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Assessment of Physiological Parameters by Non-Contact Means to Quantify Mental Stress States

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Abstract

In this study, we present a particular technique that was developed to assess and quantify mental stress states using a low-cost webcam. The input signals are recorded on human faces and image and signal processing algorithms, bases on the continuous wavelet transform, were developed to remove trends and noise generated by involuntary motion artifacts. An interactive version of the Stroop color word test was employed to induce stress. The electrodermal activity was recorded in parallel using a contact skin conductance sensor. This particular signal has extensively been used in psychophysiological experiments and is well-correlated with arousal responses. A set of basic parameters was computed from the webcam pulse rate variability, forming a stress curve that was compared to the skin conductance level. The results offer further support for the applicability of stress detection by non-contact and low-cost means, providing an alternative to conventional contact techniques.

Key words

Photoplethysmography, pulse rate variability, non-contact, stress detection, human physiology.

1. Introduction

The ability to quantify the emotional state of a person can be of interest in applications based on Virtual Reality (VR) therapies, where emotions are feedbacks that regulate the virtual environment level and intensity [1]. These physiology-driven virtual scenes are particularly employed to treat patients with anxiety disorders and phobia, like soldiers and war veterans. Recognizing an emotion by its physiological signature is a field of research that presents a particular and increasing interest, where physiological parameters like the Heart Rate (HR) and Heart Rate Variability (HRV) are reliable inputs to emotion recognition [2]. However, contact sensors can be limited in some scopes of application where a specialist must install and monitor them. When dealing with motor rehabilitation or serious games, contact sensors can disturb the interaction and may be intrusive to the privacy of the patient.

The emotional state, derived using a real-time monitoring of the physiological signals of the patient, serves as a feedback that can be interpreted by the therapist to customize and optimize virtual stimuli and situations [3]. In these psychophysiological experiments, contact sensors may generate a bias by interfering with the user, resulting practically by an erroneous emotional state estimation [4].

The HRV is a parameter used in affective computing and psychophysiology to give an index of the autonomic nervous system (ANS) activity in order to detect workload changes in real time. Its spectral analysis can provide the sympathovagal balance, a ratio that reflects reciprocal changes of sympathetic and vagal outflows [5]. The HRV tends to be rhythmic and ordered in positive emotional states. In contrast, the HRV tends to be chaotic and disordered in states of anger, anxiety or sadness. These rhythmic variations provide a state known as cardiac coherence. Assessment of physiological signals by remote technologies is particularly advantageous in applications that need to understand feelings and sentiments of a patient.

We present and investigate, in the first part of this paper, a set of published works that may be employed to remotely quantify mental stress based on physiological signals by non-contact means. Several techniques can be used to this purpose, thermal imaging being currently the most advanced in our knowledge. Webcams correspond to a ubiquitous and to the most accessible techniques in the particular purpose of mental stress detection. After all these theoretical reminders, we present a pilot study based on a new framework that was developed to detect mental workload changes using video frames obtained from a low-cost webcam. To induce stress, we have employed a computerized Stroop color word test on twelve subjects. The results offer further support for the applicability of mental workload detection by remote and low-cost means, providing an alternative to conventional contact techniques.

2. Background

2.1 Quantization of mental stress states using physiological information

Physiological manifestations are orchestrated by the autonomic nervous system. The latter is split into two sub-branches: the parasympathetic nervous system, which slows down the heart and reduces the size of the pupil (*miosis*) and the sympathetic nervous system, which in contrast accelerates the heart, dilates the pupil (*mydriasis*) and is responsible in sweating by the sweat (*sudoriferous*) glands. Stressors generally stimulate the sympathetic nervous system and inhibit the influence of the parasympathetic nervous system, these two components operating reciprocally.

2.1.1 Standard physiological signals used for stress detection

J.A. Healey and R. Picard [6] proposed to collect several physiological indicators in order to determine relative stress level of drivers. Contact sensors were used to record some basic signals like the electrocardiogram, electromyogram, electrodermal activity and the respiration during different driving conditions. A set of features were then extracted from raw signals to classify three levels of stress. They found that electrodermal activity and heart rate measurements were closely correlated with stress.

Additionally, Zhai and Barreto [7] have employed contact skin temperature sensor and pupil diameter to separate stress states from calm states during computer work. They used an interactive version of the Stroop color word test, a particular interference test, to induce stress.

Only the cardiac activity can be used to detect stress [8], specifically when computing the Heart Rate Variability (HRV), a factor that it is closely correlated to the autonomic nervous system. The acquisition is conventionally realized using contact ECG sensors but the cardiovascular pulse wave, assessed by photoplethysmography [9] can provide important information that are correlated with stress, especially the amplitudes of the pulse signal that reflects peripheral vasoconstriction or vasodilatation effects. Time and frequency [5] analysis of the HRV can be computed to observe the regularity of this series.

2.1.2 Classification: The use of machine learning methods to quantify stress

Different machine learning algorithms can be employed to quantify stress from physiological features, like *k*-nearest neighbors algorithm, Bayesian networks [7] support vector machines natural neural networks or even linear discriminant analysis [10]. All the models need to be trained offline before being used in real-time.

2.2 Contact against remote techniques: advantages and drawbacks

In intensive care units, the monitoring of vital signs like the heart rate and the saturation of peripheral oxygen are performed using contact pulse oximetry devices. These sensors are frequently plagued by motion artifacts [11] leading to frequent interventions of the medical staff due to false alerts [12]. When employing contact electrocardiographic (ECG) sensors, the presence of training personnel is required to place the electrodes onto the body of the patient. These precautions are necessary to avoid corrupted and noisy acquisitions. Non-contact technologies that are used to measure physiological signals are also sensitive to motion artifacts, except that movements are recordable when imaging devices are employed.

In some particular cases, like patients with burns, wounds or infections for example, conventional contact sensors may be inappropriate and even unusable. Some accessories and even some sensors must be replaced after each use for hygienic measures. Herein, non-contact devices are employed to reduce risks of infection and instrumentation coasts [12].

The use of non-contact means to detect physiological signals is particularly advantageous in affective computing and psychophysiology, where stress or emotions are measured. In these psychophysiological experiments, contact sensors may generate a bias by interfering with the user, resulting practically by erroneous stress quantization or emotion misclassification [4]. Herein, non-contact technologies are non-invasive but not necessarily non-intrusive.

2.3 Contact against remote techniques: advantages and drawbacks

Remote measurements of physiological signals are often accomplished using imagining devices. Thus, we will split methods based on digital cameras and webcams (visible spectrum) to the methods based on thermal imaging (infrared spectra). Concurrently, Doppler radars were used to extract heart and respiratory rates [13]. Recent works demonstrate that even speech contains hidden biological information [14] that can be assessed using microphones.

2.3.1 Doppler radars

Volumetric changes are orchestrated by the heart muscle (*myocardium*) contractions, which are partially transmitted to the chest. Radars based on the Doppler effect were proposed by E.F. Geneker [15] for sensing the heartbeat and the respiration remotely. These two physiological parameters are combined when observing chest movements. Lasers can be employed to measure the small displacements of the chest that cause frequency and phase changes in the reflected signal [13].

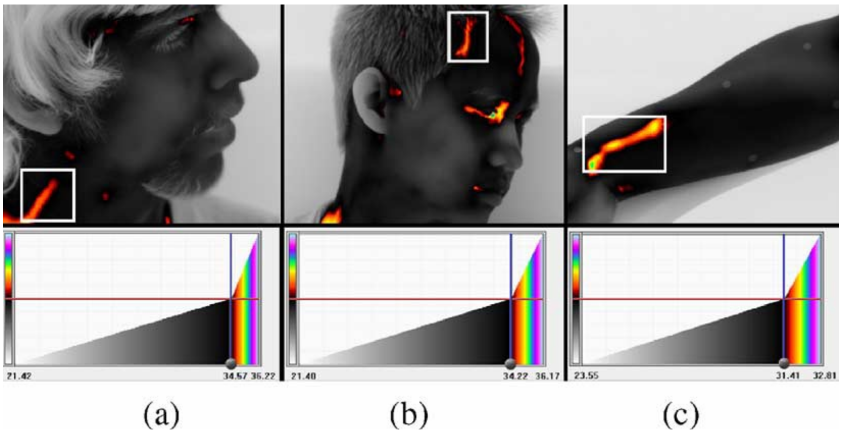

Fig.1. The carotid (a) the temporal artery (b) and even the radial artery (c) are useful locations that can be employed to sense the pulse. Figure extracted from [16].

2.3.2 Thermal imaging

2.3.2.1 Sensing of physiological signals

The heart ejects a quantity of blood that synchronously travels through the arterial network before returning to the heart by the venous network. The propagation of the cardiac pulse generates modulations in the temperature of tissues, which are produced by convection and conduction. The skin temperature waveform reflects the cardiac pulse waveform, the pulse rate being perceptible using particular thermal cameras [16]. The effect is even more perceptible in superficial blood vessels, like the carotid for example (see Fig.1). The technology is completely passive (emits no energy) and one of the most challenging aspects when using thermal cameras is to automatically track the vessels and recover the pulse from composite signals using particular processing techniques [4]. Mid-wavelength infrared cameras [16] and long-wavelength infrared cameras [17] can be employed to recover the cardiovascular pulse wave and the respiration, by tracking temperature fluctuations around the nostrils area [18].

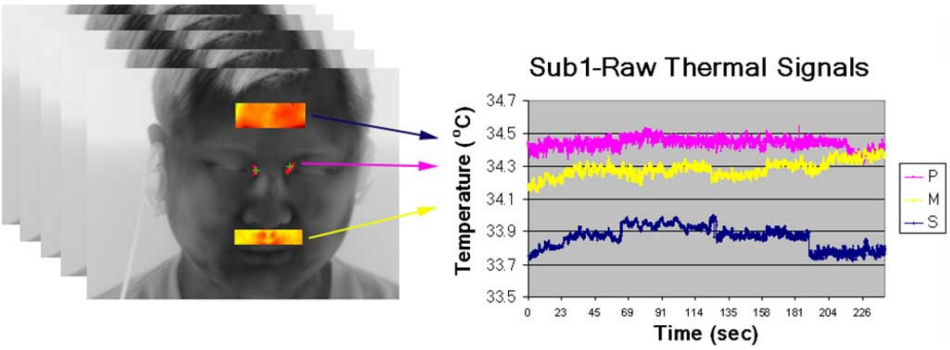

Fig.2. The supraorbital, periorbital and maxillary areas present temperature changes that are correlated with stress. Figure extracted from [19].

2.3.2.1 Stress markers using thermal fluctuations on areas of interest

Perspiration [19] can be detected by tracking changes in temperature on the maxillary area (Fig.2). These fluctuations are modulated by the sympathetic nervous system and produce a response similar to the electrodermal activity, measured typically on the palm or fingers. Previous works of these authors demonstrated that an increase of temperature in the supraorbital and periorbital areas, generated by an increased blood flow, corresponds to a ubiquitous manifestation of stress.

2.3.3 Digital cameras and webcams

Digital cameras and webcams were employed to detect and compute heart and breathing rates [20–22]. The principle, based on PhotoPlethysmoGraphy (PPG) consists in observing light variations on the skin to recover the cardiovascular pulse wave. This optical technique is mainly implemented in contact pulse oximetry sensors where infrared wavelengths are employed to detect the pulse wave. Considered in this case as noise, ambient light is now an illumination source used for PPG exploitation via high sensitivity cameras and webcams. The main drawback of this technique is that PPG signals are susceptible to motion-induced artifacts, particularly when dealing with webcams and ambient light. Independent component analysis, a blind source separation method, has been proposed by Poh et al. [20] to remove noise artifacts from face imaging PPG signal. Sun et al. [21] have compared performances between a low-cost webcam and a high-sensitivity camera to assess HR and pulse rate variability. They conclude that the functional characteristics of a 30 fps webcam are comparable to those of a 200 fps camera when interpolating signals to improve the time domain resolution. We have recently developed [22] a robust method to compute the HRV using the u^* channel of the CIE $L^*u^*v^*$ color space combined to a skin detection, an essential step that improves signal to noise ratio.

2.3.4 Microphones (speech)

People communicate basic linguistic information when they speak. The formants, the observation of relevant frequencies in the sound spectrum, indicate the phonetic quality of a vowel. It appears that the voice also contains important biological information. The cardiac activity causes short increments in the vowel speech formants [14]. This way, standard microphones can be employed to remotely detect and compute the instantaneous heart rate. Herein, noise artefacts are removed from the time-frequency representation of the raw signal. The main limitation of this method is that patients need to speak and keep a constant tone. Thus, patients with insufficient respiratory lung volume were not able to properly use the system [14].

2.3.5 Capacitively coupled ECG

Just like traditional ECG measurements, electric potentials are sensed using a couple of polarized electrodes. A conducting electrolyte gel is often used to ensure a proper resistive contact between the skin and the electrodes. Capacitive electrodes were developed to avoid this constraint and risks of skin irritation when monitoring ECG signals for long-term periods [23]. The system is able remotely sense these bioelectric signals but needs to operate in close proximity to the skin.

3. Pilot study

We have proposed [22] a new filtering technique that was developed to remotely and robustly recover the instantaneous pulse rate signal concurrently to photoplethysmographic amplitudes fluctuations from video frames acquired by a low-cost webcam. We have employed these parameters [24] to form a curve that represents mental workload changes for each of the 12 participants that were performing a computerized and interactive version of the Stroop [25] color word test.

3.1 Blood flow assessment from video frames

The overall system is composed with both image and signal processing (see Fig.3). The face is automatically detected using a cascade of boosted classifier on each frame with OpenCV library [Fig.3 (a)]. Preprocessing operations are applied on the original frame to isolate skin pixels that contain the PPG signal. A skin detection mask [Fig.3 (b)] is employed to properly collect these pixels and form the raw signal [Fig.3 (e)].

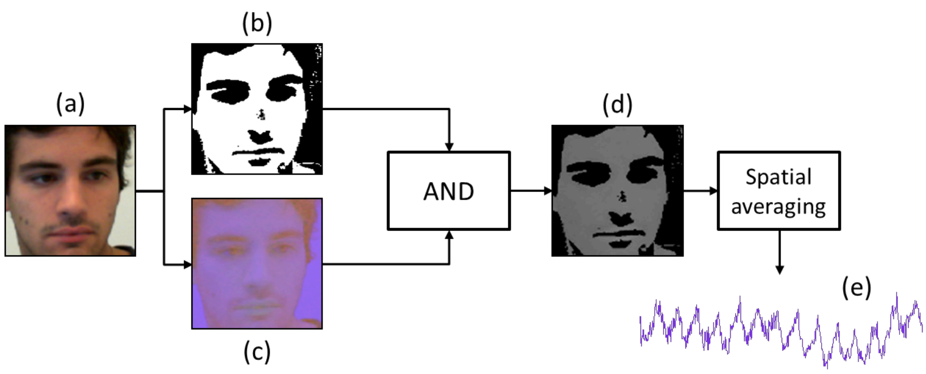

Fig.3. Algorithm overview. The face is automatically detected on each frame (a). Pixels that contain PPG information are isolated by a skin detection (b). The RGB color space is converted

to the CIE $L*u*v*$ color space (c). The $u*$ frame is merged with the skin detection (d). A spatial averaging step is performed to transform a set of frames into a single raw signal (e).

A Continuous Wavelet Transform filter was developed to remove trends and high frequency noise of the raw signal in the 0.65–3 Hz frequency band. A custom algorithm was developed to detect peaks and compute the instantaneous pulse rate trace (Fig.4). In addition, the fluctuations in the pulse wave amplitudes are assessed in this step and reflect relative changes in the vascular bed due to vasoconstriction or vasodilatation.

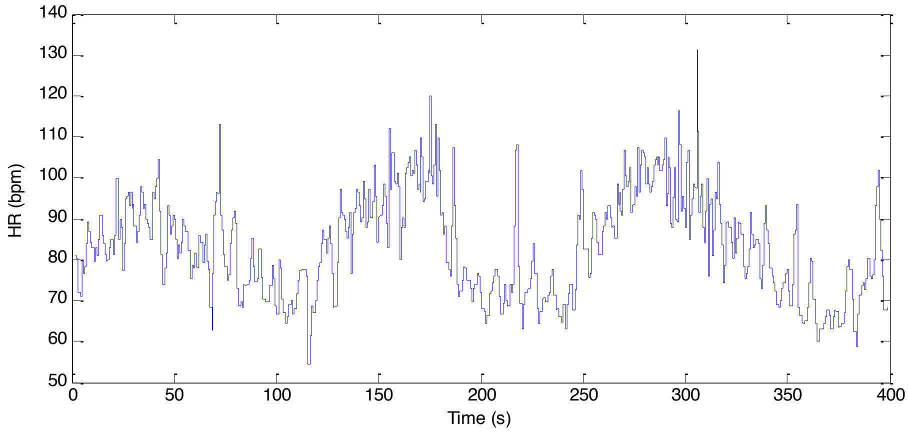

Fig.4. The instantaneous pulse rate trace is formed after the detection of all peaks, followed by the computation of the interbeat intervals.

3.2 Mental stress states estimation

Orchestrated by the autonomic nervous system, a peripheral vasoconstriction appears under stressful situations and leads PPG amplitudes to decrease [26]. A 20 seconds two-sided moving average was employed to extract the trend of the instantaneous pulse rate and the trend of PPG amplitude fluctuations.

We have employed the presented technique to form a curve that represents mental workload changes for each of the 12 participants that were performing a computerized and interactive version of the Stroop [25] color word test. Briefly, the participant has 3 seconds to click on the colored box that corresponds to the word printed in the center of the monitor (Fig.5). Some words are printed in a color not denoted by the name (incongruent, e.g. the word “green” printed in a blue ink) while the others are printed on the right color. The participants performed three sessions of the color word test, i.e. a one minute training session to familiarize the user with the virtual interface and two stress sessions (SS). Each session are separated by a one minute relaxation session (RS). A stressful music is played during both stress sessions and an alarm siren is launched the 10 last seconds. At the end of the session, the participants were asked to report their subjective experiences of stress via a 5-point Likert scale [8].

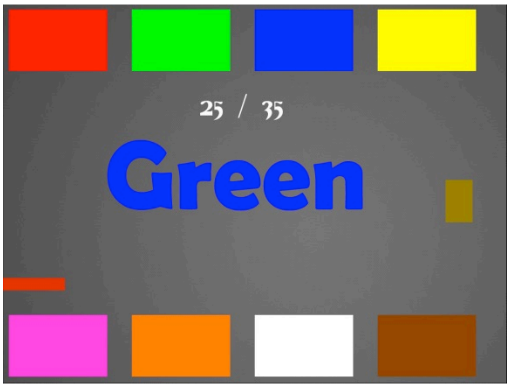

Fig.5. Screenshots of the interactive application: during the Stroop color word test (left picture) and the first relaxation video (right picture) that starts right after the training session.

Also, the electrodermal activity was recorded using a contact skin conductance sensor. This particular signal was compared to the mental workload curves assessed by the webcam (Fig.6). The boxplot of means printed in Fig.7 gives an estimation of the mental workload curves computed with the webcam measurements. As for the electrodermal activity, these curves tend to decrease during relaxation sessions and tend to increase during stress sessions. Significant differences were observed on the questionnaires between the relaxation and stress sessions.

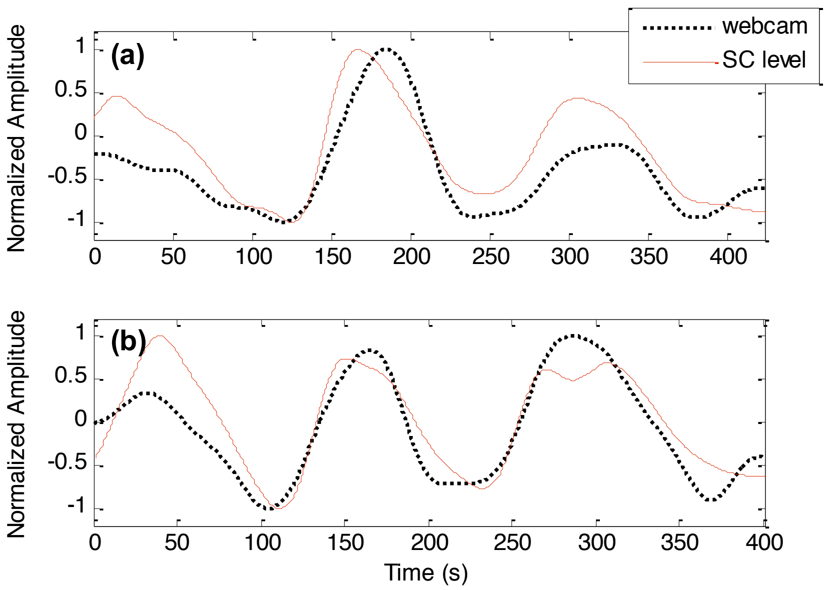

Fig.6. Results of the mental workload detection for the participant #11 (a) and #12 (b). Black plots correspond to the webcam-derived workload signal and red plots to the skin conductance level, derived from the raw electrodermal activity signal [24].

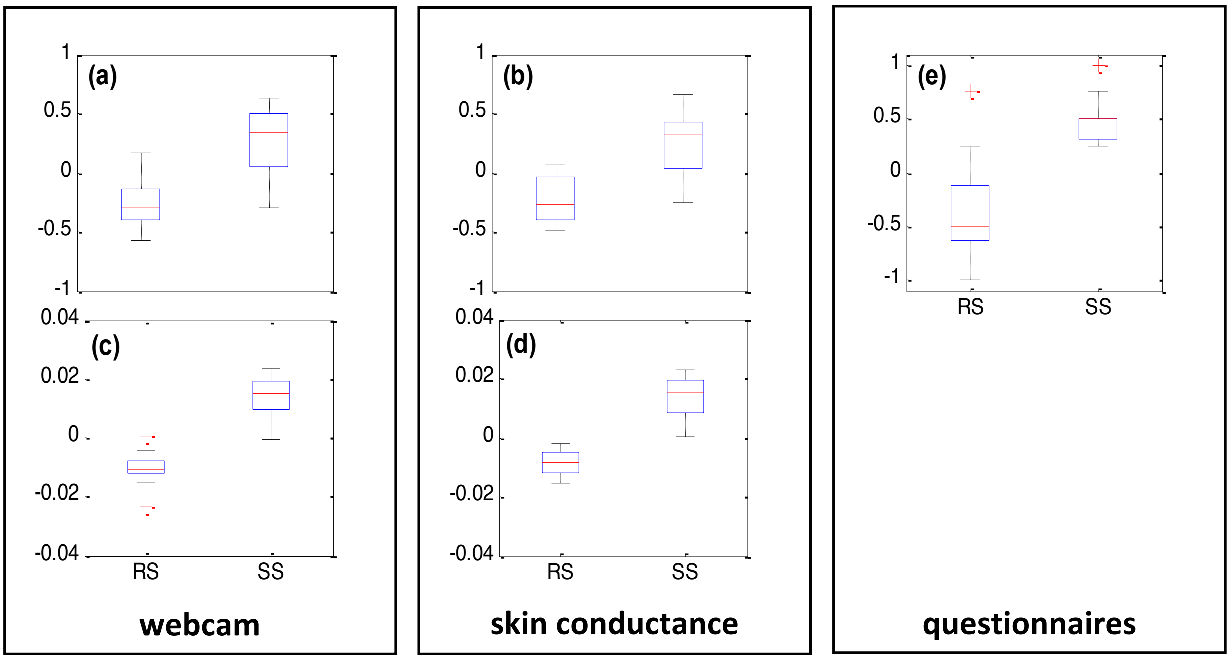

Fig.7. Boxplots representing global average measurements of means [(a) and (b)] and derivatives [(c) and (d)] for the three relax sessions and the two stress sessions. The mean values of the four most relevant factors of the questionnaires are presented in (e).

Conclusion

The results presented in this study demonstrate the feasibility of using the cardiac response derived from a low-cost webcam to assess mental workload changes. The processing methods are motion-tolerant and robust to light deficiency [22]. The instantaneous heart rate can be properly assessed even in presence of strong motion artifacts. Herein, we have demonstrated that webcams correspond to relevant non-contact sensors that can be employed to quantify the mental workload changes of a participant by computing a set of basic parameters extracted from the cardiac activity [24]. Another challenging aspect is to integrate different modalities to recognize specific emotions. For example, body postures, facial expressions and gaze tracking can be extracted from input webcams frames. Even prosodic information can be sensed using built-in microphones. Other technologies, like thermal imaging are very promising in psychophysiology because they can sense particular temperature changes orchestrated by sympathetic arousal.

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