33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Human Thermoregulatory System State Estimation using Non-invasive Physiological Sensors

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Abstract— **Small teams of emergency workers/military can often find themselves engaged in critical, high exertion work conducted under challenging environmental conditions. These types of conditions present thermal work strain challenges which unmitigated can lead to collapse (heat exhaustion) or even death from heat stroke. Physiological measurement of these teams provides a mechanism that could be an effective tool in preventing thermal injury. While indices of thermal work strain have been proposed they suffer from ignoring thermoregulatory context and rely on measuring internal temperature (IT). Measurement of IT in free ranging ambulatory environments is problematic. In this paper we propose a physiology based Dynamic Bayesian Network (DBN) model that estimates internal temperature, heat production and heat transfer from observations of heart rate, accelerometry, and skin heat flux. We learn the model's conditional probability distributions from seven volunteers engaged in a 48 hour military field training exercise. We demonstrate that sum of our minute to minute heat production estimates correlate well with total daily energy expenditure (TDEE) measured using the doubly labeled water technique (r^2 = 0.73). We also demonstrate that the DBN is able to infer IT in new datasets to within ±0.5 °C over 85% of the time. Importantly, the additional thermoregulatory context allows critical high IT temperature to be estimated better than previous approaches. We conclude that the DBN approach shows promise in enabling practical real time thermal work strain monitoring applications from physiological monitoring systems that exist today.**

I. Introduction

SMALL teams of emergency workers or military personnel can often find themselves engaged in critical, high exertion work conducted under challenging environmental conditions. Hot environments pose a risk of heat strain particularly when heavy workloads and/or protective clothing ensembles are necessary (e.g. see figure 1). Excessive heat strain can lead to collapse or even death from heat stroke [1]. In a team setting these risks can be compounded by peer pressure to continue working even if the individual is aware of feeling ill [2]. The ability to monitor thermal work strain would provide an effective safeguard against potential heat illness for these workers.

Fig. 1. Civil Support Team (CST) engaged in a chemical biological training event. Ensuring encapsulated personnel do not overheat is difficult without thermal work strain health state monitoring.

Several heat strain indices have been suggested that provide an indication of thermal work strain from physiological measures that include both heart rate (HR) and internal body temperature (IT) [3], [4]. While these indices appear to provide reasonable indications of thermal-work strain under most conditions they suffer from several drawbacks. 1) These indices do not provide any thermoregulatory context. Relying solely on IT and HR can be misleading. For example athletes can tolerate high ITs (e.g. >40.5 °C) and high HRs when their thermoregulatory system is able to successfully transfer enough heat to the environment [7]. Conversely, encapsulated workers are unable to tolerate even moderately high IT (e.g. >38.5 °C) as heat transfer to the environment is compromised [8]. 2) The requisite measurement of IT in ambulatory environments is a challenge. The traditional thermistor/thermocouple probe-based methods (i.e., rectal and esophageal) are impractical. Other external methods such as insulated skin temperature and tympanic membrane temperatures have proven unreliable [5], and even ingestible thermometer pills (e.g., Vital Sense Pill, Mini Mitter Inc. Bend, OR) suffer from several drawbacks that: (1) they cannot be used by all people

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due to Food and Drug Administration (FDA) contraindications; (2) significant errors can occur from fluid ingestion up to 10 hrs. after taking the pills [6].

In this paper we use a *computational physiology* approach to develop a graphical model of the human thermoregulatory system. Graphical models provide an intuitive way to express the physiological variables and dependencies that form the basis of biological systems. By their nature many physiological processes evolve naturally over time and can be represented as Dynamic Bayesian Network (DBN) (e.g., [9]). We present a simple DBN model of the human thermoregulatory system that allows inference of IT, heat production and heat loss, from observations of HR, skin heat flux and accelerometry.

II. METHODS

A. Dynamic Bayesian Network Model

Our DBN is represented by the graphical model shown in figure 2.

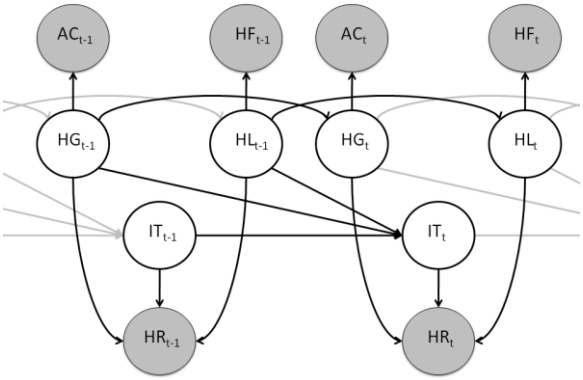

Fig. 2. Physiology-based Dynamic Bayesian Network for thermoregulation. IT = internal temperature, HG = heat gain, HL = heat loss, HR = heart rate, AC = activity from accelerometry, and HF = heat flux. White nodes represent latent variables and gray nodes are observed variables.

This DBN is based upon several constraints specific to our problem area of teams of young fit workers engaged in physical activity in warm environments. In this setting we choose one node to represent heat production or heat gain (HG) from work conducted by muscles. This heat production mechanism far outweighs heat production from other factors such as: basic metabolic rate, the thermic effect of food, or circadian rhythms. Similarly, we represent heat transfer/heat loss (HL) by one node. This node represents heat transfer from the core to the environment through the mechanism of skin blood flow and sweat, which in exercise conditions overshadows the loss of heat through respiration and the passive transfer of heat by conductance.

HR is helpful in estimating metabolic rate from work by muscles because of the well-known relationship of oxygen consumption to cardiac output derived from the Fick principle [10] where the rate of oxygen consumption is equal to the cardiac output (HR x stroke volume) multiplied by the arterio-venous difference in blood oxygen concentration. Similarly, heat transfer from the core to the skin by skin blood flow is dependent on the rate of blood flow to the skin (i.e. HR x stroke volume). Finally, HR has been shown to provide an indication of steady state IT [11], [12] Finally, we provide independent observations of HG through accelerometry (AC) and HL by heat flux (HF).

As our DBN is a directed acyclic graph, the joint distribution across all random variables (Y) can be factored by the chain rule for Bayesian networks to provide the following factors: $P(Y) =$

$P(AC|HG)P(HR|HG,HL,IT)P(HF|HL)P(HG|HG_{t-1})$
$P(HL|HL_{t-1})P(IT|HG_{t-1},HL_{t-1},IT_{t-1})$.

Our model then can be defined by the conditional probability distributions (CPDs) of these factors. By assuming that our CPD are Gaussian we can make use of the Kalman filter [13] algorithm to iteratively compute the latent variable probability density functions (PDF) for a given series of observations. The Kalman filter is defined by the following PDFs:

$$p(\mathbf{z}_t|\mathbf{z}_{t-1}) = N(\mathbf{z}_t|\mathbf{A}\mathbf{z}_{t-1},\boldsymbol{\Gamma}) \quad (1)$$

$$p(\mathbf{x}_t|\mathbf{z}_t) = N(\mathbf{x}_t|\mathbf{C}\mathbf{z}_t,\boldsymbol{\Sigma}) \quad (2)$$

Our DBN model can be defined in terms of the Kalman filter PDF's, where our latent variable vector $\mathbf{z}_t$ = [HG$_t$, HL$_t$, IT$_t$], and our observation vector $\mathbf{x}_t$ = [AC$_t$, HR$_t$, HF$_t$,]. The Kalman filter PDFs are defined by the following matrices:

$$\mathbf{A} = \begin{pmatrix} \mathbf{a_1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{a_2} & \mathbf{0} \\ \mathbf{a_3} & \mathbf{a_4} & \mathbf{a_5} \end{pmatrix} \boldsymbol{\Gamma} = \begin{pmatrix} \boldsymbol{\gamma_1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\gamma_2} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{\gamma_3} \end{pmatrix} \mathbf{C} = \begin{pmatrix} \mathbf{c_1} & \mathbf{0} & \mathbf{0} \\ \mathbf{c_2} & \mathbf{c_3} & \mathbf{c_4} \\ \mathbf{0} & \mathbf{c_5} & \mathbf{0} \end{pmatrix}$$

$$\boldsymbol{\Sigma} = \begin{pmatrix} \boldsymbol{\sigma_1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \boldsymbol{\sigma_2} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \boldsymbol{\sigma_3} \end{pmatrix} \quad (3)$$

At each time step the Kalman filter uses (1) a prediction step that estimates current latent variable estimates ($\widehat{\mathbf{z}_t}$) and their associated variances ($\widehat{\mathbf{V}_t}$) based upon the previous time step, and (2) an update step where these estimates are updated based upon the current observations. The prediction and update steps follow the basic Kalman filter equations as outlined by [14]:

(1) Prediction step:

$$\widehat{\mathbf{z}_t} = \mathbf{A}\mathbf{z}_{t-1}$$

$$\widehat{\mathbf{V}_t} = \mathbf{A}\mathbf{V}_{t-1}\mathbf{A}^T + \boldsymbol{\Gamma}$$

(2) Update step:

$$\mathbf{z}_t = \widehat{\mathbf{z}_t} + \mathbf{K}_t(\mathbf{x}_t - \mathbf{C}\widehat{\mathbf{z}_t})$$

$$\mathbf{V}_t = (\mathbf{I} - \mathbf{K}_t\mathbf{C})\,\widehat{\mathbf{V}_t}$$

$$\mathbf{K}_t = \widehat{\mathbf{V}_t}\mathbf{C}^T(\mathbf{C}\widehat{\mathbf{V}_t}\mathbf{C}^T + \boldsymbol{\Sigma})^{-1}$$

While the Kalman filter provides the basis for our inference, the model parameters $\theta = \{\mathbf{A}, \boldsymbol{\Gamma}, \mathbf{C}, \boldsymbol{\Sigma}\}$ must be learned. Expectation - Maximization (EM) [15] is an iterative algorithm that finds the maximum likelihood estimates of model parameters in cases where some of the variables are unobserved. The algorithm uses a two step process. In the first step or E-step the expected values of the latent variables (Z) are estimated using a current set of model parameters and observed data (X). In the second step, the M-Step, the model parameters are maximized according to the complete-data log likelihood $P(Z,X|\theta)$ with respect to the posterior distribution $P(Z|X,\theta)$. Bishop [16] provides an

overview of the EM approach for linear dynamical systems. Initial states for our latent variables (defined by $\mathbf{z}_0$ and $\mathbf{V}_0$) are assumed to take starting values typical of those found in a resting human.

B. Experimental Data Sets

Two distinct data sets were used for our experiments with a total of 15 volunteers. The training data set (Train) consists of physiological data collected from 7 male volunteers (age 26.8±2.1 yrs., height 1.78±0.08 m, and weight 85.7±6.2 Kg), collected continuously over a 48 hour military training exercise (air temp: 21-23.5 °C, relative humidity 77-86 %). The validation data set (A and B) consists of physiological data collected from 8 male volunteers (age 27.7±6.0 yrs., height 1.95±0.09 m, and weight 85.7±14.2 Kg) collected during two military field training events. Event A was a 5 Km road march conducted in fully encapsulating personal protective equipment (air temp. 18°C, relative humidity 72%), and Event B was a simulated patrol and ambush (air temp. 15 – 20°C, relative humidity 85 – 65%).

C. Measures and Statistics

In all data sets both observable model parameters (AC, HR, and HF) and the latent variable IT were collected. Table 1 presents the details of each of these studies. IT data were collected using an ingestible thermometer pill (Jonah™ Core Temp. Pill, Mini Mitter, Bend, OR), while the non-invasive measures of AC, HR, and HF were collected using a chest worn physiological monitor (Equivital I, Hidalgo Ltd., Cambridge UK). Data set A was used for parameter and model learning. The DBN model CPD's were learned using Maximum Likelihood (ML), or EM. These CPD's were then used in the Kalman filter to infer IT given a sequence of AC, HR, and HF observations. Differences between the Kalman filter IT estimate and the observed IT were examined using summary statistics of root mean square error (RMSE), and non-parametric Bland-Altman percentage (BAP) [17]. The BAP calculates the percentage of estimated IT points falling within an a priori zone of the actual IT (± 0.5 ºC was used in this analysis). Differences between summary statistics are examined by a paired Student's t-test.

D. Experiments

1) Model Validation - Heat Production: Our model was built assuming that the latent variable HG represents heat production as the by product from useful work by from muscles. While the model was trained on our observed variables (AC, HF, and HR) and our measured latent variable IT, the goal was to be able to differentiate both heat production and heat loss. Thus, our HG parameter should be proportional to a minute to minute estimate of active energy expenditure. To examine this relationship we sum our minute to minute estimates of HG over the course of our training data and perform least squares regression with total daily energy expenditure (TDEE) values measured using the doubly labeled water technique [18]. This method relies on differing rates of expulsion of isotopic water from the volunteers, to measure TDEE.

2) Model Validation – Internal Temperature: To test the generalizability of our model for IT estimation we examined the RMSE, and BAP with both conditions from the validation data set (A and B), and compared these results to the performance of our previous model that used HR alone [12], [19]. Data set A contains a case where our earlier baseline model had difficulty in accurately estimating IT. For this scenario the volunteer's thermoregulatory system chose to allow IT to rise while providing limited increase blood flow to the skin. This violated our previous underlying assumptions and lead to poor performance. We adapted our DBN model to identify this scenario using HG and HL.

III. Results

A. Model Validation - Heat Production

Figure 3 shows a scatter plot of ΣHG versus TDEE values for the five subjects with TDEE data. The correlation is significant ($r^2 = 0.73$, $p<0.07$).

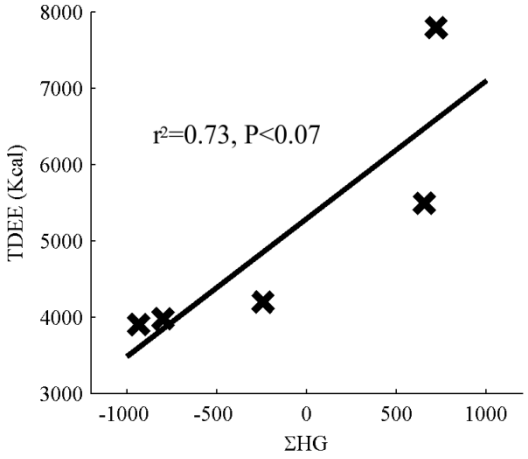

Fig. 3. Correlation of ΣHG and Total Daily Energy Expenditure from doubly labeled water technique.

B. Model Validation – Internal Temperature

Overall a RMSE of 0.28±0.16 °C, and correctly estimates IT within ± 0.5°C 83.2% for all data points. Table 1 shows the RMSE and BAP performance of the DBN model for the two validation conditions, along with the performance of our previous baseline model.

TABLE 1
DBN MODEL PERFORMANCE

Cond.	RMSE (Mean ± SD °C)		BAP (Mean ± SD %)	
	DBN Model	Previous Work	DBN Model	Previous Work
A.	0.28±0.14	0.39±0.11	86.8±15.5	70.0±11.6
B.	0.28±0.20	0.22±0.07	79.3±25.3	90.3±8.1
	0.28±0.16	**0.30±0.13**	**83.2±20.7**	**80.2±14.2**

Overall no significant differences were found between the DBN model and our previous work model for both RMSE and BAP however, For condition (A) differences in BAP are approaching significance ($p=0.052$). Figure 4 shows the observed, DBN, and previous work estimated IT group mean responses for the two validation conditions.

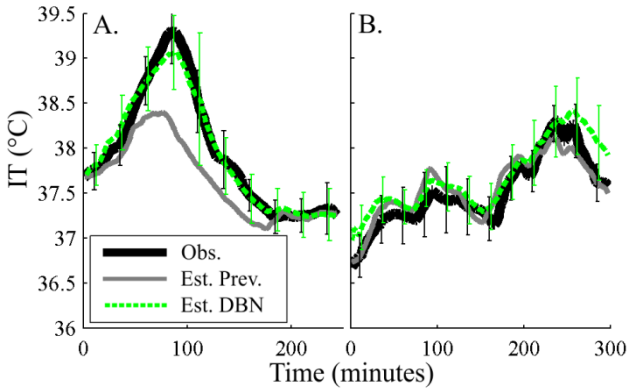

Fig. 4. Mean observed, DBN model estimation and previous work estimation of IT for the two validation conditions A and B. For observed and DBN estimated IT error bars represent ±1 SD.

IV. Discussion

Our data show that we were able to learn a DBN model of the human thermo-regulation system from a comprehensive field data set. The DBN model when applied to new data was able to provide internal temperature estimates that improved our previously work in critical high IT cases. By providing the model with additional information from accelerometry and heat flux we demonstrated that it was possible to model the heat production and, by inference, heat transfer components of thermo-regulation.

The close correlation of ΣHG and total daily energy expenditure (r^2=0.73) provides confidence that the HG estimates are within the realms of reality.

The DBN model when applied to new data was able to provide IT estimates that were statistically no different to our well validated previous model. Importantly, the use of HG and HL information allows the DBN model to more accurately model the rise in IT where our previous work failed (condition A). The improvement in the DBN model for this condition is close to significance, but the important high ITs are only about one third of the data. For context comparisons between "gold standard" methods of measuring IT (thermometer pill, rectal and esophageal probes) have RMSE a reported difference of 0.23 ± 0.07 ºC [20].

Since both HG and ΔIT are accurately estimated it follows that HL must also be well estimated. The HL component of the thermoregulatory system can provide insight into aerobic performance. Recent work has demonstrated that high skin blood flow requirements can lead to a reduction in aerobic performance [21].

V. Conclusion

Using non-invasive measures of heart rate, accelerometry and heat flux and our simple thermoregulatory model we have been able to infer heat production, heat transfer, and internal temperature. Using inferred thermoregulatory state information our model was able to improve upon previous work at critical high internal temperature peaks. We conclude that our thermoregulatory state estimation model shows promise for use in real time thermal work strain monitoring applications.

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