Online Predictive Modeling for the Thermal Effect of Implantable Devices

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***Abstract*—In this paper, a modeling method is proposed to predict the thermal effect of implantable medical devices (IMD). The method generates an accurate temperature prediction within a time window in an online fashion, while constantly updating model parameters to improve its accuracy. The performance of the proposed method is validated using an in vitro experimental system that emulates the thermal effect of IMDs. The experimental results indicate that the proposed method can accurately predict the thermal dynamics of the system with an average error of $0.131\ ^\circ$C for Gaussian input and $0.024\ ^\circ$C for filtered Gaussian input.**

***Index Terms*—Implantable medical device, thermal effect, predictive modeling**

I. Introduction

The overheating in the surrounding tissue caused by the operation of implantable device has drawn growing concern, as a temperature of a few degree Celsius above the normal body temperature could cause detrimental effect to the body. It is reported that a patient with an implanted deep brain stimulator (DBS) suffered significant brain damage after diathermy treatment, and subsequently died [1], [2]. Postmortem examinations indicated that the tissue near the lead electrodes of the DBS deteriorated due to overheating. Researchers have shown that a temperature increase greater than 1 °C could have long-term damage to the brain tissue [3].

In practice, for implantable devices with very limited power consumption and limited communication with external world or being in the sleep mode most of the time, the thermal effect is rarely an issue. However, when the implantable devices are required to constantly stimulate the body and its neural tissues with a large number of electrodes and are in continuous communication with external devices, the generated heat can be a vital issue. One such application is the neuroprothesis, whose thermal effect has become more and more significant with the incorporation of high-density, functional electronic components and as the number of stimulation channels increases. For such devices, real-time thermal management is needed to maintain thermal safety while satisfying the application requirements.

To support real-time thermal management of a bioimplant, online prediction of the thermal effect of device operation is critical. Various origins of temperature increase and the possible methods to compute or measure them are studied in [4] for a dual-unit retinal prosthesis. It is shown that the power dissipated by implanted microchip, telemetry coil and the stimulating electrodes contribute to the temperature increase in the surrounding tissue. In addition to the power dissipation of the electronics, if the implantable device uses a telemetry system to transmit power and data, the electromagnetic fields induced in the body could also lead to temperature increase. The temperature increase can be modeled by the Pennes bioheat equation [5], which can be solved via various numerical methods like finite element analysis (FEA) and finite difference time domain (FDTD) [6]. In the work of Kim et. al. [7], the numerical solution is compared with the experimental measurement for an integrated 3-D Utah electrode array (UEA) and they are in good agreement. However, the aforementioned numerical methods rely on sampling the temperature value in the whole simulation domain as they evolve in time. Their time complexity and space complexity make them unsuitable for real-time thermal management [8].

Herein, we investigate the online prediction of thermal effect of an implantable device, with a focus on neural prosthesis. As indicated above, the existing methods like FEA, FDTD and Hybird ADI [9] all have high computational cost and are not suitable for real-time thermal management. In this paper, a computationally efficient method is developed based on our previous work [10] to predict the thermal dynamics online, which employs a linear model and an iterative updating scheme to update the model parameters online according to recent input-output data within a time window. The generated parameters are then used to predict the temperature within a future time window. At the next time instance, when the new temperature measurement is recorded, the time window shifts one step.

II. Predictive Thermal Modeling

We use the OE model to predict the thermal dynamics. The proposed thermal model can be represented as

$$\hat{y}(t|\theta) = \hat{G}(q, \theta)u(t), \tag{1}$$

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where $\hat{y}(t|\theta)$ is the predicted temperature, $u(t)$ is the controllable system working status, and

$$\hat{G}(q,\theta)=\frac{\hat{N}_G(q)}{\hat{D}_G(q)}=\frac{b_1q^{-1}+\cdots+b_{n_b}q^{-n_b}}{1+a_1q^{-1}+\cdots+a_{n_a}q^{-n_a}}. \tag{2}$$

The criterion of prediction can be defined as

$$J_{MP}^N=\frac{1}{k}\sum_{j=1}^{k}J_P^N(j), \tag{3}$$

where

$$\begin{aligned}J_P^N(j)=&\frac{1}{N-n_b-j+1}\sum_{t=n_b+j}^{N}[y(t)-\hat{y}(t|t-j)]^2\\&+\gamma\theta^TP^{-1}\theta.\end{aligned} \tag{4}$$

In which, $\hat{y}(t|t-j)$ denotes the prediction of temperature output $y(t)$ given the output data up to $t-j$ and input data up to t. Prior information of the system parameters are taken into account by introducing a regularization term $\theta^TP^{-1}\theta$ into (4) with P^{-1} representing the covariance information of the parameter prior distribution. γ denotes the relative weight of the regularization term.

A. Regularized Batch Pre-processing

Before the online prediction, a batch of data is used to determine the hyperparameters of the regularization term and choose a good starting point for searching the minimum of the prediction criterion. This batch of data is called the pre-processing data and can be represented as $\mathcal{L}^o=\{u^o(1),y^o(1),\ldots,u^o(N_0),y^o(N_0)\}$. In real applications, the procedure helps to provide a reliable model estimation during the initial phase. Here, we present the batch pre-processing procedure.

First, let's reformulate (1) intio a linear regression form as

$$\hat{y}(t|\theta)=\phi(t)^T\theta. \tag{5}$$

The one-step prediction result can be concatenated into the vector form as

$$Y=\Phi\theta, \tag{6}$$

in which

$$Y=\begin{bmatrix}\hat{y}(1|\theta)\\ \vdots\\ \hat{y}(N_0|\theta)\end{bmatrix},\Phi=\begin{bmatrix}\phi(1)^T\\ \vdots\\ \phi(N_0)^T\end{bmatrix}. \tag{7}$$

Let the kernel matrix P be parameterized by hyperparameter η. Then it can be calculated with maximization of the negative log likelihood function as

$$\hat{\eta}=\arg\min_{\eta}\ Y^TZ(\eta)^{-1}Y+\log\|Z(\eta)\|, \tag{8}$$

$$Z(\eta)=\Phi P(\eta)\Phi^T+\gamma^2I_{N_0}. \tag{9}$$

Then, let's derive the iterative procedure of minimizing the prediction criterion for the pre-processing data. The output value predicted by iterating j times the one-step predictor (5) can be represented as

$$\hat{y}(t+j|t)=R_j(q)y(t)+E_j(q)\hat{N}_G(q)u(t+j), \tag{10}$$

where $R_j(q)$ and $E_j(q)$ can be calculated as

$$R_j(q)=\mathbf{C}\mathbf{A}^j\begin{bmatrix}q^{-n_a+1}\\ \vdots\\ 1\end{bmatrix}, \tag{11}$$

and

$$E_j(q)=\mathbf{C}\sum_{i=0}^{j-1}\mathbf{A}^i\mathbf{B}q^{-i}. \tag{12}$$

In which,

$$\mathbf{A}=\begin{bmatrix}0 & 1 & \ldots & 0\\ \vdots & \vdots & \ddots & \\ 0 & 0 & \ldots & 1\\ -a_{n_a} & -a_{n_a-1} & \ldots & -a_1\end{bmatrix}, \tag{13}$$

$$\mathbf{B}=\mathbf{C}^T, \tag{14}$$

and

$$\mathbf{C}=\begin{bmatrix}0 & 0 & \ldots & 1\end{bmatrix}. \tag{15}$$

The j-step-ahead predictor can be converted into:

$$\hat{y}(t+j|t)=\phi_j(t)^T\Theta_j(\theta). \tag{16}$$

$\Theta_j(\theta)$ is the j-step-ahead mapping of the predictor parameter θ.

For the batch pre-processing data, define

$$Y_{N_0}^j=\begin{bmatrix}y^o(n_b+j)\\ \vdots\\ y^o(N_0)\end{bmatrix},\Phi_j=\begin{bmatrix}\phi_j(n_b)^T\\ \vdots\\ \phi_j(N_0-j)^T\end{bmatrix}. \tag{17}$$

Let $R_j^0=\Phi_j^T\Phi_j$ and $K_j^0=\Phi_j^TY_{N_0}^j$.

The cost function of batch pre-processing is

$$J_{MP}^{N_0}(k)=\frac{1}{k}\sum_{j=1}^{k}J_P^{N_0}(j), \tag{18}$$

in which

$$J_P^{N_0}(j)=\frac{1}{N_0-n_b-j+1}\|Y_{N_0}^j-\Phi_j\Theta_j(\theta)\|^2+\gamma\theta^TP^{-1}\theta. \tag{19}$$

This cost function can be minimized by iteratively executing the Gaussian Newton method with the gradient and Hessian matrix as in (20) and (21). The calculated θ, along with R_s^0 and K_s^0 for $s=1,\ldots,k$ are used to initialize the Bayesian Recursive MSPEM, which will be presented later.

$$\begin{aligned}\nabla_\theta J_P^{N_0}(s)=&\frac{2}{N_0-n_b-s+1}\nabla_\theta\Theta_s(\theta)(R_s^0\Theta_s(\theta)-K_s^0)\\&+\gamma(P^{-1}+P^{-T})\theta.\end{aligned} \tag{20}$$

$$\begin{aligned}\frac{\partial^2}{\partial\theta^2}J_P^{N_0}(s)\approx&\frac{2}{N_0-n_b-s+1}\nabla_\theta\Theta_s(\theta)R_s^0\nabla_\theta\Theta_s(\theta)^T\\&+\gamma(P^{-1}+P^{-T}).\end{aligned} \tag{21}$$

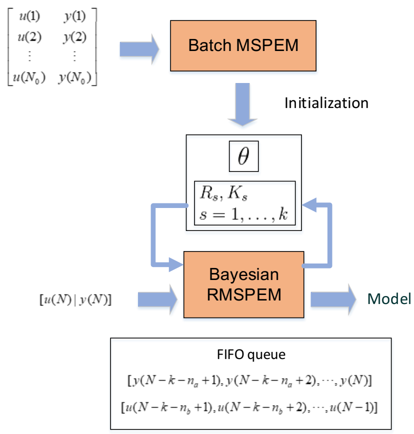


Fig. 1. The diagram of the proposed Bayesian RMSPEM method.

B. Bayesian Recursive MSPEM

Assume the test data is represented as $\mathcal{L} = \{u(1), y(1), \ldots, u(N), y(N), \ldots\}$ and the current time instant is N with the new available data being the input $u(N)$ and output $y(N)$, the Bayesian Recursive MSPEM method updates the model parameters iteratively using the Gaussian Newton method based on the prediction error of $y(N)$. The diagram of the proposed method is shown in Figure 1.

More specifically, at each time instant, the R matrix and K matrix are updated for $j = 1, \ldots, k$ as

$$R_j^N = R_j^{N-1} + \phi_j(N-j)\phi_j(N-j)^T, \quad (22)$$

and

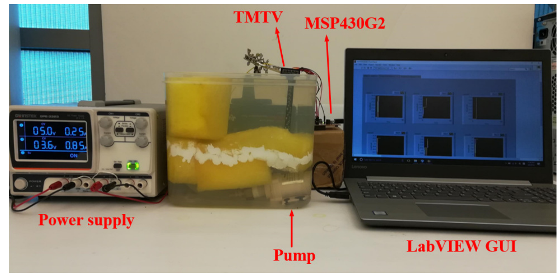
$$K_j^N = K_j^{N-1} + \phi_j(N-j)y(N). \quad (23)$$

In which, it only requires the input and output data within a finite time window to determine $\phi_j(N-j)$ and update the value of R and K matrices. The output measurements involved in the update are from time $N-k-n_a+1$ to time $N-1$ and input values necessary for the update is from time $N-k-n_b+1$ to time $N-1$. So, in practice, the input output data needed for the update of Bayesian RMSPEM can be saved in a FIFO queue of fixed size. Each time when a new temperature measurement and the corresponding input are available, the queue is updated and the Bayesian RMSPEM algorithm is executed to update the parameter estimation θ.

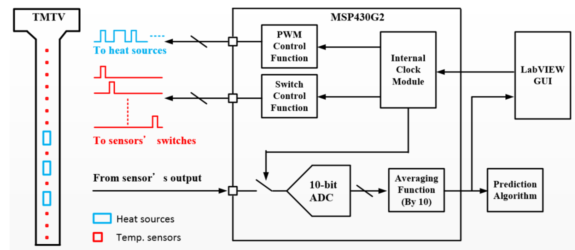
A forgetting factor is also incorporated into the prediction criterion as

$$J_P^N(j) = \frac{1}{N-n_b-j+1}\|\Lambda_N^j(Y_N^j - \Phi_j\Theta_j(\theta))\|^2 + \gamma\theta^T P^{-1}\theta, \quad (24)$$

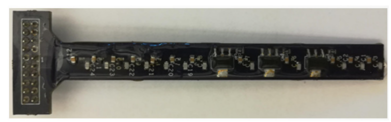
where Λ_N^j is the matrix of forgetting factor. This ensures that the past data become less relevant for the current estimation and it can capture the dynamics of the time-varying system.



(a)



(b)



(c)

Fig. 2. (a)The developed hardware testing system. (b) Hardware diagram. (c) The developed TMTV system.

III. Experimental Validation

A. Experiment System Description

To evaluate the performance of the proposed method, a hardware testing system is built to emulate the thermal effect of neural prosthesis. The system consists of three major components. The first one is a temperature monitoring and management test vehicle (TMTV) developed in the lab that has heat source and temperature sensors (TI LMT70) soldered on, which is used to emulate the implanted electronics. The temperature sensors have an accuracy around 0.1 °C and are also small in size. The second component is a water circulation system that uses a marine pump to control the flow rate and it is used to emulate the blood perfusion effect. Lastly, a monitor and control system is built with TI MSP430G2 board and Labview front end. The Labview front end on the PC is used to display and save the temperature measurements, it can also call the Matlab program which implements the thermal management algorithm. The TI MSP430G2 acts as the middleware between the TMTV and PC. It sends the control signal to the heat source on the TMTV and sends the temperature readings back to PC.

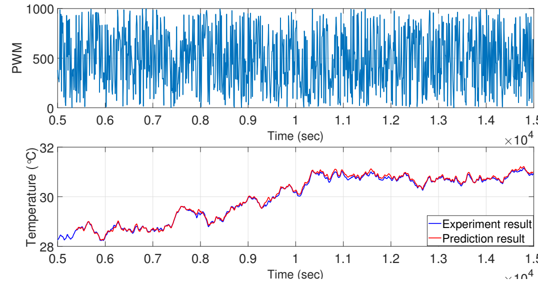
Figure 2 shows the developed hardware testing system. The container in the middle are filled with water and a marine pump is placed at the bottom to create water circulation in the container. Note that the sponge material is also glued in the container to ensure a uniform water flow in the upper portion of the container where the TMTV is placed. To simulate the heat diffusion effect of blood perfusion, the water flow generated by the pump is adjusted to be similar to the blood perfusion rate in the human brain by choosing a predetermined supply voltage.

This system provides accurate temperature measurements by calibrating each temperature sensor beforehand and applying Kalman filter to filter out the measurement noise. It can be used to evaluate the impact of different factors on the thermal dynamics and evaluate the performance of the proposed algorithm before conducting animal testing.

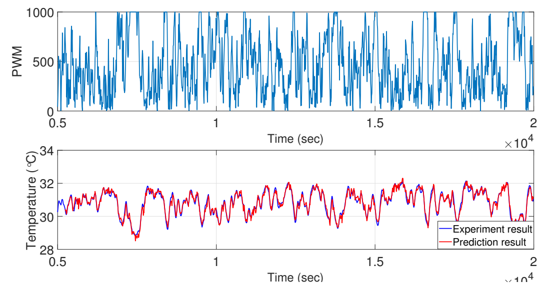
B. Experimental Results and Analysis

To evaluate the performance of the predictive modeling method , two experiments are designed. In the first experiment, we generate 2000 random PWM signals within the range of $[0, 1000]$ using Gaussian distribution and apply the PWM signals to the TMTV with a step size of 10 seconds. The temperature is measured via each of the onboard temperature sensors, which is used to compare with the temperature predicted online by the proposed Bayesian RMSPEM method and to provide real-time feedback signal for model updating. The Bayesian RMSPEM method implements a 20th order OE model and predicts the temperature measurement of 10 steps ahead. The result of this experiment is shown in Figure 3(a). It demonstrated that the Bayesian RMSPEM accurately predicts the temperature variation despite the varying PWM signal and achieves an overall prediction mean square error of 0.131 °C.

In the second experiment, a random second order low pass filter is generated and applied to 2000 random PWM signals. Then the filtered PWM signal is applied to the TMTV. This is used to emulate the output of a real thermal management system, where the computed control signal is usually a low frequency signal that depends on various inputs. In this experiment, it is shown in Figure 3(b) that the temperature output can be predicted with an 5th order OE model, which is much simpler than the 20th order OE model used in the first experiment. By taking advantage of this low order model, the computational cost of the proposed method can be greatly reduced. The overall prediction mean square error is about 0.024 °C.



(a)



(b)

Fig. 3. Experiment results (a) Gaussian input. (b) Filtered Gaussian input.

IV. Conclusion

With the emerging of more high power and complex implantable devices, the issue of thermal safety has raised growing concern. Accurate long-term prediction of the temperature increase caused by device operation is critical for achieving safe operation. The existing thermal modeling methods are based on solving Pennes' bioheat equation in the domain of interest, which is not suitable for realtime applications. In this paper, a Bayesian RMSPEM method is developed to support the real-time thermal management. The proposed method predicts the temperature increase in a future time window and iteratively updates the prediction model according to the recent input output data. An experiment system is built to validate the proposed method, which emulates the thermal effect of neural prosthesis. The experimental results demonstrate that the predictive thermal modeling method is able to generate accurate and robust temperature prediction, which provides an important tool for realtime thermal management.

References

[1] P. S. Ruggera, D. M. Witters, G. von Maltzahn, and H. I. Bassen, "In vitro assessment of tissue heating near metallic medical implants by exposure to pulsed radio frequency diathermy," *Physics in Medicine and Biology*, vol.48, pp.2919-2928, 2003.

[2] J. G. Nutt, V. C. Anderson, J. H. Peacock, J. P. Hammerstad, and K. J. Burchiel, "DBS and diathermy interaction induces severe CNS damage," *Neurology*, vol.56, no.10, pp.1384-1386, 2001.

[3] J. C. LaManna, K. A. McCracken, M. Patil, and O. J. Prohaska, "Stimulus-activated changes in brain tissue temperature in the anesthetized rat," *Metabolic brain disease*, vol.4, no.4, pp.225-237, 1989.

[4] G. Lazzi, "Thermal effects of bioimplants," *IEEE Engineering in Medicine and Biology Magazine*, vol.24, no.5, pp.75-81, 2005.

[5] H. Pennes, "Analysis of tissue and arterial blood temperatures in the resting human forearm," *Journal of applied physiology* vol.1, no.2, pp.93-122, 1948.

[6] S. C. DeMarco, G. Lazzi, W. Liu, J. D. Weiland, and M. S. Humayun, "Computed SAR and thermal elevation in a 0.25-mm 2-D model of the human eye and head in response to an implanted retinal stimulator-Part I: Models and methods," *IEEE Transactions on Antennas and Propagation*, vol.51, no.9, pp.2274-2285, 2003.

[7] S. Kim, P. Tathireddy, R. A. Normann, and F. Solzbacher, "Thermal impact of an active 3-D microelectrode array implanted in the brain," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol.15, no.4, pp.493-501, 2007.

[8] R. Chai, Y. Zhang, M. Ghovanloo, "Joint power and thermal management for implantable devices," *Biomedical Circuits and Systems Conference (BioCAS)*, pp.1-4, 2015.

[9] V. Singh, A. Roy, R. Castro, et al, "On the thermal elevation of a 60-electrode epiretinal prosthesis for the blind," *IEEE transactions on biomedical circuits and systems*, vol.2, no.4, pp.289-300, 2008.

[10] R. Chai, Y. Zhang, "Recursive Multi-step Prediction of Bioimplants Thermal Effect," *Proc. of the 11th International Workshop on Structural Health Monitoring*, 2017.