Using Thermal Images and Physiological Features to Model Human Behavior: A Survey

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Abstract

Physiological signals provide a reliable method to identify the physical and mental state of a person at any given point in time. Multiple techniques are used to extract physiological signals from the human body. However, these techniques require contact and cooperation of the individual as well as human effort for connecting the devices and collecting the needed measurement. Thermal imaging provides a non-contact approach for acquiring these signals. New applications are exploring ways to utilize physiological features extracted from thermal images to detect subtle changes in human physiology. In this paper, we provide a review of applications, which propose a variety of innovative techniques to model human behavior by analyzing thermal videos.

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.

Vital sign monitoring systems generally monitor blood glucose level, blood pressure, pulse rate, electrocardiograph patterns, respiration rate, and temperature [27]. 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.

The skin is a vital organ that receives signals from control centers in the brain to maintain the body's core temperature through a process called thermoregulation [5]. Physiological thermoregulation in humans comprises changes in heat dissipation (sweating) and heat generation (shivering) in response to various internal and external thermal stimuli [4]. Thermal imaging utilizes this principle to detect natural thermal radiation emitted by the skin, which can be interpreted in terms of physiological changes [12]. 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 [25]. The skin becomes more conductive as sweat accumulates. This process reflects the arousal of the sympathetic autonomic nervous system which accompanies various psychological processes [7].

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 applications that can benefit from these techniques.

2 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,

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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 [6, 8]. Reports dating back three decades indicated that polygraph results were false one third of the time [15].

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 [11]. Hence, additional information collected from thermal images had the potential to improve the reliability of deception detection models.

In [17], the authors described a method 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, [18] 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.

The periorbital region of the face was analyzed in [22] to perform automated deception detection. The proposed approach tracked two eye corner regions, concatenated the Region of Interest (ROI) data across all frames within the response time-line, and finally applied Principal Component Analysis (PCA) 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 explained that a leave-one-person-out cross validation method assumed that behavior and physiological responses are common traits among people of various ages, genders, culture, etc. On the other hand, the within-person approach trained 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 proposed the use of fusion models that incorporated features from more than one modality [2]. 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.

3 Emotion Recognition

Several studies in the literature have explored the use of thermal imaging for classifying human emotions. The study of affect states and arousal level is an emerging topic of interest in both neuroscience and affective computing. However, there are conflicting theories that attempt to explain how neurophysiological systems activate different emotional states. Recent studies in affective computing have designed classification methods based on a relatively recent idea in neuroscience 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" [20]. 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.

A binary classifier was designed in [16] to distinguish baseline thermal states from affective states. Facial thermal infrared data as well as contact-based blood volume pulse and respiration rate were collected 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 ROIs. 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 accuracy of 80% and 75% in classifying high and low levels of arousal and valence from 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 [26], 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.

[14] leveraged the findings of these two studies to develop a unique classification algorithm. Instead of using a binary classifier, they opted 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 explained this method for acquiring Facial Thermal Feature Points [13]. PCA and Linear Discriminate Analysis were used to perform dimensionality reduction and feature selection. The resulting facial thermal vectors were 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.

4 Facial Recognition

Facial recognition technology has advanced rapidly within the last decade. In fact, many of today's smart phones offer features that rely on facial recognition and tracking software. However, most of the research in the field has focused on detecting and recognizing faces in the visible spectrum. Visual facial recognition systems read visible light reflected off the surface of the skin to track facial features. As a result, these systems usually do not perform well in variable lighting conditions. Facial recognition in the thermal infrared spectrum has been proposed as an alternative to overcome these problems. Thermal imaging is insensitive to illumination changes and capable of detecting unique physiological characteristics beneath the skin.

The forehead region is useful for facial recognition since it is a uniform surface that overlays several superficial arterial branches [10]. There are a number of methods for segmenting the thermal imprint of these supraorbital vessels [29]. The vascular mapping can be used to classify the subject's face and to track the subject's movements [9]. The authors in [3] proposed a method for thermal facial recognition based on the fact that the contrast between the superficial vasculature and the surrounding tissue is a physiological characteristic that does not vary over time.

5 Stress Detection

"Following the perception of an acute stressful event, there is a cascade of changes in the nervous, cardiovascular, endocrine, and immune systems" [23]. Furthermore, clinical studies have demonstrated relationships between psycho-social stressors and diseases, such as cardiovascular disease, upper respiratory diseases, immunodeficiency and depression [23]. 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 [28].

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 [19, 21].

Recent studies have classified these thermal physiological markers to develop automated stress detection algorithms. [24] 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 [1], 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%.

6. Conclusion

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 innovative ways to use thermal imaging and physiological measures to develop practical solutions to real-world problems.

We wish to build upon the previous work in order to develop a fully non-contact approach for extracting high resolution physiological features from thermal videos, namely heart rate, respiration rate, skin conductance and skin temperature. Our goal is to design a multimodal feature extraction approach to aid in the development of future health monitoring systems.

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