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# Contributions

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# Contents

# 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 disctete-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 $\theta^\star$, for example, $\theta^\star = 36.7\ ^\circ C$,

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 $\mathfrak{M}^{\star}(\widehat{\theta})$, 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.

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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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[2] Yu. V. Tsyganova: *Computing the Gradient of the Auxiliary Quality Functional in the Parametric Identification Problem for Stochastic Systems.* Automation and Remote Control. **72(9)** (2011) 1925–1940.