Detecting Thermal Emotional Profile

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Keywords: Emotion Recognition, IAPS, Skin Temperature, Thermal Emotional Profile, Machine Learning, EEG, HMM (Hidden Markov Model), Infrared Camera.

Abstract: Human can react emotionally to specific situations provoking some physiological changes that can be detected using a variety of devices, facial expression, electrodermal activity, and EEG systems are among the efficient devices which can assess the emotional reactions. However, emotions can trigger some small changes in blood flow with an impact on skin temperature. In the present research we use EEG and a thermal camera to determine the emotional profile of a user submitted to a set of emotional pictures. Six experiments were performed to study the thermal reactions to emotions, and in each experiment, 80 selected standard stimuli pictures of 20 various emotional profiles from IAPS (a database of emotional images) were displayed to participants every three seconds. An infrared camera and EEG were used to capture both thermal pictures of participants and their electrical brain activities. We used several area of the face to train a classifier for emotion recognition using Machine Learning models. Results indicate that some specific areas are more significant than others to show a change in temperature. These changes are also slower than with the EEG signal. Two methods were used to train the HMM, one is training classifier per the participant self data (participant-independent), another is training classifier based on all participants` thermal data (participant-dependent). The result showed the later method brings more accuracy emotion recognition.

1 INTRODUCTION

Research in education, psychology, computational linguistics, and artificial intelligence acknowledge that emotions have an effect on learning (Heraz et al, 2007). Many works in that field focus on identifying learners' emotions as they interact with computer systems such as Intelligent Tutoring Systems (Chaffar et al, 2009) or educational games (Derbali et al, 2012).

Unfortunately, many of these types of systems only focus on external behavior like face analysis, vocal tones and gesture recognition. Most of the time, psychological methods are used to collect real-time sensing data. Despite the advances in these methods, it is still a challenging problem. The effective emotional state and its assessment lack precision. In addition, these methods are not applicable in the case of disabled, taciturn and impassive learners. Today, researches are directed toward a multi-model system that can automatically extract physiological signals changes in addition to vocal, facial or posture changes. All those features can be combined to detect and assess emotions.

1.1 Assessing Emotions

To properly interact with the learner, the emotion data collection methods have evolved from self report (Anderson, 2001) to facial expression analysis (Nkambou, 2004), to body posture and gestures interpretations (Ahn et al, 2007), and to biofeedback measurements (Heraz et al, 2007, 2009). To increase the prediction of the emotional and cognitive learner states, the approaches of combining different kinds of information collection channels were applied (Kapoor et al, 2005). Regarding biofeedback measurement, researches showed that the Electroencephalograms (EEG) is one of the most reliable and accurate physiological signal to monitor the brain activities (Heraz et al, 2007). However, the wearable EEG devices, such as Q sensor (worn on wrist), EPOC Neuroheadset (worn on head), or SomaxisMyoLink (worn on body), also limit the user's movement. It will be more convenient if there is a way to measure emotions noninvasively. In our research, our goal is to see the relation between the changes of skin temperature and emotions.

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1.2 A New Way to Measure Emotions Noninvasively

During the past half century, psychologists have discovered and studied the relationship between skin temperature and emotion changes (Baker and Tayor, 1954). They have indicated that the skin temperature is getting lower because of the production of a constriction of the arterioles when the participants are under a stressful situation. By testing 27 participants with 4 negative and 4 positive stimuli, Vos P et al (2012) found that the skin temperature is higher for expressing low intensity ~~emotions~~ negative emotions. Kuraoka and Nakamura (2010) measured the nasal region temperature changes studying emotion in macaque monkeys. They found temperature decreased when the monkeys were facing negative situations. More interestingly, the experiment in the paper (Ioannou et al. 2013) showed that when a child felt guilty after breaking a toy, his nose tip cooled off with more purple color (third picture); and after he was soothed, the thermal color turned more orange indicating his nose wormed (fifth picture) (Figure 1).

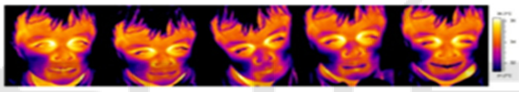

Figure 1: Five pictures of a child showing the temperature change of the nasal tip.

In this paper we present an exploratory study of using thermal camera to detect and assess emotions. After looking at the functionalities of thermal camera and their use in the industry, we present the features of Electroencephalograms devices (EEG), a well known method for assessing emotions, mental engagement and workload. Then, we present the experiments realized with a set of emotional stimuli and the two devices. We compare the measures obtained with the two devices to validate thermal assessments.

2 THERMAL CAMERA FUNCTIONALITIES

Infrared thermography is a powerful technique for non-destructive and non-invasive investigation. It has been applied in building leakage detection (Titman, 2001), in medicine area (Jones, 1998), and even in accident rescue (Doherty et al., 2007). Because of its non-invasive and non-destructive nature, the thermal detection can be rapidly completed, with slight access efforts and costs. The visibility of the output also can be interpreted immediately by a skilled practitioner (Titman, 2001).

2.1 Building Leaks

Temperature factors were used to detect where and how energy leaks from a building's envelope and substantiate proposals. The source of the problems can be revealed accurately and detailed by using IR thermography. The problems may include improperly installed or damaged insulation, thermal bridges, air leakage, moisture damages or cracks in concretes. For instance, a thermal picture can show a missing insulation as a light colored patch with distinct edges (Balaras, 2002).

Figure 2: Thermograph of an interior roof surface with missing insulation (Balaras et al. 2002).

2.2 Thermal Camera in Medicine

Measuring body temperature is one of the traditional diagnostic methods in medicine, besides, it is also applied to measure the outcome of clinical trials.

In recent decades, as a non-invasive and painless method, thermal imaging technique has been widely applied to various fields of diagnostic, such as to find the sites of fractures and inflammations, to recognize the degree of burn, to detect breast cancer and to determine the type of skin cancer tumors (Ogorevc et al., 2015).As Ring et al. (2012) mentioned in their research, the skin temperature can indicate the existence of inflammation in underlying tissue (Figure 3), osteoarthritis, soft tissue rheumatism, and complex regional pain syndrome (CPRS). A temperature difference (>= 1 °C) between the affected and the non-affected limb is one of the diagnostic criteria of CPRS (Wilson et al. 1996).

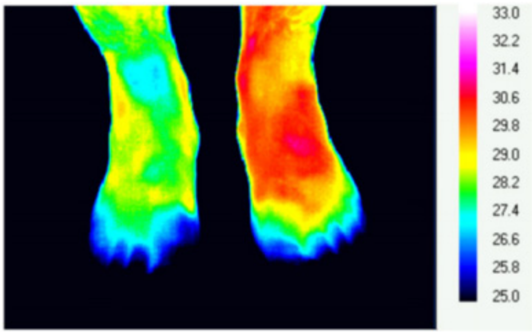

Figure 3: Chronic inflammation of the forefoot following a sport injury (Ring, 2012).

Studies showed that infrared imaging is also a powerful tool for clinical testing. Devereaux et al. (1985) used infrared thermography to quantify joint inflammation and to assess patients' response to therapy of rheumatoid arthritis. By following patients over 12 months, the researchers found that there are significant correlations for thermography with other parameters of disease activity. In recent years, per the study of Spalding et al. (2008), it was proved that three-dimensional measures and thermal imaging are able to measure a high coincidence between high temperature and swelling of figure joints.

2.3 Using Infrared Camera for Emotion Detection

2.3.1 Infrared Camera

In our study, we used an infrared camera (ICI 7320) (Figure 4)to capture real time thermal images and provide real time radiometric data streams to hard device or portable device. The camera is able to give sensitive and accurate thermal data of arrange of -20°C to 100°C. Comparing with EEG, because of the camera's non-invasive feature, it is easier to set up and configure.

Figure 4: ICI 7320 Infrared Camera.

2.3.2 Iaps

To know which emotions should be detected we used a set of emotional pictures as stimuli materials which have been categorized according to specific emotions. The Centre for the Study of Emotion and Attention (CSEA) of the University of Florida developed two large sets of affective stimuli, IAPS (International Affective Picture System) and IADS (the international Affective Digitalized Sound system), to provide standard materials for emotion and attention related studies. Based on Osgood (Osgood et al. 1962) seminal work, IAPS assessed the emotions from three dimensions: affective valence, arousal and dominance. In this research, the arousal-valence model (Figure 5) was used to represent the emotions. Valence ranges from pleasant to unpleasant and arousal ranges from calm to excited. Dominance, which is also called control, is a less strongly-related dimension. In our experiments, we selected 80 IAPS pictures from 20 various picture sets for presenting to participants and measuring their emotional reactions.

Figure 5: Arousal-valence Model.

Emotions considered were: **neutral, happy, sadness, anger, fear, disgust, sadness**. To measure them according to arousal and valence dimensions, we used the means and standard deviations (parentheses) of the rating emotion table (Figure 6) from Panayiotou (2008) research as a standard base for further machine learning.

Human skin temperature is the product of heat dissipated from the vessels and organs within the body, and the effect of environmental factors on heat loss or gain. To facilitate the detection of emotions by thermal variations we will focus on five area of the face, including **forehead, nose, mouth, left cheek and right cheek**.

Means and standard deviations (parentheses) of ratings for emotions in study 1

	Anger	Fear	Joy	Sadness	Disgust	Grief	Pl. relaxation	Neutral
Valence	1.60	1.60	6.30_a	1.76_b	1.40_b	1.21_b	4.42_a	5.02_b
	(.75)	(.76)	(.95)	(.76)	(.33)	(.77)	(.63)	(.92)
Arousal	5.98_a	6.15_a	4.66_b	5.06_b	5.88_a	6.44_a	1.75_c	2.59_c
	(.91)	(.95)	(1.30)	(.97)	(.92)	(.85)	(.68)	(.82)
Dominance	3.13_b	2.88_b	5.51_a	3.12_b	3.27_b	2.39_b	6.11_a	5.88_a
	(1.01)	(1.03)	(.97)	(1.20)	(1.22)	(1.22)	(.95)	(1.05)

Figure 6: Means and standard deviations (parentheses) of ratings for emotions (Panayiotou, 2008).

Considering that the temperature changes may require time to display on participants skin, every picture was displayed three seconds. Meanwhile, to figure out how the skin temperature is back to a ‘neutral’ status, a non-stimuli picture shows in between every two IAPS pictures.

The emotional profile, which depends on each participant, will be based on two parameters: 1) the ***rapidity*** of the thermal changes, and 2) the temperature change ***intensity***.

2.3.3 Hidden Markov Models

Six students were invited to participate into this study and they were asked to watch the eighty slide-showing pictures without any disruption. Thermal photos were taken every three seconds during the picture-displaying period. Then the thermal changes on the five areas of their face (forehead, nose, mouth, left cheek and right cheek) were trained and classified with a Hidden Markov Model, in order to obtain the thermal emotional profiles.

Hidden Markov Models (HMM) are widely used to find out the joint probability of a collection of hidden variables and observed variables. It is defined by a tuple λ=(n, m, A, π, B), where n indicates the number of hidden states, m indicates the number of observable states, A is the state transition probability, B is the emission probability density function of each state, and π is the initial state probability. In this research, recognizing emotion from a series of thermal data over the time is a typical modeling problem which can take advantage of be resolved by HMM.

As an emotion state can transfer to any other states, the state-transition topology of the emotion recognition model is an ergodic topology (Figure 7). Then we train the maximum likelihood classifier using the Baum-Welch algorithm. According to the classifiers, the hidden states – emotions (neutral, happy, sadness, disgust, anger, fear, relaxed) can be computed per the observed states (turn wormer (1), /colder (2), or no change (0) on nose, on forehead, etc.) - the thermal change states. Two training methods were used in our study: one is to train the classifier with a participant’s self previous data, which was named as *participant-independent* training. Another is to train the classifier based on all other participants’ data, named as *participant-dependent* method.

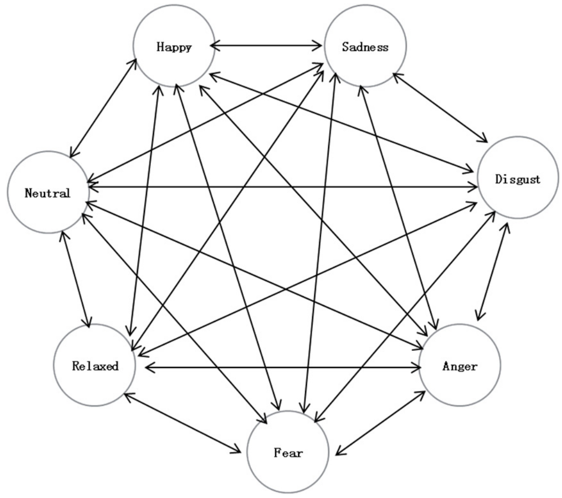

Figure 7: Training classifiers using Hidden Markov Model.

3 USING EEG TO MEASURE EMOTIONS

3.1 Emotiv Classification of Emotions

In many recent researches, EEG (Figure 8) has been applied to recognize emotions. We also took EEG as comparison reference to analyze the rapidity and intensity of thermal signals. Thus EEG signal was captured at the same time when the participants were watching the experiment pictures and when the thermal pictures were recorded.

Figure 8: Emotiv EPOC headset.

EEG detects the electrical signals released by the brain through a series of electrodes placed. The brainwaves were categorized into 6 different frequency bands which named as delta, theta, alpha, beta1, beta 2 and beta 3 waves (Figure 9.). Two of them, the alpha (8-12Hz) and beta (12-30Hz) were concentrated in our research, since alpha waves are the main indicator for an alert and beta signals are related to the active state of mind (Bos et al. 2006).

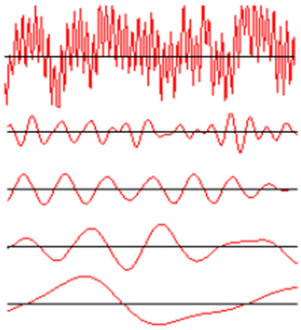

Figure 9: A raw EEG sample and its filtered component frequencies. Respectively (from the top): Beta, Alpha, Theta and Delta Brainwaves (Heraz et al. 2009).

3.2 Correlation between Two Measure Methods

For years, EEG has been used in many researches to recognize emotions. Murugappan et al. (2009) combined spatial filtering and wavelet transform to classify emotions (happy, surprise, fear, disgust, and neutral). Liu et al. (2010) implemented a real-time algorithm to recognize six emotions, including fear, frustrated, sadness, happy, pleasant and satisfied, and achieved 90% classification accuracy for distinguishing joy, anger, sadness and pleasure. EEG was also applied in monitory drivers' emotional behavior and help them to adjust their negative emotions to keep driving safely (Frasson et al. 2014).

Based on the EEG emotion recognition methods and algorithms, it is more efficient for us to apply the thermal technique into emotion detection area. We can also use the HMM or other proved model to perform classification and detect emotion changes. The only questions to consider are which thermal signals to capture, how to tailor the classifier training model to fit the thermal data processing approach, and how to check the accuracy of emotion recognition with thermal signal.

Thus, in our research, the EEG emotion detection methods were used as important inputs and reference for the study of applying thermal signal on emotion reorganization.

4 EXPERIMENT

4.1 Experiment Overview

4.1.1 Experiment Method

As shown in Figure 10, the participants were invited to watch a series of IAPS stimuli pictures. During the experiment, an Emotiv EPOC headset (Figure 8) and an infrared camera (ICI 7320, Figure 4) were used to respectively capture the real-time electroencephalogram (EEG) signal and the thermal pictures of the participants' faces. After recording both EEG and thermal pictures, we used the ICI camera software to export the 640*480 digital temperature matrix, which means totally 300k temperature data, in csv format for each infrared picture. To deal with the numerous thermal data, a data analysis agent was implemented to detect face areas, calculate average temperatures, and identify thermal changes. By comparing the EEG and thermal changes, we analyzed the thermal emotional profiles according to rapidity and intensity parameters. The details of the approach are presented in the next subsection.

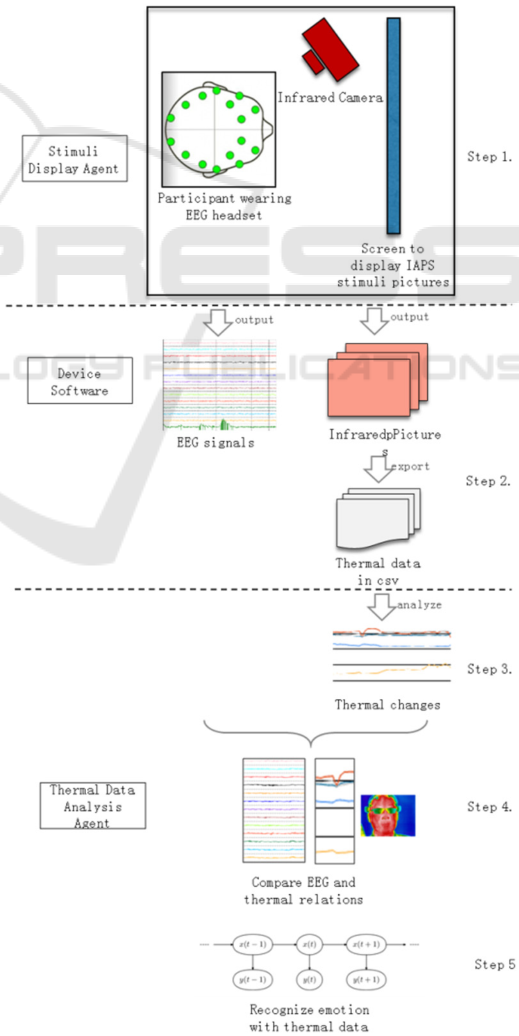

Figure 10: Experiment Method.

4.1.2 Experiment Material Selection

The International Affective Picture System (IAPS) provides the rating of a large set of emotionally-evocative color photographs across a wide range of semantic categories. In each picture set (totally 20 picture sets), 60 different IAPS pictures are varied in valence and arousal ranges. To measure participant's emotional reactions distinguishably, we selected 4 various pictures in each picture set and displayed them 3 seconds each, which means that80 IAPS pictures were selected. Meanwhile, to measure the thermal emotional changes when the participant is in neutral state, a preparation picture writing "Get ready to watch the next picture" appeared for three seconds before displaying the next IAPS picture.

4.2 Experiment Steps

The methodology of the experiment process is decomposed into five steps indicated below. Two agents Stimuli Display Agent and Thermal Data Analysis Agent) are co-working with EEG and ICI camera software in experiments. The Stimuli Display Agent was designed to associate the experiment to record participant info, experiment info and every pictures displaying time, etc. About Thermal Data Analysis Agent, it was developed to read thermal pictures, calculate face five areas temperature, and analyze thermal changes.

Step 1. Participants View Stimuli Pictures, and Devices Record EEG Data and Thermal Pictures. Six experiments were performed one by one with different participants of similar age and different gender. We helped every participant to wear the EEG headset and positioned the IR camera in front of him/her. After the devices were set properly, the participant was invited to watch the pictures slide-showed by the Stimuli Display Agent in a quiet environment. In the meantime the pictures were displaying, the EEG data were recorded in real time and the thermal pictures were taken (refer to the sample picture in Figure 11) every 3 seconds.

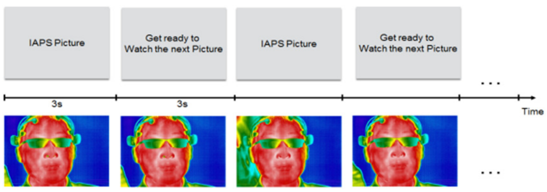

Figure 11: Step 1. The 80 stimuli pictures and 80 preparation-slides were presented each three seconds in turn. At the same time, the ICI camera was taking thermal photos every three seconds.

Step 2. Export Temperature Data for Every Thermal Picture. As mentioned in the Experiment Material Selection paragraph, in each experiment, 160 pictures were displayed to each participant and a total of 160 thermal photo accordingly. Later the thermal pictures were manually exported into related 160 cvs files (as IR Flash Software version 2.13.29.10 only supports exporting thermal matrix into csv file one by one) (Figure 12).

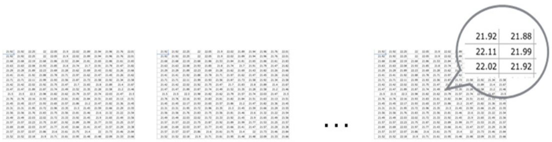

Figure 12: Using IR Flash Software to export cvs file for every thermal photo to get 640*480 temperature-matrix.

Step 3. Calculate the Mean Temperatures on Five Face Areas and Analyze Thermal Changes. The face location was detected manually and five areas were focused for further analyzing thermal changes (Figure 13). Considering that every thermal picture can generate a 640 * 480 temperature data matrix, the data volume of 160 thermal pictures reaches almost 50 millions data. To process the data efficiently, an initial analysis of calculating area average temperature were performed and the mean values were recorded instead of saving the huge amount of raw data into database, performed by the Thermal Data Analysis Agent. Then the thermal state changes (Figure 14) were identified. Please note that we focused more on the temperature changes, not the absolute temperature value since every human has different thermal activity, even when they are in the same environment.

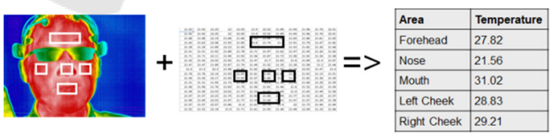

Figure 13: For each thermal photo, find five-areas (forehead, nose, mouth, left cheek and right cheek) locations, and then calculate the five-area mean temperatures.

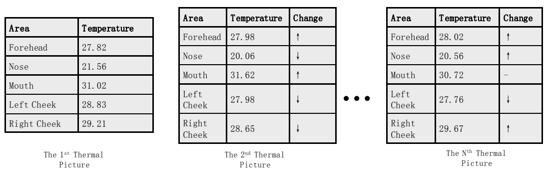

Figure 14: Comparison and extraction features of the thermal photo series.

Step 4. Compare EGG Emotional Profiles with Thermal Emotional Profiles. In this step, both EEG data and thermal changes were compared to analyze the rapidity and intensity of thermal emotional profiles (Figure 15). For the EEG data, the beta/alpha ratio (Fp1 and Fp2) were set as an indicator of the arousal state, and alpha activities (F3, F4) was used to recognize valence state (Bos, 2006). Then we use the thermal change produced in previous step to compare with the EEG arousal/valence states to figure out if thermal detection refers to the same emotional state measured by the EEG.

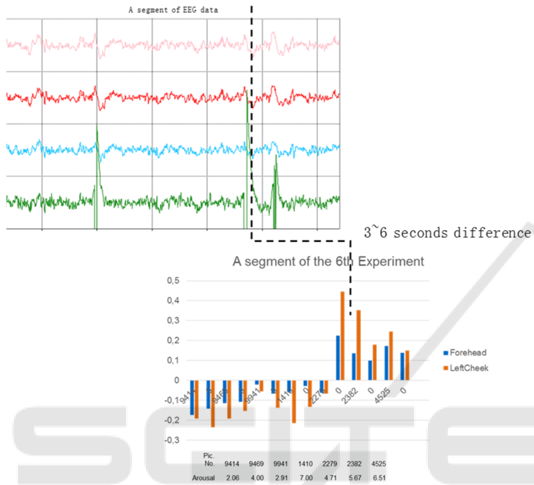

Figure 15: EEG and Thermal Data Comparison.

Step 5. In this step, we applied Hidden Markov Model on emotion recognition using thermal data. As mentioned in subsection 2.3.3,we trained the emotion classifiers based on participant ~~itself~~ data (named as participant-independent model) or based on other participants' data (named as participant-dependent model).

For the first model, only current participant's thermal signals were taken into account. The thermal data of the first 60 IAPS pictures and 60 preparation pictures were used as inputs to train the classifier for a participant, then the classifier was used to recognize the emotions when he/she was watching the rest of 20 pictures.

For the second model, the participant-dependent model, in order to recognize a participant's emotion when he/she was watching the stimuli picture, the classifiers were trained based on the other five participants' thermal data, As the training base for the second model is larger than the first model, theoretically, the emotion recognition accuracy of the second model will be better than the first one. In the next section, the experiment result shows that the inference is correct.

5 RESULTS AND DISCUSSION

5.1 Thermal Profiles on Face

By assessing all the six experiment results, we found that generally the nose temperature is lower than cheek temperature, and normally the left cheek is cooler than the right cheek which is the same as the finding of Rimm-Kaufman et al (1996).Figure 16 shows the sub segments of the 2ndand 3rdexperiment. X indicated the pictures number that the participant watched (0 refers to the preparation picture) and Y indicates the temperature.

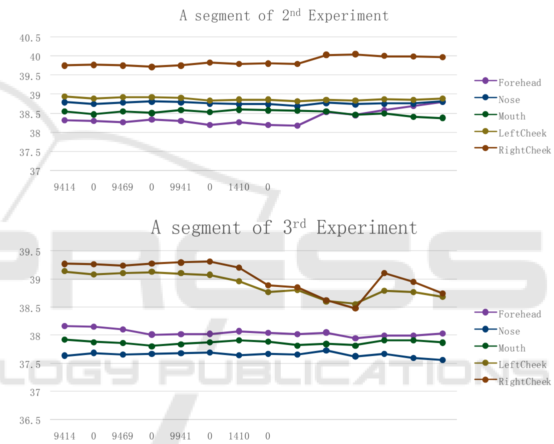

Figure 16: Two thermal signal charts of the 2nd and the 3rd experiment, showed that left cheek is cooler than the right.

5.2 Thermal Emotional Profiles: Rapidity and Intensity

Per the biological theory, the skin temperature changes because of the stimulation of nervous system, oxygen to the muscles, heart beat and blood pressure (Doucleff, 2013). So the skin thermal signal must appear slower than the brain signals. Then two questions need us to find answers: How long the thermal change can reflect on participant's skin? And what are the thermal intensities reflecting to different stimuli materials. In this section, we compare EEG and thermal data to analyze the emotional profiles from two dimensions: rapidity and intensity (Figure 17).

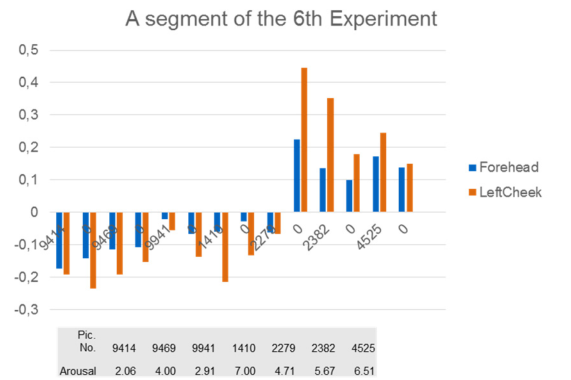

Figure 17: A similar while slower thermal arousal segment comparing with EEG arousal.

We filtered EEG data, and then used FC6 for getting the arousal levels and F3/F4 channel for getting the valence levels (Liu et al. 2010). By comparing the EEG channel signals with thermal changes which calculated in the experiment step 3, we found that around 60% similar thermal arousals on forehead and left cheek were shown 3 to 6 seconds after the EEG arousal. In terms of intensity, the temperature increase were normally within a range of 0.1°C to 0.5°C, and temperature decrease in a smaller range of 0.05 to 0.3°C, which means the skin temperature is easier to increase than to decrease.

5.3 Thermal Emotion Recognition using HMM

As mentioned in the experiment approach section, the emotion recognition was conducted using participant-independent and participant-dependent method. The method of training classifiers is based on the participant's first 60 pictures and 60 preparation slides, and then computing the probabilities and recognize emotions for the rest of 40 pictures/preparation-slides, is called participant-independent. For the participant-dependent method, as the name signifies, one participant's emotion likelihood depends on the other participants' classifications, which means that the classifier training was based on totally 800 (=160*5) thermal samples. The results in Figure 18 show that we achieved higher accuracies with participant-dependent model, which meets our inference.

Participant No.	Participant-Independent Accuracy	Participant-Dependent Accuracy
1	4.55%	38.89%
2	18.18%	23.46%
3	4.59%	35.19%
4	9.09%	30.25%
5	27.27%	28.40%
6	4.55%	30.25%
Average	11.37%	31.07%

Figure 18: The participant-independent and participant-dependent accuracy table.

From an overall point of view, there are possibilities to improve the emotion recognition accuracies to higher rate. The solutions could be to perform more experiments, to display more IAPS pictures to train the model, and to replace current manually indicated five-area locations by detecting automatically the five-area locations subject to change.

6 CONCLUSIONS

More experiments could be performed to improve the HMM classifier training, to enhance the analysis accuracy, and study the emotion profile differences by gender or ages. Furthermore, the matching learning algorithm used in this research could be applied to recognize the emotion profiles on the other normative emotional stimuli sets, such as IADS2 (the International Affective digitized Sounds). More data analysis can be applied to find which part(s) of skin temperature can provide more accurate emotion recognition. Meanwhile, as manually locating faces on thermal photo is unrealistic in high volume of data analysis, an automatic face detection method should be built out to improve the efficiency. Next target also includes the improvement of our application, Thermal Profile Analyzer to display both EEG and thermal signals for replaying the experiment and showing participant's emotional analysis result.

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