CONCEALED KNOWLEDGE IDENTIFICATION USING FACIAL THERMAL IMAGING

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ABSTRACT

In this paper, we present a non-intrusive lie detection system based on thermal imaging technologies. The system consists of the following modules: thermal camera, face detection and tracking, face landmark detection, feature extraction, and pattern recognition for concealed knowledge inference. We have discovered the most sensitive areas on the human face to monitor facial temperature changes. Detection algorithms are then developed to identify concealed knowledge from thermal imaging automatically. Face landmark tracking is used directly on the thermal video images to detect regions of interest (ROI) and extract features for concealed knowledge inference. We achieved an equal error rate (EER) of 16.5% in concealed knowledge recognition for 16 subjects on test data. Our non-contact method of concealed knowledge detection using thermal data achieves similar or better recognition accuracy as traditional intrusive methods, such as polygraph or EEG.

***Index Terms*—**Thermal imaging, facial landmark detection, matched filter, feature extraction, lie detection, pattern recognition.

1. INTRODUCTION

There is a need for identifying, at a distance, subjects concealing information at an interrogation, without the encumbrances of attaching the subject to equipment. For example, at border customs, it would be desirable to quickly determine if the subject interviewed is answering questions truthfully. The standard polygraph procedure includes measuring the scalar physiological parameters of blood volume and pulse changes, respiratory changes and electro dermal activities [1] that require the placement of electrodes and sensors on the participant. Functional magnetic resonance imaging studies (fMRI) [8] have shown that intended lies are correlated with increased brain activity in the prefrontal region. In another paradigm, Rosenfeld [2, 7] has demonstrated that a specific event-related potential (ERP) component, the P300, can be used to detect deception. Lately, functional near-infrared (fNIR) imaging has also emerged as a new way to image brain activity. Although fMRI and ERP measure brain activity, their dependence on sophisticated equipment and trained technicians limits their application in applied settings such as border control. New procedures and techniques have to be invented for this type of application.

There are several obvious potential advantages of facial thermography including the possibility of detecting and identifying deception from a distance in real time. Pavlidis and Levine [6] provided encouraging results when they studied temperature changes in the eye region as an indicator of emotional state changes. In our research, we examined the following: (1) how the thermal images of the human face are related to brain activity during a deception paradigm that has been used to elicit ERP responses; (2) what features of facial thermography (i.e., spatial and temporal components) are most sensitive to this paradigm; (3) what the limitations and precision of these features are; and (4) how to design an effective concealed knowledge detection system based on our research.

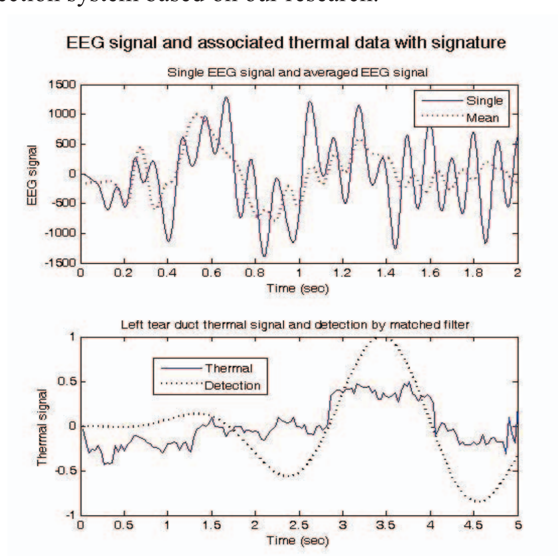

Fig 1: The EEG and thermal data from a subject that is concealing knowledge (subject instructed to conceal prior interaction with object): (A) The EEG data shows an average signal calculated over the subject's EEG signal, which shows a clear depiction of the P300 signal within the first second. (B) The thermal data shows a rise and return in temperature between the 3rd and 4th second (our signature of concealed knowledge).

This work is supported by ONR under the contract number N00014-07-C-0365. * B. Tan was with Li Creative Technologies, Inc.

2. DATA COLLECTION

2.1. Simulation of Guilt

Data were collected to compare the effectiveness of a thermal camera at detecting guilty knowledge and deception with an Event Related Potential (ERP) system and a Guilty Knowledge Test (GKT) [2]. In order to simulate guilt, the subjects were instructed to commit a mock crime (stealing a ring) before their arrival at the lab, prior to data collection. During the data collection sessions the subjects were questioned about the detail of this mock crime in an attempt to ascertain their guilty knowledge and detect their attempt to conceal information about the mock crime committed.

On returning from committing the mock crime, the subjects immediately participated in two data acquisitions sessions. The data collection was counter-balanced, with one half of the subjects first undergoing the GKT polygraph and the other half undergoing an electroencephalograph (EEG) and simultaneously recorded by a thermal camera. The subjects were then subjected to the other equipment on completion of the first data collection session. The EEG results were used to label thermal images for training for lie pattern recognition.

2.2. The EEG Protocol

The EEG protocol, designed by Dr. J. P. Rosenfeld of Northwestern University, consists of six stimuli: one Probe (*ring*), four Irrelevants (*necklace, locket, earring, cufflink*), and one Target (*watch*). Subjects were instructed to answer "yes" or "no" by clicking a given button on a mouse in response to each stimulus. They were told to answer "yes" to the word "watch" because it is their target, and responding "yes" means they recognize it. This forces the subject to pay attention to the stimuli as they are presented. They were then told to answer "no" to the remaining stimuli, meaning that they did not steal these items. So that when they answered "no" to the critical probe item, they would be lying. Each subject's face was recorded on video using the thermal camera during the test.

The test dataset consists of data derived from 16 subjects. The inter stimulus time (ISI) was 5 seconds after staggered data collection trials to allow adequate time for autonomous nervous system (ANS) responses such as thermal changes in the skin surface to be visible to non-invasive data acquisition systems.

2.3. Thermal Data

Our method of discovering concealed knowledge is based on the detection of the effort to conceal information from fluctuations in the subject's skin temperature. We use a thermal video camera to capture the dynamic skin temperature changes. Fig. 2 shows two frames from one of the thermal videos that make up our database of subject videos. The facial landmarks of interest, as noted, are: the inner and outer edges of the eyes, the outer edges of the nostrils, the tip of the nose and the outer edges of the mouth.

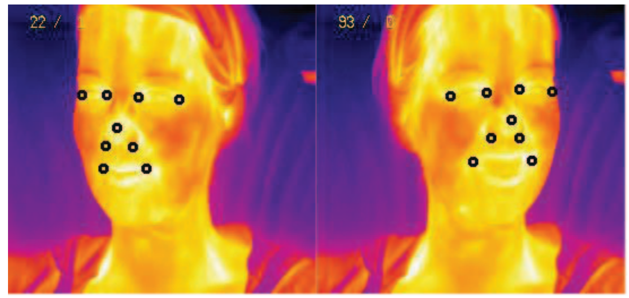

Fig 2: Still frames of the recorded thermal video with landmarks (highlighted) tracked through head poses.

Once the face has been detected based on the color difference between the subject's warm face as opposed to the cooler background we locate predefined landmarks on the subject's face, as shown in Fig. 2. Knowledge of these landmarks allows us to calculate the dimensions of the face and easily locate other features on the face. The data were processed with an algorithm to detect the landmarks directly using thermal images and track the landmarks through normal head motions [4], Fig. 2. The incorporation of dynamic information through Kalman filtering, and the face shape constraint through Active Shape Model (ASM) [3, 4] was explored. The tracking algorithm on the thermal video is important to ensure we can measure the temperature changes on the same point on the face.

3. METHODS

The thrust of our research was to identify the relevant regions of the face where the temperature signature is most informative of the subject's effort to conceal information when confronted with the Probe stimuli.

3.1. Thermal Feature Selection

The region of interest (ROI) is a window (50x100, height x width) including both tear ducts. For every frame we computed the mean temperature of the 10% hottest pixels from this region, which represents the mean temperature changes of the vasculature in the inner corners of the two eyes. This correlates with the portion of the inner eye region that has the highest blood flow rate, which explains why it is the hottest region from the experimental investigation [5]. In addition, this larger region can minimize the effects when tear duct tracking is not accurate. Fig. 3 shows some typical examples of the thermal signal in 5 seconds for the probe and irrelevant stimuli. Each 5 seconds of measured temperature traces were mean normalized prior to further processing.

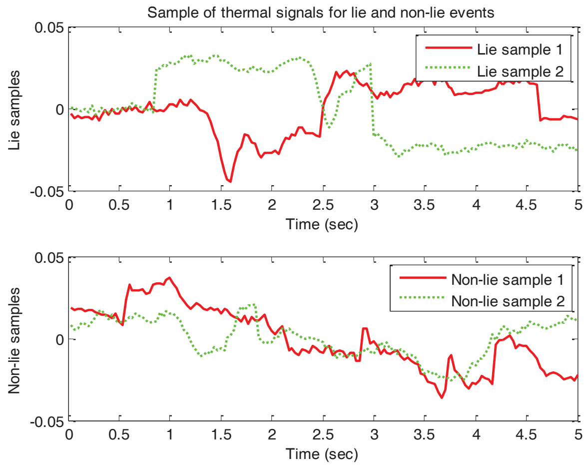

Fig 3: Sample of thermal signal for stimuli of lie and others: The upper figure shows the probe (lie) signals and the lower figure shows the Iirrelevant (non-lie) signals from the same subject. The P-thermal patterns are obvious from the upper figure; for the same subject, the delay for each stimulus is different.

3.2 Matched Filter for Lie Event Detection

As described above, we discovered the P-Thermal pattern in the thermal signals in lie events. To detect this P-Thermal pattern more clearly and robustly, we designed a matched filter to detect the lie event.

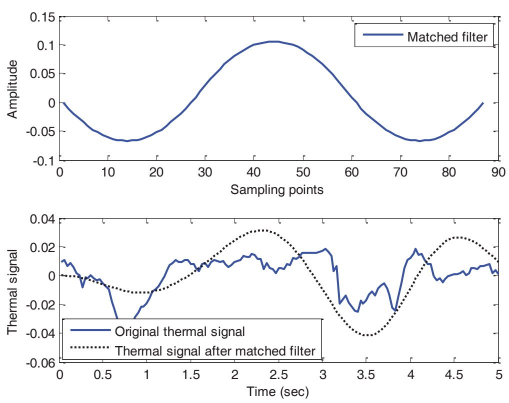

Fig 4: Passing thermal signal through matched filter: the upper is the designed matched filter and the lower is the comparison of thermal signals before and after matched filter.

For any measured thermal data, we conducted a convolution with the matched filter. Fig. 4-A shows the matched filter and Fig. 4-B shows the comparison of thermal temperature signal before and after passing through matched filter. As can be seen from this figure, the matched filter identifies the P-Thermal pattern.

3.3 Bootstrapped Amplitude Comparison

To determine whether the amplitude of the P-Thermal pattern evoked by probe stimuli is significantly higher than those that are evoked by an irrelevant within an individual or across individuals, we used the bootstrapped amplitude comparison (BAC) method. The BAC method is as follows: a computer program goes through the probe set and selects at random, with replacement, a set of N single sweeps. It averages these waveforms and calculates the maximum P-Thermal amplitude (Pm) from this average. Similarly a set of N single sweeps is selected from the irrelevant set and the maximum of P-Thermal amplitude (Im) is calculated from them. A decision can be made if the difference between these two maximum values (Pm-Im) is larger than the threshold. Here, the N value we selected is 20. Of course, a small number means a shorter testing time. We ran the bootstrapping test 100 times and calculated the maximum values for Pm and Im for every test.

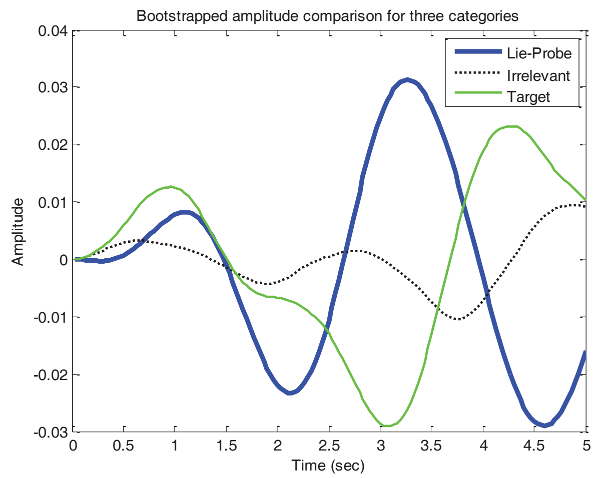

Fig 5: Bootstrapped amplitude comparison for Probe, Target and Irrelevant stimuli; each category has 20 randomly selected sweeps.

Fig. 5 shows BAC of the stimuli (Probe, Target and Irrelevant). For each set we selected 20 random sweeps. From this example, we can see the maximum bootstrapped P-Thermal amplitude is much higher than the amplitude from the irrelevant set and even the target set.

4. EXPERIMENTS AND RESULTS

For each subject, we computed 100 Pm and 100 Im values. Fig 6 shows the false accept rate (FAR) and false reject rate (FRR) curves with changing threshold for a representative subject. We observe FAR decreases with the increase of threshold while FRR increases. For this subject, the equal error rate (EER) reaches 0.165 at a threshold value of 0.19, which means the correct lie classification reaches 83.5% if we select this threshold.

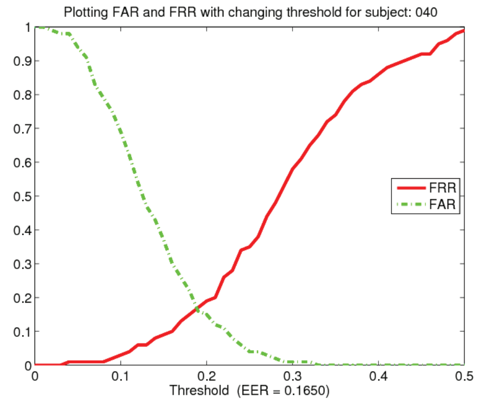

Fig 6: Plotting FAR and FRR with changing threshold.

Table 1 shows the EER for all subjects when we select 20 stimuli repeats in the BAC method. Fig. 7 shows the corresponding ROC curve. From Table 1 and Fig. 13, we can see the maximum EER is 0.485 and the minimum EER is 0.165, which means the lowest correct lie detection rate is 51.5% and the highest correct lie detection rate can reach 83.5%. This is a very promising result and indicates the thermal imaging methods described in this paper can be used for concealed knowledge detection in real applications.

Table 1: EER calculation for all subjects (20 stimuli repeats)

Subject Id	EER	Classification Rate: 1-EER (%)
024	0.335	66.5
025	0.410	59
026	0.435	56.5
027	0.21	79
029	0.38	62
030	0.33	67
031	0.43	57
032	0.45	55
034	0.41	59
035	0.405	59.5
036	0.325	67.5
037	0.42	58
038	0.47	53
039	0.375	62.5
040	0.165	83.5
041	0.485	51.5

5. CONCLUSION

From the above experimental results, the use of thermal imaging with our matched filter combined with the BAC method is a promising new solution for the detection of concealed knowledge. The correct classification accuracy using 5 second thermal video sequences was as high as 83.5% in the 16 subjects tested, which compares to 90% when using a contact EEG device [2].

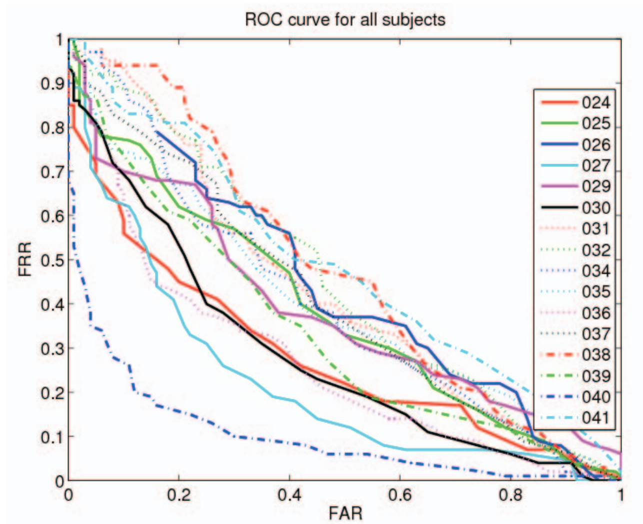

Fig 7: ROC curve for all subjects

6. ACKNOWLEDGEMENTS

The authors would like to thank Dr. J. Peter Rosenfeld of Northwestern University for the protocol design and data collection, Drs. Qiang Ji and Jixu Chen of RPI for their work in extracting facial landmarks from thermal imaging, and Dr. Jialin Zhong for initiating this project.

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