

Embedded System for ECG Biometrics

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Abstract: Biometric recognition has recently emerged as an alternative solution for applications where the privacy of the information is crucial. In this paper we present an embedded biometric recognition system based on the Electrocardiographic signals (ECG). The proposed system implements a real-time state-of-the-art recognition algorithm, which extracts information from the frequency domain, on an architecture based ARM Cortex 4. Using a sensor based on a two electrodes apparatus, the system is designed to be autonomous, non-intrusive and easy to use on different scenarios. Preliminary results show the successful real-time implementation on the embedded platform enabling its usage on a myriad of applications.

1 INTRODUCTION

Many of our daily tasks are becoming dependent of automatic and accurate identity validation systems. Traditional strategies for recognition include PIN numbers, tokens, passwords and ID cards. Despite the wide deployment of such mechanisms, the means for authentication is either entity-based or knowledge-based which raises serious security concerns with regards to the risk of identity theft (Jain et al., 2005; Jain et al., 2004; Ross et al., 2006).

The major benefit of security systems based on biometrics is the full dependency on the individual. There are no dependencies on objects or memories as it occurs on the traditional strategies. This leads to a higher use of biometric systems in order to increase the difficulty in falsification of credentials. Currently one of the major flaws of these systems is the ease of falsification of credentials. For instance, a photo can fake a face, the iris can be falsified by contact lenses and even the fingerprint may be exchanged for a gel finger (Jain et al., 2007).

Recently, physiological signals are being used for this purpose, being the electrocardiogram (ECG), an emergent and viable alternative (Agrafioti et al., 2011; Biel et al., 2001; Silva et al., 2013; Ye et al., 2010; Israel et al., 2005; Singh and Gupta, 2009; Odinaka et al., 2010). The fact that there are subject dependent features in the ECG, enhances its applicability for user recognition. Furthermore, the ECG has unique properties when looked at in traditional or

multi-biometrics approach; in particular, it is:

- universally available in live subjects, which make it a never ending source of information, allowing redundancy on undesirable pieces of acquired signal;
- measurable non-intrusively using suitable devices;
- acceptable due to the latest advances in the sensing technologies;
- not easily circumvented through latent patterns, since is rare to see an equipment acquiring at low sampling frequencies.

The main downside of an ECG recognition is the intra-person variation caused by different heart-rates (Ye et al., 2010; Israel et al., 2005; Singh and Gupta, 2009). The frequency domain approach (Odinaka et al., 2010) aims at a reduction of this thread.

Typically the ECG-based biometric systems presented in the literature, are non-integrated systems, which process the information in two phases: 1) the acquisition is performed using a dedicated apparatus capable of transmitting the signal into a processing unit; 2) the signal processing and recognition algorithm is performed on a computer (typically in an off-line process). In this paper we propose an integrated solution for ubiquitous ECG biometric recognition. It consists on an embedded system with an integrated ECG sensor based on a two electrodes apparatus that enables real-time, non-intrusive ECG acquisition at user's fingers/hands. The proposed sys-

tems focus ubiquitous solution enabling autonomous and embedded recognition based on ECG.

The proposed embedded system allows real time processing, samples the ECG using the embedded system internal Analog to Digital Converters (ADC's), and uses Odinata's recognition approach (Odinaka et al., 2010) for biometric authentication.

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. In section 3 the signal filtering, peak detection, feature selection and the classification steps are described. Section 4 presents some results and section 5 concludes the paper with some remarks.

2 EMBEDDED PLATFORM

An embedded platform is a computer system with a dedicated function within a larger mechanical or electrical system, often with real-time computing constraints. By contrast, a general-purpose computer is designed to be flexible and to meet a wide range of end-user needs.

This embedded platforms vary in many ways, often depending on the usage, or project necessity. These devices can generally divided in:

- A microprocessor is a multi-purpose, programmable, clock driven register and an arithmetic and logic unit (ALU) based electronic device. Many more microprocessors are part of embedded systems, providing digital control over myriad objects from appliances to automobiles to cellular phones and industrial process control (Godse, 2008);
- A MicroController(sometimes abbreviated μC , uC or MCU) is a small computer on a single integrated circuit containing a processor core, memory, and programmable input/output peripherals. Microcontrollers incorporates all the features that are found in a microprocessor, however, it has also added features to make a complete micro-computer system on its own. Microcontrollers are designed for embedded applications, in contrast to the microprocessors used in personal computers or other general purpose applications due to on-chip (build-in) peripheral devices (Godse, 2008);
- A Digital Signal Processor (DSP) is a specialized microprocessor with an architecture optimized for the operational needs of digital signal processing;
- A field-programmable gate array (FPGA) is, informally thought, a "blank slate" on which any

digital circuit can be configured. Moreover, the desired functionality can be configured in the field. That is, after the device has been manufactured, installed in a product, or, in some cases, even after the product has been shipped to the consumer. In short, and FPGA provides programmable "hardware" to embedded system developers (Sass and Schmidt, 2010).

In this paper the real-time constrain must be fulfilled. Samples cannot be lost and the authentication procedure must be as close as real time as it can be. Memory is also a need, in order to store the characteristics of the subjects. The microprocessor was discarded for his low versatility and costs to manufacture the embedded system, such as the FPGA for their high costs. The proposed system is a mix of a regular MCU and a DSP processor. The development MCU board, STM32F4-Discovery, was chosen due to its versatility, low power consumption, high speeds and DSP integration.

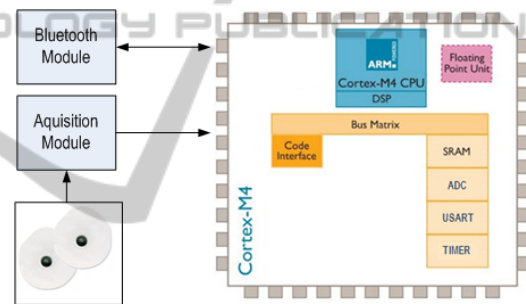


Figure 1: Hardware block diagram of the system.

An ARM-Based Cortex4 32 bit RISC STM32F407VGT6, was chosen as the processor in our system. It works at 168MHZ, with characters of strong performance and low power consumption, real-time and low-cost. The processor includes: 1M FLASH, 192K+4K RAM, and a bluetooth module will be used for communication with an auxiliary external visualization Application Programming Interface (API). The system have the A/D converter with 12 bits resolution, and the fastest conversion up to 0.41us, with 3.6 V full-scale of the system. It also includes an Floating Point Unit (FPU) and a DSP inside the processor, making floating point mathematics faster than integers calculus.

Figure 1 shows the processor peripherals and hardware used. The bluetooth module uses a standard serial communication (USART) to flow the data from/to microprocessor. The acquiring module amplifies the ECG signal to the range used by the ADC peripheral, and digitalizes it using 1000 Hz.

Bluetooth communication allows the system con-

figuration (selecting between train and test scenarios) and shows the authentication result. Additionally it can also be used as debug or simple signal display.

3 RECOGNITION ALGORITHM

The problem of human recognition based on a biometric system, can be formulated in the pattern recognition framework. Fig. 2 contextualize the steps involved in such a system: 1) first the signal is acquired by the sensors; 2) the signal is preprocessed and described in a convenient representation; 3) features are extracted; 3) from the extracted features the most discriminative are selected; 4) a classification block processes the features and delivers a decision corresponding to the recognition of the subject (Wang et al., 2008).

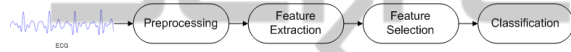


Figure 2: Classic structure of a reckoning system applied to an identification issue.

The proposed approach follows a partial fiducial approach (Agrafioti et al., 2011), using the wave onset, peak (the R complex) as characteristic point for segmentation. The feature extraction is based on a frequency approach, and follows Odinaka algorithm (Odinaka et al., 2010). In Odinaka’s work (Odinaka et al., 2010) each single heartbeat is segmented into 64ms windows with an overlap between of 54ms. The analysis is performed in the frequency domain computing the short time Fourier transform (STFT) (Oppenheim and Schaffer, 1975) for each window (an Hamming is used for better estimation), in order to estimate a mean and a variance of each frequency bin.

The performance of this method, and its suitability for a real time implementation on embedded system implementation, were the main aspects considered on choosing this method for this implementation.

3.1 Frequency Extraction Approach and Implementation in embedded System

In Fig. 3 we represent the block diagram of the implemented approach. 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 140ms windows without overlap, instead of Odinaka’s 64ms windows

(Odinaka et al., 2010). The processing routine starts by the arrival of a new digitalized sample, which induces an 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) (Zong et al., 2003) algorithm, which enables the detection of the R-complex. The delineation of a single-heartbeat consists on 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.

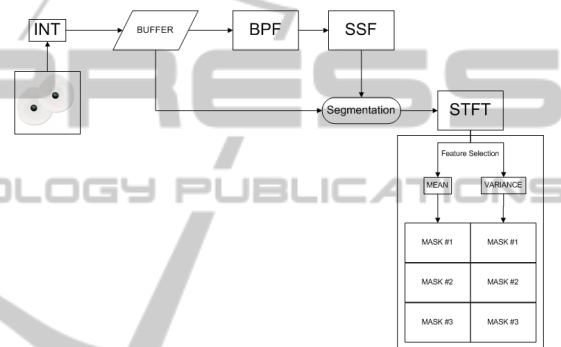


Figure 3: Software block diagram of the system.

The STFT uses a spectral zoom approach, *i.e.*, it makes 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 interested of biometric applications is mostly focused on this frequency bandwidth. 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.

A study has been made to determine the frame size and overlap time between frames, which results in terms of Equal Error Rate (EER) and identification performance are presented in figures 4, 5, 6, 7. Frame size tests were performed without any overlap and overlap tests were performed with a frame size of 140ms, being this the top performance value. These tests were performed with 50 separated runs in order to create a mean and a variance for each variable (frame size and overlapped time). Regarding the experiment, the best solution is an 140ms frame size without overlap. Overlapping barely increase the performance and substantially increases processing time.

The STFT is applied to each of the 140ms win-

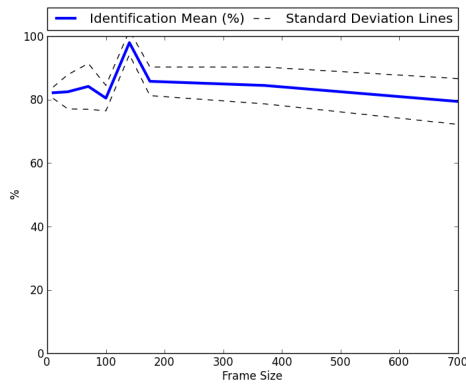


Figure 4: Identification performance over frame size variance.

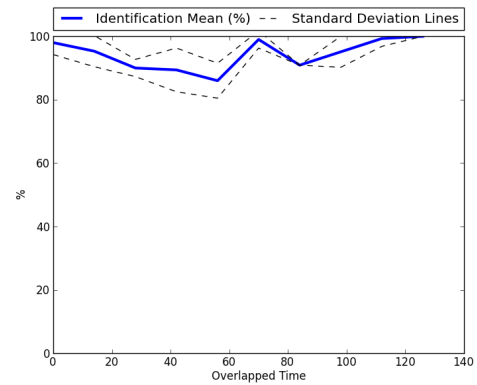


Figure 6: Identification performance over overlap time between frames.

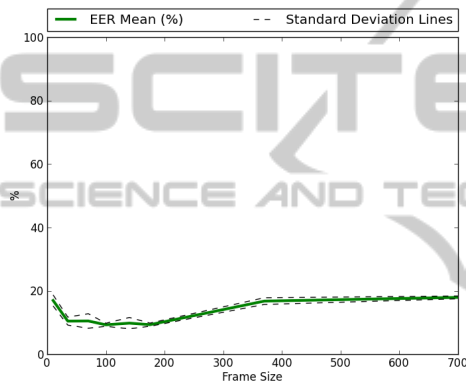


Figure 5: Equal Error Rate (EER) performance over frame size variance.

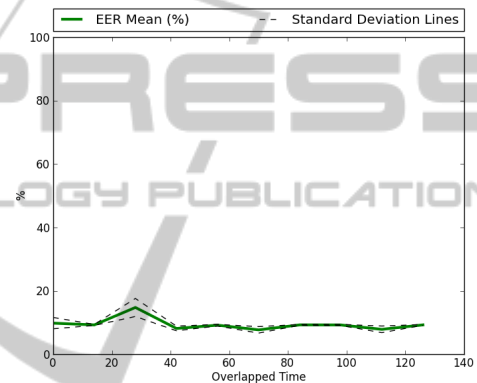


Figure 7: Equal Error Rate (EER) performance over overlap time between frames.

dow, leading to the creation of 50 frequency bins, totaling a vector with 250 features. The l -th feature corresponds to the STFT obtained over each segment window.

3.2 Feature Selection and Classification

Odinaka's work (Odinaka et al., 2010) 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 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. The Kullback-Leibler divergence is a non-symmetric measure of

the difference between two probability distributions P and Q , defined by

$$D(p||q) = \int p \log \frac{p}{q}. \quad (1)$$

The symmetric relative entropy between the two densities is defined as

$$d(p, q) = D(p||q) + D(q||p) \quad (2)$$

For the Gaussian distributions used in this model, the symmetric relative entropy between $\mathcal{N}(\mu_{il}, \sigma_{il}^2)$ and $\mathcal{N}(\mu_{0l}, \sigma_{0l}^2)$ is

$$d(\hat{\theta}_i(l), \hat{\theta}_0(l)) = \frac{\sigma_{il}^2 + (\mu_{il} - \mu_{0l})^2}{2\sigma_{0l}^2} + \frac{\sigma_{0l}^2 + (\mu_{il} - \mu_{0l})^2}{2\sigma_{il}^2} - 1 \quad (3)$$

where the nominal model is obtained by using the spectrograms of all the subjects in the database and $\hat{\theta}$ denotes the maximum likelihood estimate for the individual in test, $\hat{\theta}_i(l)$, and the train database, $\hat{\theta}_0(l)$. 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):

$$\Lambda = \sum \left[\frac{p_i(Y(l)|\hat{\theta}_i(l))}{p_0(Y(l)|\hat{\theta}_0(l))} \right] I_{d(\theta_i(l),\theta_0(l))>\kappa} \quad (4)$$

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 expression 4 is compared with a threshold τ , so that if $\Lambda > \tau$, the heartbeat with the claimed identity is accepted, otherwise the heartbeat is rejected.

4 EXPERIMENTAL EVALUATION

The dataset used to evaluate the this approach was acquired using the proposed system. It is composed by 11 subjects, with two recording sessions per subject. The acquired signals were obtained following the recent trend “the off-the-person approach”, where the ECG data is acquired at the fingers with dry Ag/AgCl electrodes. The ECG sensor consists of a custom, two lead differential sensor design with virtual ground, found in (Silva et al., 2011). Figure 8 presents the prototype, composed by the STM32F4-Discovery board and ECG sensor, used in the experiments.

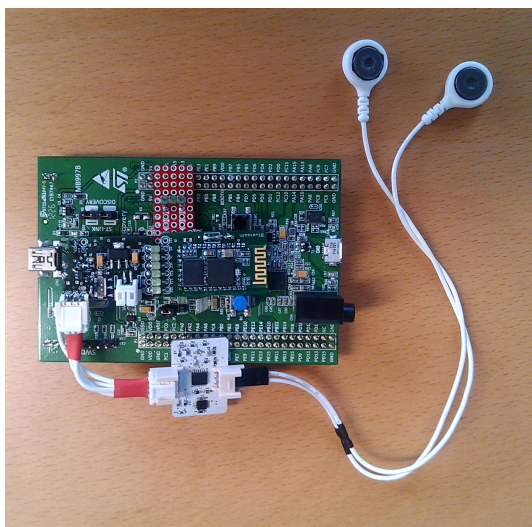


Figure 8: Prototype of the embedded system.

The features used in this work consist in frequency-domain representation. In figure 9 we illustrate the potential of this representation, showing for two different users, the time (on the left) and frequency (on the right) domain representation. Observing both the figures, it is possible to distinguish visually the difference between both subjects. In the literature, frequency domain representation is considered

more robust to heart-rhythm variation than the time domain counterpart (Odinaka et al., 2012).

The performance evaluation over the entire dataset is summarized in figure 10, where we plot the false acceptance rate (FAR) and the false rejection rate (FRR) curves in terms of the threshold of the system. We superimpose the equal error rate (EER) point, corresponding to the point where the FAR is equal to the FRR, and in this case corresponds to EER=9.3%. With this approach we achieve a 100% identification rate with 30 seconds of train signals.

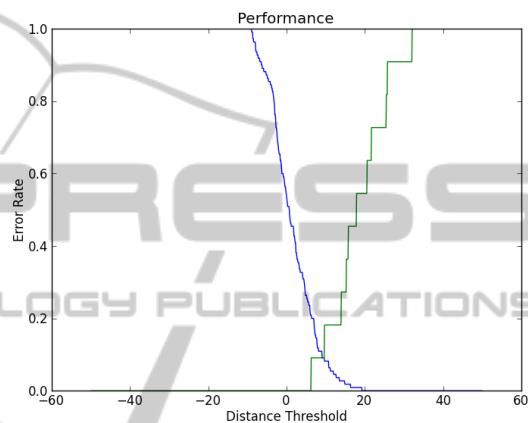


Figure 10: FAR vs FRR curve.

5 CONCLUSIONS 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, and the ECG is one such case.

In this paper we present an embedded system where we implemented a state-of-the-art method for ECG-based recognition. The implement method is based on a frequency-domain representation adapted from Odinaka et. al. (Odinaka et al., 2010). Our system also includes an ECG sensor that enables the acquisition at the fingers with dry Ag/AgCl electrodes, and implements all the steps of recognition workflow focusing real-time processing.

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

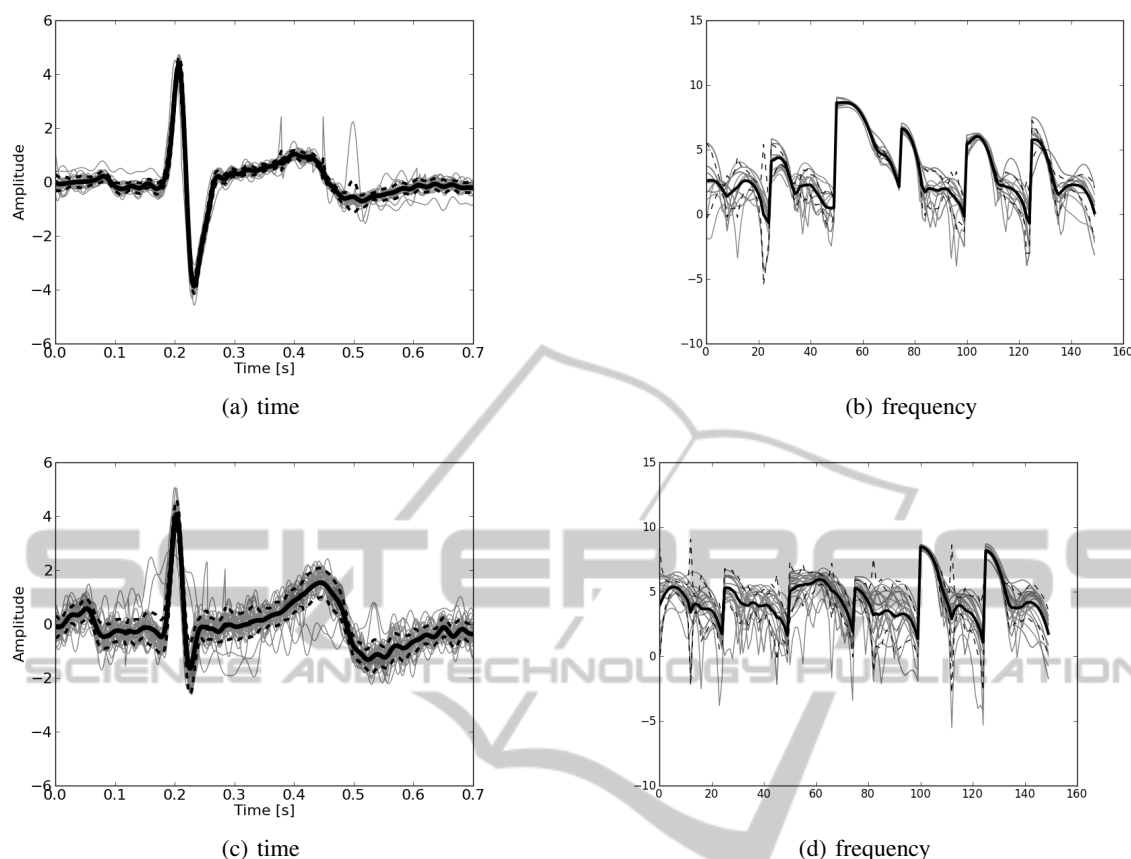


Figure 9: Comparison of time and frequency domain representation for two different users (arranged by line).

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