A Survey on Extracting Physiological Measurements from Thermal Images

Christian Hessler
Computer and Information Science
University of Michigan, Dearborn
Dearborn, MI, USA
cahessle@umich.edu

Mohamed Abouelenien
Computer and Information Science
University of Michigan, Dearborn
Dearborn, MI, USA
zmohamed@umich.edu

Mihai Burzo
Mechanical Engineering
University of Michigan, Flint
Flint, MI, USA
mburzo@umich.edu

ABSTRACT

Multiple techniques are used to extract physiological signals from the human body. These signals provide a reliable method to identify the physical and mental state of a person at any given point in time. However, these techniques require contact and cooperation of the individual as well as human effort for connecting the devices and collecting the needed measurement. Moreover, these methods can be invasive, time-consuming, and infeasible in many cases. Recent efforts have been made in order to find alternatives to extract these measurements using non-contact and efficient techniques. In this paper we provide a survey that explores different approaches for extracting vital signs from thermal images as well as review applications that could potentially leverage these techniques.

CCS CONCEPTS

• **Computing methodologies → Artificial intelligence**;

KEYWORDS

Physiological, Thermal, non-contact, human behavior

ACM Reference Format:
Christian Hessler, Mohamed Abouelenien, and Mihai Burzo. 2018. A Survey on Extracting Physiological Measurements from Thermal Images. In *PETRA '18: The 11th PErvasive Technologies Related to Assistive Environments Conference, June 26–29, 2018, Corfu, Greece.* ACM, New York, NY, USA, 8 pages. https://doi.org/10.1145/3197768.3197792

1 INTRODUCTION

In recent years there has been a growing interest in developing automated systems that are capable of monitoring human physiological responses in order to provide a real-time assessment of a person's general health and well-being. Such measurements include heart rate, temperature, respiration rate, among other skin responses. With the proper assessment, these physiological measurements can identify the physical and mental state of a person. In addition, the fact that the human body often exhibits unique physiological characteristics in response to external stimuli, made it possible to detect and predict a person's behavior or psychological state, such as emotions, mood, stress level, distraction, and deceit. Hence, different studies are exploring the feasibility of incorporating physiological monitoring into a wide array of different applications.

However, there are limitations to the traditional methods and devices used to collect physiological measurements, such as the requirement to connect the devices and sensors to the human body. Attaching these sensors can be time consuming, uncomfortable, and impractical for certain applications. Devices such as ECG sensors require electrodes to be attached to specific areas of the body. These devices can cause discomfort and may require the presence of trained personnel to set up the device. Other sensors may introduce noise if leads do not have solid contact with the skin. Even worse, some sensors may not provide reliable measurements outside of a controlled environment. [23] designed a network for monitoring patients' vital signs during health emergencies. The authors noted that exposure to cold temperatures restricts blood flow to the fingers which can disrupt pulse oximeter readings collected from a finger sensor. Therefore, new approaches are proposed to avoid the usage of wearable sensors to collect such data. In particular, thermal image processing has been proposed as a potential method for acquiring physiological data.

Vital sign monitoring systems generally monitor blood glucose level, blood pressure, pulse rate, electrocardiograph patterns, respiration rate, and temperature [67]. Certain vital signs are thought to be better indicators of specific physiological abnormalities than others. Researchers explored ways to harness physiological data for applications in a number of areas, such as health care, sports, military, and surveillance. Moreover, physiological monitoring may be more effective at diagnosing certain disorders that are difficult to diagnose from external symptoms alone.

For instance, heart rate is useful in diagnosing cardiovascular disease (CVD), which is a leading cause of death worldwide. In particular, there is evidence linking resting heart rate to CVD risk factors such as hypertension, obesity, family history and work stress [60]. Another example can be seen in studies suggesting that changes in the respiratory rate may be a more effective measure for discriminating between stable patients and those that are at risk. In fact, evidence suggests that an adult with a respiration rate of over 20 breaths per minute (bpm) is probably unhealthy, while an adult with a respiration rate of over 24 bpms is likely to be critically ill [17]. Irregular increases in respiration rates have been observed in patients suffering from panic attacks and sleep bruxism (teeth grinding) [33, 44]. Taking more than one vital sign into account has also proven to be beneficial in diagnosing certain ailments. There is evidence indicating that elevated heart and respiration

PETRA '18, June 26–29, 2018, Corfu, Greece

ACM ISBN 978-1-4503-6390-7/18/06…$15.00
https://doi.org/10.1145/3197768.3197792

rates observed immediately after trauma are acute predictors of delayed post traumatic stress disorder [12].

Skin is another vital organ that receives signals from control centers in the brain to maintain the body's core temperature through a process called thermoregulation [18]. Physiological thermoregulation in humans comprises changes in heat dissipation (sweating) and heat generation (shivering) in response to various internal and external thermal stimuli [15]. Thermal imaging utilizes this principle to detect natural thermal radiation emitted by the skin, which can be interpreted in terms of physiological changes [30]. Skin conductance is another physiological measurement that refers to the varying electrical properties of the skin in response to sweat secreted from eccrine sweat glands [61]. The skin becomes more conductive as sweat accumulates. This process reflects the arousal of the sympathetic autonomic nervous system which accompanies various psychological processes [21].

While the usage of thermal images to detect peripheral skin temperature is apparent, recent research has shown interesting potential of using thermal images to extract multiple physiological signals from the human body. In this paper, we provide a survey of the approaches proposed for that purpose as well as a number of applications that can benefit from these techniques.

2 EXTRACTING PHYSIOLOGICAL FEATURES

This section presents different methods for extracting heart rate, respiratory rate, skin temperature, and skin conductance from thermal videos. Many of these techniques use a procedure called Eulerian Video Magnification (EVM), which can reveal hidden information by magnifying subtle color changes and imperceptible motions using spatio-temporal processing [65]. This process can indicate subtle variations in the blood flow through the face.

2.1 Heart Rate

Several studies have proposed methodologies to extract heart rate from thermal images by tracking superficial blood vessels on the face. Blood flow regulates skin temperature due to heat exchange between vessels and the surrounding tissue. These changes in skin temperature are most prominent along superficial blood vessels. Extracting the blood vessels from the face is often challenging due to the low contrast between the edges of the blood vessels and the surrounding facial tissue. This is a result of heat diffusion, which creates a smooth gradient temperature between hot and cold areas. Fortunately, there are several methods for segmenting blood vessels from the face to create what is known as a vascular map. Figure 1 demonstrates one such example using a technique called white top hat segmentation. There are two forms of top hat segmentation: white top segmentation enhances bright objects and black top hat segmentation enhances dark objects. White top segmentation is effective for enhancing the ridge-like structures of the blood vessels, which are represented by hot or bright areas in the image [13].

The thermal signal detected along a blood vessel presents a composite signal that includes extraneous physiological and environmental signals in addition to the pulse [24]. [58] proposed a method to extract the pulse by applying a Fast Fourier Transform (FFT) to several points along the blood vessel in order to isolate the thermal propagation component. They followed this by using an

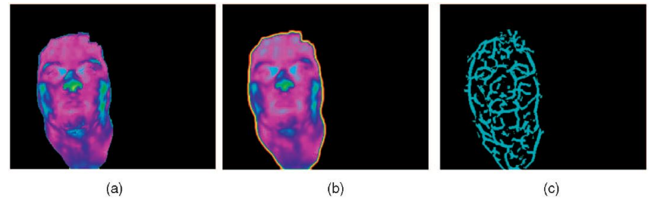

Figure 1: Example of vascular mapping extraction. (a) Original segmented image, (b) Anisotropically diffused image and (c) Blood vessels extracted using white top hat segmentation. Figure from [13].

adaptive estimation function to quantify the pulse based on current and past measurements. The authors were able to achieve an overall accuracy of 92.1% based on ground truth measurements collected from a piezoelectric pulse transducer.

In [25], the authors introduced several improvements based on previous work [13, 16, 26, 27, 57, 58]. First, they incorporated a blood-perfusion model to more accurately create vascular maps, segment the forehead, and enhance the raw thermal data. Second, once they identified suitable blood vessels on the face, they applied wavelet based filtering in place of FFT analysis. In the final step they were able to automate the entire process by presenting a systematic approach to select appropriate vessel segments from the vascular map.

A slightly different approach was taken in [10] for extracting heart rate by applying the EVM method to thermal videos. The goal of their research was to remedy the fact that EVM may amplify indiscriminate noise in addition to the true heart rate signal. In their experiment, the subject wore a smart shirt (a shirt containing various textile sensors) to capture the ECG signal while a thermal camera recorded video of the subject. They applied two passes of EVM. The first pass applied a wide band pass filter with a low amplification factor to identify the region of interest (ROI) most likely to reveal the true heart rate. In this case, the subject's chest was defined as the region of interest. The second pass applied a narrow band pass filter with a high amplification factor to the signal acquired from the ROI. Figure 2 reveals that the resulting signal was highly correlated with the true heart rate signal collected from the smart shirt.

2.2 Respiration Rate

Many methods have been proposed to extract respiration rate from thermal videos using different combinations of image processing and facial tracking techniques. Figure 3 depicts a common procedure for extracting physiological features from facial thermal images. This begins with image correction and enhancement in order to make certain features more distinguishable. Examples of image enhancement techniques were briefly discussed in the previous section. A facial detection algorithm is often employed to segment the face from the background image. Once the face has been isolated, regions of interest (ROI) are defined in order to focus on particular areas of the face that are known to display the desired thermal characteristics. Finally, a variety of image processing techniques are applied to the ROI in an attempt to find a

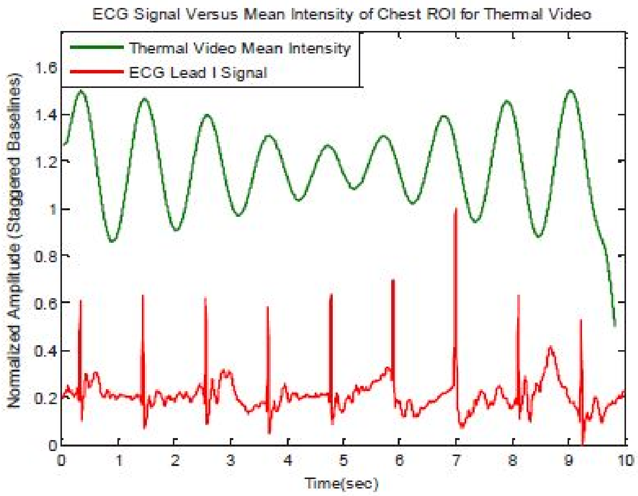

Figure 2: Thermal video ROI mean intensity signal (EVM bandpass filter 0.75 to 1 Hz) versus ECG signal. Figure from [10].

correlation between the temporal features within the thermal and physiological domains. [11] followed this procedure to compare temperature-based methods to motion-based methods for extracting respiration rate from thermal videos. The temperature-based method employed segmentation-based image processing and image tracking algorithms to capture temperature variations over time. They presented a variety of pre-processing methods including image enhancement, noise removal, edge-detection, and facial recognition, all of which were used to identify the subject's nostrils as the ROI. The respiration signal was then calculated as the mean intensity within each ROI subjected to low pass filtering to remove noise.

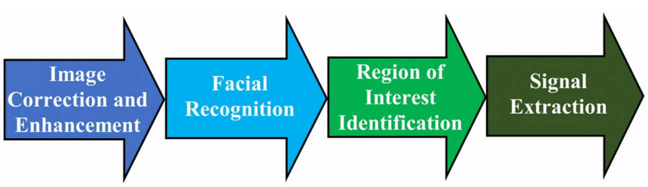

Figure 3: Image Processing Procedure. Figure from [11].

The motion-based analysis was carried out by simply calculating the absolute differences between the first frame and all succeeding frames, then once again applying a low pass filter to remove noise. The temperature-based analysis worked better for detecting the volume of airflow while the motion-based analysis provided better results for detecting irregular breathing, such as hyperventilation and the absence of breath. Neither method outperformed the other in detecting the respiration rate for all breathing patterns. Hence, the authors recommended the development of fusion algorithms that could combine multiple methods for extracting respiration rates from thermal videos.

[9] developed a facial tracking method to monitor respiration rate in real time. One departure from previous work was the use of an Otsu-based thresholding algorithm to segment the face from the background image. Figure 4 demonstrates the performance of various thresholding algorithms. Tsai's method under-segmented areas below the neck and even part of the face. Kapur's method performed slightly better but still under-segmented areas below the face. The Otsu method proved to be the most effective and was even efficient enough to allow for real time face detection and tracking. Lastly, they applied noise filtering techniques and FFT to extract the respiration rate from the ROI. This system was able to process each frame in 40ms, making the system feasible for deployment in real-time applications. Other studies followed a similar procedure to extract the respiration rate using different methods to perform noise removal and signal processing. Additional methodologies for extracting the respiration signal include clustering and harmonic analysis [66], wavelet analysis [20] and high pass filtering [35].

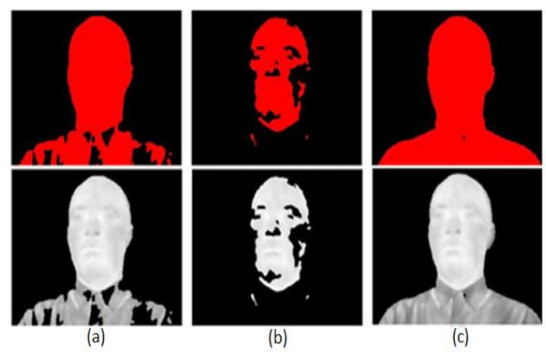

Figure 4: A comparison of thresholding methods (a) Kapur's, (b) Tsai's and (c) Otsu's. Figure from [9].

2.3 Skin Temperature

Body temperature depends on core temperature and skin temperature. Generally speaking, core temperature is the temperature of the blood in circulation, which is regulated by the brain, whereas skin temperature is primarily influenced by blood flow and environmental conditions [36]. Heat stress is a condition in which skin blood flow increases, followed by a rise in skin temperature, which releases heat from the body. Cold stress describes the opposite effect in which skin blood flow and temperature decrease, actively conserving heat in the body. This is the process by which the human body is able to maintain a constant core temperature. Modern high resolution thermal cameras have given researchers the ability to observe physiological thermal regulatory response in real time.

A significant variation in body temperature is often an indication of illness such as fever or hypothermia. In the interest of preventing the spread of disease, several studies have explored the feasibility of designing fever-based detection systems for use in airports and mass transits [41, 56]. The literature also discusses the many challenges involved in designing such a system. As of writing, the only reliable way to acquire an accurate core temperature reading is to measure temperature from the rectum or esophagus [39]. In spite of this, several studies have reported the inner corners of the eyes to be the most suitable area for fever detection [42].

There is also a desire to better understand the relationship between thermoregulation and athletic performance in sports medicine. [59] recorded thermal videos of athletes running on a treadmill as well as their resting states before and after the exercise. Surprisingly, the skin temperature of the athletes began to decline immediately upon starting to run even at low speeds. A continuous increase in exercise intensity caused the skin temperature to decrease even further. On the other hand, thermal images of the athletes during motionless recovery revealed a rapid increase in skin temperature as well as the appearance of hyper-thermal spots as shown in Figure 5. The hyper-thermal spots are most likely a sign of vasodilation caused by a reduction of warm blood flow to active muscles. These findings are supported by the results of previous work done by [40], in which the skin temperature of trained and untrained subjects was recorded during exercise. Their results revealed that the minimal skin temperature of trained subjects was significantly lower than those of untrained subjects when they stopped exercising.

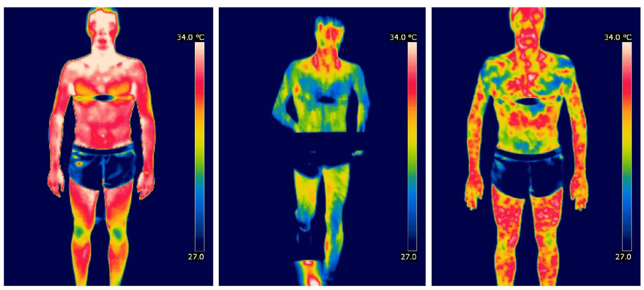

Figure 5: Infrared thermal images of the anterior body during graded load exercise.
From left to right: before exercise, during 15min exercise, and immediately after exercise. Figure from [59].

Thermal images clearly reveal variable amounts of heat radiating from different areas of the human body during periods of rest and physical labor. However, research shows little variation in facial skin temperature in response to cold stimuli and corresponding changes in core temperature. In [29], subject's skin and core body temperatures were measured using thermocouples and an ingestible thermometer pill. When the subjects were exposed to a cold environment, skin temperatures of the hands and feet decreased substantially while the forehead remained reasonably constant. This poses a difficulty for applications that hope to extract body temperature from thermal facial images alone.

2.4 Skin Conductance

To the best of our knowledge, limited experiments have been conducted to extract skin conductance via thermal imaging. Electrodermal activity is usually described in terms of tonic and phasic components. The tonic component of skin conductance is the absolute level of conductance at a given moment in the absence of phasic response. Phasic components are defined as decreases in resistance, which are superimposed on the tonic component [18]. Many papers will refer to the tonic and phasic components as the skin conductance level and skin conductance response, respectively. One such study has explored the idea of extracting the galvanic skin response signal strictly from thermal images. [55] measured three areas for sympathetic responses, which were the periorbital (area around the eyes), supraorbital (forehead), and maxillary (jaw) regions. For the ground truth measurements, the authors collected data from GSR and thermistor sensors attached to the palm, given that sweat gland activation is considered to be strongest in the palm during periods of arousal. A Laplace distribution was then used to model the GSR signal in order to fit the exponential fluctuations that occur during arousal states. Moreover, the authors used wavelets to analyze the thermal and GSR signals at different frequency scales without loss of time information. They concluded that the maxillary channel contains enough information to detect sympathetic response nearly as well as the GSR channel measured from the palm.

In some cases the wavelets of the GSR and periorbital signals displayed nearly identical response timing and overall trend. However, precise estimation is difficult due to residual noise caused by errors in tracking and segmentation. [34] proposed a technique for measuring eccrine sweat gland activity from thermal images by counting the number of active pores on the surface of the skin on subjects' fingers and faces. They designed an algorithm to identify active pores within a predefined ROI using a matched filtering technique and a 7 x 7 pixel template representing an active pore. ROIs on both the fingers and face were manually defined to only include relevant skin surfaces. Hence, regions of the face containing features such as hair, eyes, nose, and mouth were excluded in order to reduce the false-positive detection rate. The results revealed that pore activation response (PAR) on the face was consistent with PARs from the fingers. Furthermore, the highest levels of pore activity on the face were observed on the lips, the nose, cheeks, brow line, and forehead. Another interesting observation was that the thermal profile of an activated pore was much larger than the size of the actual pore.

3 APPLICATIONS

In this section, we review some of the applications that extracted multiple features from thermal images in order to achieve their goal. Most of these applications are related to modeling of human behavior. Some of them integrated these features with contact-based physiological measurements and, hence, they can potentially benefit from the aforementioned techniques.

3.1 Deception Detection

Polygraph testing remains the standard tool used by law enforcement in the U.S. to verify whether or not a subject is telling the truth during questioning. Polygraph tests monitor the subject's blood volume pulse, respiratory changes, and electrodermal activity. Employing polygraph tests was shown to be unreliable in many cases as it requires decisions from human experts, which is subject to bias and error [19, 22]. Reports dating back three decades indicated that polygraph results were false one third of the time [37].

Hence, research was conducted to find alternatives, including the usage of thermal imaging as a mean for deception detection. Most experiments in this field begin by establishing the baseline physiological characteristics of the subject prior to the interview. This generally involves asking the subject a series of control questions designed to elicit a particular physiological response. However, research suggests that guilty subjects who are trained on using physical or mental countermeasures are able to defeat polygraph tests by corrupting the initial baseline measurements [28]. Hence, additional information collected from thermal images have the potential to improve the reliability of deception detection models.

In [45], a method was described for classifying a person's responses as deceitful or truthful based on changes in blood flow rate as observed from thermal images of the person's face. In this method, raw thermal data was transformed into blood flow rate data using a number of different processing techniques, such as segmentation algorithms and heat transfer modeling. Although different regions might be used, [46] found that the periorbital region (area around the eyes) carried the most significant discriminating power. They observed that the slope of the periorbital blood flow rate as a function of time grows steeper during a deceptive answer.

Accuracy of thermal imaging as a lie detection tool in airport screening was tested in [63]. Their results revealed that the skin temperature of liars rose significantly during the interview, whereas, the skin temperature of truth tellers remained constant. Baseline measurements did not reveal any significant difference between passengers who were instructed to tell the truth and those who were instructed to lie. Therefore, the authors concluded that deception detection systems based on skin temperature alone would not be suitable for rapid screening of passengers at an airport.

[52] is another study that analyzed the periorbital region of the face to perform automated deception detection. They tracked two eye corner regions as shown in Figure 6, concatenated the ROI data across all frames within the response time-line, and finally applied principal component analysis to obtain thermal features. One unique aspect of their research was the fact that they compared the predictive ability of a within-person classification to a between-person classification. A between-person approach was shown to have poor predictive performance. The authors explain that a leave-one-person-out cross validation method assumes that behavior and physiological responses are common traits among people of various ages, genders, culture, etc. On the other hand, the within-person approach trains a classifier specific to each subject using the aforementioned baseline measurement as training data. Their model was able to achieve an overall accuracy of 87% using a k-nearest neighbor classifier.

More recent studies propose the use of fusion models that incorporate features from more than one modality [1, 3–7, 14, 48, 49]. The authors analyzed thermal videos, facial expressions, and other visual features to identify areas of the face that are the most indicative of deceptive behavior. Their approach generated feature vectors by transforming each ROI into a thermal map represented by the Hue Saturation Values pixel representation. In contrast with previous work by Pavlidis, they found that thermal features extracted from the forehead region were the most effective for discriminating between truth and deceit. This may be attributed to the different methods that were used to extract thermal features; heat transfer modeling versus thermal mapping.

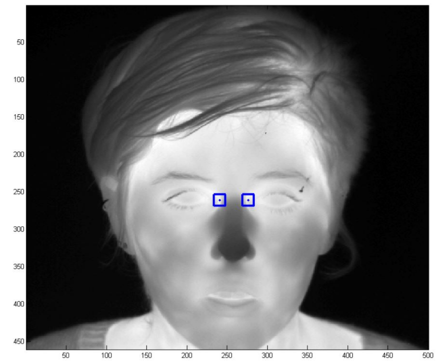

Figure 6: A thermal image of a participant's face during questioning. The left and right eye corners were defined as regions of interest for tracking. Figure from [52].

3.2 Emotion Recognition

Many studies in the literature have explored the use of thermal imaging for classifying human emotions. The study of affect states and arousal levels is an emerging topic of interest in both neuroscience and affective computing. However, there are conflicting theories that attempt to explain how nuerophysiological systems activate different emotional states. Recent studies in affective computing have designed classification methods based on a relatively recent idea in nueroscience known as the circumplex model. "The circumplex model of affect proposes that all affective states arise from cognitive interpretations of core neural sensations that are the product of two independent neurophysiological systems" [50]. This model is based on the idea that emotional states are not discrete categories but rather a result of varying degrees of arousal and valence as shown in Figure 7.

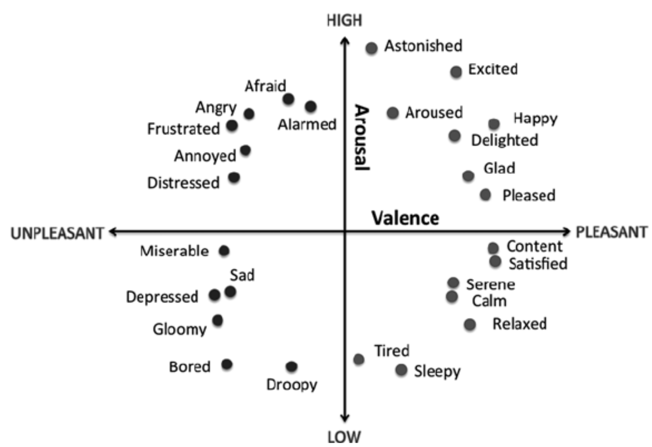

Figure 7: Two-dimensional model of valence and arousal. Figure from [62].

[43] designed a binary classifier to distinguish baseline thermal states from affective states. Facial thermal infrared data, blood volume pulse, and respiration rate were recorded while subjects were shown visual stimuli designed to elicit different affective states.

Arousal and valence levels during stimulus onset were measured using the International Affective Picture System. The Periorbital, supraorbital, and nasal regions of the face were selected and tracked as regions of interest. Wavelet analysis was used to extract features and remove noise from the thermal infrared data. Finally, a genetic algorithm was used to select optimal features to be used for training a linear discriminate analysis classifier. This classification procedure was able to achieve accuracies of 80% and 75% in classifying high and low levels of arousal and valence from the baseline, respectively.

Other studies took advantage of the fact that different facial expressions are generally associated with certain emotional states. Research has demonstrated that thermal cues may provide a more effective means for recognizing facial expressions compared to visual cues. In [64], a thermal-based facial expression classifier outperformed a visual based classifier due to the fact that thermal images are unaffected by variations in illumination and skin complexion.

[32], leveraged the findings of these two studies to develop a unique classification algorithm. Instead of using a binary classifier, they chose to use a clustering algorithm to model affective states as clusters in a multi-affect and multi-arousal discriminant space. The thermal images were analyzed using accompanying visual images to find points along major facial muscles that displayed the greatest thermal variation. Previous research explains this method for acquiring Facial Thermal Feature Points [31]. Principal Component Analysis and Linear Discriminate Analysis were used to perform dimensionality reduction and feature selection. The resulting facial thermal vectors are used to construct a smaller feature space. The authors used the distance between the optimal feature vectors and the centroids of arousal levels for affect assessment. Their thermal expression recognition system was able to correctly classify approximately 96% of happy and sad expressions.

3.3 Stress Detection

"Following the perception of an acute stressful event, there is a cascade of changes in the nervous, cardiovascular, endocrine, and immune systems" [53]. Furthermore, clinical studies have demonstrated relationships between psycho-social stressors and diseases, such as cardiovascular disease, upper respiratory diseases, immunodeficiency and depression [38, 53]. Physiological responses to stress may include an increase in blood pressure, redirected blood flow, and vasoconstriction as well as dilated pupils, accelerated heart rate, paling or flushing in the face, and an increase in perspiration [68].

Research has successfully demonstrated the use of thermal imaging to detect the onset of stress from observing physiological changes in subjects' faces. Different activities produce distinct facial thermal patterns. Thermal videos of anxious subjects who were exposed to stressful situations revealed an increase in temperature around the eyes and forehead as a result of heat dissipation caused by increased blood flow [47, 51].

Recent studies have classified these thermal physiological markers to develop automated stress detection algorithms. [54] analyzed spatio-temporal facial patterns in videos captured from both the thermal (TS) and visible (VS) spectrums. Subjects were recorded watching stressful and calming video clips. The authors extracted features from the videos using a technique known as local binary patterns on three orthogonal planes (LBP-TOP). This method was specifically used to analyze the temporal dynamics of muscle movements by extracting features, which incorporated appearance and motion. In addition, they proposed a new feature set to model thermal images, which captured normalized dynamic thermal patterns in histograms (HDTP). The goal of this method is to enhance participant-independent recognition of symptoms for stress and to reduce individual bias. The HDTP features extracted from the thermal videos produced better stress recognition rates compared to the LBP-TOP features used for binary classification. A fusion of HDTP and LBP-TOP features extracted from TS and VS video, respectively, achieved the best results with a recognition rate of 72%.

In [2], contact-based physiological measures and facial thermal images were used to train a stress detection classifier. Ground truth measurements were based on the perceived stress of subjects in stressful situations. Thermal features were extracted using a variety of methods to perform face segmentation, tracking, and transformation. Facial bounding boxes were manually defined, the Shi-Tomasai corner detection algorithm was used to identify discriminating points within the face. A fast Kanade-Lucas-Tomasi (KLT) tracking algorithm was used to track the points throughout the entire response. The background in the image was discarded using image binarization and cropping. Lastly, features were extracted by creating a thermal map in which hue saturation value (HSV) colors represented temperature values. HSV values were organized in a histogram and normalized to form a probability distribution over all bins. Moreover, the thermal features were integrated with the contact-based physiological features including the heart rate, respiration rate, skin temperature, and skin conductance. They trained a decision tree classifier using their features, which was able to detect stress with an accuracy of 75%.

4 OUR SUGGESTED APPROACH

The research presented throughout this paper has laid the groundwork for designing applications to extract and analyze physiological data contained in thermal facial images. We wish to build upon our previous work [2, 3, 7, 8] in order to develop a non-contact approach for extracting high resolution physiological features from thermal videos, namely heart rate, respiration rate, skin conductance and skin temperature. These features can be integrated with additional thermal features to develop reliable non-contact classification systems. In particular, our goal is to design a multi-modal feature extraction system to aid in the development of non-contact health monitoring applications.

5 CONCLUSION

There are numerous benefits associated with the use of thermal imaging for health monitoring and modeling of human behavior. Recording thermal video is far more convenient compared to attaching multiple sensors to the body. Contact-based sensors and electrodes attached to the body may cause discomfort, which can alter the subject's physiological state. Thermal cameras, on the the other hand, are unobtrusive and therefore less likely to influence the subject or introduce bias. Moreover, thermal cameras can potentially screen people in seconds compared to the time-consuming task of outfitting someone with an array of sensors. Modern technology is facilitating the development of real-time thermal imaging systems that are sensitive to minute variations in skin temperature.

The literature suggests that the skin's unique role in thermoregulation make it a suitable channel for detecting distinct physical and psychological responses to external stimuli. A number of studies presented in this paper have proposed several methods for extracting thermal features that are more or less consistent with physiological signals collected from traditional contact-based sensors. More comprehensive studies have explored possible ways to apply these methods to develop practical solutions to real-world problems. Future work will undoubtedly continue to find innovative solutions to draw physiological insight from thermal videos.

REFERENCES

[1] Mohamed Abouelenien, Mihai Burzo, and Rada Mihalcea. 2015. Cascaded Multimodal Analysis of Alertness Related Features for Drivers Safety Applications. In *Proceedings of the 8th ACM International Conference on PErvasive Technologies Related to Assistive Environments (PETRA '15)*. ACM, New York, NY, USA, Article 59, 8 pages. https://doi.org/10.1145/2769493.2769505

[2] Mohamed Abouelenien, Mihai Burzo, and Rada Mihalcea. 2016. Human acute stress detection via integration of physiological signals and thermal imaging. In *Proceedings of the 9th ACM International Conference on PErvasive Technologies Related to Assistive Environments*. ACM, 32.

[3] Mohamed Abouelenien, Rada Mihalcea, and Mihai Burzo. 2016. Analyzing Thermal and Visual Clues of Deception for a Non-Contact Deception Detection Approach. In *Proceedings of the 9th ACM International Conference on PErvasive Technologies Related to Assistive Environments*. ACM, 35.

[4] Mohamed Abouelenien, Veronica Pérez-Rosas, Rada Mihalcea, and Mihai Burzo. 2014. Deception Detection Using a Multimodal Approach. In *Proceedings of the 16th International Conference on Multimodal Interaction (ICMI '14)*. ACM, New York, NY, USA, 58–65. https://doi.org/10.1145/2663204.2663229

[5] Mohamed Abouelenien, Verónica Pérez-Rosas, Rada Mihalcea, and Mihai Burzo. 2017. Multimodal Gender Detection. In *Proceedings of the 19th ACM International Conference on Multimodal Interaction (ICMI 2017)*. ACM, New York, NY, USA, 302–311. https://doi.org/10.1145/3136755.3136770

[6] Mohamed Abouelenien, Verónica Pérez-Rosas, Bohan Zhao, Rada Mihalcea, and Mihai Burzo. 2017. Gender-based Multimodal Deception Detection. In *Proceedings of the Symposium on Applied Computing (SAC '17)*. ACM, New York, NY, USA, 137–144. https://doi.org/10.1145/3019612.3019644

[7] M. Abouelenien, V. PÃĨrez-Rosas, R. Mihalcea, and M. Burzo. 2017. Detecting Deceptive Behavior via Integration of Discriminative Features From Multiple Modalities. *IEEE Transactions on Information Forensics and Security* 12, 5 (May 2017), 1042–1055. https://doi.org/10.1109/TIFS.2016.2639344

[8] M. Abouelenien and X. Yuan. 2012. SampleBoost: Improving boosting performance by destabilizing weak learners based on weighted error analysis. In *Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012)*. 585–588.

[9] Abdulkadir Hamidu Alkali, Reza Saatchi, Heather Elphick, and Derek Burke. 2013. Facial tracking in thermal images for real-time noncontact respiration rate monitoring. In *Modelling Symposium (EMS), 2013 European*. IEEE, 265–270.

[10] Stephanie L Bennett, Rafik Goubran, and Frank Knoefel. 2016. Adaptive eulerian video magnification methods to extract heart rate from thermal video. In *Medical Measurements and Applications (MeMeA), 2016 IEEE International Symposium on*. IEEE, 1–5.

[11] Stephanie L Bennett, Rafik Goubran, and Frank Knoefel. 2017. Comparison of motion-based analysis to thermal-based analysis of thermal video in the extraction of respiration patterns. In *Engineering in Medicine and Biology Society (EMBC), 2017 39th Annual International Conference of the IEEE*. IEEE, 3835–3839.

[12] Richard A Bryant, Mark Creamer, Meaghan O'Donnell, Derrick Silove, and Alexander C McFarlane. 2008. A multisite study of initial respiration rate and heart rate as predictors of posttraumatic stress disorder. *The Journal of Clinical Psychiatry* (2008).

[13] Pradeep Buddharaju, Ioannis T Pavlidis, Panagiotis Tsiamyrtzis, and Mike Bazakos. 2007. Physiology-based face recognition in the thermal infrared spectrum. *IEEE transactions on pattern analysis and machine intelligence* 29, 4 (2007), 613–626.

[14] Mihai Burzo, Mohamed Abouelenien, Veronica Perez-Rosas, Cakra Wicaksono, Yong Tao, and Rada Mihalcea. 2014. Using Infrared Thermography and Biosensors to Detect Thermal Discomfort in a BuildingâĂŹs Inhabitants. In *ASME 2014 International Mechanical Engineering Congress and Exposition*. American Society of Mechanical Engineers, V06BT07A015–V06BT07A015.

[15] Nisha Charkoudian. 2003. Skin blood flow in adult human thermoregulation: how it works, when it does not, and why. In *Mayo Clinic Proceedings*, Vol. 78, no. 5. Elsevier, 603–612.

[16] Sergey Y Chekmenev, Aly A Farag, William M Miller, Edward A Essock, and Aruni Bhatnagar. 2009. Multiresolution approach for noncontact measurements of arterial pulse using thermal imaging. In *Augmented vision perception in infrared*. Springer, 87–112.

[17] Michelle A Cretikos, Rinaldo Bellomo, Ken Hillman, Jack Chen, Simon Finfer, and Arthas Flabouris. 2008. Respiratory rate: the neglected vital sign. *Medical Journal of Australia* 188, 11 (2008), 657.

[18] Michael Dawson, Anne Schell, and Diane Filion. 2007. The electrodermal system. *Handbook of psychophysiology* 2 (2007), 200–223.

[19] Maarten Derksen. 2012. Control and resistance in the psychology of lying. *Theory and Psychology* 22, 2 (2012), 196–212.

[20] Jin Fei and Ioannis Pavlidis. 2010. Thermistor at a distance: unobtrusive measurement of breathing. *IEEE Transactions on Biomedical Engineering* 57, 4 (2010), 988–998.

[21] Bernd Figner, Ryan Murphy, et al. 2011. Using skin conductance in judgment and decision making research. *A handbook of process tracing methods for decision research* (2011), 163–184.

[22] Theresa Gannon, Anthony Beech, and Tony Ward. 2009. *Risk Assessment and the Polygraph*. Nova Science Publishers, 129–154.

[23] Tia Gao, Dan Greenspan, Matt Welsh, Radford R Juang, and Alex Alm. 2006. Vital signs monitoring and patient tracking over a wireless network. In *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*. IEEE, 102–105.

[24] Marc Garbey, Nanfei Sun, Arcangelo Merla, and Ioannis Pavlidis. 2007. Contact-free measurement of cardiac pulse based on the analysis of thermal imagery. *IEEE Transactions on Biomedical Engineering* 54, 8 (2007), 1418–1426.

[25] Travis Gault and Aly Farag. 2013. A fully automatic method to extract the heart rate from thermal video. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*. 336–341.

[26] Travis R Gault, Nicholas Blumenthal, Aly A Farag, and Tom Starr. 2010. Extraction of the superficial facial vasculature, vital signs waveforms and rates using thermal imaging. In *Computer Vision and Pattern Recognition Workshops (CVPRW), 2010 IEEE Computer Society Conference on*. IEEE, 1–8.

[27] Travis R Gault and Aly A Farag. 2012. Computationally light forehead segmentation from thermal images. In *Image Processing (ICIP), 2012 19th IEEE International Conference on*. IEEE, 169–172.

[28] Charles R Honts and John C Kircher. 1994. Mental and physical countermeasures reduce the accuracy of polygraph tests. *Journal of Applied Psychology* 79, 2 (1994), 252.

[29] Charlie Huizenga, Hui Zhang, Edward Arens, and Danni Wang. 2004. Skin and core temperature response to partial-and whole-body heating and cooling. *Journal of Thermal Biology* 29, 7-8 (2004), 549–558.

[30] Bryan F Jones and Peter Plassmann. 2002. Digital infrared thermal imaging of human skin. *IEEE Engineering in Medicine and Biology Magazine* 21, 6 (2002), 41–48.

[31] MM Khan, RD Ward, and M Ingleby. 2005. Distinguishing facial expressions by thermal imaging using facial thermal feature points. In *Proceedings of HCI*. 5–9.

[32] M. Khan, R. Ward, and M. Ingleby. 2017. Toward Use of Facial Thermal Features in Dynamic Assessment of Affect and Arousal Level. *IEEE Transactions on Affective Computing* 8, 3 (July 2017), 412–425. https://doi.org/10.1109/TAFFC.2016.2535291

[33] Samar Khoury, Guy A Rouleau, Pierre H Rompré, Pierre Mayer, Jacques Y Montplaisir, and Gilles J Lavigne. 2008. A significant increase in breathing amplitude precedes sleep bruxism. *CHEST Journal* 134, 2 (2008), 332–337.

[34] Alan T Krzywicki, Gary G Berntson, and Barbara L O'Kane. 2014. A non-contact technique for measuring eccrine sweat gland activity using passive thermal imaging. *International Journal of Psychophysiology* 94, 1 (2014), 25–34.

[35] Gregory F Lewis, Rodolfo G Gatto, and Stephen W Porges. 2011. A novel method for extracting respiration rate and relative tidal volume from infrared thermography. *Psychophysiology* 48, 7 (2011), 877–887.

[36] Chin Leong Lim, Chris Byrne, and Jason KW Lee. 2008. Human thermoregulation and measurement of body temperature in exercise and clinical settings. *Annals Academy of Medicine Singapore* 37, 4 (2008), 347.

[37] David T. Lykken. 1984. Polygraphic interrogation. *Nature* 307, 5953 (1984), 681–684.

[38] Katherine A McGonagle and Ronald C Kessler. 1990. Chronic stress, acute stress, and depressive symptoms. *American journal of community psychology* 18, 5 (1990), 681–706.

[39] James B Mercer and E Francis J Ring. 2009. Fever screening and infrared thermal imaging: concerns and guidelines. *Thermology International* 19, 3 (2009), 67–69.

[40] A Merla, P Iodice, A Tangherlini, G De Michele, S Di Romualdo, R Saggini, and GL Romani. 2006. Monitoring skin temperature in trained and untrained subjects throughout thermal video. In *Engineering in Medicine and Biology Society, 2005. IEEE-EMBS 2005. 27th Annual International Conference of the*. IEEE, 1684–1686.

[41] Yosuke Nakayama, Guanghao Sun, Shigeto Abe, and Takemi Matsui. 2015. Non-contact measurement of respiratory and heart rates using a CMOS camera-equipped infrared camera for prompt infection screening at airport quarantine stations. In *Computational Intelligence and Virtual Environments for Measurement Systems and Applications (CIVEMSA), 2015 IEEE International Conference on*. IEEE, 1–4.

[42] Eddie YK Ng, GJL Kawb, and WM Chang. 2004. Analysis of IR thermal imager for mass blind fever screening. *Microvascular research* 68, 2 (2004), 104–109.

[43] Brian R Nhan and Tom Chau. 2010. Classifying affective states using thermal infrared imaging of the human face. *IEEE Transactions on Biomedical Engineering* 57, 4 (2010), 979–987.

[44] Laszlo A Papp, Jose M Martinez, Donald F Klein, Jeremy D Coplan, Robert G Norman, Randolph Cole, Marybeth J de Jesus, Donald Ross, Raymond Goetz, and Jack M Gorman. 1997. Respiratory psychophysiology of panic disorder: three respiratory challenges in 98 subjects. *American Journal of Psychiatry* 154, 11 (1997), 1557–1565.

[45] I. Pavlidis. 2005. System and method using thermal image analysis for polygraph testing. (Feb. 15 2005). https://www.google.com/patents/US6854879 US Patent 6,854,879.

[46] Ioannis Pavlidis and James Levine. 2002. Thermal image analysis for polygraph testing. *IEEE Engineering in Medicine and Biology Magazine* 21, 6 (2002), 56–64.

[47] Ioannis Pavlidis, James Levine, and Paulette Baukol. 2001. Thermal image analysis for anxiety detection. In *Image Processing, 2001. Proceedings. 2001 International Conference on*, Vol. 2. IEEE, 315–318.

[48] Verónica Pérez-Rosas, Mohamed Abouelenien, Rada Mihalcea, and Mihai Burzo. 2015. Deception Detection Using Real-life Trial Data. In *Proceedings of the 2015 ACM on International Conference on Multimodal Interaction (ICMI '15)*. ACM, New York, NY, USA, 59–66. https://doi.org/10.1145/2818346.2820758

[49] Verónica Pérez-Rosas, Mohamed Abouelenien, Rada Mihalcea, Yao Xiao, CJ Linton, and Mihai Burzo. 2015. Verbal and Nonverbal Clues for Real-life Deception Detection. In *2015 Conference on Empirical Methods in Natural Language Processing, EMNLP 2015*. Association for Computational Linguistics, 2336–2346.

[50] Jonathan Posner, James A Russell, and Bradley S Peterson. 2005. The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and psychopathology* 17, 3 (2005), 715–734.

[51] Colin Puri, Leslie Olson, Ioannis Pavlidis, James Levine, and Justin Starren. 2005. StressCam: non-contact measurement of users' emotional states through thermal imaging. In *extended abstracts on Human factors in computing systems*. 1725–1728.

[52] Bashar A Rajoub and Reyer Zwiggelaar. 2014. Thermal facial analysis for deception detection. *IEEE transactions on information forensics and security* 9, 6 (2014), 1015–1023.

[53] Neil Schneiderman, Gail Ironson, and Scott D Siegel. 2005. Stress and health: psychological, behavioral, and biological determinants. *Annu. Rev. Clin. Psychol.* 1 (2005), 607–628.

[54] Nandita Sharma, Abhinav Dhall, Tom Gedeon, and Roland Goecke. 2013. Modeling stress using thermal facial patterns: A spatio-temporal approach. In *Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on*. IEEE, 387–392.

[55] Dvijesh Shastri, Arcangelo Merla, Panagiotis Tsiamyrtzis, and Ioannis Pavlidis. 2009. Imaging facial signs of neurophysiological responses. *IEEE Transactions on Biomedical Engineering* 56, 2 (2009), 477–484.

[56] Guanghao Sun, Tadafumi Saga, Takao Shimizu, Yukiya Hakozaki, and Takemi Matsui. 2014. Fever screening of seasonal influenza patients using a cost-effective thermopile array with small pixels for close-range thermometry. *International Journal of Infectious Diseases* 25 (2014), 56–58.

[57] Nanfei Sun, Marc Garbey, Arcangelo Merla, and Ioannis Pavlidis. 2005. Imaging the cardiovascular pulse. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, Vol. 2. IEEE, 416–421.

[58] Nanfei Sun and Ioannis Pavlidis. 2006. Counting heartbeats at a distance. In *Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE*. IEEE, 228–231.

[59] G Tanda. 2015. The use of infrared thermography to detect the skin temperature response to physical activity. In *Journal of Physics: Conference Series*, Vol. 655, no. 1. IOP Publishing, 012062.

[60] Julian F Thayer, Shelby S Yamamoto, and Jos F Brosschot. 2010. The relationship of autonomic imbalance, heart rate variability and cardiovascular disease risk factors. *International journal of cardiology* 141, 2 (2010), 122–131.

[61] Marieke van Dooren, Joris H Janssen, et al. 2012. Emotional sweating across the body: Comparing 16 different skin conductance measurement locations. *Physiology & behavior* 106, 2 (2012), 298–304.

[62] Peter Walla, Keith Nesbitt, Karen Blackmore, Geoffrey Hookham, and Frances Kay-Lambkin. 2015. Using the Startle Eye-Blink to Measure Affect in Players. In *Serious Games Analytics*. 401–434.

[63] Lara Warmelink, Aldert Vrij, Samantha Mann, Sharon Leal, Dave Forrester, and Ronald P Fisher. 2011. Thermal imaging as a lie detection tool at airports. *Law and human behavior* 35, 1 (2011), 40–48.

[64] Avinash Wesley, Pradeep Buddharaju, Robert Pienta, and Ioannis Pavlidis. 2012. A comparative analysis of thermal and visual modalities for automated facial expression recognition. In *International Symposium on Visual Computing*. Springer, 51–60.

[65] Hao-Yu Wu, Michael Rubinstein, Eugene Shih, John Guttag, Frédo Durand, and William Freeman. 2012. Eulerian video magnification for revealing subtle changes in the world. *ACM Transactions on Graphics* 31, 4 (2012), 1–8.

[66] Ming Yang, Qiong Liu, Thea Turner, and Ying Wu. 2008. Vital sign estimation from passive thermal video. In *Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on*. IEEE, 1–8.

[67] Tuba Yilmaz, Robert Foster, and Yang Hao. 2010. Detecting vital signs with wearable wireless sensors. *Sensors* 10, 12 (2010), 10837–10862.

[68] Peter Yuen, Kan Hong, Tong Chen, Aristeidis Tsitiridis, F Kam, James Jackman, David James, Mark Richardson, L Williams, William Oxford, et al. 2009. Emotional & physical stress detection and classification using thermal imaging technique. (2009).