A First-Order Markov Model for Wellness Mobile Applications

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***Abstract*—The concept of *wellness mobile* by incorporating continuous monitoring of biometrics on wireless handheld devices has been attracting a lot of attention from both industrialists and academia. In this paper, we propose a probabilistic inference algorithm for the wellness mobile applications by monitoring fluctuations in biometric(s) in order to provide effective inference about human wellness in an efficient and timely manner. Wellness state recognition can be achieved through dynamic probabilistic inference from the sensory data using multiple-modality sensors. Since the overriding goal is to embed this feature into a cellular phone, the proposed algorithm cannot be computationally complex and rely on too many biometrics. Here, the proposed algorithm relies on a single biometric, in which the dynamic probabilistic inference depends on a temporal window of observations of the biometric. Specifically, we monitor skin temperature variations during different activities in order to track the variations in human stress. The algorithm can be generalized by a temporal Bayesian network (TBN) framework. The simplicity of the technique makes it a favorable candidate for implementation on cellular phones with existing biometric sensors that are available in most smart phones today.**

***Index Terms*—Temporal Bayesian networks, wellness mobile, wellness monitoring, wireless healthcare**

I. Introduction

The burgeoning wireless technology and advances in the fields of signal processing and microelectronics have been the impetus for transforming wireless handheld devices such as cell phones as *lifestyle devices*. In this era of indispensable electronic gadgets, cell phones are being touted as the next generation *healthcare platforms* [1]. Today, cell phones are being used to respond to disease outbreaks, educate the local populace about illnesses, and remind patients to take their medications. Accessing and sharing medical records among healthcare professionals and patients, and communicating with healthcare providers, patients, insurance providers, and pharmacists using cell phones is becoming common in many developed and developing countries.

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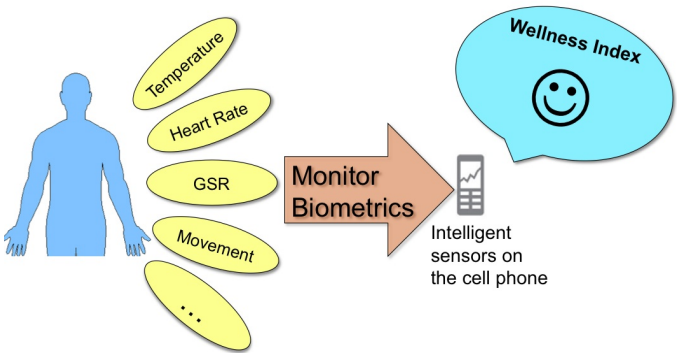

Fig. 1. Mobile phone to enhance users' "Quality-of-Life."

Wellness is defined as "an integrated and dynamic level of functioning oriented toward maximizing potential, dependent upon self-responsibility" whereas, *health* is defined as the lack of disease [2]. Fig. 1 illustrates the proposed approach for a *wellness mobile*. Different physiological and physical traits of the cell phone user such as temperature, heart rate, galvanic skin resistance (GSR), etc., will be monitored by deploying existing biometric sensors on cell phones, prevalent in the state-of-the-art smart phones today. This could then be combined with other information, possibly also obtained using the cell phone to compute a 'wellness index' that could customized to the cell phone user's daily lifestyle. In this way, the concept of wellness mobile envisioned can improve the quality-of-life for the cell phone user by facilitating frequent and better quality measurements, instantaneous feedback, improving the quality of medical information and enhancing patient compliance.

Some well-known wellness inhibitors are stress, fatigue, diseases and ailments. In this paper, we choose *stress* as an indicator of wellness in human beings. In

this paper, a probabilistic framework is proposed for the wellness mobile for stress recognition and monitoring capability based on variations in biometrics during emotional, visual, and physical event-driven stress stimuli. The proposed algorithm tracks the deviations in temporal windows of skin temperature measurements to generate *evidence* and *inference* models in order to predict stress states. Even though our model can be extended to multiple-modality tracking, embedding it on a cell phone will increase the form factor, memory, processing requirements, and the cost of the phone. For the approach described in the paper, it is possible to utilize some of the existing features/sensors available on the cell phones without requiring any additional hardware for stress detection but only through software implementation. For the demonstrability of the proposed algorithm, we choose the index finger for extracting the biometrics during different context-based stress stimuli. We justify our choice based on the findings from [3], thereby making it phone-user friendly.

The rest of the paper is organized as follows. Section II described the related works. The proposed temporal Bayesian stress monitoring model is presented in Section III. Section IV outlines the methodology and experiments conducted. Experimental results are discussed in Section V and conclusions are presented in Section VI.

II. Related Works

This paper adopts the physiologists' view-point that high stress is accompanied with large deviations from normal processes such as body temperature, heart rate, etc. It is a known fact that stress, emotional or physical can cause sharp fluctuations in biometrics such as body temperature [4]. Many physiological measures such as heart rate variability, skin conductivity, facial expressions and gestures [5]–[9] have been used to model a wellness or an *affective* state recognition system for humans.

Lately, researchers have been applying probabilistic-reasoning approaches to model user affect using graphical models like hidden Markov models (HMM), Bayesian networks (BN) and influence diagrams (ID). In [10], an HMM is used to model the transitions among three affective states: interest, joy and distress. The authors in [11] propose a temporal decision network to monitor a users emotions and engagement during the interaction with educational games. However, their work uses only bodily expression related features and also lack of validation. A temporal Bayesian network (TBN) with preset thresholds to recognize user fatigue and provide timely assistance was proposed in [12]. To the best of our knowledge, only [13] and [14] have proposed state-of-the-art TBN frameworks for monitoring fatigue and stress. Further, while [13] provide a framework for inferring fatigue and stress using only mental stressors, [14] proposes a stress detection technique exclusively for driving test.

Relying on instantaneous fluctuations of a single modality to infer about wellness state may not be very reliable. However, deploying multiple-modality frameworks could increase the hardware and computation burden on a wireless handheld device. Therefore, in this paper, we propose a simple reliable 'single-modality' TBN framework to detect user-stress that predicts affective states based on a *group* of biometric measurements. Here, we have chosen *skin temperature* as the biometric because it overcomes the problems of physical discomfort and difficulty associated with taking measurements of the physical quantities in human beings [15]. More recently, [13] proved that there is a high correlation between the skin temperature as a measure for stress and fatigue.

III. Temporal Bayesian Stress Model

Here, we propose a first-order Markov model, a special case of a TBN for monitoring human stress and tracking stress transitions. The stress stimuli are specific activities that described in Section IV based on skin temperature variations. We denote the ambient and instantaneous temperatures at time instant l as $T_{a,l}$ and T_l, respectively. It is remarked that for the experiments conducted the ambient temperature was kept constant. So, for the remainder of this paper, the time-subscript will be dropped and the ambient temperature will be denoted by just T_a. Let a temporal window of measurements comprise $l = 1, 2, \ldots, L$ samples, where $L \in \mathbb{Z}$. Then, the deviation in the k-th temporal window, ρ_k is computed iteratively using the following equation:

$$\rho_k = \max_l (T_a - T_l) - \min_l (T_a - T_l), \text{ for } k = 1, 2, \ldots \quad (1)$$

The goal of this paper is to model the associations between the different experiments that were conducted, and the participants' stress levels as a TBN. A single time slice BN is a graphical model, which represents conditional dependencies between any set of random variables. A generic TBN is a three-level architecture comprising of event variables, hidden state variables, and the observable variables. The time state extension of a single time slice BN results in the TBN as illustrated in Fig. 2. By using the probabilistic associations between the different sets of variables, and the observable variables (i.e., skin temperature samples), the goal is to accurately infer and track transition of the hidden state variables, in this case the human stress. In our

case, the three variables of interests are activity, $A = \{A_1, A_2, \ldots, A_N\}$, stress states, $S = \{S_1, S_2, \ldots, S_N\}$, and the deviations in temporal windows of temperature measurements, $\rho = \{\rho_1, \rho_2, \ldots, \rho_N\}$. Our system models an activity that causes stress, which in turn causes 'observable' symptoms, i.e., fluctuations in skin temperature.

The general mathematical setup for the proposed TBN-based stress tracking algorithm is as follows. Let the stress transition model be defined as $p(S_{k+1}|S_k)$, where S_{k+1} and S_k are the stress states at steps $k+1$ and k, respectively. The detection model is defined as $p(\rho_k|S_k)$, where ρ_k are the observations, i.e., the deviations in the temporal windows of temperature measurements. The temporal window for the experiments described in Section IV spanned four minutes and comprised 20 samples each.

The detection model comprises conditional probabilities, which were generated experimentally. Lastly, we define the inference model to be $p(S_k|\rho_{1:k})$. The inference model is updated in a recursive fashion at each step. At step $k = 0$, the model reduces to $p(S_0)$. We choose S_0, the initial stress state to be very low (~ 0.1), our choice justified by the responses that were obtained from the 'truthful' test-taker. These parameters are usually determined empirically or assumed in accordance with the existing literature such as [13], [16], and references within.

As illustrated in Fig. 2, the end goal of a Bayesian approach is to compute $p(S_{k+1}|\rho_{1:k+1})$ iteratively using $p(S_k|\rho_{1:k})$, i.e., to estimate the stress state based on the observations up to step k. This is done in two stages following the approach of [13]. First, we compute the stress state in step $k+1$ using observation up to step k. We use Bayes' rule for this.

Thus, we have:

$$p(S_{k+1}|\rho_{1:k}) = \sum_{S_k} p(S_k|\rho_{1:k}) p(S_{k+1}|S_k). \quad (2)$$

Next, the stress state in the $k+1$-st step is computed using the observation in the $k+1$-st time step. Using the Chapman-Kolmogorov equation, we express this as:

$$p(S_{k+1}|\rho_{1:k+1}) = \frac{p(\rho_{k+1}|S_{k+1}) p(S_{k+1}|\rho_{1:k})}{\sum_{S_{k+1}} p(\rho_{k+1}|S_{k+1}) p(S_{k+1}|\rho_{1:k})}. \quad (3)$$

IV. Experiments and Data Analysis

The existing results from psychological studies show that occupational stress is affected by the workload [13], [17]. Here, we adopt the approach of engaging participants emotionally, visually, mentally, and physically, during various activities that are representative of different stress levels. This is the premise for our event-based wellness monitoring framework. Thus in our framework, we change the activity to change the stress stimuli and the participants stress level. In order to measure the temperature of the participants, the Kidz-Med Thermofocus Non-Contact Infrared Clinical Thermometer [18] was used. In order to ensure accuracy of the measurements, the measurements were carried out using two different calibrated thermometers.

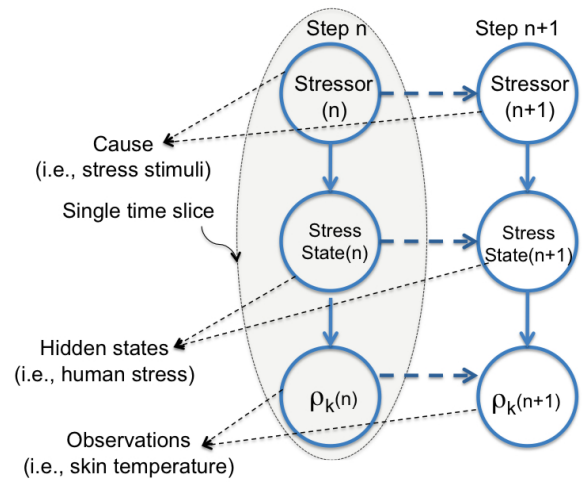

Fig. 2. Proposed temporal Bayesian stress state tracker.

A. Stress Stimuli

The stressors vary in the extent to which they engage the participant, and are aimed at isolating the cause (stress associated with the activity) and the effect (fluctuations in the skin temperature). The stressors used in this paper can be broadly classified as psychological, arithmetic, and gaming stressors, the descriptions of which follow:

- *Psychological Stressor* - Each user was asked to watch a series of clips on a home-theater system. The clips were chosen from a pool of horror, comedy, thriller, and drama movies. Each participant performed this activity for 10 minutes after which they had a break of two minutes. The experimenter was in the room recording the temperature. A total of 10 measurements were done for every two minutes per participant.

- *Arithmetic Stressor* - The Arithmetic Stressor had three segments. In the first segment, participants were asked to iteratively subtract the prime number

13 from 967 until they were left with a number smaller than the prime number they started out with. They had to perform this recursive subtraction in their minds and say out loud the numbers every time they did the subtraction. No pen and paper were allowed during the experiment. If they made an error, they had to start from the last correct number. They had five minutes to complete this activity, and there was a prize for the person who completed this with the fewest number of errors and shortest time if they could finish in less than five minutes.

In the second segment, the participants performed the recursive subtraction, but after every minute they heard a loud buzzer. During the last minute, buzzers went off after every 20 seconds. The purpose of the sudden buzzers was to rush the participant, and make the activity more stressful. In the third segment, the participants had to repeat the activity, only this time they had to say the number with a metronome. The beats of the metronome were altered to vary the engagement of the participant. The fourth and final segment involved the participant to say the number with a looping animation. The animation clip was of a ball bouncing on the ground, and the speed of bouncing increased with time.

- *Gaming Stressor* - Findings suggest that when participants cope with a competition, they assess it in such a way that it activates a psychobiological coping response [20]. Therefore, the participants were asked to engage in a combination of multi-player combat and racing games in which the player primarily assumes the role of a fictional character and have a plot. Theses games engaged the player intensely with their good game plots, characters, extreme graphics, and were chosen to simulate real-life scenarios where the goal was to 'stay alive' or 'win a race,' both of which activate the fight-flight system that increases stress levels. In order to facilitate ease of temperature measurements, the participants were asked to be seated. The gaming consoles used were the Playstation 2 (PS2) console operated by both hands, and a PS2 universal serial bus (USB) personal computer (PC) gun, which could be operated by one hand.

B. Statistical Parameters Extraction

1) Data for Learning: Previous works in the literature such as [13], [14] considered conditional probability tables (CPTs) generated by experts in the literature, and generated some data points from human participants they tested to validate their model. The approach adopted was to use a learning algorithm such as the expectation maximization (EM) algorithm to fix and refine the missing parameters and train the TBN. Since the statistical deviations in the temporal windows of temperature measurements are used to infer about stress, there was a need to generate new conditional probabilities for the detection model, $p(\rho_k|S_k)$, which is basically the probability that the temperature deviation at step k, ρ_k, is caused by the stress state at step k, S_k. For this purpose, we studied 20 participants (14 males and six females) working in the Silicon Valley to obtain the needed CPTs, and this will be referred to as our 'training data.' For the gaming stressor, in order to obtain enough training data, each participant played with at least three other people including the computer. However, to obtain the real data, the participants took part in a round-robin competition and each game lasted for 5-10 minutes. In total, 10 readings were taken every two minutes.

2) Validating 'Unrealiable' Ground-Truth and Stress Metric: The different activities were designed to engage the participants differently. Based on the training data, it was possible to map four ranges of ρ_k to four discernable stress levels, namely, 'Null,' 'Low,' 'Moderate,' and 'High.' For the sake of simplicity, only four stress levels were chosen. The next step was to relate a specific activity and the stress inferred by observing ρ_k. The participants were also asked to to rate how stressful the activity was by giving a number between 0 and 1. Every time a response was asked, the participant was presented with simple two-digit arithmetic activities, and the response times were recorded before and after or during a stress stimuli. This was used to corroborate the ground truth, and in generating the conditional probabilities. For example, it was seen that about 75-80% of the participants found the gaming stressors to be highly stressful. Almost 60-70% of the participants found the different segments of arithmetic stressor to be moderately to highly stressful.

3) Real Data: The 'real data' was obtained when three participants (three males) performed these activities in a predetermined sequence continuously for 80 minutes. Each participant underwent a series of temperature measurements (on the index finger, thumb, palm, and forehead) just before, during, and upon completion of the activity. There was a break of two minutes between the psychological and arithmetic stressors. The sequence of activities was the same for all the participants. A set of data points (35 minutes) for each of the three test participants were used as learning data, while the rest were used to validate our probabilistic model.

TABLE I
STATISTICAL PARAMETERS OBTAINED FROM THE EXPERIMENTS.

Statistical parameter	Value
p-value (ANOVA)	0.0234
p-value (Kruskal-Wallis)	0.0042
Mean Correlation	0.9453

V. RESULTS AND DISCUSSIONS

A. Statistical Analysis

In order to study the relation between the temperature measurements and stress, 'p-value,' defined as the probability of the null hypothesis of observing a result independent of the stress levels associated with the activities, and the correlation coefficients were computed. The p-values were 0.0234 and 0.0042 using the analysis of variance (ANOVA) and Kruskal-Wallis tests for the three participants, respectively. Since the p-value is less than 0.05, it is believed the test result is statistically significant, which means that stress level is sensitive to the activity. For correlation analysis, the correlation coefficients between each individual measure and stress are computed over time to reveals the variation of the measure with the stress. The computed coefficients show that the temperature variations are closely correlated to the stress level of the activity and the mean correlation coefficient was 0.9453, and the statistical parameters obtained from the experiments are listed in Table I.

B. Stress Recognition and Tracking Performance

The participants performed the activities in the following pre-determined sequence: *low*, *moderate*, and *high* stress activities. Fig. 3 is a plot of the skin temperature variations, and it can be observed that the skin temperature of the participant decreased as the stress level associated with the activity increased. The temporal window for the experiments spanned four minutes comprising 20 samples each. As shown in Fig. 4, the decrease in skin temperature can be viewed as the observable effect of an increased level of engagement in a activity or the workload (solid line), which is the performance of the Bayesian stress tracker as a function of time. The solid curve denotes the workload and was same for all the three test participants. The workload was computed using the training data, and is represented as stress levels normalized to a value between 0 and 1.

Here, we assumed that the stress level associated with a activity is time-invariant. On the other hand, the dotted curve in Fig. 4 is a plot of (3) for a single participant. The quantitative conditional probabilities were used to iteratively compute the stress states for the participant.

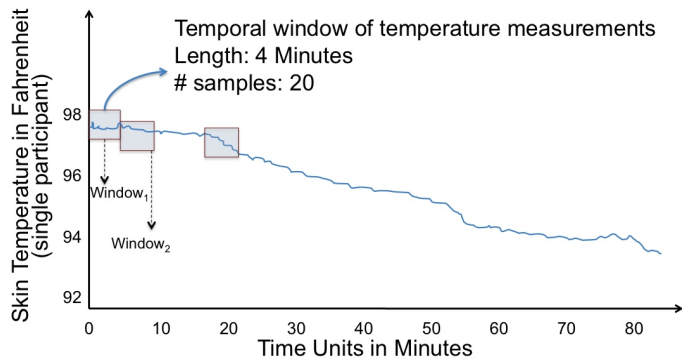

Fig. 3. Skin temperature variations for a single participant.

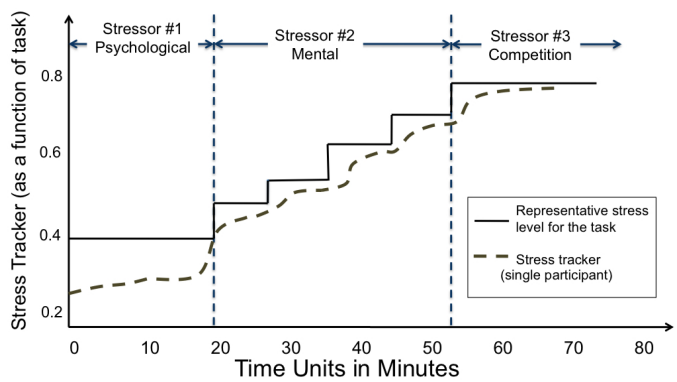

Fig. 4. Bayesian stress recognition algorithm for tracking the stress transition for a single participant. The solid line represents the stress levels associated with the different activities that were the same for all the three test participants.

It can be seen that probability-based approach tracks the workload (and the stress associated with the activity) reasonably well for the participant. Here, we have shown that one can accurately track the stress levels associated with a series of activities using the deviations in clusters or a window of measurements.

This approach offers a few flexibilities for the user. First, when implemented on a cell phone or any wireless handheld device, the user can assign the 'size' of the window for periodic sampling. Next, since we observe the deviations in a temporal window of the temperature measurements, we can reduce the probability of instantaneous spikes and false alarms. Finally, activity-induced temperature fluctuations can be tracked better by increasing the number of samples in a window or shortening the time-length of a window.

Fig. 5 is a plot of the 'estimated stress levels' versus the 'actual stress level.' It is remarked that for computing the actual stress level, the training data was used. The re-

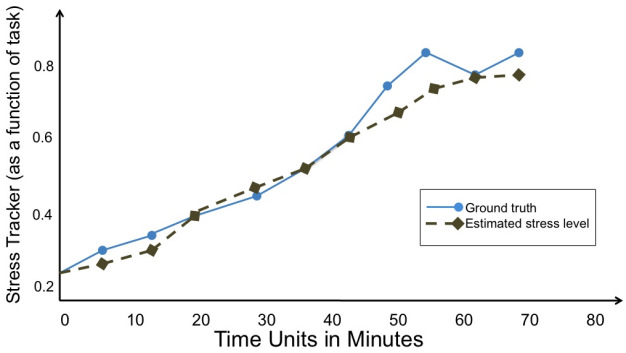

Fig. 5. Estimated stress levels and the actual stress levels for a single participant.

sponses from the test participants were used to compute the actual stress. As mentioned before, at each instance a response was collected, the test participant had to also perform some simple activities and the response times were used to validate the 'ground truth.' Even though the ground-truth is sometimes unreliable; we use the participants' responses to demonstrate the functionality of our TBN-based stress recognition algorithm. It is evident that the two curves variations match each other reasonably well, which validates the performance of the proposed algorithm.

VI. Conclusions

This paper proposes a probabilistic inference algorithm to recognize and track activity-induced stress state transitions in humans based on fluctuations in biometrics (skin temperature). The proposed *single modality* algorithm reliably tracks human stress states and is suitable for practical usage because it is envisioned that most future smart phones will be embedded with at least one of these inexpensive biometric sensors. Though the demonstrability of the proposed model using single-modality tracking algorithms has been presented in paper, it is straight forward to extend this concept to multiple-modality tracking. Through this algorithm, the users can monitor their stress levels periodically and mend their life accordingly. Future work comprises extensive data collection to generate a more comprehensive wellness scale to enable self-wellness monitoring into daily life, and incorporating multiple-modality tracking.

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