Lie Detection - Recovery of the Periorbital Signal through Tandem Tracking and Noise Suppression in Thermal Facial Video

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ABSTRACT

Previous work has demonstrated the correlation of periorbital perfusion and stress levels in human beings. It has also been suggested that periorbital perfusion can be quantified through processing of thermal video. The idea has been based on the fact that skin temperature is heavily modulated by superficial blood perfusion. Proof of this concept was established for two different types of stress inducing experiments: startle and mock-crime polygraph interrogations. However, the polygraph interrogation scenarios were simplistic and highly constrained. In the present paper, we report results on a large and realistic mock-crime interrogation experiment. The interrogation is free flowing and no restrictions have been placed on the subjects. We propose a new methodology to compute the average periorbital temperature signal. The present approach addresses the deficiencies of the earlier methodology and is capable of coping with the challenges posed by the realistic setting. Specifically, it features a tandem condensation tracker to register the periorbital area in the context of a moving face. It operates on the raw temperature signal and tries to improve the information content by suppressing the noise level instead of amplifying the signal as a whole. Finally, a pattern recognition method classifies stressful (Deceptive) from non-stressful (Non-Deceptive) subjects based on a comparative measure between the interrogation signal (baseline) and portions thereof (transient response). The successful classification rate is 87.2% for 39 subjects. This is in par with the success rate achieved by highly trained psychophysiological experts and opens the way for automating lie detection in realistic settings.

Keywords: Thermography, Polygraph, Tracking, touchless monitoring

1. INTRODUCTION

Stress has long been associated with deceptive behavior during interrogation. It emanates from a brain center and manifests itself in the peripheral senses through a variety of physiological signatures, including perspiration, pulse, and breathing rate [1, 2]. Polygraph examinations are based exactly on this principle. However, polygraph technology is based on contact sensors and heuristic analysis of signals by experts [3]. As a result, the comfort of subjects is compromised, which is very important in psychophysiology, as it is believed to contaminate the experiment [4]. The analysis of the results is slow because it is performed manually by several experts who later have to reconcile their findings. The processing of a typical 10 minute interrogation session may take several hours. Finally, due to the heuristic nature of the analysis the outcome cannot be embraced with high confidence and always has a suggestive nature.

Traditionally, polygraph examination is used by the U.S. Government to check periodically the veracity of employees that hold security clearances. It is also favored in some instances by private companies for screening during the hiring process. This is primarily for potential employees who will assume sensitive positions. Due to the problems of the existing polygraph technology, polygraph examinations are inadmissible in court. In recent years and with the intensification of the war on terror, there has been a clear desire for improving or replacing the polygraph technology with something better. There is a real need for administering real-time, highly automated veracity tests inside the country and around the globe, where human intelligence is being collected. At the same time, similar technology may be useful for quick screening of potential suspects in ports of entry [5].

Pavlidis et al. have discovered a physiological signature on the face directly associated with stress levels [6]. Specifically, they demonstrated that during stress produced by startle stimuli in the lab, subjects exhibited elevated blood perfusion in the periorbital area, which resulted into localized elevated temperature. They further suggested that such a heat signature can be captured by a highly sensitive thermal imaging system and analyzed using pattern recognition methods. Based on this principle, they have later developed an imaging system for quantifying stress during polygraph examinations. The system was put into comparative test with traditional polygraphy in an experiment designed and prosecuted by the Department of Defense Polygraph Institute (DoD PI). The accuracy between the two modalities was found to be equivalent (around 80%), thereby establishing the feasibility of the idea [7].

The DoD PI experiment was small in scale (20 subjects) and highly contrived. Questions were posed to subjects multiple times and there where long pauses between each question. The subjects had to give a binary answer (‘yes/no’) to impose uniformity on the time scale [8]. The subjects were also instructed to stay as still as possible. This is quite apart from the natural interrogation scenario where there are no motion restrictions and the flow is continuous and non-uniform. Actually, the pace of the interrogation accelerates or decelerates at times to build up psychological pressure.

Recently, the Psychology Lab at Rutgers University in cooperation with the Infrared Imaging Group in the University of Houston designed and executed a large mock-crime experiment, where all the aforementioned restrictions during interrogations were removed. Facial thermal video along with audio was recorded for every subject. The analysis of the thermal imagery demonstrated the limitations of the earlier methodology proposed by the way of the DoD PI experiment. Then, the problem of signal fading was addressed through transformation from the temperature to the blood perfusion domain via bioheat modeling. This magnified the scale of the phenomenon but also amplified the noise levels.

In this paper, we propose an entirely different methodology, which addresses the issue of automatic deception detection under the most realistic conditions and for a statistically significant number of subjects. The only similarity between the present and the past approaches is that the periorbital region continues to be the region of interest.

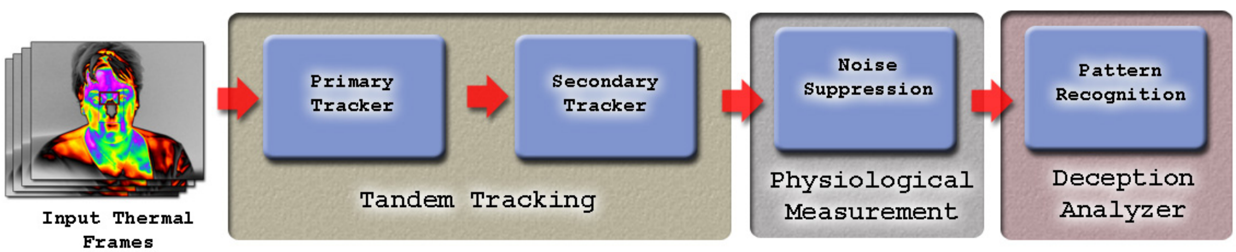

Fig. 1: System Architecture.

In section 2 we provide an overview of the experiment and the proposed imaging solution. In section 3 we describe the facial and periorbital tracking algorithm, which enables acquisition of temperatures from the tissue of interest despite head motion. In section 4 we describe the physiological measurement and our noise suppression methodology. In section 5 we present the pattern recognition algorithm that operates on the filtered temperature signal to perform the binary classification (‘Deceptive’ or ‘Non-Deceptive’). In section 6 we discuss the experimental results and ponder the strong and weak points of our approach. We conclude the paper in section 7.

2. OVERVIEW OF OUR APPROACH

Our objective is to extract the average temperature signal in the periorbital area of the subject through the course of the interrogation. Fig. 1 depicts the system architecture that realizes this objective. Specifically, we have a specialized tissue tracker that registers the subject's periorbital region despite the presence of motion. The temperature signal output by the tracker is marred by noise. While some systemic noise from the electronics of the thermal imaging system is present, the major source of noise stems from imperfections in the tracker. Therefore, a noise reduction algorithm (filter) is necessary to improve the quality of the signal. Finally, we have a pattern recognition algorithm that compares the overall outlook of the filtered signal (baseline) versus specific instances of high psychophysiological value (transient response). This comparison constitutes the basis of a binary classification rule ('Deceptive' or 'Non-Deceptive').

3. TANDEM FACIAL TRACKING

Condensation tracking in various forms has proved effective both in the visible [9] and infrared spectra [9]. Tracking accuracy fluctuates because occasionally the method is fooled by a local extremum. If tracking is regained momentarily, then the effect in typical applications (e.g., surveillance) is minimal. However, in physiological monitoring applications such as ours, even temporary loss of tracking creates serious problems. It results in spikes in the temperature signal of the tracked tissue, which are falsely indicative of strong physiological responses. This may mislead the pattern recognition algorithm.

Tracking is most challenging for the periorbital region, since it is a small highly uniform tissue area and its projection is greatly affected by the pan and tilt angles of the head. Even when tracking is maintained, it typically drifts over time. To address this issue, we have introduced the novel concept of *tandem tracking*. Simultaneously with the periorbital region we track a central facial region that is rich in contrasting features (see Fig 2) and more invariant than the periorbital region to pan and tilt rotations. The quality of tracking for this central region is better on average and can be used to correct the estimate of the periorbital tracker.

The scheme works as follows:

1. The operator selects two rectangular regions on the initial frame of the thermal clip - the central facial and periorbital.
2. The two regions are tracked by two independent condensation trackers. The feedback measurement for each tracker is based on a regular grid template. In essence, this is a sub-sampling of the rectangular region of interest. We have determined experimentally that a surprisingly small sub-sample of the original area produces the same tracking result as the full area.
3. The relative spatial position of the central and periorbital regions is established in the initial frame.
4. In subsequent frames the condensation trackers come up with independent position estimates. The position estimate of the central facial tracker is considered more reliable. Since the relative position of the periorbital region to the central facial region has been established in the initial frame, the position probability suggested by the central tracker for the periorbital region is weighted against the independent estimate of the periorbital tracker itself. The combined estimate provides for a robust solution and helps the periorbital tracker to overcome local extrema (see Fig 2).

4. PHYSIOLOGICAL MEASUREMENT AND NOISE SUPPRESSION

For every frame we compute the average temperature of the 10% hottest pixels from within the periorbital region of interest. We have found experimentally that this represents the average temperature on the vasculature in the inner corners of the eyes (see Fig 3). It is the periorbital region with the highest perfusion rate (that's why it is the hottest) and is minimally affected in the imagery by blinking. Therefore, assuming that tracking is accurate, it provides a temperature signal that is indicative of blood perfusion activity in the eye musculature. We consider that the periorbital temperature signal, as defined above, it consists of several components:

1. A low varying component indicative of the long term trend of perfusion levels, which is of high information value.

2. A mid frequency component, which is associated with temporary disturbances in blood perfusion caused by stress in specific Question and Answer (Q&A) sessions. This is also of high information value.

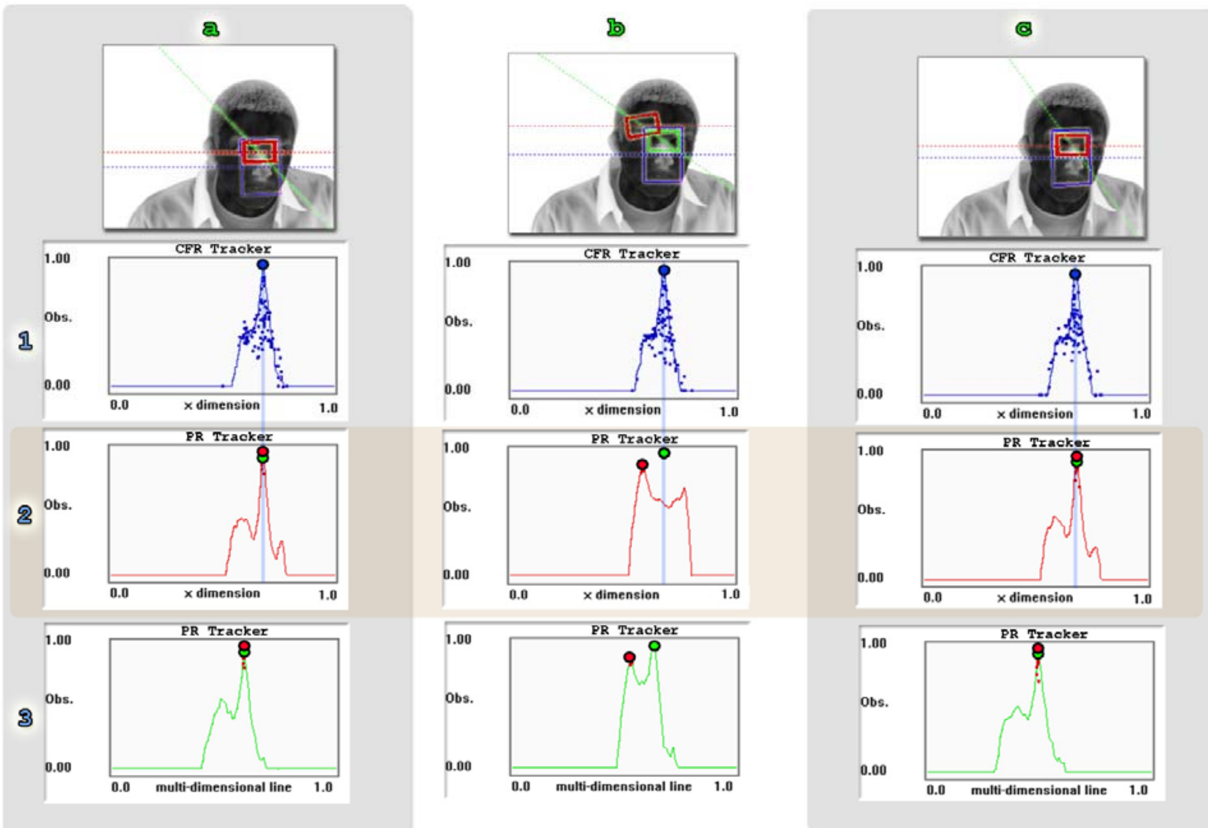

Fig 2. Tandem Facial Tracking. (a) Initial frame (F = 1) where the central facial region selection appears in blue while the periorbital region selection in red. (b) Intermediate frame (F = 330) that shows loss of tracking for the implementation of the periorbital region that is not tandem tracked. (c) Subsequent frame (F = 343) that shows regain of tracking after tandem tracking is reconstituted. (1) Observation densities along the mid horizontal (dotted blue line) for the Central Facial Region (CFR) tracker. The solution is identified with a blue disk. The three graphs correspond to the three frames a, b, and c. (2) Observation densities along the mid horizontal dimension (dotted red line) for the Periorbital Region (PR) Tracker. The solution is identified with a red disk. The three graphs correspond to the three frames a, b, and c. The PR tracker was set to ignore the influence of the CFR tracker in frame b (F = 330) and the result is temporary loss of tracking. (3) Observation densities along the green line crossing through the centers of the two PR regions in frame b. Since a parallel PR tracker without tandem influence is spawned only in frame b, this is the only instance that the respective PR regions are differentiated. One can observe that the non-tandem PR tracker selects a local maximum (red disk in graph 3b), which does not correspond to the global maximum caught by the tandem PR tracker (green disk in graph 3b).

3. A high frequency component caused primarily by tracker instability and systemic noise.
4. An impulse component caused by temporary tracking failures.

Our noise suppression effort is focused on eliminating the impulse and high frequency components.
We use a mean filtering method to remove the impulse noise. We define the average periorbital temperature signal as $T[n], 1 \le n \le N,$ where N is the number of frames in the thermal video clip. We compute the mean absolute inter-frame temperature difference as:

$$\overline{\Delta T} = \frac{1}{N-1}\sum_{i=2}^{i=N} | T[i] - T[i-1] | \quad (1)$$

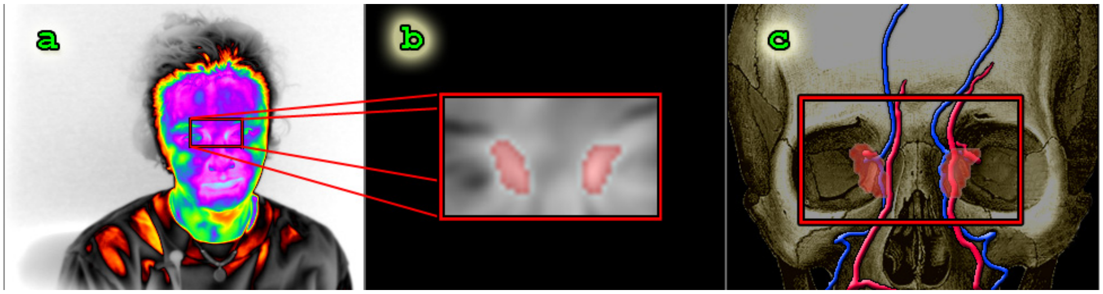

Fig 3: (a) Facial thermal frame of a subject with the periorbital region of interest superimposed. (b) Blow-up of the selected region of interest with the 10% hottest pixels marked in pink. (c) The periorbital region of interest with its 10% hottest subset superimposed on the facial and ophthalmic arteriovenous complex. The heat convected by the blood perfusion in this complex is responsible for the elevated temperature with respect to the rest of the periorbital region. Supply of additional blood to the eye muscle is realized through this complex. Therefore, monitoring the conduit in the eye corners is sufficient to detect the 'fight or flight' syndrome during stress.

We consider the signal value $T[i]$ as impulse noise (spike) if $| T[i] - T[i-1] | > \Delta T$. In this case, we replace $T[i]$ with the following interpolated value:

$$S[i] = \begin{cases} T[i-1] - \overline{\Delta T} & \text{if } T[i] < T[i-1], \\ T[i-1] + \overline{\Delta T} & \text{if } T[i] > T[i-1]. \end{cases} \quad (2)$$

The result of the impulse removing operation f is a new signal $S[n] = f\left(T[n]\right), 1 \le n \le N$ (see Fig 4). We remove the high frequency component of signal $S[n]$ through novel application of Fourier decomposition. Specifically we have the following algorithmic steps:

Step 1: We apply the Fast Fourier Transform (FFT) on signal $S[n]$ to get the power spectrum:

$$S(\omega) = F(S[n]). \quad (3)$$

The FFT method was first introduced by Cooley and Tukey [11]. Thereafter, it was used widely in signal analysis due to its high efficiency in comparison to other methods, such as the solution of linear equations or the correlation method [12]. To apply the FFT on the impulse filtered signal $S[n]$, first we use a low order trigonometric polynomial as follows [13]:

$$\begin{aligned} u[n] = s[n] = (\alpha \cos(n) + \beta), \\ \text{with } \alpha = \tfrac{1}{2}(s[0] - s[N-1]), \beta = \tfrac{1}{2}(s[0] + s[N-1]). \end{aligned} \quad (4)$$

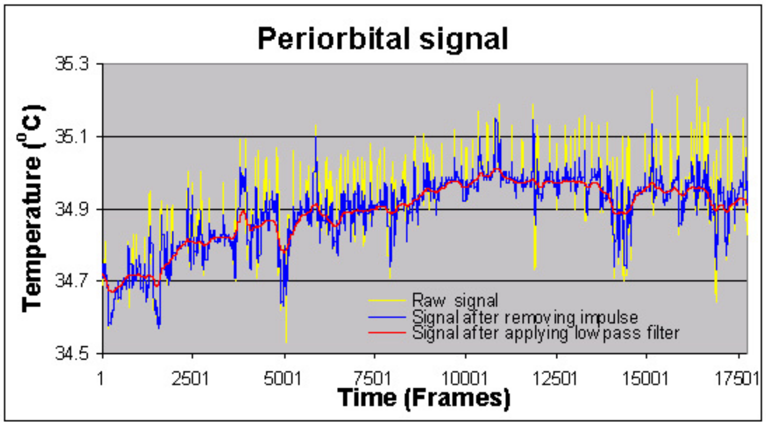

Fig 4: Periorbital temperature signal before (yellow) and after (blue) removing the impulse noise. The red curve shows the low-pass filtered signal after the application of the Fourier decomposition.

This ensures that the shift will not affect the stability of the scheme by minimizing the Gibbs phenomenon. Then, we extend $u[n]$ to a $2N$ periodic function as follows. First, we apply the symmetry [13]:

$$\forall n \in [0, N], u[N-n] = -u[n] \tag{5}$$

and second the periodic extension:

$$\forall n \in [0, 2N], \forall k \in \mathbb{Z}, u[n+k2N] = u[n] \tag{6}$$

We apply a classical decimation-in-time (Cooley and Tukey) 1D base-2 FFT method given in [14].

Step 2: We apply a low-pass filter on the power spectrum $S(\omega)$ to suppress high frequency noise. The filter is constructed using an exponential function:

$$H(e^{\omega 0.1}) = \sum_{n=0}^{\infty} u[n] - e^{\omega 0.1n}. \tag{7}$$

Step 3: We move back to the time domain by applying the inverse FFT on the filtered spectrum $S'(\omega)$:

$$\tilde{u}[n] = F^{-1} S'(\omega), \tag{8}$$

followed by re-normalization: $\tilde{s}[n] = \tilde{u}[n] + (\alpha \cos[n] + \beta).$ (9)

The low-pass filtered signal $\tilde{s}[n], 1 \le n \le N$ is fed to the pattern recognition module.

5. PATTERN RECOGNITION

We are interested in deriving a decision scheme, which will separate the Deceptive (D) from the Non-Deceptive (ND) subjects, based on the noise-cleaned temperature signals. Our previous research has indicated that elevated levels of stress are associated with elevated periorbital perfusion and temperatures [6, 7]. However, the degree of temperature elevation depends not only on the intensity of stress but also on the psycho-physiology of the subject. Different subjects react with different intensity to the same stress stimuli [8]. Therefore, an effective decision scheme has to normalize inter-individual variability through an intra-individual measure. We compute the slope D_i of the filtered temperature signal $\tilde{s}[n]$ that corresponds to the entire length of the interrogation for each subject *i*. This represents the trend or baseline response of the subject to the experiment. We also compute the slope d_{i4} of the portion of the signal that corresponds to the Q & A session with the highest *impact factor*. We define as impact factor, the level of perceived psychological stress a question has per unit time. In other words, for a question to have a high impact factor it is not only necessary to be 'tough,' but also short. It should also be preceded by a series of questions that slowly build pressure on a subject up to a culmination point. In our interrogation scheme, question 4 qualifies as such question. In the computation of d_{i4} we consider the signal from the beginning of question 4 to the beginning of the respective answer. Per the psychophysiological theory [15] this is the interval of interest in a Q & A session.

Our decision scheme is based on the comparison of slope d_{i4} with D_i for subject *i*:

$$d_{i4} - D_i \rightarrow \begin{cases} > 0 \text{ subject } i \text{ is D,} \\ \leq 0 \text{ subject } i \text{ is ND.} \end{cases} \tag{10}$$

In other words, if the physiological change in the critical question is greater than the baseline change, then the subject is classified as deceptive. This binary classification rule can be relaxed by establishing a third 'indecision' class when $d_{i4} - D_i$ is very close to 0.

6. EXPERIMENTAL SETUP AND RESULTS

The experiment was designed by the Psychology Lab of Prof. M.G. Frank in Rutgers University. Subjects were a sub-sample of 39 (19 males, 21 females) taken randomly from a larger population of 150 developed by Frank & Ekman [16]. They were all members of politically active groups both on and off campus. The subjects responded to either face to face or e-mail enquiries to participate in a communication skills experiment. When they appeared in the laboratory, they were told that deception is a part of communication, and that is the skill under examination for this experiment. They then completed a number of demographic and personality inventories. Afterward, they were presented with their specific instructions for the deception situation. They were told that there was a check in an envelope hidden down the hall. This check was made out to a group that the subject adamantly opposed (e.g., prolife subject, check made out to pro-choice group, and vice versa). The subject was told to find the check, and then decide whether or not to 'steal' it. If they stole it, they were to put it in their pocket. Whether or not they took the check, they then returned to the experimenter. The subject was then interrogated by a person whom they believe belongs to (or is a strong supporter of) a group they oppose (e.g., the subject who is pro-life will be interrogated by a person whom they believe is pro-choice). This means that a subject who stole the check lied about it under interrogation. If they fooled the interrogator, they were able to tear up the check (thus depriving their hated group of money), and they obtained $75 for themselves and this $100 would go to their group instead. If they failed to convince the interrogator of their innocence (i.e., caught lying), the $100 check would go to the group that the subject despised, the subject and their group would get no money, and the subject must withstand 30 minutes of loud, startling blasts of noise delivered via headphones. If the subject did not take the money, and they were judged truthful, they received $25 for themselves and $25 for their group, and the despised group would not get $100 but a smaller sum instead. If the subject was mistakenly judged as lying, then neither they nor their group got any money, the despised group got less money, and the subject was to face the loud startling blasts of noise. Note that no subjects were actually punished with the loud startling blasts of noise and all received at least some money for participation. What was important was for subjects to feel there was a punishment for not being seen as truthful.

The interrogation questions were derived by a panel of homicide and counter-terrorism professionals in conjunction with behavioral scientists [16]. Two of the questions specifically tested the idea's around a popular interrogation technique called the Reid technique [15], whereas the others were designed to elicit maximum useful nonverbal behaviors. In particular, it was composed of the following questions:

1. Describe in detail everything you saw down the hall.
2. Describe your actions while you were down the hall.
3. What was going through your mind regarding whether to take or leave the check?
4. Did you remove the check from the envelope?
5. Is there anything else you wish to tell me about the check or what you did?
6. Is everything you have told me about the check the truth?
7. What would you say if later I determined you lied to me about the check?
8. Where did you put the check?
9. What should happen to a person who took a check like this?
10. Have you ever told a lie to get out of serious trouble?
11. I know who that check was made out to. It is very understandable that you would not want to see money going to that organization. If I were in your shoes, I probably would have done anything in my power to avoid having money go to this organization. Now tell me the truth, did you take that check or not?
12. If you were to take a polygraph (lie detector machine) test, what do you think the results of this test would be?
13. Why do you think that someone would take this check?

The experiments conducted through the course of 12 months in a standard room. Three different environmental conditions were realized through the course of the experiments, each spanning several months in duration. Initially, the subjects were illuminated with a strong photographic light, which was causing significant elevation of the facial temperature. The setting was simulating to a certain degree outdoor conditions, where the subject would have been exposed to the sun. This initial batch of subjects is marked as Tape I in Table 1. Midway in the course of the experiments the photographic light was removed and the room was heated (winter time) to a typical indoor temperature ($25^{0}C$) while the subjects were dressed moderately. This is marked as Tape II in Table 1. Towards the end of the experiment the room was maintained to a typical indoor temperature ($27^{0}C$) without heating (spring time) and the subjects were lightly dressed. This is marked as Tape III in Table 1.

Interrogations were recorded with the University of Houston specialized thermal imaging system along with a separate synchronized voice channel. The recorded thermal clips were processed per the methodology outlined in sections 3 - 5. The voice channel was used to delineate the interrogation and the critical question 4 intervals in the frame sequences. The decisions supported by our scheme were compared against the ground-truth released by the Psychology Lab of Prof. M.G. Frank. The detailed classification results are shown in Table 1. The results clearly demonstrate the beneficial role of the impulse removal and lowpass filtering algorithms. It is also interesting to note that the method is more successful in detecting Deceptive (D) rather than Non-Deceptive (ND) subjects.

Based on the trend exhibited by the current experimental results, it is reasonable to expect that the performance of the method can improve simply by improving the accuracy of the tracking algorithm and the quality of the thermal imaging system.

7. CONCLUSIONS

We have presented a new methodology for recovering the periorbital signal from thermal facial sequences. It depends on tandem tracking and noise suppression. Tandem tracking ensures that the poorly featured periorbital region of interest is tracked accurately by weighing in feedback from the rich in features central facial region. Noise suppression removes spikes and high frequency components from the periorbital signal, which are due to tracking imperfections and electronic interference. The filtered signal is classified as Deceptive (D) or Non-Deceptive (ND) based on the slope differential between the entire curve and portions thereof (question 4 in our case). Subjects who exhibit higher change in critical moments with respect to their interrogation baseline are classified as D. Our method scored an 87.2% accurate prediction rate on 39 subjects interrogated by the Psychology Lab at Rutgers University per the designed mockcrime protocol. This is in par with the performance exhibited by seasoned interrogation experts.

This work follows up on the authors' previously reported methodology and results by the way of the DOD PI experiments [8]. This time the sample is double in size (39 versus 20 subjects) and the conditions quite realistic. The old method of amplifying the signal through transformation from the temperature to the blood flow domain was abandoned in favor of a noise suppression method. The periorbital region of interest has been more clearly defined as the inner corner of the eyes, where the facial and ophthalmic arteriovenous complex is supplying blood flow to the eye musculature. The importance of tissue tracking to cope with motor and fidgeting motion has been brought to the fore.

Our research further demonstrates the efficacy of automated lie detection by shedding more light into the associated physiological mechanism and coping with increasingly more realistic experiments. We are currently working on improving the performance of the tracking algorithm and computing the curve slopes through polynomial interpolation. At the same time we plan on processing more subjects to ensure that the method continues to scale up in larger data set.

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	SubjectID	Ground-Truth	Original Signal	Impulse Filtered Signal	Lowpass Filtered Signal
TAPE I	S20	D	0	0	1
	S21	D	0	0	1
	S23	D	0	0	0
	S24	D	0	0	1
	S26	D	1	1	1
	S27	D	1	1	1
	S29	D	1	0	1
	S31	D	1	1	1
	S19	ND	1	1	1
TAPE II	S57	D	1	1	0
	S62	D	1	1	1
	S63	D	0	1	1
	S65	D	1	1	1
	S68	D	0	0	1
	S69	D	0	0	1
	S75	D	0	1	1
	S80	D	1	1	1
	S81	D	0	0	1
	S87	D	1	1	1
	S88	D	1	1	1
	S92	D	1	1	1
	S49	ND	1	1	1
	S52	ND	1	1	1
	S58	ND	0	0	1
	S73	ND	0	0	1
	S76	ND	1	1	1
	S86	ND	0	0	0
	S91	ND	0	0	1
TAPE III	S99	D	0	0	0
	S104	D	1	1	1
	S110	D	1	1	1
	S165	D	0	0	1
	S96	ND	1	1	1
	S97	ND	1	1	1
	S111	ND	1	1	1
	S161	ND	0	0	0
	S162	ND	0	1	1
	S168	ND	1	1	1
	S172	ND	1	1	1
Overall Success Rate for D			54.2%	58.3%	87.5%
Overall Success Rate for ND			60.0%	66.7%	86.7%
Overall Success Rate			56.4%	61.5%	**87.2%**

Table 1: Experimental Results. Successful prediction is marked as ‘1’, while unsuccessful prediction as ‘0’.

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