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Imitative Neural Mechanism-Based Behavior Intention Recognition System in Human–Robot Interaction

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This paper is concerned with an imitative neural mechanism for recognizing behavior intention in human–robot interaction system. The intention recognition process is inspired by the neural mechanism of the mirror neurons in macaque monkey brain. We try to renovate a standard neural network with parametric biases as a reference model to imitate between sensory-motor data pair. The imitation process is primarily directed toward reproducing the goals of observed actions rather than the exact action trajectories. Several experiments and their results show that the proposed model allows to develop useful robotic application for human–robot interaction system application.

Keywords: Mirror neuron system; imitative learning; intention recognition; recurrent neural network with parametric biases; human–robot interaction.

1. Introduction

Imitation of behaviors is a highly interesting subject for both human cognitive sciences and humanoid robotics. In spite of the studies on infant, the areas where human–robot interaction (HRI) using the imitation is rapidly expanding with development of smart devices, such as social robotics. Many neuroscientific and psychological data suggest hypothetical approaches of the mechanisms and the researchers have tried to model the functional peculiarities of imitation in human brain. Recent research agenda covers the reciprocal use of neuroscientific evidences and robotics applications for mutual advantage. We will show that the understanding of the neural mechanisms of the imitation will enable us to design sophisticate and robust (HRI human-robot interaction) system that can perform the adaptive and interactive services. The robots that are able to imitate could take advantage of the same sorts of social interaction and learning scenarios that humans readily use, opening the way for a novel role in robot service market: Not only confined in laboratories anymore, but also being teammates in difficult or dangerous working situations, assistants for care needing people and companions in living environments.

To develop the HRI application it is necessary to be clear on the definition of imitation and the scope of this definition. What we mean by imitation is mimicking a goal of the observed action of the demonstrator. This is one of the peculiar capacities of human to easily interact with other individuals to acquire and learn new knowledge and new skills. There are four levels of neural mechanism of imitation in human interaction including kinematic level, skill level, goal level, and intention level.[1,2] From the observer's point of view the kinematics and dynamics of limbs have critical effects on the imitation. For example, hand poses very different challenges to human brain compared to hand gesture imitation when we observe our hands in the scene of the action. It is important to extract primitive features of the goal of the action by using the reciprocal relations between the object and the limbs of the demonstrator.

In this paper, we are concerned with the neural mechanism of the imitation leads toward that the observer enables to reproduce the observed action into one's own repertories. These procedures are mediated through a neural circuit, called mirror neurons (in Macaque monkeys) or mirror neuron systems (in human brain).[2,3] It was well known that the mirroring property of the mirror neuron system contributes to imitate the objective-directed action by understanding the multiple level of goals.[2,4] The biologically inspired computation model may outperform the traditional approaches. For the purpose of the face recognition or obstacle avoidance, the existing studies have used a well-organized machine learning algorithm, such as linear discriminant analysis,[20] Fuzzy logic,[21] and so on.

This paper describes the implementation of a computational model of mirror neuron system for behavior intention recognition. This work focuses on an interaction and imitation task between a human demonstrator and a robot observer based on computer vision image processing and a biologically inspired neural mechanism accompanied by machine learning issues. The neural process of the mirror neuron systems is primarily directed toward reproducing the representation of the observed actions with goal level rather than kinematic or skill level. In particular, the aim is to design the core mirror circuit of the mirror neuron systems which is emulated by using multiple time scale recurrent neural network with spike response model.

2. Related Works

2.1. *Mirror neuron systems*

The existing experiments using macaque monkey have shown that specific neuronal regions in the cortex area of brain become activated not only when the monkey executes objective-directed behaviors (e.g., grasping, placing and eating), but also when they observe similar behaviors with the same goal which are executed by other monkey or human executer.[4] Additional researches to find the same neuronal areas in human brain was spurred on by finding the mirror neurons. However, direct evidence for the existence of mirror neurons in human is still lacking. Instead, a vast amount of experimental data prove that a mirror neuron system does exist in humans.[5,6] It is analogous to mirror neurons of the monkey's brain which are involved in action understanding. The action understanding means that the certain firing rates of the sensori-motor neurons are modulated by the goal of the action. Its functionality closely related with cortical regions including mirror neurons perform a higher cognition process. This process has critical effects on the imitation: Mapping the sensory data into proper motor codes.

2.2. *Computational modeling concepts*

Previous approaches have focused on the stochastic methodology, such as extended Kalman filter (EKF). EKF is widely used in stochastic model. The existing study shows a good performance to model the vision based robot formation using fuzzy controller and EKF based on vision system.[18] Recently, there has been an increasing computational model of mirror neuron systems for the imitation with promising learning algorithm to transfer the knowledge and skills from demonstrator (e.g., human) to observer (e.g., robot). The overall conceptual reviews of the computational models are described in the existing literatures.[7–9] Several model generalized the cortical processes of the mirror neuron systems. The crucial feature of an auto-associative memory hypothesis is that a partial representation of a stored pattern can be used to reconstruct the whole. In the mirror neuron system, this representation can be applied (with additional circuitry) to imitate the observed action. When the action is presented with incomplete stimuli that are partially matched to one of the stored patterns, the associated memory of motor command representation can be retrieved automatically. The most useful architecture for auto-associative memory is based on contents addressable neural network (e.g., Hopfield network).[3] Another example is the modular selection and identification for control (MOSAIC) model can be utilized for imitation and action recognition.[10] The learning is based on decentralized automatic module selection so as to achieve best control strategy for the task. The basis unit is configured with predictor-controller pairs. The key principle is cooperation and competition between the units by using forward-inverse model. As a controller, inverse model receives input (desired visual information) and output necessary states. On the other hand, forward model plays a role as a predictor receives input as current states and output next likely states.

The auto-associative memory and MOSAIC model are generalized conceptual model of the mirror neuron system. In the robotics, it has an advantage that the model emphasized the partial functionality of the mirror neuron systems goal specified action recognition instead of the generalized model. The imitation of object-directed action requires a mechanism responsible for extracting the local feature describing the action. There is a distributed representation scheme in a sensory-motor supervised learning context by using a recurrent neural network (RNN) model, which is characterized by its additional control neural units called the parametric biases (PBs). It was shown that a set of movement patterns can be learned distributed in a network in which those patterns are recalled by modulating the PBs.[11] This method plays an important role in this work and we will describe the details of the RNNPB in the next section.

2.3. *Reference model: Recurrent neural network with parametric biases (RNNPB)*

Several existing approach for modeling the mirror neuron systems were focused on that the models are involved in simulating the perceptual consequences of actions through recurrent neural networks. RNNPB which is originally introduced by Tani *et al.*[11] has advantage in terms of a distributed representation scheme. RNNPB consists of three (input, hidden and output) layers and the terms of PBs are characterized by generating modulation vectors associated with spatio-temporal patterns of the sensory-motor sequences. The imitation process using RNNPB is based on three phases: learning, generation and recognition. The computation of the values of the nodes and the weights for each phase are manipulated by the modulation of PBs as vector form. The role of learning is to self-organize the mapping between the PBs and spatio-temporal patterns of the observed action. The PBs for each learning pattern is self-determined in unsupervised manner. Because of the inherent PBs, the well-trained system is able to works for both action recognition and generation as a mirror neuron system. The computation process for PBs is based on an iterative inverse computation when given target patterns to be recognized. The data propagation architecture of the RNNPB is shown in Fig. 1.

A typical neural network has input, output and hidden units. In the RNNPB, additional units, context units, are involved except PBs. The context units form self-feedback loop and its activation represent the internal state of the RNNPB. For each input units receives input sequence $u_i(t)$ which is composed by sensory and the motor data.

In the learning phase, a set of motor patterns are learned through the forward model of the RNNBP by self-determining both the PBs $\rho_j(n)$ (assigning separately for each movement pattern index n), and synaptic weights matrix $\boldsymbol{W}_1$, $\boldsymbol{W}_2$ (1: input-hidden, 2: hidden-output, common for all the patterns). The learning is conducted using both target sequences of motor-sensory values. When given $u_i(t)$ in the input layer, the network predicts their values at the next time step in the output layer as $u_i(t+1)$. The outputs are compared with their incoming target values $u_i(t+1)$ and the error is generated. This error is used for updating the synaptic weights and PBs by using backpropagation through time (BPTT) algorithm.[12]

After the learning is completed, the generation phase is worked by the forward dynamics of the RNNPB with the fixed PBs. Also, the RNNPB can be operated in a closed-loop where the next time's sensory-motor prediction output are fed back to current time as inputs. This means the RNNPB can generate imaginary sensory-motor sequences without receiving the external data. The PBs can be inversely

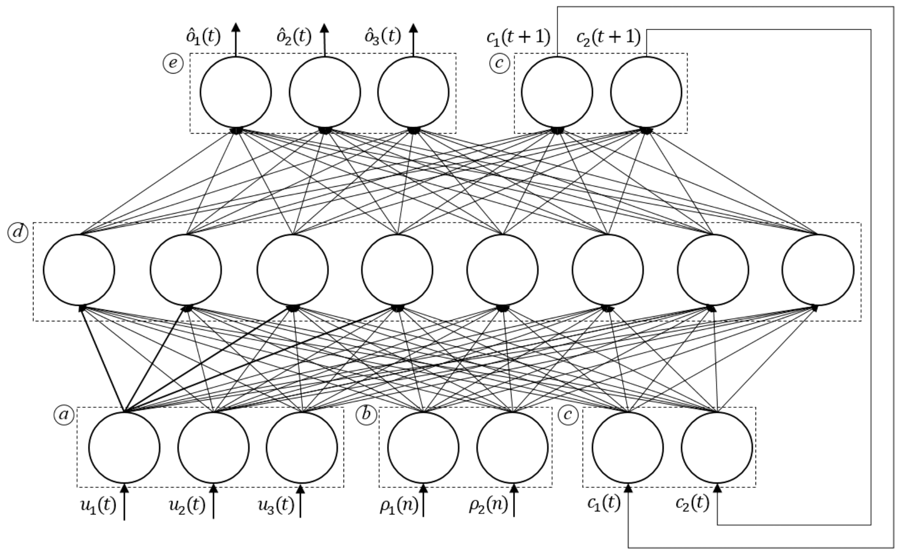

Fig. 1. This figure shows a RNNPB architecture. The solid arrows denote the propagation of output for each unit (a) Input units, (b) parametric biases, (c) context units, (d) hidden units and (e) output unit.

computed for the given target sensory sequences and this is the start of the recognition phase of RNNPB. When the RNNPB receives the current sensory input only $u_i(t)$, RNNPB tries to predict their next time step output $\hat{o}_i(t)$ by using the obtained PBs. The generated prediction error from the target value $\varepsilon_i(t) = \hat{o}_i(t) - u_i(t+1)$ is back-propagated to the PBs and the current PBs are updated in the direction of minimizing the error. The computation of the PBs is conducted by using regression window of immediate past time steps for modulating smoothly through the time steps. The details of these three phase of RNNPB and their polynomial description are shown in the existing literatures.[11,13]

However, an important issue which is missing in the RNNPB model is the goal-directed abstracting in generation or recognition process. As used in the RNNPB often requires the synchronization of the demonstrator's bodily joints on the observer's kinematic joints. This is limited in the sense that the RNNPB model requires similar bodies of actor and observer.[14] In order to understand the goal of the demonstrator's action, an additional step is required. In this work we try to tackle this problem by extending the RNNPB model with a goal representation.

3. Neural Mechanism of Imitation Based on Computational Model of Mirror Neuron Systems

3.1. *Model concepts and schemes*

In the last decades, neuroscience researches provide various theoretical and experimental results of the interpretation of the neural mechanism of the mirror neuron system. In particular, it appeared that the neural areas involving mirroring properties are linked each other and build a neural circuit for imitation of the objective-directed actions. For example, these areas include inferior parietal lobule (IPL) PF/PFG, premotor cortex F5, superior temporal sulcus (STS), prefrontal cortex (PFC). In this paper, the neural areas are responsible for the partial functionalities and their combination leads to the computational scheme of the mirror neuron system. Each of the neural areas play a different role in the mirror neuron system. The STS transfers the description of the sensory input to IPL. The PFC actually encodes final goals from the feedback of internal states and sensory input. Also, it has to be an early model selection mechanism to guide the propagation of activities of the motor primitives. And then, we should deal with a goal matching issue which can be matched with an observed sensory inputs and retrieved the corresponding motor codes of imitation from the repertories by using IPL. The motor input is observer's kinematic states of the joint of effector correspond to the demonstrator's bodily joints. The motor input is generated by the abstraction of the corresponding motor codes in F5. Figure 2 shows the interactive relationship between the neural areas.

In the experimental evidences of the existing studies of the mirror neuron systems, when observers see an objective-directed action that shares local features with a similar action present in their motor repertoire, they are primed to repeat it. On the basis of this property, sensory-motor coupling data is utilized as a first condition of the modeling. In this work, image sequence involving an object, an effector of the demonstrator and their action becomes a sensory input of the model. To tackle the image processing issue, first, we choose the human action dataset capture by using Kinect sensor to train for each RNNPB basis. Based on the depth and the

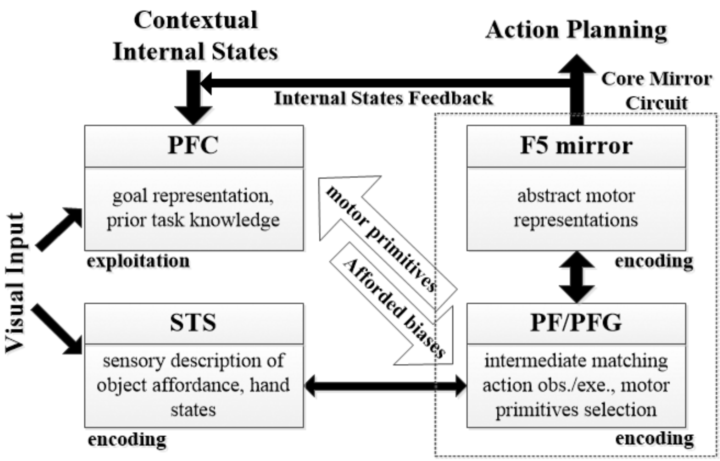

Fig. 2. This figure shows a computational scheme of mirror neuron systems.

estimated 3D joint position, we can utilize a local feature called local occupancy pattern (LOP) feature.[15]

This methodology plays a role of the STS in Fig. 2. The sensory description of the object affordances and the states of the effector are represented by the LOP feature vector form. This vector transfer to the IPL to match with the motor code repertories of the observer intermediately. The motor code selection issues is tackled by a renovation of the RNNPB is used for the selection mechanism. Because of the sequential property of the input data, the computational model of the IPL are composed of multiple timescale RNN.

3.2. *Mathematical model*

On the basis of the model concepts of the mirror neuron systems, a mathematical model was designed by reflecting the activity propagation of the organisms. We should know about the elementary processing in the synapses which are connected by each neuron with intricate patterns. A neuronal signal from pre-synaptic neurons consists of short electrical pulses which are results from voltage-activated, calcium-activated and transmitter-activated ion channels. The mathematical model of transmitter-activated ion channel is described by the diffusion of the transmitter molecules from one side of the cleft (synapse) to other side of the cleft. The diffusion activates receptors that are located in the postsynaptic membrane. The activation of receptor results in the opening of certain ion channels and, GABA receptor as an inhibitory synapse and NMDA, AMPA receptors as an excitatory synapse are distinguished. The RNNPB implementation, we adopted includes transmitter activated channel including AMPA, NMDA and GABA receptors producing a highly realistic model of the spiking response. This synaptic relationship of neurons can be represented by a leaky integrate-and-fire model.[16] The details of the model derivation is described in the literatures. The leaky integrate-and-fire model is represented as follows:

$$\tau_m \frac{du_i(t)}{dt} = -u_i(t) + R\sum_j w_{ij} \sum_d h_i(t - t_j^{(d)}) + RI_i^{\mathrm{ext}}(t). \tag{1}$$

When neuron i and j are connected and i receives, there is an external stimulus input $I_i^{\mathrm{ext}}(t)$, a membrane time constant τ_m and w_{ij} means synaptic weights between neuron i and j. Then, the neuron i receives postsynaptic current $h_i(t - t_j^{(d)})$ from neuron j at time $t_j^{(d)}$. If we make an attempt to acquire the membrane potential $u_i(t)$, its dynamics can be solved by Eq. (1). The model involves inhibitory and excitatory group of neurons which play a role of modeling the excitatory-inhibitory connection between the groups. This property approximates Eq. (1) as shown in Eq. (2).

$$\tau_m \frac{du_i(t)}{dt} = -u_i(t) + \sum_j w_{ij}^{\mathrm{exc}} f(u_i(t)) + \sum_j w_{ij}^{ihb} f(u_i(t)) + RI_i^{\mathrm{ext}}(t). \tag{2}$$

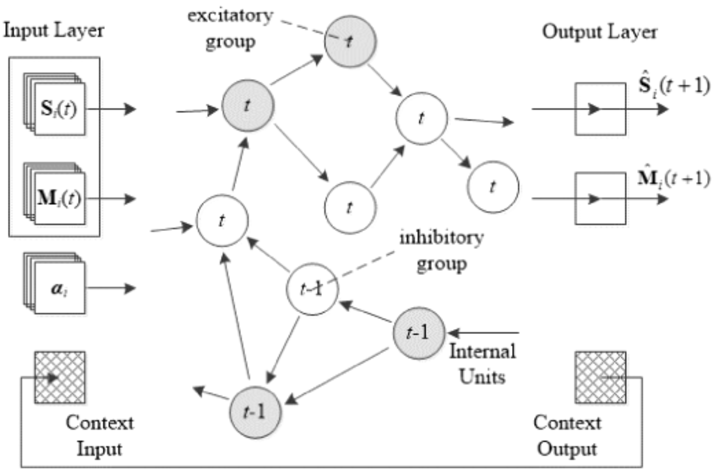

Fig. 3. This figure shows an architecture of renovated RNNPB for modeling mirror neuron systems.

The synaptic weights w_{ij}^{exc} and w_{ij}^{ihb} are represented by using neuronal distribution based a decay function with Gaussian, $N(A, \sigma^2)$.

$$w_{ij}^{\text{exc}} = A \exp\left[-\frac{i-j}{2\sigma^2}\right], \quad w_{ij}^{\text{exc}} = -w_{ij}^{ihb}. \tag{3}$$

The activation function of the neuron $f(u_i(t))$ is characterized by hyperbolic tangent form. This application makes faster conversions of the network model.

On the basis of the mathematical model, the architecture of the mirror neuron system is drawn as shown in Fig. 3. The architecture is represented by renovated RNNPB with the above equations. The key of this architecture is afforded bias vector α_i as a bifurcation parameter for each sensory input data. The calculation process of the vector is similar with normal RNNPB, but its initial value is computed by the affordance of the target object involved in the sensory input (observed scene of the objective-directed action).

It was known that the glial cell controls the neural plasticity of the neural areas of organisms and the PFC of the model concepts plays a role of the glial cell by managing the selection of the final goals. The α_i has closely related with neural plasticity in the neurophysiological point of view. In this paper, the α_i is regarded as a part of PFC and implement it based on the mathematical model.

4. Experiments and Analysis

4.1. *Experimental set up*

In this paper, we choose MSR-Action3D dataset[17] to evaluate the simulation of the neural mechanism of the imitation using computational model of the mirror neuron systems. The 3D joint positions are extracted from the depth sequences by using the

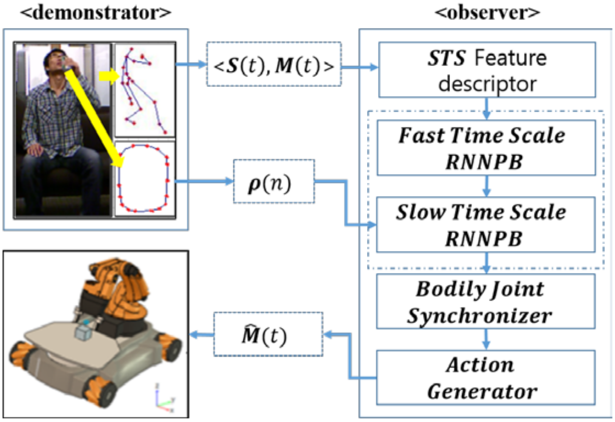

Fig. 4. This figure shows an experiment for the imitation of objective-directed action by using computational model of the mirror neuron system.

real-time skeleton tracking algorithm and libraries.[19] We assume that the robot agent as an observer has restraints in the performance range of the objective-directed action. Therefore, we use a virtual machine environment in the laboratory level so that the HRI can be more easily implemented by minimizing the physical constraints. We use virtual robot experimentation platform v-rep from Coppelia robotics. The repertory of the motor codes of the observer, robot agent, responds to the scope of the actions performed by demonstrator, human subject. The goal imitation is an estimation of whether the observer reproduce the responding action within the scope of its motor repertory. Since there is no human-object co-detection procedure in the skeleton tracking algorithm, we applied specified identities of the target objects in the observed action scene separately. The overall process for the imitation of the objective-directed action using computational model of the mirror neuron system is designed as shown Fig. 4.

4.2. *Experimental results*

In order to evaluate the imitative interaction by recognizing the simultaneous actions, specific interaction scenarios have to be considered. Assumptions of the interaction activities corresponding to the two major intentions are described in below Fig. 5.

On the basis of the proposed computational model of the mirror neuron system, we can acquire the results of Fig. 6. This result shows simple result of the experiment with virtual agent assuming that it has similar bodily configuration with demonstrator.

In Fig. 6, the trajectory of action with different goals are imitated by using the goal level imitation. This result shows a possibility of the proposed model can be used to interact between human and robot with more complicated purposes.

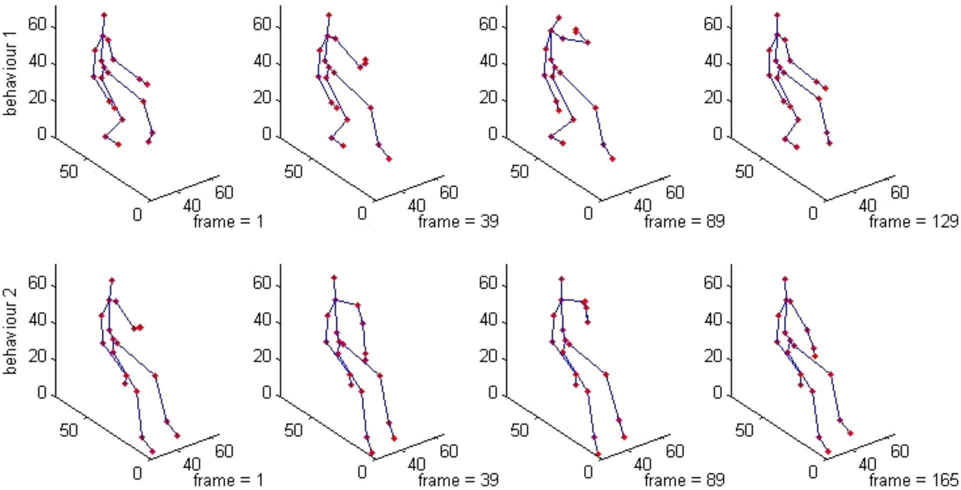

Fig. 5. This figure shows time-series sensory input data: (upper) objective-eat, object-snack, (lower) objective-drink, object-coffee.

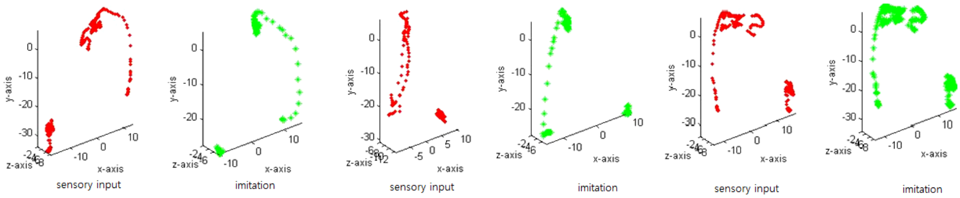

Fig. 6. This figure shows results of the imitation of the observed objective-directed action with same bodily joint configuration.

5. Conclusion

This paper introduces a method for recognizing intention the objective-directed actions by using neural mechanism of imitation. To design the computational model of the mirror neuron system, we applied reference methodology, recurrent neural network with parametric biases and renovated it to being multi-timescale model. The proposed computational model of the mirror neuron system shows a possibility of goal-level imitation the objective-directed actions with simple experiments with virtual robot experimentation platform.

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