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# Stress detection and monitoring based on low-cost mobile thermography

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## Abstract

The high level of stress in modern life is one of the huge problems of the 21st century society, especially in the context of the Covid-19 pandemic. With the pandemic, the need for inexpensive, portable and easy-to-use health monitoring tools (mental and physical) has increased. Of particular importance here is mobile (smartphone) thermography, as it enables the initial detection and self-control of stress, which being intensified nowadays, is the cause of many diseases, depression and health problems. The smartphone thermal imaging camera responds to the strict sanitary guidelines, offering contact-free, painless and non-invasive operation. Additionally, it is included in the group of low-cost solutions available for home use. It is an alternative to commonly used (often expensive and unavailable to everyone): EMG, ECG, EEG, GSR or other high-cost stress detection tools. Thermal imaging by analyzing abnormalities or temperature changes allows for detection application. Therefore, the aim of this work is to determine the possibilities of a low-budget mobile thermal imaging camera in detecting stress, detecting and analyzing stress by identifying the characteristics of psychophysiological signals with the individual characteristics of the participants, along with the correlation. The participants' reactions to the film introducing stress tension up to the climax of the action were recorded thermographically. Data was processed in OpenCV. In the usual observation, stress often remained unnoticed. However, the thermographic analysis provided detailed information on the impact of the film's stressful situation on the participants, with the possibility of distinguishing the stages of stress. The results of the preliminary pilot study were presented, which indicated the variability of temperature and heart rate as important indicators of stress – with the simultaneous significance of individual characteristics of the participant. Smartphone stress thermography is a promising method of monitoring human stress, especially at home.

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## 1. Introduction

Stress, as a state of imbalance, contributes to various mental diseases, e.g. depression, and physical diseases, e.g. pre-infarct heart conditions. Adequate control and reduction of stress, protects a person against loss of health and mental comfort. From an IT point of view, stress detection techniques based on the processing of psychophysiological signals, such as blood pressure [1, 2], facial gestures [3, 4], skin conductivity [5, 6], cortisol levels [7, 8] are very helpful. It is worth noting that the most popular solutions in the field of stress detection are based on the use of EMG, ECG, EEG, EDA, GSR or wearable sensors [9]. Unfortunately, the devices used in these solutions are often expensive, inaccessible to an ordinary person, requiring knowledge of the specificity of the devices – that is why they are often used mainly in research laboratories or by specialists. With this in mind, and noting the increase in stress due to a long-term pandemic situation (Covid-19), this article analyzes a low-cost detection solution focusing on the use of mobile (smartphone) thermography in recognizing stress. In the pilot study, the possibilities of a low-budget thermal imaging camera were examined, thermal recordings of participants in various states of stress induced by watching a stressful film were analyzed. Thermal imaging was also chosen due to its non-invasive and non-contact nature, which is important with the current strict sanitary guidelines. In addition, thermography overcomes the disadvantages of methods requiring the attachment of sensors or components of measurement tools to the body of the participants. The possibility of making a smartphone thermal imaging camera as a diagnostic (supporting) tool in home use is also important.

## 2. Related Work

The use of low-cost thermal imaging equipment to record important psychophysiological features may be disputed in terms of measurement accuracy. However, researchers [10, 11, 12, 13, 14, 15, 16, 17] confirmed the correctness of the use of a smartphone thermal imaging camera mainly in biomedical fields, during, for example: limb surgery [10, 11], infrainguinal vein bypass surgery [12], diagnosis of burns [13, 14], preliminary tests before surgery or subclinical tests [15, 16, 17]. In terms of detection of stress, the leaders are still known solutions using signals from the brain, heart, blood, etc. However, thermal imaging stress is also beginning to be in field of interest. Table 1 presents a list of selected, current research approaches in the field of stress detection. Selected thermographic approaches were also taken into account, which are analyzed in more detail later in this chapter.

Table 1. Summary of research approaches in the field of stress detection.

Authors	Stress signal	Method	Comments
Zubair M. et al. [2] (2020)	Cheap PPG sensor	QDA, SVM	Use of Mental Arithmetic Tasks (MAT) Use of the SFFS algorithm (Sequential Forward Floating Selection)
Can Y. et al. [18] (2020)	Smartwatch, EDA Explorer, Matlab	MLP, kNN, SVM	A hybrid approach to grouping stress on a personal level
Scherz W.D. et al. [19] (2020)	Mobile ECG	R peaks (heart signal), RR intervals	Portable ECG – preventive monitoring of heart signals
Cheema A. et al. [20] (2019)	PCG, ECG	LS-SVM	Use of the STAI Form Y questionnaire Use of the EMD technique Use of the Kruskal-Wallis test
Rizwan Md F. et al. [21] (2019)	ECG, EDR	SVM	Using data from the Physionet platform

Fernandez J.R.M et al. [22] (2018)	Bioradar BioRASCAN-4	RQA, Perceptron	Using RQA function from respiratory signals (previously used for heart rate)
Anishchenko L. et al. [23] (2020)	Bioradar	CatBoost	Improved detection method 89% accuracy
Cho Y. et al. [24] (2017)	Respiratory signals	CNN	Use of a thermal imaging camera (respiration variability spectrograms) Use of SCWT and Mental Computation tests Accuracy: 84.59% (binary), 56.52% (3-class)
Kaga S. et al. [25] (2019)	EKG, NIRS, NST	SVM	Use of near infrared spectroscopy 76.5% accuracy
Rachakonda L. et al. [26] (2018)	<i>iStress system</i>	Fuzzy logic Mamdari	Use of temperature, humidity and acceleration sensors 97% accuracy
Chandrasekaran S.T. et al. [27] (2020)	EKG, bio-inspired RC computer tank	RCML	RC consisting of 50 multiplex neurons Use of the WESAD dataset 93% accuracy
Meshram S. et al. [28] (2020)	Hybrid model + Twitter data	CNN	Use of data from social media (Twitter) A model that measures textual, visual and social attributes (based on factor graphics)

In the case of proposals involving thermal imaging, researchers use various types of thermal imaging cameras, mainly industrial ones. A stress detection system using a cheap thermal imaging camera has been proposed in [24]. Researchers focused on detecting respiratory signals, and their division was made by respiratory variability spectrograms (breathing without stress, with low stress, with high stress). Stress was induced by the SCWT and Mental Computation tests. Using the CNN classifier, 84.59% accuracy was achieved for the binary classification and 56.52% for the 3-class classification.

An interesting study that takes into account the correlation of stress with thermal changes in the face is presented in [29]. The thermal behavior of the face and differences in vascular and inflammatory responses caused by social stress were analyzed by examining 30 people (15 women and 15 men). At the same time, mean blood pressure, interleukin-6 was checked. The result of the analyzes (six areas of the face) was an increase in blood pressure and inflammatory activity in stressful situations at different levels in women and men.

The researchers [30] used the temperature patterns from the nose and forehead to determine stress in a non-invasive way. 9 participants were filmed while performing TSST tasks. In addition to determining ROI, the self-organizing maps of GHSOM and the Viola-Jones classification were also used. Temperature in ROI areas was extracted as a function of time in order to identify patterns of stress build-up.

In [31], the focus was on the detection of physical stress through hyperspectral imaging (HSI) of the saturation of facial tissues with oxygen (StO<sub>2</sub>). In 20 participants, the level of StO<sub>2</sub> was analyzed, simultaneously determining 5 regions of interest (ROI). SVN and 5-fold validation were used for the classification. The combination of five ROIs allowed for the achievement of the highest stress recognition rate at 82.11%.

The stress load measured by ECG, near infrared spectroscopy (NIRS) and nasal temperature (NST) has been proposed in [25]. For the extraction of features and selection of biosignals, the random forest method and the

stepwise method (STEP) were used, and SVM – for the classification of the stress state. As a result of model learning, 76.5% accuracy was achieved and the usefulness of NST in stress detection was justified.

It is also worth noting the works containing extensive reviews of the literature relating to machine learning techniques in stress research [32, 33] as well as taking into account the use of low-cost sensors along with machine learning [34] and smartphones and wearable sensors [35].

### 3. Material and Methods

#### 3.1. Purpose and assumptions of the pilot study

The current, pandemic situation in the world and the phenomenon of increased stress in people (the result of an uncertain future, helplessness, limitation of human contacts) were the motivation to undertake research focused on the detection and analysis of stress using low-budget household devices. The ability to check reaction to stressful situations and analyze it at home becomes an alternative to the laboratory approach. Self-awareness is very important, and in the case of stress – also preventive, as controlling stress can prevent depression or contributing to illness (both mentally and physically).

In connection with the above, the topic of stress detection and analysis was undertaken, adopting three criteria: the use of thermal imaging, the use of low-cost devices, and home use. As part of the pilot study, it was decided to: check the detection capabilities of the mobile (smartphone) thermal imaging camera, test the available methods of detecting features from images and video (thermal video is demanding), register and analyze the stress caused by a stressful film in the participants, observe and indicate the correlation of parameters, changes in temperature and distribution over time.

#### 3.2. Measuring tools

The Flir One Pro mobile thermal imaging camera was used in the pilot study. Offering 4x native resolution, this device provides sharper images enhanced by Flir VividIR™ image processing. Measuring temperatures in the range of -20°C to 400°C (-4°F to 752°F), it allows for precise detection of thermal objects (up to 35m). A thermal imaging camera is quite sensitive equipment – it is required that the test sites have a constant temperature of approx. 21°C, no additional heat and light sources, no air drafts, with a minimum air humidity of 50%. The Flir camera models capture temperature differences up to 70 mK, which means that quantitative and in-depth measurement is possible.

Another device used in the study is the ART Hankfit S-FIT18 fitness smartband. Through the modes: heart rate monitor and blood pressure monitor, the pressure and pulse of the participants were monitored.

#### 3.3. Research procedure

Seven volunteers aged 18-59 (three men, four women) were invited to participate in the pilot study. One of the participants had a visual and motor dysfunction (disability), while one participant reported stress nervousness, so she needed more time to acclimatize and calm down before the research.

In accordance with the research procedure, at the beginning the participant was acclimatized in the home room. In order to reduce stress with the study itself, before the study the participants were interviewed, trying at the same time to make them relax and take a calm approach to the study. It was ensured that the temperature in the room was 21°C, humidity 50%. It was also checked if the participant had no additional emissivity sources, e.g. clothes with reflectors. Then, the participant sat down in front of the monitor to which a smartphone with a thermal imaging camera was attached. Due to the fact that it was important to register the entire face, the camera had to be located close to the participant's face – max. 50cm from the face. In some of the participants, this fact resulted in partial obstruction of the right eye and reduced comfort of watching the video. An important issue was to calibrate the camera. Immediately after recording with the camera, the participants were asked for a questionnaire interview, in which they indicated the moment of feeling the strongest stress, assessed the level of feeling stress during the video projection on a 1-10 scale, and then received feedback on their reaction. The data was obtained thanks to post-processing in OpenCV – the main stages of operation are shown in Figure 1 (general stages).

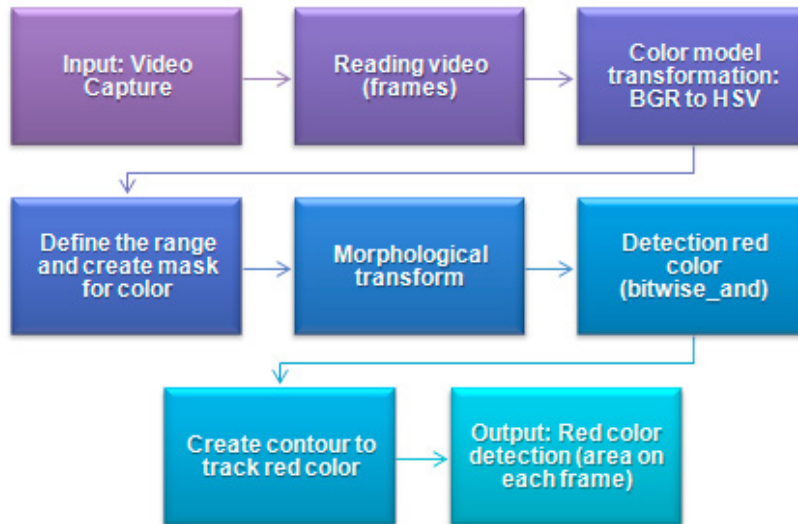


Fig. 1. Main stages of post-processing in OpenCV.

#### 3.4. Research registration – testing methods

The temperature distribution on the face with changes over time is the basis for the detection of this study. Facial features (especially the temperature) change over time. So it was considered right to test several face identification algorithms by checking their operation on thermal recordings. The methods tested were: feature cascade with Haar classifier, model 68 face landmark detection, HOG feature detection, face point detection with shape predictor, ROI drawing with frame comparison, real-time detection of one or more colors. Unfortunately, most models incorrectly recognized the thermal features of the face or did not indicate areas of changes. The most appropriate method for the pilot study turned out to be the method of detecting areas of the dominant color, with a variable range – in this case, the red color.

#### 3.5. Selection of the detection method and video post-processing in OpenCV

The method of color detection with the greatest dynamics of changes (in this case the range of red color) was the basis of the thermal analysis in this study. The aim of the analysis was to locate and control areas in the red color range, which showed the highest dynamics of changes in video frames. Thermal video post-processing was done in OpenCV. The stages of data processing in OpenCV include, among others: video conversion from BGR to HSV model, masking, morphological transformations, defining boundaries for the color with the highest change dynamics. It was important to obtain information on the temperature variability of the face in a stressful situation (from the moment of stress arousal, through the culmination of stress, to the return to normal state) and the location of the most active areas of the face during a stressful situation. Figure 2 shows the view of selected frames with the detection of face areas with red color variation (temperature variation at the same time).

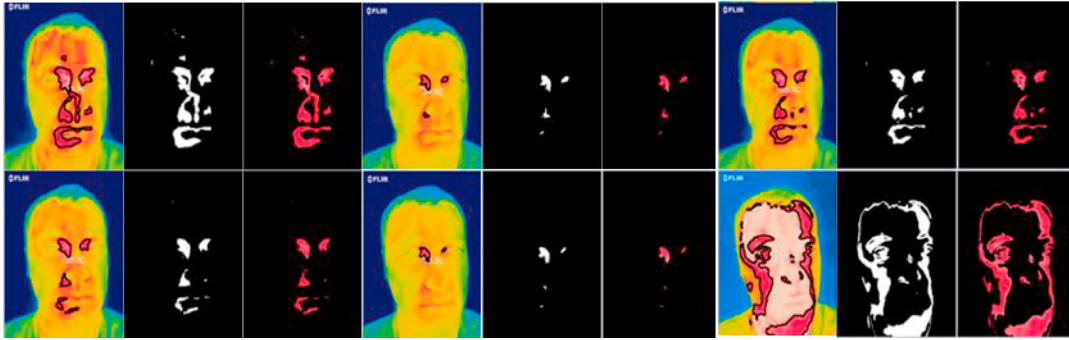


Fig. 2. Thermal recording view of selected frames with masks and areas of red color (using OpenCV).

#### 4. Discussion and Results

As a result of the pilot study, the detection capabilities of a smartphone thermal imaging camera were confirmed. The registration detail regarding the temperature of the facial area, visible during the analysis of the frames of the thermal recording, allowed determining the correlation between the temperatures and the responses to increasing stress. The main notable correlation is the increase in temperature in the forehead, eyes, nose and mouth areas with increasing stress tension. This is the result of increasing the blood supply to the face as a result of the body's response to stressful situations. It is important that a stressful film can be divided into 3 phases: introducing and building stressful tension (00:00-1:45), climax (approx. 1:50) and the recovery phase. The culminating action in the film translated into the culmination of participants stress and the achievement of the greatest temperature change in the entire face. Immediately afterwards, there was a return to normal, noticeable by the temperature shift of the facial areas towards the input parameters. Figure 3 shows the view of changes in the red areas on the face of the selected participant (selected frames of the thermal recording) and the graph correlating with the projection of stress phases. For the detailed analysis, in OpenCV in a single frame of the recording, the following values were also calculated: mean, medians, sums – for red in HSV, in order to check compliance with the values of red areas.

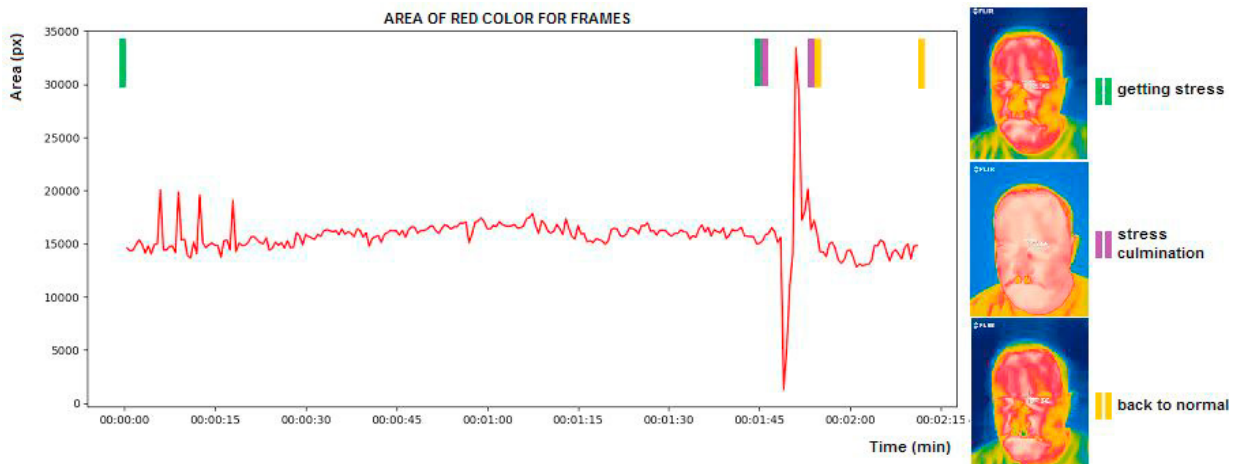


Fig. 3. Red area changes through the thermal recording and phase of stress video.

Tab 1. Pilot study results – red color area values and physiological values (received from OpenCV).

Person	Red areas values (pixels)					Before the research		After the research		Feeling stress level (scale 1-10)
	Min	Max	Start	End	Stress spike (S/C/E)	Pressure BPM	Pulse MMHg	Pressure BPM	Pulse MMHg	
1	2257	25661	9441	15279	21012/2257/24229	69/117	67	70/120	71	9
2	3605	23506	13679	11978	18879/3605/23145	70/108	83	68/118	80	8
3	91	25690	3608	10289	198/25690/8967	69/117	75	77/120	88	6
4	7785	35034	15685	23952	31847/7785/29506	71/116	88	74/116	90	10
5	1277	33421	14594	14817	15609/1277/33421	72/108	98	76/112	96	8
6	2083	40165	13675	17627	13482/2083/40165	66/116	78	74/117	84	7
7	3821	31318	27689	22288	23571/3821/23203	77/108	82	75/105	83	10

Table 1 shows the results for the red areas on the face of the participants – at the beginning of the test (*start*), at the moment of stress culmination (*stress spike S/C/E*), at the end of the registration (*end*) and values: *min*, *max*. The designation S/C/E means: *S-start*, *C-center*, *E-end* and refers to the culmination of stress, where there is a sudden and temporary change in the face temperature value. Information on the pulse and pressure of the participants was also included. When analyzing the data from Table 1, it can be seen that in 71% of the participants the value of the red color area was much higher at the end of the study than at the start, even though the input values for red seemed to be large. This large change correlates with increased psychophysiological activity due to stress. It is also visible in the field of pressure and pulse, where the parameters of the participants usually increased with the stress tension, and after the test parameters tended to normal. The participants' feelings about the stress level correlate with the level inferred from the analysis of frames – the stronger the stress reaction, the greater the perceived level of stress. After the study, the participants were additionally asked about the moment when they felt the greatest stress and how they felt at the beginning and at the end of watching the video. Everyone confirmed that the greatest stress appeared with the climax of the action on the video. From the beginning of the video, they experienced increasing stress levels, and the climax allowed them to maximize the stress and return to stress-free normality. It is also important that the participants appreciated the home conditions of the study, stating that in the laboratory conditions they would feel the additional stress of the study site.

## 5. Conclusions

Stress is a significant problem of the modern world, and during a pandemic – even an inseparable element of everyday life. Therefore, in the field of stress detection, researchers should focus on solutions that offer low-cost, availability (especially at home), speed of stress detection for analysis, neutralization or elimination so that there is no chronic form of stress (very destructive). In the era of the popularity of smartphones, increased use of thermography, increasing stress (increased temperature measurements and stress due to Covid-19), the author considers the use of smartphone thermal imaging very right. A low-budget, smartphone thermal imaging camera provides solid possibilities of recording thermal changes caused by stress, which was confirmed by a pilot study. In a controlled home environment, the research could go on without interruption. Conducting a similar study, but in typical real conditions (inside/outside the room, during household activities) requires many thoughtful decisions taking into account the specificity of the thermal imaging camera in the smartphone version or the recommendations of psychologists regarding the personalization of models adapting to the individual differences in the perceived level of stress. Thermal data obtained by mobile was characterized by very good registration detail. This translated into effective data processing in OpenCV, allowing to observe the dependence of changes in physiological signals on the feeling of stress. The individual characteristics of the individual and their optimal level of feeling stress, which is quite subjective, are important. However, the analysis of the frames of thermal recordings showed a correlation – the stronger the stress reaction, the greater the perceived level of stress and the variability of the values of physiological signals. In the field of stress thermography, the author plans further research activities taking into account aspects, including: the impact of external and internal factors on human stress (e.g. climate change, development of civilization), adaptation of the mobile thermal imaging camera for health control at home, differentiation of the level



of individual stress in the field of psychological and IT, developing a system of multi-level classification of stress states, creating thermal data processing algorithms with the integration of selected physiological features.

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