Contact force estimation from flexible tactile sensor values considering hysteresis by Gaussian process

Takato Horii*, Francesco Giovannini†, Yukie Nagai*, Lorenzo Natale†, Giorgio Metta†, and Minoru Asada*

*Graduate School of Engineering, Osaka University, 2-1 Yamada-oka, Suita, Osaka, Japan

Email: takato.horii@ams.eng.osaka-u.ac.jp

†iCub Facility, Istituto Italiano di Tecnologia, Via Morego, 30 16163, Genova, Italy

I. Introduction

Flexible tactile sensors are important elements for facilitating the physical interaction between robots and uncertain environments. For instance, tactile information is used by the robot to grasp objects and interact with humans. A model-based approach is one technique for building a relationship between tactile sensor values and task-relevant information such as force, slip, and temperature. However, it is difficult to create models of flexible tactile sensors for converting sensor signals beforehand due to a nonlinear relation between a contact and the deformations of the flexible form caused by its hysteresis [1]. In contrast, machine learning techniques can be adopted to represent these relationships. For example, Tada et al. [2] proposed a model to acquire the relationship between tactile sensor values and slip vibration using a neural network.

The purpose of this study was to develop computational models for learning the association between the force applied to a tactile sensor and the sensor value by compensating for the hysteresis in the sensor. We used the tactile sensor of an iCub fingertip in order to apply our models to cognitive studies. This paper first presents our proposed models that consider a Markov property of taxel (tactile sensor elements) values, and then reports experimental results.

II. Method

A. Setup

We measured the taxel values and force-torque (F/T) sensor values to conduct a learning experiment. Fig. 1(a) shows the experimental setup. We attach an iCub's fingertip to a grip, as shown in Fig. 1(b). The fingertip is composed of two types of silicone, a flexible PCB, and an inner support [3]. Twelve electrodes are distributed on the PCB, which construct capacitors with the conductive silicone layer. When a force is applied to the fingertip, the capacitance changes due to the deformation of the silicone. This sensor is known to have hysteresis between a contact force and the taxel values [3].

In the experiment, an experimenter periodically pressed the tactile sensor in the direction of gravitational force on the center of the F/T sensor. We use a Nano 17 F/T sensor (ATI Industrial Automation) to measure the force along the Z-axis F_z. We measured the taxel values as a 12-dimensional vector and F/T sensor values at a 50 Hz sampling rate.

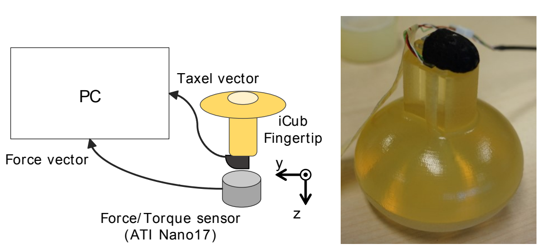
B. Gaussian process and proposed models

We employed a Gaussian process (GP) to learn the relationship between taxel values as the input $\boldsymbol{\theta}$ and force values as the output $f(\boldsymbol{\theta})$. A GP is a probabilistic model given by $f(\boldsymbol{\theta}) \sim \mathrm{GP}(m_f, k_f)$, where m_f and k_f are its mean function and a covariance function, respectively [4]. We chose a zero mean function and a squared exponential covariance function, which provides the covariance element between any two samples $\boldsymbol{\theta}_p$, and $\boldsymbol{\theta}_q$. This function is given by

$$k(\boldsymbol{\theta}_p, \boldsymbol{\theta}_q) = \sigma_f^2 \exp(-\frac{1}{2}(\boldsymbol{\theta}_p - \boldsymbol{\theta}_q)^T \boldsymbol{M}(\boldsymbol{\theta}_p - \boldsymbol{\theta}_q)), \tag{1}$$

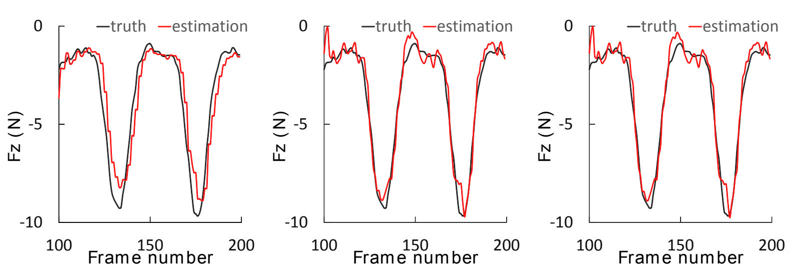
with $\boldsymbol{M} = l^{-2}\boldsymbol{I}$. Here, $\boldsymbol{I}$ is the identity matrix and the signal variance σ_f^2 and the length-scale l are the hyperparameters. We used a marginal likelihood to optimize the hyperparameters of the covariance function [4].

We propose two GP models, which assume the Markov chain of taxel values in order to compensate for the hysteresis of the tactile sensor. The first model employs multi-step time series data of input signals. For instance, if we assume a Markov



(a) Experimantal setup (b) Grip

Fig. 1. Experimental setup and grip with fingertip.



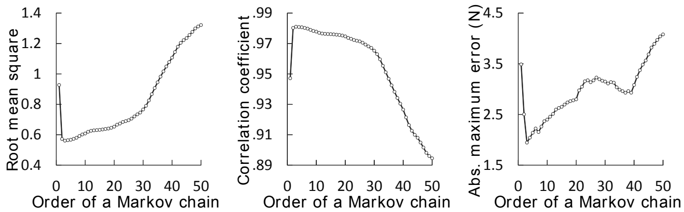
(a) Normal GP model (b) First proposed model (c) Second proposed model

Fig. 2. Estimation results of each model.

TABLE I

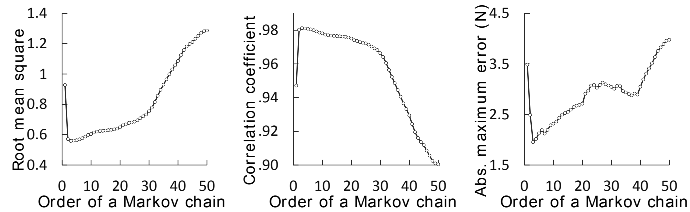
PERFORMANCE OF EACH MODEL

Condition	Root mean square	Correlation coefficient	Abs. maximum error (N)
Normal GP model	1.035	0.933	3.625
Considering Markov chain model ($n = 3$)	0.561	0.981	**1.944**
Considering $\Delta\theta_t$ in addition to Markov chain model ($n = 3$)	**0.559**	**0.981**	1.952



(a) Root mean square (b) Correlation coefficient (c) Abs. maximum error

Fig. 3. Performance of first proposed model with different Markov orders.



(a) Root mean square (b) Correlation coefficient (c) Abs. maximum error

Fig. 4. Performance of second proposed model with different Markov orders.

chain of order n, this model requires the assembled input data given by $\boldsymbol{\Theta}_t = [\boldsymbol{\theta}_t, \boldsymbol{\theta}_{t-1}, \cdots, \boldsymbol{\theta}_{t-n}]^T$ to estimate applied force at time t. The second model uses the difference between two consecutive input signals in addition to the multi-step time series data. Here, the difference is given by $\Delta\boldsymbol{\theta}_t = \boldsymbol{\theta}_t - \boldsymbol{\theta}_{t-1}$. The learning data with an n-order Markov chain are described by $\boldsymbol{\Theta}_t = [\boldsymbol{\theta}_t,\ \Delta\boldsymbol{\theta}_t, \boldsymbol{\theta}_{t-1}, \cdots, \boldsymbol{\theta}_{t-n+1}, \Delta\boldsymbol{\theta}_{t-n+1}, \boldsymbol{\theta}_{t-n}]^T$ at the time t.

III. EXPERIMENTS AND RESULTS

We trained all models to compare their accuracy in terms of estimating the force value from unknown taxel signals. Fig. 2 shows the model estimations. Table I summarizes the performance of all the models. We calculated the root mean squared error, correlation coefficient between the true force and estimated force, and absolute maximum error. A normal GP model that does not consider a Markov chain of the sensor signals was used for comparison.

A. Normal GP model

This model generally provided accurate the estimation as depicted in Fig. 2(a). However, the error between the true and estimated values increased when the force had a peak value at $F_z \simeq -10$ N. The estimation has a step form and delay compared to the true value. Using only current taxel values, the GP was unable to estimate the force data precisely due to the hysteresis.

B. Considering n-order Markov chain of tactile signals

We tested the first proposed model using the same dataset as in the previous experiment. Fig. 2(b) shows the estimated values. The estimation was closer to the truth than the normal GP model, especially at the force peak points. The performance clearly improved compared to the previous model, as presented in Table I. Fig. 3 shows the change in the estimation accuracy with different Markov orders n. The model performed the best when $n = 3$.

C. Considering $\Delta\theta_t$ in addition to n-order Markov chain of tactile signals

Fig. 4 shows the performance of this model with different Markov orders n. When $n = 3$, the model exhibited the best accuracy, just like the first proposed model. Fig. 2(c) shows the estimated values from the same data used in the previous experiments. The root mean squared error slightly reduced from the first proposed model. This is because the learning data included deformation directions of the sensor, which are important for representing the hysteresis as a dynamic phenomenon.

IV. DISCUSSION AND CONCLUSION

We proposed models based Gaussian process using the Markov chain of taxel values in order to compensate for the hysteresis of a tactile sensor. Our models were able to accurately estimate the force applied to the tactile sensor. These models can also be applied to various types of flexible tactile sensors other than those embedded in the iCub robot.

We assume that the GP can internally represent differences between two consecutive signals because of the slight difference in the accuracy between the first and second proposed models. Further studies are needed in order to examine the internal representation of our proposed models.

ACKNOWLEDGMENT

This work was supported by JSPS Core-to-Core Program, A. Advanced Research Networks and was conducted in the framework of the European CODEFROR project (PIRSES-2013-612555).

REFERENCES

[1] R.S. Dahiya et al. *IEEE Transactions on Robotics*, Vol. 26, No. 1, pp. 1–20, 2010.
[2] Y. Tada and K. Hosoda. *Advanced Robotics*, Vol. 21, No. 5-6, pp. 601–617, 2007.
[3] A. Schmitz et al. *2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pp. 2212–2217, 2010.
[4] C. Rasmussen and C. Williams. *Gaussian processes for machine learning*. MIT Press, 2006.