Undefined-behavior guarantee by switching to model-based controller according to the embedded dynamics in Recurrent Neural Network

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Abstract—For robotic applications, the robots task performance and operation must be guaranteed. In usual robot control, achieving robustness to various tasks as well as controller stability is difficult. This is similar to the problem of the generalization performance of machine learning. Although deep learning is a promising approach to complex tasks that are difficult to achieve using a conventional model-based control method, guaranteeing the output result of the model is still difficult. In this study, we propose an approach to compensate for the undefined behavior in the learning-based control method by using a model-based controller. Our method switches between two controllers according to the internal representation of a recurrent neural network that established the dynamics of task behaviors. We applied our method to a real robot and performed an error-recovery operation. To evaluate our model, we designed a pick–place task, and induced external disturbances. We present results in simulation and on a real robot.

I. INTRODUCTION

Although deep neural network (DNN) has shown high generalization ability in various fields, the model output result can still not be guaranteed. In the field of robotics, there exist methods to generate a motion trajectory by using end-to-end sensor information \cite{15,16,35}. However, a learning-based control method experiences difficulty in predicting undefined behaviors that are not included in the training data. Even in the case of self-supervised learning \cite{11,15,25} and generative adversarial imitation learning \cite{10,24}, the ability of the trained model depends on the design of rewards or training data. This is a major issue of the current DNN method that depends on the training assumptions. Thus, a method that balances the generalization ability and output-result guarantee must be established.

An example of that indicates a requirement of guarantee in output results in robot work is the recovery of errors from a failed operation. To operate the robot without damage to the working environment, it is necessary to guarantee that an unexpected behavior will not occur. There are many types of disturbances in the real environment, and preparing training data for behaviors in advance is difficult. Although there exist methods to detect unknown generation results \cite{6,18}, it is necessary to design a threshold or model for handling high-dimensional sensor information. Therefore, the controller must contain models for learning the task experience and guaranteeing the output result.

In this study, we propose a method for guaranteeing the unexpected output of the learning-based method. In addition, our model controls undefined behavior by using a model-based method. Unlike the learning-based method, the model-based method controls the target by satisfying a particular constraint, according to which the optimality and convergence of the generated operation are guaranteed.

To realize proper switching between two controllers, it is important to know how to determine undefined behavior during task operation. Our model determines whether the current trajectory is included in the motion trajectories trained from the past motion trajectory that was predicted by the task-trained recurrent neural network (RNN). By reusing the internal representation of the RNN to predict past motion trajectories, the learning-based method is able to determine undefined behaviors while retaining its task-performance ability. In addition, for a more advanced switching of the controller dynamics, we adopted the motion-switching method, which designs dynamical systems of RNN \cite{13,28}. By using the proposed switching strategies, the robot is controlled by deep learning during task operation, and when the robot assumes an unexpected posture, the model-based controller performs an error-recovery operation.

The primary contributions of this study are as follows.

1) A model is proposed to guarantee undefined behaviors by combining learning- and model-based controllers.
2) This study evaluated the error-recovery and generalization abilities in the case of disturbances in task operations.

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II. RELATED WORKS

A. Combining learning- and model-based methods

Not limited to the robot control field, studies have proposed a concept of combining a high-efficiency and low-reliability model with a low-efficiency and safe model. In the field of software engineering, Ortega et al. [23] and Simard et al. [27] analyzed a mixed system design of conventional deductive and inductive systems based on machine learning. The mixed system monitors the input and output of a machine learning system and incorporates exception processing, recovery processing, and multiplexing. In the present study, we applied this concept to robot control. Our method evaluates the trained task-behavior dynamics and incorporates error recovery according to the model-based method. However, it is challenging to incorporate such processing into robots owing to complex real-world dynamics, including sensor information.

In reinforcement-learning approaches, methods often adopt a model-based controller in the supporting role in the training. However, several extant studies have used model-based controllers to obtain prior knowledge during training without focusing on guaranteeing behaviors [12][21]. Moreover, target tasks are limited to motions designed by the experimenter. Research has been conducted on automatic driving that corrects the predicted trajectory of learning-based controller to the standard target trajectory [22]. Although Onishi et al. [22] used a model-based controller for augmenting training data during learning, they did not discuss its performance in a real environment. In the field of control engineering, methods for combining machine learning and conventional control techniques have been studied. Duan et al. [5] proposed a method using neural networks to learn the appropriate parameters of a controller. Sasaki et al. [26] and Vamvoudakis et al. [32] proposed a method to learn the feedback coefficient matrix of the linear quadratic regulator through reinforcement learning. The above literature review shows that there is little research on guaranteeing the undefined behavior of learning-based control. This could be because of the difficulty of switching controllers in the case of multiple high-dimensional sensor information.

B. Error recovery in robot tasks

Error recovery in robot operation has been studied extensively from the manufacturing perspective. Previous studies [17][19] tried to classify and layer errors; however, this is difficult to realize in practice. Although some studies have focused on the derivation of the recovery process by using a Petri-net [4][20], the switching strategy with high-dimensional sensor information has not been discussed. In control engineering, there exists a method that uses a control barrier function to perform control that satisfies the required conditions [1][3]. These are useful for expressing collision-avoidance constraints; however, they can impair task performance. Kase et al. [13] realized error recovery by combining trained subtasks without manually designing the error-recovery operation. A switching strategy based on embedding dynamics is promising from the viewpoint of design costs, such as switching conditions. However, since the robot behaviors depend on the training data, there is no guarantee that stable error-recovery operation is possible.

In this study, we extend the works in [13] and [28] and propose a switching strategy of learning- and model-based controllers. First, to embed the dynamics, which compensate for the undefined behaviors, into the RNN, we designed an RNN that trains task behavior according to a model-based controller. The embedded dynamics accurately represent the transition of the training motion trajectory. By using new neurons to predict the past motion trajectory from the internal representation of the RNN, the model is able to judge the undefined behavior. This research differs from module switching between NNs [7][31][33] in that it uses the dynamics of an optimal controller while generating task operation online. As per the knowledge of the authors, this is the first study to discuss how to guarantee the undefined behavior of the learning-based method from the viewpoint of appropriate switching to model-based control.

III. METHOD

The goal of this study is to achieve both the task performance of deep learning and the guarantee of undefined behaviors by model-based control. The proposed method consists of two DNNs (image feature extractor and RNN) and one optimal controller. The RNN learns sensory-motor information and the dynamics of the model-based control that controls the convergence to a specific posture (Section III.A). The internal state of the RNN functions as an input for training new neurons to predict past motion trajectories (Section III.B). For switching between the controllers, our method adjusts the input and output of the RNN based on the error of the predicted past motion trajectory and real motion trajectory (Section III.C).

A. Training task behaviors with two controllers

The learning-based method using RNN shows high generalization performance for the trained task operation [14][35]. We adopted the RNN as a learning-based controller for the task operation with a multi-DOF robot arm in a real environment. To embed the dynamics of two controllers, we trained the RNN by using a motion trajectory in which the sensory-motor information and return operation are mixed.

Learning-based controller: To learn the sensory-motor information, appropriate feature extraction from a high-dimensional image is important. Our model extracts low-dimensional image features from camera images by using a CAE. The CAE is a sandglass-type multilayered NN [9], and the model comprises fully connected, convolutional, and deconvolutional layers. By training the CAE to provide an output that is equal to the input data, the model can extract feature vectors that reflect the relation between the robot arm and manipulated object on a central hidden layer.

The proposed method uses multiple time-scale RNN (MTRNN) [34], which is a hierarchical RNN, to learn the relationship between sensory-motor information to generate
task behaviors. MTRNN predicts the next state from current image feature $f_t$ extracted from the CAE and the robot joint angle, $m_t$. The MTRNN is composed of three types of neurons: input-output (IO), fast context (Cf), and slow context (Cs) neurons. Each type of neuron has a different time constant value of $\tau$. Because of this difference, the model effectively memorizes the dynamics of trained sequences as combinations of fast-changing dynamics in the Cf neurons and slow-changing dynamics in the Cs neurons. In forward dynamics, the internal value of a neuron at step $t$, $u_t$, is calculated as follows:

$$u_t = \left(1 - \frac{1}{\tau}\right) u_{t-1} + \frac{1}{\tau} \sum w x_{t-1}$$

(1)

where $\tau$ is the time constant, $x_t$ is the input value, and $w$ is the weight value. In this research, we designed dynamical systems in the context layers for switching dynamics of the RNN. These are detailed in Sections III.C and IV.

Model-Based Controller: To retain the generalization ability of the RNN while referring to the model-based controller, the RNN must be embedded with the dynamics of the model-based controller. We connected the optimal controller to the RNN by using a skip connection [8]. In this study, we used a linear quadratic regulator (LQR) as the model-based controller for error recovery. LQR is a simple optimal controller used in many control studies. We designed the LQR to control the joint angles to converge to the initial posture of the robot. By training the residual function with the LQR, the RNN learns the required output, $\Delta m_{t+1}^R$, for the desired task by canceling the output of the LQR, $\Delta m_{t+1}^L$.

$$\Delta m_{t+1}^L \leftarrow \alpha \Delta m_{t+1}^R + \Delta m_{t+1}^L$$

(2)

where $\alpha$ is the coefficient for switching controllers while generating behavior online. In this training phase, we set $\alpha = 1.0$. By training RNN for the total output of $m_{t+1}^R + \Delta m_{t+1}^L$, the model becomes robust against perturbations that occur when the method switches controllers.

B. Prediction of past motion trajectories

To realize the switching function of two controllers, the model must determine whether the generated behavior is a trained motion trajectory. We trained additional neurons to predict a past motion trajectory from internal representations of the RNN. These neurons are connected in the middle context layer and output the past joint angle, $m_{t-n}^L$, up to $N$ steps. By referring to the past motion trajectory, the error of the generated behavior could be calculated. The error represents the capability of the internal representation to predict the next step, in other words, the representation represents whether a current trajectory is embraced by the set of training trajectories. We performed a time-series comparison between predicted past motion and actual past motion to enable the...
method to determine the behavior whether the robot posture is in the trained motion trajectory even for a moment. The model minimizes the square error $D$.

$$D = \begin{cases} 
\frac{1}{N} \sum_{n=1}^{N} (m_{t-n}^R - m_{t-n})^2, & \text{if } t \geq N, \\
0.0, & \text{otherwise}
\end{cases} \quad (3)$$

During this training phase, the weight and bias of the neural network that trained the main task behavior are fixed. This makes it possible to perform training to judge a motion trajectory without losing the original task performance. We used $D$ in the switching strategy, as described in the next subsection.

C. Switching controller from embedded dynamics in RNN

Finally, we explain how to switch controllers when generating robot motions online. The proposed method consists of two switching strategies: RNN I/O adjustment based on prediction of a past motion trajectory and designing a dynamical system in RNN for the switching subtask.

To allow the robot to return to the initial posture in a stable manner, we configured the RNN so that the output of the LQR, $\Delta m_{t+1}^L$, is prioritized while the robot possesses an undefined posture (Switching Strategy 1). The proposed model determines whether the current posture is abnormal, based on the prediction result of a past motion trajectory, as described in Section III.B. The comparison between the predicted past motion trajectory, $m_{t-1}^{L_{t-1}}$, and real motion trajectory, $m_{t-1}^{L_{t-1}-N}$, obtained from the robot showed that $D$ increases when the current robot state shows an undefined behaviors. The input and output of RNN are adjusted according to coefficient $\alpha$ that scales $D$.

$$\alpha = \frac{1}{1 + \exp(-\beta(D - \gamma D))} \quad (4)$$

where $\bar{D}$ is the average of $D$ obtained by performing continuous motion generation 10 times, and $\beta$ and $\gamma$ are the parameters that adjust the sensitivity of controller switching with $N$. In this study, we set their values at $\beta = 30$, $\gamma = 2$, and $N = 10$ according to the experiment. When $\alpha$ increases, the output of RNN, $\Delta m_{t+1}^L$, is restricted, and the model switches to the LQR controller (eq. 2). The input of the RNN is also adjusted to a closed-loop according to $\alpha$. This allows the output of the RNN to not be affected by disturbances (eq. 5).

After the robot returns to the initial posture because of the LQR, the RNN must restart the task operation appropriately. We designed a dynamical system in RNN to generate behaviors according to the sensory information obtained when the error recovery is completed (Switching Strategy 2). The RNN is trained on the repetitive motion to form an attractor that blends into the trained motion trajectory. By designing the subtasks in a task operation to have the same specific internal state, a switching point is formed at the dynamics of the context layer in the RNN [13][28]. At this embedded switching point, the state of each subtask reaches equilibrium, and the RNN can branch to an appropriate behavior according to the input information. In this study, we designed the initial posture of the robot as a switching point. When the robot returns to the initial posture of the trained behavior, $\alpha$ decreases, and the output of RNN is prioritized. This enables the RNN to re-execute the operation according to the input camera information after error recovery.

IV. Experiment

The primary goal of our experiments is to examine the compatibility between the abilities to guarantee undefined behavior and task execution. In particular, we designed the experiments to answer the following two questions:

1) Does each controller play an appropriate role during an unexpected disturbance?
2) Does the method execute an appropriate subtask after the error-recovery operation?

A. Design of Task Behavior

We designed a pick–place task, in which the task success depends on the selection of the subtask after error recovery (Fig. 3 (a)). This task consists of two subtasks: (1) the robot picks a dish placed on a desk and places it on a vacant position on the shelf; (2) the robot must execute the appropriate subtask according to the camera information. The acquired camera images indicate where the object is or whether the robot is grasping the object. As training data, we prepared combinations of the picking and placing subtasks at nine and two object positions, respectively. By training multiple object positions, the model attains the ability to generalize the object position.
For both the simulation and real robot experiments, we used the Toobo ARM [30]. We obtained 7-dimensional joint angles and 1-dimensional gripper open/close information as the robot behavior. The RGB images were recorded from a fixed camera pointed at the robot. The input images to our model were downsampled to $112 \times 112 \times 3$ pixels. When the method generates a task behavior, the robot is controlled by inputting each joint angle from the model to the robot online.

B. Evaluation Metrics

In this study, we verified the compensation ability to undefined behaviors in real robots. The robot was made to perform a task while being disturbed by the experimenter. Various cases of disturbances were assumed but the following two cases were considered in the experiment (Fig. 3 (b)).
1) Move the current robot posture to an undefined posture
2) Stop the robot posture when in motion
   In both conditions, disturbances were assumed as human collisions.

We evaluated the success rate of the controller switching for error recovery. A disturbance was induced randomly during the task operation. The transition posture in disturbance B was determined randomly within the range of the posture that does not damage the experimental environment. Finally, we verified the recovery operation and generalization ability of our method.

C. Training Setup

We obtained the training data by direct teaching. Each task operation comprised 1057 steps, and a series of operations utilized approximately 60 s. To embed behaviors in the RNN as the attractor trajectory, the length of each task motion was reduced to 100 steps and repeated three times. Furthermore, we added constraints in the context layer to form a switching point of subtasks. The value input to RNN was scaled to $[-1.0, 1.0]$.

Table I shows the parameters of our model. The CAE extracts 30-dimensional image features from input images. Further, the MTRNN has 38-dimensional I/O neurons that accept image features, joint angles, and gripper value. The LQR controls joint angles to move to the initial posture of the task operation. Here, the LQR adjusts the parameters so that its output $\Delta m_{t+1}$ does not exceed the scaling range of the MTRNN. For training, we used mean squared error as the cost function and Adam[2] as the optimizer.

| Network | Dims |
|---------|------|
| CAE     | input@3chs - conv@64chs - conv@32chs - conv@16chs - full@1000 - full@30 - full@1000 - dconv@16chs - dconv@32chs - dconv@64chs - output@3chs |
| MTRNN   | IO@38 - $C_f@80(\tau:2)$ - $C_{s}@20(\tau:10)$ |

![Fig. 4](image-url) **Fig. 4.** Final training loss of predicting past joint angles occurring every five steps. The prediction performance decreases as the prediction target becomes past.

![Fig. 5](image-url) **Fig. 5.** The output of each controller, alpha value, and joint angles of the robot when disturbance is induced during simulator operation. The solid lines of each controller indicate the absolute value of $\Delta m$. The red frame indicates the timing at which the disturbance was induced.

V. Results

We first conducted a preliminary experiment by using a simulator to investigate the switching ability of our model. We then applied our model to a real robot. The model generated a task operation online with disturbance induced by the experimenter. Furthermore, we visualized the representations of RNN and provided its detailed analysis.

A. Simulation Experiments

The main contribution of the proposed method is the switching of controllers by using the prediction of the past motion trajectory from embedded dynamics in the RNN. First, we verified the predicting ability of the RNN for the past time series of the task motion trajectory. We observe past motion prediction errors to see internal representation capability.
When switching between multiple controllers, sensitivity is usually an issue. Some perturbations due to complex dynamics are input during generating motions online in the real world. As the proposed method determines the error state in terms of a time series, it can perform the task without switching to the model-based control in the case of small perturbations. In addition, although camera occlusion was caused by human disturbance, the robot was able to generate motion.

Table II shows the success rate of controller switching under some conditions. The disturbance was induced at random times during the subtask operation. We tested each condition 15 times. A total success rate of controller switching shows 80%, indicating the effectiveness of the proposed method. In the case of disturbance A, the success rate was lower than that for disturbance B because it comprised some disturbance postures that did not change much from the current posture. Although the success rate of the object grasping in subtask A was low, we could confirm that the robot tried to grasp the appropriate object position in each case. This can be improved by redesigning hardware or collecting more training data. In this experiment, we adopted the simple LQR for the return operation; however, the method can be extended to a more flexible return operation by using torque sensors or a controller that imposes some restrictions [1][3].

### Table II: Success rate of switching controller

|                  | disturbance A | disturbance B |
|------------------|---------------|---------------|
| (1) subtask A    | 86.7% (13/15) | 80.0% (12/15) |
| (2) subtask B    | 80.0% (12/15) | 73.3% (11/15) |

Fig. 4 shows the training loss of predicting past joint angles occurring every five steps. In the prediction target in the past 15 steps, the accuracy of the RNN prediction drops considerably. This implies that the internal state of the RNN is embedded with the latest dynamics needed to perform the task. The proposed method predicts the past motion trajectory by using this embedded information. We decided to use the prediction up to 10 steps for determining the undefined behaviors. This is because of the problem of the robot’s sensitivity to disturbance.

We performed numerical experiments through a simulator to avoid any hardware accident. Panel (1) in Fig. 5 shows the result obtained without a disturbance. Panels (2) and (3) show the results under the conditions of disturbances A and B induced in steps 25–50, respectively. The result indicates that the method restricted the output of RNN after the disturbance by multiplying the α value. The controller prioritized the output of LQR. Then, after the occurrence of the disturbance, the output of RNN was found to be disordered (Fig. 5 (2 and 3)). This unexpected output of the learning-based controller may damage the surrounding environment.

### B. Real Robot Experiments

We evaluated our model by using the real hardware with respect to the pick-place task, including human disturbance. In contrast to simulation results, the sensory-motor information and complex real-world dynamics introduced additional challenges on the real robot.

To estimate the proposed method’s abilities of generalization and error recovery, we had the robot perform the pick-place task with a new object position while including human disturbance (Fig. 6). In the experiments, we located the object in a random position. The robot was able to switch the controller properly during the occurrence of an undefined posture due to human disturbance. In addition, the robot succeeded in grasping the object accurately, even when the object position changed. This indicates that our method enables the robot to perform return operation while showing the generalization ability of deep learning. Another behavior with respect to disturbance A can be found in the supplementary video. Also, we used the MTRNN in this experiment; however, the result has not lost generality, so the result should be similar even if we use other RNNs such as LSTM.

Fig. 6. Online motion generation of the robot while being disturbed by humans. After the robot grasped the object, the experimenter paused the robot motion forcibly (Fig. 6B). Remove the object from the robot’s hand and place it again in a different position (Fig. 6C). The model switches the controller from RNN to LQR and returns the robot to the initial posture (Fig. 6D). After that, the robot restarted the task operation based on the camera information (Fig. 6E–6H).
To verify the effectiveness of switching strategy 2, we visualized the internal state of the MTRNN by principal component analysis (PCA). The visualized dynamics includes the generated motion, as shown in Fig. 6. Fig. 7 (a) indicates the internal state of Cf neurons, and Fig. 7 (b) indicates the transition of the $\alpha$ value during operation. The projected space was spanned by the 3rd and 4th PCs with contribution ratios of 5.79% and 4.77%, respectively. After the task operation was interrupted manually, the $\alpha$ value increased, and the model switched its control to the LQR controller. At this moment, by changing the input of RNN to a closed-loop, the RNN controller continued to predict the task motion that behaved as an attractor. The internal state of the MTRNN then returned to the designed switching point (blue arrow in Fig. 7 (a)). When the robot returned to the initial posture, $\alpha$ decreased, and the model switched to the RNN controller (blue arrow in Fig. 7 (b)). As shown, the model transitioned to the appropriate subtask by receiving image information at the switching point (red arrow in Fig. 7 (a)). This result indicates that the proposed method can select subtasks based on the designed dynamic system while including the dynamics of the model-based control.

VI. CONCLUSIONS

In this study, we proposed a method for guaranteeing undefined behaviors in the learning-based control method. When the current robot state is not included in the trained data, the method switches the controller to a model-based controller for error recovery. For switching between learning- and model-based controllers, our method predicts past motion trajectory from embedded dynamics in RNN and determines whether the current trajectory is in the trained task operation. By reusing the internal representation of the RNN to predict past motion trajectories, the method is able to determine undefined behaviors while retaining its task-performance ability. We demonstrated the robot to perform pick–place tasks, including motion interruption. Our experiments showed that the proposed method possesses the generalization ability because of the RNN and the ability to guarantee the undefined behavior because of the model-based controller. We plan to extend our method to predict torque sensors and more complex recovery operations in the future.

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