

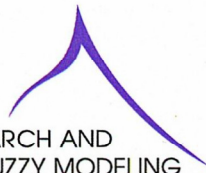
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### **Contributions**



**INSTITUTE FOR RESEARCH AND  
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# Human Body Temperature Daily Variation: Time Series Modeling, Simulation, and Estimation

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The talk deals with a set of mathematical models for human body daily temperature variation (HBDTV). The set is built with the purpose of subsequent fitting the models to experimental data by using our adaptive Kalman filtering technique [1]. The end goal of this research is to solve two main problems: (1) satisfactory model parameters identification and (2) quickest change point detection. Some averaged charts of HBDTV obtained from the healthy adults are used as a benchmark data. Measurement errors and many other factors affecting HBDTV, are taken into account by using stochastic differential and difference equations. The paper is structured by the following pattern: from deterministic models to stochastic models and then to stochastic discrete-time models. In conclusion, time series simulation and computational experiments with the filter are discussed.

## 1 Baseline model

Human body temperature regulation is a great example of how the homeostatic mechanism works. Consider human body temperature daily variation as it can be seen in many sources, for instance, in ANTRANIK.org (Fig. 1).

Consider the experimental data similar to Fig. 1 as a sample from a continuous-time stochastic process. Decompose it into the following additive components:

- $\bar{\theta}_t$ , a mathematical expectation of temperature variation relative to daily mean temperature  $\theta^*$ , for example,  $\theta^* = 36.7^\circ C$ ,

Table 4: Experimental results for estimating parameter  $\lambda$  (N stands for hours of measurements collection).

N	MEAN	RMSE	MAPE
0.5	0.01673842	0.00176175	8.53495848
1	0.01668899	0.00128099	6.00706384
3	0.01677946	0.00007005	3.24514550
6	0.01669467	0.00005602	2.80900894
12	0.01665221	0.00004990	2.37861756
24	0.01670608	0.00004936	2.40873864
48	0.01664612	0.00004899	2.43864040
72	0.01669707	0.00004534	2.20453053

Table 5: Experimental results for estimating parameter  $\sigma$  (N stands for hours of measurements collection).

N	MEAN	RMSE	MAPE
0.5	0.32169022	0.34800311	96.09089193
1	0.31693915	0.30205901	81.97886696
3	0.30406180	0.18993025	49.42388770
6	0.27961800	0.12641243	32.91595681
12	0.29865439	0.08187854	22.40155093
24	0.29767603	0.06173083	16.00851023
48	0.29723777	0.03914056	10.35061636
72	0.29601063	0.03366058	9.09541878

daily variation adaptive stochastic modeling.

The baseline HBTDV model has been patterned after the physical data available. The adaptive model  $\mathfrak{M}^*(\hat{\theta})$ , a replica of the Kalman filter for the standard observable data model, has been specified.

Computational experiments have been made to demonstrate the applicability of our Active Principle of Adaptation to bioinformatics problems.

#### Acknowledgement

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Table 6: Experimental results for estimating parameters  $\rho$  (N stands for hours of measurements collection).

N		MEAN	RMSE	MAPE
0.5	$\bar{\rho} =$	$\begin{bmatrix} 0.01659436 \\ 0.10575119 \end{bmatrix}$	0.28056287	85.14674225
1	$\bar{\rho} =$	$\begin{bmatrix} 0.01669789 \\ 0.11527021 \end{bmatrix}$	0.27826336	84.28790200
3	$\bar{\rho} =$	$\begin{bmatrix} 0.01658014 \\ 0.16829851 \end{bmatrix}$	0.22572891	65.65149641
6	$\bar{\rho} =$	$\begin{bmatrix} 0.01669664 \\ 0.23287266 \end{bmatrix}$	0.16211670	44.23780054
12	$\bar{\rho} =$	$\begin{bmatrix} 0.01666193 \\ 0.27265297 \end{bmatrix}$	0.08541397	22.48302905
24	$\bar{\rho} =$	$\begin{bmatrix} 0.01672629 \\ 0.28222717 \end{bmatrix}$	0.06480563	17.75995499
48	$\bar{\rho} =$	$\begin{bmatrix} 0.01668300 \\ 0.29025029 \end{bmatrix}$	0.03909148	10.45862558
72	$\bar{\rho} =$	$\begin{bmatrix} 0.01666895 \\ 0.29820202 \end{bmatrix}$	0.03539374	9.21590355

## References

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