165	63	77	66	total correct	958	
	1-omiss	70	62	99	76	83	96	97	93	79	99	74	total avail	1184	
	identified	1	1	1	1	1	1	1	1	1	1	1	% correct	81	
	1=correct												% false neg	0	
													% false pos	9	

5.4 Dissemination

The concept of information dissemination is largely omitted from the early system design. Common problems caused by an incomplete design or an integration of material solutions with a firm functional decomposition are stovepiped or non-interoperable

applications, inefficient data processing and exploitation, and inappropriate size of the hardware. Usually these problems are realised when a system is transitioned into an operational environment.

It is expected that heartbeat biometrics will be used in remote locations away from standard guard based access protections. Yu et al. (2008) showed that biometrics working in conjunction with a token based system provides additional protection unavailable to token based systems alone. Hernandez et al. (2001) showed the privacy concerns with exploiting the internet and HIPAA compliance. Kozat et al. (2009) performs a process similar to steganography to embed metadata into the ECG trace without losing the subject specific information. Similarly, Sufi and Khalil (2009) developed an algorithm to encrypt ECG based upon a source key strategy for simple un-encryption.

These studies point to a basic challenge for biometric systems based on heartbeat, namely the protection of personal information. Unlike fingerprint and face, the heartbeat data could contain health-related information as well as the personal identification information. This suggests a need for greater care in the collection, storage, and transmission of such data. Although technological advances can help address this challenge, it is fundamentally a policy issue that must be considered in any operational application.

6 Conclusions

This paper reviewed the processing, exploitation, and dissemination of heartbeat data for biometric applications. We laid down the system's functional blocks and those researchers performing in these areas. The limitations of the data and algorithms to characterise individuals are being reduced though supplementary understanding of the operational environment.

The expected performance for a biometric system will depend on the nature of the biometric task, the sensing and processing system, system enrolment procedures, and the sensing environment. For example, identity verification of cooperative individuals using contact measurements appears within reach for a modest number of enrolled individuals (Irvine and Israel, 2009). Extending these methods to the general identification problem will require additional development, but current methods hold promise. Three important issues, however, require further investigation: stability of the signatures over long period (e.g. years), robustness to variation in mental and emotional state, and scalability to larger populations. The initial analysis of these issues suggests that robustness and scalability can be addressed (Irvine et al., 2008; Israel et al., 2009). Extensions to non-contact sensing methods, especially with non-cooperative subjects, will require more development to insure reliable acquisition of the cardiac signal.

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