Real-time automatic detection of accelerative cardiac defense response

Giancarlo Fortino
DIMES - University of Calabria, Italy
g.fortino@unical.it

Raffaele Gravina*
DIMES - University of Calabria, Italy
rgravina@deis.unical.it

ABSTRACT

Cardiac Defense Response (CDR) is a basic psychophysiological response that precedes the emotion of fear. In the context of automatic emotion recognition, it is a relevant effort the definition of algorithms to identify, by analyzing in real-time physiological signals, the CDR because if it is maintained for long periods of time (i.e. its activation is too frequent and not associated to proper danger stimuli) can pose to health risk, hinder the normal functioning of the involved organs and eventually develop into severe psychophysical disorders, such as hysteria and schizophrenia. Therefore, providing tools for automatic identification of this defense mechanism can help psychologists in understanding the patient's mental and health status. This work proposes a novel algorithm specifically designed to detect the CDR in real-time by analyzing the electrocardiogram (ECG) signal acquired by means of a wearable sensor and processed by a personal mobile device. Hence, a key advantage of the proposed approach is that it is suitable for embedded implementations on current commercial wearable sensing and mobile computing devices. It is based on the extraction of specific features from a signal directly generated from the ECG which are compared against an ad-hoc computed reference CDR template. The proposed approach has been compared against a previously published work and performance evaluation showed better and more robust results. The algorithm has been tested on real ECG traces, a number of them containing full activation of the CDR pattern, and the results obtained show 67% sensitivity, 83% specificity, and 80% precision.

Keywords

Emotion recognition, Wearable Computing, Cardiac Defense Response.

*Corresponding author.

BODYNETS 2014, September 29-October 01, London, Great Britain

DOI 10.4108/icst.bodynets.2014.256997

1. INTRODUCTION

Emotions can be generically seen as a change from the normal psychophysical state of a person, accompanied by an impulse to action in conjunction with some specific internal physiological reactions, each of which is expressed through different parameters and designating different emotional responses, such as joy, sadness, anger, and fear.

In addition to physiological response, emotions have clearly motivational, cognitive and communicative relevance. At a physiological level, both central nervous system and the autonomic nervous system play a central role, responsible for specific internal reactions related to the manifestation of various emotions and for regulating the levels of stress and anxiety. These changes are accompanied by cognitive aspects, capable of mediating the relationship with the environment, assessing and giving meaning to what is happening around the person.

Among the many emotions, in this work we focused on fear, a primal and intense emotion derived from the perception of a threat or danger (either real or simply supposed so by the subject). It is one of the primary and basic emotions, common to many species of the animal kingdom, because it is dominated by the instinct (i.e. impulse) with the fundamental goal of survival to any potential hazardous situation. The emotion of fear is accompanied by many internal and external (visible and invisible) phenomena [4], including acceleration of the heart and respiratory rate, with the aim of preparing the organism to react (both at mental and physical level) against the perceived danger with proper defensive actions.

Any stressor that disturbs the organism homeostasis immediately recalls regulatory reactions at psychological, emotional, locomotor, hormonal and immunological levels.

It is worth noting that today many of these internal reactions can be observed and analyzed by acquiring certain physiological signals. Among them, electroencephalogram (EEG), electrocardiogram (ECG), and skin resistance (galvanic skin response - GSR), represent the most promising alternative to conventional methods for enabling automatic emotion recognition [2].

Specifically, the use of these signals for emotions recognition can give an answer to issues suffered by other known methods:

- evaluation of facial expressions through computer vision techniques is problematic in terms of video capture in free unconstrained environments;

- analysis of movements and gestures is often not achievable in practice and heavily influenced by noise;

- speech processing has zero relevance in the many situations in which the subject is silent and is significantly affected by environmental noise in real-world applications.

In addition, biosignals have the advantage of being relatively free from privacy concerns (particularly with respect to camera-based approaches) and can be measured by non-invasive wearable sensors, making them appropriate for a wide range of real-world everyday applications.

In this work, we focused on the emotion of fear, and specifically on the basic cardiac defense mechanism, called Cardiac Defense Response (CDR) [11], which is related and precedes this emotion. In particular, this paper describes a novel method for automatic CDR detection. As aforementioned, CDR is a physiological reaction with a protective and primal defensive role; however, if it is activated too often or maintained for long periods, the subject can develop severe psychological disorders such as stress, anxiety, phobia, and depression.

Therefore, we claim that it is important to define a method to detect CDR activations automatically, so to provide clinicians with a valuable tool to help understanding the psycho-physiological state of subjects with certain types of know psychological conditions.

To detect the CDR, we use the electrocardiogram (ECG) signal, that is the graphical representation of the electrical activity of the heart during its operation, recorded from the body surface (specifically, attaching electrodes on the skin in specific locations in proximity of the heart).

The reminder of the paper organized as follows. Section 2 describes in detail the CDR mechanism and its psychophysical relevance. Section 3 covers the related work. Section 4 discusses our proposed approach for automatic CDR detection and compares it with a previous work, showing by means of performance evaluation the significant improvements that we achieved. Section 5 discusses some interesting findings of our experiments. Finally, Section 6 concludes the paper and provides insight for future developments.

2. CARDIAC DEFENSE RESPONSE

The cardiac defense response (CDR) refers to the idea that organisms react physiologically to the presence of danger or threat [2], [11]. 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 prepare the organism for struggle or escape, therefore to react to threats priming for fighting or fleeing [13]. If the CDR is maintained for long periods, this mechanism may result in health risks, degrading the physiological response to anxiety [11]. Excessive physiological reactivity is indeed one of the main causes of emotional stress and other psychological disorders [18]. The CDR mechanism shows how a person reacts to unexpected dangerous situations: on average, within the first 3 seconds the person will react with a basic CDR response (the brain determines whether the external stimulus represents an actual imminent danger). If the event is classified as not dangerous, the body returns to a normal state and the heart rate stabilizes. On the contrary, it takes around 6 seconds further to develop a sense of fear and the brain decides what action to take. In the case of an actual danger, the person can either move away ("flight") to avoid it (e.g. dodging a skidding car), or fight the threat and self-defense. However, if the fear generated by events is often irrational (i.e. there is an evident misclassification of the stimulus), it can generate - in the long term - anxiety, phobias, panic attacks, and depression.

The description of the "defense cascade" is described as a (accelerative and decelerative) cardiac response model with activation of the sympathetic nervous system but also with parasympathetic influences. It involves an attentional component also with motivational significance, thus highlighting the dynamic nature of this defense reaction. The defense reaction follows a dynamic sequence (or cascade) of reactions; during the initial stages attentional factors predominate (i.e. detection and analysis of the potential danger), while in the later stages, motivated actions must to take place (i.e. attack/escape strategies must be activated). Therefore, depending on the type and severity of the danger, its spatial and temporal proximity, and the success or failure of the initial stages to cope with it, different components of the defense reaction may take place subsequently.

The complex pattern of heart rate changes that characterizes the cardiac defense mechanism can also be analyzed under a naturalistic perspective. The rate alteration pattern observed in response to aversive unexpected and intense stimuli, with two consecutive accelerative/decelerative components, seems to reflect the sequence of two defensive phases described earlier: a first protection phase related to attentional low latency acceleration/deceleration causes the interruption of ongoing activity and forces the analysis of the potential danger, and a latter motivational protection phase related to long latency acceleration/deceleration prepares for active defense.

Therefore, the cardiac defense model would represent the transition from attention to action:

- first acceleration/deceleration component: interruption of ongoing and heightened attention to external stimuli;
- second acceleration/deceleration component: preparation for active defense and recovery if the danger does not occur.

The protective function of the CDR mechanism is therefore clear. However, if it is too intense or prolonged, it can lead to serious risk for mental and physical health. Fear and anxiety are typical emotional reactions to the presence of danger and are closely related to the concept of defense. Since pathological fear and anxiety are also closely linked to defense, there is a growing research interest on how (and when) this defense response may become pathological (e.g. in the case of panic attacks), due to important implications for the on human health [19].

3. RELATED WORK

Figure 1 depicts two distinct typical CDR patterns. Over the years, in fact, many studies [11], [12] on the CDR led to define two different types of CDR activation.

In particular, we can distinguish two group of subjects with different CDR patterns:

1. *accelerative* CDR,
2. *decelerative* CDR.

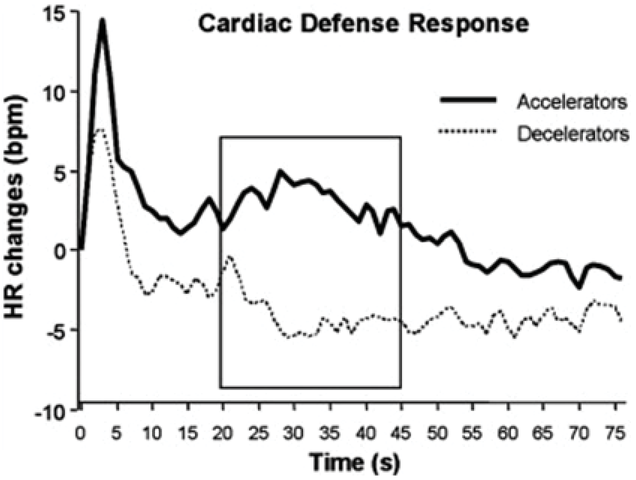

Figure 1: Accelerative and Decelerative patterns as described by López et.al [11].

The former presents a complete response pattern (solid black line in Figure 1), consisting of four distinct components: a sequence of two acceleration/deceleration phases.

The latter is characterized by the lack of the second accelerative component (dotted line in Figure 1).

Specifically, the CDR is characterized by a rapid increase in heart rate immediately followed by a rapid decrease, after a period ranging of 6-10 seconds from the external stimulus. Depending on the type of CDR, a low latency second accelerative component may occur after 20-25 seconds from the stimulus. Decelerative CDR do not show the second accelerative component; a slight deceleration with a minimum peak around 30-40 seconds after the stimulus is conversely observed.

There are several factors influencing the type of CDR activation: individual and inter-individual differences were found by Vila and Beech [12] and by Eves and Gruzelier [6]. The latters differentiated three groups of subjects:

- "*Accelerators*",
- "*Decelerators*",
- "*Atypical*".

"Accelerators" are characterized by presence of a clear long latency cardiac acceleration; "Decelerators" presented a significant deceleration; the "atypical" group did not present any particular response to artificial stimuli during their experiments.

Accordingly, Fernández and Vila [7] classified two groups of subjects, one that presented the complete response pattern and the other characterized by not showing the second accelerative component. They also found significant differences between men and women in the second acceleration: men tend to show higher values.

Other interesting insights were provided by Richards and Eves [14] that investigated whether the presence or absence of acceleration could be predicted by personality features. Specifically they tried to determine whether "accelerators" and "decelerators" presented differences in all personality traits, selecting personality features with behavioral profiles stable over time and consistent in different situations.

Figure 2: Wearable 4 leads ECG sensor (using Shimmer2R node) and the smartphone used to collect data.

It is worth noting that the state-of-the-art is more focused on the psycho-physiological relevance of the CDR and the classification of its pattern inside the ECG traces recorded during the experiments is performed offline, essentially manually by visual inspection of the signal.

To the best of our knowledge, there are no published studies on automatic CDR detection. More precisely, we presented a first attempt to define a method and implement a system for automatic online detection of CDRs [5]. However, as discussed in the next section, we believe that the present work is a novel contribution and particularly a significant improvement to our previous approach.

4. METHODS

Our approach for the detection of CDR mechanism activation consists of real-time collection and analysis of the ECG trace, extraction of RR series and finally decision making process. Specifically, the raw ECG signal acquisition system is shown in Figure 2 and is composed of a wearable ECG sensor consisting of a Shimmer2R [16] unit equipped with a dedicated ECG expansion daughter-board. ECG signal is sampled at 150Hz and data are periodically sent over Bluetooth to an Android-based smartphone. The incoming ECG signal is processed online by the mobile device which constructs the RR interval series (as depicted in Figure 3). This generated signal is the input for both our proposed CDR detection algorithms. In the following subsections we first briefly describe the first method, which aims at an indirect CDR detection based on the concept of *non-stationary index*, that we discussed in detail in [5]. Then we focus on a novel method which aims at recognizing the CDR pattern directly and we show how the latter improves CDR detection performance significantly with respect to the former.

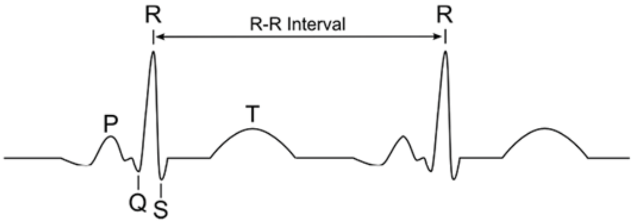

Figure 3: Peak-to-peak interval (RR).

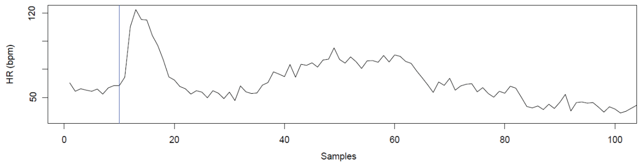

Figure 4: Accelerative CDR pattern generated by averaging all the CDRs detected in our experiments.

4.1 Non-stationary index-based approach

In a previous work [5], we aimed at detecting CDR with an algorithm designed to detect changes in signal stationary.

The background motivation is that 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 CDR [2, 11, 18].

The basis for the CDR algorithm is that sudden changes in heart rate regulation due the CDR can be detected by analyzing the non-stationary transitions between normal heart rate regulation and during the CDR. The CDR algorithm employs the cross-correlation integral method to quantify the amount of stationary present in a signal [10].

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 close 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 non-stationary changes and transitions of 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 define such percentage as the *non-stationary index* (NSI). If the NSI index exceeds a certain threshold, the algorithm detects a CDR.

However, there are a number of limitations with this approach. First, it is not possible to distinguish the different types of CDR pattern (See Section 3). Secondly and probably most important, in real-life scenarios - where abrupt heart rate changes might be due to several factors other than defense response - any short term heart rate acceleration/deceleration pattern might be incorrectly classified as potential CDR activation. Finally, although we have implemented a real-time CDR detection system for CDR detection based on Android OS mobile devices, it uses the "Rserve" [15] library to communicate with an R server responsible for remote execution of the CDR algorithm. As a consequence, this approach is not currently suitable for full embedded/mobile implementation as it needs to rely on a remote server (or Cloud computing back-end) running the NSI signal generator. For the sake of completeness, the system was programmed atop the SPINE (Signal Processing In Node Environment) framework [9, 8, 17, 3] to communicate with a Shimmer2R wearable sensor [16] used to capture the ECG signal [1].

4.2 Novel proposed approach

Accelerative CDRs are more frequent than decelerative CDRs [12]. Our experimental data also show 65% of CDRs are accelerative. This initial analysis has led us to focus our studies to define an algorithm tailored for automatic detection of accelerative CDRs.

Starting from visual analysis of the ECG traces obtained during our experiments, we generated an accelerative CDR template. To do this, we created a single template by averaging all the RR signal segments in which we visually recognized accelerative CDR activations (we identified 50 accelerative CDRs inside the recorded ECG signals). Specifically, we applied our aggregation technique to 75 seconds signal segments, thus the resulting template, depicted in Figure 4, is also 75 seconds long. The pictures shows how we obtained consistent results with respect to previous literature (compare our template with solid black line in Figure 1).

After having identified a reference template for the accelerative CDR pattern, we decided to adopt the same approach described in [19] to reduce the size of the input for our pattern recognition problem.

Specifically, as proposed by Vila et.al., we perform a transformation of the heart rate (HR) signal using the 'method of the medians'. This method gives a simplified representation of the averaged response based on 10 points corresponding to the medians of 10 progressively longer intervals: 2 of 3s, 2 of 5s, 3 of 7s, and 3 of 13s. This representation simplifies pattern recognition without altering the topographic characteristic of the response [19].

The approach performs the calculation of the median values over non constant time intervals to better adapt to the nature of the event of interest. More precisely, the intervals to which each of the 10 median values is calculated, are sized as follows:

- first two intervals include 3 RR values each;
- two intervals include 5 RR values each;
- three intervals include 7 RR values each;
- last three intervals include 13 RR values each.

This methodology is very useful as it tends to drastically reduce individual changes in the CDR pattern, and is robust

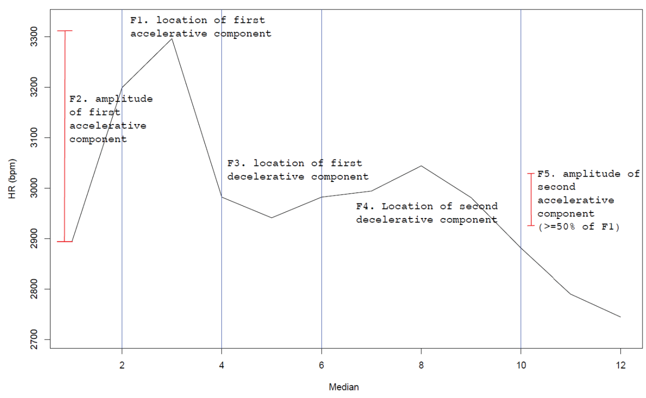

Figure 5: Our proposed CDR pattern - expressed in terms of medians of 10 intervals - and its five significant features.

against motion artifacts or other noise that might be present in the original ECG signal.

The graph in Figure 5 represents the application of the described method to the CDR reference template shown in Figure 4.

We realized a CDR detection algorithm based on the extraction of following five features:

- F1. Occurrence of the first maximum (i.e. first accelerative component) in the medians signal between the second and fourth median interval;
- F2. amplitude of the first accelerative component at least 16% above the previously measured HR baseline;
- F2. Occurrence of the minimum between the fourth and seventh median interval;
- F3. Occurrence of the second maximum (i.e. second accelerative component) between the sixth and tenth median interval;
- F5. amplitude of the second accelerative component peaking at a value that is at least 50% of F2;

During real-time and online execution, the algorithm analyzes the incoming medians signal searching for the appearance of a pattern that satisfies, in the correct sequence, the aforementioned features. If all of them are satisfied, the algorithm detects a CDR activation; conversely, as soon as it detects a non corresponding feature, the potential match is discarded and the algorithm starts from the beginning, analyzing new incoming signal portions.

4.3 Results

To evaluate the performance of the proposed approach and to compare it against the NSI-based method, we used the same dataset that was collected during a set of experiments conducted according to a well-defined experiment protocol [5].

The aim of the experiment protocol was to elicit the CDR by exposing the subject to sudden, unexpected, beep sounds (at a frequency of 440Hz and duration of 750ms) [18]. This has the effect of producing the typical startle reflex response when a sudden threat is perceived by the brain.

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 cardiac effect of the startle reflex is indeed the CDR.

More specifically, during each experiment, we recorded the ECG signal and extracted the RR signal over a period of 30 minutes. The participants were blindfolded and exposed to four beep sounds played at roughly regular intervals via professional headphones. We recruited 40 healthy younger adults: 15 women (average age of 25) and 25 men (average age of 29). Ethical consent was obtained from each of the participants.

Their ECG signal was recorded using a wearable Shimmer2R [16] unit equipped with a dedicated ECG expansion daughter-board. The ECG signal was sampled at a rate of 100Hz and sent over Bluetooth to an Android-based smartphone.

To compare the two methods, we calculated the following performance indexes:

"*Sensitivity*" is the ability of the system to detect a CDR. This value is the ratio between the number of detected CDRs and CDRs actually occurred.

$$sensitivity = \frac{TP}{TP + FN} \tag{1}$$

"*Specificity*" is the ability of the system to avoid false positives. Intuitively, it is the ability to detect a CDR only if this has actually occurred.

$$specificity = \frac{TN}{TN + FP} \tag{2}$$

"*Precision*" is the ability of the system to properly distinguish both the occurrences of the CDR and its lack.

$$accuracy = \frac{TP + TN}{P + N} \tag{3}$$

The parameters of each equation are defined as follows:

- P represents the number of CDR activations after the auditory stimuli;
- N is the number of times that the beep sound did not elicit the CDR;
- *True Positive* (TP): a CDR actually occurred after the stimulus and the detection method was able to identify the event.
- *False Positive* (FP): there is no appreciable cardiac reaction after the stimulus, but the method (incorrectly) detects a CDR activation;
- *True Negative* (TN): there is no appreciable cardiac reaction after the stimulus and the method does not detect the CDR;
- *False Negative* (FN): a CDR actually occurred after the stimulus, but the detection method did not identify it.

Table 1 summarizes the values of the performance indexes obtained by our two approaches.

The table clearly shows the improvement obtained with the current proposed approach.

Table 1: Performance indexes obtained by our two different proposed CDR detection approaches.

Index	NSI-based alg.	Template-based alg.
Sensitivity	0,39	0,67
Specificity	0,65	0,83
Precision	0,53	0,80

4.4 Discussion

An interesting finding of our experiments is that the CDR activation is constantly more pronounced after the first auditory stimulus while its effect on the HR signal fades out with the following beep sounds; in most of the cases, the third and fourth stimuli did not elicited the CDR at all.

This phenomenon can be attributed to the adaptation of the subject after the first auditory stimulus, so the first beep elicits a clear CDR response while the heart rate alteration due to the following beeps shows, instead, weaker changes and occasionally unusual patterns, until the defense response becomes completely undetectable.

The boundary between physiological and pathological CDR activation can be indeed linked to this adaptation as it is related to the concept of fear learning. The subjects that do not adapt to the auditory stimuli are more exposed to pathologic effects of the CDR in the real life.

5. CONCLUSIONS

In this paper we presented a novel method for automatic real-time CDR detection based on wearable ECG sensor and mobile devices. The proposed approach has been compared against a previous work and performance evaluation showed significant improvement.

Ongoing works are devoted to run our experiment protocol over a greater sample composed of 100 participants. In addition, we are investigating new CDR detection methods based on cross-correlation and Dynamic Time Warping techniques. Future works will include the application of our method in a real world, unconstrained scenario so to obtain a better understanding of its accuracy outside the context of laboratory settings. The idea is to continuously monitor subjects in their daily life throughout a whole week with the only requirement of annotating date and time in case of sudden events that generated in the subject sense of startle, fear, or panic. It would be also interesting to enhance the CDR recognition to classify correctly not only accelerative CDRs but also the decelerative ones.

6. ACKNOWLEDGMENTS

Our thanks to Filippo Rachiele for his support prototyping and validating the proposed method. This work has been partially supported by the "2007-2013 NOP for Research and Competitiveness for the Convergence Regions (Calabria, Campania, Puglia and Sicilia)" with code PON04a3 00238.

7. REFERENCES

[1] 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. *Lecture Notes in Electrical Engineering*, 75 LNEE:369–389, 2010.

[2] R. Bauer. Physiologic Measures of Emotion. *J. of Clinical Neurophysiology*, 15(5):388–396, Sep. 1998.

[3] 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*, 41(3):237–265, Mar. 2011.

[4] W. E. Blatz. The Cardiac, Respiratory, and Electrical Phenomena Involved in the Emotion of Fear. *J. of Experimental Psychology*, 8(2):109, 1925.

[5] R. Covello, G. Fortino, R. Gravina, A. Aguilar, and J. Breslin. Novel method and real-time system for detecting the Cardiac Defense Response based on the ECG. In *In Proc. of IEEE Symposium on Medical Measurements and Applications*, May 2013.

[6] F. Eves and J. Gruzelier. Individual differences in the cardiac response to high intensity auditory stimulation. *Psychophysiology*, 21:342–352, 1984.

[7] M. Ferníandez and J. Vila. The cardiac defense response in humans: Implications for behavior and health. *Int'nl J. of Psychophysiology*, 7:195–196, 1989.

[8] 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*, 43(1):115–133, Jan 2013.

[9] R. Gravina, A. Andreoli, A. Salmeri, L. Buondonno, N. Raveendranathank, V. Loseu, R. Giannantonio, E. Seto, and G. Fortino. Enabling Multiple BSN Applications Using the SPINE Framework. In *2010 International Conference on Body Sensor Networks*, BSN 2010, pages 228–233, June 2010.

[10] B. Kiremire and T. Marwala. Nonstationarity detection: The use of the cross correlation integral in ECG, and EEG profile analysis. In *CISP '08*, pages 373–378, May 2008.

[11] R. López, R. Poy, M. Pastor, P. Segarra, and J. Moltó. Cardiac defense response as a predictor of fear learning. *J. of Psychophysiol.*, 74(3):229–235, 2009.

[12] M. N. P. Marfil, M. del Carmen Ferníndez Santaella, A. G. León, G. Turpin, and J. V. Castellar. Individual Differences Associated With Cardiac Defence Response: Psychophysiological and Personality Variables. *Psychology in Spain*, 3(1):54–62, 1999.

[13] Philip G. Zimbardo and Ann L. Weber and Robert L. Johnson. *Psychology (3rd Edition)*. 1999.

[14] M. Richards and F. Eves. Personality, temperament and the cardiac defense response. *Personality and Individual Differences*, 12:999–1007, 1991.

[15] Rserve website. www.rforge.net/rserve, 2014.

[16] Shimmer website. www.shimmersensing.com, 2014.

[17] SPINE website. http://spine.deis.unical.it, 2014.

[18] J. Vila, M. Fernández, J. Pegalajar, M. N. Vera, N. Pérez, M. B. Sánchez, I. Ramírez, and E. Ruiz-padial. A New Look at Cardiac Defense: Attention or Emotion? *Spanish J. of Psychology*, 6(1):60–78, May 2003.

[19] J. Vila, P. Guerra, M. Munoz, C. Vico, M. V. del Jesús, L. Delgado, P. Perakakis, E. Kley, J. Mata, and S. Rodríguez. Cardiac defense: from attention to action. *Int'nl J. Psychophysiol.*, 66(3):169–182, 2007.