

Comparison on nonlinear regression algorithms for prediction of skin temperature in Lower Limb Prostheses

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Abstract

Introduction: Monitoring and predicting the residual limb skin health in amputees is of principal importance as the socket of the prosthesis creates an airtight, warm and damp environment that encourages growth of bacteria and skin breakdown. Elevated stump skin temperatures are one of the major factors that affect the tissue health in that region [1]. Monitoring interface temperature at skin level is notoriously complicated. The problem might be considered notorious because embedding wires and sensors in an elastomer eventually results in elastomer failures because of the high strain induced when donning a liner (amputees roll the liners onto their limbs). Another reason is because placing sensors and wires directly against the skin could cause irritation and chaffing over just a short period of time. The heat dissipation in prosthetic sockets is greatly influenced by the thermal conductive properties of the socket and interface liner materials [2]. This leads to a hypothesis that if the thermal properties of the socket & liner materials are known then the in-socket stump temperature could be accurately predicted by just measuring the prosthetic socket or liner temperature. A mathematical model using the Gaussian processes for machine learning to predict the residual limb skin temperature of the amputee by measuring the in-socket temperature has been developed [3]. Here we compare the performance of Gaussian processes for regression to the other computational method namely support vector machines (SVM).

Methods: To investigate the correlation between the position of thermocouples (skin and in-socket), one trans-tibial traumatic amputee was recruited to perform in a 35 minute laboratory protocol (see Table). To monitor and record the skin and in-socket temperatures, four K-type thermocouples via a data logger were used. Two thermocouples were taped onto the residual limb in lateral and medial position. The other two thermocouples were put on the corresponding positions on the liner (in-socket).

Activity	Time (minutes)
Resting/Sitting	10
Walk at self-selected pace of 0.62 metres/second on a treadmill	10
Final rest	15

The temperature profiles of the liner and the residual limb skin were recorded for ambient temperatures of 10°C, and then the same protocol was repeated for 15°C, 20°C, and 25°C. All experiments were conducted in a climate controlled chamber with zero wind velocity and 40% humidity level. It was seen that at any given ambient temperature, the trace of the liner temperature follows that of the residual limb skin. This suggested a possibility to model the liner temperature as a function of skin temperature and create a mathematical model of the same. Different modelling techniques for machine learning were utilized and the results from the Gaussian processes model and support vector regression technique are compared in this study.

Results: The results (see Figure) indicate the predictive capability of both Gaussian Processes and SVM modelling techniques at the lateral side at an ambient temperature of 10°C. The key assumption in Gaussian Process modelling is that our data can be represented as a sample from a multivariate Gaussian distribution. A Gaussian process model infers a joint probability distribution over all possible outputs for all inputs. This form enables the implementation of Bayesian framework where the covariance function is taken in the squared exponential form as in equation (1)

$$C_f = \theta_1 e^{-\frac{(x_i - x_j)^2}{2l^2}} + \sigma_n^2 \delta_{ij} \quad (1)$$

where the set of hyperparameters $\Theta = \{\theta_1, l, \sigma_n\}$ and δ_{ij} is a delta function whose value is zero for all $i \neq j$. After optimizing the hyperparameters, the predictions lie in the 95% confidence interval (± 2 standard deviations). This is indicated in (a) in the figure.

The SVM modelling technique relies on defining the loss function that ignores errors, which are situated within the certain distance of true value. This epsilon intensive loss function measures the cost of the errors on the training points.