Contactless Physiological Assessment of Mental Workload During Teleworking-like Task

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Abstract. Human physiological parameters have been proven as reliable and objective indicators of user's mental states, such as the Mental Workload. However, standard methodologies for evaluating physiological parameters generally imply a certain grade of invasiveness. It is largely demonstrated the relevance of monitoring workers to improve their working conditions. A contactless approach to estimate workers' physiological parameters would be highly suitable because it would not interfere with the working activities and comfort of the workers. Additionally, it would be very appropriate for teleworking settings. In this paper, participants' facial videos were recorded while dealing with arithmetic tasks with the aims to 1) evaluate the possibility to estimate their Heart Rate (HR) through facial video analysis, and 2) assess their mental workload under the different experimental conditions. The HR was also estimated through last-generation smartwatches. The results demonstrated that there was no difference between the HR estimated via the contactless technique and smartwatches, and how it was possible to discriminate the two mental workload levels by employing the proposed methodology.

Keywords: Contactless · Physiological signals · Autonomic parameters · Teleworking · Mental workload · Heart rate

1 Introduction

According to the Eurofund report, in 2018 approximately 3.2 million non-fatal and 3.793 fatal work-related accidents occurred in Europe [1], and the 7.4% of the EU population suffered from one or more work-related health problems [1]. Among the principal causes of work-related accidents there is the Human Factor (HF) [2, 3]. In fact, it has been demonstrated that human errors are the main causes of work-related accidents [4–6]. Workers' common errors are largely correlated with the condition of

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high mental workload, tiredness and distractions [7, 8]. These findings clearly indicate the relevance of being able to monitor in real time worker's psychophysical state, such as mental workload and tiredness, in working operational environments [9]. In this context, scientific literature largely highlighted the limit of using subjective methodologies to evaluate such HFs [10–12]. As a potential countermeasure, in the last decades neuroscientific disciplines have been dedicating a great effort in investigating human physiological correlates of user's mental states in order to develop monitoring tools able to detect incoming cognitive impairments (e.g. mental overload) on the basis of specific biomarkers (e.g. skin sweating increasing, heart rate variability, brain electrical activity increasing in specific rhythms over particular cortical sites) [13–15]. Nevertheless, it is evident the need of reducing at minimum the invasiveness related to monitoring methodologies during the working tasks to do not negatively interfere with the workers' activities and comfort [16]. This last consideration is very consistent with the concept of remote and contactless monitoring.

The remote monitoring of workers in coping with variable complexity tasks could play a significant role in workers' wellbeing and safety improvements. Nowadays, the relevance and interest in such a methods have grown consistently in parallel to the huge increase of the teleworking adoptions by several companies all around the world, especially following the pandemic COVID-19 [17]. The remote monitoring methodology is also compatible with the recent World Health Organization provisions related to the physical distancing practices to cope with the health emergency [18, 19]. From a pure physiological perspective, several human biomarkers have been correlated with mental workload dynamics [13, 20]. One of the most relevant autonomic parameters involved in the mental workload evaluation is the *Heart Rate* (HR) [21–23]. The HR is a physiological measure derived by the Electrocardiographic signal (ECG). The HR is modulated by the sympathetic and parasympathetic systems: the sympathetic activation increase the HR and the parasympathetic activation decrease the HR [24]. It has been largely demonstrated that the HR increases when the mental workload increases [22, 25]. The present study is based on an innovative technique that aims to estimate the HR through the analysis of the user's face video recorded by mean of the PC webcam. Such a contactless methodology has been already explored in prior works [26, 27], and its principle concept is based on the modulation of the reflected ambient light from the skin by the absorption spectrum of haemoglobin in the blood [26]. In other words, the analysis is based on the extraction and processing of the Red component of the facial video. The minute colour variations on the skin are created by the blood circulation and they module the Red component of the video signal along the time. In this article, the physiological parameter of HR was extracted during teleworking-like activities. This proposed study is part of the European project named "WorkingAge: Smart Working for All Ages" (GA: 826232). Therefore, the present study is based on the experimental hypothesis that HR is a physiological feature sensitive to human mental workload fluctuations accordingly to scientific literature above introduced. Thus, it aimed at addressing two main objectives:

- Comparing the HR estimation of the contactless method (i.e. via webcam) with the one provided by last-generation smartwatch equipped with three photoplethysmographic (PPG) sensors to assess its reliability.

- Employ the proposed contactless method to assess the user's mental workload while performing an arithmetic task under different difficulty conditions.

2 Materials and Methods

2.1 The Experimental Protocol

Eight participants, six male and two females (31.1 $\pm$ 3.9 years old), from the Sapienza University of Rome were recruited and involved on a voluntary basis in this study. The experiment was conducted following the principles outlined in the Declaration of Helsinki of 1975, as revised in 2000. Informed consent and authorization to use the video graphical material were obtained from each subject on paper, after the explanation of the study. The embedded PC webcam was used for the experimental protocol. The RGB camera was set with a resolution of 640 $\times$ 480 pixels at 30 frame per second. The last-generation smartwatches were considered as the *gold standard* and their HR values were recorded at the beginning and at the end of each experimental condition. The experimental protocol consisted initially in a baseline phase where the participants were asked to look at a black cross on white background picture, and then a white cross on black background picture for 30 s each. Finally, the participants performed an arithmetic task under two different conditions: the easy ("Easy Math task") was characterized by single and double-digits sums and one-carry, while the hard ("Hard Math task") was characterized by triple-digits sums with two-carry (Fig. 1, please refer to Subsect. 2.2). The participants had 15 s to answer each mathematical computation by the PC keyboard. During the whole protocol the facial video has been recorded through the software Free2X Webcam Recorder. Finally, the Reaction Time (RT) and the Correct Response Rate (CRR) have been collected during the two mathematical tasks. These parameters were combined to compute an Inverse Efficiency Score (IES) [28] for each participant in each mathematical task to assess both the accuracy and the speed of the user within one synthetic index. The IES has been computed using the formula provided below:

$$IES = \frac{RT}{1 - PE} = \frac{RT}{CRR}.$$

Where RT is the reaction time corresponding to the correct answers, PE is the error rate and CRR is the correct response rate.

2.2 The Arithmetic Task

The two arithmetic tasks have been chosen in order to elicit two different levels of mental workload. In particular, the mathematical task consisted in solving repeated additions proposed to the subjects through a desktop computer: each subject was asked to solve the additions trying to achieve his/her best performance (i.e. to provide the correct answer within the least time possible). The two levels of task difficulty (to elicit two different levels of mental workload) were designed accordingly to the principles adopted by Zarjam and colleagues [29]. More in detail, the 3-min-long EASY task consisted in a *1- and 2-digits numbers with one carry* sum (e.g. 5 + 54, *Very low* level in [29]), while the

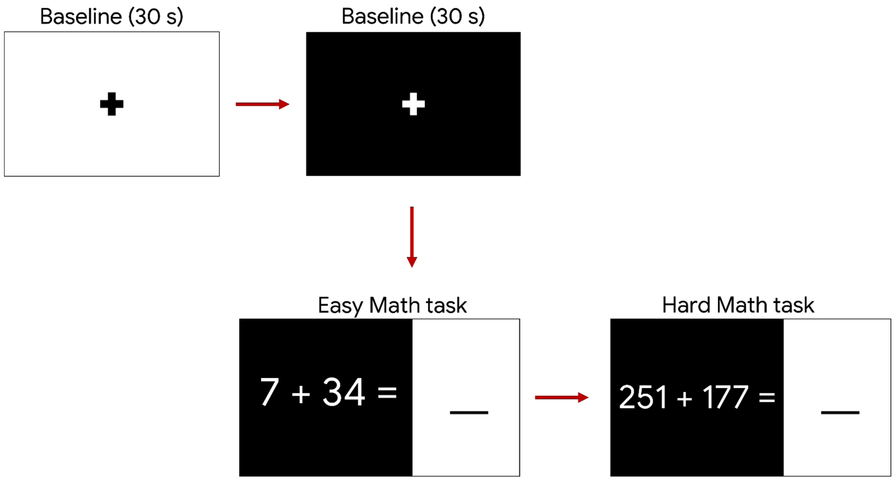

Fig. 1. The three different phases of the experimental protocol: i) during the baseline the participants were asked to look at a white-screen video and then at a black-screen video; during the ii) easy and iii) hard arithmetic tasks the participants were asked to perform, respectively, double-digits and triple-digits sums.

3-min-long HARD task consisted in a *2- and 3-digits numbers with 1 carry* sum (e.g. 31 + 477, *High* level in [29]). This task was chosen because there is a rich literature on the concepts and procedure of mental arithmetic operations [30, 31], while in [32] it is shown that the manipulation of the number of carry operations and the value of the carry is an important variable in varying the difficulty of arithmetic sums. Each subject took confidence with the mathematical task [33, 34], while the order of the two tasks has been randomized among subjects, in order to avoid any habituation effect.

2.3 Data Collection and Data Processing

The image frame is the fundamental part of the video, and two regions of interest (ROI) were selected on each image frame within the participant's face area (Fig. 2).

Thereafter, the Fast Fourier Transform (FFT) and Principal Component Analysis (PCA) were applied to extract the Red component from the raw video signal. The PCA algorithm was used also to remove the Red component fluctuations due to the motion artefacts, while the FFT was applied to extract the frequency corresponding to the HR. Such a frequency corresponds to the highest power spectrum within a specific operational frequency band (Fig. 3).

A specific Python library named Dlib [35] coupled with an adaBoost classifier was used to select a certain number of visual feature on the participant's face. Two ROIs were selected on both the participant's cheeks (green rectangles in Fig. 2). The ROIs were selected taking as references the participant's eyes and nose [27]. The Python library allowed us to automatically detect the participant's face and follow the head movements during the experiments, as long as they were included in the field of view (FOV) of the webcam. The Red (R), Green (G), Blue (B) colour values are the fundamental

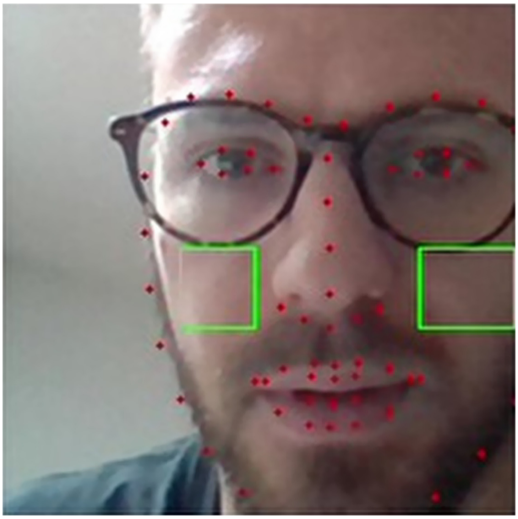

Fig. 2. Two regions of interest automatically identified on the participant's face. Informed consent and authorization to use the video graphical material were obtained from each subject on paper, after the explanation of the study. The use of facial pictures is here necessary to illustrate the employed methodology: for this purpose, explicit consent was provided by the subject. (Color figure online)

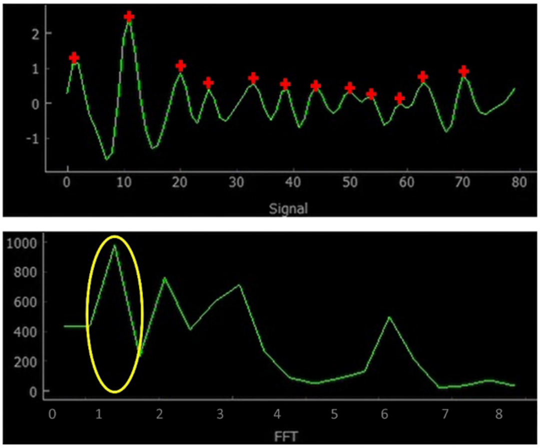

Fig. 3. The image shows the highest frequency band selected to extract the HR from the signal. (Color figure online)

components of the RGB video. These elements were extracted from the two ROIs as a 3×1 matrix, where in each raw the RGB component were stored (Fig. 3). Finally, only the Red component was selected and extracted as a bidimensional signal in time domain. The three RGB components were extracted by using the PCA methodology, fully implemented in the *sklearn.decomposition. PCA* Python library related to the larger Scikit-Learn Python library [36].

The signal detrend was applied to remove unwanted trending from the time series. In this case, the potential unwanted trends were represented by the effect of the illumination variations during the experiments, mainly due to PC's display contents variation which were partially reflected on the participant's skin. This kind of trend could generate drifting and noising on the signal of interest. Therefore, the R-component was detrended using the methods proposed by [37] based on smoothness priors approach using a smoothing parameter $\lambda = 10$ and a cut-off frequency = 0.060 Hz. After the signal detrending, the Red component extracted in each image frame was filtered by Hamming window characterized by 128 points, between 0.6 and 2.2 Hz, such a frequency range corresponds to a normal HR value interval between 36 and 132 beats per minute (BPM). The filtered signal was normalized using z-score by the formula provided below (Fig. 4):

Fig. 4. The three video components (Red, Green and Blue) automatically identified for each image frame. The use of facial pictures is here necessary to illustrate the employed methodology: for this purpose, explicit consent was provided by the subject. (Color figure online)

$$X_i = \frac{Y_i(t) - \mu_i(t)}{\delta_i}.$$

To extract the HR value a sliding time window corresponding to 100 image frames was considered. HR values were extracted for each experimental phase ("Baseline", "Easy Math task" and "Hard Math task"), and for each condition the HR values estimated by the facial video (*HR_RGB*) and the smartwatches (*HR_Smart*) were reported.

3 Results

3.1 Behavioural Data

The Wilcoxon signed rank tests performed on the IES parameter showed a significant increase of the IES during the Hard Math task ($Z = 9.52$; $p = 0.0078$) (Fig. 5).

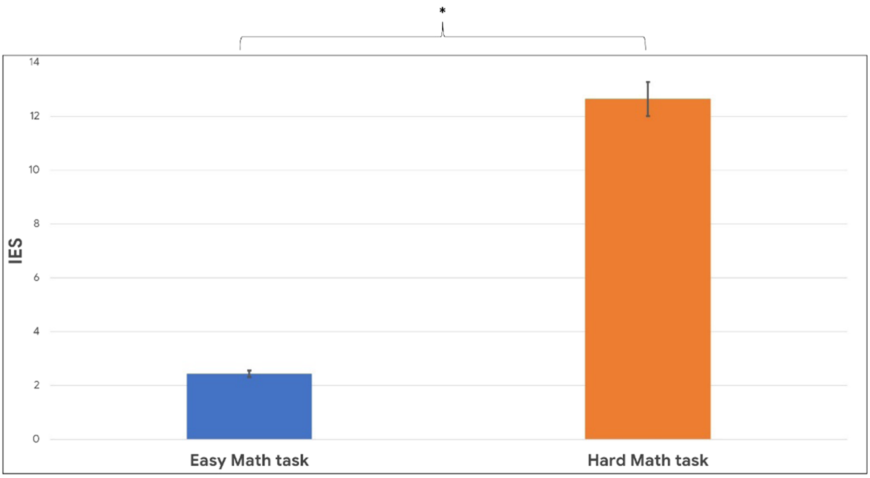

Fig. 5. The IES score significantly increase ($p = 0.0078$) during the Hard Math task.

3.2 Heart Rate

The Wilcoxon signed rank test performed on the HR values obtained for each subject for each task with respectively the camera-based algorithm and the smartwatch sensors (Fig. 6) revealed a non-significant effect of the used methodology ($Z = -3.12$; $p = 0.2969$). In other words, the HR values estimated through the contactless approach (HR_RGB) were not statistically different from the ones estimated through the smartwatches (HR_Smart).

On the contrary, the Wilcoxon signed rank tests revealed a significant difference of both the HR_RGB and HR_Smart between the easy and hard conditions of the arithmetic task (HR_RGB: $Z = 4.27$; $p = 0.0069$; HR_Smart: $Z = 4.18$; $p = 0.0078$) (Fig. 7).

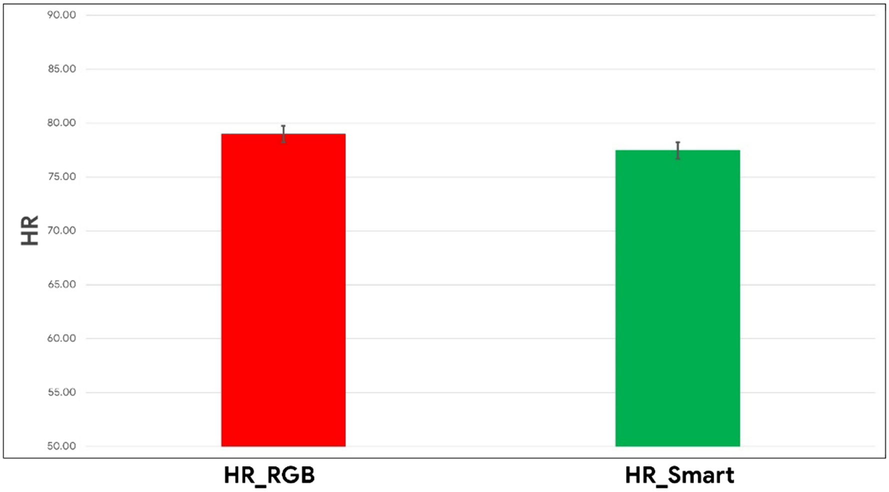

Fig. 6. The HR value evaluated through the contactless methodology was not significantly different ($p > 0.05$) to the HR values evaluated through the smartwatches.

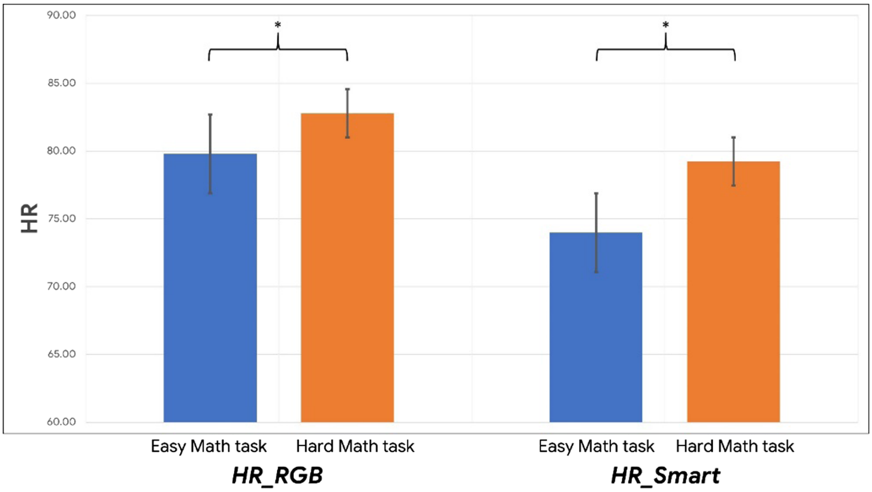

Fig. 7. Both the HR_RGB and HR_Smart significantly increased ($p = 0.0069$; $p = 0.0078$, respectively) during the Hard Math task.

4 Discussion and Conclusions

The present study aimed to evaluate the capability and reliability of a contactless methodology for the estimation of the Heart Rate (HR), and for developing a remote monitoring technology able to assess user's mental workload. The methodology considered is relatively easy to implement and implies low cost as it requires a standard PC webcam.

Also, it is compatible for both real time measurements and offline evaluations. In particular, the methodology consists in the HR estimation through the user's facial video analysis and extracting the Red component among the video features. We employed such a methodology to assess the mental workload while accomplishing an arithmetic task under different difficulty levels. In particular, 8 subjects were enrolled in the study: for each of them a facial video was recorded using a webcam. The HR value was estimated from the video, through the Red component analysis (HR_RGB). Simultaneously, the HR value was collected using a smartwatch (HR_Smart) to evaluate the reliability of the proposed contactless methodology.

The results showed no significant differences ($p = 0.2969$) between the HR values evaluated through the contactless technique (HR_RGB) and the smartwatches (HR_Smart) as demonstration of the reliability of the proposed methodology. However, the results showed a slight tendency to overestimate the HR by the contactless methodology compared to the HR estimated by the smartwatches: this aspect will be carefully investigated in the next study, enlarging the sample size. With respect to the mathematical task, behavioural measures, i.e. performance results in terms of Inverse Efficiency Score (IES), demonstrated that the two mathematical tasks were actually different in terms of difficulty demand, since performance during the Hard task were significantly worse than those during the Easy task, therefore validating the experimental hypothesis at the basis of the following analysis. Then, the physiological results showed a significant increment of the both HR_RGB and HR_Smart values during the hard arithmetic condition as described from previous literature evidences [22], therefore validating the use of such a contactless technique (webcam) as a reliable alternative to traditional contact-based sensors (smartwatch).

Although the promising and interesting results, there are some limitations to be discussed. Firstly, the sample size consisted in 8 participants, therefore in the next phase we will enlarge it to better support and validate the methodology proposed in this work. Secondly, the estimation of the HR was performed by analysing offline the facial video of the participants. In the next study we will implement the data processing and analysis in real time in order to assess the user's mental workload while dealing with working activities and be GDPR compliant avoiding relevant privacy issues. Moreover, different illumination conditions will be considered to better investigate the potential HR overestimation abovementioned. It has to be noted that the proposed contactless methodology is very promising in different applications as it is fully compatible with teleworking and social distancing practices, and does not negatively interfere with the user's activities, therefore paving the way for future safety-oriented applications [21, 38–40], other mental states assessment like stress [41], vigilance [42], and cognitive control behaviour [43], as well as employment despite of social restrictions [17].

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