Learning Sensor Feedback Models from Demonstrations via Phase-Modulated Neural Networks

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Abstract—In order to robustly execute a task under environmental uncertainty, a robot needs to be able to reactively adapt to changes arising in its environment. The environment changes are usually reflected in deviation in sensory traces from nominal. These deviations in sensory traces can be used to drive the plan adaptation, and for this purpose, a feedback model is required. The feedback model maps the deviations in sensory traces to the motion plan adaptation. In this paper, we develop a general data-driven framework for learning a feedback model from demonstrations, replacing hand-design processes. We utilize a variant of a radial basis function network structure—with movement phases as kernel centers— which can generally be applied to represent any feedback models for movement primitives. To demonstrate the effectiveness of our framework, we test it on the task of scraping on a tilt board. In this task, we are learning a reactive policy in the form of orientation adaptation, based on deviations of tactile sensor traces. As a proof of concept of our method, we provide evaluations on an anthropomorphic robot.

I. INTRODUCTION

The ability to handle unexpected sensor events is key to robustly executing manipulation tasks. Humans, for instance, can predict how it should feel to pick up an object and correct a grasp if the actual experience deviates from this prediction. Phrased differently, humans can map errors in sensory space to corrections in action space. In order to endow our robots with this ability, two problems need to be tackled: First, the system needs to be able to predict what sensor measurements to expect. Second, it needs to learn how to map deviations from those predictions to changes in actions.

Learning what sensor measurements to expect at any moment in time, anywhere in the state space, is a challenging problem with no known viable solution. However, associating sensor information with successful executions of motion primitives has been shown to be promising [1], [2]. When such sensor traces have been associated with a primitive, the robot can try to correct the primitive’s nominal actions when the actual sensor readings deviate from what is expected.

In order to do so, a feedback model that maps errors in sensor space to the corrective actions needs to be created. In initial implementations of such Associative Skill Memories (ASMs) [1], a linear feedback model was used. This feedback model essentially multiplies the sensor trace error with a manually defined feedback gain matrix to compute acceleration changes. While hand-designing feedback models can work well for specific problem settings, this approach is not expected to generalize beyond the scenario it was tuned for. Furthermore, when considering high-dimensional and multi-modal sensory input, such as haptic feedback, manually designing a feedback policy quickly becomes infeasible. For example, in this work we consider tactile-driven manipulation with tools. Manipulation tasks involving tools is challenging due to inaccurate tool kinematics models and non-rigid contacts between tactile sensors and the tool.

Thus, the larger goal of this research is to equip Associative Skill Memories with a general feedback modulation learning framework, as depicted in the block diagram in Figure 1. Data driven approaches to learning such feedback models have been proposed [3], [4], [5] in the past. Here, we present a learning framework that improves such data-driven approaches in generality and experimental validation. First we contribute towards the goal of generality by introducing phase-modulated neural networks (PMNNs). Our previous work [4] shows that feedforward neural networks (FFNNs) have greater flexibility to learn feedback policies from human demonstrations than a hand-designed model. In this paper, we show that FFNNs cannot capture phase-dependent sensory features or corrective actions, which contribute to superior learning performance in PMNNs. Second, we present detailed insight on our experimental pipeline for learning feedback models on a tactile-driven manipulation task. Furthermore, we extensively evaluate our learning approach on this manipulation task across multiple task variations and successfully deploy our approach on a real robot.

This paper is organized as follows. Section II provides some background on the motion primitive representation and related work. In Section III we provide the details on our approach for learning feedback policies from demonstrations. We then present insights into our experimental system setup in Section IV. Finally, we evaluate our approach in Section V and conclude with Section VI.
II. BACKGROUND AND RELATED WORK

Here we review background material on our chosen motion primitive representation and related work in learning feedback model approaches, including tactile feedback learning.

A. Quaternion DMPs

The Associative Skill Memories framework, as proposed in [2], uses Dynamic Movement Primitives (DMPs) [6] as a motion primitive representation. DMPs are a goal-directed behavior described as a set of differential equations with well-defined attractor dynamics. It is this formulation of DMPs as a set of differential equations that allows for online modulation from various inputs, such as sensor traces, in a manner that is conceptually straightforward and simple to implement, relative to other movement representations. In our work, DMPs need to represent both position and orientation of the end-effector. We refer the reader to [4] for our position DMP formulation. Here we focus on reviewing Quaternion DMPs, which we use for orientation representation in our learning-from-demonstration experiments.

Quaternion DMPs were first introduced in [1], and then improved in [7], [8] to fully take into account the geometry of $SO(3)$. Like position DMPs, they consist of a transformation system and a canonical system, governing the evolution of the orientation state and movement phase, respectively.

The transformation system of a quaternion DMP is$$\tau^2 \dot{\omega} = \alpha_\omega (\beta_\omega 2 \log (Q_g \circ Q^*) - \tau \omega) + f + C \quad (1)$$
where $Q$ is a unit quaternion representing the orientation, $Q_g$ is the goal orientation and $\omega, \dot{\omega}$ are the 3D angular velocity and angular acceleration, respectively. $f$ and $C$ are the 3D orientation forcing term and feedback/coupling term, respectively. The forcing term encodes the nominal behavior, while the coupling term encodes behavior adaptation which is commonly based on sensory feedback. In this paper, we focus on learning a feedback model that generates the coupling term, which is described in Sub-Section III-B.

During unrolling, we integrate $Q$ forward in time to generate the kinematic orientation trajectory as follows:

$$Q_{t+1} = \exp \left( \frac{\omega \Delta t}{2} \right) \circ Q_t \quad (2)$$

where $\Delta t$ is the integration step size. We set the constants $\alpha_\omega = 25$ and $\beta_\omega = \alpha_\omega / 4$ to get a critically-damped system response when both forcing term and coupling term are zero. $\tau$ is set proportional to the motion duration.

The movement phase variable $p$ and phase velocity $u$ are governed by the second-order canonical system as follows:

$$\tau \ddot{u} = \alpha_u (\beta_u (0 - p) - u) \quad (3)$$

$$\tau \dot{p} = u \quad (4)$$

We set the constants $\alpha_u = 25$ and $\beta_u = \alpha_u / 4$ to get a critically-damped system response. The phase variable $p$ is initialized with 1 and will converge to 0. On the other hand, the phase velocity $u$ has initial value 0 and will converge to 0. Note, for a multi degree-of-freedom (DOF) system, each DOF has its own transformation system, but all DOFs share the same canonical system [6].

The forcing term $f$ governs the shape of the primitive and is represented as a weighted combination of $N$ basis functions $\psi_i$ with width parameter $h_i$ and center at $c_i$, as follows:

$$f(p, u; w) = \sum_{i=1}^{N} \psi_i(p) w_i \quad (5)$$

where

$$\psi_i(p) = \exp \left( -h_i (p - c_i)^2 \right) \quad (6)$$

Note, because the forcing term $f$ is modulated by the phase velocity $u$, it is initially 0 and will converge back to 0. The $N$ basis function weights $w_i$ in equation [5] are learned from human demonstrations of baseline/nominal behaviors, by setting the target regression variable:

$$f_{target} = -\alpha_\omega (\beta_\omega 2 \log (Q_{bd} \circ Q^*) - \tau \omega_{bd}) + \tau^2 \omega_{bd} \quad (7)$$

where $\{Q_{bd}, \omega_{bd}, \tau_{bd}\}$ is the set of baseline/nominal orientation behavior demonstrations. Then we can perform linear regression to identify parameters $w$, as shown in [6]. Finally, we include a goal evolution system as follows:

$$\tau \omega_g = \alpha_\omega 2 \log (Q_G \circ Q^*) \quad (8)$$

where $Q_g$ and $Q_G$ are the evolving and steady-state goal orientation, respectively. We set the constant $\alpha_\omega g = \alpha_\omega / 2$. The goal evolution system has two important roles related to safety during the algorithm deployment on robot hardware. The first role, as mentioned in [6], is to avoid discontinuous jumps in accelerations when the goal is suddenly moved. The second role, as mentioned in [9], is to ensure continuity between the state at the end of one primitive and the state at the start of the next one when executing a sequence of primitives. Here we ensure continuity between primitives for both position and orientation DMPs by adopting [9].

B. Related Work on Learning Feedback Models

The ability to adapt movement plans to changes in the environment requires feedback models. In previous work, researchers have hand-designed feedback models for specific purposes. For instance, [10], [11] devised feedback models for obstacle avoidance. [12] designed a human-inspired feedback model for performing robotic surface-to-surface contact alignment based on force-torque sensing. Force-torque sensing is also used in [1], where a hand-designed feedback gain matrix maps deviations from the expected force-torque measurements to the grasp plan adaptation. Previous work on robotic tactile-driven manipulation with tools has tried to learn feedback models to correct the position plans for handling uncertainty between tools and the environment, via reinforcement learning [5] or motor
bubbling [13]. In our work, we propose to bootstrap the learning of feedback model from human demonstrations. Abu-Dakka et al. [14] iteratively learned feedforward terms to improve a force-torque-guided task execution over trials, while fixing feedback models as constant gain matrices. Learning by demonstrations is also employed in [15] to train separate feedback models for different environmental settings. Gaussian Process regression is used to interpolate between these learned models to predict the required feedback model in a new environmental setting. Our work, directly uses a single model to handle multiple settings.

In [16], a partially-observable Markov decision process (POMDP), which is parameterized by deep recurrent neural networks, is used to represent a haptic feedback model. In general, POMDPs models are not explicitly provided with the information of the movement phase which is essential for making prediction on the next corrective action. Our proposed approach, can learn phase-dependent corrective actions.

III. LEARNING FEEDBACK MODELS VIA PHASE-MODULATED NEURAL NETWORKS

In this section we describe our framework to learn general feedback models from human demonstrations. The process pipeline of learning feedback models is visualized in Figure 2. For a specific instance of this pipeline in our experiment, please refer to Sub-Section IV-C.

Our framework comprises 3 core components: learning expected sensor traces; learning the feedback model to map sensor trace errors to corrections; and finally we introduce PMNNs, a feedback model representation that is flexible enough to capture phase-dependent features and can learn across multiple task settings.

A. Learning Expected Sensor Traces

The core idea of ASMs [1], [2] rests on the insight that similar task executions should yield similar sensory events. Thus, an ASM of a task includes both a movement primitive as well as the expected sensor traces associated with this primitive’s execution in a known environment. We term this execution as the primitive’s nominal behavior, the known environment as the nominal setting, and the expected sensor traces as $S_{\text{expected}}$. To learn the $S_{\text{expected}}$ model, we execute the nominal behavior and collect the experienced sensor measurements. Since these measurements are trajectories by nature, we can encode them using DMPs to become $S_{\text{expected}}$. This has the advantage that $S_{\text{expected}}$ is phase-aligned with the position and orientation primitives’ execution.

B. Learning Feedback Models from Demonstration

When a movement primitive is executed under environment variations and/or uncertainties, the perceived sensor traces, denoted as actual sensor traces $S_{\text{actual}}$, tend to deviate from $S_{\text{expected}}$. The disparity $S_{\text{actual}} - S_{\text{expected}} = \Delta S$ can be used to drive corrections for adapting to the environmental changes causing the deviated sensor traces. Previous work [5], [17] uses reinforcement learning to learn these corrective behaviors, also in form of feedback models. However, learning a good feedback policy via trial-and-error from scratch is a very slow process. Therefore, we would like to bootstrap this process by learning feedback models from demonstrations. In our supervised learning framework, the disparity $\Delta S$ is used as the input to a feedback model, mapping them to the motion plan adaptation or the coupling terms $C$ (from Equation 1), as follows:

$$C = h(S_{\text{actual}} - S_{\text{expected}}) = h(\Delta S) \tag{8}$$

We pose this as a regression problem, and similar to learning the nominal behavior, we can also learn this feedback model $h$ from human demonstrations of corrected behavior, i.e. the demonstrated behavior when the feedback is active. To perform the learning-from-demonstration, we need to extract the target output variable, i.e. the target coupling term $C_{\text{target}}$, from demonstrations data, which can be done as follows:

$$C_{\text{target}} = -\alpha_{\omega}(\beta_{\omega}2\log(Q_{\omega,cd} \circ Q_{\omega,cd}) - \tau_{\omega,cd}) + \tau_{\omega,cd} - f \tag{9}$$

where $\{Q_{\omega,cd}, \omega_{cd}, \omega_{cd}\}$ is the set of corrected orientation behavior demonstration. Next, we describe our proposed general learning representation for the feedback model.

C. Phase-Modulated Neural Network Structure

We use neural network (NN) structures for representing feedback term models due to its ability to learn task-relevant feature representations of high-dimensional inputs from data. In this paper, we improve upon our previous work [4], in which we used a regular fully-connected feedforward neural network (FFNN) to represent the feedback model. Our new neural network design is a variant of the radial basis function network (RBFN) [18], which we call the phase-modulated neural networks (PMNNs) as depicted in Figure 3. PMNN has an embedded structure that allows encoding of the feedback model’s dependency on movement phase, which FFNN structure lacks of. The PMNN consists of:

- input layer
  - The input is $\Delta S = S_{\text{actual}} - S_{\text{expected}}$.
- regular hidden layers
  - The regular hidden layers perform non-linear feature transformations on the high-dimensional inputs. If there
are $L$ layers, the output of $l$-th layer is:

$$h_l = \begin{cases} a_l (W_{h_l} \Delta S \Delta S + b_{h_l}) & \text{for } l = 1 \\ a_l (W_{h_l} h_{l-1} + b_{h_l}) & \text{for } l = 2, \ldots, L \end{cases}$$

(10)

$a_l$ is the activation function of the $l$-th hidden layer, which can be tanh, RELU, or others. $W_{h_l} \Delta S$ is the weight matrix between the input layer and the first hidden layer. $W_{h_l} h_{l-1}$ is the weight matrix between the $(l-1)$-th hidden layer and the $l$-th hidden layer. $b_{h_l}$ is the bias vector at the $l$-th hidden layer.

* **final hidden layer with phase kernel modulation**

This special and final hidden layer takes care of the dependency of the model on the movement phase. The output of this layer is $m$, which is defined as:

$$m = G \odot (W_{m,h_l} h_L + b_m)$$

(11)

where $\odot$ denote element-wise product of vectors. $G = \begin{bmatrix} G_1 & G_2 & \ldots & G_N \end{bmatrix}^T$ is the phase kernel modulation vector, and each component $G_i$ is defined as:

$$G_i (p, u) = \sum_{i=1}^{N} \psi_i (p) u$$

(12)

with phase variable $p$ and phase velocity $u$, which comes from the second-order canonical system defined in Equation 3 and 4. $\psi_i (p)$ is the radial basis function (RBF) as defined in Equation 6. We use $N = 25$ phase RBF kernels both in the PMNNs as well as in the DMPs representation. The phase kernel centers have equal spacing in time, and we place these centers in the same way in the DMPs as well as in the PMNNs.

* **output layer**

The output of this layer is the one-dimensional coupling term $C$, which is defined as:

$$C = w^{T}_{C,m} m$$

(13)

$w_{C,m}$ is the weight vector. Please note that there is no bias introduced in the output layer, and hence if $m = 0$ which occurs when the phase velocity $u$ is zero, then the coupling term $C$ is also zero. This ensures that the coupling term is initially zero when a primitive is started. The coupling term will also converge to zero because the phase velocity $u$ is converging to zero.

For a $M$-dimensional coupling term, we use $M$ separate PMNNs with the same input vector $\Delta S$ and the output of each PMNN corresponds to each dimension of the coupling term. This separation of neural network for each coupling term dimension allows each network to be optimized independently from each other.

We implemented PMNN in TensorFlow [19]. To avoid overfitting, we used dropout technique as introduced in [20].

### IV. LEARNING TACTILE FEEDBACK MODELS: SYSTEM OVERVIEW AND EXPERIMENTAL SETUP

This work is focused on learning to correct tactile-driven manipulation with tools. Our experimental scenario involves a demonstrator teaching our robot to perform a scraping task, utilizing a hand-held tool to scrape paint off the surface of a dry-erase board (see Figure 4). The system is taught this skill at a nominal tilt angle, and needs to correct when the board is tilted away from that default angle. Neither vision nor motion capture system is used, thus we only rely on tactile sensing to inform the correction. One of the main challenges is that the tactile sensors interact indirectly with the board, i.e. through the tool adapter and the scraping tool via a non-rigid contact, and the robot does not explicitly encode the tool kinematics model. This makes hand-designing a feedback gain matrix difficult. Next, we explain the experimental setup and some lessons learned from the experiments.

#### A. Hardware

The demonstrations were performed on the right arm and the right hand of our bi-manual robot. The arm is a 7-degrees-of-freedom (DoF) Barrett WAM arm which is also equipped with a 6D force-torque (FT) sensor at the wrist. The hand is a Barrett hand whose left and right fingers are equipped with biomimetic tactile sensors (BioTacs) [21]. The two BioTac-equipped fingers were setup to perform a pinch grasp on a tool adapter. The tool adapter is a 3D-printed object designed to hold a scraping tool with an 11mm-wide tool-tip.

The dry-erase board was mounted on a tilt stage whose orientation can be adjusted to create static tilts of ±20° in roll and/or pitch with respect to the robot global coordinates as shown in Figure 4. Two digital protractors with 0.1° resolution (Wixey WR 300 Digital Angle Gauge) were used to measure the tilt angles during the experiment.

#### B. Robot’s Environmental Settings and Human Demonstrations with Sensory Traces Association

For our experiment, we considered 5 different settings, and each setting is associated with a specific roll angle of the tilt stage, specifically at 0°, 2.5°, 5°, 7.5°, and 10°. At
each setting, we fixed the pitch angle at $0^\circ$ and maintain the scraping path to be roughly at the same height. Hence, we assume that among the 6D pose action (x-y-z-pitch-roll-yaw), the necessary correction is only in the roll-orientation. For each setting, we collected 15 demonstrations. The setting with roll angle at $0^\circ$ is selected as the nominal setting, while the remaining settings become the corrected ones. For the demonstrated actions, we recorded the 6D pose trajectory of the right hand end-effector at 300 Hz rate, and along with these demonstrations, we also recorded the multi-dimensional sensory traces associated with this action. The sensory traces are the 38-dimensional tactile signals from the left and right BioTacs’ electrodes, sampled at 100 Hz.

C. Learning Pipeline Details and Lessons Learned

DMPs provide kinematic plans to be tracked with a position control scheme. However, for tactile-driven contact manipulation tasks such as the scraping task in this paper, using position control alone is not sufficient. This is because tactile sensors require some degree of force control upon contact, in order to attain consistent tactile signals on repetitions of the same task during the demonstrations as well as during unrolling of the learned feedback models.

Moreover, while it is possible to perform corrected demonstrations solely by humans, the sensor traces obtained might be significantly different from the traces obtained during the robot’s execution of the motion plan. This is problematic, because during learning and during prediction phases of the feedback terms, the input to the feedback models are different. Hence, instead we try to let the robot execute the nominal plans, and only provide correction by manually adjusting the robot’s execution at different settings as necessary. Therefore, we use the force-torque (FT) sensor in the robot’s right wrist for FT control, with two purposes: (1) to maintain tool-tip contact with the board, such that consistent tactile signals are obtained, and (2) to provide compliance, allowing the human demonstrator to perform corrective action demonstration as the robot executes the nominal behavior. For simplicity, we set the force control set points in our experiment to be constant. We need to set the force control set point carefully: if the downward force (in the z-axis direction) for contact maintenance is too big, the friction will block the robot from being able to execute the corrections as commanded by the feedback model. We found that 1 Newton is a reasonable value for the downward force control set point. Regarding the learning process pipeline as depicted in Figure 2, here we provide the details in our experiment:

1) Nominal primitives acquisition: While the robot is operating in the gravity-compensation mode and the tilt stage is at $0^\circ$ roll angle, the human demonstrator guided the robot’s hand to kinesthetically perform a scraping task, which can be divided into three stages, each of which corresponds to a movement primitive:

(a) primitive 1: starting from its home position above the board, go down (in the z-axis direction) until the scraping tool made contact with the scraping board’s surface (no orientation correction at this stage),

(b) primitive 2: correct the tool-tip orientation such that it made a full flat tool-tip contact with the surface,

(c) primitive 3: go forward in the y-axis direction while scraping paint off the surface, applying orientation correction as necessary to maintain full flat tool-tip contact with the surface.

We used Zero Velocity Crossing (ZVC) method [22] and local minima search refinement on the velocity signal in the z and y axes, to find segmentation points of primitives 1 and 3, respectively. The remaining part – between the end of primitives 1 and the beginning of primitive 3 – becomes the primitive 2. We encode each of these primitives with position and orientation DMPs.

## Table I: Force-torque control schedule for steps 2-4.

| Step   | Force-Torque Control Activation Schedule |
|--------|------------------------------------------|
| 2      | Primitive 1 : $z$ 1 N, roll 0 Nm         |
| 3      | Primitive 2 : $z$ 1 N                    |
| 4      | Primitive 3 : $z$ 1 N, roll 0 Nm         |

For the following pipeline steps (2, 3, and 4), in reference to Table I, which indicates what force-torque control mode is being active at each primitive of these steps. "$z$ 1 N" refers to the 1 Newton downward z-axis proportional-integral (PI) force control, for making sure that consistent tactile signals are obtained at repetitions of the task; this is important for learning and making correction predictions properly. "roll 0 Nm" refers to the roll-orientation PI torque control at 0 Newton-meter, for allowing corrective action demonstration.

2) Expected sensor traces acquisition: Still with the tilt stage at $0^\circ$ roll angle, We unroll the nominal primitives 15 times and record the tactile sensor traces. We encode each dimension of the 38-dimensional sensor traces as $S_{expected}$, using the standard DMP formulation.

3) Feedback model learning: Now we vary the tilt stage’s roll-angle to $2.5^\circ$, $5^\circ$, $7.5^\circ$, and $10^\circ$, one-at-a-time, to encode different environmental settings. At each setting, we let the robot unroll the nominal behavior. Beside the downward force control for contact maintenance, now we also activate the roll-orientation PI torque control at 0 Newton-meter throughout primitives 2 and 3. This allows the human demonstrator to perform the roll-orientation correction demonstration, to maintain full flat tool-tip contact relative to the now-tilted scraping board. We recorded 15 demonstrations for each setting, from which we extracted the supervised dataset for the feedback model, i.e. the pair of the sensory trace deviation $\Delta S$ and the target coupling term $C_{target}$ as formulated in Equation 9. Afterwards, we learn the feedback models from this dataset with PMNN.

4) DMP and Feedback Model Unrolling/Testing: We test the feedback models on different settings on the robot.

V. Experiments

To evaluate the performance of the learned feedback model, we first evaluate the regression and generalization ability
of the PMNNs trained offline using the demonstration data. Second, we show the superiority of the PMNNs as compared to the FFNNs, for feedback models learning representation. Third, we investigate the importance of learning both the feature representation and the phase dependencies together within the framework of learning feedback models. Fourth, we show the significance of the phase modulation in the feedback model learning. Finally, we evaluate the learned feedback model’s performance in making predictions of action corrections online on a real robot.

For the purpose of our evaluations, we evaluate feedback models only on primitives 2 and 3, for roll-orientation correction. In primitive 1, we deem that there is no action correction, because the height of the dry-erase board surface is maintained constant across all settings.

We use normalized mean squared error (NMSE), i.e. the mean squared prediction error divided by the target coupling term’s variance, as our metric. To evaluate the learning performance of each model in our experiments, we perform a leave-one-demonstration-out test. In this test, we perform \( K \) iterations of training and testing, where \( K = 15 \) is the number of demonstrations per setting. At the \( k \)-th iteration:

- The data points of the \( k \)-th demonstration of all settings are left-out as unseen data for generalization testing, while the remaining \( K - 1 \) demonstrations’ data points are shuffled randomly and split 85%, 7.5%, and 7.5% for training, validation, and testing, respectively.
- We record the training-validation-testing-generalization NMSE pairs corresponding to the lowest generalization NMSE across learning steps.

We report the mean and standard deviation of training-validation-testing-generalization NMSEs across \( K \) iterations. On all models we evaluated, we use \( \tanh \) as the activation function of the hidden layer nodes. We use the Root Mean Square Propagation (RMSProp) [23] as the gradient descent optimization algorithm and set the dropout [20] rate to 0.5.

### A. Fitting and Generalization Evaluation of PMNNs

The results for primitive 2 and 3, using PMNN structure with one regular hidden layer of 100 nodes, are shown in Table II. The PMNNs achieve good training, validation, testing results, and a reasonable generalization results for both primitives.

|                       | Training | Validation | Testing | Generalization |
|-----------------------|----------|------------|---------|----------------|
| **Prim. 2**           | 0.15±0.05| 0.15±0.05  | 0.16±0.06| 0.36±0.19       |
| **Prim. 3**           | 0.22±0.05| 0.22±0.05  | 0.22±0.05| 0.32±0.13       |

**TABLE II: NMSE of the roll-orientation coupling term learning with leave-one-demonstration-out test, for each primitive.**

### B. Performance Comparison between FFNN and PMNN

We compare the performance between FFNN and PMNN. For PMNN, we test two structures: one with no regular hidden layer being used, and the other with one regular hidden layer comprised of 100 nodes. For FFNN, we use two hidden layers with 100 and 25 nodes each, which is equivalent to PMNN with one regular hidden layer of 100 nodes but de-activating the phase modulation. The results can be seen in Figure 5 (Left). It can be seen that PMNN with one regular hidden layer of 100 nodes demonstrated the best performance compared to the other structures. PMNN with one regular hidden layer is better than the one without regular hidden layer, most likely because of the richer learned feature representation, without getting overfitted to the data.

### C. Comparison between Separated versus Embedded Feature Representation and Phase-Dependent Learning

We also compare the effect of separating versus embedding the feature representation learning with overall parameter optimization under phase modulation. Chebotar et al. [5] used PCA for feature representation learning, which was separated from the phase-dependent parameter optimization using reinforcement learning. On the other hand, PMNN embeds feature learning together with the overall parameter optimization under phase modulation, into an integrated training process.

In this experiment, we used PCA which retained 99% of the overall data variance, reducing the data dimensionality to 7 and 6 (from originally 38) for primitive 2 and 3, respectively. In addition, we also implemented an autoencoder, a non-linear dimensionality reduction method, as a substitute for PCA in representation learning. For PMNNs, we used two kinds of networks: one with one regular hidden layer of 6 nodes (such that it is become comparable with the PCA counterpart), and the other with one regular hidden layer of 100 nodes.

Figure 5 (Middle) illustrates the superior performance of PMNNs, due to the feature learning performed together with the overall phase-dependent parameters optimization. Of the two PMNNs, the one with more nodes in the regular hidden layer performs better, because it can more accurately represent the mapping, while not over-fitting to the data. Based on these evaluations, we decided to use PMNNs with one regular hidden layer of 100 nodes and 25 phase-modulated nodes in the final hidden layer for subsequent experiments.

### D. Evaluation of Movement Phase Dependency

In this part, we visualize the trained weight matrix mapping the output of 100 nodes in the regular hidden layer to the 25 nodes in the final hidden layer being modulated by the phase RBFs. This weight matrix is of dimension 25 × 100, and each row shows how each of the 100 nodes’ output (or “features”) in the regular hidden layer being weighted to become the input to a particular phase RBF-modulated node. In Figure 5 (Right), we only display the top 10 dominant regular hidden layer node output for each phase RBF-modulated node (in yellow color), and the rest (colored in blue) are the less dominant ones. We see that between different phase RBF-modulated nodes, the priority ranking...
E. Unrolling the Learned Feedback Model on the Robot

In Figure 6, we show the snapshots of our robot unrolling the primitives together with the online correction prediction computed by the trained feedback models on a setting with $10^5$ roll-angle of the tilt stage. We see that if we turn off the coupling term (nominal behavior execution, first row of the figure set), there was no correction applied to the tool-tip orientation and the scraping result was worse than when the online-computed corrections were applied (second row of the figure set). We also show the coupling term that was computed online by the trained feedback model, alongside the corresponding sensor trace deviation during the robot execution in Figure 7, plotted in red. When applying the coupling term computed by the trained feedback model, the sensor trace deviation is close to those from demonstrations, as shown in the bottom row of Figure 7. Video can be seen in https://youtu.be/7Dx5Imy1Kcw. In the video, we show the robot’s scraping task execution at two settings, at $5^5$ and $10^5$ roll-angle of the tilt stage, while applying the corrections predicted online by the trained feedback model.

VI. Conclusion

We introduced a general framework for learning-from-demonstration of feedback models, mapping sensory trace deviation to the action correction. In particular we use the phase-modulated neural network (PMNNs), which we have shown to be able to represent feedback models in general for Dynamic Movement Primitives. And finally, we demonstrate the superior performance of our PMNN-based framework compared to feedback models in previous works, as well as its capability in performing online correction on a real robot.

APPENDIX

Unit quaternion is a hypercomplex number which can be written as a vector $Q = [r \ q^T]^T$, such that $|Q| = 1$ with $r$ and $q = [q_1 \ q_2 \ q_3]^T$ are the real scalar and the vector of three imaginary components of the quaternions, respectively. For computation with orientation trajectory, several operations needs to be defined as follows:

- quaternion composition operation:

$$Q_A \circ Q_B = \begin{bmatrix} r_A & -q_A1 & -q_A2 & -q_A3 \\ q_A1 & r_A & -q_A3 & q_A2 \\ q_A2 & q_A3 & r_A & -q_A1 \\ q_A3 & -q_A2 & q_A1 & r_A \end{bmatrix} \begin{bmatrix} r_B \\ q_B1 \\ q_B2 \\ q_B3 \end{bmatrix}$$

(14)

- quaternion conjugation operation:

$$Q^* = \begin{bmatrix} r \\ -q \end{bmatrix}$$

(15)

- logarithm mapping ($\log(\cdot)$ operation), which maps an element of $SO(3)$ to $so(3)$, is defined as:

$$\log(Q) = \log\left(\begin{bmatrix} r \\ q \end{bmatrix}\right) = \frac{\arccos(r)}{\sin(\arccos(r))}q$$

(16)
Fig. 7: The roll-orientation coupling term (top) versus the sensor traces deviation of the right BioTac finger’s electrode #6 (bottom) of primitive 2, during the scraping task on environmental setting with the roll-angle of the tilt stage vary from 2.5° (left-most) to 10° (right-most), with +2.5° increments each step. Comparison is between human demonstrations (blue), during unrolling on robot while applying the coupling term computed online by the trained feedback model (red), during unrolling the nominal behavior on the robot (green), the human demonstration’s mean trajectory (dashed black), and the range of the human demonstration within 1 standard deviation from the mean trajectory (solid black). On the top plots, we see that the trained feedback model can differentiate between different tilt stage’s roll-orientations and apply the approximately correct amount of correction/coupling term.

\[
\exp(\omega) = \begin{bmatrix} \cos(\|\omega\|) \\ \sin(\|\omega\|) / \|\omega\| \end{bmatrix}
\]  

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