Thermal State Estimation Model Development Using Time Series Machine Learning Techniques

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EXECUTIVE SUMMARY

This paper reports a series of experiments to investigate the hypothesis that a Hidden Markov Model (HMM) may provide the basis for estimating core body temperature from observed variables such as heart rate and skin temperature. The hypothesis suggests that core body temperature can be estimated successfully if the temporal nature of core body temperature transitions is know along with the probabilities of observing heart rate and skin temperature for a given core temperature are also known. In the first two experiments an HMM is learned from a set of 12 subjects engaged in a simple exercise regime on a treadmill. The HMM is tested against a set of hold out data of an additional 31 subjects. The HMM in both experiments performs worse than a simple least squares linear regression. It is concluded that skin temperature actually hinders the HMM and that substantially more data over a greater dynamic range are needed. In the third experiment the HMM is learned directly from a data set of seven subjects engaged in a multi-day military field exercise. This HMM however, performs worse than the HMM trained from the laboratory data. It is concluded that noise in the field data collection artificially allows very rapid transitions of the core temperature effectively negating the time dependent nature of the core temperature transitions. Experiment 4 builds an HMM from the same field data but models the core temperature transition probabilities with a lite tailed probability density function, and the observation probabilities with a Normal distribution. The mean and sigma for the normal distribution are derived directly from the field data. This HMM model performs well against the laboratory data on average beating the least squares regression by 0.05ºC. In Experiment 5 the HMM developed in Experiment 4 is tested against a second completely different set of field data. The second field data set comprises 5 subjects engaged in a one day military exercise. The HMM model performance is compared to a real time thermoregulatory physics model (Initial Capability Decision Aid (ICDA)). On average the HMM model provides a significantly closer estimate of core temperature 0.3 vs 0.4 ºC than the ICDA model and a significantly higher correlation of R=0.72 vs R=0.59 than the ICDA model. It is concluded that the developed HMM model can be used as a basis for core body temperature estimation in real time monitoring situations, and that the model provides scope for individualization.

INTRODUCTION

Heat stress and the possibility of heat injury is a very real concern to the military during both training and active operations (Steinman, 1987). In 2005, the US Army reported over 1100 cases of heat injury, with 204 cases of heat stroke. ("US Army Heat Injuries", 2006). Heat illness concerns are not just confined to a military setting. Firefighters and first responders while encapsulated in personal protective ensembles have an increased risk of thermal stress (Muza et al, 2001; Givoni et al, 1972). Thermal strain has also been suggested as a possible contributing factor in the sudden cardiac death of firefighters -- the leading cause of US firefighter deaths (Fahy and LeBlanc 2006) -- where the cardiovascular system is stressed from the competing needs of thermoregulation and strenuous work (Smith, 2001).

Various techniques have been suggested to monitor and assess thermal strain/stress. The National Institute for Occupational Safety and Health (NIOSH) suggest the monitoring core body temperature, skin temperature, sweat, and heart rate may be appropriate to indicate thermal strain ("Occupational Exposure to Hot Environments" (1986)). The convergence of core body temperature and skin surface temperature has also been put forward as a criterion for heat tolerance (Pandolf, 1978). Because of the complex interactions between physiological parameters, clothing, and environmental conditions finding a universal heat strain index has been difficult (Moran et al, 1998). Moran reviews and compares a number of historical heat stress indices and proposes a new Physiological Strain Index (PSI) for evaluating heat stress using core body temperature and heart rate. Retrospective data analysis has demonstrated the efficacy of PSI for determining heat stress for Hot-Dry and Hot-Wet environments with or without personal protective clothing (Moran 2000). Thus it follows that with an effective index, heat stress can be monitored and heat injury or illness can be prevented.

The US Army's warfighter physiological status monitoring – initial capability (WPSM-IC) (Tharion et al 2007, Buller et al 2005) is a wearable integrated system of sensors and algorithms that was developed to allow remote monitoring of a number of health states including thermal state. The WPSM-IC system utilizes PSI as a primary means of assessing the thermal state. Although PSI is quite robust, its continuous use in an ambulatory setting is hampered by the need to obtain reliable core body temperatures. In the lab or even a controlled field experiment core body temperatures can be obtained from rectal or esophageal probes. During continuous operations, be they training or real missions, these instruments are untenable. In certain circumstances a thermometer radio pill (e.g. Mini Mitter Inc. Bend, OR) can be ingested and used (O'brien 1998) in these settings. However, continual use of this device, is restricted by the logistical burden imposed by continually replacing pills every day or so.

To overcome the difficulties of measuring core body temperatures directly a number of methods have been developed to estimate core body temperature from indirect and more readily obtainable physiologic measures. Models based upon thermodynamic equations and physiological models of heat production and heat loss to the environment have been proposed as one solution. SCENARIO (Kraning & Gonzalez, 1997) takes a range of inputs: metabolic work rate, environmental conditions, clothing configurations, and biometric data as inputs, and estimates core body temperature. However, these models replace the difficulty of measuring core body temperature with the problem of estimating work rate which is difficult to accurately measure in the field (Hoyt et al., 2004).

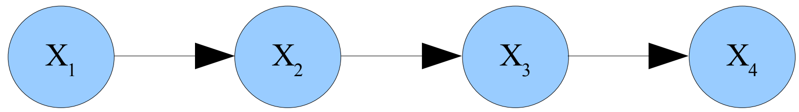
Other methods try to find surrogate measures for core body temperature. The measurement of heat flux does appear to show some promise as a core temperature surrogate (Gunga HC, 2005) but has been plagued with practicalities of location and mounting. Skin temperature is often proposed for a core temperature surrogate but individually this technique has been shown to have some complications (Taylor NAS & Amos D, 1997).

While individual parameters may not provide robust core body temperature surrogates recent work has shown that the use of multiple physiological measures used in conjunction can provide insight into thermal state (Yokota et al 2005, Buller et al 2008). Buller demonstrated that heart rate and chest skin temperature, together, could accurately classify individuals into PSI based thermal state categories of "At Risk" and "Not At Risk". Additionally, future core body temperature values have been successfully predicted given a sequence of previous core temperature values (Gribok et al 2008, 2007). By applying time series statistical machine learning learning techniques to multiple physiological parameters such as skin temperature and heart rate, this work hopes to to generate a model that can estimate core body temperature based upon a time series of readily observable parameters. This work effort has three phases: theoretical model development, model experimentation and refinement using laboratory data, and model training and validation using field data. This paper focuses on model development and refinement from experimentation.

HIDDEN MARKOV MODELS

The autoregressive core body temperature time series work of Gribok et al (2008) has shown that core body temperature data can predict future core body temperature values with some success. In this work the core temperature data are not treated as independent and identically distributed (i.i.d.) observations, but as having time related dependencies. Very simply the work follows the intuition that a future core temperature value at time t+1 will be very similar to the core temperature value at time t. In its simplest form this can be modeled by a first order Markov chain shown in figure 1.

Figure 1: First Order Markov Chain



In this first order Markov model the probability of observing any sequence of N observations can be written as:

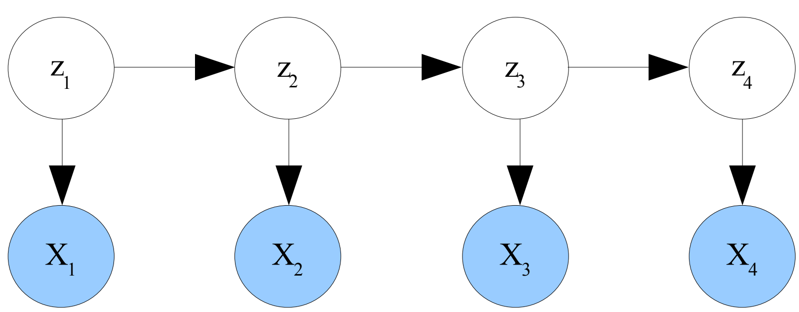
$$p(x_{1,} \cdots, x_N) = p(x_1) \prod_{n=2}^{N} p(x_n | x_{n-1}) \tag{1}$$

Thus the probability of any observation at time n, given all the prior observations simplifies to:

$$p(x_n | x_{1,} \cdots, x_{n-1}) = p(x_n | x_{n-1}) \tag{2}$$

Here the probability of the observation x_n depends only on the probability of the observation itself given the previous observation. However, in our case the goal is to estimate core temperature from more readily observed parameters such as heart rate and skin temperature. In this case we can treat the core temperature as a latent variable. Here at each time point we do not observe core temperature directly but observe other physiological parameters that are dependent on core temperature. The graphical model is depicted in Figure 2 and indicates that the observed variables (X_1, ..., X_N) - where X can be a single parameter or a vector of multiple parameters such as heart rate and skin temperature - are not dependent on each other but dependent on the current core temperature (Z_t) which itself is dependent on the previous core temperature.

Figure 2: Markov Chain of Latent Variables and Observed Dependent Variables



Thus it is possible to generate a model that can explain a sequence of observed parameters by identifying the most likely sequence of latent variables. This can be found from the model joint probability distribution:

$$p(X_1, \cdots, X_N, z_1, \cdots, z_N) = \underbrace{p(z_1)}_{1}\left[\prod_{n=2}^{N} \underbrace{p(z_n|z_{n-1})}_{2}\right]\prod_{n=1}^{N} \underbrace{p(X_n|z_n)}_{3} \tag{3}$$

The model is composed of three components. Component 1, $p(z_1)$, is the probability of latent variable start value. Component 2, $p(z_n|z_{n-1})$, can be thought of as the transition probability, or the probability distribution of how the latent variable may change from the previous time step to the current time step. Component 3, $p(X_n|z_n)$ is the probability of observing variables given the current latent variable. If the latent variable is discrete the model takes the form of a Hidden Markov Model (HMM).

If our core temperature problem is posed as an HMM we wish to answer the following question. Given a set of observations (X_1, ..., X_t) where X_t is a vector containing (HR_t, $Tskin_t$, and maybe other readily measured physiological parameters) what is the most likely sequence of core temperature states? This question can be solved by using the dynamic programming approach of the Viterbi algorithm.

PHYSIOLOGICAL BASIS OF AN HMM

To construct an effective HMM model we need to understand the physiological basis of how each of our model parameters can be expected to behave. For example, how does core temperature change over time. How do heart rate and skin temperature respond or reflect changes in core temperature.

Core Body Temperature

As "warm blooded" creatures our bodies regulate our internal body core temperature usually between 36.5 and 38.5 ºC. Temperatures outside of this range increasingly begin to negatively affect our well being. Heat is either lost or gained by the body depending on environmental conditions. Heat is generated in our bodies by our base metabolic functions and any additional work performed by our muscles. The body thermoregulates by applying several control mechanisms. If the body is getting too hot, warm blood will be diverted from the core to the skin surface increasing the skin surface temperature, additionally sweat will be produced to allow fast evaporative cooling of the skin and thus of the blood. Cooler blood will then return to the core allowing the core temperature to drop. If the body is getting too cold, blood will be diverted away from the skin to try and reduce the speed of cooling. Additionally the skin will raise the hairs to trap air and increase the insulation around the body. If cooling is still occurring the body will begin to shiver to produce heat from muscle action (Castellani 2003).

Since the body is mostly composed of water changes in internal temperature are not rapid (usually no more than 0.2 ºC per minute) , and will often show a temporal lag from the initiation of work or a temperature control mechanism until the desired change has been accomplished.

Heart Rate

In a young and fit military population the major driver of heart rate is exercise. Other non-exercise drivers may affect heart rate such as fear and the thermoregulation system (Moore 2006).

A simple assumption is made that heart rate provides both an indication of the amount of work being conducted and the degree of thermoregulatory stress the body is experiencing.

Skin Temperature

Skin temperature can vary by external temperature, and whether the body is trying to shed or conserve heat. If the body is trying to shed heat, skin temperature may increase as blood flow increases to the skin and then decrease as sweating and evaporative cooling decreases the skin temperature.

The assumption is made that skin temperature provides some information regarding the thermoregulataory system control mechanisms, but should be taken in the context of the environmental temperature.

Model Construction

To construct an HMM model the state transition probabilities of core temperature and the observation probabilities of heart rate and skin temperature need to be determined. In our case these can be learned directly from model training data sets. In constructing these probabilities several questions need to be addressed:

1. How does core temperature vary over time?

2. What order of Markov model does core temperature change exhibit?

3. If there is a lag in the change of core temperature how do past heart rates provide a better understanding of current core temperature than current heart rate?

4. Does Tskin play a confounding role during normal thermoregulation?

5. Does Tskin play a helpful role when thermoregulation is under stress or collapsed?

METHODS

A series of experiments are planned to incrementally develop a core temperature HMM.

Experiment 1: Proof of Concept Hidden Markov Model

The goal of experiment 1 was to generate a proof-of-concept HMM to demonstrate the potential of this technique, and to provide an initial performance baseline.

In this experiment 43 subjects from a heat tolerance study (Moran 2004) exercised at 1.39 m/s at a 2% grade on a treadmill in shorts and a t-shirt for approximately 2 hours in an environment of 40 ºC with 40% relative humidity. Twelve subjects were labeled as "non-heat tolerant" and 31 subjects labeled as "heat tolerant". The "non-heat tolerant" subjects exhibited a larger range of core temperature data over the exercise period and were thus used as the HMM training data.

The HMM comprised of core temperature (discretized into 30 states ranging from 36.0ºC to 42.0ºC in 0.2ºC increments) as the first order Markov chain latent variable; and heart rate and skin temperature as the observed variables. Heart rate was discretized into 30 observed values in the range 50 BPM to 200 BPM in 5 beat increments, and skin temperature was also discretized into 30 observed values in the range 30ºC to 45ºC in 0.5ºC increments. The observed variables were combined into a single observation variable with 900 possible values.

A discrete transition probability distribution was formed from the training data by computing the state transition frequency counts and normalization term for each training subject and then combining these transition frequencies and normalization terms to provide discrete transition probability distribution. The observation probability distributions given each state were computed from all training subjects in a similar way.

The learned HMM model described by the transition probability matrix and the state observation matrix was then tested against the 31 "heat tolerant" subjects. The model was tested by generating the most likely state sequence given each subject's set of observed heart rates and skin temperatures. The most likely core temperature sequence was then compared to the actual recorded core body temperatures using the root mean squared deviation (RMSD) descriptive statistic.

$$\text{rmsd} = \sqrt{\sum_{t=1}^{N} (\hat{T}_t - T_t)^2} \qquad (4)$$

Where t = each 1 minute time step.

For a comparison core temperature was also estimated using a linear regression of heart rate and skin temperature to predict core body temperature. The multivariate regression model was learned from the training data, and used to estimate core temperature for each of the 31 test subjects. The RMSD descriptive static was also calculated for the regressed core temperatures.

Results Experiment 1

Figure 3 shows the typical physiological responses of the subjects during the experimental exercise bout. Table 1, shows the RMSD of HMM and Linear Regression estimated core temperature values from actual core temperature values. Appendix A contains plots for each of the 31 test subjects showing the actual core temperature during the course of the exercise bout along with the core temperature estimated from the regression model and core temperature estimated from the HMM.

Figure 3: Typical Laboratory Test Data (Subject 20)

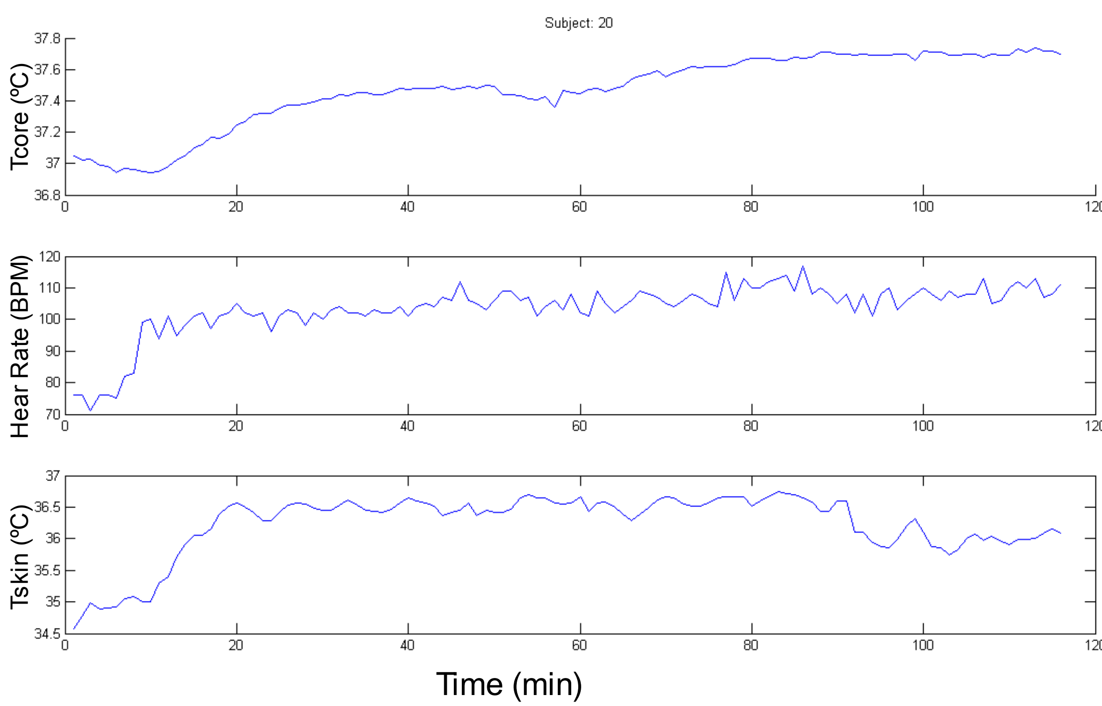


Table 1: RMSD of HMM and Linear Regression estimated core temperature values from actual core temperature values

Subject	RMSD Linear Regression (ºC)	RMSD HMM (ºC)
1	0.3145	0.5798
2	0.1487	0.213
3	0.136	0.3283
4	0.3057	0.3029
5	0.3238	0.4393
6	0.1695	0.3667
7	0.2265	0.2283
8	0.1619	0.2623
9	0.3037	0.2365
10	0.2419	0.4822
11	0.4044	0.5464
12	0.3207	0.4612
13	0.4687	0.9007
14	0.2495	0.2245
15	0.262	0.2112
16	0.2394	0.4899
17	0.2926	0.4503
18	0.1812	0.2600
19	0.186	0.2982
20	0.2545	0.3691
21	0.2901	0.3623
22	0.2778	0.3567
23	0.3208	0.3856
24	0.4904	0.3629
25	0.4227	0.6457
26	0.1462	0.2805
27	0.2206	0.3264
28	0.264	0.4349
29	0.4359	0.4200
30	0.8908	0.8459
31	0.2459	0.3054
Mean	**0.2967**	**0.3992**
SD	**0.1444**	**0.1677**
Max	**0.8908**	**0.9007**

Discussion Experiment 1

The simple HMM did not perform as well as the multivariate linear regression model with a mean RMSD of 0.40ºC vs 0.30ºC; indicating that on average the HMM model estimated core temperature was within +/- 0.4ºC of the actual core body temperature. Given the fact that the HMM model was discretized in 0.2ºC increments this result would indicate that the HMM was on average +/- two states off from the true core temperature state. Additionally, with the limited training data and 900 possible observation values from the combination of the two observed variables the observation probability distributions likely suffer from very low frequency counts.

Experiment 2: Proof of Concept HMM No Tskin

The goal of experiment 2 was to examine whether the large number of observation states in experiment 1 were a factor in the HMM poor performance. In this experiment the same data from experiment 1 were used.

The HMM comprised of core temperature (discretized into 30 states ranging from 36.0ºC to 42.0ºC in 0.2ºC increments) as the first order Markov chain latent variable; and only heart rate was used as the observed variable. Heart rate was discretized into 30 observed values in the range 50 BPM to 200 BPM in 5 beat increments.

A discrete transition probability distribution was formed from the training data by computing the state transition frequency counts and normalization term for each training subject and then combining these transition frequencies and normalization terms to provide discrete transition probability distribution. The observation probability distributions given each state were computed from all training subjects in a similar way.

As in experiment 1 the learned HMM model described by the transition probability matrix and the state observation matrix was tested against the 31 "heat tolerant" subjects. The model was tested by generating the most likely state sequence given each subject's set of observed heart rates. The most likely core temperature sequence was then compared to the actual recorded core body temperatures using the root mean squared deviation (RMSD) descriptive statistic.

Results Experiment 2

Table 2, shows the RMSD values of the HMM from experiments 1 and 2, and the Linear Regression estimated core temperature values from the actual core temperature values. Appendix B contains plots for each of the 31 test subjects showing the actual core temperature during the course of the exercise bout along with the core temperature estimated from the regression model and core temperature estimated from the HMM.

Table 2: RMSD of Experiment 1 HMM and Linear Regression estimated core temperature values from actual core temperature values

Subject	RMSD Linear Regression (ºC)	RMSD Exp 1: HMM (ºC)	RMSD Exp 2: HMM (ºC)
1	0.3145	0.5798	0.4355
2	0.1487	0.213	0.3833
3	0.136	0.3283	0.203
4	0.3057	0.3029	0.3695
5	0.3238	0.4393	0.4719
6	0.1695	0.3667	0.3315
7	0.2265	0.2283	0.1774
8	0.1619	0.2623	0.2564
9	0.3037	0.2365	0.1772
10	0.2419	0.4822	0.3954
11	0.4044	0.5464	0.2669
12	0.3207	0.4612	0.5202
13	0.4687	0.9007	0.7821
14	0.2495	0.2245	0.1446
15	0.262	0.2112	0.2489
16	0.2394	0.4899	0.4958
17	0.2926	0.4503	0.502
18	0.1812	0.2600	0.2613
19	0.186	0.2982	0.233
20	0.2545	0.3691	0.3536
21	0.2901	0.3623	0.4545
22	0.2778	0.3567	0.3006
23	0.3208	0.3856	0.3865
24	0.4904	0.3629	0.3373
25	0.4227	0.6457	0.4595
26	0.1462	0.2805	0.2329
27	0.2206	0.3264	0.397
28	0.264	0.4349	0.1491
29	0.4359	0.4200	0.2432
30	0.8908	0.8459	0.7269
31	0.2459	0.3054	0.407
Mean	**0.2967**	**0.3992**	**0.3582**
SD	**0.1444**	**0.1677**	**0.1522**
Max	**0.8908**	**0.9007**	**0.7821**

The mean RMSD for the HMM estimated core temperature from experiment 2 is significantly better than that from experiment 1 (0.3582 and 0.3992 respectively, $t=2.16$, $df=30$, $P=0.039$).

Discussion Experiment 2

While the simple HMM did not perform as well as the multivariate linear regression model with a mean RMSD of 0.36ºC vs 0.30ºC the simplified model did provide improved results over experiment 1. However, a closer examination of the HMM responses from Appendix B indicate that the HMM very rapidly transitions through the core temperature states to arrive at a core temperature with the most likely observed heart rate. The actual core temperature data indicate that this transition process is much slower than that captured in the HMM model.

Experiment 3: HMM Generated from Field Data (Discrete Probability Distribution)

The goal of experiment 3 was to develop a more realistic core temperature transition matrix and heart rate observation matrix from a data set with significantly more data points and containing a larger dynamic range of observed variables.

In this experiment data from 8 subjects collected continuously over a 5 day period were used to generate the HMM. The subjects were engaged in a military field training exercise where sleep deprivation and hard physical activity was normal (Hoyt et al 2004). The data set comprised of over 16,000 data points.

The HMM comprised of core temperature (discretized into 150 states ranging from 36.0ºC to 39.0ºC in 0.02ºC increments) as the first order Markov chain latent variable. Heart rate was discretized into 145 observed values in the range 55 BPM to 200 BPM in 1 BPM increments.

A discrete transition probability distribution was formed from the field data by computing the state transition frequency counts and normalization term for each training subject and then combining these transition frequencies and normalization terms to provide a discrete transition probability distribution. The observation probability distributions given each state were computed from all field exercise subjects in a similar way.

The trained HMM model described by the transition probability matrix and the state observation matrix was tested against the 31 "heat tolerant" subjects from experiment 1. The model was tested by generating the most likely state sequence given each subject's set of observed heart rates. The most likely core temperature sequence was then compared to the actual recorded core body temperatures using the root mean squared deviation (RMSD) descriptive statistic.

Results Experiment 3

Table 3, shows the RMSD values away from the true core temperature of the HMM from experiments 1, 2, 3, and the Linear Regression estimated core temperature. Appendix C contains plots for each of the 31 test subjects showing the actual core temperature during the course of the exercise bout along with the core temperature estimated from the regression model and core temperature estimated from the HMM.

Table 3: RMSD values of Experiment 1,2 & 3, HMMs and Linear Regression estimated core temperature values from actual core temperature values

Subject	Linear Regression (ºC)	Exp 1: HMM (ºC)	Exp 2: HMM (ºC)	Exp 3: HMM (ºC)
1	0.3145	0.5798	0.4355	0.6082
2	0.1487	0.213	0.3833	0.696
3	0.136	0.3283	0.203	0.5187
4	0.3057	0.3029	0.3695	0.6986
5	0.3238	0.4393	0.4719	0.4259
6	0.1695	0.3667	0.3315	0.6041
7	0.2265	0.2283	0.1774	0.285
8	0.1619	0.2623	0.2564	0.6195
9	0.3037	0.2365	0.1772	0.7769
10	0.2419	0.4822	0.3954	0.3253
11	0.4044	0.5464	0.2669	0.7147
12	0.3207	0.4612	0.5202	0.3124
13	0.4687	0.9007	0.7821	0.774
14	0.2495	0.2245	0.1446	0.7294
15	0.262	0.2112	0.2489	0.2189
16	0.2394	0.4899	0.4958	0.6512
17	0.2926	0.4503	0.502	0.4805
18	0.1812	0.2600	0.2613	0.846
19	0.186	0.2982	0.233	0.5538
20	0.2545	0.3691	0.3536	0.6138
21	0.2901	0.3623	0.4545	0.6915
22	0.2778	0.3567	0.3006	0.7312
23	0.3208	0.3856	0.3865	0.4656
24	0.4904	0.3629	0.3373	0.6896
25	0.4227	0.6457	0.4595	0.6541
26	0.1462	0.2805	0.2329	0.6416
27	0.2206	0.3264	0.397	0.5739
28	0.264	0.4349	0.1491	0.587

29	0.4359	0.4200	0.2432	0.7846
30	0.8908	0.8459	0.7269	0.9815
31	0.2459	0.3054	0.407	0.7508
Mean	**0.2967**	**0.3992**	**0.3582**	**0.6130**
SD	**0.1444**	**0.1677**	**0.1522**	**0.1717**
Max	**0.8908**	**0.9007**	**0.7821**	**0.9815**

The mean RMSD for the HMM estimated core temperature from experiment 3 is significantly worse than that from experiment 2 (0.6130 and 0.3582 respectively, $t=-6.80$, $df=30$, $P<0.00001$).

Discussion Experiment 3

The field data trained HMM perform significantly less well than the HMM trained from the laboratory data. The HMM responses from Appendix C again show that the HMM transitions very rapidly through the core temperature states to arrive at a core temperature with the most likely observed heart rate. The actual core temperature data indicate that this transition process is a much slower than that captured in the HMM model. A closer examination of the field data revealed that there were a significant number of "noisy" data points. So while the transition probabilities could be captured from the field data rapid transitions would also be represented as having probabilities >0, leading the model to rapidly transition to the state with the most likely observation value.

Experiment 4: HMM Generated from Field Data (Modeled Probability Distributions)

The goal of experiment 4 was to develop a core temperature transition probability matrix based upon the underlying field data but with a light tail. That is for every core temperature only a limited number of transitions are possible. Transitions above or below a certain rate will be assigned a zero probability of occurring. This experiment also aims to model the observation probability matrix with a Gaussian distribution.

The field data from experiment 3 were used to generate the HMM in this experiment. Again the HMM comprised of core temperature (discretized into 150 states ranging from 36.0ºC to 39.0ºC in 0.02ºC increments), and heart rate discretized into 150 observed values in the range 50 BPM to 200 BPM in 1 BPM increments.

Core Temperature Transition Probability Model

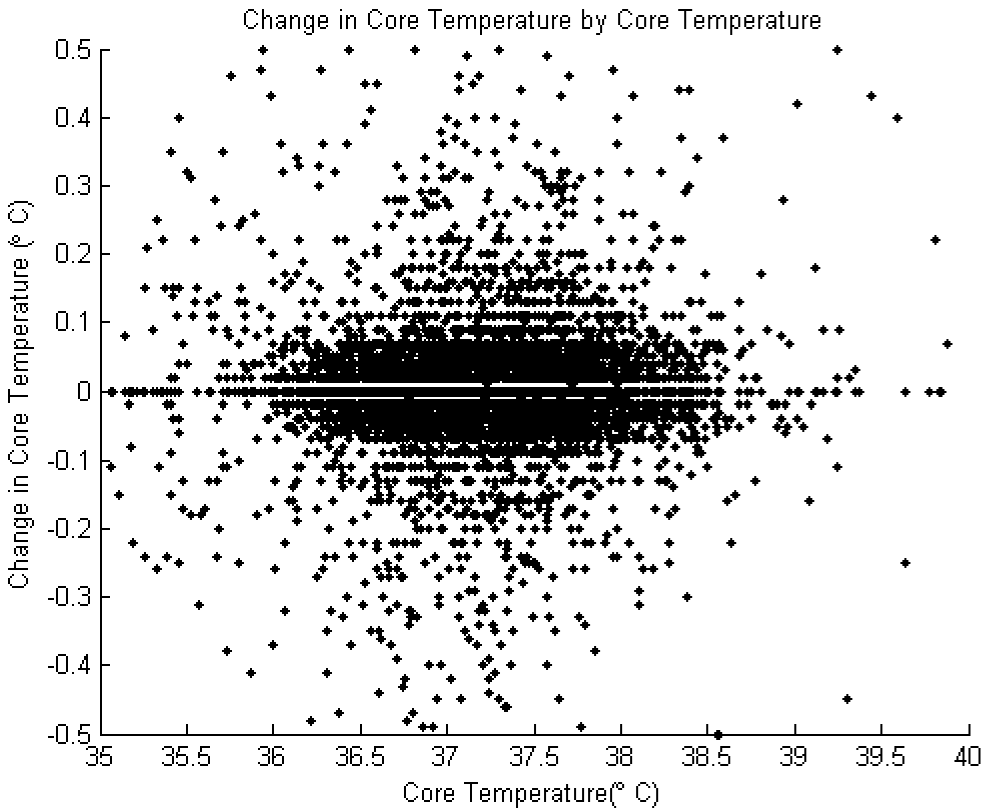
To build a general core temperature transition probability matrix model several questions had to be examined:

1) Do transition probabilities vary with respect to core body temperature?

2) What are the transition probabilities?

To examine whether the transition probabilities vary with core temperature the correlation coefficient was calculated for the change in core temperature by temperature. The correlation coefficient was close to zero (0.0163) indicating that change in core temperature varies independently of the actual core temperature value. Figure 4 shows a plot of change in core temperature by core temperature.

Figure 4 Change in core temperature by core temperature



Given that the core temperature changes independently of core temperature value a histogram of absolute core temperature changes was developed. Figure 5 shows a histogram of the absolute change in core temperature over a one minute interval. The figure shows the raw values with no filtering for outliers. It should be noted that there are very few 0.01ºC changes found in the data set. This is due to the limitations of the core temperature pill and receiver technology in use at the time. The core temperature pill technology in use at that time indicated temperature by the transmission frequency. The receiver technology was only capable of reliably decoding 0.02ºC changes in pill temperature. Given this fact odd changes in temperature were ignored and a symmetric discrete probability distribution was generated from the even temperature changes. This probability distribution is shown in figure 6.

Figure 5: Histogram of absolute change in core temperature during a one minute period.

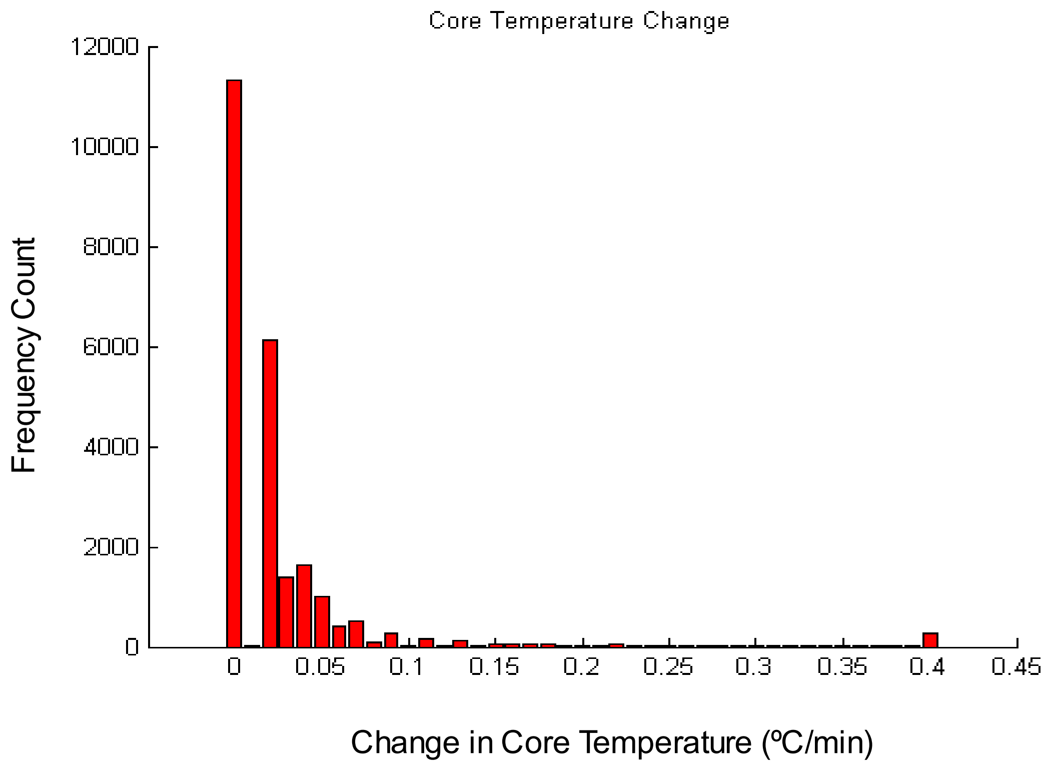


Figure 6 Discrete Probability Distribution for Change in Core Temperature

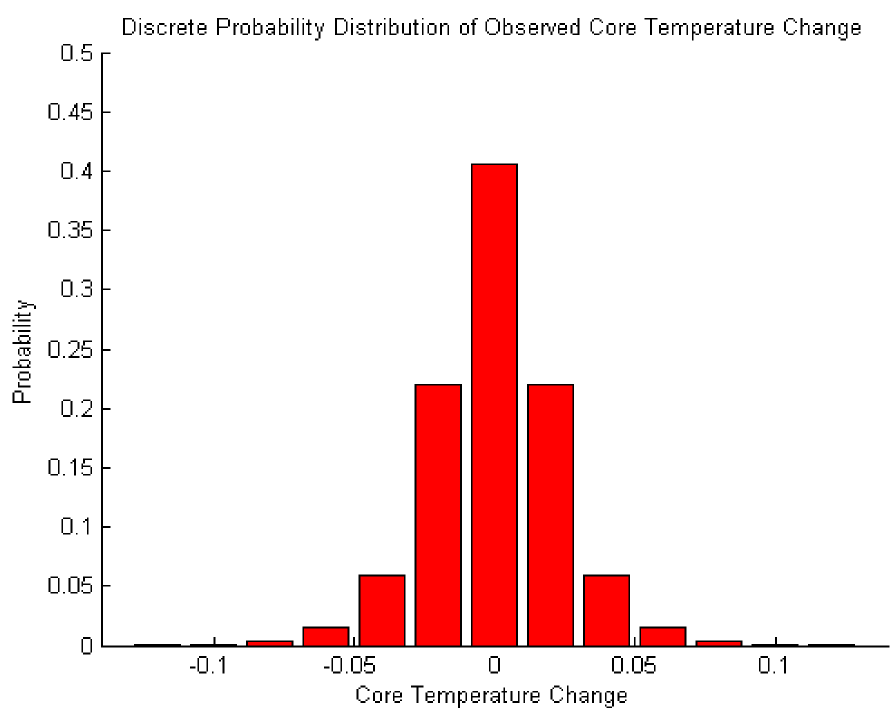


Table 4 shows the core temperature probability distribution used to define the core temperature transition probability matrix for every discrete core temperature.

Table 4 Discrete Probability Distribution for Change in Core Temperature

dTc (+/-)	0.00	0.02	0.04	0.06	0.08	0.10	0.12
P	0.4051	0.2197	0.0586	0.0147	0.0030	0.0010	0.0004

Heart Rate Observation Probability Model

In developing the Heart Rate Observation Probability Matrix several questions were asked. First to ensure that no complex interactions existed between core temperature change and heart rate the following questions were examined:

1) Is there a relationship between heart rate and change in core temperature?
2) Is there a relationship between the change in heart rate and the change in core temperature?

To answer both of these questions correlation coefficients for change in core temperature by heart rate and change in core temperature by change in heart rate were calculated. The correlation coefficients for both of these analyses were close to 0 (0.0162 and -0.0053 respectively) indicating no relationship existed. Figure 7 shows a plot of change in core temperature by heart rate and figure 8 shows a plot of change in core temperature by change in heart rate.

Figure 6 Change in Core Temperature Per Minute By Heart Rate

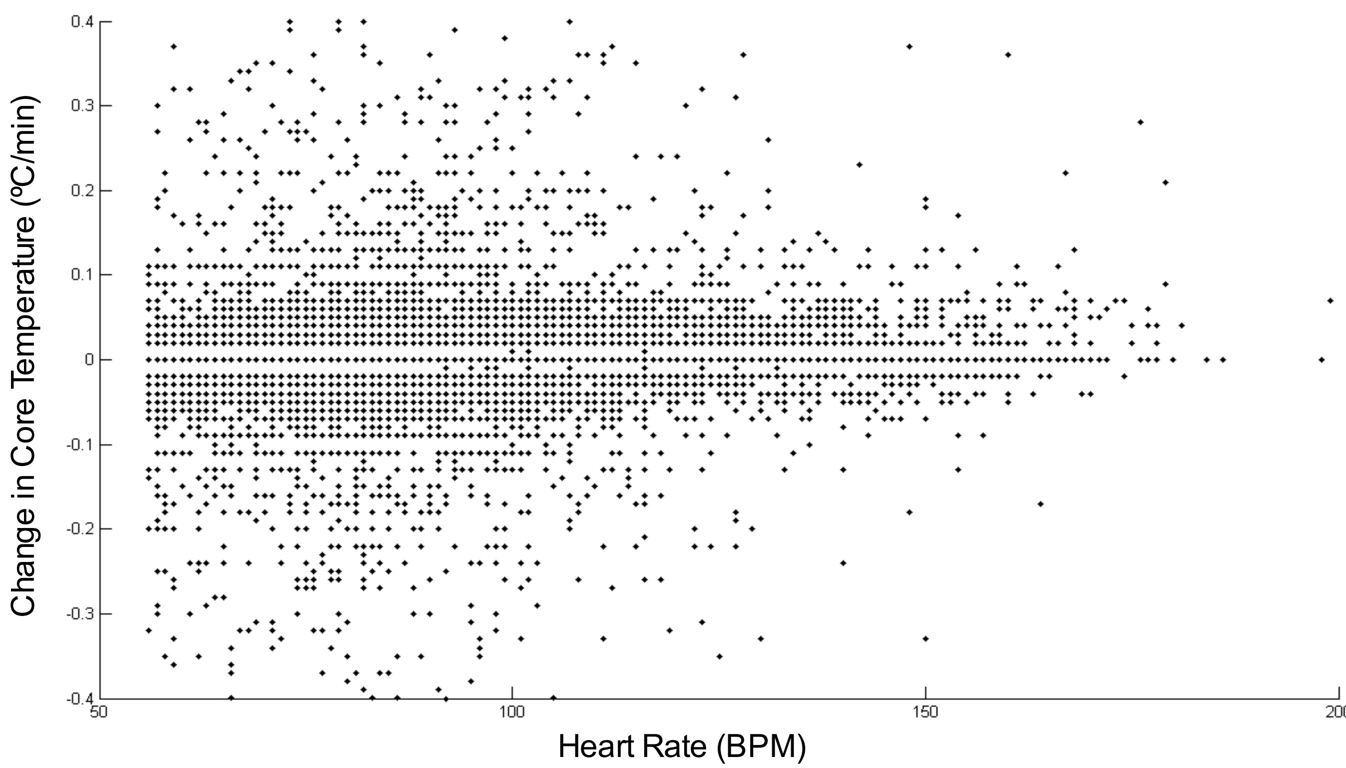
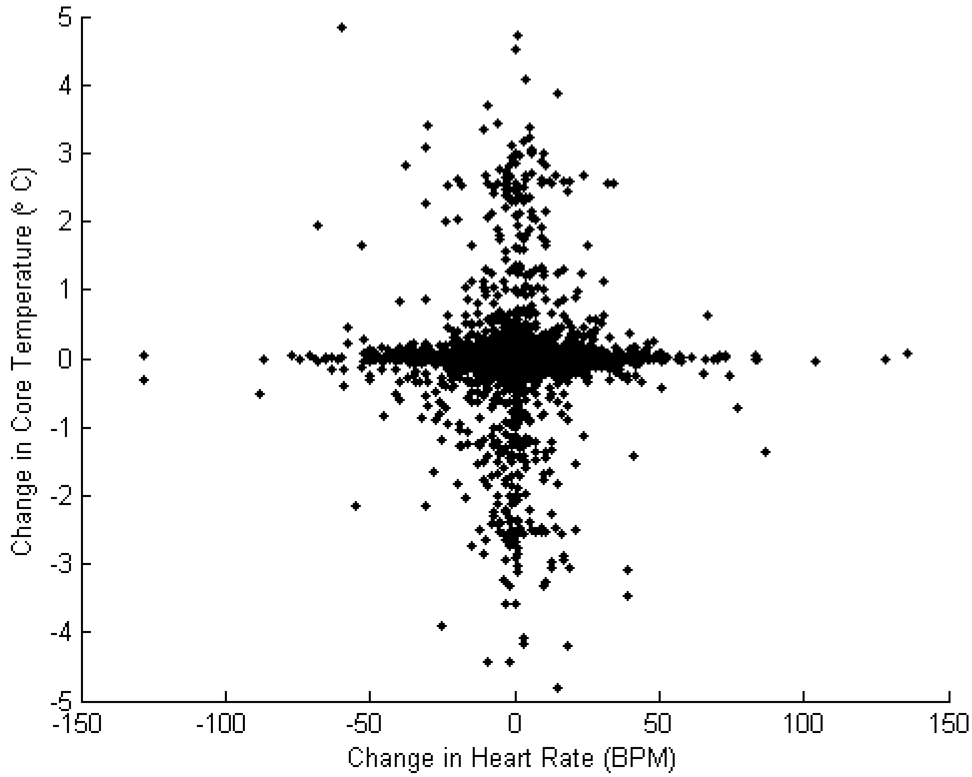


Figure 8 Change in Core Temperature by Change in Heart Rate



A correlation coefficient was calculated for the relationship between core temperature and heart rate (r=0.43 P<0.05) . We know that due to the thermal heat capacity of water a rise or fall in core temperature lags behind an input or emission of heat. With this in mind correlation coefficients were calculated for each subject for the relationship between core temperature at time t=0 and heart rates from t=0 to t=-32. Figure 9 shows the mean correlation coefficients at each of the time points for heart rate. The highest correlation between core temperature and heart rate occurs with heart rates from 16 minutes earlier than the current core temperature. Thus, the heart rate observation probability matrix was built using the heart rate data 16 minutes prior to the core temperature data. Figure 10 shows a scatter plot of core temperature (t=n) and heart rates (t=n-16). A linear least squares regression derived from the data shown in figure 10 forms the basis of the heart rate observation probability matrix.

Figure 9 Correlation Coefficient for Core Temperature at time t=0 and Heart Rate at Time t=0 to t=-32 Min.

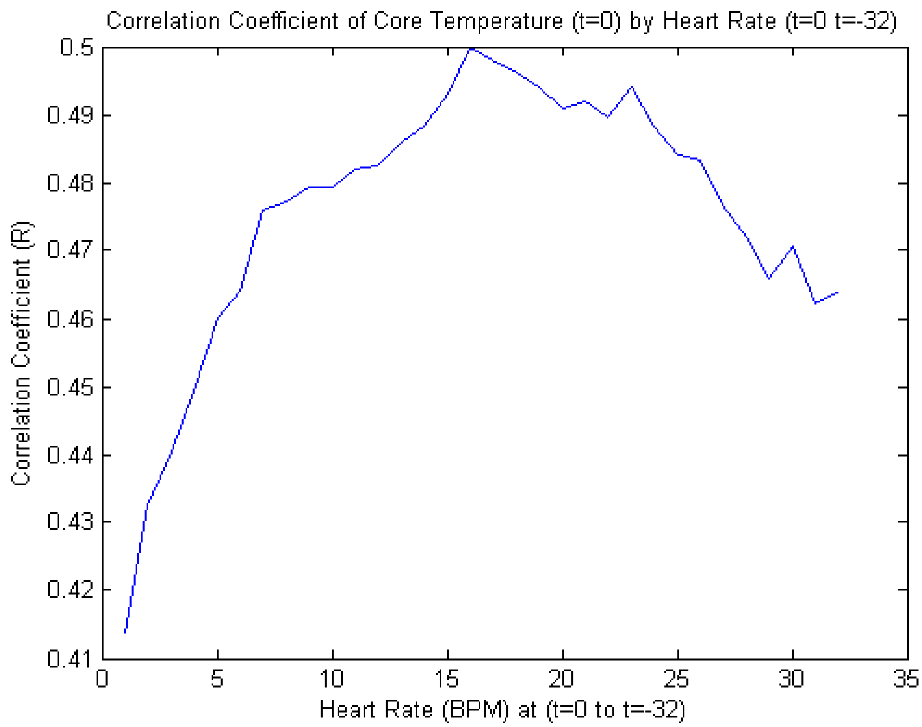
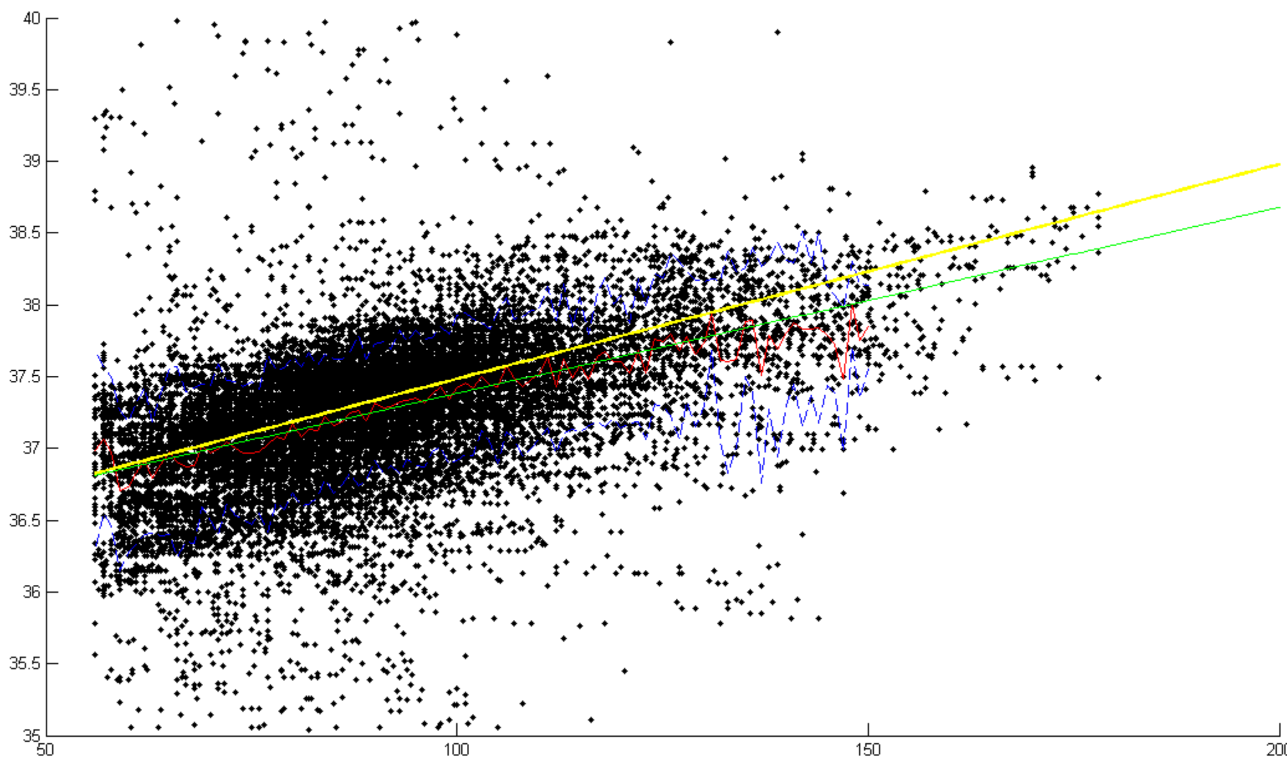


Figure 10. Scatter Plot of Core Temperature By Heart Rate



For a given core temperature the heart rate observed probability distribution is given by a Gaussian distribution with the mean calculated from a least squares linear regression of core temperature and heart rate from the data shown in figure 10. Heart rate is given by the following formula:

$$\mu_{\mathrm{HR}} = 66.6667 \cdot \mathrm{T}_{\mathrm{core}} - 2400 \tag{4}$$

The standard deviation for the Gaussian distribution was also derived from experimental field data. For every discrete core temperature a mean heart rate and standard deviation was calculated. Over all discrete core temperatures the median standard deviation was 18. Thus for each discrete core temperature the probability of observing a given heart rate is estimated from:

$$P(HR|T_{core}) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(\frac{-(HR-\mu_{HR})^2}{2\sigma^2}\right) \tag{5}$$

The trained HMM model described by the transition probability matrix and the state observation matrix was tested against the 31 "heat tolerant" subjects from experiment 1. The model was tested by generating the most likely state sequence given each subject's set of observed heart rates. The most likely core temperature sequence was then compared to the actual recorded core body temperatures using the root mean squared deviation (RMSD) descriptive statistic.

Results Experiment 4

Table 5, shows the RMSD values away from the true core temperature of the HMM from the current experiment, experiment 2 and the Linear Regression estimated core temperature. Appendix D contains plots for each of the 31 test subjects showing the actual core temperature during the course of the exercise bout along with the core temperature estimated from the regression model and core temperature estimated from the HMM.

Table 5: RMSD values of Experiment 2 & 4, HMMs and Linear Regression estimated core temperature values from actual core temperature values

Subject	**RMSD Linear Regression (ºC)**	**RMSD Exp 2: HMM (ºC)**	**RMSD Exp 4: HMM (ºC)**
1	0.3145	0.4355	0.1668
2	0.1487	0.3833	0.2395
3	0.136	0.203	0.2498
4	0.3057	0.3695	0.2098
5	0.3238	0.4719	0.0515
6	0.1695	0.3315	0.27
7	0.2265	0.1774	0.07
8	0.1619	0.2564	0.2781
9	0.3037	0.1772	0.4507
10	0.2419	0.3954	0.1015
11	0.4044	0.2669	0.1906
12	0.3207	0.5202	0.1363
13	0.4687	0.7821	0.605
14	0.2495	0.1446	0.387
15	0.262	0.2489	0.4138
16	0.2394	0.4958	0.3668
17	0.2926	0.502	0.3115
18	0.1812	0.2613	0.134
19	0.186	0.233	0.3719
20	0.2545	0.3536	0.102
21	0.2901	0.4545	0.4179
22	0.2778	0.3006	0.1703
23	0.3208	0.3865	0.0948
24	0.4904	0.3373	0.1866
25	0.4227	0.4595	0.2487
26	0.1462	0.2329	0.1831
27	0.2206	0.397	0.1484
28	0.264	0.1491	0.0697
29	0.4359	0.2432	0.1825
30	0.8908	0.7269	0.5707
31	0.2459	0.407	0.3079
Mean	**0.2967**	**0.3582**	**0.2480**
SD	**0.1444**	**0.1522**	**0.1438**
Max	**0.8908**	**0.7821**	**0.6050**

The mean RMSD for the HMM estimated core temperature from experiment 4 is significantly better than that from experiment 2 (RMSD = 0.2480 and 0.3582 respectively, $t=3.76$, $df=30$, $P<0.0008$). While the mean RMSD score of the current experiment is less than that of the linear regression it is not significantly different (RMSD = 0.2480 and 0.2967 respectively, $t=-1.68$, $df=30$, $P<0.103$).

Figures 11, 12, and 13 show examples of the HMM performance with selected subjects. Figure 11 and 12 show how the HMM accurately models the gradual rise in core temperature, while Figure 13 is an example where the HMM does not model the response as well.

Figure 11 HMM estimated and actual core temperature for laboratory subject 5

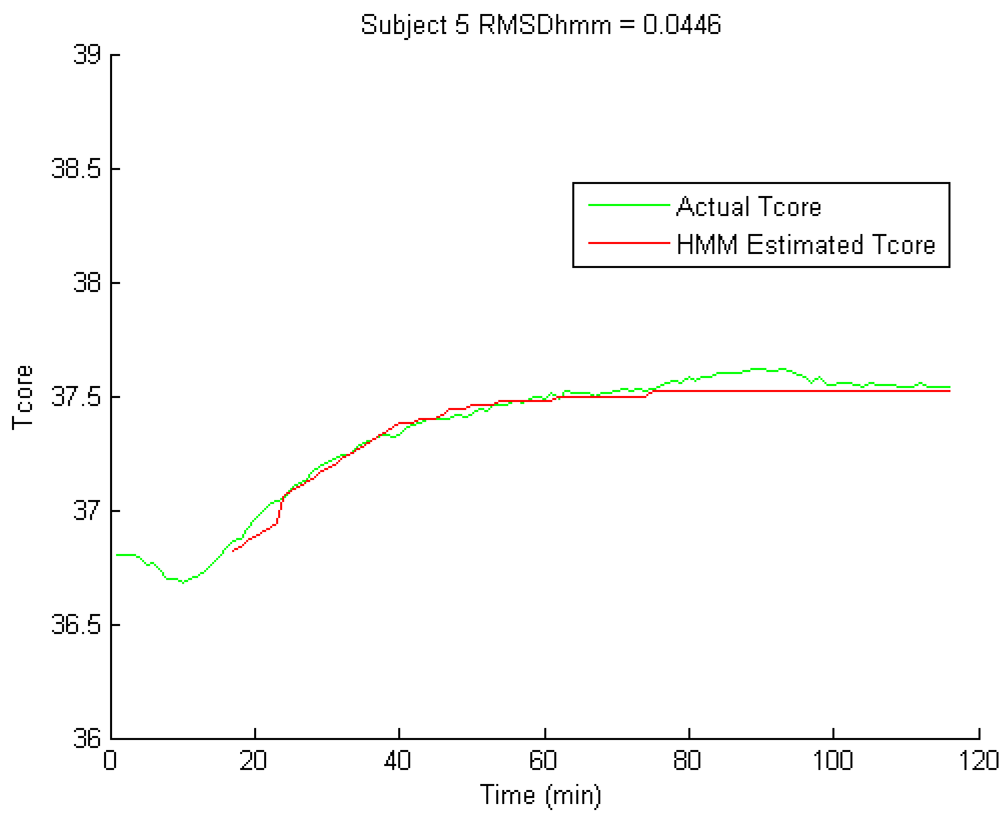


Figure 12 HMM estimated and actual core temperature for laboratory subject 28

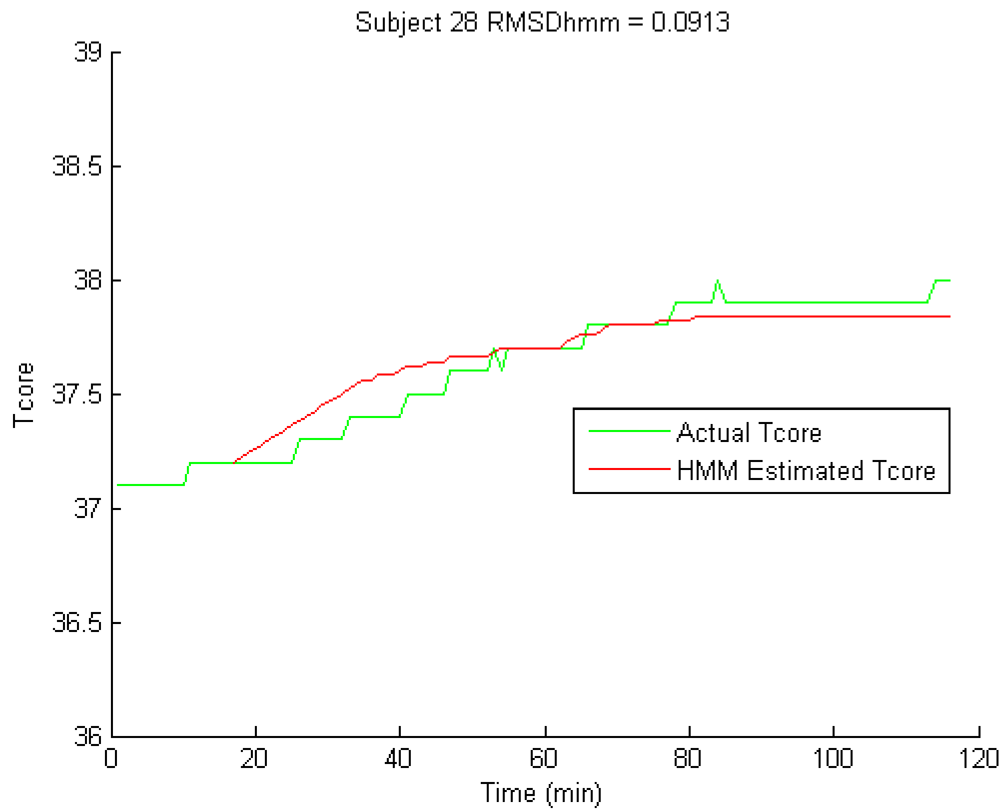
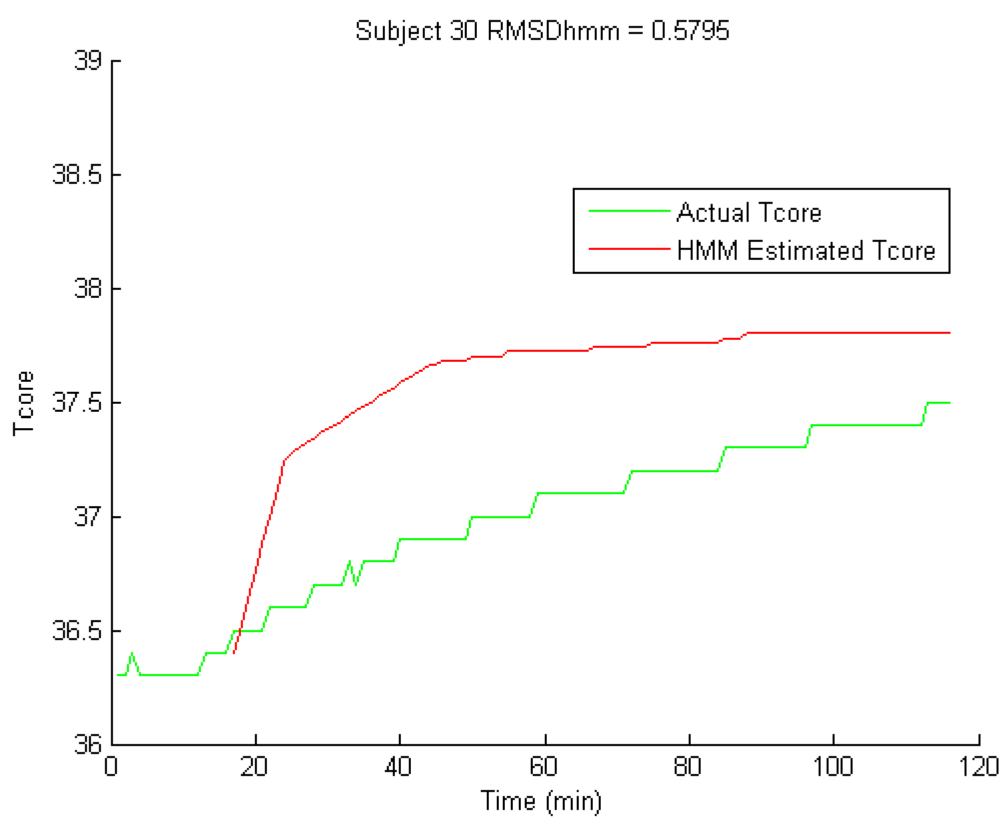


Figure 13 HMM estimated and actual core temperature for laboratory subject 30



Discussion Experiment 4

The field data trained with modeled probability distributions performs better than the HMM trained with the laboratory data. Figures 11 and 12 demonstrate how the lite tailed core temperature transition probability matrix effectively models the true core temperature transitions. While in general this model is effective there are some subjects where the model fails to capture the rise in core temperature or transitions too quickly to a high core temperature. This difference between subjects could be expected as the model is based upon probabilities derived from group data. Given enough data individual transition and observation probability matrices could be learned.

Experiment 5: Validation of HMM Model With Field Data

The goal of this experiment is to test the HMM model developed in experiment 4 against a set of field data and compare the results to a physics based core temperature prediction model. Data from five subjects engaged in a multi-day military field exercise (Yokota et al 2004) are used to examine the performance of the HMM model. The core temperature for one day of the exercise is estimated for the five subjects using the HMM, and the Initial Capability Decision Aid (ICDA) (Yokota and Berglund 2006). ICDA is a light weight physics based model that simulates the human thermoregulatory physiological system. The ICDA model requires the following inputs: Height, Weight, Clothing Configuration, Ambient Temperature, Relative Humidity, Solar Load, Wind Speed, and Heart Rate to estimate metabolic work rate. RMSD and correlation coefficients are calculated for both the HMM and ICDA models compared to the actual core temperature. The relative performance of the two models are compared using a paired Students t-test.

Experiment 5 Results

Table 6 shows the RMSD and correlation coefficients for the ICDA and HMM techniques. Figures 14 though 18 show the actual core temperatures and the core temperatures estimated from the HMM and ICDA models.

Table 6: RMSD and Correlation Coefficients for ICDA and HMM models

	RMSD		Correlation	
Subject	**HMM**	**ICDA**	**HMM**	**ICDA**
1	0.275	0.338	0.891	0.840
2	0.231	0.343	0.827	0.663
10	0.257	0.389	0.356	0.238
11	0.211	0.292	0.766	0.567
15	0.522	0.604	0.751	0.657
Mean	**0.299**[*1]	**0.393**[*1]	**0.718**[*2]	**0.593**[*2]
SD	**0.127**	**0.123**	**0.210**	**0.222**

[*1] HMM RMSD is significantly lower than ICDA (t=-7.58, P<0.002)
[*2] HMM Correlation Coefficient is significantly larger than ICDA (t=2.13, P<0.009)

Figure 14: Actual, ICDA, and HMM estimated core temperatures - subject 01

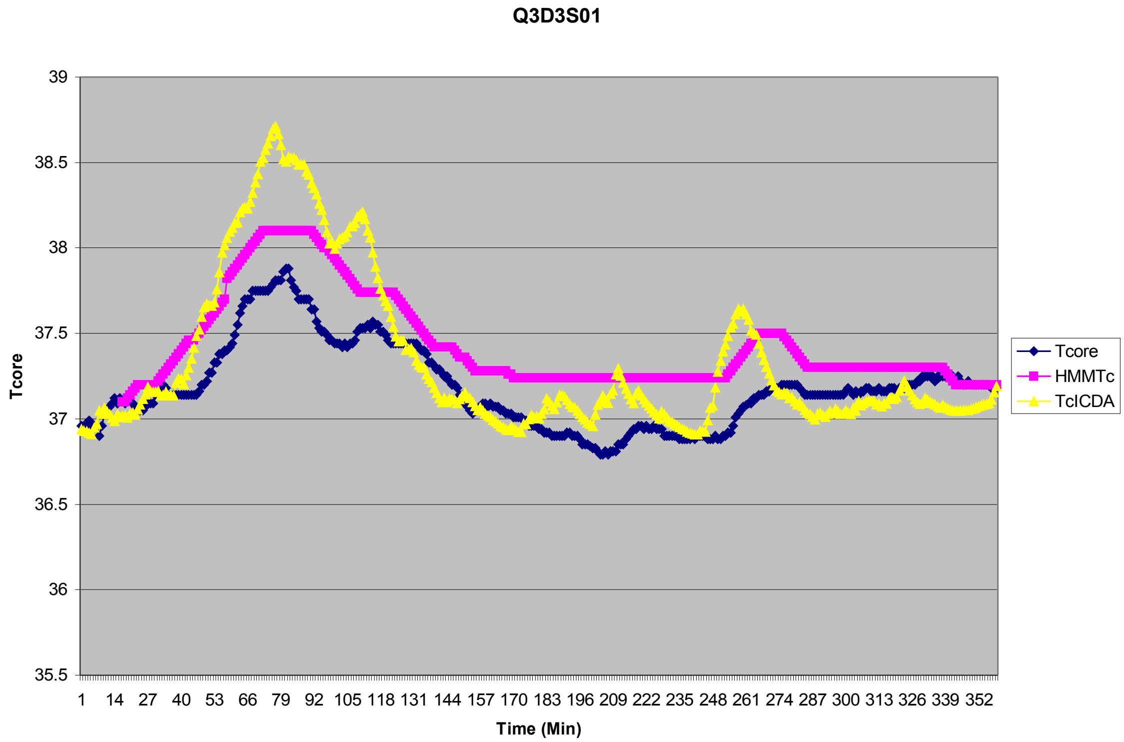


Figure 15: Actual, ICDA, and HMM estimated core temperatures - subject 02

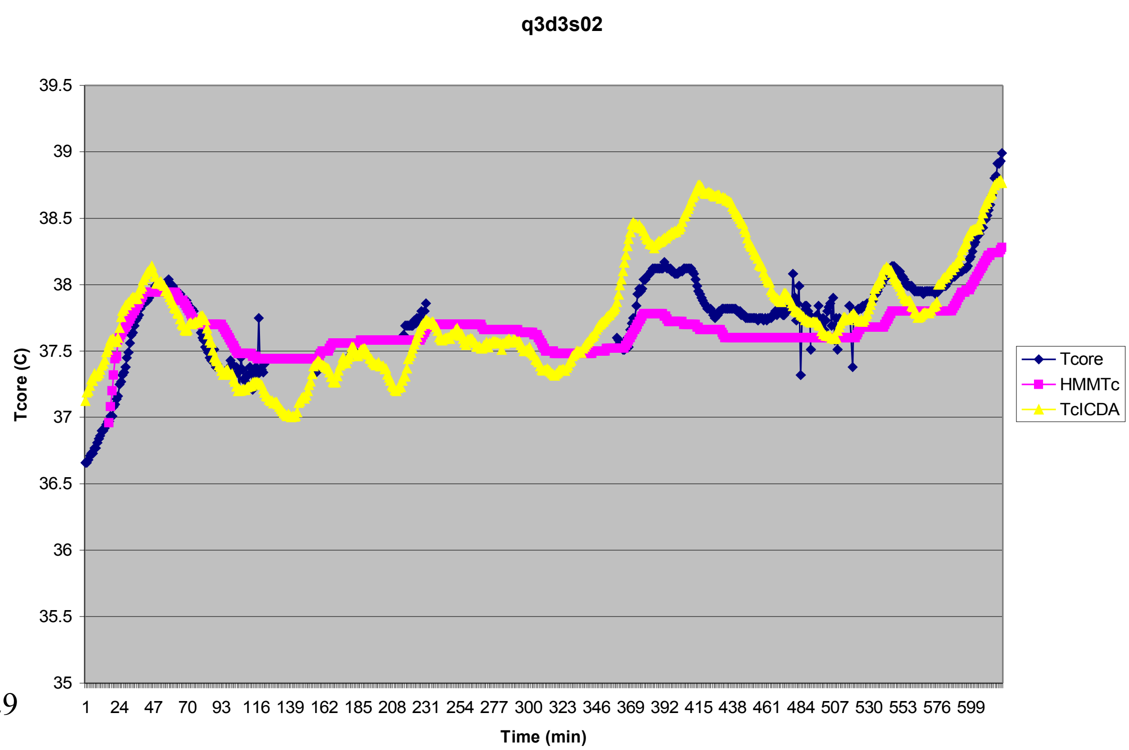


Figure 16: Actual, ICDA, and HMM estimated core temperatures - subject 01

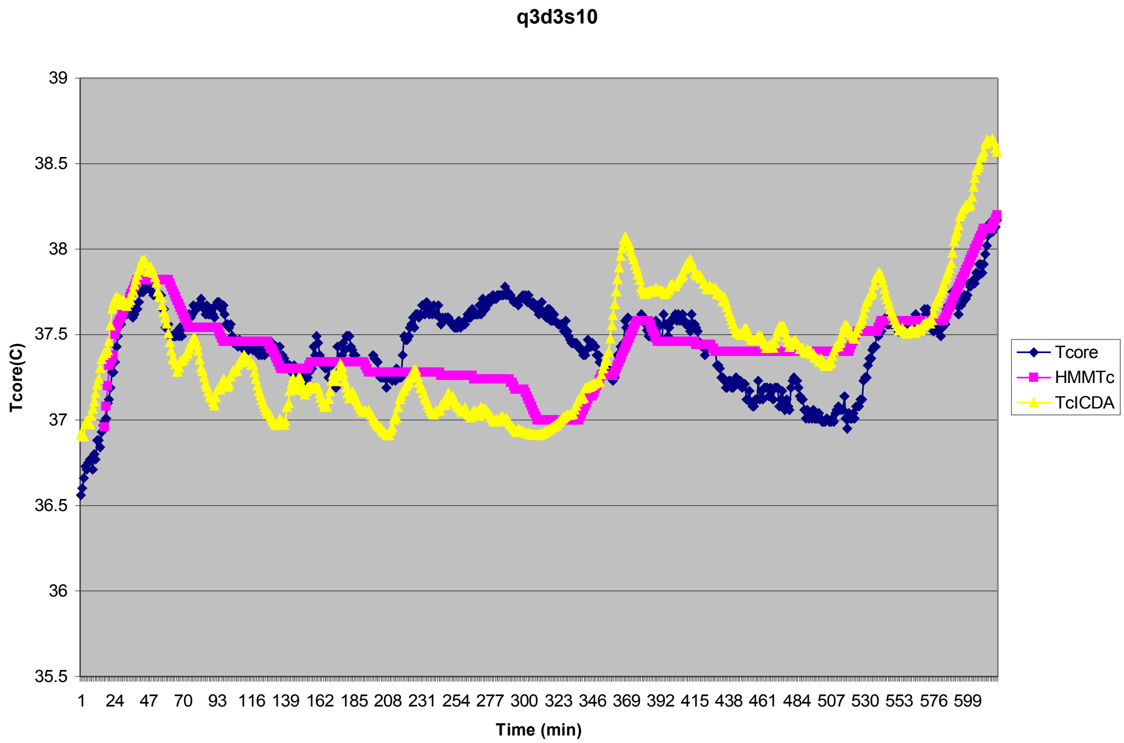


Figure 17: Actual, ICDA, and HMM estimated core temperatures - subject 11

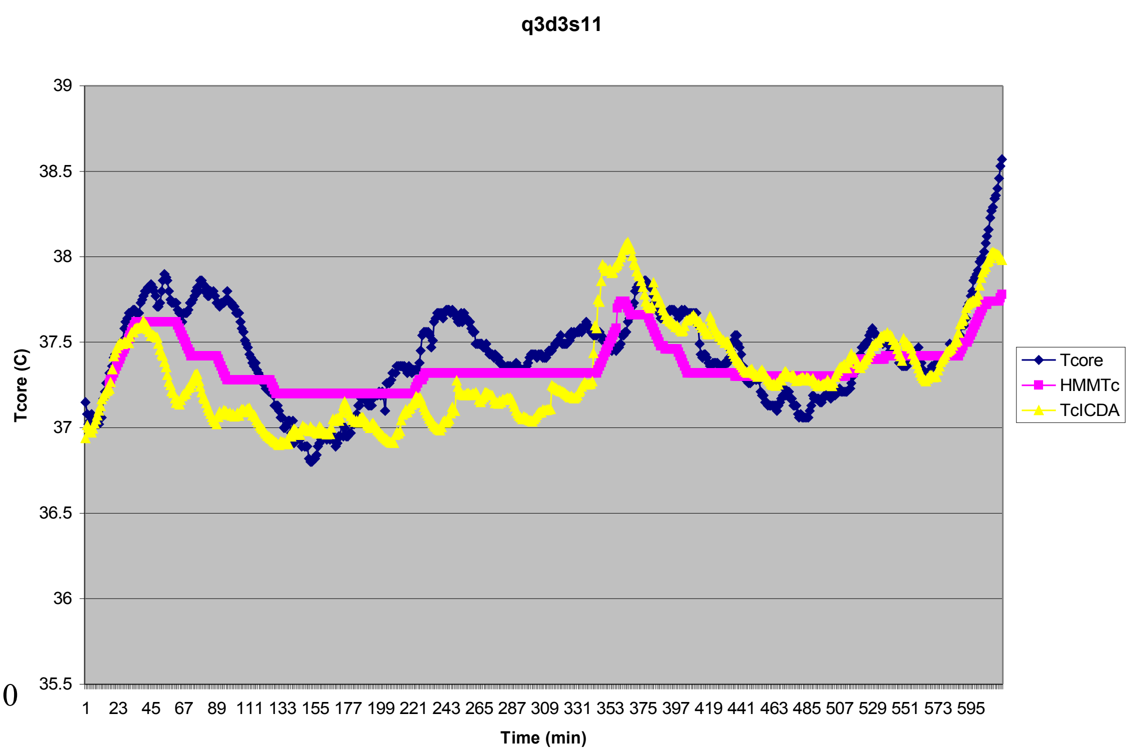
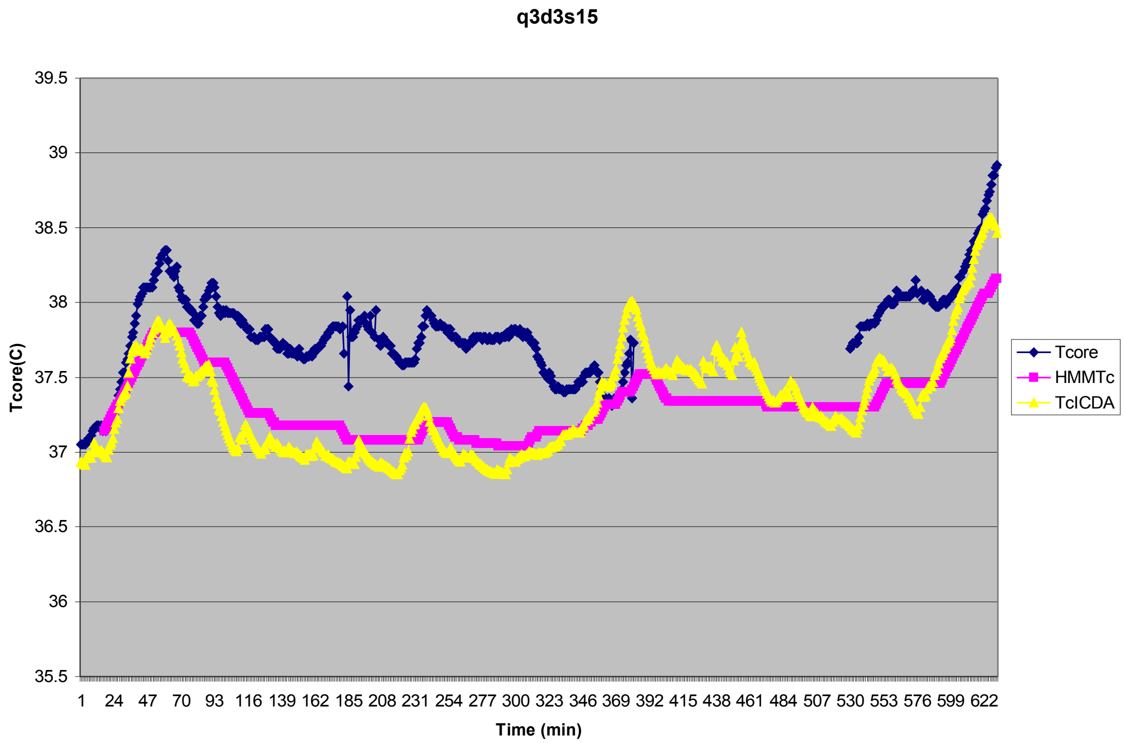


Figure 18: Actual, ICDA, and HMM estimated core temperatures - subject 15



Experiment 5 Discussion

The HMM provides a significantly closer estimation of core temperature than the ICDA model and also has a significantly higher correlation with the actual core temperature than the ICDA model. Additionally the HMM is predicting core temperature 16 minutes into the future using only one input parameter - heart rate. Conversely the ICDA model is predicting core temperature at the current time step using 5 input parameters and subject individualization parameters (height, weight, and clothing configuration).

CONCLUSIONS

This series of experiments has lead to the successful construction of an HMM that can estimate core body temperature 16 minutes into the future more accurately than the state of the art physical core temperature estimation model.

To the original five questions the experiments provide the following answers:

1. How does core temperature vary over time?

Core temperature varies in a systematic way that can be modeled by a light tailed probability distribution.

2. What order of Markov model does core temperature change exhibit?

A first order Markov model appears to be adequate.

3. If there is a lag in the change of core temperature how do past heart rates provide a better understanding of current core temperature than current heart rate?

Heart rates sixteen minutes in the past provide a better understanding of the current core temperature.

4. Does Tskin play a confounding role during normal thermoregulation?

There is probably not enough data to answer this question fully, however, the HMM trained on the laboratory data showed a significant improvement when skin temperature was removed as an input variable.

5. Does Tskin play a helpful role when thermoregulation is under stress or collapsed?

There currently is not enough data to address this question. However, theoretically skin temperature will add information in these circumstances.

It can be concluded that the HMM developed in this series of experiments can be used as the basis for core body temperature estimation in real time monitoring situations. The model provides scope for individualization, and for use in conjunction with other real time models.

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