Human Acute Stress Detection via Integration of Physiological Signals and Thermal Imaging

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ABSTRACT

Daily pressure, work load, and family responsibilities among other factors impose increasing levels of stress on different individuals. Hence, detecting stress as early as possible can potentially reduce the severe consequences and risks that someone may experience. In this paper, we develop a novel dataset to detect acute stress using 50 subjects. We additionally analyze different features extracted automatically from the thermal and physiological modalities. Furthermore, we develop a system that integrates both thermal and physiological features for improved stress detection rates. Our system achieves promising results exceeding 75% accuracy and has the potential to be further improved by adding additional modalities, which can provide a useful and reliable approach in early detection of stress.

Categories and Subject Descriptors

I.2 [**Artificial Intelligence**]: Miscellaneous

Keywords

acute stress; thermal ; physiological; modality

1. INTRODUCTION

Stress is a major problem that can result in severe consequences. In the most recent report of an annual study conducted by the American Psychological Association (APA) to identify and analyze various critical elements associated with stress, it was found that money, work, family responsibilities, and health concerns were the most significant stressors for 3,068 study subjects[1]. Apart from the fact that stress is known to be associated with serious chronic diseases, e.g., depression, diabetes, and hypertension, either due to a defined pathological mechanism or due to other factors (e.g., genetic factors) that patients may have, stress can pave the way for healthy patients to acquire such diseases through driving them to follow unhealthy behaviors to cope with their problems. For instance, 42% of the study participants resorted to staying awake at night, and 33% adopted poor eating habits (e.g., overeating or consuming unhealthy food) to relief their stress. Adults from age 18-35 were found to be the most stressed group among all the other age groups. Interestingly, women (49%) were found to be more stressed than men (38%) in particular due to monetary responsibilities. As a result, finding that more women (29%) experienced loneliness/isolation compared to men (19%) becomes logical.

Stress can be divided into three types, namely, acute stress, episodic acute stress, and chronic stress. Many people exhibit some form of acute stress during their life. It occurs with the daily pressures and demands. Instances of acute stress exist with incidents such as small accidents, work pressure, and traffic among others. However, as an individual is subject to extended amount of acute stress, he becomes a victim of multiple types of diseases such as upset stomach, distress, and tension headaches among others.

As acute stress occurs more frequently/periodically, it transforms to episodic acute stress. In this form, people become short-tempered, tense, easily irritated, and anxious. They suffer symptoms such as persistent headaches, hypertension, and heart disease. Episodic acute stress requires professional intervention to avoid severe consequences. The third and most problematic type is the chronic stress. This type exists with unrelenting demands and requirements as well as terrible experiences such as wars, struggles, poverty, childhood abuse, and traumatic memories. Chronic stress affects personality and wears an individual physically and mentally. It could be fatal in many cases and results in suicide, heart attacks, violence, and stroke. It requires extended treatments and professional intervention.

In order to avoid the severe consequences of stress, scientists explored multiple ways to detect and prevent stress as early as acute stress starts to occur. In general, stressors, which are the factors triggering different levels of stress, can be divided to physical and psychological stressors [11]. Physical stressors are in direct contact with the human body while psychological stressors affect the individuals emotion-

[1]http://www.apa.org/news/press/releases/stress/2014/stress-report.pdf

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ally and/or mentally. In order to automatically detect stress, different types of stressors are employed followed by data collection from sensors or video recordings, usually collected in lab-settings using a group of volunteers [10, 16, 23]. The data is finally processed to determine the stress level of an individual.

Examples of physical stressors include a running or walking activity [7, 18]. The data in these cases are collected before and after the exercises. The cold presser test is another example where participants immerse their hands in an ice water container. On the other hand, the majority of stressors fall in the psychological category. Examples of these stressors are providing the subjects with an arithmetic problem or a quiz [22], work meetings [5], exams [16], watching stressful vs. relaxing video clips [33], using a driver simulator [6], and playing games [10]. Additional tests used to stimulate stress include the Stroop color word test [23], which assesses cognitive processing by asking subjects to read words and name colors in a timely manner.

The stress detection problem was tackled using different technical approaches. Earlier approaches relied on contact-based sensors based on the assumption that experiencing stress caused physiological arousal which elevated the sensors readings. Different physiological measurements were collected and processed to analyze these variations such as heart rate, electrocardiogram (ECG) signals, galvanic skin responses (skin conductance), respiration rates, and skin temperatures [20, 23, 30, 38]. Variations in behavioral patterns were also observed when people were under stress such as their keystroke dynamics when typing [15]. Additionally, stress affects the visual signature of different subjects, which can be observed in the temporal domain as variations in their eyebrows, mouth and lips movements, and general emotions as well as facial expressions [18, 26, 34]. The advantage of this approach is its non-evasiveness compared to the contact-based sensors.

More recently, thermal imaging techniques were utilized to determine the level of stress. There were indications of increased blood flow in the superficial blood vessels of the face and in particular those in the periorbital area when a person is under stress [24,27,35]. This increase was reflected in an elevation of the temperature of the facial skin, which can be detected using thermal recordings and proper computational processing.

As the need arises to detect stress as early as possible to provide stress-sufferers with the appropriate feedback to prevent further complications, this paper addresses the acute stress detection problem and provides three contributions. First, we collected a novel stress dataset using a set of 50 participants, which is one of the largest reported populations for a stress detection study. Another aspect of this dataset is the novelty of the employed scenarios presenting the psychological stressors to induce stress. Second, we analyze which features are more capable of indicating stress using a set of four physiological sensors measuring the heart rate, respiration rate, skin conductance, and skin temperature in addition to thermal imaging. Finally, we integrate features from both the physiological and thermal modalities to create a more reliable acute stress detection system. While there have been attempts to follow a multimodal approach to detect stress by combining behavioral, physical and cognitive features or by combining some visual features with physiological electrocardiogram [6, 10, 31], this is the first work to fuse these four physiological signals with facial thermal features.

This paper is organized as follows. Section 2 surveys related work. Section 3 describes the dataset we collected. Section 4 analyzes the features and details our approach in detecting acute stress. Our experimental results are discussed in Section 5. Finally, our concluding remarks and future work are provided in 6.

2. RELATED WORK

Methods to detect human stress can be divided into physiological, behavioral, visual, thermal and multimodal. Heart rate variability was shown to be effective in detecting stress levels [21]. In particular, variations between consecutive heart beats and higher-order statistical features in the time and frequency domains [22] indicated that the individual could be under different stress levels. By extracting electrical and muscular functions of human heart in terms of ECG [23], scientists were able to relate changes in these functions to acute stress as well as different stress levels [32]. Features from GSR sensors were used to recognize stressful states in humans owing to its ability of indicating the physiological arousal. For example, stress levels were detected from GSR features using a population of 16 adults with an accuracy exceeding 70% [25]. However, such features suffered from elevated levels of noise due to movements among other factors [5]. EEG power spectrum ratio and Spectral Centroids techniques were used to improve stress detection rates [37]. Furthermore, the fusion of different physiological measurements such as ECG, HRV, and skin conductance achieved improved accuracy rates for detecting stress [20, 22, 23, 30, 38].

As stress affects human behavior, recent research focused on key stroke dynamics and text patterns. By collecting keystroke patterns, Epp et al. [12] were able to identify the rhythm of the subject's typing to determine their stress level. A more detailed analysis of the time duration between keystrokes and the addition of linguistic analysis targeted a more precise detection of human stress and emotional levels [13, 15].

Visually, the human faces can indicate their levels of stress by tracking their eyebrows, mouth, and lips movements [26] and by analyzing their facial emotions [14]. More recently, thermal facial patterns were used to indicate stress [18, 34]. Cross et al. [11] developed a system to extract and evaluate responses to physical and psychological stressors using electro-optical and mid-wave infrared cameras in order to mask responses capable of indicating stress, anxiety, and fear. Features from the visible and thermal spectra were also integrated to capture dynamic thermal patterns in histograms for stress recognition [33].

Multimodal analysis showed to achieve an improved performance in a variety of applications such as deception detection, driver's alertness, and thermal discomfort [1–3, 8, 9, 28, 29]. Attempts to integrate features from different modalities was recently explored to improve stress detection rates [4, 31]. Carneiro et al. [10] used eight behavioral, physical and cognitive features extracted from a set of 19 subjects to analyze the features associated with acute stress. Using facial features such as eyes blinking, yawning, and head rotations combined with the physiological ECG and galvanic skin response, a system was developed to detect stress for driver's safety applications [6].

3. DATASET

3.1 Subjects

Our dataset consists of recordings collected from 50 undergraduate and graduate volunteering students from the University of Michigan. The subjects included 35 females and 15 males. All participants expressed themselves in English, belonged to several ethnic backgrounds, and had an age range between 20 and 35 years.

3.2 Experimental Procedure

The subjects were asked to sit comfortably in the experiments station and were informed that they were participating in a lie detection study. No information regarding the stress study was directed to them. Moreover, the subjects were not told any prior information regarding the details of the scenarios involved.

In order to collect our data we used three different cameras and four physiological sensors. In particular we used a top-of-the-line FLIR SC6700 thermal camera with a resolution of 640x512 and 7.2 M electrons capacity, reaching a frame rate of approximately 100 frames/second. We also used two visual cameras.

In addition, we employed four bio-sensors to collect physiological responses, namely blood volume pulse (BVP sensor), galvanic skin response (GSR sensor), skin temperature (ST sensor), and abdominal respiration (BR sensor). Two skin conductance electrodes were placed on the second and third fingers. The skin temperature and blood volume pulse sensors were placed at the little and index fingers, respectively. The respiration sensor was placed comfortably around the thoracic region.

Participants were instructed to avoid excessive movements in order to obtain high quality data from the cameras and reduce interference with the physiological sensors.

3.3 Scenarios

Three scenarios were designed for the experiments. The subjects were informed of the topic matter before each individual recording. In two scenarios, namely, “Abortion” and “Best Friend”, subjects were allowed to speak freely once truthfully and once deceptively, while in the third scenario “Mock Crime”, the subjects had to respond to questions asked by the interviewer.

3.3.1 Abortion

In this scenario participants were asked to provide first a truthful and then a deceptive opinion about their feelings regarding abortion and whether they think it is right or wrong and if it should be legalized. The experimental session consisted of two independent recordings for each case.

3.3.2 Best Friend

In this scenario subjects were instructed to provide an honest description of their best friend, followed by a deceptive description about a person they cannot stand. In the second part, they had to describe the individual they cannot stand as if he or she was their best friend. Therefore, in both cases, the person was described positively.

3.3.3 Mock Crime

This scenario was employed in a different manner by allowing the subjects to respond only once with their choice of being truthful or deceptive. In particular, a $20 bill was hidden in an envelope in a box beside the participants. The subjects were told that the interviewer would leave the room and that it was their choice to steal the money. Additionally, they were told that the interviewer would return back to the room to ask them questions regarding the missing bill in a one-on-one interview, and that they should make their own decisions whether they would lie to the interviewer or not. Hence, the subjects had to choose one of four options; steal the money and deny it, steal the money and admit taking it, leave the money and falsely claim they took it, or leave the money and simply say the truth. The interview was conducted as follows:

1. Are the lights on in this room?
2. Regarding that missing bill, do you intend to answer each question truthfully about that?
3. Prior to 2012, did you ever lie to someone who trusted you?
4. Did you take that bill?
5. Did you ever lie to keep out of trouble?
6. Did you take the bill from the private area of the lab?
7. Prior to this year, did you ever lie for personal gain?
8. What was inside the white envelope?
9. Please describe step by step, in as much detail as you can, what you did while you were in the room and I was outside.
10. Do you know where that missing bill is right now?

3.3.4 Inactivity

Before recording the three scenarios, the subjects were asked to relax and sit comfortably in the chair for a one-minute recording with no activity on their side. The same process was repeated at the end of recordings, i.e., after recording the three scenarios. We will refer to the earlier recording as “Inactive 1” and the last recording as “Inactive 2”.

Table 1: Distribution of the self-assessment of the 50 subjects for the most and least stressful scenarios they experienced during the recordings.

Scenario	Most Stressful	Least Stressful
True Abortion	14	2
False Abortion	10	0
True Best Friend	1	14
False Best Friend	15	1
Mock Crime	8	0
Inactive 1	2	13
Inactive 2	0	20

3.3.5 Self-Assessment

Subjects were compensated for participating in the study. Their performance in deceiving the interviewer in the “Mock Crime” scenario was additionally rewarded. Hence, each subject had 7 recordings resulting in a total of 350 responses.

Once the recordings were finalized and the subjects were compensated, they were asked to self-assess the responses that were the most stressful and least stressful for them. Table 1 shows the overall distribution of the chosen responses. These assessments were used as the ground-truth in labeling the stress and non-stress classes. Therefore our final dataset was formed of 50 stress-labelled instances and 50 non-stress labelled instances.

4. METHODOLOGY

4.1 Physiological Features

The physiological features include raw physiological measurements of the heart rate, respiration rate, skin conductance, and peripheral skin temperature. Additionally, we extract statistical descriptors of the raw measurements such as the maximum and minimum values, means, power means, standard deviations, and mean amplitudes (epochs) using the Biograph Infinity Physiology suite[2]. The data is extracted at a rate of 2048 samples per second and the final set consists of a total of 59 physiological features. The features include 40 extracted heart rate features, five skin conductance features, five skin temperatures features, and seven respiration rate features. Furthermore, two features are extracted from the BVP and the respiration rate sensors combined, namely, the mean and heart rate max âĂŞ min difference, which is a measure of breath to breath heart rate variability. The final vector for each response is averaged over all samples.

4.2 Thermal Features

The thermal features are extracted to detect the temperature variations of the subjects as they are subject to stress and non-stress situations. In order to extract the features, we locate the thermal faces and track them through the thermal videos. Specifically, the process is performed in three steps: face segmentation, tracking, and development of a thermal map.

First, we manually locate the facial areas of the subjects in the first frame of each video by determining its bounding box. Interesting points are then detected in this region using Shi-Tomasi corner detection algorithm. These points are located in areas with sharper changes in colors, i.e., temperatures. Following this, the detected points are tracked through the entire response using a fast Kanade-Lucas-Tomasi (KLT) tracking algorithm [36]. We additionally calculate the Forward-Backward Error [19] by tracking the points forth to the current frame and back to the previous frame in order to eliminate outliers and avoid the uncertainty associated with some points.

Following the tracking process, a geometric transformation [17] is applied to map the interesting points between the frames and determine the new bounding boxes. The backgrounds of the frames are additionally discarded to eliminate their effect on the quality of the extracted features by multiplying the original image by the binarized image. This is followed by cropping the boxes surrounding the facial areas. Hence, in our cropping process, all the eliminated areas are blackened pixels. The binarization and cropping processes are briefly shown in Figure 1.

[2]http://www.thoughttechnology.com/physsuite.htm

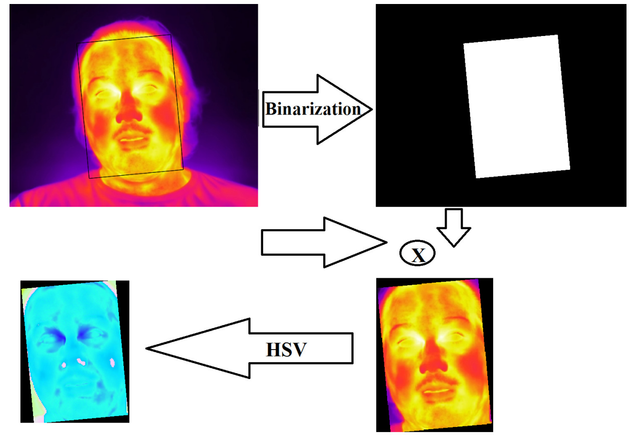

Figure 1: A diagram showing the binarization and cropping processes of the tracked face with the bounding box. The cropped face is then converted to the HSV pixel representation for feature extraction.

Once the facial thermal areas are located in each frame, thermal features are extracted using the Hue Saturation Value (HSV) color representation by creating a histogram of 255 bins for each band given that different degrees of colors presented different temperatures. The HSV channels represent the colors of the pixels using cylindrical coordinates. Hue is the angular dimension locating different colors at different angles. The distance from the central axis of the cylinder to the outer surface is referred to as Saturation and represents the purity of the colors. The height of the cylinder refers to the Value channel and represents the brightness of the colors, i.e., another form of calculating the gray scale level of the pixels.

The histograms are normalized to form a probability distribution over all bins. Moreover, we extract pixel-level temperature measurements such as the average temperature, overall minimum and overall maximum temperatures, the mean of the 10% highest pixel values, and the standard deviation. The final set consisted of 780 thermal features from each facial frame using all frames in each response, i.e., none of the frames are dropped unless rejected during tracking. The final vector is averaged over all the frames.

In order to account for the normal thermal variations between different subjects, the same set of features is extracted from the frames of a few seconds at the beginning of the inactivity recordings. The actual features are divided by this set for normalization purposes. The same normalization scheme is followed for the physiological features as well. The feature extraction processes of both the thermal and physiological modalities are synchronized to start and end at the same second.

4.3 Stress Classification

After the features are extracted from each of the two modalities, we test their performance individually and combined. We employ a decision tree classifier and a leave-one-subject-out cross validation scheme to report the average overall accuracy and the average recall of the stress and the non-stress classes. The classifier was employed from the statistical toolbox in Matlab R2015a using Gini's diversity in-

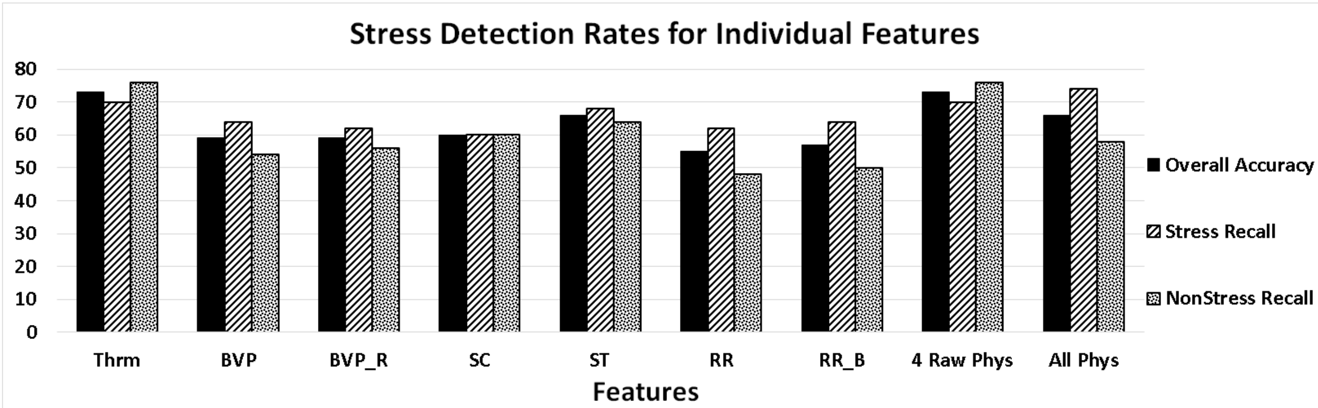

Figure 2: The overall accuracy as well as the recall of the stress and non-stress classes using individual sets of features formed of the thermal (Thrm), heart rate (BVP), heart rate including 2 features extracted from the BVP and respiration rate sensors combined (BVP_R), skin conductance (SC), skin temperature (ST), respiration rate (RR), respiration rate including the two features in common with BVP (RR_B), four raw physiological (4 Raw Phys), and all physiological (All Phys) features.

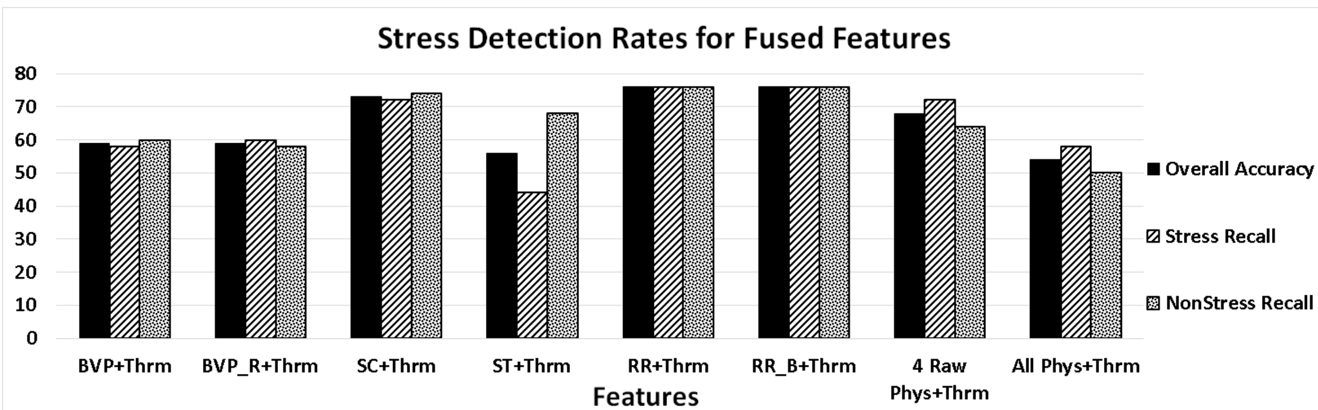

Figure 3: The overall accuracy as well as the recall of the stress and non-stress classes using the fused sets of modalities and features formed of the fusion of the heart rate and thermal (BVP+Thrm), heart rate with the two respiration rate features and thermal (BVP_R+Thrm), skin conductance and Thermal (SC+Thrm), skin temperature and thermal (ST+Thrm), respiration rate and thermal (RR+Thrm), respiration rate with the two BVP features and thermal (RR_B+Thrm), four raw physiological features with thermal (4 Raw Phys+Thrm), and all physiological and thermal features (All Phys+Thrm).

dex as the splitting criterion. In the leave-one-subject-out cross validation scheme, both the stress and non-stress instances of each subject are used for testing at each fold, whereas the instances of all other 49 subjects are used for training. This scheme is followed for a fair evaluation and to avoid any subject dependencies that might bias the results.

Given that the two classes are balanced, the baseline is at 50%. Moreover, we evaluate the performance of individual sets of features to specify the set with the highest capability of indicating stress. Furthermore, we analyze whether feature fusion of the physiological and thermal modalities could further improve the acute stress detection rates.

5. EXPERIMENTAL RESULTS

The final dataset consists of a total of 100 instances including 780 thermal features and 59 physiological features. In order to specify which features achieve the best performance, we start by evaluating individual sets of features. Figure 2 shows the overall accuracy as well as the recall of the stress and non-stress classes using the thermal (Thrm), the heart rate (BVP), heart rate including 2 features extracted from the BVP and respiration rate sensors combined (BVP_R), skin conductance (SC), skin temperature (ST), respiration rate (RR), respiration rate including the two features in common with BVP (RR_B), the four raw physiological, i.e., without the statistical descriptors (4 Raw Phys), and all physiological (All Phys) features.

The thermal features as well the four raw physiological features achieve the highest overall accuracy at 73% and the highest recall of the non-stress class. This confirms that there exist thermal variations in the participantsâĂŹ faces as they are subject to stressful situations. The skin temperatures and all physiological achieve the second highest accuracy and all physiological features additionally achieve the highest recall for the stress class. The individual phys-

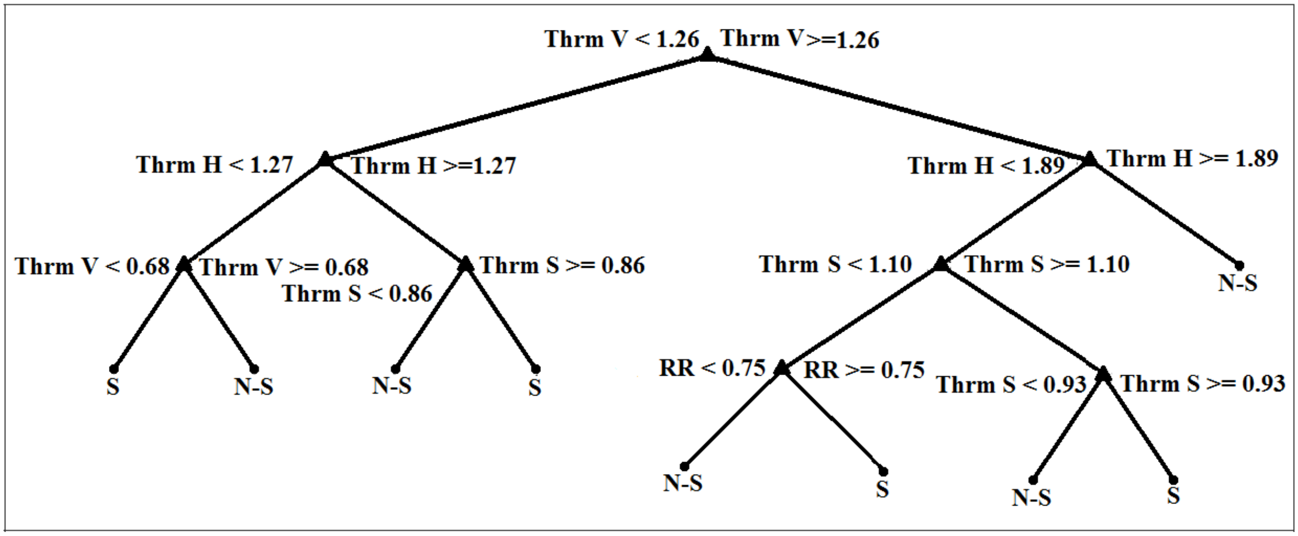

Figure 4: Decision tree model created using the dataset. "S" denotes the stress class and "N-S" denotes the non-stress class. The modality type of each feature selected for node splitting is shown beside the node. "Thrm V", "Thrm S", and "Thrm H" denote the thermal V, S, and H channels, respectively. "RR" denotes respiration rate.

iological features exhibit a close performance. Moreover, the combination of all physiological features outperforms the employment of single sensors. All the features have a performance that is above the baseline. The performance shows that the thermal and all physiological features are as effective in determining the acute stress levels of humans. Based on these results, the thermal modality can be useful for non-invasive stress detection approaches.

Figure 3 displays the overall accuracy and class recall for the fusion of the heart rate and thermal (BVP+Thrm), heart rate with the two respiration rate features and thermal (BVP_R+Thrm), skin conductance and Thermal (SC+Thrm), skin temperature and thermal (ST+Thrm), respiration rate and thermal (RR+Thrm), respiration rate with the two BVP features and thermal (RR_B+Thrm), four raw physiological features and thermal (4 Raw Phys+Thrm), and all physiological and thermal features (All Phys+Thrm).

The fusion of the features from the thermal modality with the respiration rate features outperforms all other combinations as well as the individual sets of features in the overall accuracy and also the recall of the stress and non-stress classes. The improvement in the overall accuracy exceeds 4% compared to the individual thermal and the four raw physiological features. Moreover, this particular fusion achieves a relative accuracy improvement of 26.6% over the individual heart rate and skin conductance features, and 38.2% over the respiration rate features. The second best performance is achieved by the fusion of the skin conductance and the thermal features, which agrees with previous research claiming the capability of the GSR sensor features to detect stress.

5.1 Decision Tree Model

In order to illustrate which particular features in the training model are the most capable of discriminating between stressful and non-stressful instances, we visualize the decision tree model trained on the dataset composed of the respiration rate features combined with the thermal features as can be seen in Figure 4.

It can be seen that most of the tree nodes are constructed from the thermal features. In particular, the root node is created from the value channel while the first level nodes are formed from the hue channel. Lower tree levels are formed from the saturation channel as well as one respiration rate feature, which represents the respiration rate epoch mean. This construction of nodes achieves the best separation between acute stress and non-stress states.

6. CONCLUSION

In this paper, we investigated the capability of the thermal and physiological features of indicating stress. In particular, this paper had three main contributions. First, we developed a novel dataset with unique scenarios including one of the largest reported number of subjects to detect acute stress. Second, we investigated the ability of different sets of features to discriminate between stress and non-stress. Finally, we integrated features extracted from both the physiological and the thermal modalities in order to analyze their effect on the stress detection rates.

Our experimental results indicated that the thermal features achieved similar and in several cases improved performance compared to the physiological features, which paves the way towards non-invasive and efficient stress detection approaches that can be employed in clinics and variety of applications. Moreover, the usage of data derived from all physiological sensors exhibited better performance compared to the employment of single sensors. Furthermore, the integration of some physiological features, and in particular the respiration rate, with the thermal features outperformed all other individual and fused sets of features. Visualization of our decision tree model specified the bands of the thermal features and the epoch mean of the respiration rate as the most useful features in constructing an improved classifier to detect stress. This also showed that multimodal approaches that employ and gather data from multiple sources such as sensors and cameras provide an improved and more reliable stress detection rates.

Our data was collected in lab-settings with no serious consequences in order to detect the earliest and most common types of stresses: acute stress. We expect our system to achieve higher detection rates with real-life situations. In future, we are planning to collect such data using quizzes, public presentations, and mind-term and final exams, where students would experience real-life stressors. Additionally, we will add features from the linguistic and visual modalities where the usage of specific word usages and gestures can further improve our system. Such a reliable system can deliver proper feedback to individuals on their acute stress level and eventually reduce the risks associated with episodic acute stress, and chronic stress.

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