A Correlation-based Biometric Identification Technique for ECG, PPG and EMG

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***Abstract*—With the increase in the number of nodes connected to a wireless body area network (WBAN), transmitting biomedical data with the purpose of continuous health monitoring, authentication is a key element to maintain confidentiality in an open environment. In this context, this paper investigates the employment of biometrics extracted from biomedical signals, namely electrocardiogram, photopletysmogram and electromyogram, monitored by the WBAN nodes for user identification. The proposed biometric feature extraction technique is based on cross-correlating the biomedical signal to a reference signal. As such, biometrics extraction is solved with a procedure similar to the morphological analysis of the biomedical signal. Simulation results prove the applicability of the proposed technique.**

***Keywords*—biometrics, biomedical signals, cross-correlation, non-fiducial feature, user identification**

I. Introduction

There is a continuous increase in the number of monitoring devices people carry with them every day. At first, this was due to the necessity of health monitoring. Lately, this shifted towards self-monitoring of the health status in the context of ubiquitous health care. This can be achieved by employing a variety of sensors that monitor the individual's physiological parameters, aiming for the remote evaluation of the requirements to provide medical services.

Such a network of nodes for the monitoring of physiological parameters comes in the shape of a Wireless Body Area Network (WBANs) [1]. Since data transmission between the network nodes is performed in an open environment in a wireless fashion, data could be easily intercepted by an uninvolved party. Thus, authentication is crucial to maintain the trustworthiness of the biomedical data.

Reliable user data gathering is indeed a concern in WBANs. As such, current procedure in current wireless health monitors is to perform a key-based authentication, ensuring a secure way of communication between sensor nodes. As an alternative, technical literature recognizes the employment of biometrics for authentication and security [2].

This paper proposes the employment of biomedical signal-based biometrics, namely electrocardiogram (ECG), photoplethysmogram (PPG) and electromyogram (EMG), for individual identification in WBANs. Identification based on the biomedical waveform features is typically performed by estimating their similarity to some reference features. Solutions for identification in a transformation domain are reported for example as follows: Fourier transform for both ECG and EMG in [2], Wavelet transform for PPG in [3] or Karhunen-Loève transform for PPG in [4]. Alternatively, solutions for user identification in a model domain are reported for example: dynamic modelling for biopotentials in [5], clustering and encoding for EMG in [6] or encoding based on the Lempel-Ziv and Ziv-Merhav algorithms for ECG in [7].

In this work, we develop a simple time-domain non-fiducial feature extraction technique which is applicable to the bio-potentials targeted by WBANs. The proposed technique is based on the cross-correlation of the biomedical signal to a reference signal. The strength of this approach resides in the fact that cross-correlation is also applied for the assessment of the biomedical signal morphology. Accordingly, the extraction of non-fiducial features doesn't add consistent computational burden to the network node.

This article is organized as follows. Section II presents the correlation-based non-fiducial feature extraction technique. Section III presents the application of the proposed technique for feature extraction on ECG, PPG and EMG signals. Simulation results obtained in Matlab are presented in Section IV. Some conclusions are finally drawn.

II. The Correlation-based Non-fiducial Feature Extraction Technique

Biomedical signal processing aims for the extraction of fiducial features with the purpose of health assessment and diagnosis. Extraction of the non-fiducial features on the other hand aims for the determination of discriminative information contained in the biomedical signals. In comparison to fiducial features, which are influenced by a variety of factors, e.g. sensor positioning, state of anxiety, etc., non-fiducial features have the property of being invariant to the time and conditions of acquisition [8].

The biometrics-based user authentication approach proposed in this work is based on the premises that the similarity of the non-fiducial features can be assessed directly in time-domain on the biomedical signal. For this purpose, we

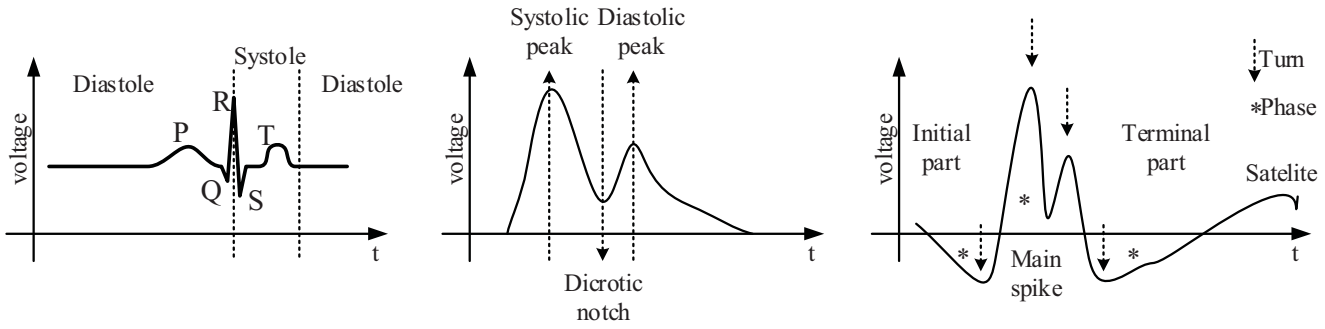

Fig. 2. Units of the targeted biopotentials: (a) ECG, (b) PPG and (c) EMG

aim to evaluate and investigate the cross-correlation of the individual's biomedical signal to a reference signal. Consistently with the premises of this work, the cross-correlation result should be unique to every individual.

For situations where cross-correlation is insufficient, as for example EMG-based identification, we investigate a transformation-based non-fiducial feature extraction approach, based on the work of Belgacem et al. [2]. This determines the auto-correlation (AC) of both the reference and the individual's biomedical signal. In contrast to Belgacem et al. however, who computes the discrete Fourier transform (DFT) of both AC functions and compares the DFT coefficients to perform individual authentication, we cross-correlate the AC functions and evaluate the cross-correlation maximum for identification.

III. Application of the Proposed Processing Technique to ECG, PPG and EMG

An ECG unit illustrated in Fig. 1 (a), corresponding to the two-phase cardiac cycle: diastole and systole, exhibits of a sequence of 5 waves: the P wave, the QRS complex and the T wave [2, 8]. These are the fiducial features of the ECG. Morphological analysis of the ECG assumes the identification of the fiducial features aiming for health monitoring and diagnostics purpose. While the R peak and the S wave are easily determined by comparison to a threshold value, the P, Q and T waves require a different approach. In previous work reported in [9], we have applied cross-correlation of an ECG signal to a reference ECG in order to identify the constituent waves. Accordingly, in the framework of our previous work, application of cross-correlation of non-fiducial feature extraction and individual identification is straightforward.

The ECG signal was acquired with a Mikroelektronika ECG Click board with a 2660 Hz sampling frequency. Pre-processing of the ECG signal assumed a 0.1 Hz – 60 Hz bandpass filtering. Additionally to ECG processing for wave identification reported in [9], both the individual's ECG and reference ECG were normalized to the same amplitude range.

In this work, ECG signal processing for user identification aims to correlate the individual's R-R interval to a reference ECG R-R interval. For this purpose, R-wave identification is performed with a peak detection function, followed by the extraction of each individual R-R intervals. To overcome the effect of noise and artefacts which haven't been filtered out during the pre-processing stage, an averaging of a number of the R-R intervals has been considered [2].

The cross-correlation of the individual's averaged ECG R-R interval and the reference ECG R-R interval was computed. Local maxima of the cross-correlation function correspond to the ECG waves in the R-R interval. The magnitude of the cross-correlation local maxima however enables individual identification.

A PPG unit consisting of a systolic peak, a dicrotic notch and a diastolic peak is illustrated in Fig. 1 (b) [3, 5]. Morphological analysis of the PPG waveform assumes the identification of systolic peaks, which then lead to the estimation of the heartrate. The systolic peak is easily identified with a peak detection function. The dicrotic notch and the diastolic peak can then be identified by means of cross-correlation to a reference PPG unit.

The PPG signal was acquired from an individual's right-hand index finger using a SparkFun SLEEP-11574 sensor with a 10 Hz sampling frequency. The sensor uses a blue-green LED as light source and an APDS-9000 ambient light sensor as the photodetector. Pre-processing of the PPG signal assumed a 0.1 Hz – 5 Hz filtering, and normalization of both individual's PPG and the reference PPG into the same amplitude range.

In this work, PPG signal processing for user identification aims to correlate the individual's peak to peak interval to a reference PPG peak-to-peak interval. An averaging of a number of the peak-to-peak intervals has been considered.

The cross-correlation of the individual's averaged PPG peak-to-peak interval and the reference PPG peak-to-peak interval was computed. Local maxima of the cross-correlation function correspond to the PPG wave peaks and notch respectively. The magnitude of the cross-correlation maxima on the other hand enable individual identification.

Electromyographic signals consist of a composition of motor unit action potentials (MUAP) [10], each corresponding to a group of muscle fibers. A MUAP is illustrated in Fig. 1 (c) and is mainly characterized by an initial part, a main spike, a terminal part and eventually a satellite. The morphological characteristics of MUAPs, expressed in terms of turns (arrow) and phases (asterisk), are constant for specific motor units, therefore allowing the identification and assessment of muscular activity for health monitoring and diagnostics purpose [13]. The shape of the turns and area of the phases on

the other hand may be considered discriminative for every individual and can therefore be employed for biometric identification.

The EMG signal was acquired with a Mikroelektronika EMG Click board with an 800 Hz sampling frequency. Pre-processing of the EMG signal assumed a 5 Hz – 50 Hz bandpass filtering and segmentation with 64-sample non-overlapping windows.

EMG signal processing for user identification, aiming the correlation of MUAPs to a reference signal, is performed in this work as follows. Muscular activity is first identified on the EMG signal if two metrics, namely the mean absolute value (MAV) and root mean square (RMS), exceed a certain threshold. Two further metrics, namely the zero crossing (ZC) count and the slope sign changes (SSC), are computed in those signal sections where muscular activity has been identified. The rationale for computing the ZC and SSC is that MUAPs belonging to the same motor unit will determine similar ZC and SSC values. Accordingly, cross-correlation between the individual's EMG signal and the reference EMG signal is expectedly performed targeting the same motor unit.

IV. Simulation Results

The proposed authentication algorithms were validated on a pool of 30 electrophysiological signals, namely first lead ECG, right-hand index finger PPG and lower-limb EMG. The electrophysiological signals were acquired with a Digilent Analog Discovery 2 board from 5 individuals at different moments of time. The Data Logger was used to export the recorder data using its native Export capabilities plot information in .csv format. The .csv files were then imported to Matlab for further processing, which aims for the extraction of non-fiducial features to perform individual identification.

The percentage of successful user identification, based on each of the three targeted electrophysiological signals, is listed in Tab. I. Both ECG and PPG-based user identification exhibit very good results with a correct identification rate larger than 95%, comparable to values reported in literature, thus validating the proposed authentication procedure. EMG-based identification on the other hand exhibits a correct identification rate of only 12%, a rather small rate, yet comparable to rates reported in literature. The reason for this value is two-fold. On one hand, correct EMG-based identification is very sensible on the proper classification of the MUAPs. On the other hand, the shape of the EMG signal, and consequently of the isolated MUAPS, changes with electrode placement. This phenomenon was observed by having correct identification among various recordings during the same session, i.e. same electrode placement, and incorrect identification with recordings at a different moment of time, i.e. different electrode placement, although the type of activity was the same for both recordings.

TABLE I. Percentage of Successful Indifidual Identification

User authentication	Electrophysiological signal		
	ECG	*PPG*	*EMG*
Percentage of correct identification	96%	98%	12%

The proposed electrophysiological signal-based identification methodology is exemplified further on to discriminate between two individuals, denoted as User 1 and User 2, in order to identify User 2. The reference R-R interval, the average of 3 R-R intervals of both users, as well as their cross-correlation to the reference signal are plotted in Fig. 2. As illustrated, the cross-correlation of both User 1's and User 2's ECG R-R interval to the reference signal result in a maximum peak in the origin, along with a number of local maxima corresponding to the ECG waves [9]. To be noticed is that the local maxima next to the central cross-correlation peak is due to the different length of the R-R interval as a result of heart rate variation. Nevertheless, the magnitude on the cross-correlation maximum peak in the origin serves for user identification. As illustrated, the cross-correlation maximum of User 2's ECG to the reference R-R interval is considerably larger than that of User 1's.

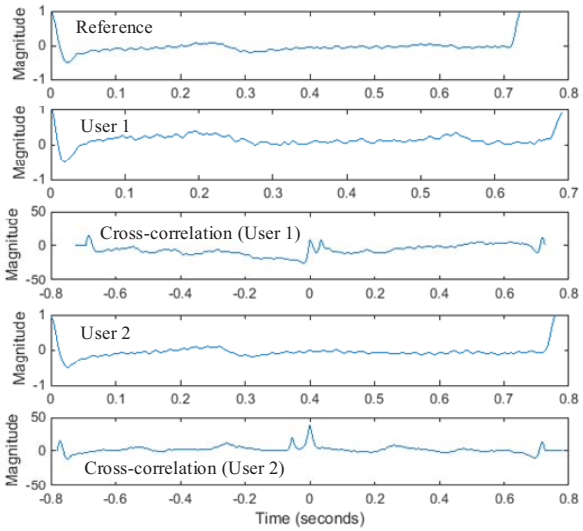

Fig. 2. Cross-correlation of the User's R-R intervals, determined from the ECG signals, to the reference R-R interval

Three PPG segments, corresponding to the reference PPG and the user's PPG, are plotted in Fig. 3 along with their cross-correlation to the reference signal. As illustrated, the cross-correlation outcome yields a larger maximum peak in the origin for User 2, thus allowing for user identification.

Two EMG signals, recorded from the same individual, are plotted in Fig. 4, along with signals illustrating activity detection and the corresponding ZC and SSC measures. The aim of evaluating ZC and SSC was to cross-correlate MUAPs corresponding to the same muscle unit. In contrast to ECG and PPG processing however, where segment initiation is identified via peak detection as an R wave or a Systolic peak, MUAP isolation in the proposed work is limited by window size. Therefore, cross-correlating MUAPs won't yield satisfactory results. Alternatively, we have computed the auto-correlation of MUAPs, and afterwards, we have evaluated the similarity between the auto-correlation functions by means of cross-correlation. The results are plotted in Fig. 8.

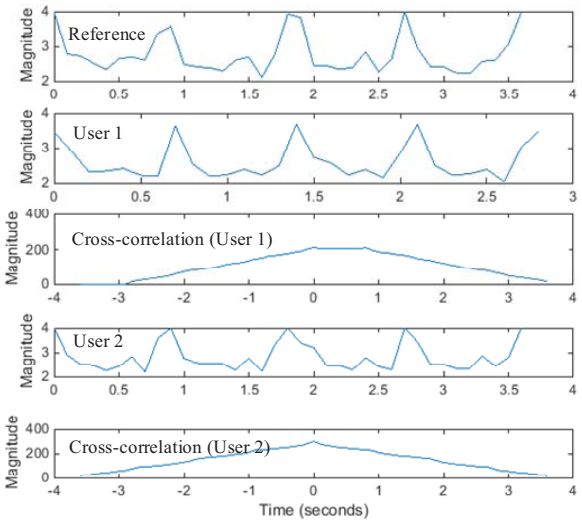

Fig. 3. Cross-correlation of the User's PPG sections to a reference PPG

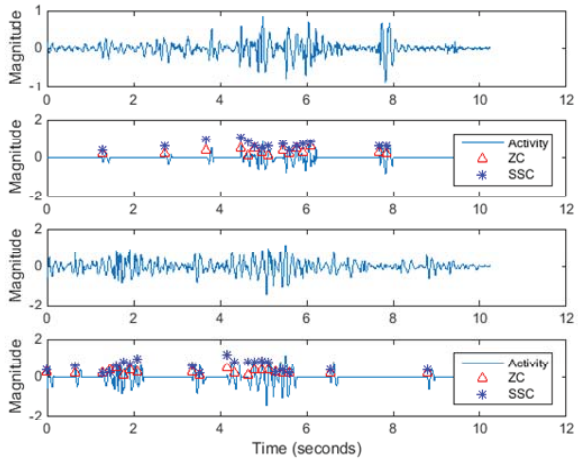

Fig. 4. Lower-limb EMG recordings for User 2 during normal walk, with the illustration of activity detection, ZC and SSC

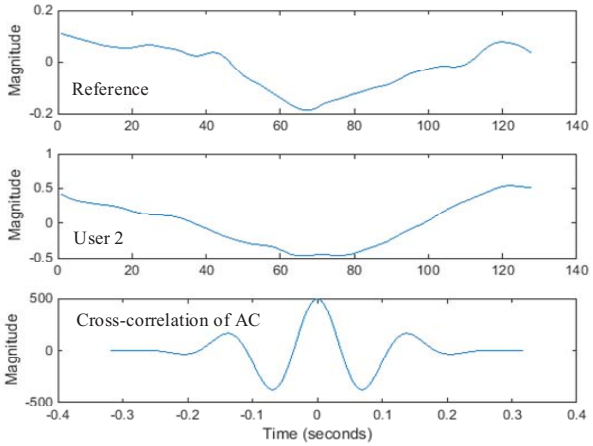

Fig. 5. MUAPs and the cross-correlation of their auto-correlation

V. Conclusion

This paper presented a simple time-domain technique, based on cross-correlation, for the assessment of non-fiducial features from biomedical signals with the purpose of individual identification. The proposed technique correlates the individual's biomedical signal to a reference and performs user identification by assessing the magnitude of the cross-correlation outcome.

This technique is aimed for implementation in WBANs, where the nodes are actually monitoring the biomedical signals targeted by the feature extraction technique. Moreover, correlation-based methods are readily employed for the morphological analysis of the biomedical signal. Therefore, the proposed technique doesn't add much computational burden to the WBAN nodes.

Simulation results prove the applicability of the proposed technique to ECG, PPG or EMG-based identification. As future work, we target the validation of the proposed technique with the MIT-BIH database.

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