Towards Emotion Related Feature Extraction based on Generalized Source-Independent Event Detection

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Abstract. Emotion recognition is of major importance towards the acceptability of Human-Computer Interaction systems, and several approaches to emotion classification using features extracted from biosignals have already been developed. This analysis is, in general, performed on a signal-specific basis, and can bring a significant complexity to those systems. In this paper we propose a signal-independent approach on marking specific signal events. In this preliminary study, the developed algorithm was applied on ECG and EMG signals. Based on a morphological analysis of the signal, the algorithm allows the detection of significant events within those signals. The performance of our algorithm proved to be comparable with that achieved by signal-specific processing techniques on events detection. Since no previous knowledge or signal-specific pre-processing steps are required, the presented approach is particularly interesting for automatic feature extraction in the context of emotion recognition systems.

1 Introduction

The ability to recognize emotion is of upmost importance with the increasing development of intelligent and adaptive computer systems, allowing them to sense and respond appropriately to user's affective feedback [1]. Emotions are one of the least explored frontiers of intuitive Human-Computer Interaction (HCI) [2], and its understanding is expected to improve the acceptability of those systems. This requires, however, robust emotion recognition systems, capable of guaranteeing acceptable recognition accuracy, and adaptable to practical applications [3].

Emotion recognition systems still present relevant challenges, as it is very hard to uniquely correlate emotion-relevant signal patterns with a certain emotional state. Furthermore, these patterns may widely differ from person to person, and between different situations [3]; there is a lack of ground-truth datasets in order to develop user-independent systems, which would be essential for practical applications [4, 5]. There have been many attempts to built automatic emotion recognition systems [3, 6–9], which mostly rely on supervised pattern classification approaches. However, some of the major problems still verified are the low recognition rates when considering subject-independent classification and generalization to more than one task [10]. A generally

Santos R., Sousa J., J. Marques C., Gamboa H. and Silva H..
Towards Emotion Related Feature Extraction based on Generalized Source-Independent Event Detection.
DOI: 10.5220/0003891900710078
In *Proceedings of the 2nd International Workshop on Computing Paradigms for Mental Health* (MindCare-2012), pages 71-78
ISBN: 978-989-8425-92-8

applicable recognition system, for realistic online applications, would have to automatically select the most significant features and specific classifiers to several data sets obtained from different natural contexts [8].

Emotions are inherently multi-modal, and several studies on their recognition work by fusing features extracted from multiple modalities (facial expression [11], voice [12] or gesture [13] and biosignals). The work around biosignals include the heart rate, skin temperature, electrodermal and electromyographic activity or respiration rate [1, 14]. The areas of speech and face recognition are far more explored, mostly because it is a very hard task to uniquely map physiological patterns onto specific emotional states and some of the sensors used to acquire those biosignals may be sensitive to motion artifacts [6]. However, the size of such sensors is decreasing and this method is considered to be less disturbing than the standard audiovisual techniques [2]. Moreover, biosignals allow us to continuously gather information on the user's affective state, and should be more robust against possible artifacts of human social masking, since they are directly controlled by the human autonomous nervous system [3, 8].

Feature extraction from biosignals is a complex multivariate task, requiring a broad insight into biological processes related with neuropsychological functions [6]. Standard specific processing techniques in which the results are highly dependent on the input parameters are usually applied, bringing an added complexity to these feature extraction systems. In this paper we propose a signal-independent approach to the detection of specific signal events, in order to accomplish an accurate feature extraction based on the results of a generic algorithm. The performance of the generic events detection approach is also compared with that of signal-specific standard algorithms.

The following section presents a brief description of the biosignals considered in this preliminary approach, as well as the applied signal processing methodologies. The obtained results are presented and discussed in section 3. In the last section some final remarks and future work steps are referred.

2 Materials and Methods

2.1 Biosignals

This subsection introduces the biosignals that were considered in this preliminary study, including the main features usually extracted in the context of emotion classification systems. Those types of signals were selected based on their characteristic waveshapes, in which the events are clearly distinguishable. As such, an intuitive evaluation of the algorithm performance on that signals is accomplished. Furthermore, these signals are strong related to mental diseases and they are very helpful into infers about the mental health condition of the patients.

With these signals we only intend to exemplify the application of the developed algorithm, since their origin, as respectively described, is not related to the testing protocols usually followed in emotion classification studies [1, 3].

Electrocardiography. The electrocardiogram (ECG) is the recording, on the body surface, of the electrical activity generated by the heart. From the ECG processing one can extract features as the Heart Rate (HR) and the Heart Rate Variability (HRV). HRV has become the conventionally accepted term to describe variations of both instantaneous heart rate and RR interval. In a continuous ECG record, each QRS complex is detected, and the so-called normal-to-normal (NN) intervals or the instantaneous heart rate is determined. Simple time domain variables that can be calculated include the mean NN interval, the standard deviation of the NN intervals (SDNN) or the mean heart rate. Spectral analysis is also usually performed, since there is a correlation between the relative power of the low frequencies (LF) and high frequencies (HF) ranges and the sympathetic and parasympathetic nervous systems activity. Non-linear methods based on chaos theory and fractal analysis are also used on HRV analysis to better understand the HR fluctuations. The common example of non-linear methods is the Poincaré plot, which reflects the graphical correlation between consecutive RR intervals [15].

Since HRV and the automatic heart modulation are correlated, HRV analysis is a powerful tool for clinical use. The HRV analysis allows a better understanding of the SA node automatic modulation. For example, the spectral analysis reveals that the vagal activity is the major contribution to the high frequencies component. Furthermore, it is also argued that the LF and HF ratio reflects the sympathovagal balance or the sympathetic modulation. These parameters are very important since some authors defend that there is a significant increase of LF band and significant increment of the HR for panic disorders patients and significant lower values of R-R intervals and HF peak of spectral analysis in depressive patients than in the health people. In general, both the HR and the HRV are dependent on the activity level of the autonomic nervous system, which in turn is dependent on emotional stimuli [4]. A low HRV can indicate a state of relaxation, while an increased HRV can be caused by mental stress or frustration [2].

The ECG signals here considered were obtained from a public database (PhysioBank) at PhysioNet library [16]. Those were acquired from healthy people, with normal sinus rhythm, during 4 seconds and at a sampling frequency of 125 Hz. A total of 26 ECG signals was considered.

Electromyography. Electromyography (EMG) signal arises from the flow of charged particles across the muscle membrane when its cells are electrically activated. This biosignals can record both voluntary and involuntary muscle activation, in addition to the action potentials produced by external stimulation, such as motor evoked potentials after central or peripheral nerve stimulation [17]. EMG signals have been shown to correlate with negatively valenced emotions [18]. The signals here considered were acquired in the context of a study aiming at accessing the performance of the right leg during the execution of an emergency brake in a car simulator [19]. EMG signals of the *Rectus Femoris*, *Vastus Medialis*, *Tibialis Anterior* and *Gastrocnemius* muscles were acquired while 3 subjects performed the emergency brake test. From that data set, a total of 40 EMG signals was considered in this study, comprising 10 signals of each considered muscle. Bipolar EMG sensors (emgPLUX) were used to access the muscle activation. The sensors were connected to a wireless acquisition unit, bioPLUX research [20], which performed the acquisition at a sampling frequency of 1000 Hz.

2.2 Generalized Signal Processing Approach

The main features that guided the development of the introduced signal processing methodology have been the signal-independence, implying no specific pre-processing steps. The immunity to noise and artifacts and the simplicity, in order to allow a real-time implementation, were also considered.

The basis of the developed algorithm is the identification of time-domain specific morphological parameters that can clearly distinguish events, such as onset and offset instants and transient waveshapes, within a signal. In practise, after a signal segmentation, those events are computed as the split points for which the absolute values of the difference between the standard deviation of the successive segments are maximized. A further optimization step is then applied through an iterative change of the input parameters of the previously described processing steps. The optimal solution is selected as the one which assures a better fitting of all the signal segments, between the detected events, to linear regressions models.

A detailed description and performance evaluation of this signal processing approach can be found in [21]. This paper extends that events detection approach to application in different biosignals and evaluates its performance by comparison with standard signal-specific algorithms.

2.3 Standard Signal-specific Algorithms

In order to evaluate the performance of the proposed signal processing approach, its results were compared with those from signal-specific standard techniques for EMG onset and ECG waveshape detection.

An adaptation of the QRS complex detector algorithm proposed by Pan and Tompkins [22] was implemented as a standard method for performance evaluation on detecting heartbeats within an ECG signal. ECG signal pre-processing steps included the application of a 2^{nd} order Butterworth lowpass filter with a 30 Hz cutoff frequency, to remove some possible high frequency noise due to electronic devices interference. A 2^{nd} order Butterworth high pass filter with 2 Hz cutoff frequency was also applied to remove some possible baseline fluctuations and other respiration artifacts.

Considering EMG signals, a standard onset detector proposed by Hodges et al.[23] was implemented. This approach implies the EMG signal to be pre-processed in order to reduce the high frequency noise and obtain the signal's envelope. After subtracting the mean value from the EMG signal and obtaining the rectified wave, a sixth-order digital butterworth filter with 50 Hz cutoff frequency was applied, following the implementation procedure described in [24], completing the envelope detection.

The muscle activity onset was identified as the instant from which the mean of the following N samples from the EMG envelope exceeds the baseline activity level by a specified multiple h of standard deviations. The baseline activity was adaptively determined, at each instant, by averaging M previous signal samples [24]. With a cutoff frequency of 50Hz, the set of criteria {N=25, h=3} and {N=50, h=1} are those reported as able to identify the EMG onset more accurately [23]. Hodges detector was implemented with both set of parameters, considering the baseline activity level computed from M=100 and M=200, respectively [24].

3 Results and Discussion

The signal processing methodology described in sub-section 2.2 was applied to the selected raw biosignals. No signal-specific pre-processing steps were applied. Graphic representations exemplifying the obtained results are presented in Figure 1.

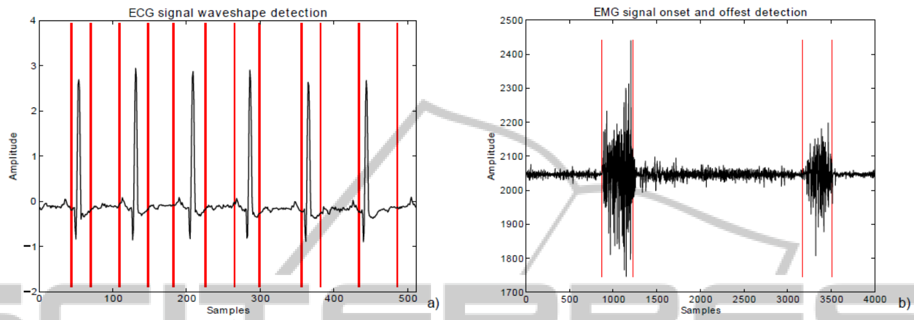

Fig. 1. Graphic example of: a) detected ECG waveshapes and b) EMG onset and offset points applying the developed events detection algorithm. The events are marked by vertical red marks.

As exemplified in Figure 1a), the developed algorithm allows the ECG waveshape discrimination, from the electrical baseline, detecting two events around it. Choosing one of those instants, parameters such as the HR and the HRV can be easily accessed. Furthermore, this events marking could be used for a further and more complete features extraction based on the waveshape morphology, such as the position of each of the P, Q, R, S and T waves and the respective amplitude. After applying Pan and Tompkins adapted algorithm to ECG signals, the resulting graphics were then visually examined and, for both algorithms, the percentage of detected ECG waveshapes and the number of extra detected events were registered. Table 1 exposes the mean values of those parameters.

Table 1. Results obtained from the proposed events detection algorithm and from Pan and Tompkins adapted algorithm while performing the ECG signals QRS complex detection. The results follow the format $mean(\pm standard\ deviation)$.

	Events detection algorithm	*Pan and Tompkins* algorithm
Percentage of detected ECG waveshapes	93.84% (± 15.64 %)	92.63% (± 21.90%)
Number of extra detections	1.35 (± 1.52)	0.38 (± 1.06)

These results show that the mean percentage of detected events within a given signal is significant for both algorithm, being slightly bigger for the events detection algorithm proposed in this paper. Considering the number of extra detections, however, this is more significant when considering our events detection algorithm than for Pan and Tompkins adapted algorithm. This extra events detection is mostly due to the detection of some pronounced T waves in some signals.

Figure 1b) exemplifies our tool's ability to accurately mark both onset and offset instants in EMG signals. This is extremely important towards an accurate posterior features extraction, such as the signal amplitude and the duration of each activation. For performance evaluation on onset detection, the results of our approach and those of Hodges detector were compared with those obtained previously by visual inspection. In order to minimize the error from intra-rater variability, results from 3 examiners were considered and averaged, in each signal, to define the "true" onset value. For each signal the difference between the "true" onset and those detected for each one of the implemented computational methods was computed. In case that a computational method detected no onset time, that was also registered. Table 2 exposes the mean error (considering only the signals for which the onset detection was achieved) and the percentage of missing detections verified for each of compared methods.

Table 2. Results obtained from the proposed events detection algorithm and Hodges detector while performing the EMG signals onset detection. The "true" onset values were determined by visual inspection. The results follow the format $mean(\pm standard\ deviation)$.

	Events detection algorithm	*Hodges detector* {N=25, h=3}	*Hodges detector* {N=50,h=1}
Mean error (samples)	-22.94 (± 115.09)	—	12.65 (± 81.85)
Percentage of missing detections	0%	100%	5%

These results show that the proposed events detection algorithm achieved a superior, though not significant, absolute mean error than that verified for Hodges detector implemented with the parameter set {N=50, h=1}. An high standard deviation value was verified for mean error values of both approaches. Therefore, there is no clear tendency of either the algorithms to perform an early or late onset detection.

Considering the events detection algorithm results, no missing onset detections were verified. Hodges detector implemented with the parameters set {N=50, h=1} missed 2 out of 40 onset detections. However, when applied with the criteria {N=25, h=3}, no onset was detected applying Hodges algorithm. This clearly exemplifies the sensibility of this single-threshold based algorithm to its input parameters, in agreement with that previously reported in other studies [23, 24].

In general, the algorithm here proposed showed to have a comparable efficiency and higher reliability than that of standard signal events detectors, without the previous knowledge or specific pre-processing steps required in those approaches.

4 Conclusions and Future Work

In this paper we have introduced a generalized approach on biosignals analysis, aiming at an accurate events detection for posterior features extraction. The performance of our algorithm proved to be comparable with that achieved by ECG and EMG signals specific processing techniques on events detection. Since no previous knowledge or signal-specific processing steps are required, our approach is particularly suited to application in the context of automatic emotion recognition, bringing simplicity and scalability to those systems.

In future work it is our intention to perform its application on a wider range of biosignals used for emotion recognition, such as the electrodermal response and the respiration signals. The integration of the developed algorithm with features classification tools will also provide means to evaluate its performance towards an automatic emotion recognition system, when compared with standard signal-specific features extraction techniques.

Acknowledgements

This work was partially supported by National Strategic Reference Framework (NSRF-QREN) under projects "LUL" and "Affective Mouse", by Seventh Framework Programme (FP7) program under project ICT4Depression and under the grant SFRH/BD/65248/2009 from Fundação para a Ciência e Tecnologia (FCT), whose support the authors gratefully acknowledge.

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