Robotic Model of the Mirror Neuron System: a Revival

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Abstract. Action understanding is a vital cognitive capacity for robots interacting with humans. The role of mirror neurons in action understanding has been widely discussed and modeled in the field of cognitive robotics. A mirror neuron system (MNS)-based neural machinery allows the robot to link the high-level representation of the observed action with a high-level representation of the same or similar action within its own motor repertoire and thus facilitate the understanding of the observed scene. We present a novel version of a multi-layer connectionist model of MNS for a cognitive robot that connects visual and motor modalities in a hierarchical fashion. It is based on an existing model for a humanoid iCub robot that learns to perform and understand grasping actions. We adapted our MNS model for the humanoid NICO robot. Our preliminary results indicate that our model is able to form mutual representation for perception and action and show us a promising perspective of developing action understanding and imitation in the future.

Keywords: cognitive robotics, mirror neurons, action understanding, iCub, NICO, bio-inspired modeling

1 Introduction

Cognitive robotics aims at studying cognition of humans through the method of *understanding by building* [16]. Typically this involves connectionist bio-inspired models for perception and action employed in humanoid robots performing tasks in multimodal environments in interaction with humans. While building the cognitive capacities in such robots we can get inspiration from the hierarchical organization of processing in the brain, from low-level feature detection or motor control up to high-level association areas.

According to the common coding theory [7] there is a common high-level representational base for perception and action, i.e. the motor component of the action is tightly linked to it perceptual consequences. Further on, it has been shown, that perception of action automatically activates the motor areas, which is referred to as motor resonance measured in terms of the EEG μ-rhythm desynchronization [17]. This motor response to a perceived action was discovered in monkeys also via direct cell recording and coined as the theory of mirror neurons [20]. The neurons in macaque F5 area typically active when executing goal-directed hand and mouth movements were discovered to also fire when the monkey observed the same actions executed by the experimenter. The mirror neurons were also later discovered in humans [13]. The mirror neuron system (MNS) [20] is assumed to give us the possibility to ,,step into the shoes" of the observed agents and thus provide us with deeper *understanding of the observed actions*, which are typically processed by the visual STS area. Additionally, the mirror neuron area F5 is linked with the STS area bidirectionally and is assumed to ease up the exhaustive processing of the visual input via the insight from one's own motor experience [24].

In this paper we revisit an existing modular neural architecture of mirror neuron circuitry for a cognitive robot. The contributions of this papers are: the novel adaptation of the existing MNS system with a new bidirectional biologically motivated neural model UBAL and the extension of the new model to a different robotic platform, corroborated by our preliminary results.

2 Related Work

There have been many attempt at modeling the mirror neuron circuitry for robots. A majority of these models are mimicking the actual neural circuitry in a modular fashion, where the modules or components directly represent particular parts of the monkey's brain, for instance the FARS model [2], MNS1 [15] or MNS2 [1]. Along the most classical works also the forward and inverse model paradigm [27] could be interpreted as a kind of mirror neuron function in action recognition and imitation.

Within the most recent works, attention has been shifted from modular to the currently most popular end-to-end architectures. One of such models or mirror neurons utilizes a multi-modal variational autoencoder (VAE) for the humanoid iCub robot, which build a multi-modal common representations of perception and action and allows the robot to imitate an observed movement [28]. In a follow up work the VAE has been outperformed by the new deep modality blending networks (DMBN) [22] which also allowed the robot to retrieve the missing information of the associated modal information, including different perspectives in the visual data. The classical problem of the association of the viewpoint of the observed action and the self-view that is typical for the stage of acquisition of the motor knowledge has also been addressed using a VAE [4].

2.1 Robotic MNS for iCub

The robotic MNS model that we built upon is a hierarchical neural architecture for a simulated iCub robot [25] that learns and observes grasping actions. It maintains bidirectional connection between high-level association areas connecting the motor and visual representations and implements the motor facilitation theory [24] in the domain of cognitive robotics. The aim of the model was to use the visuomotor connection account for the problem of translating between the different viewpoints from which the actions are observed.

At each level of the architecture there is a different neural bio-inspired mechanism. The motor execution module is trained via reinforcement learning and produces the robot's grasping actions in terms of joint angles (Fig. 1). Similarly the vision module maintains the positions of the joints observed from four different viewpoints (self - 0°, 90°, 180°, and 270°). The temporal nature of sensory and motor sequences is captured on the higher level in the association areas modeled by the special type of recurrent self-organizing maps, namely the merge-SOMs (MSOM) [23]. These are to resemble the *F5* and *STS* areas of the monkey's MNS in form of topologically organized maps of the actions.

When trained, the MSOMs indeed get organized by the action type (3 different grasps) in the *F5* and by viewpoints and subsequently action types in the *STS*. The activations from the MSOMs are binarized via the k-WTA method, which selects k winners (most active neurons) on the map and sets them to 1, other neurons are set 0 (Fig. 1). This way biologically plausible sparse neural representations of the visual and motor aspects of actions emerge. The connection between the visual and motor representations is maintained by the bidirectional activation based learning neural network model BAL [3].

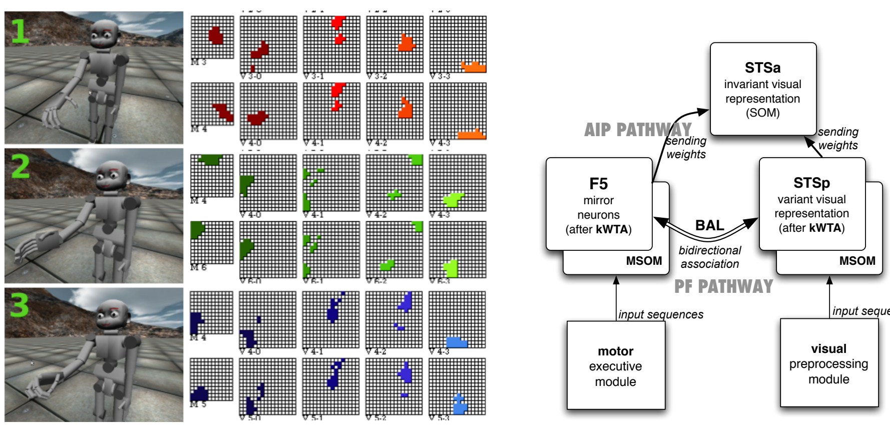

Fig. 1: From left to right: examples of iCub's grasping actions of three types with respective activations of *F5* (MSOM 12×12) and *STS* (MSOM 16×16) for each view-point, both binarized with $k = 16$. On the rightmost side the schema of the MNS model is depicted. All figures adapted from [18].

The mirror neurons as such in this models are formed in the topmost area that is modeled as a self-organizing map (SOM) [9] of perspective-invariant multimodal representations of actions. The way how theses associations are formed in the robot learning scenario is inspired by imitation learning in infants. It has been hypothesized that children learn the association between the executed and the observed because parents tend to involuntarily imitate them right after they produce an action allowing a Hebbian like association between perception and action [5].

In this previous the original BAL model was not able to learn the one-to-many mappings required to associate different visual representations with one motor representation and thus the model was aided with its topmost association part. However, with the emergence of the subsequent UBAL model which has similar inspiration and properties, yet is more complex and universal, this association should indeed be possible.

2.2 UBAL Model

Among its predecessors, the UBAL model [12] presents an alternative to classical error-backpropagation learning, the most prominent learning algorithm for neural network nowadays, which is effective, but biologically implausible. UBAL is a successor of the BAL model [3] and is mainly inspired by the recirculation algorithm for the autoencoder by Hinton [6], and by the Generalized Recirculation and Contrastive Hebbian Learning [14].

UBAL shares features with its predecessors and related models, but is also very unique. It is a heteroencoder that maintains separate weight matrices $\boldsymbol{W}$ and $\boldsymbol{M}$ for two different activation propagation directions (F and B) between inputs and output. Fig. 2 (left) shows a model with two visible layers $\boldsymbol{x}$ and $\boldsymbol{y}$ and hidden layer $\boldsymbol{h}$. Activation states in the network are also propagated backwards via *echo* connection E as indicated in Table 1, which shows general propagation rules between any connected layers $\boldsymbol{p}$ and $\boldsymbol{q}$. Additionally, the activation in UBAL also propagates backwards within (echo) the model forming the model's own projections of its internal states.

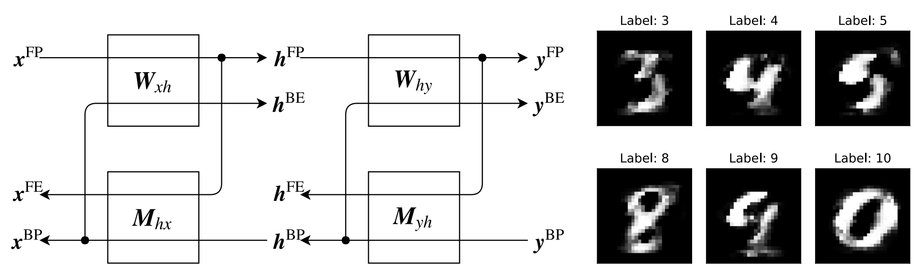

Fig. 2: Schema of 3-layer UBAL (left) adapted from [12] and MNIST digits generated by trained UBAL (right) adapted from [11].

UBAL model learns by a local learning rule, which means that the weights are only adapted based on presynaptic and postsynaptic neuron activations. The learning takes into account all the activations variables (Table 1) transferred into intermediate terms (Table 2) modulated by special hyperparameters β and γ

forming a Hebbian-anti-Hebbian learning rule:

$$\Delta \boldsymbol{W}_{pq} = \lambda\ \boldsymbol{t}_p^{\mathrm{B}}(\boldsymbol{t}_q^{\mathrm{F}} - \boldsymbol{e}_q^{\mathrm{F}}) \tag{1}$$

$$\Delta \boldsymbol{M}_{qp} = \lambda\ \boldsymbol{t}_q^{\mathrm{F}}(\boldsymbol{t}_p^{\mathrm{B}} - \boldsymbol{e}_p^{\mathrm{B}}) \tag{2}$$

Table 1: Activation propagation.

Activation Phase	Note	Computation
Forward Prediction	$\boldsymbol{q}^{\mathrm{FP}}$	$f(\boldsymbol{W}_{pq}\boldsymbol{p}^{\mathrm{FP}} + \boldsymbol{b}_p)$
Forward Echo	$\boldsymbol{p}^{\mathrm{FE}}$	$f(\boldsymbol{M}_{qp}\boldsymbol{q}^{\mathrm{FP}} + \boldsymbol{d}_q)$
Backward Prediction	$\boldsymbol{p}^{\mathrm{BP}}$	$f(\boldsymbol{M}_{qp}\boldsymbol{q}^{\mathrm{BP}} + \boldsymbol{d}_q)$
Backward Echo	$\boldsymbol{q}^{\mathrm{BE}}$	$f(\boldsymbol{W}_{pq}\boldsymbol{p}^{\mathrm{BP}} + \boldsymbol{b}_p)$

Table 2: Learning rule terms.

Term	Computation
$\boldsymbol{t}_q^{\mathrm{F}}$	$\beta_q^{\mathrm{F}}\boldsymbol{q}^{\mathrm{FP}} + (1-\beta_q^{\mathrm{F}})\boldsymbol{q}^{\mathrm{BP}}$
$\boldsymbol{e}_q^{\mathrm{F}}$	$\gamma_q^{\mathrm{F}}\boldsymbol{q}^{\mathrm{FP}} + (1-\gamma_q^{\mathrm{F}})\boldsymbol{q}^{\mathrm{BE}}$
$\boldsymbol{t}_p^{\mathrm{B}}$	$\beta_p^{\mathrm{B}}\boldsymbol{p}^{\mathrm{BP}} + (1-\beta_p^{\mathrm{B}})\boldsymbol{p}^{\mathrm{FP}}$
$\boldsymbol{e}_p^{\mathrm{B}}$	$\gamma_p^{\mathrm{B}}\boldsymbol{p}^{\mathrm{BP}} + (1-\gamma_p^{\mathrm{B}})\boldsymbol{p}^{\mathrm{FE}}$

Endowed with the echo mechanism and a universal learning rule, UBAL is able to master various qualitatively different tasks such as association (memory), denoising and classification based on how hyperparameters β and γ are set up. Since UBAL approaches any problem as a bidirectional heteroassociation (including classification from many data points to labels), it has intriguing emergent properties, such as generation of patterns it learns to classify without being trained with the objective to do so [11]. Fig. 2 (right) illustrates the model imagination, i.e. the output of the model when only the label is inputted to the model.

3 Robotic MNS: a Revival

With a novel universal heteroassociative model on hand, we revisit the old MNS model [19] described in 2.1 and replace the BAL module with UBAL [12] described in 2.2 also removing the topmost SOM-based association area of the original MNS model. We assume that the hidden layer of UBAL will represent the connection between the modal representations. Since we know about the generative properties of the UBAL model we assume that it could also make such projections about the visual representation which is mapped to the motor representation in an "unfair" way (4 viewpoints to 1 movement), similarly to UBAL being able to make its own projection about the handwritten digits from the labels. Additionally, UBAL can also be trained to classify and distinguish the grasp types.

The schema of our new robotic MNS model is depicted in Fig. 3. In line with the previous research we assume the low level modules for perception and action can be any neural models and need to be tailored for the used robotics platform. The positions of key joints of the observed counterpart could be extracted via a deep neural network tailored for that task or just used out of the shelf. For instance, we find the MediaPipe [10] library as a good candidate for this task. The joint information in terms of angles and positions in the Cartesian space (as extracted in the vision modules) are then fed to the respective modules of

F5 and *STS* consisting of MSOMs and processed with k-WTA to form the high-level sparse representations as in the original model. Subsequently, associations of these different motor and visual representations are formed via UBAL, completing the mirroring connection between the observed and the executed actions.

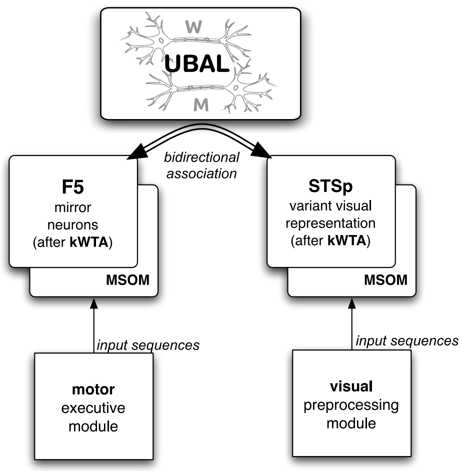

Fig. 3: Schema the new robotic MNS.

3.1 NICO Robot and Grasping Actions

For our new robot MNS we have chosen the NICO (Neuro-Inspired COmpanion) robot platform [8]. NICO is slightly smaller and simpler compared to the famous iCub robot and comes in various versions. The one we have in the physical form has the RH6D hand with 15 degrees of freedom in the hand, with three-segment fingers and an opposable thumb, driven by intelligent actuators [21].

To replicate the previous work and have a proof of concept for our model, we have not endowed the robot with autonomous grasping capability, but rather recorded actions using the software NICO Control GUI[1]. Our grasping data consisted of 3 different grasp types (Fig. 4), 10 different grasping sequences per type, all with the length of 16 to much the original experiment with the iCub [19] as much as possible.

We also followed the original MNS model in terms of acquisition of the processed visual data in terms of positions of the robot's joints in the Cartesian space viewed from different viewpoints. For this we used the NICO simulator[2] based on the MyGym software [26], implemented a forward kinematics model

[1] NICO Control GUI is available at `https://github.com/andylucny/nico/tree/main/nicogui`, demo at: `https://www.youtube.com/watch?v=iRyn1FJB3FU`

[2] NICO simulator is available at `https://github.com/incognite-lab/myGym/tree/nico-sim2real`

to accompany the existing inverse kinematics model. We also adapted the existing URDF model of our NICO robot's hand, which was missing the thumb (Fig. 5) thus obtaining a good model for the future work with training NICO to grasp autonomously via inverse kinematics or reinforcement learning. The sources were published as the outcome of Jakub Mišovký's master thesis and are freely available online.[3]

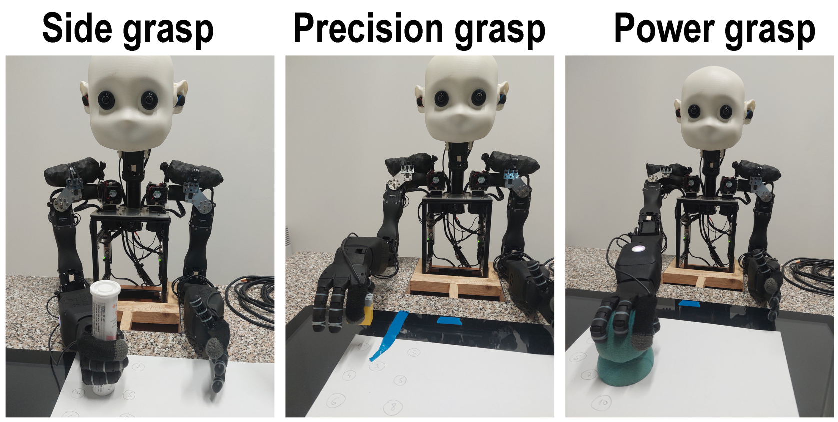

Fig. 4: Examples of three actions executed by NICO, from left to right: side grasp, precision grasp, power grasp.

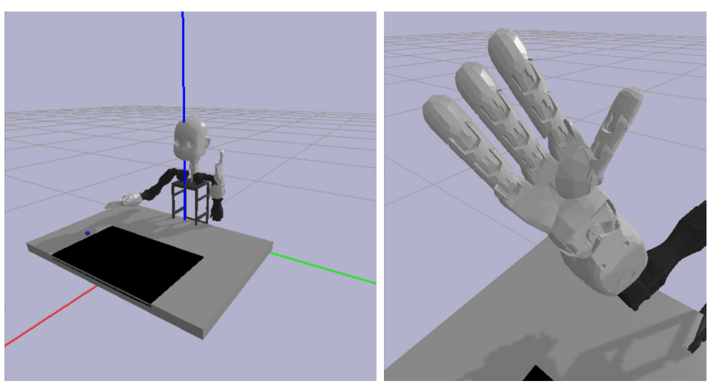

Fig. 5: The NICO robot in the simulator (left) and NICO's hand with an opposing thumb (right).

[3] `https://github.com/misovsky3/RobotNICO_Master_thesis`

3.2 MNS model training and preliminary results

When we collected and preprocessed the data we were able to train the MSOM models of *F5* and *STS*. We have experimented with various hyperparameters of the MSOM including the map size yielding the best size for *F5* 8×8 neurons and for *STS* it was 12×12 neurons. The distribution of winners on the trained maps according to grasp types and viewpoints is shown in Fig. 6.

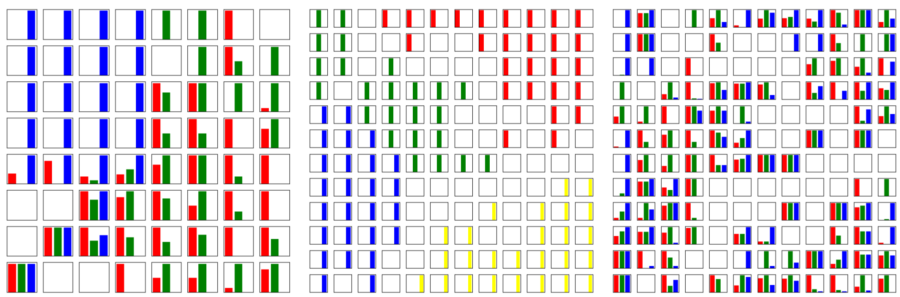

Fig. 6: From left to right: trained *F5* organization according to grasp types and trained *STS* organization according to viewpoints and grasp types. Note that similarly to the original model the *STS* gets organized primarily based on viewpoint.

With the trained MSOMs we collected the activations for each of the input sequences and collected a dataset to train the UBAL model. We experimentally achieved best values of k to be used for k-WTA as $k = 8$ for motor area *F5* and $k = 12$ for visual area *STS*. The k-WTA processed data of *F5* were inputed at the visible layer x of the UBAL model and the *STS* data at the y layer. We performed two different experiments, one with just the $0°$ viewpoint and a second one with all 4 viewpoints. Note, that the motor data needed to be copied to match the motor counterpart for each of the viewpoints. Thus the model learned 1:4 association between the motor and the visual representations.

Hyperparameters for UBAL used in the experiments are shown in Table 3. We trained the models for 25 epochs. We used the cross-validation technique with 5 folds and 10 repetitions per fold. The training progress is displayed in Fig. 7. The best achieved testing accuracy in the case of one viewpoint matching was: in the *F5*-to-*STS* association $99.59\% \pm 0.3\%$ and in the opposite direction from *STS*-to-*F5* $86.68\% \pm 3.43\%$. In the second experiment the accuracy was $90.6\% \pm 0.6\%$ and $83\% \pm 2.2\%$. We expected the performance of the model to be worse in the case of mapping 4 viewpoints of the same action to just 1 motor sequence, however, the difference was surprisingly smaller then expected. Even though it is a hard task to match the unevenly distributed representations, we can conclude UBAL masters it quite well.

Table 3: UBAL hyperparameters

Hyperparameter	**Value**	β^{F} (per layer)	1.0 - 1.0 - 0.9
Architecture	64–70–144	γ^{F} (per weight matrix)	1.0 - 1.0
Learning rate	0.05	γ^{B} (per weight matrix)	0.9 - 1.0
Weight initialization	$\mathcal{N}(0.0, 0.5)$	β^{B} (per layer)	0.0 - 0.0 - 0.1

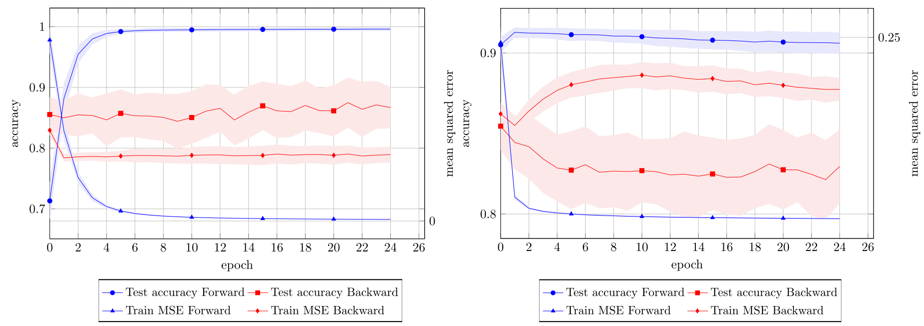

Fig. 7: Training progress of UBAL with association of 1 viewpoint (left) and all 4 viewpoints (right).

3.3 Discussion and future work

With the pilot experiments yielding good results we have many prospects to follow. Our next goals will indeed include building and training a neural-based control module (low level) for the NICO robot to perform actions autonomously and learn new actions. The accompanying neural modules should also consider some visual processing of the scene and evaluation of the target object to be manipulated with.

Within the next steps of developing our MNS model, understanding of motor actions of humans will be implemented. For this, an out of the shelf deep neural network library such as MediaPipe [10] will be utilized. This way the robot should not only "understand" actions of the human partner, but also be able to imitate or mimic new actions within its own joint space. Since the transformation from the observed to the motor counterpart takes place on the higher level, the direct transformation for human joints to robot joints is not necessary. This could be and advantage for our future research in human-robot interaction and collaboration.

4 Conclusion

Modeling the cognitive capacities of robots with the bio-inspired methods is a main goal of the field of cognitive robotics. Here we presented our attempt at revisiting the concept of modeling the mirror neuron system for a cognitive robot and corroborate our methodology with preliminary experimental results. The use of bio-inspired neural network methods such as self-organization or local heteroassociative learning (UBAL) still seems as a promising approach we would like to follow in the future.

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