AN EMBEDDED SYSTEM FOR ON FIELD TESTING OF HUMAN IDENTIFICATION USING ECG BIOMETRIC

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ABSTRACT

In this paper a complete system for on field testing of the human identification using Electrocardiograms (ECG) biometric is proposed. The enrollment and test procedures are realized in software, while the recognition is implemented in real time on an embedded platform. It uses the wearable Vitalsens wireless sensor with ECG electrodes placed on the chest of the person to be identified, the ECG sensors communicate via Bluetooth with the LM058 Bluetooth adapter connected to the RS232 interface of the RC10 Field Programmable Gate Array (FPGA) prototyping board. A new human identification method based on the fiducial independent feature extraction from ECG signals is implemented on the low power Spartan 3L FPGA chip available on the board. The Principal Component Analysis (PCA) is exploited to select the main significant features. The projected ECG signals on the principal components are then compared by using the Euclidian distance metric. By occupying just the 45% of logic resources and 75% of the BRAM blocks, the embedded system reaches an identification accuracy of 90% .

Keywords: Electrocardiogram (ECG), Embedded System, Principal Component Analysis (PCA), Human Identification

1. INTRODUCTION

Security systems require automatic human identification methods which are not vulnerable to falsification. Authorizations through password and ID-card are prone to be falsified, to be lost or stolen. In order to assure more secure levels, biometrics are a promising solution. In fact, biometrics consider anatomical, physiological or behavioral characteristics which are unique for a person to be identified. Thanks to the significant advances in computer processing allowing for fast and accurate measurements and execution of complex computation algorithms, in the last few years, biometric identification approaches have been employed in a wide range of applications including civilian, commercial, governmental, criminal and forensic investigation fields.

The human features which are more commonly used in biometric recognition systems are the fingerprint, voice, face, retina and iris. Unfortunately, falsification attacks are reducing the vulnerability of these methods; in fact, face images are easily stolen, finger prints are copied, eye features are reproduced with lens, the voice is easily recorded. Electrocardiogram (ECG) signals are recently considered as a biometric to be used for robust identification [1]. The ECG is a representation of the electrical activity of the heart which is recorded by electrodes placed on the body surface. Deeply studied in medicine for diagnosis and monitoring of heart health, the ECGs have been demonstrated to have unique features to be used for identification [2,3].

In order to recognize significant features in ECG signals, two main approaches are used [4]. The fiducial approach searches for specific points of interest to extrapolate timing and magnitude measurements. Typical features are linked to the peaks and time duration of the P-QRS-T waves representing the heart activity in terms of depolarization and repolarization of the atria and ventricles. Fiducial independent approaches do not consider features of the ECG directly related to the physical functionality of the heart, but extract statistical and analytical features from the morphology of the signal waveforms. A fiducial approach based on the multi resolution Daubechies D4 and D6 wavelet transforms was proposed in [5] to detect the QRS complex and the onsets and offsets of the P and T waves on the MIT-BIH database [6], reaching a positive recognition of 98%. In [7] a quadratic Spline wavelet based framework is developed for the automatic analysis of single lead ECGs for human recognition; the QRS, P and T fiducial points are detected by searching the maxima, minima and zero crossing values in the wavelet coefficient reconstruction of the ECG signals at different scales. A recognition rate of 99.61% is reached on the MIT-BIH database. In [8], the QRS complex is detected as fiducial feature for ECG classification through Haar wavelet transformation and the Euclidian distance measurement. The fiducial independent approach was used by [9] reaching a recognition rate of 99.6%; the wavelet coefficients are extracted by using the Daubechies wavelet of order eight, the Independent Component Analysis (ICA) is used to find the independent components from the statistical independent random variables, finally the Principle Component Analysis (PCA) is used to reduce the feature dimensionality. In [10], a fiducial independent approach was used for the feature extraction of MIT-BIH ECG database; the wavelet transformation was executed using Daubechies wavelet of level 4 and decomposition level 4, finally the PCA is used to reduce the dimensionality and extract the features. Most of the research in literature explore only theoretically the possibility to use ECG signals for human identification, while the real implementation of a complete ECG identification system for on field testing of the recognition process is not present in the literature, except for the embedded implementation of individual building blocks of the complete identification system [11-14]. In [11], an an ECG-QRS complex detection was implemented on the Xilinx Virtex-II pro FPGA, an accuracy of 99.681 % was reached by testing the MIT-BIH database. In [12], an FPGA based implementation was proposed for a different application: the ECG classification for detecting arrythmia patterns. Finally, two embedded implementations are proposed not for the human identification problem but for the ECG signals denoising, and the filtering and compression in [13] and [14], respectively. In order to provide a solution for real testing in practical applications, a complete identification system is here proposed, where the enrollment phase is executed in software to extrapolate the features of interest and to build a reference dataset saving the information required to identify the registered persons in terms of the selected features. An embedded system built onthe RC10 FPGA board implements the recognition system, the latter exploits the PCA in order to select the features, while the Euclidian distance metric is used for matching the ECG of the person to be identified with one of the ECG of the registered persons, in terms of the principal components. The system reaches a recognition rate of 90% when tested on MIT-BIH database and for on field acquired ECG signals through the Vitalsens wireless ECG sensor. The proposed embedded system is an efficient implementation of an ECG identification method on reconfigurable hardware, moreover it is particularly appropriate for further experimentation of new algorithms in real applications.

2. THE IDENTIFICATION SYSTEM

The adopted identification process consists of two main processes: the enrollment and the recognition. The former is executed a number of times equal to the number of persons who need to be identified by the system, the latter is executed every time a person needs to be recognized by the automatic system. As shown in Fig. 1, the enrollment consists in a first phase of acquisition of ECG signals eventually preprocessed through filtering operations to the aim of creating an ECG dataset storing the correspondence between ECG signals and identity numbers of the persons from whom the ECG was acquired. After the registration phase, the feature selection phase establishes the more representative features for better distinguishing the different ECG signals. Once the significant feature set is established, each ECG signal can be expressed in terms of the significant feature set through their corresponding weights, the latter are used to say how much of each feature is present in an ECG signal. The feature weight extraction is repeated for each registered ECG signal in order to create an entire referencedata base of feature weights. Thus the enrolment phase is concluded when two datasets are generated: the reference feature weight dataset and the set of significant features. Each time an identification is required, a recognition process needs to be executed by acquiring and filtering the ECG signal of the person to be identified. Subsequently, the feature weights extraction is executed relatively to the same set of features selected during the enrolment phase. The matching between the ECG signal acquired in the recognition phase with one of the previously registered ECG signals is performed by searching for the minimum dissimilarity among the corresponding weights. Finally, the match is validated if the minimum dissimilarity is lower than a fixed threshold value. The latter can be used to increase the confidence level of the matching. Fiducial dependent approaches fix a priori the features to be investigated during the ECG classification by selecting some specific temporal and/or morphological parameters which are supposed to uniquely identify a person when considered together. On the contrary, the proposed fiducial independent identification system selects the features of interest depending on the specific registered ECG Database, by searching for those features which mostly are able to put in evidence the differences among the different registered ECG signals. In other words, the aim of using variable feature selection depending on the ECG Database consists in focusing only on the characteristics which are the main cause of the differences among the registered ECG signals, thus neglecting the common characteristics. At this aim, the proposed approach investigates the use of the PCA of the ECG signals for the feature selection process. In fact, the PCA [15] furnishes an analytical solution from linear algebra for the selection of the main important features which characterize the signals of interest; by ordering the principal components respect to their significance, it is possible to select only those components which will account for meaningful amounts of variance, with the advantage of significantly reducing the complexity of the calculus by a data dimensional reduction with just a small amount of information lost, thanks to redundancy elimination. The minimum Euclidian distance between the principal component contributions is used as the metric for the calculus of the matching dissimilarity.

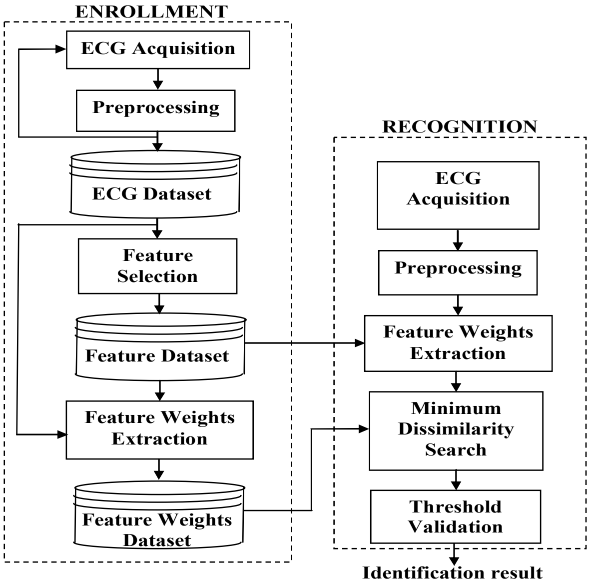

Figure 1. The Identification process.

3. FEATURING ECG SIGNALS THROUGH PCA

The feature selection in the enrollment phase of the proposed identification system is provided by PCA in order to identify the most meaningful basis to express the data set consisting of the registered ECG signals. Thus, the acquisition phase generates a data set of ECG signals which are stored in the $n*m$ matrix T, where n is the number of acquired ECG signals, and m is the number of samples for each signal. In order to have a meaningful dataset, all the acquired ECG data signals have to be of the same length and resolution, moreover they need to be centered respect to the same reference point like for example the R-wave.The first step consists in calculating the covariance matrix C of the matrix T, as in (1), where A is equivalent to the T matrix after subtracting the mean value of each dimension.

$$C = (1/n\text{-}1)AA^T \qquad (1)$$

The matrix of principal components F, which represents the selected features, is obtained by calculating the matrix of eigenvectors for C. Among all the eigenvectors, only the most significant ones are included in the feature matrix F, i.e. the eigenvectors corresponding to the eigenvalues greater than a certain threshold, opportunely selected to reduce the dimensionality of the original dataset. The eigenvectors of C which form the matrix F are then used as the new basis to represent the ECG signals. The registered ECG signals and every new acquired ECG signal to be recognized are then projected in the principal component space in order to be compared. The projected matrix P, calculated as in (2), represents the feature weight dataset of the identification process in Fig. 1, while the projected vector$y$ of the ECG signal x to be identified, after preprocessing and mean subtraction, is calculated as in (3).

$$P = F^T A \qquad (2)$$

$$y = F^T x \qquad (3)$$

The matching search between the ECG signal to be identified and the registered ones is executed by finding the minimum dissimilarity between the projected signal y and the projected dataset P. The metric used for the dissimilarity evaluation of the n distances of y respect to P is the Euclidian distance as reported in (4).

$$d(i) = \sum_{j=1}^{m}(y(j) - P(i,j))^2 \quad i = 1..n \quad (4)$$

The minimum value $d*$, calculated as in (5), is further compared with a threshold value δ in order to validate the identification.

$$d^* = d(i^*) = \min_{i=1..n} d(i) \qquad (5)$$

Finally, if $d* < \delta$ then $i*$ represents the identification number.

4. THE PROPOSED EMBEDDED SYSTEM FOR ECG IDENTIFICATION

The proposed identification system has been designed and implemented for running in the complete hardware setup reported in Fig. 2.
For the acquisition of the ECG signals, the Intelesens VS100 sensors were used [16]. The latter is a wireless sensor able to measure the ECG signals, the heart rate, the motion through the acceleration, and the temperature. It is powered by a lithium ion battery which guarantees a working period of at least 24 hours, while a class II Bluetooth is used for the wireless transmission in a range of 10m. The ECG sampling frequency is 360Hz, and the data resolution is 12 bit. Moreover an analog filtering before the AD conversion is introduced for noise reduction. The hardware frequency response is 0.5 Hz to 25Hz with a gain of 500. The ECG is recorded via a patch electrode on the chest,one electrode is attached to the right chest and a second electrode is placed below the left chest. The VS100 sensor is simply clipped onto the patch, which has the advantage of a minimum signal path from the electrodes to the electronics for clearer signals. Furthermore, the VS100 sensor is unobtrusive to wear because of its small dimensions and light weight. The ECG recordings during the enrollment phase and the entire enrollment procedure are executed by the general purpose computer illustrated in Fig. 2. The recognition process is implemented on the RC10 FPGA prototyping board opportunely connected to the LM Technologies LM058 Bluetooth adapter [17] for the communication with the VS100 sensors. The RC10 [18] is equipped with the Xilinx Spartan 3L FPGA chip. Utilized peripherals include the serial RS232 interface for the connection with the LM058 Bluetooth adapter, the 16 MByte Flash memory for storing the enrollment reference data, the on-board LEDs for logging the actual processing steps, and the seven segment displays for showing the recognized ID.

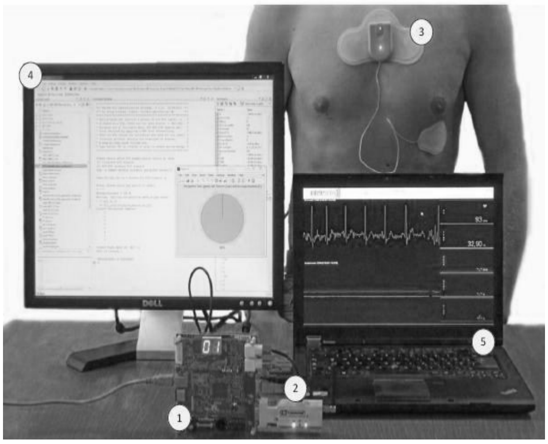

Figure 2. The implemented ECG identification system and its hardware setup.

4.1. The enrollment and test system

The first step in the enrollment system is the acquisition of the ECG signals; two modalities are provided: the on field acquisition through the VS100 sensors and the acquisition from the MIT-BIH database. In order to record the sampled signals by the VS100 sensors in e a text file, the VitalsensFrontEnd software furnished by Intelesens was employed. The acquired ECG signals are elaborated in Matlab for the enrollment and the test phase, as shown in Fig. 3. In order to build a training and test database, a preprocessing step extracts the aligned ECG signals, by selecting 300 and 100 samples for the VS110 and MIT-BIH acquisitions respectively. The alignment is executed respect to the R-wave, automatically detected by searching for the maximum value. While signals from the VS100 sensor are already filtered, in order to reduce the noise and baseline drift of the MIT-BIH signals, the mean is subtracted from every ECG signal and the DWT filter is applied. In order to evaluate the best effects of reducing high frequency noise caused by muscle contractions and sensor interferences, different types of wavelet algorithms were tested at different decomposition levels: Daubechies, Coiflet5 and Haar. The enrollment phase executes the PCA furnishing in output the feature matrix *F* of the eigenvectors forming the principal components and the projection *P* of the training ECG signals to be used as the reference dataset. The simulation test uses the feature matrix *F* to calculate the projection *y* of the testing ECG signal into the principal components basis as in (3), and then the minimum value of the Euclidian distance between *y* and the projected training set *P* furnishes the candidate ID which is validated after a threshold comparison.

4.2. The recognition system

The recognition process is implemented in the embedded system shown in Fig. 4, which includes the VS100 sensor for the ECG acquisition, the LM058 Bluetooth adapter for the wireless communication and the RC10 board for the identification.

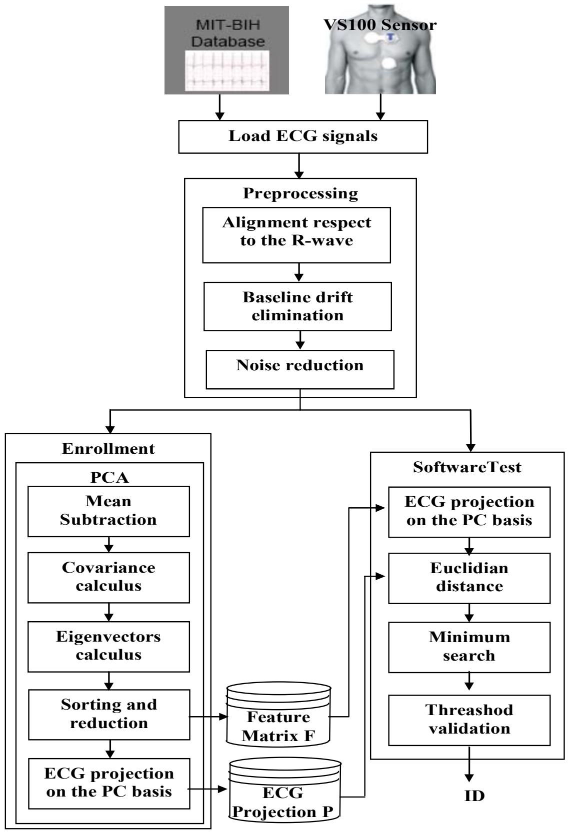

Figure 3. The enrollment and test system.

The feature matrix *F* and the projection *P* of the training ECG dataset on the principal component basis, calculated by the enrollment system, are stored in the 16MB flash memory provided in the RC10 board.

All the functional blocks are implemented in the Xilinx Spartan3L chip. The enrollment data loading module reads the enrollment dataset from the flash memory and store it into two buffers for *F* and *P* matrices respectively, in a 16bit signed integer format inside the FPGA BRAM blocks. At each identification requirement, the Bluetooth Communication module is used to acquire the ECG samples from the VS100 sensors; the sampled signals are transferred serially to the RS232 port of the RC10 board by the LM058 Bluetooth adapter. Sensor data are represented as message strings including communication information. The Bluetooth communication module implements a three layer structure for realizing the entire communication, one layer implements the RS232 serial interface, the second layer executes the message string composition and decomposition, while the third level implements the control unit as a finite state machine (FSM). The alignment of the ECG samples is executed by searching for the maximum value which represents the R peak in the R wave detection module, and splitting the data in order to save 300 samples centered in the R peak. The selected signal is processed by subtracting the mean value, the projection *y* is calculated respect to the principal component basis *F*, then the Euclidian distance is calculated respect to each projected registered ECG signal present in *P*.

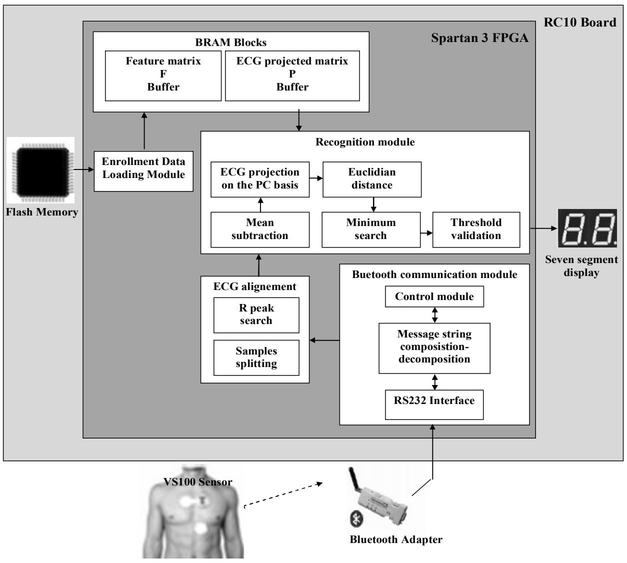

Figure 4. The recognition system.

The resulting ID is calculated as the argument of the minimum distances, the matching is validated only if the minimum is below a fixed threshold value. Finally, the display module is used for the visualization of the ID in the seven segment display.

5. RESULTS

Table I reports the results in terms of FPGA chip utilization and performances, while Fig. 5 shows the FPGA chip layout respect to the ECG identification circuit, the Bluetooth ECG acquisition and the other utility libraries. The circuit occupies 5,996 slices (45% of total resources), 24 BRAM blocks, 6 MULT18x18 embedded multipliers, reaching the maximum working frequency of 36MHz, and dissipating 258 mW when working at 33MHz (the power was estimated by using the Xilinx X-Power tool). The entire identification system was tested through both Matlab simulations and on field experimentations. The MIT-BIH database was used, 20 different ECG signals of 100 samples each were considered. The VS100 sensors were used to acquire the ECG signals from 8 different persons. The test of the MIT-BIH ECG signals required a filtering preprocessing step for noise reduction by using the Wavelet coif5 algorithm and the decompsition level 2. The VS100 sensors include an analog band pass filtering inside, thus there was no need for a digital filter implementation inside the recognition embedded system. As shown in Fig. 6, the ECG signals from Vitalsens sensor contain very low noise levels and no baseline drift.

TABLE I FPGA utilization and performances

FPGA	#Slices	#BRAM	#MULT	MaxFreq [MHz]	Power [mW]
Xilinx Spartan3 3S 1500L-4	5,996 (45%)	24 (75%)	6 (18%)	36	258

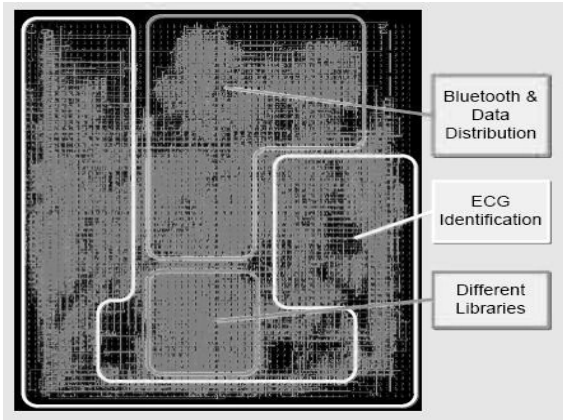

Figure 5. The FPGA layout of the recognition system.

Comparisons between the software simulation and the real system show the same final results, even if there are some differences in the calculations due to different number representation, in fact the FPGA computation considers only 16 bit sign integer numbers by ignoring fractional values. The achieved recognition rate is 90%, which is a great result for a real and not ideal identification system based on ECG biometric. In fact, even if, during the experimentations, the ECG acquisitions were made in the same conditions for preserving the ECG characteristics respect to the enrollment phase, small differences like body movements and different heart rates decreased the total accuracy causing false recognitions.

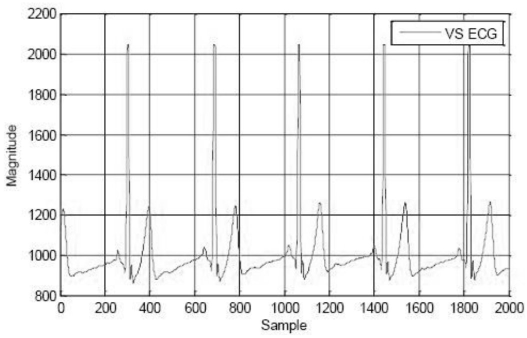

Figure 6. The ECG signals from Vitalsens sensor.

The main contribution is the realization of a real system for the human identification through the ECG, in fact in literature only few implementations are present, but none of them include an on field ECG acquisition system. Table II reports some comparisons with the implemented solutions present in literature.

TABLE II Comparison results

System	Identification Method	ECG Acquisition	Accuracy [%]	FPGA	HW Resources #Slices #BRAM #MULT	Max Freq [MHz]
New	PLA	V100 Sensors + MIT-BIH	90	Xilinx Spartan 3	5,996 24 6	36
[11]	ALS	MIT-BIH	98	Xilinx Virtex II Pro	1,112 3 n.a.	200

In [11], an Adaptive Lifting Scheme (ALS) is used to detect an ECG-QRS complex, with a very high accuracy result of 99.681 %. The algorithm was implemented on the Xilinx Virtex-II pro FPGA chip occupying just 8% of the logic resources; unfortunately all the results were obtained by using the MIT-BIH database.

6. CONCLUSIONS

A complete embedded system for people identification using ECG biometric has been proposed. The main focus of the proposed paper was to provide an embedded system for on field testing of real time acquired ECG signals in human identification. The proposed system was used to evaluate a new identification method based on a fiducial independent approach. A preprocessing filtering based on DWT or analog filtering when the V100 sensors are used, is the first step in the ECG processing. The PCA is used for the feature selection and feature extraction of the reference registered ECG dataset during the enrollment phase and later in the recognition phase. The ECG to be identified is matched with one of the registered ECG signals when the minimum Euclidian distance of the projected ECG respect to the principal component basis is below a certain threshold of confidence. The software simulation, the software enrollment system and the hardware implemented embedded recognition system provide a complete setup system for on field testing the identification process. Experimentations on the MIT-BIH database and the ECG signals of 8 persons acquired by the embedded system provided with VS100 sensors demonstrated the validity of the identification system with an accuracy of 90%. The system setup represents the basis for more experimentations which will be focused on the improvements of the following aspects: research of more accurate algorithms to implement in the embedded system, evaluation of ECG signals acquired in different conditions than the registered ECG signals during the enrollment phase, increase the number of persons to be tested for a more representative set of measurements, and deployment of the proposed system for patients tracking and identification in hospital's wards.

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