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Embedded system for individual recognition based on ECG Biometrics

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Abstract

Biometric recognition is emerging has an alternative solution for applications where the privacy of the information is crucial. This paper presents an embedded biometric recognition system based on the Electrocardiographic signals (ECG) for individual identification and authentication. The proposed system implements a real-time state-of-the-art recognition algorithm, which extracts information from the frequency domain. The system is based on a ARM Cortex 4. Preliminary results show that embedded platforms are a promising path for the implementation of ECG-based applications in real-world scenario.

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1. Introduction

Many aspects of our every day lives are becoming dependent of automatic and accurate identity validation. The wide deployment of recognition mechanisms, based on something that people has (entity-based: tokens and ID cards) or something that people known (knowledge-based: PIN numbers and passwords), raises securities concerns regarding the risk of identify theft [7,8,15].

The major benefit of security systems based on biometrics is the full dependency on the individual [9]. There are no dependencies on objects, or memories as it occurs on traditional strategies. This research is leading to the widespread of biometric systems, thus, increasing the difficulty of individual credentials falsification. Currently, credentials falsification is one of the major flaws of the common biometrics identification systems [9]. Take as example, the face recognition systems, where simple photo can fake a face, or in iris recognition systems, an iris can be falsified by contact lenses, or even on fingerprint recognition systems, a fingerprint may be forged by a gummy gel finger [9].

Recently, physiological signals are also being considered as an alternative biometric traits, being the electrocardiogram (ECG) an emergent and viable alternative [3,4,17]. In 2001, the pioneer work of Biel [4], revealed that this

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signal has subject dependent features, and it can be used as a biometric trait. Furthermore, the ECG has other unique properties, namely, it is:

- universally available in live subjects, which make it a never ending source of information;
- measurable non-intrusively using suitable devices, for example the acquisition can be done at at subject hands, which is socially more friendly, when compared with the traditional chest based acquisitions;
- not easily circumvented through latent patterns, since the heart is an internal organ, and the acquisition of the ECG requires the direct contact with a sensor.

This paper proposes an ubiquitous biometric recognition system based on the ECG using an embedded platform. In order to make this an ubiquitous solution, we propose that the ECG acquisition is performed at the hands of the subject. Most of the ECG-based biometric systems are implemented using a paradigm where the signal is collected using a sensor and the signal processing and recognition algorithm are performed on a computer [11].

The proposed approach, as opposed to common biometric systems, uses an embedded system based on the ARM Cortex4 architecture, that samples the ECG with internal Analog to Digital Converter (ADC), processes the signal and implement a method based on Odinaka's algorithm [13] to authenticate the user.

The remain of the paper is organized as follows. Section 2 introduces the architecture of the embedded platform, focusing the capacities, advantages and disadvantages of the system compared to other possible solutions. Section 3 resumes state-of-the-art methods for biometric recognition. Section 4 describes the signal filtering, peak detection, feature selection, and the classification steps. Section 5 presents some results and Section 6 concludes the paper with some remarks.

2. Embedded Platform

An ARM-Based Cortex4 32 bit RISC STM32F407VGT6, was chosen as the processor in our system. It works at 168MHZ, and it is characterized by its low power consumption, low-cost, and strong performance, which enables real-time processing. The processor includes: 1MB FLASH, 192KB+4KB RAM, and a bluetooth module, which will be used for communication with an auxiliary external application programming interface (API). The system has a 12 bits ADC, which as the fastest conversion up to $0.41m\mu$, with 3.6 V full-scale of the system. It also includes a Floating Point Unit (FPU) and a digital signal processor (DSP) inside the processor, making floating point operations faster than integers calculus. The system is powered by an external 5v power source (battery or USB power). Fig. 1 shows the processor peripherals and hardware used.

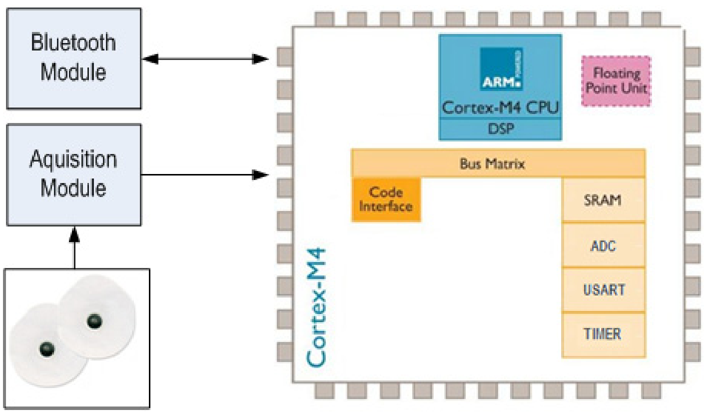


Fig. 1. Hardware block diagram of the system

3. State of the Art

Recent works in the ECG biometric recognition field can be categorized as either fiducial points dependent or independent [3]. Fiducials are specific points of interest on the ECG heart beat. Therefore, fiducial based approaches [4,6,16,23] rely on local features of the heart beats for biometric template design, such as the temporal or amplitude difference between consecutive fiducial points. On the other hand, non-fiducial approaches [1,2,5,10,12,13,21,22] treat the ECG signal or isolated heart beats holistically to extract features statistically based on the overall morphology of the waveform.

Both approaches have advantages and disadvantages. While fiducial oriented features risk to miss identifying information hidden behind the overall morphology of the biometric, holistic approaches deal with a large amount of redundant information that needs to be eliminated. The challenge in the later case, is to remove this information in a way that the intra-subject variability is minimized and the inter-subject is maximized. For the ECG case, detecting fiducial points is a challenging process due to the high variability of the signal.

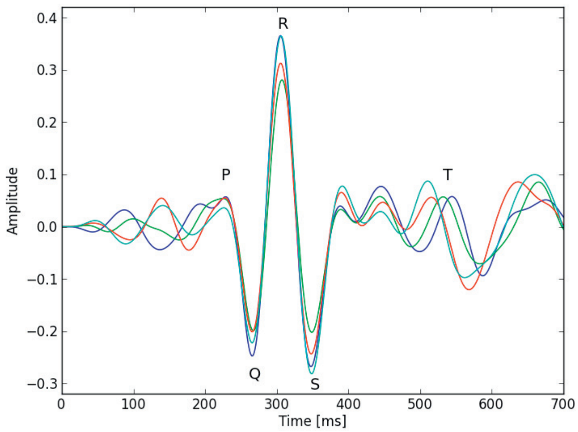


Fig. 2. Variability surrounding the QRS complex among heart beats of the same individual

The “the off-the-person approach” [17–19] proposes to acquire the ECG at the hands of the subject improving the usability of the sensing apparatus, but also increasing the challenges on the processing of the data, since more noise and artifacts are integrated in the data. Fig. 2, shows an example of such a signal. It shows the variability on the acquisition, superimposing different single heartbeats of the same user, aligned using the QRS complex. It is evident that there is significant variability surrounding the P and the T wave, due to electromyographic noise caused by acquiring the signal at the hands. This type of acquisition leads to additional challenges, since the delineation of ECG, and detection of P, and T waves onsets is a harder task [3,19], than on tradional chest-based ECG acquisitions.

4. Recognition Algorithm

The problem of human recognition based on biometric systems, can be formulated in the pattern recognition framework. Fig. 3 contextualize the steps involved in such systems: 1) first the signal is acquired by the sensors; 2) the signal is preprocessed and described in a convenient representation; 3) features are extracted; 4) from the extracted features the most discriminative are selected; 5) a classification block processes the features and delivers a decision corresponding to the recognition of the subject [20].

The proposed approach follows a partial fiducial approach [3], using the wave onset, peak (the R complex) as characteristic point for segmentation, as in the Slope Sum Function algorithm [24]. The feature extraction is based on a frequency approach and is based on Odinaka algorithm [13]. In [13] each single heartbeat is segmented into 64ms windows with an overlap of 54ms. The analysis is performed in the frequency domain, computing the short time

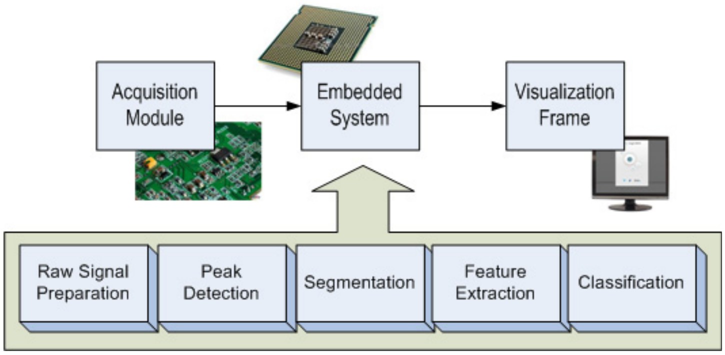


Fig. 3. Classic structure of a reckoning system applied to an identification issue

Fourier transform (STFT) [14] for each window, where for each frequency bin, an estimate of the mean and variance is stored.

4.1. Slope Sum Function (SSF)

Slope sum function was originally developed for detecting the onset of arterial blood pressure (ABP) pulses [24]. This work proposes the use of this algorithm for the detection of ECG's QRS wave. The motivation of this work is the on-the-fly processing algorithm offered by this detector. The algorithm employs a windowed and weighted slope sum function (SSF) to extract QRS waveform features from the heartbeat. Adaptive thresholding and search strategies are applied to the SSF signal to detect QRS pulses and to determine their peak.

The algorithm consists of three phases:

- **Low-pass filter:** The purpose of the low pass filter is to suppress high frequency noise that might affect the QRS peak detection.
- **Slope sum function:** The purpose of the slope sum function is to enhance the upslope of the R pulse and to suppress the remainder of the electrocardiogram waveform. The windowed and weighted slope sum function at time i, z_i, is defined as follows:

$$z_i = \sum_{k=i-w}^{i} \Delta u_k, \quad \Delta u_k = \begin{cases} \Delta y_k & : \Delta y_k > 0 \\ 0 & : \Delta y_k \leq 0 \end{cases}$$

  where w is the length of the analyzing window; $1 + w \leq i \leq N$, N is the total number of heartbeats samples in the record; $\Delta y_k = y_k - y_{k-1}$, and y_k is the low-pass filtered ECG signal as defined above. To maximize the SSF, w is set to a value approximately equal to the typical duration of the upslope of the R pulse. In the proposed algorithm, w = 300 ms or 300 samples for the sampling frequency of 1000 Hz. The onset of the SSF pulse generally coincides with the onset of the QRS pulse as the SSF signal can only rise when the ECG signal (or noise not removed by filtering) rises. Since the SSF signal is a simpler signal to process, the pulse onset will be detected by processing the SSF signal on-the-fly, making it suitable for real-time processing.
- **Decision rule:** This task is split into two: First, it is applied an adaptive threshold to the SSF signal in order to detect SSF pulses of appropriate amplitude. Next, a local search strategy is employed around the detection point to confirm the detection and to identify the likely onset of the pulse. During the threshold step, a threshold base value is established and is initialized at three times the mean SSF signal (averaged over the first five/ten seconds of the recording). The threshold base value is adaptively updated by the maximum SSF value for each SSF pulse detected. The actual threshold is set to 60% of the threshold base value. When the SSF signal crosses this threshold, the algorithm searches for the minimum and the maximum SSF values in a 100ms window preceding and succeeding the threshold-crossing point, respectively. The pulse detection is accepted only if the difference between the maximum and minimum exceeds a certain value; otherwise the pulse detection is rejected. When

the pulse is accepted, the algorithm searches backward in time from the threshold-crossing point for the onset of the SSF pulse. The onset point is determined when the SSF signal exceeds 1.0% of the maximum SSF value. The calculated QRS onset is adjusted to compensate the low-pass filters phase shift. Finally, to avoid double detection of the same pulse, a 300ms eye-closing (refractory) period is applied, during which no new pulse detection is initiated.

This approach to QRS pulse onset detection is based on the transformation of a low-pass filtered ECG signal into a slope sum function signal, in which the initial up slope of the QRS wave form is enhanced and the remainder is suppressed. The transformation leaves the location of the pulse onset unaltered, except for the fixed filter delay, and detection of the pulse onset based on the slope sum function signal is straight forward.

4.2. Frequency extraction approach and implementation in embedded system

In Fig. 4 the block diagram of the implemented approach is presented. Our target is to design the system for real time operation. Since each sample comes periodically each 1 ms (sampling frequency 1KHz), the system has this time frame for processing all the information. This real time constrain lead to a segmentation of every heartbeat waveform in 100ms windows without overlap, instead of Odinaka's 64ms windows [13]. The processing routine starts with a new digitalized sample, which induces a high-priority interrupt (INT) that adds it to a First In First Out (FIFO) array. This array is used for two different tasks: 1) single heart beat segmentation; 2) feature extraction. For the segmentation the raw signal is filtered with a band-pass filter (BPF) with pass-band $[5, 15]$Hz, and then fed to the Slope Sum Function (SSF) [24] algorithm, which enables the detection of the R-complex. The delineation of a single-heart-beat consists of a fixed window of 700 ms, beginning 200ms prior to the peak, and ending 500 ms after the peak. The STFT of each segment is then computed using each segmented piece of the single-heartbeat.

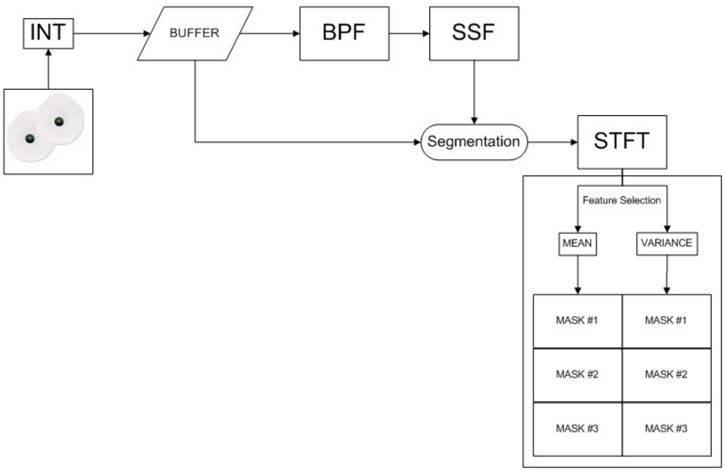


Fig. 4. Software block diagram of the system

The STFT uses a spectral zoom approach, which means making a 1024 point STFT for each 50ms window and subsequently cutting the results to the first 50 STFT points. This creates a low pass digital filter with approximately $[0, 50]$Hz pass-band, to remove noise present at the acquisition conditions and since the band of interest for biometric applications is mostly focused on this bandwidth of frequencies. This STFT computation is the step that is most time-consuming, taking 1.2ms for each STFT alone, making a total of 8.4ms for all the STFT phase.

The STFT is applied to each of the 100ms window, leading to the creation of 50 frequency bins, totalizing a vector with 350 features. Each feature corresponds to the STFT obtained over each segment window.

4.3. Feature Selection and Classification

Odinaka's work [13] proposes an effective way to select informative features using a robust feature selection method. The two key elements considered in this feature selection method are distinguish-ability and stability. The feature should help distinguish the subject from a reasonably large subset of other subjects, and it should be stable across sessions. Let μ_{il} and σ_{il} be the mean and standard deviation of the l-th feature of the i-th subject.

The l-th feature of the i-th subject is selected if the symmetric relative entropy, i.e. the symmetric Kullback-Leibler divergence, between $\mathcal{N}(\mu_{il}, \sigma_{il}^2)$ and the nominal distribution $\mathcal{N}(\mu_{0l}, \sigma_{0l}^2)$ is larger than a threshold $\kappa > 0$, being $(\mu_{0l}, \sigma_{0l}^2)$ the maximum likelihood estimate from all database.

For the Gaussian distributions used in this model, the symmetric relative entropy is given by:

$$d\left(\hat{\theta}_i(l), \hat{\theta}_0(l)\right) = \frac{\sigma_{il}^2 + (\mu_{il} - \mu_{0l})^2}{2\sigma_{0l}^2} + \frac{\sigma_{0l}^2 + (\mu_{il} - \mu_{0l})^2}{2\sigma_{il}^2} - 1 \tag{1}$$

where the nominal model is obtained by using the spectrograms of all the subjects in the database. Using the symmetric relative entropy for feature selection ensures that only those bins whose distributions are far from the nominal are selected for each subject, thereby ensuring distinguish-ability.

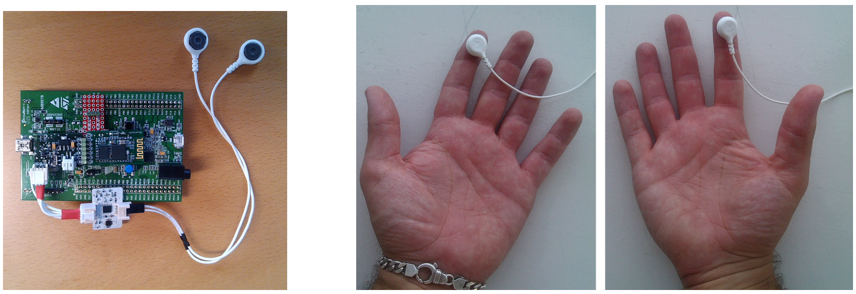
The score of a test heartbeat using the i-th subject's model is given by the log-likelihood ratio (LLR):

$$\Lambda = \sum \left[\frac{p_i(Y(l)|\hat{\theta}_i(l))}{p_0(Y(l)|\hat{\theta}_0(l))} \right] I_{d(\theta_i(l), \theta_0(l)) > \kappa} \tag{2}$$

where I is the truth function indicating which time-frequency bins are selected; l is the index of the bins. For authentication, the LLR given in equation (2) is compared with a threshold τ, so that if $\Lambda > \tau$, the heartbeat with the claimed identity is accepted, otherwise the heartbeat is rejected.

5. Experimental Evaluation

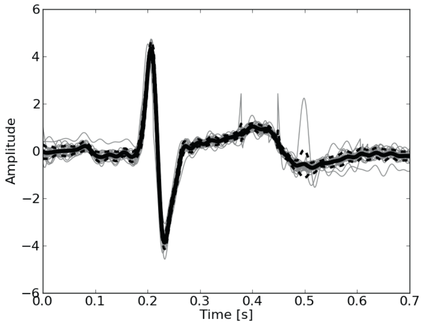
The dataset used to evaluate this approach was acquired using the proposed system. It is composed by 10 subjects, with two recording sessions per subject. The acquired signals were obtained following the recent trend "the off-the-person approach", with the subjects in a rest-situation in both recording sessions. The ECG were acquired at the fingers with dry Ag/AgCl electrodes, and using a custom ECG sensor which consists of a differential sensor design with virtual ground, found in [18]. Fig. 5(a) represents the prototype, composed by the STM32F4-Discovery board and the ECG sensor, and the electrodes placement on the hands.



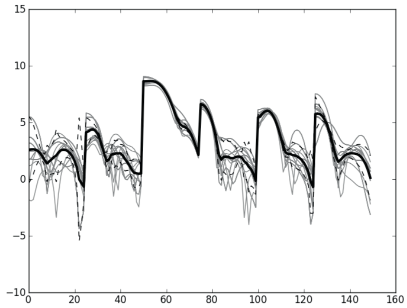
(a) Prototype (b) Electrodes

Fig. 5. Prototype of the embedded system.

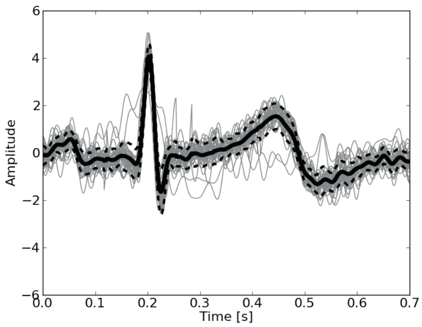
The features used in this work consist in frequency-domain representation. Fig. 6 illustrates the potential of this representation, showing for two different users, the time (on the left) and frequency (on the right) domain representation. Observing both figures, it is possible to distinguish visually the difference between both subjects. In the literature the frequency domain representation is considered more robust to heart-rhythm variation then the time domain counterpart.



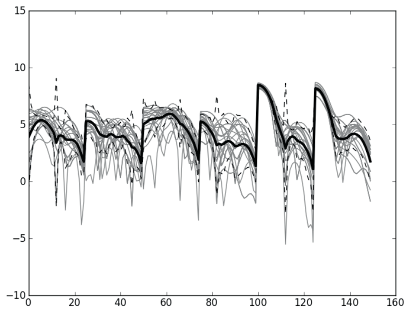
(a) time



(b) frequency



(c) time



(d) frequency

Fig. 6. Comparison of time and frequency domain representation for two different users (arranged by line).

The performance evaluation over the entire dataset is summarized in Fig. 7, where the false acceptance rate (FAR) and the false rejection rate (FRR) curves are plotted in terms of the system threshold. Superimposing the equal error rate (EER) point, corresponding to the point where the FAR is equal to the FRR, it corresponds to EER=14%. This approach achieves 100% identification rate for 30 seconds of train signals.

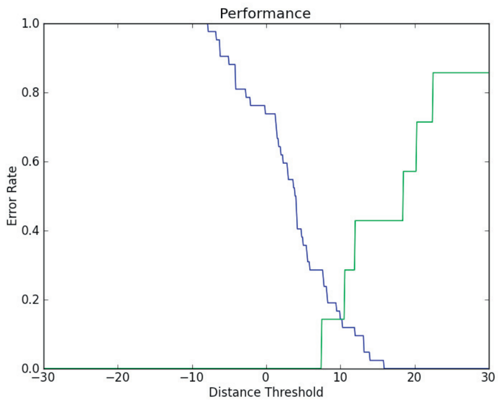


Fig. 7. FAR vs FRR curve.

6. Conclusion and Future Work

Biometric systems are moving towards multi modal approaches, combining several modalities to overcome some of the limitations exhibited by each separately. Some behavioural biometrics modalities have the potential to complement existing approaches due to their intrinsic nature, the ECG is one such case.

In this paper we present an embedded system where it is implemented a state-of-the-art method for ECG-based recognition. The implemented method is based on a frequency-domain representation adapted from Odinaka et. al. [13]. Our system also includes an ECG sensor that enables the acquisition at the fingers with dry Ag/AgCl electrodes, and it implements in real-time all the steps of recognition workflow.

As future work, we intend to test the proposed method with a larger datasets and compare with other state-of-the art methods.

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