Automatic methods for the detection of accelerative cardiac defense response

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***Abstract*—Cardiac Defense Response (CDR) is a basic psychophysiological response that precedes the emotion of fear. In the health-care context, the definition of methods to automatically identify the CDR is a relevant issue, because frequent CDR activations (not associated to proper danger stimuli) can pose the subject to health risk and eventually develop into severe psychophysical disorders, such as hysteria and schizophrenia. Therefore, providing tools for automatic identification of this defense mechanism can significantly help psychologists and caregivers in understanding the patient's mental and health status. This work discusses and compares different methods and specifically proposes a novel algorithm designed to detect the CDR by analyzing the electrocardiogram (ECG) signal. 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 method has been tested on real ECG traces, a number of them containing full activations of the CDR pattern, and compared against other techniques, discussed in the paper, reaching an improvement of 10% in sensitivity, 18% in specificity, and 24% in precision with respect to the best performance of the other related methods.**

***Index Terms*—Emotion recognition, ECG analysis, Pattern recognition, Cardiac Defense Response.**

I. 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 designates 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 and autonomic nervous system play a central role, responsible for specific internal reactions related to the manifestation of various emotions and for regulating the intensity of stress and anxiety. These changes are accompanied by cognitive aspects, capable of mediating the relationship with the environment, assessing and giving significance to surrounding events.

Among the many emotions, this work focuses on fear, a primal and intense emotion derived from the perception of a threat or danger (either real or simply perceived so by the subject). It is one of the primary and most basic emotions, common to many species in the animal kingdom, because it is dominated by the instinct (i.e. impulse) with the primal goal of survival to any potential hazardous situation. The emotion of fear is accompanied by many internal and external (visible and invisible) phenomena [1], including acceleration of the heart and respiratory rate, with the aim of preparing the organism to react (both mentally and physically) against the perceived danger with proper defensive reactions.

Any stressor disturbing the organism' homeostasis immediately recalls regulatory reactions at psychological, emotional, locomotor, hormonal and immunological level.

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 known issues suffered by other literature methods [3], [4]:

- 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 heavily influenced by noise and often not achievable in practice;
- speech processing has zero relevance in the many situations in which the subject is silent; it is also significantly affected by environmental noise in real-world scenarios.

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 specifically focus on the basic cardiac defense mechanism, called Cardiac Defense Response (CDR) [5], which is related and precedes the fear. This paper represents a significant extension of our previous work [6] and describes, compares and evaluates four different methods of automatic CDR detection; one of them, in particular, represents a significant improvement to the state-of-the-art. To the best of our knowledge, this is the first work addressing such systematic analysis and proposing a practical and effective answer to the problem of automatic CDR detection.

As aforementioned, CDR is a physiological reaction with a protective and primal defensive role; however, it can lead to

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severe psychological disorders (such as stress, anxiety, phobia, and depression), if its activation is too frequent or maintained for long periods [5], [7], [8].

Indeed, the CDR could be also used to detect emotions and emotional states, (e.g. fear, fluster, and panic); this would imply its use in the context of emotion recognition and its potential impact on the affective computing area.

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

To detect the CDR, we exploit the electrocardiogram (ECG) signal, that is the graphical representation of the electrical activity inside 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 ECG is used to obtain a new signal that is more convenient for processing. Our algorithm searches for the presence of typical CDR pattern (using a reference CDR template) inside this generated signal. The general concept is that, having characterized the CDR template by means of certain features, we look for portions inside the incoming signal that match the reference pattern. A significant experimentation discussed in Section IV demonstrates the effectiveness of the proposed method against other pattern recognition techniques known in literature.

The reminder of the paper is organized as follows. Section II describes the scientific background of our work, focusing in detail on the psycho-physiological relevance of the CDR mechanism and on related work in terms of the different pattern recognition techniques that we applied for CDR detection (including a description of our previously published CDR detection approach [9]). Section III discusses how we applied these techniques and specifically describes our novel approach for automatic CDR detection that significantly outperforms previous methods. Section IV describes the experiment protocol used to generate experimental data for performance evaluation; the section then compares the results obtained with the different detection methods and finally discusses some interesting findings of our experiments. Finally, Section V concludes the paper and provides insights for future developments.

II. Background

A. Cardiac Defense Response

The cardiac defense response (CDR) refers to the idea that organisms react physiologically to the presence of danger or threat [2], [5]. 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 [7].

An interesting experiment, videorecorded by happenstance, revealed that emotions (including fear) can quickly transform according to the progressive interpretation of the event dynamics [10]. During an indoor video recording, a bird flew into an open window hitting a windowsill. The recording documented all the scene. Immediately, a woman in the room oriented toward the sound stimulus. The very first reaction was surprise, immediately after she moved away from the threat (a *flight* response) but at the same time she grabbed an umbrella as improvised weapon (a *fight* response). A few moments later, however, her concern moved from herself to the bird, as it was trapped in the hairs of another person in the room and in danger of being hurt. Finally, she took a napkin to rescue the bird by wrapping and releasing it out the window.

Authors hence observed a progression from surprise about the unexpected event, to concern for self-protection, to final concern for others, including what was originally perceived as threat. The dynamics evolved from flight to fight to compassion in less than 3 seconds.

In any case, there are increased health risks if the CDR is maintained for long periods, degrading the physiological response to anxiety [5], [8]. Excessive physiological reactivity is indeed one of the main causes of emotional stress and other psychological disorders [11]. 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 which action has to be taken. 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.

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: (i) 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 (ii) a latter motivational protection phase related to long latency acceleration/deceleration prepares for active defense.

Therefore, the cardiac defense model would represent the

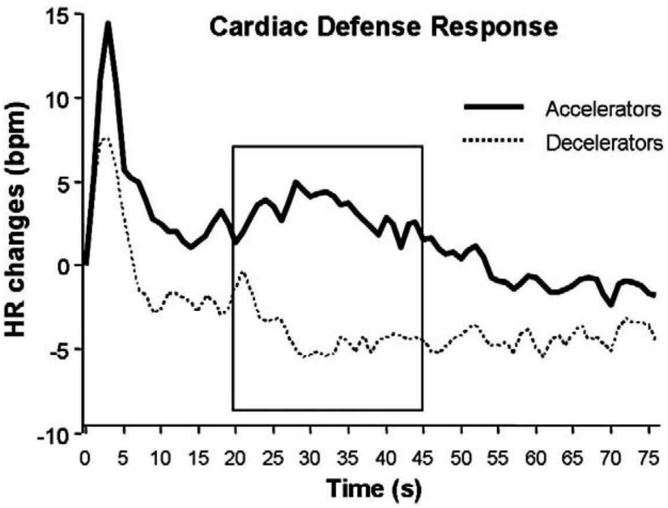

Fig. 1. Accelerative and Decelerative patterns as described by López et al. [5].

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), leading to important implications on human health [12].

Figure 1 depicts two distinct typical CDR patterns. Over the years, in fact, many studies [5], [13] 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.

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 long 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 [13] and by Eves and Gruzelier [14]. The latter 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 [8] classified two groups of subjects, one that presented the complete response pattern and the other characterized by not showing the second accelerative component. Essentially, Vila suggested to collapse Decelerators and Atypical groups into one. 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 [15] 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.

B. Related Work

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 [9] that we briefly describe in the following (subsection "*non-stationary index*"). The following subsections present other two traditional pattern recognition techniques that we applied for CDR detection and whose details and results are provided in Section III and IV. However, as we discuss hereafter, we claim that the proposed work here presented is a novel contribution and particularly a significant improvement to our previous approach.

1) Sum of squared differences:

A simple and lightweight algorithm of pattern recognition is the *Sum of Squared Differences* (SSD) [16], which, in signal processing, is used to measure the similarity of two series as a function of the distance of one relative to the other. It has been successfully applied for image processing to obtain an estimation of similarity between two images. In this domain, the algorithm computes the difference among each pixel of the source image block with the corresponding pixel of the template image. These differences are summed up to obtain a simple similarity metric. Since the target template image might be present into a bigger source image, in practice is typically necessary to apply a brute force approach to calculate the SSD over a range of x, y displacements to find the minimum SSD value, which would correspond to the best alignment offset. Therefore, the general idea is that for matching images the SSD is small [17]. Although other methods (e.g. based on *Normalized Cross Correlation*) [18] are typically more effective, the SSD is often chosen for its simplicity and low computational cost.

As discussed in Section IV, starting from the natural intuition of considering a time series as a one-dimensional image, we applied the SSD on cardiac signals to detect CDR patterns using the following equation:

$$SSD = \sum_{i=0}^{n} (x_i - y_i)^2 \tag{1}$$

Where x and y are the reference CDR template pattern and the actual incoming signal, respectively. After an appropriate signal alignment, if the obtained minimum SSD value is below a certain threshold, the algorithm will detect the occurrence of a CDR pattern into the source signal portion. The value $x_i - y_i$ represents the differences between corresponding points of the two series. The difference is squared to obtain always positive difference values so avoiding to let summation decrease if y occasionally goes above x (which would clearly reduce the quality of the similarity estimation).

2) Derivative Dynamic Time Warping:
Dynamic time warping (DTW) [19] is a template matching technique for measuring time series similarity. Given two sequences n' and m, the goal of DTW is finding the best warping path that realizes the alignment between the two time series, under certain conditions. Its advantage is the minimization of shifting (translation) and distortion (amplitude scaling) effects. However, although DTW has been successfully applied in several domains, it can fail in certain conditions. In fact, this algorithm may try to explain variability in the Y-axis by warping the X-axis. Another critical problem is that it fails to find obvious alignments between two series simply because a feature of one series is slightly higher or lower than its corresponding feature in the other one (this situation is referred as "singularity").

Therefore, an optimization of DTW has been proposed [20]. It is called Dynamic Derivative Time Warping (DDTW) and rather than using the raw series, it considers only their (estimated) local derivatives.

Let $Q = \{q_1, q_2, ..., q_n\}$ and $C = \{c_1, c_2, ..., c_m\}$ be two time series. There is a n by m matrix D where

$$d(i,j) = (q_i - c_j)^2. \tag{2}$$

In the original DTW, the distance between q_i and c_j is given by equation 2. However, in DDTW, the square of difference of the estimated derivatives of q_i and c_j replaces $d(i,j)$. The q_i value is estimated with

$$D_i(q) = \frac{(q_i - q_{i-1}) + (q_{i+1} - q_{i-1})/2}{2} \tag{3}$$

Similarly, the derivative of C can also be obtained with equation 3 and is denoted with $Dj(c)$.

Thus, the distance used with the DDTW is given by

$$D'(i,j) = \left(D_i(q) - Dj(c)\right)^2 \tag{4}$$

The original D is therefore replaced by D' and the rest of DDTW algorithms is same of DTW [19], [20].

3) Non-stationary Index:
In our previous work [9] we aimed at detecting CDR with an algorithm designed to detect changes in signal stationary. The background motivation is that physiological signals, including the ECG, are generally 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 the ECG signal, 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, due to the physiological changes associated to responses to basic emotions such as fear and more specifically the effects of the CDR [2], [5], [11].

The basis for this 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 algorithm employs the cross-correlation integral [21] method to quantify the amount of stationary present in a signal [22].

By using the concept of *Poincare recurrence points* [23], a time series can be mapped into phase space by time delay embedding. Let $\{x(i), i = 1, 2, ...\}$ be a scalar time series; vectors can be constructed as follows:

$$\overrightarrow{x_i} = [x(i), x(i+L), ..., x(i+(m-1)L)] \tag{5}$$

where m is the embedding dimension and L the time delay. Thus $\{\overrightarrow{x_i}, i = 1, 2, ..., \overrightarrow{n}\}$ represents a trajectory in m-dimensional space, where $\overrightarrow{n}$ is the total number of vectors.

For two separate time series $x(i)$ and $y(i)$ the cross correlation integral is defined as follows:

$$C_m(x,y) = P\left(\left\|x^m(i) - y^m(j)\right\| < \epsilon\right) = \frac{1}{N^2}\sum_{i,j=1}^{N} \Theta\left(\epsilon - \left\|x^m(i) - y^m(j)\right\|\right) \tag{6}$$

where:

- ϵ is a given minimal tolerance distance,
- N is the size of the series, and
- Θ is the Heaviside step function and $\left(\epsilon - \left\|x^m(i) - y^m(j)\right\|\right)$ is set to 1 if Θ is positive and to 0 if Θ is negative.

In brief, the cross-correlation integral provides a probability that a particular signal is stationary. A probability close to 1 indicates that the signal is stationary; conversely, a probability close to 0 indicates that the signal is highly non-stationary.

In our previous method [9], (i) we cyclically calculate the cross-correlation integral over a moving-window (10% of the

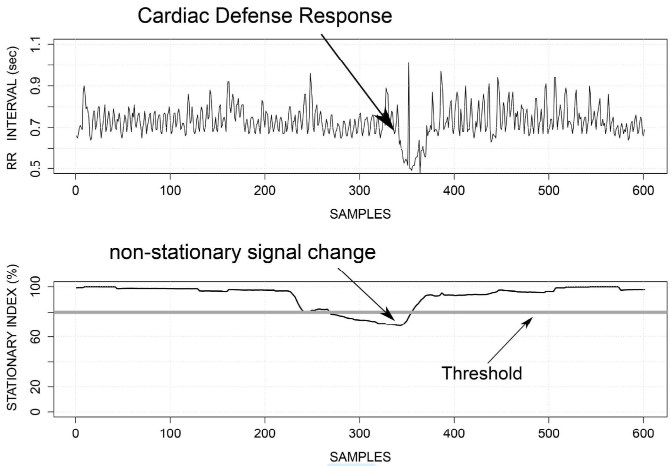

Fig. 2. NSI applied to an RR signal.

length of the signal) to produce multiple samples of the cross-correlation integral and, finally, and (ii) we convert the cross-correlation integral samples to percentages within a range from 0 to 100%, by calculating the *non-stationary index* (NSI) as follows:

$$NSI = \frac{C_m(x,x) - C_m(x,y)}{C_m(x,x) + C_m(x,y)}100 \quad (7)$$

The NSI allows us to detect non-stationary changes and transitions of the signal by running the CDR algorithm as a function of time. In fact, if the NSI value is above a certain, empirically assigned threshold, it means that the signal is highly non-stationary (extremely non-stationary signals would give NSI value close to 100 [22]) and at this point the algorithm detects the occurrence of a CDR (see Figure 2).

However, we found a number of limitations with this approach. First, it is not possible to distinguish the different types of CDR patterns (see Section III). Secondly, and probably most important, in real-life scenarios - where abrupt heart rate changes might be due to several factors other than defense response - with the NSI method, any short term heart rate acceleration/deceleration pattern might be incorrectly classified as potential CDR activation.

III. Proposed Method

Accelerative CDRs are more frequent than decelerative CDRs [13], this is our reasoning to focus on the definition of an algorithm tailored for automatic detection of accelerative CDRs.

In addition to the methods discussed in Section II.B, we propose a method aiming at recognizing the CDR pattern directly. We found the proposed method to be the most effective among others related approaches, as discussed in Section IV.

Our approach consists of real-time collection and off-line analysis of the ECG trace. The algorithm is composed of a number of processing blocks, as depicted in Figure 3.

First, the original raw ECG signal is analyzed to obtain the *tachogram* signal. The tachogram (or RR signal) is an interval series in which each point represents the time interval (usually expressed in *ms*) between an heartbeat and the previous one,

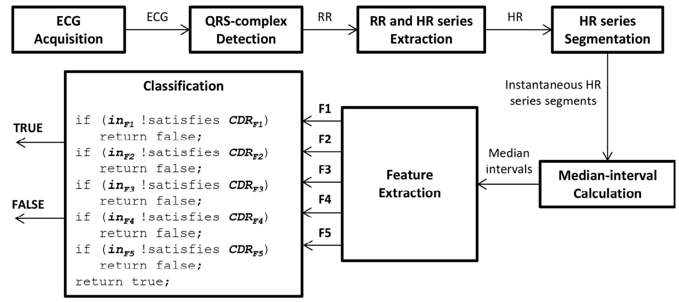

Fig. 3. Block diagram of the proposed CDR detection method.

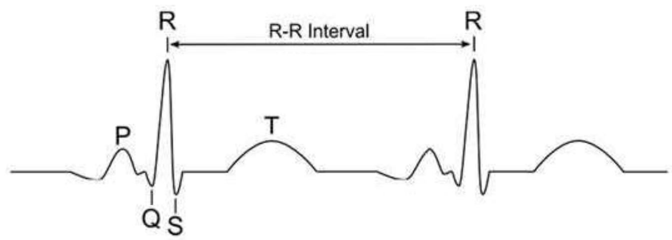

Fig. 4. Peak-to-peak interval (RR).

as depicted in Figure 4. We identify and timestamp the occurrence of heartbeats by detecting the QRS complex (the intra-cardiac indication of the ventricular contraction) inside the raw ECG signal, using a dynamic threshold-based QRS detection algorithm [9].

RR intervals are useful to quickly obtain the instantaneous (i.e. beat-by-beat) heart rate (HR) signal. Let RR_i be the time interval, expressed in seconds, between the ith heart beat and the previous one. Then, the corresponding instantaneous heart rate, expressed in BPM (beats per minute), is simply given by:

$$HR_i = \frac{60}{RR_i} \quad (8)$$

The HR series are then segmented. Specifically, according to consolidated studies [5], [11], [13] (see also Figure 1), we assume the duration of the accelerative CDR pattern is equal to 75 seconds; thus, our segments are also 75 seconds long.

Then, to reduce the size of the input for our pattern recognition problem, following the same approach proposed by Vila et al., we perform a transformation of the HR signal using the '*method of the medians*' [12]. This method gives a simplified, compact representation 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

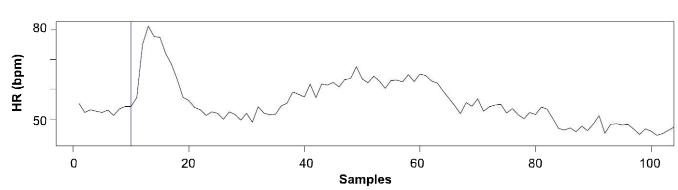

Fig. 5. Accelerative CDR pattern generated by averaging all the CDRs detected in our experiments.

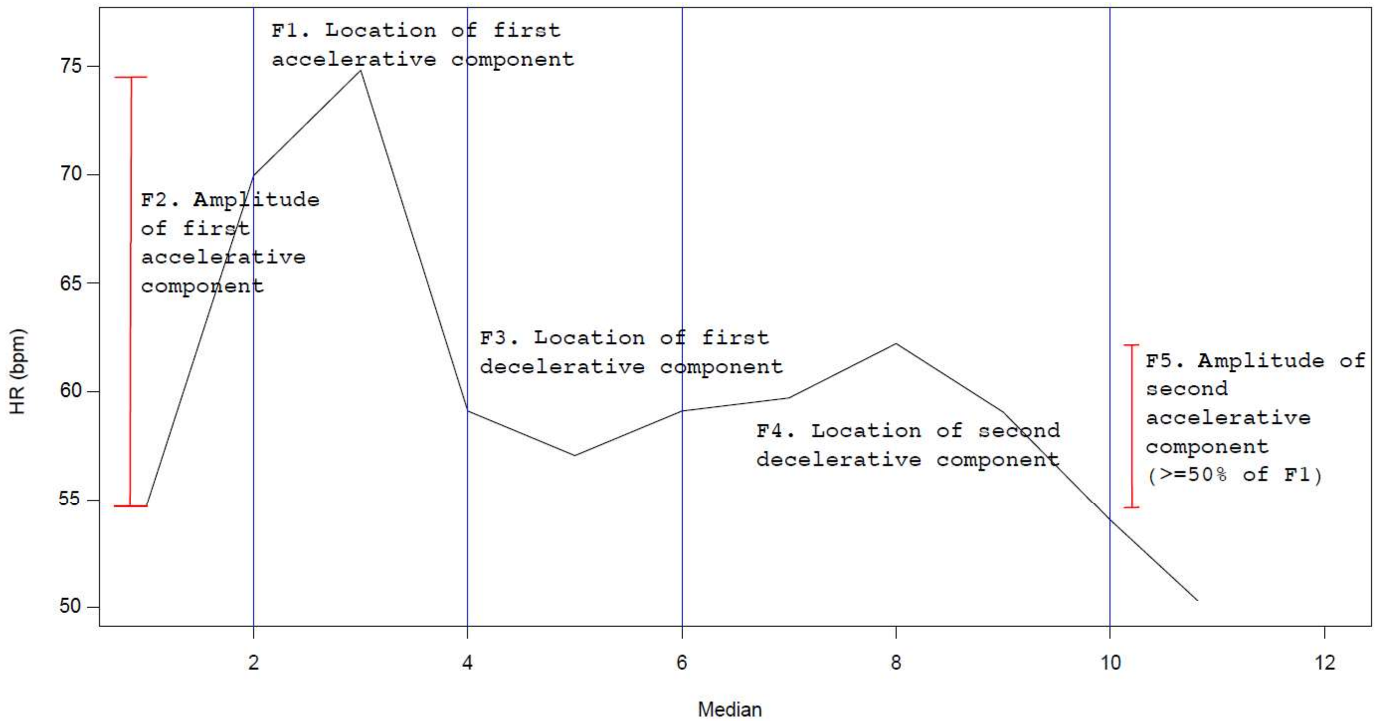

Fig. 6. Our proposed CDR pattern - expressed in terms of medians of 10 intervals - and its five significant features.

the response [12]. The calculation of the median values is performed 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 it is robust against motion artifacts or other noise that might be present in the original ECG signal. The plot in Figure 6 represents the application of the method of the medians to the CDR reference template shown in Figure 5.

We then characterize the median-interval series with the following five features:

- *F1*. Location 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 20% above the average HR value, calculated during the previous minute;
- *F2*. Location of the minimum between the fourth and seventh median interval;
- *F3*. Location 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.

These "structural" features closely characterize the physiology of the accelerative CDR pattern [5]: low latency, rapid heart rate increase (F1, F2) followed by a second, long latency, slower and less pronounced heart rate increase (F3, F4, F5). Their values have been obtained by empirical analysis of our experiments; we created a reference CDR template (depicted in Figure 5) by averaging all the HR signal portions (whose data come from our experiments) in which we visually identified accelerative CDR activations. It is worth noting that the template we obtained is fully consistent with previous literature (compare qualitatively our CDR template with solid black line in Figure 1; note that our plot contains 100 instantaneous HR samples, roughly corresponding to 75 seconds), confirming the significance of our experiments and, consequently, our feature characterization.

The last step of our CDR detection algorithm is the classification, which, thanks to the previous processing steps, becomes very simple: with *if-then-else* blocks, the algorithm analyzes the incoming medians signal portion, searching for the appearance of a pattern that satisfies, in the correct sequence, the CDR 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.

IV. Performance Evaluation

To evaluate the performance of the proposed approach and to compare it against the other methods described so far, we used the same dataset that was collected during a set of experiments conducted according to a well-defined experiment protocol [9].

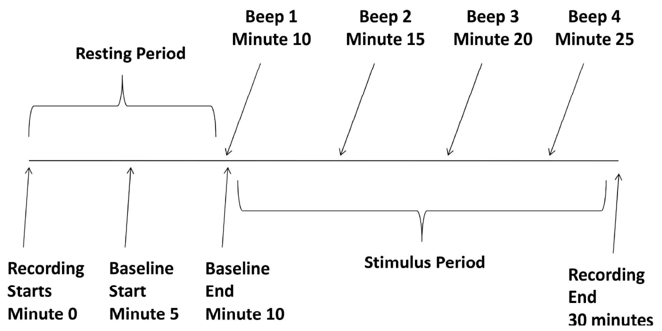

Fig. 7. Protocol used to elicit the start reflex and CDR using sounds.

Fig. 8. Experiment participant right before (left) and during the startle produced by the auditory stimulus (right).

A. Experiment Protocol

The aim of the experiment protocol, summarized in Figure 7 was to elicit the CDR by exposing the subject to sudden, unexpected, beep sounds (at a frequency of 440Hz and duration of 750ms) [11]. This has the effect of producing the typical startle reflex response when a sudden threat is perceived by the brain.

Figure 8 shows one of the participant during the experiment. In particular, the picture on the left of the figure depicts the subject a moment before hearing the auditory stimulus with his headphones: the subject appears calm and his facial expression is relaxed. The picture on the right of the figure depicts the subject just in the moment of the beep sound being played in the headphones: although he was not among the ones exhibiting very pronounced startles with their body or face (unfortunately, we could not obtain written permission to show pictures from other participants), we can still clearly observe his startle reflex by his facial expression. For instance, a clear indication is given by the open mouth. Mouth opening can have indeed functional significance, as an instinctive act of favoring inhalation to oxygenate the blood in preparation for a fight or flight response [10].

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 counterpart of the (motor) startle reflex is indeed the CDR [7].

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 7. 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.

Specifically, the raw ECG signal acquisition system is shown in Figure 9 and is composed of a wearable ECG sensor consisting of a Shimmer2R [24] unit equipped with a dedicated ECG expansion daughter-board. Full list of specifications is given in Table I.

ECG signal is sampled at 150Hz and data are periodically sent over Bluetooth to an Android-based smartphone.

TABLE I
SPECIFICATIONS OF THE WEARABLE SENSOR PLATFORM USED FOR THE EXPERIMENT.

Description	Specification
Sensor Platform	Shimmer 2R with ECG-daughter board
Programming Environment	TinyOS/NesC
Retail Price	350 (includes ECG board)
Microcontroller	8MHz Texas Instrument MSP430
Low power Radio Chip	Chipcon CC2420 (IEEE 802.15.4)
Bluetooth Radio Chip	Roving Networks RN42 (Class 2 BT)
Local Storage	2GByte on microSD card
Battery type	280mAh Li-Ion rechargeable
ECG Type	four leads, with disposable electrodes
ECG Maximum sampling rate	159Hz
ADC resolution	12 bit
Bandwidth	8.4 kHz
Input range	differential dynamic, 800 mV
Total weight	35 grams (includes ECG board)
Total dimensions	53 x 37 x 15 mm

The incoming ECG signal is processed online by the mobile device to generate the RR interval series and the corresponding instantaneous HR signal. These generated signals (as well as the raw ECG trace) are saved locally to file allowing for offline CDR analysis.

B. Other Related Methods

To evaluate the effectiveness of our proposed method, we applied other two state-of-the-art pattern recognition approaches to compare their performances in recognizing our accelerative CDR template. These alternative methods are based on the *sum of squared differences* and *derivative dynamic time warping* (see Section II.B), respectively and are discussed in the following subsections.

1) Sum of squared differences:

We first applied the *Sum of Squared Differences* (SSD), a simple and lightweight algorithm to measure the similarity between our CDR template pattern and the actual heart rate signal.

We did not obtain satisfactory results with the SSD approach. The biggest issue has been found when the two signals present similar average heart rate values. Figure 10(a)

Fig. 9. Wearable 4 leads ECG sensor (using Shimmer2R node) and the smartphone used to collect data.

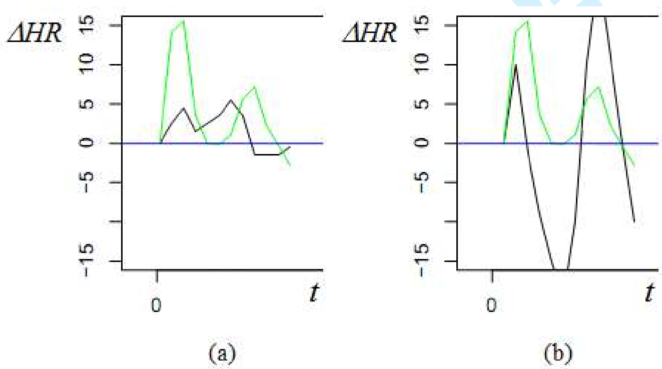

Fig. 10. SSD-based algorithm failure examples: (a) with a false positive CDR detection, (b) with a false negative CDR detection.

shows a practical example in which data refers to one of the participants to our experiment: signal in green represents our CDR template while in black is the incoming signal; although their SSD value is equal to 378 (that should generally suggest that the signals are somewhat similar), the incoming signal does not contain any CDR activation.

Conversely, we found many other cases in which the algorithm fails to detect an accelerative CDR pattern simply because it was stretched over the y axis. Figure 10(b) shows a practical example: in this case the two series present $SSD = 1518$ which should generally suggest that the signals are significantly different.

As a consequence, it is impossible to identify a SSD threshold to discriminate with sufficient accuracy the presence of an accelerative CDR inside the incoming signal. As summarized is Table II, the highest results we obtained with this algorithm are yet poor.

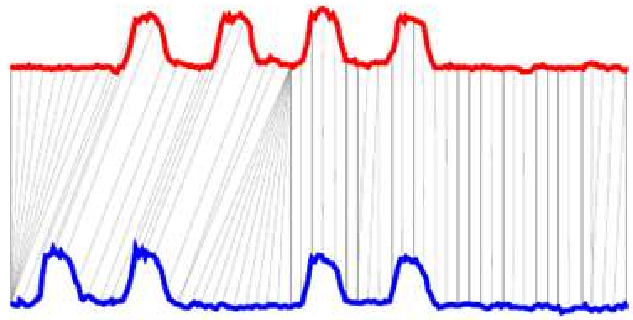

Fig. 11. Visual representation of DDTW signal matching.

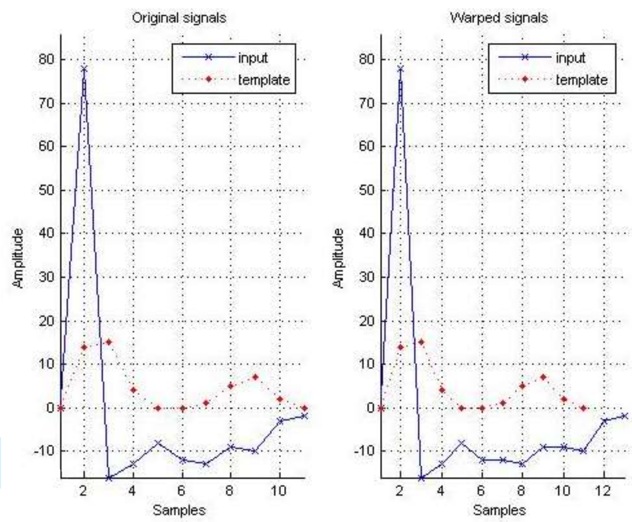

Fig. 12. DDTW warping effect to a HR signal containing an accelerative CDR.

2) Derivative Dynamic Time Warping: DDTW is a template matching technique for measuring time series similarity. The fundamental concept of this algorithm is finding the best warping path that allows the alignment between two time series by a non linear distortion (see Figure 11) with respect to the independent variable (typically, the time).

It is worth noting that this pattern recognition method is particularly effective on series in which only individual components have features that can vary in function of time.

We have applied this algorithm to our RR series aiming at finding a satisfactory warping to align a certain portion of the incoming RR signal to our CDR template, so to help the subsequent classification phase. Unfortunately, we found out that our incoming RR series and the CDR template often presented similar features with respect to time but very different in terms of amplitude (y scaling, see Section II.B.2). Although DDTW has been proposed to improve standard DTW performance specifically in cases of amplitude distortion between the sequences, it did not lead to excellent results either (see Figure 12).

Howeverm, we found that the main issue of applying this algorithm for CDR detection is that misalignments on RR

TABLE II
PERFORMANCE INDEXES OBTAINED BY OUR DIFFERENT PROPOSED CDR DETECTION APPROACHES.

Index	NSI-based	SSD-based	DDTW-based	Template-based
Sensitivity	40%	40%	58%	68%
Specificity	65%	54%	49%	83%
Precision	57%	50%	52%	81%

series can actually appear both over x and y axis, as there exists variations (with respect to the CDR template) both in terms of heart rate (specifically the intensity of the second accelerative component presents significant variance among subjects) and over time (the overall duration of the CDR response is never exactly the same).

C. Results

To compare the different methods described so far, 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.

$$sensitivity = \frac{TP}{TP + FN} \tag{9}$$

"*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.

$$specificity = \frac{TN}{TN + FP} \tag{10}$$

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

$$Precision = \frac{TP + TN}{P + N} \tag{11}$$

The parameters of each equation are defined as follows:

- P: the total number of actual CDR activations that are present in the available data;
- N: the number of times in which the auditory stimulation 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 II summarizes the values of the performance indexes obtained by the described CDR detection approaches. The table clearly shows the improvement obtained with the current proposed approach.

D. 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.

V. CONCLUSIONS

In this paper we have presented a novel method for fully automatic detection of CDR pattern, a basic cardiac response that is a natural physiological reaction but that can lead to serious psycho-physiological implications if its activation occurs too often and for prolonged periods. We discussed and compared different methods to detect the CDR by analyzing the ECG signal and in particular we proposed an effective and efficient CDR detection algorithm based on the extraction of specific features from the (ECG-derived) instantaneous HR series which are then compared against an ad-hoc computed reference CDR template. The proposed method has been tested on real ECG traces (obtained after an experiment involving 40 subjects), a number of them containing full activations of the CDR pattern, and it reached 68% sensitivity, 83% specificity, and 81% precision. Our results present a reference for future studies aiming at proposing alternative CDR detection approaches.

With a vision of open data, ongoing works are devoted to release all our experiment datasets and our source code with free access in the framework of the SPINE Project [25], [26], [27], [28]. In addition, we are evaluating the feasibility of implementing the proposed CDR detection method as a fully operating mobile application based on Android and a wearable ECG sensor. 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 given prolonged period 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.

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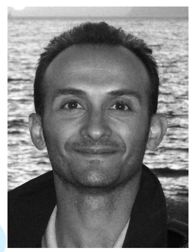

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