Low-invasive Neurophysiological Evaluation of Human Emotional State on Teleworkers

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Abstract: Human emotions decoding and assessment is a hot research topic since its implications would be relevant in a huge set of clinical and social applications. Current emotion recognition and evaluation approaches are usually based on interactions between a “patient” and a “specialist”. However, this methodology is intrinsically affected by subjective biases and lack of objectiveness. Recent advancements in neuroscience enable the use of traditional biosensors and maybe commercial wearable devices, which lead to a certain grade of invasiveness for the subject. The proposed study explored an innovative low-invasive hybrid method, based on the use of video data and smart bracelet, to overcome such technological limitations. In particular, we investigated the capability of an Emotional Index (EI), computed by combining the Heart Rate (HR) and the Skin Conductance Level (SCL) estimated through video-based and wearable technology, in discriminating Positive and Negative emotional state during interactive webcalls. The results revealed that the computed EI significantly increased during the Positive condition compared to the Negative one ($p = 0.0008$) and the Baseline ($p = 0.003$). Such evidences were confirmed by the subjective data and the classification performance parameters. In this regard, the EI discriminated between two emotional states with an accuracy of 79.4%.

1 INTRODUCTION

The wide field of emotion recognition and emotion evaluation is approached through different methodologies. The present work is related to the neurophysiological characterization of the emotional state. In this regard, different works widely explored the emotional state evaluation through the computation of an Emotional Index (EI) (Vecchiato et al., 2014), deriving information from the Heart Rate (HR), usually extracted from the Electrocardiographic (ECG) or Photoplethysmographic (PPG) signals, and the Skin Conductance Level (SCL), one of the two component of the Electrodermal Activity (EDA). In this context, the emotional state was evaluated both in one (Bustamante, Lopez Celani, Perez, & Quintero Montoya, 2015; Samadiani et al., 2020) and in two dimensions (Brouwer, van Dam, van Erp, Spangler, & Brooks, 2018; Guo et al., 2016; Moharreri, Dabanloo, & Maghooli, 2018). In particular, the neurophysiological changes associated to the emotional state were evaluated in terms of valence and arousal. Regarding the unidimensional emotional state evaluation, Ho Choi and colleagues (Choi et al., 2017) proposed a method to discriminate between positive and negative states in a controlled environment through the HR and Heart Rate Variability (HRV) analysis, while Vecchiato and colleagues successfully explored the bidimensional

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emotional state evaluation during TV commercials through the EDA and PPG signals analysis (Vecchiato et al., 2014).

However, these works required the physical contact between the sensors and the participants. In scientific literature, different studies were conducted by using professional and laboratory devices, such as the Shimmer GSR3+ (Fiorini, Mancioppi, Semeraro, Fujita, & Cavallo, 2020; Giorgi et al., 2021; Girardi, Lanubile, & Novielli, 2018; Laureanti et al., 2020) or the Biopac BSL-HOME (Flagler, Tong, Allison, & Wilcox, 2020; Villar, Viñas, Turiel, Carlos Fraile Marinero, & Gordaliza, 2020) for the EDA and PPG measurements, or more commercial wearable devices, such as the Empatica E4 (Giorgi et al., 2021; Ragot, Martin, Em, Pallamin, & Diverrez, 2018). The present study explored an innovative approach in this assessing the reliability of a partial video-based EI evaluation, computed by combining the HR, remotely evaluated through the participant's face video analysis, and the SCL evaluated through a wearable device, the Empatica E4. The video-based methodology for the HR evaluation does not require any physical contact between the sensor and the participants, as it does not require any technical support to manage the signal collection. The proposed methodology for HR evaluation was already explored in prior works with promising results (Borghini et al., 2020; Rahman, Ahmed, & Begum, 2020; Rahman, Uddin Ahmed, Begum, & Funk, n.d.; Ronca et al., 2021), and it is based on the modulation of the reflected ambient light from the skin by the absorption spectrum of haemoglobin in the participant's blood (Rahman et al., 2017). In other words, such analysis is based on the extraction and processing of the Red component of the participant's facial video. The minute - colour variations on the skin are created by blood circulation, and they module the Red component of the video signal along the time. In particular, this video-based methodology was already assessed in terms of reliability in telemedicine and mental workload evaluation (Ronca et al., 2021, 2020), and it could gain great potential in emotional state evaluation context, especially in real-world applications (Samadiani et al., 2020). This methodology is also compliant with social distancing practices and scenarios in which the physical contacts between people must be avoided or mitigated, such as in health emergency situations (Robb et al., 2020), as well as in applications where some non-contact user's monitoring systems could improve safety (e.g. measuring the stress of a car driver, in fact some modern cars are already equipped with interior cameras to monitor driver's ocular behaviour (Di Flumeri et al., 2018; Ji & Yang, 2002). In summary, the present work aimed at addressing the following experimental question:

- Is the considered video-based EI capable of discriminating between a Positive and a Negative emotional state?

2 MATERIAL AND METHODS

2.1 Participants

The informed consent for study participation, publication of images, and to use the video material were obtained from a group of 14 students, seven males and seven females (30.2 ± 3.3 years old) from the Sapienza University of Rome (Italy) after the description of the study. The experiments were conducted following the principles outlined in the Declaration of Helsinki of 1975, as revised in 2000. The study protocol received the ethical board approval by the Ethical Committee of the Sapienza University of Rome (protocol n. 2507/2020 approved on the 04/08/2020). The study involved only healthy participants, recruited on a voluntary basis. Furthermore, the students were free to accept or not to take part to the experimental protocol, and all of them have accepted to participate to the study. Only aggregate information will be presented while no individual information were or will be diffused in any form.

2.2 Experimental Protocol

To elicit two different emotional levels during the experimental protocol, two interactive web calls (WEB) were performed by the participants with the support of one experimenter. The calls consisted in three conditions: i) Baseline condition, in which the participants looked at the web platform interface without reacting; ii) Positive condition, in which the participants were asked to report the most positive memory of their life; iii) Negative condition, in which the test persons were asked to report the most negative memory of their life.

The Positive condition of the task was always performed before the Negative one to avoid transients due to strong negative memories. The Baseline lasted 60 seconds, while the other two conditions lasted 120 seconds.

The experimental protocol also included other two tasks, i.e. the n-Back and the Doctor Game tasks, which were included in the presented study exclusively for the classification procedure. More details are provided in Classification performance evaluation sub-paragraph.

2.2.1 Subjective Data: SAM Questionnaire

In order to validate EI computed by the neurophysiological data, the Self-Assessment Manikin (SAM) questionnaire (Lang, Bradley, & Cuthbert, 2008) was included in the experimental protocol. The SAM consists in a picture-oriented (Figure 1) questionnaire specifically developed to measure three parameters: i) the valence/pleasure (from unhappy to happy); ii) the perceived arousal (from calm to excited) and iii) the perceptions of dominance/control (from low to high levels) associated with a person's emotional reaction to a variety of stimuli. In particular, the participants were asked to fill the SAM after each experimental condition (Baseline, Positive, and Negative). by providing three simple responses along each emotional dimension (on a scale from 1 to 9) that best described how they felt during the condition just executed. This questionnaire was selected to have a subjective indication about the current state of the participants in terms of pleasure, arousal and control with the respect of each experimental condition of WEB task (Bynion & Feldner, 2017).

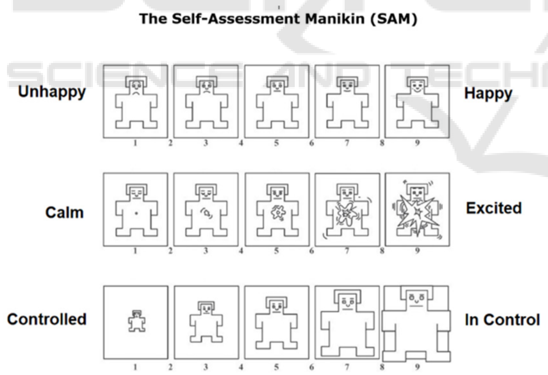

Figure 1: The Self-Assessment Manikin questionnaire.

2.2.2 Heart Activity Recording and Analysis

The HR was estimated by means of the video – based methodology. The participant's facial video was recorded through a PC webcam placed in front of the participant (Figure 2). The RGB camera was set to a resolution of 640 × 480 (pixel) at a frame rate of 30 (fps). and the video was analysed offline. Firstly, 68 visual facial feature required for the facial recognition were identified using the Dlib Python library (King, 2009) coupled with the adaBoost classifier (Yu, Yun, Chen, & Cheng, 2018). The classifier performed the facial recognition and it was based on the YCbCr Color model (King, 2009). This model is capable of performing facial features identification according with the luminance and chrominance variations of the video. Secondly, the Fast Fourier Transform (FFT) was used to select and extract the Red (R) component from the raw signal, while the Principal Component Analysis (PCA) was also applied for fluctuations removal from the R component, technically implemented in the sklearn.decomposition.PCA Python library included in the Scikit-Learn Python library ("sklearn.decomposition.PCA — scikit-learn 0.23.1 documentation," 2014). The considered signal was collected within the participant's cheeks frame by frame and referenced to the participant's eyes and nose (Rahman et al., n.d.). Then, the R component was detrended using the method proposed by Tarvainen (Tarvainen, Ranta-aho, & Karjalainen, 2002). Subsequently, Hamming filtering (128 point, 0.6 – 2.2 Hz) was applied to the R detrended component. Finally, the z-score normalization was applied on the filtered signal (Tarvainen et al., 2002). The HR values were computed every 60 seconds for each experimental condition. The main steps of the described video - signal processing for HR estimation are presented in Figure 3.

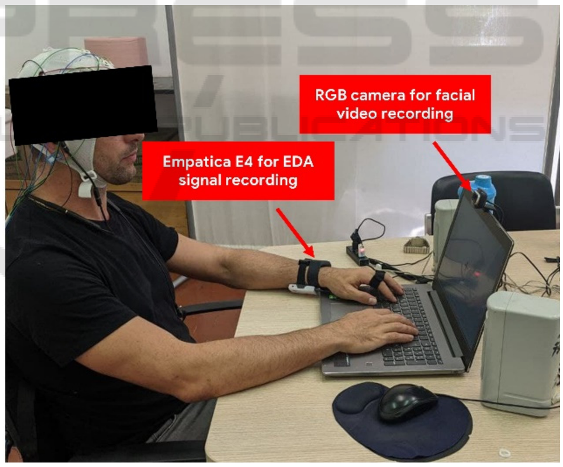

Figure 2: Overview of the experimental settings. The Empatica E4 was placed on the participant's wrist while the RGB camera in front of the participant. Other acquisition devices were present although they were not used for the purposes of this study.

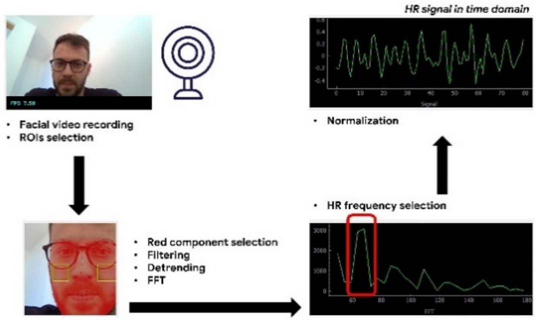

Figure 3: Main steps of the video-signal processing for heart rate (HR) estimation. Starting from the bottom left, the facial video is recorded by mean of a PC webcam and the regions of interest (ROIs) are selected. Then, the R, G and B components are selected by mean of Principal Component Analysis (PCA) algorithm. The Heart Rate (HR) frequency is extracted after detrending, filtering and fast Fourier transformation. Finally, the HR values in time domain are obtained after z-score normalization.

2.2.3 EDA Recording and Analysis

The EDA was recorded employing the Empatica E4 (Empatica, Milan, Italy) wearable device, with the sampling frequency of 4 (Hz). The Empatica E4 was placed on the participant's wrist, according to the position of the two electrodes, placed on the bottom part of the wrist. The EDA was firstly low-pass filtered with a cut-off frequency of 1 (Hz) and then processed by using the Ledalab suite (Bach, 2014), a specific open-source toolbox implemented within MATLAB environment for EDA processing. Then the SCL component was extracted from the EDA. As described by Vecchiato et al. (Vecchiato et al., 2014), this component is associated with the the activity of the sweat glands on the hands and, therefore, with the participant's arousal (Gatti, Calzolari, Maggioni, & Obrist, 2018; Wang et al., 2018). The SCL, as well as the HR parameter, was evaluated as the average within each experimental condition.

2.2.4 Emotional Index

Subsequently, the HR and SCL parameters were combined to compute a synthetical index for the emotional state evaluation. In particular, an Emotional Index (EI) was defined as follows (Vecchiato et al., 2014):

$$EI = |SCL_{mad}| * HR_{mad} \tag{1}$$

where SCL_{mad} and HR_{mad} are the mad-normalised (Kappal, 2019) values of the SCL and HR, respectively, averaged within the considered experimental conditions.

2.2.5 Statistical Analysis

The Shapiro–Wilk test was used to assess the normality of the distributions related to each of the considered neurophysiological parameters. In case of normal distribution, Student's t-test would have been performed to pairwise compare the conditions (e.g., '*Positive* vs. *Negative*'). In case of non-normal distribution, the Wilcoxon signed-rank test was performed. For all tests, statistical significance was set at $\alpha = 0.05$.

2.2.6 Classification Performance Evaluation

In order to assess the efficiency of the proposed EI in discriminating between the two elicited emotional state, i.e. *Positive* and *Negative*, the classification performance were computed. First, a threshold related to the EI was computed for each participant within all the tasks designed in the experimental protocol, including the other two experimental tasks and excluding the *Positive* and *Negative* conditions of the WEB task, as follows (Hernández-Orallo & Flach PETERFLACH, 2012):

$$Threshold = median(X) \tag{2}$$

where, the X was the distribution of the EI averaged within all the tasks.

Secondly, the classification capability of the EI during the WEB task was evaluated by computing three parameters:

- *Classification sensitivity*, defined as the proportion of true *Positive* conditions that are correctly identified. This parameter refers to the ability of the method in terms of correct detection of a specific condition on the tested distribution. For example, in clinical context the sensitivity of a test is the ability in to correctly classifying an individual as "diseased". The sensitivity was calculated as follows:

$$Sensitivity = \frac{TP}{TP + FN} \tag{3}$$

- *Classification specificity*, defined as the proportion of true *Negative* conditions that are correctly identified. This parameter tells how well the classification method predicts the true negative case. In other words, high specificity means a low rate of false positive. For example, in clinical context the specificity of a test is the ability in correctly classifying an individual as disease-free. The specificity was calculated as follows:

$$Specificity = \frac{TN}{TN + FP} \quad (4)$$

- *Classification accuracy*, defined as the fraction of the correct predictions on the total number of predictions. This parameter combines both the sensitivity and the specificity. Therefore, the accuracy can provide more general information about the classification performance than the abovementioned parameters. The accuracy was calculated as follows:

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

The three above presented classification performance parameters were selected according with the perfect balance between the two classes, i.e. *Positive* and *Negative*, in terms of presentation frequency within the experimental task (Gupta, Rawal, Narasimhan, & Shiwani, 2017).

3 RESULTS

3.1 Subjective Results

The Wilcoxon signed-rank test performed on the SAM score showed a significant increase in terms of valence during the *Positive* condition of the WEB task compared to the *Negative* one ($p = 0.003$). The SAM score in terms of dominance and perceived arousal did not significantly differ (SAM dominance: $p = 0.5$; SAM perceived arousal: $p = 0.6$) between the *Positive* and *Negative* conditions of the WEB task (Figure 4).

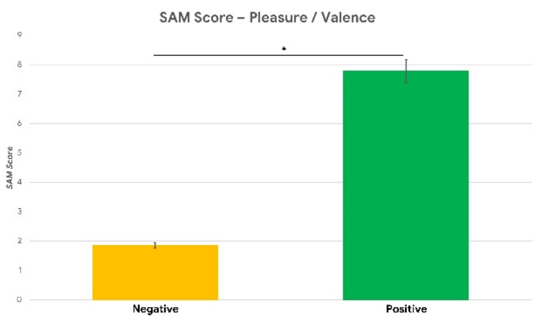

Figure 4: The average SAM Score in terms of Pleasure / Valence during the Negative (yellow bar) and the Positive (green bar) conditions of the Webcall (WEB) task. * indicates a statistical difference between the represented parameter.

3.2 Emotional State Evaluation

The Wilcoxon signed-rank test performed on the EI estimated during the WEB task revealed a significant increase of the index during the *Positive* condition compared to the *Negative* one ($p = 0.0008$) and the *Baseline* ($p = 0.003$). The EI evaluated during the *Negative* condition did not statistically differ from the one evaluated during the Baseline ($p = 0.1$) (Figure 5).

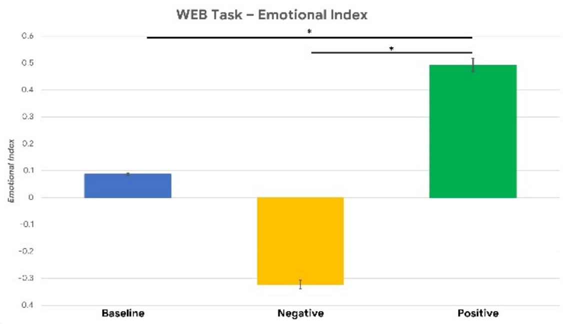

Figure 5: The average Emotional Index (EI) during the Baseline (blue bar), the Negative (yellow bar) and the Positive (green bar) conditions of the WEB task. * indicates a statistical difference between the represented parameter.

3.3 Classification Results

The classification performance parameters, i.e. the Sensitivity, Specificity and the Accuracy, were evaluated within the two experimental conditions (*Positive* and *Negative*) of the WEB task. The Table 1 presents such classification performance parameters.

Table 1: Classification performance parameters describing how the Emotional Index (EI) discriminated between the Positive and the Negative conditions of the Webcall (WEB) task.

Classification Parameter		
Sensitivity	***Specificity***	***Accuracy***
86.2%	***72.7%***	***79,4%***

4 DISCUSSION

The presented results revealed that the proposed EI permitted to correctly discriminate between the *Positive* and *Negative* conditions of the WEB task. Furthermore, the statistical analysis demonstrated that the proposed EI was significantly higher during the *Positive* condition compared to the *Negative* one and the *Baseline*, while no significant differences were found in terms of EI between the *Negative* condition and the *Baseline*. These evidences are supported by the subjective measures, i.e. the SAM questionnaire, which demonstrated that the *Positive* and *Negative* conditions of the WEB task were actually different in terms of perceived pleasure and valence.

Although the promising results, there are some limitations to be discussed. Supporting this, it can be observed in Table 1 how the proposed partial video-based EI was more capable in discriminating the true *Positive* conditions than the true *Negative* ones. Even if the classification parameters demonstrated the general reliability of the proposed EI, since they were all above 72%, the Specificity was lower than the Sensitivity, revealing that the proposed EI was more sensitive to the Positive conditions than the Negative ones, as it can be derived by observing Equations (3) and (4). This could be explained by the fact that the *Negative* condition of the WEB task was not sufficiently well-designed for eliciting a measurable neurophysiological change in the participant's emotional states, especially because of the interaction with a non-familiar person during the simulated webcall. It can be argued that it was easier for the participants speaking about happy and positive memories, while negative memories may often be very private. Future works will be directed to better investigate such an aspect, possibly designing more structured *Negative* experimental conditions. The proposed EI was only partially video-based, since the SCL was gathered by mean of the Empatica E4 wearable device. In this regard, further studies will aim at exploring the video-based methodology in estimating other neurophysiological parameters, such as the respiration rate, which could lead to a full video-based EI (Hameed, Sabir, Fadhel, Al-Shamma, & Alzubaidi, 2019; Kantono et al., 2019).

The presented results are consistent with prior works (Cartocci et al., 2017; Ragot et al., 2018; Zupan, Buskas, Altimiras, & Keeling, 2016) and they pave the way for applying the video-based methodology for the neurophysiological parameters evaluation, already successfully explored in mental workload estimation and telemonitoring applications (Ronca et al., 2021, 2020), also in emotional states evaluation.

5 CONCLUSIONS

The presented study explored the reliability of a very low-invasive approach to evaluate the emotional state of participants while performing a simulated working task. This approach was based on the evaluation of the participant's SCL through the Empatica E4, a wearable and portable device, and the participant's HR, evaluated through an innovative and contactless methodology based on the video analysis.

The promising results permit to hypothesize a further development of the proposed low-invasive methodologies. In particular, a remote approach will be explored to evaluate neurophysiological parameters positively correlated with the SCL, such as the respiration rate, to compute a full-contactless tool to evaluate the emotional status.

REFERENCES

Bach, D. R. (2014). A head-to-head comparison of SCRalyze and Ledalab, two model-based methods for skin conductance analysis. *Biological Psychology*, *103*(1), 63–68. https://doi.org/10.1016/j.biopsycho.2014.08.006

Borghini, G., Bandini, A., Orlandi, S., Di Flumeri, G., Arico, P., Sciaraffa, N., Babiloni, F. (2020). Stress Assessment by Combining Neurophysiological Signals and Radio Communications of Air Traffic Controllers. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, *2020-July*, 851–854. https://doi.org/10.1109/EMBC44109.2020.9175958

Brouwer, A.-M., van Dam, E., van Erp, J. B. F., Spangler, D. P., & Brooks, J. R. (2018). Improving Real-Life Estimates of Emotion Based on Heart Rate: A Perspective on Taking Metabolic Heart Rate Into Account. *Frontiers in Human Neuroscience*, *12*, 284. https://doi.org/10.3389/fnhum.2018.00284

Bustamante, P. A., Lopez Celani, N. M., Perez, M. E., & Quintero Montoya, O. L. (2015). Recognition and regionalization of emotions in the arousal-valence plane. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, *2015-Novem*, 6042–6045. https:// doi.org/10.1109/EMBC.2015.7319769

Bynion, T.-M., & Feldner, M. T. (2017). Self-Assessment Manikin. In *Encyclopedia of Personality and Individual Differences* (pp. 1–3). https://doi.org/10.1007/978-3-319-28099-8_77-1

Cartocci, G., Caratù, M., Modica, E., Maglione, A. G., Rossi, D., Cherubino, P., & Babiloni, F. (2017). Electroencephalographic, Heart Rate, and Galvanic Skin Response Assessment for an Advertising Perception Study: Application to Antismoking Public Service Announcements. *Journal of Visualized Experiments: JoVE*, (126).

Choi, K. H., Kim, J., Kwon, O. S., Kim, M. J., Ryu, Y. H., & Park, J. E. (2017). Is heart rate variability (HRV) an adequate tool for evaluating human emotions? – A focus on the use of the International Affective Picture

System (IAPS). *Psychiatry Research*, *251*, 192–196. https://doi.org/10.1016/j.psychres.2017.02.025

Di Flumeri, G., Borghini, G., Aricò, P., Sciaraffa, N., Lanzi, P., Pozzi, S., … Babiloni, F. (2018). EEG-Based Mental Workload Neurometric to Evaluate the Impact of Different Traffic and Road Conditions in Real Driving Settings. *Frontiers in Human Neuroscience*, *12*, 509. https://doi.org/10.3389/fnhum.2018.00509

Fiorini, L., Mancioppi, G., Semeraro, F., Fujita, H., & Cavallo, F. (2020). Unsupervised emotional state classification through physiological parameters for social robotics applications. *Knowledge-Based Systems*, *190*, 105217. https://doi.org/10.1016/j.knosys.2019.105217

Flagler, T., Tong, J., Allison, R. S., & Wilcox, L. M. (2020). Validity Testing the NeuLog Galvanic Skin Response Device. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *2020-Octob*, 3964–3968. https://doi.org/10.1109/ SMC42975.2020.9283465

Gatti, E., Calzolari, E., Maggioni, E., & Obrist, M. (2018). Data Descriptor: Emotional ratings and skin conductance response to visual, auditory and haptic stimuli. *Scientific Data*, *5*(1), 1–12. https://doi.org/10.1038/sdata.2018.120

Giorgi, A., Ronca, V., Vozzi, A., Sciaraffa, N., di Florio, A., Tamborra, L., … Borghini, G. (2021). Wearable Technologies for Mental Workload, Stress, and Emotional State Assessment during Working-Like Tasks: A Comparison with Laboratory Technologies. *Sensors*, *21*(7), 2332. https://doi.org/10.3390/s21072332

Girardi, D., Lanubile, F., & Novielli, N. (2018). Emotion detection using noninvasive low cost sensors. *2017 7th International Conference on Affective Computing and Intelligent Interaction, ACII 2017*, *2018-Janua*, 125–130. https://doi.org/10.1109/ACII.2017.8273589

Guo, H. W., Huang, Y. S., Lin, C. H., Chien, J. C., Haraikawa, K., & Shieh, J. S. (2016). Heart Rate Variability Signal Features for Emotion Recognition by Using Principal Component Analysis and Support Vectors Machine. *Proceedings - 2016 IEEE 16th International Conference on Bioinformatics and Bioengineering, BIBE 2016*, 274–277. https://doi.org/10.1109/BIBE.2016.40

Gupta, N., Rawal, A., Narasimhan, V. L., & Shiwani, S. (n.d.). *Accuracy, Sensitivity and Specificity Measurement of Various Classification Techniques on Healthcare Data*.

Hameed, R. A., Sabir, M. K., Fadhel, M. A., Al-Shamma, O., & Alzubaidi, L. (2019). Human emotion classification based on respiration signal. *ACM International Conference Proceeding Series*, 239–245. https://doi.org/10.1145/3321289.3321315

Hernández-Orallo, J., & Flach PETERFLACH, P. (2012). A Unified View of Performance Metrics: Translating Threshold Choice into Expected Classification Loss C` esar Ferri. In *Journal of Machine Learning Research* (Vol. 13).

Ji, Q., & Yang, X. (2002). Real-time eye, gaze, and face pose tracking for monitoring driver vigilance. *Real-Time Imaging*, *8*(5), 357–377. https://doi.org/10.1006/rtim.2002.0279

Kantono, K., Hamid, N., Shepherd, D., Lin, Y. H. T., Skiredj, S., & Carr, B. T. (2019). Emotional and electrophysiological measures correlate to flavour perception in the presence of music. *Physiology and Behavior*, *199*, 154–164. https://doi.org/10.1016/j.physbeh.2018.11.012

Kappal, S. (2019). *Data Normalization using Median & Median Absolute Deviation (MMAD) based Z-Score for Robust Predictions vs. Min-Max Normalization*.

King, D. E. (2009). Dlib-ml: A Machine Learning Toolkit. In *Journal of Machine Learning Research* (Vol. 10).

Lang, P., Bradley, M., & Cuthbert, B. (2008). *International affective picture system (IAPS): Affective ratings of pictures and instruction manual*.

Laureanti, R., Bilucaglia, M., Zito, M., Circi, R., Fici, A., Rivetti, F., Russo, V. (2020). Emotion assessment using Machine Learning and low-cost wearable devices. *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, *2020-July*, 576–579. https://doi.org/10.1109/EMBC44109.2020.9175221

Moharreri, S., Dabanloo, N. J., & Maghooli, K. (2018). Modeling the 2D space of emotions based on the poincare plot of heart rate variability signal. *Biocybernetics and Biomedical Engineering*, *38*(4), 794–809. https://doi.org/10.1016/j.bbe.2018.07.001

Ragot, M., Martin, N., Em, S., Pallamin, N., & Diverrez, J. M. (2018). Emotion recognition using physiological signals: Laboratory vs. wearable sensors. *Advances in Intelligent Systems and Computing*, *608*, 15–22. https://doi.org/10.1007/978-3-319-60639-2_2

Rahman, H., Ahmed, M. U., & Begum, S. (2020). Non-Contact Physiological Parameters Extraction Using Facial Video Considering Illumination, Motion, Movement and Vibration. *IEEE Transactions on Biomedical Engineering*, *67*(1), 88–98. https://doi.org/10.1109/TBME.2019.2908349

Rahman, H., Uddin Ahmed, M., Begum, S., & Funk, P. (n.d.). *Real Time Heart Rate Monitoring From Facial RGB Color Video Using Webcam*. Retrieved from http://stressmedicin.se/neuro-psykofysilogiska-matsystem/cstress-

Robb, C. E., de Jager, C. A., Ahmadi-Abhari, S., Giannakopoulou, P., Udeh-Momoh, C., McKeand, J., Middleton, L. (2020). Associations of Social Isolation with Anxiety and Depression During the Early COVID-19 Pandemic: A Survey of Older Adults in London, UK. *Frontiers in Psychiatry*, *11*. https://doi.org/10.3389/fpsyt.2020.591120

Ronca, V., Giorgi, A., Rossi, D., Di Florio, A., Di Flumeri, G., Aricò, P., … Borghini, G. (2021). A Video-Based Technique for Heart Rate and Eye Blinks Rate Estimation: A Potential Solution for Telemonitoring and Remote Healthcare. *Sensors*, *21*(5), 1607. https://doi.org/10.3390/s21051607

Ronca, V., Rossi, D., Di Florio, A., Di Flumeri, G., Aricò, P., Sciaraffa, N., … Borghini, G. (2020). Contactless Physiological Assessment of Mental Workload During

Teleworking-like Task. *Communications in Computer and Information Science*, *1318*, 76–86. https://doi.org/10.1007/978-3-030-62302-9_5

Samadiani, N., Huang, G., Luo, W., Chi, C.-H., Shu, Y., Wang, R., & Kocaturk, T. (2020). A multiple feature fusion framework for video emotion recognition in the wild. *Concurrency and Computation: Practice and Experience*, e5764. https://doi.org/10.1002/cpe.5764

sklearn.decomposition.PCA — scikit-learn 0.23.1 documentation. (n.d.). Retrieved June 10, 2020, from https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA.html

Tarvainen, M. P., Ranta-aho, P. O., & Karjalainen, P. A. (2002). An advanced detrending method with application to HRV analysis. *IEEE Transactions on Biomedical Engineering*, *49*(2), 172–175. https://doi.org/10.1109/ 10.979357

Vecchiato, G., Cherubino, P., Maglione, A. G., Ezquierro, M. T. H., Marinozzi, F., Bini, F., … Babiloni, F. (2014). How to Measure Cerebral Correlates of Emotions in Marketing Relevant Tasks. *Cognitive Computation*, *6*(4), 856–871. https://doi.org/10.1007/s12559-014-9304-x

Villar, B. F., Viñas, P. F., Turiel, J. P., Carlos Fraile Marinero, J., & Gordaliza, A. (2020). Influence on the user's emotional state of the graphic complexity level in virtual therapies based on a robot-assisted neuro-rehabilitation platform. *Computer Methods and Programs in Biomedicine*, *190*, 105359. https://doi.org/10.1016/j.cmpb.2020.105359

Wang, C. A., Baird, T., Huang, J., Coutinho, J. D., Brien, D. C., & Munoz, D. P. (2018). Arousal Effects on Pupil Size, Heart Rate, and Skin Conductance in an Emotional Face Task. *Frontiers in Neurology*, *9*, 1029. https:// doi.org/10.3389/fneur.2018.01029

Yu, M., Yun, L., Chen, Z., & Cheng, F. (2018). Research on video face detection based on AdaBoost algorithm training classifier. *1st International Conference on Electronics Instrumentation and Information Systems, EIIS 2017*, *2018-Janua*, 1–6. https://doi.org/10.1109/EIIS.2017.8298627

Zupan, M., Buskas, J., Altimiras, J., & Keeling, L. J. (2016). Assessing positive emotional states in dogs using heart rate and heart rate variability. *Physiology and Behavior*, *155*, 102–111. https://doi.org/10.1016/j.physbeh.2015.11.027