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Compensation for Tactile Hysteresis Using Gaussian Process with Sensory Markov Property

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Abstract— **Flexible tactile sensors have been studied to enable robots to interact with objects in unstructured environments. However, due to nonlinearity caused by the hysteresis of tactile materials, it is difficult to accurately convert sensor signals into task-relevant information such as force and slip.**

To compensate for the hysteresis of flexible tactile sensors, we propose a model based on a Gaussian process. The key idea of our model is to include the Markov property of sensory input. The proposed model not only uses the current tactile signal, but also its time-series signals, to extract the influence of the past states on the current state. We evaluate the accuracy of force estimation using the proposed model in comparison to the normal Gaussian process model, which does not take the Markov property into account. The experimental results demonstrate that the performance of our model improves on the normal Gaussian process in terms of root mean squared error, correlation coefficient, and absolute maximum error between the actual and the estimated force. We discuss the advantages of accounting for the sensory Markov property and the potential ability of the Gaussian process to internally acquire the representation of the deviation of sensory signals.

I. Introduction

Tactile sensors play an important role in introducing robots into human society. Like humans, robots should be able to manipulate objects and interact with humans through tactile information. To this end, flexible tactile sensors comprising many sensor elements, which may cover all or part of a robot's body, have been widely studied to improve the quality and adaptability of tactile interaction.

When robots use data from tactile sensors to accomplish a task, they need to convert the sensory signals into task-relevant information such as force, slip, and vibration. For example, in a grasping task, robots need to detect reaction force and slip for manipulating objects. The method for processing these sensor signals to acquire task-relevant information needs to initially compensate for the hysteresis of flexible sensors due to the nonlinear relation between applied force and deformation of the sensors [1]. The hysteresis hinders the estimation of task-relevant information: in this phenomenon, the sensor outputs different values from the same input, depending on context. For instance, sensor outputs are different depending on a phase, which the sensor is pushed or released.

A model-based approach is a technique to represent such a relationship between sensor signals and task-relevant information. A Bouc-Well model [2] is often used to represent the hysteresis phenomenon in which the input-output dynamics involves the memory effect such as the deformation of soft materials. This model is composed of a first-order nonlinear differential equation and several parameters that modify the behavioral characteristics of the model, depending on context. Sánchez-Durán et al. [3] applied a Prandtl–Ishlinskii model to their tactile sensors to reduce the effects of hysteresis from the output voltage of a sensor element. The Prandtl–Ishlinskii model consists of an arctangent or exponential equation that represents the hysteresis curves. These models, however, only represent the relationship between single input and single output. When it is necessary to estimate applied force distribution and direction from extensive tactile sensors (many tactile sensor elements, hereafter taxels), compensation models require a priori knowledge of the positional relations of sensor elements to integrate the information.

In contrast, machine learning techniques are applicable for representing relationships between multi-input sensor signals and task-relevant information. For example, Tada et al. [4] developed a neural network model to determine the relationship between tactile sensor values and slip, detected as visual information. Takamuku et al. [5] proposed an object recognition model based on a self-organizing map implemented in a robot hand with flexible tactile sensors. The self-organizing map utilized taxel values after the robot's hand grasped objects intermittently ten times. However, these studies did not focus on the dynamical change of taxel values due to hysteresis of the tactile sensor, which diminishes the estimation accuracy.

This paper proposes a model based on the Gaussian process to compensate for the nonlinearity of flexible tactile sensors. One key idea is to integrate the Markov property of the sensory input, to reduce the effect of hysteresis of tactile sensors. The proposed model uses the history of tactile signals in addition to the current signal, to examine the influence of past states on the current state. We compare the accuracy of force estimation by both a normal Gaussian process, which does not consider the Markov property and the proposed method, using an iCub fingertip [6]. Our expected result is that the proposed model shows higher accuracy in the estimation than the normal Gaussian process model thanks to the richness of the input signals. We discuss the advantages of integrating the sensory Markov property into the Gaussian process.

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II. Model to compensate for hysteresis

A. Gaussian process

We employ a Gaussian process (GP) [7] to build the relationship between taxel values as input $\boldsymbol{\theta}$ and force values as output $f(\boldsymbol{\theta})$. $f(\cdot)$ is a latent function of the output. This model estimates $f(\boldsymbol{\theta})$ from $\boldsymbol{\theta}$ by using an infinite number of joint Gaussian distributions. A GP is a probabilistic process given by its mean function m_f and a covariance function k_f:

$$f(\boldsymbol{\theta}) \sim \mathrm{GP}(m_f, k_f). \tag{1}$$

We assume a zero mean function and a squared exponential covariance function, which provides the covariance element between any two samples θ_p and θ_q. This function is given by

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

where $\boldsymbol{M} = l^{-2}\boldsymbol{I}$. Here, $\boldsymbol{I}$ is an identity matrix and the length-scale l and the signal variance σ_f^2 are the hyperparameters.

Given learning dataset $\mathcal{T}$, which consists of input vectors $\boldsymbol{\theta}_1, \cdots, \boldsymbol{\theta}_D$ and an output vector $\boldsymbol{v} = [f(\boldsymbol{\theta}_1), \cdots, f(\boldsymbol{\theta}_D)]^T$, the output $f(\boldsymbol{\theta}_*)$ for an unknown input $\boldsymbol{\theta}_*$ is estimated as a distribution of

$$P(f(\boldsymbol{\theta}_*)|\mathcal{T}, \boldsymbol{\theta}_*) = \mathcal{N}(\mu(\boldsymbol{\theta}_*), \sigma^2(\boldsymbol{\theta}_*)) \tag{3}$$

$$\mu(\boldsymbol{\theta}_*) = \boldsymbol{k}_*^T(\boldsymbol{K} + \sigma_n^2 \boldsymbol{I})^{-1}\boldsymbol{v} \tag{4}$$

$$\sigma^2(\boldsymbol{\theta}_*) = k(\boldsymbol{\theta}_*, \boldsymbol{\theta}_*) - \boldsymbol{k}_*^T(\boldsymbol{K} + \sigma_n^2 \boldsymbol{I})^{-1}\boldsymbol{k}_*, \tag{5}$$

where $\boldsymbol{k}_* = [k(\boldsymbol{\theta}_1, \boldsymbol{\theta}_*), \cdots, k(\boldsymbol{\theta}_D, \boldsymbol{\theta}_*)]^T$, $\boldsymbol{K}$ is a matrix composed of $K_{i,j} = k(\boldsymbol{\theta}_i, \boldsymbol{\theta}_j)$. σ_n^2 is the noise variance. We use a marginal likelihood to optimize all hyperparameters [7].

B. Proposed models

We propose a GP model using sensory Markov property to reduce the effect of the hysteresis of flexible tactile sensors. Our model utilizes the multistep time series taxel values as the input. Fig. 1 shows the graphical representation of this model. If we assume the Markov property of order n, input data $\boldsymbol{\Theta}_t^n$ at time t are given by

$$\boldsymbol{\Theta}_t^n = [\boldsymbol{\theta}_t, \boldsymbol{\theta}_{t-1}, \cdots, \boldsymbol{\theta}_{t-n}]^T. \tag{6}$$

If the dimension of current sensor signal vector $\boldsymbol{\theta}_t$ is d, the dimension of input vector $\boldsymbol{\Theta}_t^n$ becomes $d \times (n+1)$.

III. Experimental setup

A. iCub fingertip

Fig. 3(a) shows an iCub fingertip (a black part) attached on a grip for an experimenter to manipulate it. The iCub fingertip consists of an inner support, a flexible printed-circuit board (PCB) attached on this support, and two types of silicone: dielectric silicone placed on the PCB and conductive silicone covering the fingertip [8]. Twelve electric round pads are distributed on the PCB, which form capacitors with the conductive silicone. When a force is applied to the fingertip, the capacitance changes due to the deformation of the silicone. The size of fingertip is 14.5 mm long and 13 mm wide. In our experiment, we use a new type of fingertip, which is covered by fabric instead of the conductive silicone.

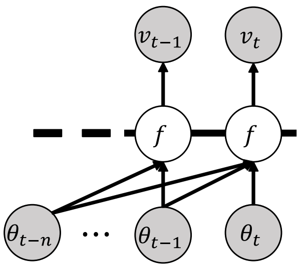


Fig. 1. Graphical representation of GP model with n-order Markov chain

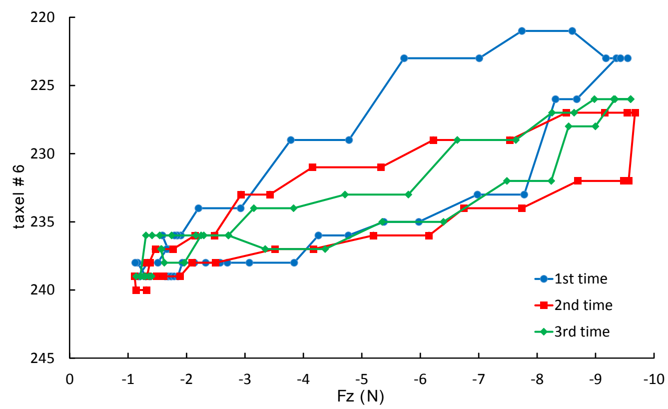


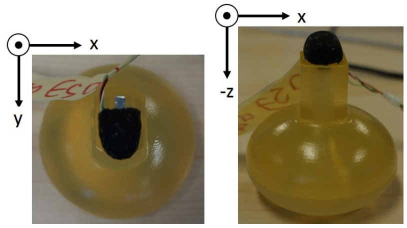
Fig. 2. Hysteresis of iCub fingertip under our experimental conditions

This fingertip is known to have hysteresis [8]. Fig. 2 shows the hysteresis property of the iCub fingertip. The horizontal and vertical axes denote the applied force and the value of a taxel out of the number six sensor, respectively. The blue line indicates the results for the first pushing movement, whereas the red and the green lines show the successive movements. It is clear that the property of the initial deformation is different from that of subsequent deformations.

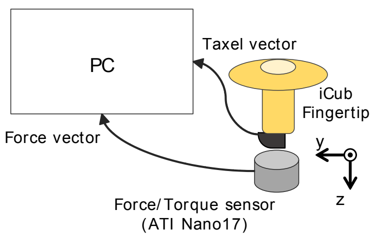
B. Data collection

We record taxel values and force-torque (F/T) sensor values to test our model. Fig. 3(b) shows the experimental setup. We use a Nano 17 F/T sensor (Fig. 3(c)), a product by ATI Industrial Automation, to measure force and torque in three axes (i.e. F_x, F_y, F_z, T_x, T_y and T_z).

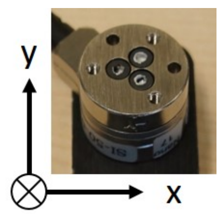
The fingertip is periodically pressed on the center of the F/T sensor by an experimenter, first independently in the X-, Y-, and Z-directions, then simultaneously. We measure the taxel values as a 12-dimensional vector and the F/T sensor values with a 50 Hz sampling rate. Figs. 4(a) and 4(b) plot the recorded data under one-directional force (Z-axis) and three-directional force conditions, respectively. The collected data are divided into a learning dataset (80%) and a testing dataset (20%). The testing dataset is indicated by red in Figs. 4.



(a) Screwed fingertip on grip

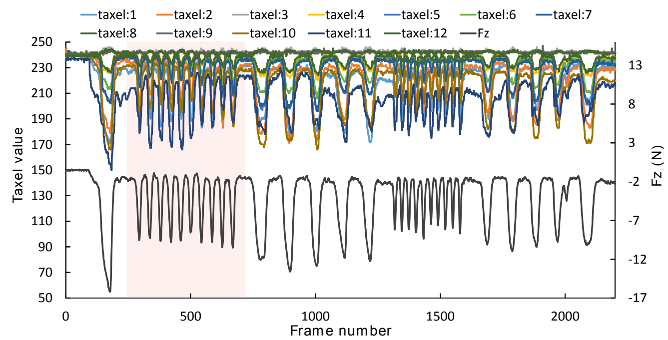


(b) Experimental setup

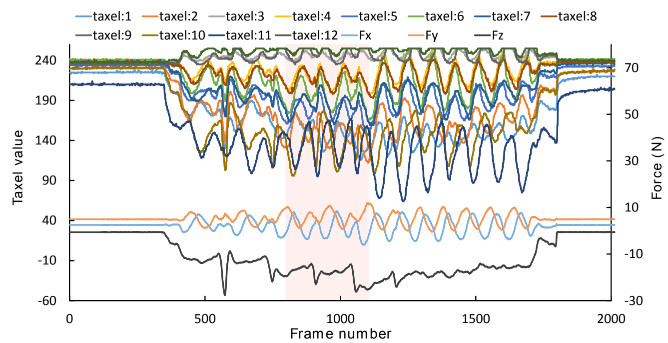


(c) F/T sensor

Fig. 3. Experimental setup and grip with fingertip



(a) One-dimensional force condition (Z-axis)



(b) Three-dimensional force condition

Fig. 4. Recorded taxel values and force value from each experiment

IV. Results

There are three conditions in our experiment:

One-directional force condition:

An experimenter pushed the fingertip periodically in each of the three directions (X, Y, or Z), while maintaining the contact point between the fingertip and the F/T sensor. The proposed model trained with a single directional force was tested with the data for the same direction.

Three-directional force condition:

The fingertip was simultaneously pressed in the three directions. As under the one-directional conditions, the contact point was maintained throughout the experiment.

Cross learning condition:

We trained our model by using the dataset for the three-dimensional force condition, then tested the model with the data for each direction.

A. One-directional force condition (Z-axis)

1) Normal GP model: First, we estimated F_z under the one-directional force condition. The normal GP model, which does not consider a Markov chain of the taxel values, was examined for predicting the time series of force values from unknown input. The performance of this model is summarized in Table I. We evaluated root mean squared error (RMSE), correlation coefficient (CC) and absolute maximum error (AME) between the actual and the estimated force.

The output of this model is presented in Fig. 5(a). The estimation of this model is generally accurate. However, the error between the actual and the estimated values increases around the peaks of the force value at $F_z \simeq -10$ N (Fig.5(b)). It is clear in Fig. 6(a) that the estimation shows a stepped form, while lagging behind the actual value. This temporal delay is attributable to the hysteresis of the tactile sensor, which is caused by the nonlinear deformation of the flexible material. The GP using only the current taxel values was unable to predict the force value with sufficient accuracy because it is less capable representing the hysteresis of the tactile sensor as dynamic phenomenon.

2) GP model with n-order Markov chain: We evaluated our model by using the same dataset as in the previous experiment. The estimation accuracy of the model with different Markov orders n (see Eq. 6) is compared in Fig. 7. This model achieved the best performance when $n = 3$. Significant improvements in the performance of this model compared to the normal GP are listed in Table I.

Additionally, the delay in the estimation decreased from the previous model. Fig. 6(b) shows the estimated value similar to Fig. 6(a). The estimation is closer to the measured value than the normal GP, particularly at the force peak points.

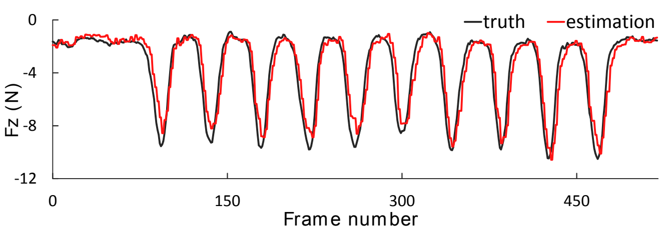
B. One-directional force condition (X- and Y-axes)

Typically, a tactile sensor consisting of sensor elements, which are placed planarly, can only measure normal force because flat sensors are unable to detect shearing stress. However, the iCub fingertip is composed of sensor elements that are placed on a curved surface. Therefore, it is able to measure the shearing force such as F_x and F_y.

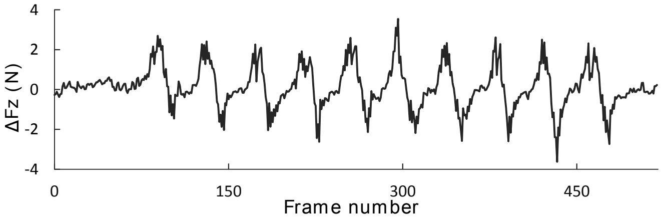
We trained each model by using a dataset of experimental conditions at X- and Y-axes. The performance of each condition is shown in Table I. The accuracy of our model is greater than that of the normal GP model under both directional force conditions.

TABLE I
PERFORMANCE OF ALL MODELS AND CONDITIONS

Condition	Model	F_x			F_y			F_z		
		RMSE	CC	AME (N)	RMSE	CC	AME (N)	RMSE	CC	AME (N)
One-dimensional force condition	Normal GP model	0.955	0.959	2.847	0.645	0.979	3.055	1.035	0.933	3.625
	Proposed model	**0.718**	**0.977**	**2.000**	**0.447**	**0.989**	**2.014**	**0.561**	**0.981**	**1.944**
	Markov order		$n = 6$			$n = 6$			$n = 3$	
Three-dimensional force condition	Normal GP model	0.792	0.979	2.115	0.549	0.980	1.654	1.493	0.879	3.941
	Proposed model	**0.714**	**0.983**	**1.932**	**0.518**	**0.981**	**1.503**	**1.006**	**0.948**	**3.210**
	Markov order		$n = 5$			$n = 11$			$n = 10$	
Cross learning condition	Normal GP model	1.664	0.870	4.218	**1.505**	**0.877**	2.813	1.963	0.734	4.943
	Proposed model	**1.472**	**0.901**	**3.210**	1.530	0.873	**2.740**	**1.739**	**0.798**	**4.785**
	Markov order		$n = 7$			$n = 1$			$n = 2$	

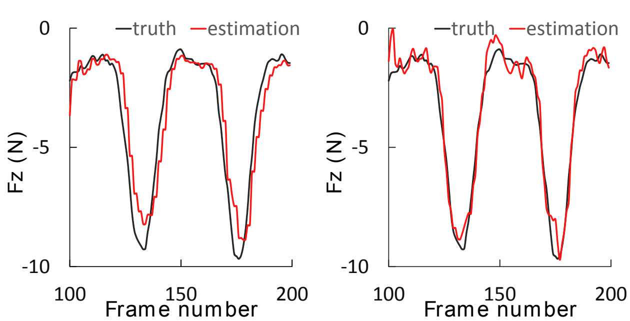


(a) Actual and estimated force



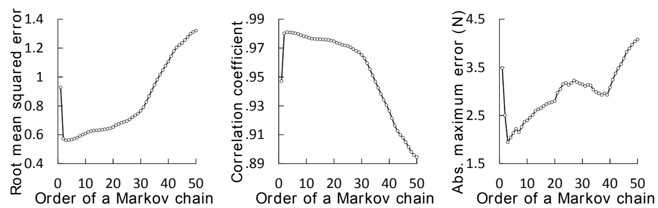
(b) Error between actual and estimated force

Fig. 5. Estimation result and error of normal GP model under one-directional force condition (Z-axis)



(a) Normal GP model (b) Proposed model

Fig. 6. Estimation results of each model



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

Fig. 7. Performance considering multistep time series data model.

C. Three-directional force condition

In the previous experiments, we focused on the uniaxial contact force applied to the fingertip. However, in actual tasks such as grasping an object the exerted force includes components of all directions. It is critical for the model to simultaneously estimate the three-axis directional contact force by using common taxel values. We tested our model when the tactile sensor grip was handled as in drawing a circle. As Fig. 4(b) illustrates, the applied force to the fingertip has different period and intensity values in all axial directions. Furthermore, taxel values did not synchronize unlike the one-directional condition shown in Fig. 4(a).

The actual and output values of our model for each axis are shown in Fig. 8. There is a small error between the actual and estimated values; however, the estimation is almost accurate in each direction.

Table I presents the accuracy of each model for each direction. The Markov order with which the proposed model exhibits the best accuracy is not the same because probably of the different period in the three axes. Additionally, the increase in the accuracy of our model compared to the normal GP is smaller than the under the one-dimensional force condition. This might be because the F/T sensor output has a large variance for the same taxel signal in this experimental datasets due to complex movements.

D. Cross learning condition

To allow robots to use our model to estimate task-relevant information from unknown sensor signals, the model must be trained by using datasets collected in advance. In previous experiments, we divided the data, which were collected in a single session for the learning and testing datasets. Here, we tested our model by using the other session data for learning. That is, the model was first trained with the dataset of the three-directional force condition and then tested with that of the one-dimensional force condition.

Fig. 9 shows the estimation results of our model. The error is much larger than in the previous experimental results. In particular, Fig. 9(c) shows a large estimation error in the Z-direction. This is attributable to the difference in the property for the learning and testing datasets. On one hand, the datasets for the X- and Y-directions include periodic patterns for both the learning and testing (see Figs. 4(b), 9(a) and 9(b)). On the other hand, the dataset for the Z-direction consists of a periodic force only in the testing but not in the learning.

All results of this experiment are summarized in Table I. Our model improves the force estimation accuracy under the X- and Z-directional conditions compared to the normal GP model as well as in the previous experiments. By contrast, the normal GP model shows the best performance for RMSE and CC under the Y-directional condition. We have to confirm the relation between the Markov order n and the change of performance to discuss this result.

V. Discussion

The performance of our model, which considers the Markov property of taxel values, is better than that of the normal GP model, which does not take the Markov property of taxel values into account for most experiments. It can be suggested that the n-order Markov chain of input allows the covariance function to represent n sets of the temporal change of the tactile signals than the normal GP model. However, the higher order Markov property does not always perform well. The experimental results show that there is an optimum Markov order n for each condition. In order to investigate what determines the optimum n, we additionally conducted an experiment, in which the frequency of a periodic force was modified. Fig. 10 shows the RMSE for three different force patterns: Type A is a periodic force with 0.46 Hz, B is with 1.18 Hz, and C with 1.71 Hz. The result demonstrates that the RMSE exhibits a minimum value with different n depending on the force pattern: n = 14 for Type A, n = 3 for Type B, and n = 3 for Type C. It suggests that the smaller the frequency of the input force is, the longer the required Markov property is.

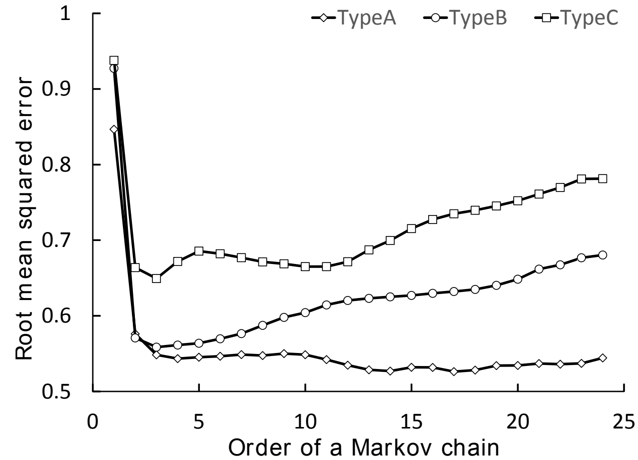


Fig. 10. Comparison of changes or RMSE values with respect to order of Markov property

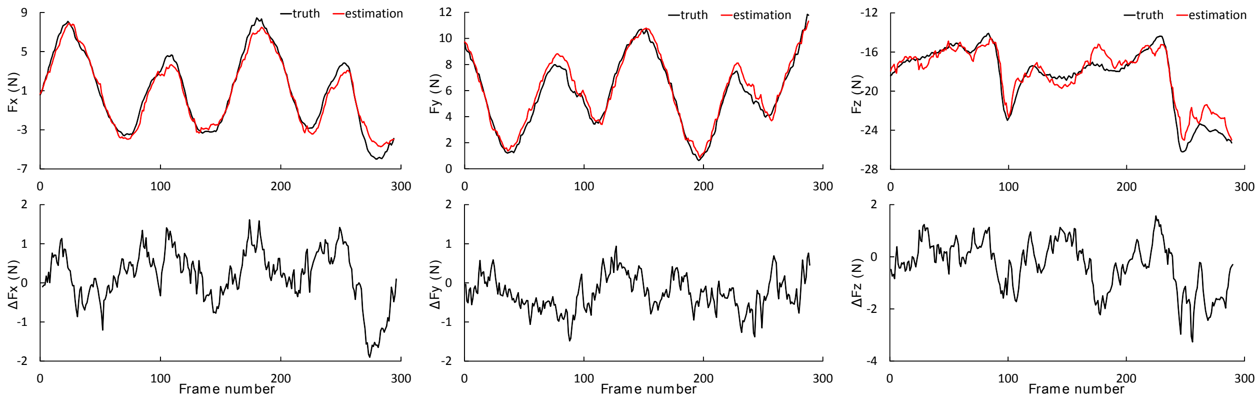
We then investigated what temporal dynamics of sensory signals was represented in the GP model. To infer the internal representation, we designed a comparative GP model, which employed not only the history of sensory signals but also the temporal difference of the signals $\Delta\boldsymbol{\theta}_t = \boldsymbol{\theta}_t - \boldsymbol{\theta}_{t-1}$ as the input. The input with an n-order Markov chain is thus given by

$$\boldsymbol{\Theta}_t^n = [\boldsymbol{\theta}_t,\ \Delta\boldsymbol{\theta}_t, \boldsymbol{\theta}_{t-1}, \cdots, \boldsymbol{\theta}_{t-n+1}, \Delta\boldsymbol{\theta}_{t-n+1}, \boldsymbol{\theta}_{t-n}]^T. \quad (7)$$

We expected that $\Delta\boldsymbol{\theta}_t$ might improve the accuracy of the force estimation compared to our model. Table II presents the accuracy of the two models under the one-directional force condition (Z-axis). There is only a slight difference between the models: the RMSE and the CC are better for the comparative model whereas the AME is better for the proposed model. One reason for this result is that a GP has the ability to internally represent the difference information of two consecutive sensory signals. Our model used a squared exponential covariance function, which calculated the distance between two input signals. In our experiment, the distance corresponds to a temporal change in sensory signals (i.e., $Delta\boldsymbol{\theta}_t$). This might be why our model could achieve as good performance as the comparative model. However, if we take the computational cost into account, our model outperforms the comparative model. It is known that $O(D^3)$ cost is required to compute the squared exponential covariance function. Taken together, our model is reasonable in terms of both the estimation accuracy and the computational cost. In the current experiment, the force estimation by our model took 62.9 sec while the comparative model took 158.9 sec. Adding the difference value significantly increases the amount of calculation.

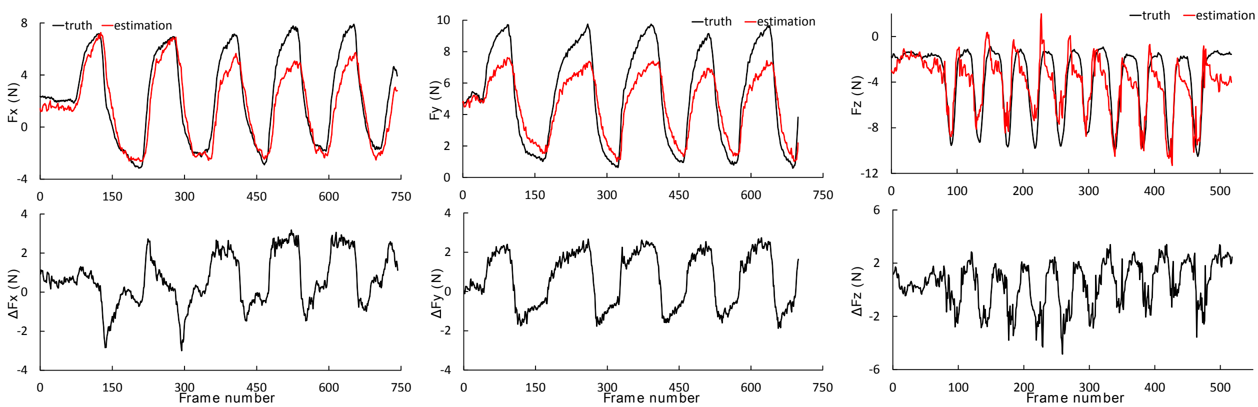
VI. Conclusion

We proposed a model to compensate for the hysteresis of flexible tactile sensors by using Gaussian process with sensory Markov property. Our model was able to estimate the force more accurately than the normal GP model. The results of our experiments suggest that our model provides an optimal compromise between computational efficiency and model robustness. This model can additionally be applied to various types of flexible tactile sensors, other than those embodied on the iCub robot.



(a) In the X-axis direction (b) In the Y-axis direction (c) In the Z-axis direction

Fig. 8. Estimation results of three-directional force condition



(a) In the X-axis direction (b) In the Y-axis direction (c) In the Z-axis direction

Fig. 9. Estimation results of cross learning condition

TABLE II

PERFORMANCE OF PROPOSED AND COMPARISON MODELS

Model	RMSE	CC	AME (N)
Proposed model ($n = 3$)	0.561	0.981	**1.944**
Comparison model ($n = 3$)	**0.559**	**0.981**	1.952

For future improvements, we wish to compare our model with Gaussian process dynamical models [9]. Furthermore, we plan to propose a model that represents hysteresis as a latent state. Latent states are able to model contexts of hysteresis considering the Markov chain of previous states without multistep time series inputs. If proposed model is able to represent hysteresis by using a latent state model, we can reduce the computational cost due to the low dimensional input.

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