Novel method and real-time system for detecting the Cardiac Defense Response based on the ECG

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***Abstract*—This paper describes a novel integrated system for detecting human emotions using the electrocardiogram (ECG) signal. We describe two different algorithms to detect the heartbeat (QRS complex) in the ECG signal. Their output is used by a third algorithm used to detect a basic emotion response, known as Cardiac Defense Response (CDR), which precedes the emotion of fear. We implemented these algorithms in a real-time system for mobile devices using the SPINE Android programming framework. The proposed system has been validated on 40 subjects during controlled experiments and recognized correctly the activation of the CDR mechanism reaching an overall accuracy of 65%.**

I. Introduction

Emotion recognition using physiological signals is a relatively new research area that is receiving much attention. The most common physiological parameters used to detect and recognize emotions are facial expression and speech signals; other parameters that could be used are: skin conductance, skin temperature, respiratory rate, blood pressure, and heart rate [1].

This paper describes a system for recognizing basic emotional responses such as fear, which is the physiological response when a person is in danger. The basic emotion response that generates the state of fear is the Cardiac Defense Response (CDR) [2]. This is a physiological reaction that has a protective and defensive role; however, if the CDR occurs during long periods it could develop into several psychological disorders such as stress, anxiety, phobia, and depression. Therefore, it is important to identify the CDR mechanism and provide clinicians with a valuable tool that could be used to study the psychological state of the subject.

The electrocardiogram (ECG) is the standard method for measuring the electrical and functional activity of the heart. A typical ECG tracing of the cardiac cycle is shown in Figure 1 and consists of a P wave, a QRS complex and the T wave. The QRS complex corresponds to the time occurrence of the heartbeat. The time interval between two consecutive R waves is called R-R interval.

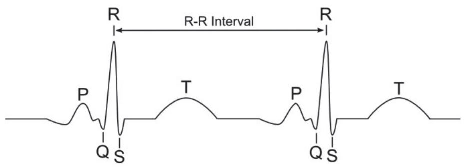

Figure 1. ECG Signal.

Traditionally, the ECG is used to diagnose cardiovascular diseases and rhythm abnormalities [3]. Recently, the ECG has been used for emotion recognition and detection of stress [4]. The ECG signal is an ideal signal to study changes due to physiological responses when emotion or other external factors occur.

The advantage of using the ECG signal for detecting basic emotions is that a person can be monitored using non-invasive wearable cardiac sensors. In contrast, facial recognition methods are more invasive because they require the placement of electrodes and cameras to detect subtle changes in the person's face.

In this paper, we describe a system which uses the ECG signal to detect basic human emotions. The ECG is needed to extract the R-R intervals and heart rate (HR).

As part of our system, we developed two QRS detector algorithms; the first algorithm uses a fixed threshold to extract the QRS complex (heartbeat) while the second algorithm uses an adaptive mechanism which automatically estimates the optimal threshold to extract the QRS complex from the ECG signal. These algorithms generate the R-R interval series which are used as the input to a third algorithm which detects the CDR. These algorithms have been developed and implemented using the SPINE Android programming framework (see Section V-A) [5], [6], [7].

II. QRS Detection Algorithms

A QRS detector algorithm is used to detect the QRS complex of an ECG signal. The QRS complex refers to the ECG waves which identify the heartbeat as shown in Figure 1. Developing an accurate and reliable QRS detection algorithm is of fundamental importance as it is used to calculate the heart rate and the R-R intervals signal which will be used for detecting the cardiac defense response.

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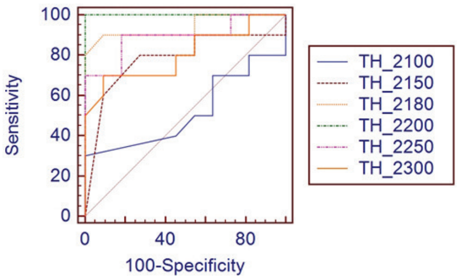

Figure 2. ROC Analysis - ROC curves for different thresholds.

Specifically, the R-R signal consists of values representing the time that elapses between two consecutive peaks in the ECG signal.

A. Fixed Threshold-Based QRS Detection

The QRS detection algorithm with fixed threshold identifies heartbeats (or peaks) in the ECG signal. It uses a manually-fixed threshold, which is used to discriminate the peaks actually corresponding to heartbeats.

To find the best threshold that could correctly detect the largest number of peaks, we performed Receiver Operating Characteristic (ROC) analysis on a table containing the number of spikes (i.e. heartbeats lost by the algorithm) registered for each participant to the experiment (See Section IV) applying different thresholds. Figure 2 shows the resulting ROC curves corresponding the analyzed thresholds. In general, the point on the ROC curve that is closer to the upper left corner represents the best trade-off among sensitivity and specificity; the greater the area underneath the curve is, the higher the accuracy of that threshold will be. Therefore, among the analyzed thresholds, the best one corresponds to 2200.

B. Adaptive QRS Detection

The Adaptive QRS Detection algorithm automatically determines the QRS peak threshold, adapting it to the real-time ECG signal. Figure 3 depicts a schematic block diagram of the proposed QRS detection algorithm. It is composed of three main processing steps: a moving average-based high-pass filtering (HPF), a nonlinear low-pass filtering (LPF), and a decision making block [8]. This adaptive algorithm works as follows:

1) An ECG recording is processed by the linear HPF in order to accentuate the QRS complex while suppressing the undesired waves (e.g. P or T waves), as well as the baseline wander. This filtering stage is composed of an 5-point moving average filter (MAF) whose output is then subtracted, point-by-point, from the delayed input sample so that the entire system becomes an FIR HPF with linear phase.
2) The linear HPF output is then processed by a full-wave rectification and nonlinear amplification followed by a sliding-window summation, thus resulting in an envelope-like feature waveform. All the operations addressed above can be attributed to a nonlinear LPF process. This is to smooth down the high-frequency, low-amplitude artifacts while preserving the QRS feature.
3) An adaptive threshold is applied to the feature waveform to perform decision-making for completing the QRS complex detection.

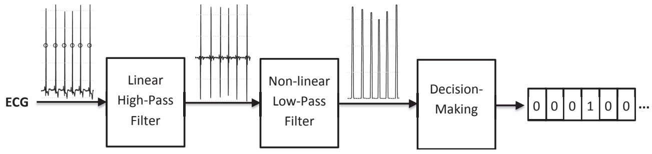

Figure 3. Block diagram of the Adaptive QRS detection system.

TABLE I
FIXED-THRESHOLD AND ADAPTIVE QRS DETECTION ALGORITHMS COMPARISON.

	Accuracy per Subject										Average Accuracy
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	
Fixed Threshold-Based QRS Detection algorithm Accuracy	100%	98,60%	99,80%	99,78%	99,74%	99,89%	99,94%	99,82%	99,44%	99,83%	**99,84%**
Adaptive QRS Detection algorithm Accuracy	100%	99,94%	100%	100%	100%	100%	99,94%	100%	99,89%	99,89%	**99,98%**

C. Algorithms Comparison and Evaluation

Both the described algorithms can identify the QRS complex within the ECG signal and can be easily implemented on resource-constrained devices such as smartphones or tablets. However, the QRS detection algorithm with fixed threshold cannot adapt to temporary changes in the baseline of the ECG signal. Furthermore, a new threshold must be estimated each time a different ECG sensor is used and possibly re-estimated "ad-personam" to obtain better results. The advantage of the adaptive QRS detection algorithm is that it does not require any initialization parameters, and it can be used on ECG signals acquired using different sampling rates.

The adaptive QRS detection algorithm offers an improvement on the fixed-threshold algorithm. There are many QRS detection algorithms available with different levels of accuracy and performance. However, the two QRS detection algorithms worked quite well in terms of performance and accuracy in a mobile platform (such as Android OS). In comparison to the existing QRS detection algorithms which often rely on more complex schemes (e.g. Neural networks, Wavelets, hardware DSP), our algorithms are implemented and run efficiently "in-software" without the need of dedicated hardware DSP or more complex calculations. Running the QRS algorithms in-software provides a good trade-off between performance, accuracy, and battery life (utility) in mobile devices.

Table I reports the heartbeat recognition accuracy by the algorithms, both per each subject (for clarity, only 10 significant examples have been reported) and on average. The accuracy of the QRS detection algorithm with fixed threshold reached 99.84% while the adaptive algorithm reaches 99.98%.

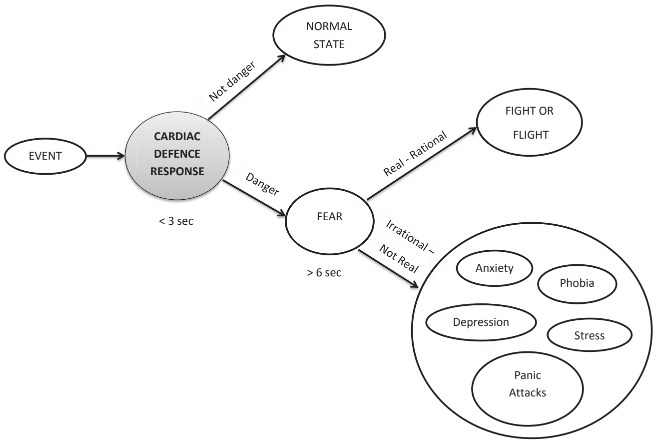

Figure 4. Physiological events associated to the cardiac defense response [10].

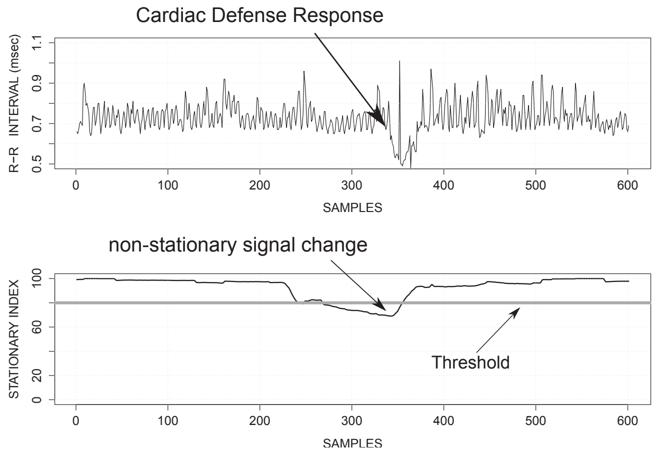

Figure 5. CDR algorithm applied to an R-R signal.

III. The Cardiac Defense Response

The cardiac defense response (CDR) refers to the idea that organisms react physiologically to the presence of danger or threat [1], [2]. This reactivity has a protective function, as it provides the basis for adaptive behaviors such as the "fight-or-flight" response. This response is the first stage of a sequence of internal processes that prepares the aroused organism for struggle or escape, therefore to react to threats priming for fighting or fleeing [9].

If the CDR is maintained for long periods, this mechanism may result in health risks, degrading the physiological response to anxiety [2]. Excessive physiological reactivity is one of the main causes of emotional stress and other psychological disorders [10].

The CDR mechanism is summarized in Figure 4. The diagram shows how a person reacts to a sudden dangerous situation; in the first 3 seconds the person will react with a basic CDR response (i.e. the brain will determine whether that event represents an actual danger). If the event is not considered dangerous, the body returns to a normal state and the heart rate stabilizes, otherwise it takes 6 further seconds to develop a sense of fear and thereby the brain decides what action to take. In the case of an actual danger, the person can either run to avoid it (e.g. dodging a skidding car), or fight (to remove the threat and self-defense). If the fear generated by the event is irrational it can generate anxiety, phobias, panic attacks, and depression in the long-term.

A. CDR Detection Algorithm

To detect the CDR, we have developed an algorithm which is designed to detect changes in signal stationary. Physiological signals such as the ECG and its derived R-R interval signals are highly stationary. In formal terms, a signal is stationary if the mean and standard deviation of the signal do not change during signal acquisition. In turn, a signal is non-stationary if the mean and standard deviation of the signal change during signal acquisition. In ECG and R-R interval signals, non-stationary events are due to external factors, such as changes in posture, changes in respiration patterns, and other factors. We put forward a hypothesis that emotions can introduce non-stationary events in the ECG and R-R interval signals due to the physiological changes associated to responses to basic emotions such as fear and more specifically the effects of the cardiac defense response [1], [2], [10].

The basis for the CDR algorithm are that sudden changes in heart rate regulation due the cardiac defense response can be detected by looking at the non-stationary transitions between normal heart rate regulation and during the cardiac defense response. The CDR algorithm employs the cross-correlation integral method to quantify the amount of stationary present in a signal [11]. The cross-correlation integral provides a probability that a particular signal is stationary. A probability close to one will indicate that the signal is stationary; a probability closer to zero will indicate that the signal is highly non-stationary. In our CDR algorithm, we calculate the cross-correlation integral in a moving-window fashion (10 percent of the length of the signal) to produce multiple samples of the cross-correlation integral. This allows us to detect changes and transitions in non-stationary in the R-R interval signal by running the CDR algorithm as a function of time. Finally, we convert the cross-correlation integral samples to percentages within a range from 0 to 100 percent; we call this the non-stationary index (NSI).

To validate the CDR algorithm, we ran the algorithm on 40 health subjects and calculated their NSI. To establish if the cardiac defense response was observed in a subject, we considered that if a reduction in the NSI was less than or equal to 80 percent for a typical subject, we considered this as a true positive. The 80 percent threshold was selected empirically by visually observing the data from all 40 subjects. As part of future work, we will perform statistical analysis to find the optimal threshold using a larger number of subjects.

Is is worth noticing that the CDR algorithm is an original contribution of the paper. What makes this approach new is that it detects changes in non-stationary transitions which may indicate abrupt changes in heart rate regulation (specifically autonomic nervous system regulation) due to a fear or startle event. Furthermore, we use the R-R interval data (from ECG) as a faster signal to the detect the CDR in comparison to other approaches where images and questionnaires are used on participants to indicate if they experienced startles. At the technical level, unique features of our algorithm and approach include:

- it does not detect patterns in the signal but changes in heart rate signal regulation: the algorithm does not detects specific patterns in the signal (e.g. peaks or slopes) but rather detects if the signal has had any non-stationary transitions/changes which would indicate changes in regulation of the heart rate signal.
- the CDR event is detected in real-time, while existing approaches in psychological studies are based on off-line analysis [1], [2].
- the algorithm can pin-point the time and location of the CDR in the R-R interval data (from ECG) by detecting the abrupt changes in signal non-stationary.

The CDR algorithm was implemented using the R scripting language. Figure 5 shows an example of the R-R interval signal from a healthy subject (top) and the corresponding non-stationary index (bottom). As it can be seen in Figure 5, a change signal stationary can be observed when the subject experienced the cardiac defense response triggered from the sudden beep sound used in our study protocol (see Section IV), the change in this particular subject is more than 20 percent and crosses the 80 percent threshold.

IV. Methods

A. Experiment Setting

The experiment has been conducted on 40 subjects following the protocol shown in Figure 6. The aim of the protocol was to elicit the cardiac defense response by exposing a subject to a sudden sound beep (440Hz) [10]. This has the effect of producing the typical startle reflex response when a sudden threat is perceived by our brain (e.g. when our brain detects a dangerous situation). The startle reflex is natural in humans and animals. A characteristic of the startle reflex is that it can trigger the emotion of fear (if a person is under danger) and further progress to other states such as anxiety, panic attacks, and heart palpitations. The physiological effect of the startle reflex is the CDR. The CDR occurs just immediately after a startle episode and it is responsible for triggering the "fight-or-flight" mechanism [10]. The CDR is characterized by a rapid increase in heart rate followed, within a period of 6-10 seconds, by its rapid decrease [1], [10].

During the experiment, we measured and detected the CDR after startle episodes in a group of young adults. We recruited data from healthy 6 women (mean age 25) and 15 men (mean age 29) and ethical consent was obtained from each of the study participants.

The participants were blindfolded and were exposed to a series of short beeping sounds played via headphones to elicit the startle. Their ECG signal was recorded using wearable

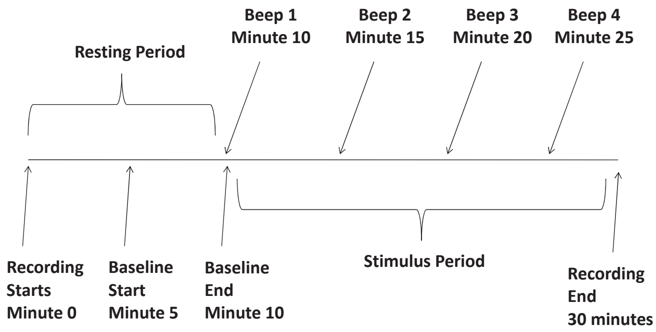

Figure 6. Protocol used to elicit the start reflex and CDR using sounds.

wireless sensors and sent over Bluetooth to a smartphone where our system performed data analysis.

In this experiment we used a Shimmer2R [12] sensor node equipped with the dedicated ECG expansion module that we sampled at 100Hz (See Section V).

B. Discussion

The study of emotions and consequently the CDR is complex as each person reacts to events in different ways. During the analysis of the data produced by the algorithm we found that the first beep is always the most important to detect the CDR; after that, the subject is expecting the beep and will not react as strong as the first beep. We also noted occasional discrepancies between the output provided by the algorithm and the physical reaction of some participants. In particular, there were cases in which a subject did not visibly show a startle to the "beep" stimulus, even though the CDR reaction was detected by the algorithm. We formulate two hypotheses to justify this situation:

- A possible explanation is that different people have different reaction times, for example, in our experiment women were more reactive to the beep sounds than men;
- the cardiac response to the beeping sound was so not loud enough to provoke a visible startle reaction. Another possible explanation is that the subjects were trying to control themselves during the experiment.

The preliminary results obtained from the application of CDR algorithm in 40 subjects showed a detection accuracy of 65%. As part of future work, we will test the algorithm on a larger number of people.

V. A Real-time System To Detect Basic Emotion Response

We have designed and implemented a real-time system for smartphones and other mobile devices running Android OS that can monitor and detect basic human emotions, and in particular the CDR mechanism. This system is implemented using the SPINE framework (see Section V-A) [5], [6], [7] to communicate with Shimmer sensors and acquire the ECG signal, while the smartphone uses the library "Rserve" [13] to communicate with an R server responsible for remote execution of the CDR algorithm, whose output is reported

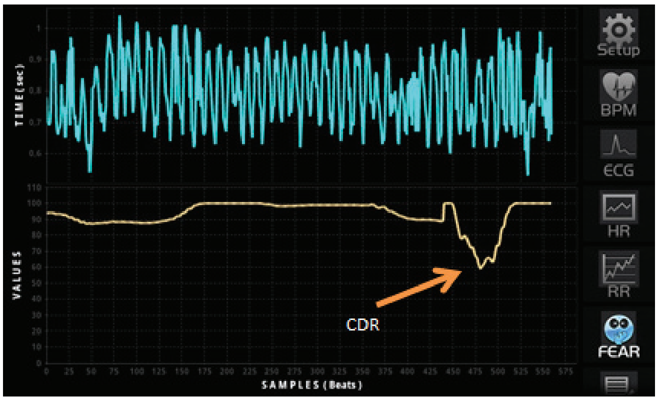

Figure 7. A screenshot of the Android-based system using the SPINE framework.

in Figure 7. Furthermore, the application displays in real time the BPM value, the ECG trace, the R-R signal, and the HR chart.

A. The SPINE Framework

The Signal Processing In-Node Environment (SPINE) Framework [5], [6], [7] is a domain-specific framework for programming BSN applications. SPINE supports networks organized with star topology, with one coordinator node as center of the star and one or multiple sensor nodes as edges. This design choice fits the BSN domain requirement for which the wearable sensor nodes stay within radio range and communicate only with their own coordinator device. The wearable devices can be equipped with several type of physiological sensors and are able to wireless transmit raw sensor signal as well as locally processed sensor data to their corresponding coordinator. The coordinator device (which can be a PC, smart-phone or a tablet) is, instead, in charge of managing sensor nodes setup, signal acquisition, processing, and storage and if necessary may forward the physiological signals or higher-level patient status information to Internet servers or Cloud services to enable remote monitoring.

VI. Conclusion

This paper examines the basic emotional response known as Cardiac Defense Response (CDR), which generates a state of fear that can lead to serious health risks if maintained for long periods. The accurate detection of the CDR is important for the monitoring of stress and prevention of psychological disorders in people. The main contributions of our research is summarized as follows:

1) Definition and implementation of two QRS detection algorithms (with fixed and adaptive threshold) which identify QRS complexes inside the ECG signal and subsequently produce the R-R interval series and HR signals.
2) Implementation of the algorithm used to identify CDR.
3) Application of the CDR detection algorithm on 40 people (25 men, 15 women).
4) Development of a real-time system designed and implemented for Android OS smartphones, capable to monitor and detect basic human emotions (CDR).

The following significant results have been achieved:

- The QRS detection algorithm with fixed threshold does not identify 59 beats from 37530 heartbeats (approx 0,16%) recorded during the experiments.
- The adaptive algorithm for QRS detection has improved detection performance (0,016% undetected heartbeats).
- The CDR algorithm had an average detection accuracy of 65%.

As part of future work we plan to perform further experiments on a more significant sample of subjects (at least 100 people). In addition, we plan an extended emotion recognition system, using different physiological sensors combined with the ECG, such as the Galvanic Skin Response (GSR) sensor and the Electromyography (EMG) sensor which are often used to measure skin conductance and muscle activity.

Acknowledgment

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References

[1] R. Bauer, "Physiologic Measures of Emotion," *Journal of Clinical Neurophysiology*, vol. 15, no. 5, pp. 388–396, Sep. 1998.
[2] R. López, R. Poy, M. Pastor, P. Segarra, and J. Moltó, "Cardiac defense response as a predictor of fear learning," *International Journal of Psychophysiology*, vol. 74, no. 3, pp. 229–235, Dec. 2009.
[3] G.S. Wagner, *Marriott's Practical Electrocardiography*, Lippincott Williams & Wilkins, Ed., 2007.
[4] A. Andreoli, R. Gravina, R. Giannantonio, P. Pierleoni, and G. Fortino, "SPINE-HRV: A BSN-Based Toolkit for Heart Rate Variability Analysis in the Time-Domain," in *Wearable and Autonomous Biomedical Devices and Systems for Smart Environment*, ser. Lecture Notes in Electrical Engineering. Springer Berlin Heidelberg, 2010, vol. 75, pp. 369–389.
[5] F. Bellifemine, G. Fortino, R. Giannantonio, R. Gravina, A. Guerrieri, and M. Sgroi, "SPINE: A domain-specific framework for rapid prototyping of WBSN applications," *Software: Practice & Experience*, vol. 41, no. 3, pp. 237–265, Mar. 2011.
[6] G. Fortino, R. Giannantonio, R. Gravina, P. Kuryloski, and R. Jafari, "Enabling Effective Programming and Flexible Management of Efficient Body Sensor Network Applications," *IEEE Trans. Human-Mach. Syst*, vol. 43, no. 1, pp. 115–133, Jan 2013.
[7] SPINE website, "http://spine.deis.unical.it," 2012.
[8] H. Chen and S. Chen, "A Moving Average based Filtering System with its Application to Real-time QRS Detection," in *Proceedings of Computers in Cardiology*, ser. CinC 2003, Sep. 2003, pp. 585–588.
[9] Philip G. Zimbardo and Ann L. Weber and Robert L. Johnson, *Psychology (3rd Edition)*, Addison Wesley Longman, Ed., 1999.
[10] J. Vila, M. C. Fernández, J. Pegalajar, M. Vera, N. Pérez, M. B. Sánchez, I. Ramírez, and E. Ruiz-padial, "A New Look at Cardiac Defense: Attention or Emotion?" *Span J Psychol.*, vol. 6, no. 1, pp. 60–78, May 2003.
[11] B. Kiremire and T. Marwala, "Nonstationarity detection: The use of the cross correlation integral in ECG, and EEG profile analysis," in *Proceedings of the Congress on Image and Signal Processing*, ser. CISP '08, May 2008, pp. 373–378.
[12] Shimmer website, "http://www.shimmer-research.com," 2012.
[13] Rserve website, "http://www.rforge.net/rserve," 2012.