StressCam: Non-contact Measurement of Users' Emotional States through Thermal Imaging

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Abstract

We present a novel methodology for monitoring the affective states of computer users. The method is based on thermal imaging of the face. To the user, the imaging system appears much like a video-conferencing camera. The method does not require contact with the subject and is passive; therefore, monitoring can be continuous and transparent to the computer user. We have found that user stress is correlated with increased blood flow in the frontal vessel of the forehead. This increased blood flow dissipates convective heat, which can be monitored through thermal imaging. The system has been evaluated on 12 subjects, and compared against real-time measurements of Energy Expenditure (EE). The new method is highly correlated with the established, but awkward EE methodology. The StressCam methodology is applicable to many instances where the real time measurement of users' emotional state is needed.

Author Keywords

Human-Computer Interaction, user frustration, thermal imaging.

ACM Classification Keywords

H5.2 Information Interfaces and presentation: User Interfaces-- Interaction styles, Theory and methods.

INTRODUCTION

Everyday life is awash in frustration, whether it is derived from dealing with bureaucracies or driving on a busy road. Frustration is caused by the occurrence of an unexpected result from an event. An individual may expect a particular reward for an action and when that reward is not received, such as succeeding at a simple task after several attempts, frustration can ensue [1].

CHI 2005, April 2–7, 2005, Portland, Oregon, USA.

ACM 1-59593-002-7/05/0004.

Unfortunately, computers are also a significant source of frustration and the automated detection of a user's emotional state, particularly frustration, has been the focus of considerable study. Early detection of a user's emotional state can be used for better management of computers and software. A computer and its software can respond to an individual's changing psychophysiology by either eliciting feedback from the user as to what is causing the frustration, or by offering assistance and guidance. By monitoring the resulting physiological patterns of frustration during use, a program may adapt and learn to make itself easier to use.

A number of approaches have been researched for detecting frustration and other emotions [4] [5]. A major limitation with both voice and facial-based approaches is that humans can be quite skilled at masking emotion conveyed through these modes. A number of physiological parameters have been explored as emotion indicators including heart rate, galvanic skin response, blood volume pulse (BVP), and electromyelography (EMG) [12]. An advantage of the physiological emotion indicators is that they are primarily under the control of the autonomic nervous system and are less susceptible to conscious manipulation. A major limitation to current physiological approaches is the need for sensors to be in direct contact with the user, or implanted [10]. As a result, such sensors are impractical for most routine user environments.

We present a novel methodology to quantify emotions for use within the Human Computer Interaction (HCI) context. Specifically, we propose to collect sensory data with a small thermal imaging camera. The thermal camera can be connected to the computer as a typical peripheral and pointed towards the face of the user. Thermal imaging is a passive modality that requires no contact with the subject. Therefore, it is suitable for continuous monitoring. Imaging of the face is not only convenient but also advantageous. The face of the computer user is typically exposed. It also features a thin layer of tissue, which facilitates observation by a surface modality such as thermal infrared. We can extract a variety of physiological variables from the facial thermal video through bioheat modeling. Certain localized measurements of physiological variables are related to the peripheral nervous system and are indicative of emotional states precipitated from the relevant intelligence centers. In this paper we focus on frustration, while in future work we plan on researching other emotional states.

ALGORITHMIC METHODOLOGY

We have found that during stress, there is an increase in blood flow to the forehead region of a subject. The increase in blood flow is centered on the frontal vasculature of the forehead at and just above the corrugator or "frowning muscle." The increase in blood flow, in-turn, leads to an increase in temperature in the local region of the forehead. This increase in temperature can be measured through a thermal imaging sensor.

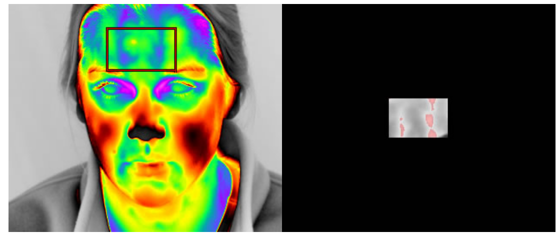
We have focused our thermal video processing on the frontal vessels of the subject. In the past, we reported in the literature that elevated perfusion levels in the periorbital area, which are manifested as higher skin temperatures, are indicative of elevated stress caused by a startle response or polygraph examination [7]. Rapid eye movement during computer use prevents periorbital measurement. Consequently the current work focuses on the temperature and associated perfusion levels in the frontal vasculature in order to determine mounting stress levels.

For each subject we select a Region of Interest (ROI) in the forehead that includes the frontal vessels (see Figure 1(a)). A tracking algorithm registers this ROI throughout the course of experiments. Tracking allows meaningful application of physiological computations despite subject motion. The computation is performed on the 10% of the hottest pixels in the selected ROI. We have found experimentally that this typically coincides with the frontal vessels in the forehead ROI (see Figure 1(b)).

We compute the mean temperature of the 10% hottest pixels on the ROI for every frame in the thermal clip. We thus produce a forehead temperature signal (see Figure 2). We then use the bioheat model we proposed in the past [8] to compute the blood flow on the frontal vessels based on the dynamic thermal input from the ROI.

EXPERIMENTAL DESIGN

To evaluate the StressCam, frustration was induced in 12 subjects and the physiological stress measured. For this study, we utilized the computerized version of a psychological tool called the Stroop Color Word Conflict Test [6] [15]. The Stroop test is a well established method for inducing stress. During the Stroop, the user is presented with the names of colors that are displayed in a discordant coloration. For example, if a word is spelled as "BLUE," but is colored green, then the subject is expected to report green as an answer (see Figure 3). As the Stroop test progresses, the time allotted to report a color for an answer is reduced. The diminished time acts to artificially induce stress by decreasing the required response time and increasing the error rate of the subject in reporting the colors.



(a) (b)

Figure 1: (a) Region of Interest (ROI) on the subject's forehead. (b) The frontal vessels (~10% hottest pixels in ROI) is marked in pink.

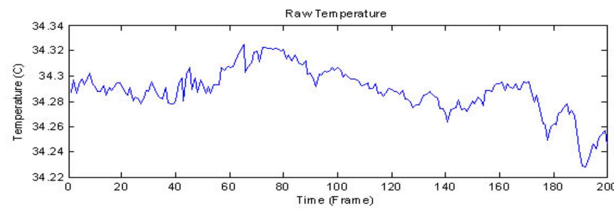


Figure 2: Forehead temperature signal.

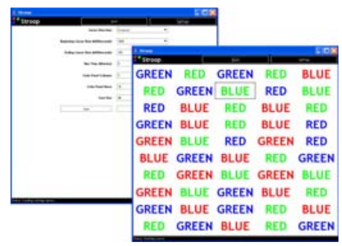


Figure 3: Screenshot of the Stroop test application. The boxed word indicates to the subject which color to report, irrespective of how the word is spelled [6].

Every subject underwent two sequential test sessions. In the first session we outfitted the subject with a metabolic rate measurement device to gauge Energy Expenditure (EE). In the second session we recorded the subject's face with our thermal imaging system. Every session included a baseline part (10 minutes) where the subject was at rest and a supervised Stroop testing part (10 minutes). We have included the EE measurement session as a validation standard for our novel thermal imaging approach to frustration detection. It has been documented in the literature that EE is a reliable stress indicator [13]. Ideally, we should have carried out thermal image recording of the face and EE measurement simultaneously on every subject. However, this was impractical due to the gas masks worn by the subjects in the EE measurements (see Figure 4) and can cause spurious noise to be interjected into the measurement collection process.

We quantified EE by analyzing the subject's respiratory activity using a cardiopulmonary stress test device, the Vmax Spectra from SensorMedics [14]. The measurement is based on the premise that the volume of oxygen consumed by a subject is proportional to the current EE of

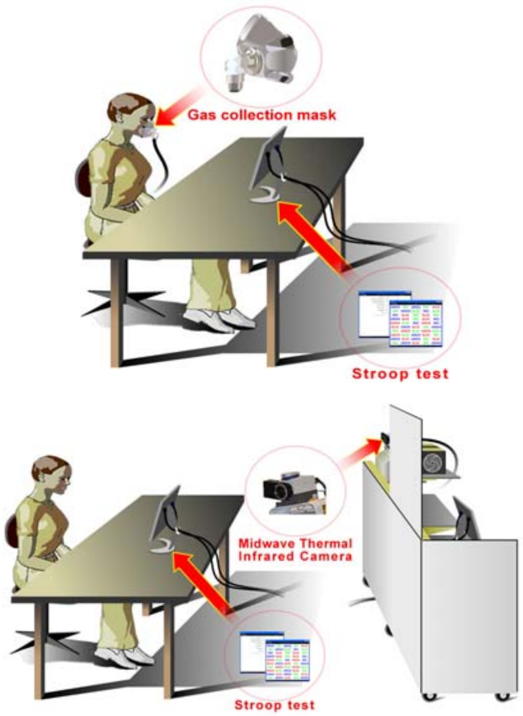


Figure 4: Upper Inset: monitoring the Energy Expenditure of a subject during Stroop testing. Lower Inset: recording thermal facial information of a subject during Stroop testing.

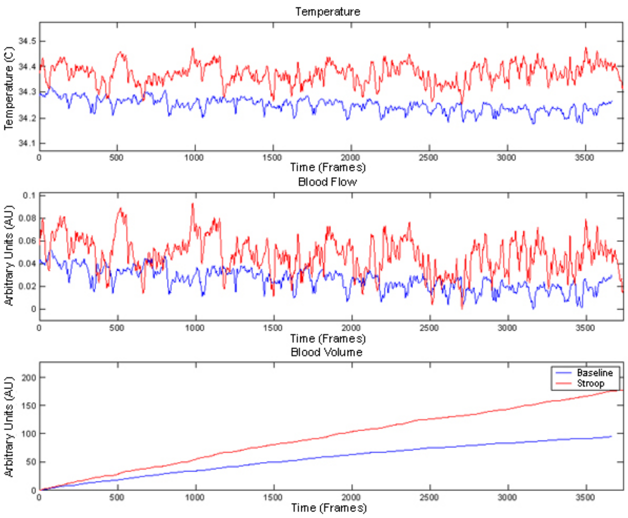


Figure 5: Top Graph: Original forehead temperature signals. Middle Graph: Blood flow signals. Bottom Graph: Blood volume signals. Red denotes signals for the Stroop session while blue for the baseline session.

the individual. We express the EE, or metabolic rate measurement, in Calories.

For the facial thermal image recording, we used our specialized Automatic Thermal Monitoring System (ATHEMOS). The centerpiece of the system is an Indigo Phoenix Mid-Wave Infra-Red (MWIR) camera with an Indium Antimonite (InSb) detector operating between 3 – 5 µm [3]. The camera has a maximum focal plane array

Subject	Ground Truth (EE)	Thermal Infrared
1	48	47.75077
2	4	10.42709
3	30	22.5545
4	60	56.136
5	21	24.20816
6	9	6.267478
7	28	17.33416
8	19	16.77886
9	33	40.23413
10	19	3.330412
11	34	27.12757
12	80	14.69287

Table 1: Ground truth data compared to thermal infrared data.

(FPA) resolution of 640×512 pixels and a maximum capture rate of 120 frames per second (fps); however, all of the thermal clips were taken at a resolution of 320×256 pixels and processed in a Dell Precision 650 with a Xeon CPU (2.66 GHz) [2]. This resolution was chosen to keep the frame capture rate at 31 fps as well as to keep the storage size at a minimum. Because the thermal parameters are computed on each frame, the difference between the baseline and the stressed (Stroop) was computed as the average root mean square of the frame-by-frame differences.

The experimental subject set included 12 individuals of varying ethnicity and distributed between 7 males and 5 females. The room temperature at the time of the experiments was measured between 19.4° - 22.2° C.

EXPERIMENTAL RESULTS

For each subject, we produced 6 curves, 3 curves for the baseline and 3 curves for the Stroop measurements: temperature, blood flow, and blood volume. We used the resultant blood volume curves to compute the thermal stress indicators (see Figure 5).

Due to the differences in units for the EE and the StressCam measurements, the results have been normalized for comparison (see Table 1 and Figure 6). In all but one subject, the comparison metric showed a difference no greater than 16 points from the respective ground truth metric; that is the corresponding EE.

In most cases the difference was within 8 points (subjects 1, 2, 3, 4, 5, 6, 8, 9, and 11). The correlation of the thermal infrared information to the ground truth data can be found and quantified by computing the Pearson correlation factor r ($-1 \le r \le 1$) [9]. For all subjects, the Pearson correlation value is r=0.52. If the one outlier subject (subject 12) is excluded from our computation, the correlation value becomes r=0.91. The results indicate that the thermal imaging methodology correlates very well with the ground truth EE data for typical subjects. The blatant outlier drives the correlation sharply downwards due to the small size of the set.

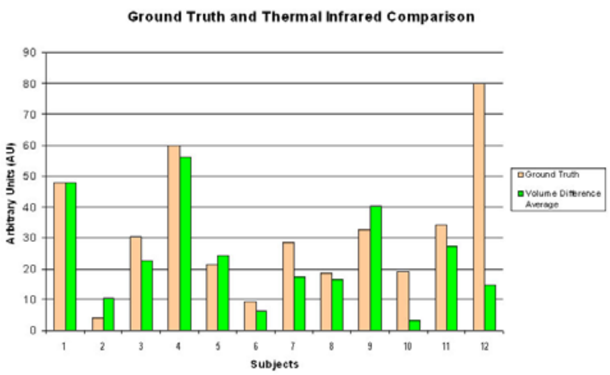


Figure 6: Comparison bar graph of the difference measures indicating relative stress levels measured using the ground truth EE and the novel thermal methodology respectively.

CONCLUSION

The motivation for this work is to overcome two major shortcomings of previous efforts, that is, the contact nature of conventional physiological sensors and the relatively low prediction accuracy.

These studies demonstrate that information collected from the thermal signature of frustration can be quantified. We use as an indicator of blood flow activity the blood volume evolution function, which we compute through bioheat modeling from the original temperature data collected from the sensor. We form a difference measure of the blood volume between a baseline and a Stroop session. Then, we compare this measurement with an established EE measurement as the indication of physiological stress which is measured through the employment of an invasive cardio-pulmonary device. The correlation between the two measurement methodologies is high. For 12 subjects the Pearson correlation factor is over 0.9 if we exclude one outlier. The results confirm that thermal imaging is a viable method for monitoring individuals during computer use.

There are many potential uses for the StressCam. Measurements during conventional usability testing could help identify user interface features that increase user stress, even if the user is not consciously aware of them. Use of a StressCam during computerized testing could identify questions that are unusually stress-inducing. Monitoring of software users on a routine basis, could identify software issues not uncovered by usability testing. In the future, software or operating systems could adapt dynamically to the user's emotional state, for example, suspending non-essential processes when the users are under considerable stress. Such monitoring also raises privacy and ethical issues, beyond the scope of this paper [11].

Although the results are highly encouraging and are well rooted on physiological knowledge, more experiments are needed to reveal the full picture and this is what we are currently pursuing.

ACKNOWLEDGEMENTS

We would like to thank the National Science Foundation (grant # IIS-0414754) and Dr. Ephraim Glinert, for their support and encouragement during the lifetime of this burgeoning research project. Equally, we would like to thank the Computer Science Department of the University of Houston for providing additional support. Finally, special thanks to Jonathan Dowdall from the Infrared Imaging Group at the University of Houston for his invaluable tracking algorithms and suggestions for capturing pertinent vasculature features. The views expressed by the authors in this paper do not necessarily reflect the views of the funding agencies.

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