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Continuous Physiological Monitoring

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***Abstract*— Our research aims to add a new dimension in human-computer interaction. This will be to endow computers with the capability to monitor continuously the physiology and comfort of the users and take appropriate actions when warranted. Computers will gradually assume the role of "guardian angels" and ensure the well-being of the people with whom they are in daily contact.**

***Index Terms*— Thermal imaging, physiology, preventive medicine, bioheat modelling.**

I. Introduction

Our research aspires to use the abundant computing resources at the office and at home in combination with novel sensing, algorithmic, and interface methods in order to create a new preventive medicine paradigm. The coupling of information technology and medicine in such a ubiquitous manner is a grand challenge problem. It touches upon several difficult issues. Specifically, our work address the following:

- Identify a sensing modality that is passive and can be employed as a multimedia accessory. In this context, we study the use of thermal imagers as computer peripherals.
- Develop mathematical models for cutaneous physiology and the environment that will capitalize upon the raw thermal data.
- Develop pattern recognition methods that associate dynamic 2D physiological and environmental patterns with the onset or existence of specific health and comfort states.
- Study human-computer interaction mechanisms for crisis management.

The expected outcome of our research is the development of a working prototype system. The system will incorporate monitoring of physical inactivity, anxiety, and comfort in the human-computer interface. It may incorporate headache monitoring, provided this higher risk component of our research is successful. Most important, it will spur further interest in the scientific community across a broad spectrum. More features, like monitoring of skin cancer and stroke propensity will be researched and incorporated into the human-computer interface. The expansion possibilities will be limited only by the imagination of future researchers.

In the present paper we focus on issues related to mathematical modelling of physiology. Details about the other aspects of our research will appear in future publications.

II. Relation to the Present State of Knowledge in the Field

This research is unique and there is no previous work with regard to the totality of our undertaking. There is, however, some previous research that is relevant to certain components of our work. It is a widespread belief in the human-computer interaction community that new computing ideas should focus on human needs [1]. One idea that was researched in this direction was emotional interaction between humans and computers [2]. Although, such efforts were pioneering they were rather narrow in scope (i.e., emotional monitoring as opposed to broader health monitoring). They were also deficient in the sensing elements they were using. These were usually a smorgasbord of invasive devices that were rather awkward and impractical for continuous daily use, and were hardly qualifying as computer peripherals.

The selection of thermal imaging as the modality of choice is very important. It renders our approach non-invasive and allows the screening of multiple states and health problems under a single sensing regime. We will be using state-of-the-art thermal imagers the size of a typical digital camera.

Thermal imaging has been used in medical applications but in a quite different manner than the one proposed in this project. Most of the efforts were focused on the detection of breast cancer off-line. One common characteristic of these efforts were their reliance on heuristic interpretation of raw thermal images [3], [4]. Very few methods differentiated themselves by putting forward a rigorous physiological and mathematical model amenable to computation [5], [6].

We propose to screen for a variety of health symptoms and not the manifestations of a specific ailment (e.g., cancer). Moreover, we propose the screening to be automated, continuous and, performed via a computer peripheral. For such a screening to be successful a variety of physiological variables have to be computed dynamically and accurately. Such variables include blood flow, metabolic, perspiration, and breathing rates as well as temperature distribution. The evolution of these variables along the timeline and across the 2D space can reveal important clues about anxiety, impeding headaches, and comfort levels. Amazingly, all the aforementioned physiological variables are related in some way to the heat transfer mechanism of the human body and is theoretically possible to be computed from the raw thermal imagery.

III. Mathematical Modelling for Physiology

The purpose of modelling is to compute a number of physiological and environmental parameters that will be useful in determining the health and comfort state of the computer user. A prerequisite for meaningful modelling is the segmentation of the different parts of the scene and the tracking of the user's face. Therefore, the modelling work should be divided

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into three parts: 1) scene segmentation and facial tracking, 2) physiological modelling and 3) environmental modelling. Fig. 1 depicts diagrammatically the detailed relation between these three parts and provides a snapshot of our overall research. In the rest of the paper we will elaborate on our approach to scene segmentation and physiological modelling only.

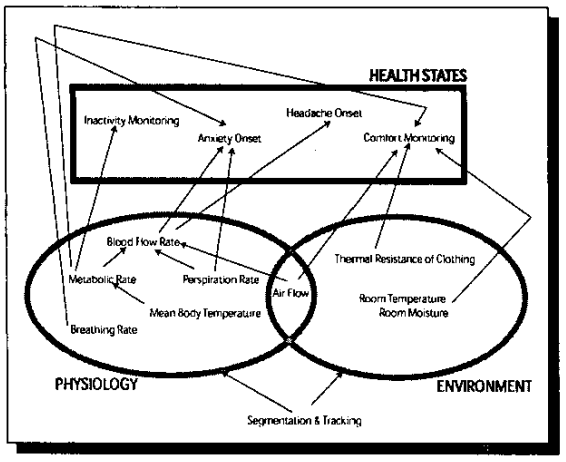


Fig. 1. The relation between tracking, physiological and environmental variables, and the health and comfort states under monitoring.

A. Scene Segmentation and Facial Tracking

We propose the design of a hierarchical segmentation scheme:

- *Level I.* First, a binary segmentation algorithm will delineate the skin from the no-skin region. The no-skin region encompasses the background as well as the covered skin areas. It is unproductive to attempt to locate initially the covered skin region, because its thermal signature is often similar to the background's (see Figs. 2(a), 2(b), and 2(c)). This is a common mistake of other approaches [7].
- *Level IIa.* Another segmentation algorithm will delineate the covered skin from the background within the no-skin region. The covered skin part corresponds to the user's upper body (see Fig. 2(a)). Both the covered skin and the background parts will be useful in the computation of environmental parameters.
- *Level IIb.* Yet another segmentation algorithm will locate the various anatomical features within the skin region. In our case, the (exposed) skin region corresponds to the user's face and neck. The specific anatomical features that need to be delineated include the forehead, the periorbital area, the cheeks, the nostrils, the mouth, and the neck. The anatomical features will accommodate the localized physiological computations.

For the Level I segmentation we propose a **novel statistical method**. The method features a powerful representation model that captures well the scene phenomenology. It also features an effective and lean model update mechanism. In each thermal frame we represent pixels that belong to skin and no-skin regions as mixtures of multi-Normals. This scheme is supported well by preliminary experimental data (see Fig. 2(b)). The exposed skin region is expected to have *hot* and *cold* areas. Hot areas of the face feature high density of superficial vasculature (e.g., periorbital area). Cold areas feature low density of superficial vasculature (e.g., cheeks). Equivalently, the background is expected to have a large area with uniform mild temperature (e.g. room furniture and walls) and small areas with high temperature (e.g., computer screens and lamps).

Therefore, at time t every pixel is described by a mixture of four Normal distributions:

$$f_{i,t-1} \sim N(\mu_{i,t-1}; \sigma^2_{i,t-1}); \quad i = 1 \ldots 4, \tag{1}$$

where two of them represent skin and the other two no-skin. At this time also an incoming pixel x_t is observed. The incoming pixel is assumed to follow a distribution $g_t \sim N(\mu_{g,t}; \sigma^2_{g,t})$, where the mean will be the observed value (i.e., $\mu_{g,t} = x_t$) while the $\sigma^2_{g,t}$ will be a known number representing the accuracy of the thermal camera. This is new evidence that initiates the model update mechanism. First, we have to find if the new value represents skin or no-skin and then we have to update the existing mixture model accordingly. We propose to use the Jeffrey's divergence measure as the matching criterion $J(f_{i,t-1}; g_t)$ [8]. Once the four discrepancy measures have been computed we find the density $f_{j,t-1} (1 \leq j \leq 4)$ for which:

$$J(f_{i,t-1}; g_t) = \min_{1 \leq i \leq 4} \{J(f_{i,t-1}; g_t)\} \tag{2}$$

and we will have a match between $f_{j,t-1}$ and g_t. Then, the new pixel value will be characterized as skin or no-skin depending on whether the $f_{j,t-1}$ represents a skin or no-skin distribution. The update cycle will complete by modifying the mixture parameters with the method of moments [9]. Once the algorithm labels every pixel in the incoming thermal frame as skin or no-skin, then the skin region can be delineated by applying blob analysis [10].

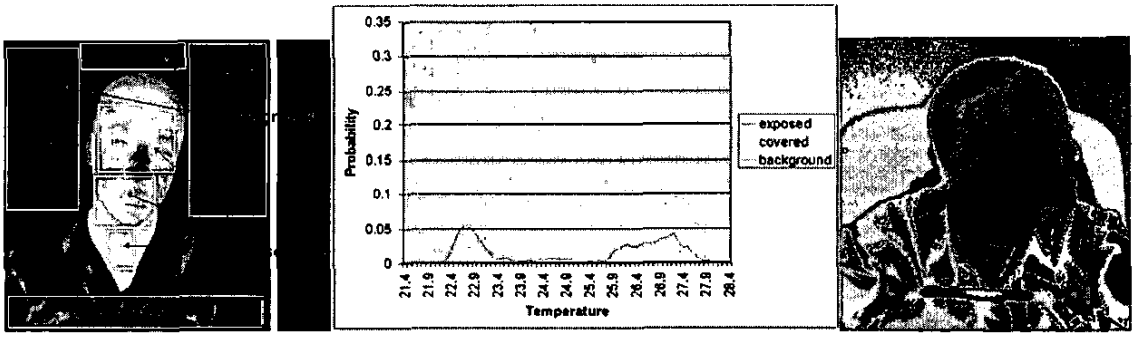
The next step (Level IIa segmentation) will be to segment within the no-skin region the background from the covered skin region. Our algorithm will capitalize on the physical constraints of the scene to carry out this segmentation step. Specifically, the covered skin part is at the bottom of the exposed skin part and has a characteristic rectangular shape defined by the shoulders of the subject (see Fig. 2(a)).

The final segmentation step (Level IIb segmentation) will be the delineation of the anatomical regions of the face. We plan on using the method of integral projections for that. It is a very effective and efficient method for locating facial features once the facial region has been segmented (see Fig. 3) [11].

Segmentation will be accompanied by tracking. We plan on investigating the use of the condensation algorithm [12] as the most promising solution to the tracking problem.

B. Physiological Modelling

Within the delineated anatomical features we can model the heat transfer mechanism and extract valuable physiological parameters. The proposed model views the computer user (human) as a heat producing engine. Heat is produced at the body due to metabolic processes and is transported to the cutaneous level through two mechanisms: conduction



(a) ***Segments.*** **(b)** ***Temperature Distributions.*** **(c)** ***Visualization.***

Fig. 2. **(a)** The primary segments of interest in a typical thermal scene involving a computer user are the background, exposed skin, and clothed skin regions. **(b)** Temperature distributions for the background, exposed, and covered skin regions of the computer user in Fig. 2(a). The distributions clearly show the bimodality assumed in our mixture model. They also show substantial overlapping between the covered skin and background distributions that will mar any initial attempt to differentiate between these two regions. **(c)** Visualization of the segmentation between the background (black), exposed (red), and covered (green) skin regions of the computer user scene in Fig. 2(a). The labelled image clearly shows the difficulty in segmenting between the covered skin and background regions.

and convection. Then, the heat dissipates to the environment through three different transports: radiation, evaporation, and air-flow convection. Therefore, according to our model the bio-heat transfer equation is:

$$\rho_s c_s \frac{\partial T_s^{\bar{x}}}{\partial \tau} = \lambda_s \nabla^2 T_s^{\bar{x}} + \omega_{bl}^{\bar{x}} c_{bl} (T_s^{\bar{x}} - T_{bl}) + q_m - q_r - q_e - q_a, \quad (3)$$

where ρ_s and c_s are the density and specific heat of skin, $T_s^{\bar{x}}$ is the skin temperature at point $\bar{x}$ of the exposed skin, λ_s is the thermal conductivity of skin, $\omega_{bl}^{\bar{x}}$ is the blood flow rate at point $\bar{x}$ of the exposed skin, c_{bl} is the specific heat of blood, q_m is the metabolic heat generation rate, q_r is the heat radiation rate, q_e is the heat evaporation rate, and q_a is the heat loss rate due to air-flow.

In Equation (3) we extend the classical bio-heat transfer model [13] by accounting for the radiative, evaporative, and convective heat losses. Our model assumes that the blood maintains its own temperature T_{bl} until it reaches the capillaries where momentarily equilibrates with the skin tissue. The skin temperature $T_s^{\bar{x}}$ is imaged by the thermal camera across the exposed skin region. Therefore, if we find ways to determine the parameters ($\rho_s, c_s, \lambda_s, c_{bl}$, and T_{bl}) and the heat components (q_m, q_r, q_e, and q_a), then we can solve according to $\omega_{bl}^{\bar{x}}$ in Equation (3) and **compute the blood flow rate** for every point $\bar{x}$ of the user's exposed skin. Regional blood flow rate will serve as the primary indicator of elevated anxiety levels and impeding headaches.

The metabolic heat generation rate q_m is in general dependent on temperature [14]. Our proposed general formula for the computation of the metabolic heat Q_m is:

$$Q_m = M \times B^{(T-310)/0.5}, \quad (4)$$

where T is the mean radiant temperature of the body, computable from the dynamic temperature map. The parameters M and B will be determined experimentally by measuring the metabolic rate in feverish patients through a cardiopulmonary device. Equation (4) expresses the percent increase in metabolic heat for every 0.5^0C increase in body temperature.

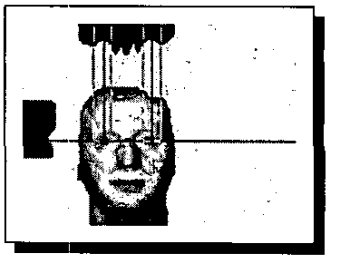


Fig. 3. Segmented exposed skin region of a computer user from a thermal frame. The dips of the horizontal and vertical projections correspond to the eyes. This is due to the lower temperature of the corneas with respect to the surrounding tissue.

The metabolic heat rate q_m will be useful in the computation of the blood flow rate and will also serve as a secondary indicator of the user's inactivity and comfort levels (see Fig. 1).

The computation of the heat radiation rate q_r will be based on the Stefan-Boltzmann Law [15]. The heat evaporation rate q_e depends on the perspiration rate. We propose a **novel thermal image processing method** to compute the perspiration rate of the computer user. Sweat glands create a minute cooling effect on the skin (see Fig. 4). This effect increases along with the perspiration rate. In our case, the visible anatomical area that features the highest concentration of sweat glands is the forehead. Therefore, we can apply the relevant image analysis in this pre-segmented region only. The perspiration rate is analogous to the density of the "cold" blobs that are centered around the sweat glands in the thermal image. These "cold" blobs expand or contract as the perspiration rate increases or decreases. The location, size, and overall density of the blobs can be determined by applying morphological processing. The heat evaporation rate q_e will be useful in the computation of the blood flow rate and will also serve as a secondary indicator of elevated anxiety levels (see Fig. 1).

Physiological parameters such as $\rho_s, c_s, \lambda_s, c_{bl}$, and T_{bl} in Equation (3) are either assumed or pre-computed. Researchers typically opt to use average values from the medical literature [16]. Since these parameters differ slightly for each individual,

Fig. 4. Thermal image of cold sweat glands on a small piece of skin. The blob nature of the glands lends itself to image processing computation.

a cookbook approach introduces an error, which may preclude the observation of subtle physiological phenomena. We propose a **novel method** that will establish accurate values for the physiological parameters through an automated process. Initially, a laser velocimeter co-registered to the thermal imaging equipment will provide ground-truth blood flow rate values for a single point at the exposed skin of the user. These ground-truth values can drive an optimization process at Equation (3) that will establish an optimal set of values for all the physiological parameters pertaining to the particular user. This initialization process needs to take place only once. It could be performed in computer stores much the same way that blood pressure measurement can be performed in pharmacies. The data can be stored in a digital medium to be used by the user's personal thermal imaging interface at home or the office from that point on.

In addition to the physiological variables associated with Equation (3) we can also determine the user's breathing rate. As the user inhales and exhales, air is flowing in and out of her/his nostrils. This air flow creates a periodic heat convective effect that is localized in the nostrils area. This local effect can be modelled and the flow and direction of air can be determined by applying Newton's Law of Cooling [15]. The breathing rate will serve as a secondary indicator of elevated anxiety levels (see Fig. 1).

IV. Conclusion

The implications of this research are ground-breaking and far-reaching. Our research leverages the most touted technology of our time, that is, information technology, to redefine the way people think and practice health care. Under the new paradigm, part of health care will not be administered periodically, off-line, at special locations, and at great expense. But, it will be administered continuously, on-line, in a highly automated fashion, at home and at the office, and with minimal expense. Health care and comfort functions will become an integral part of the human-computer interface.

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