An Associator Network Approach to Robot Learning by Imitation through Vision, Motor Control and Language

Mark Elshaw, Cornelius Weber, Alex Zochios and Stefan Wermter
Centre for Hybrid Intelligent Systems
School of Computing and Technology
University of Sunderland
Sunderland, SR6 0DD, UK
www.his.sunderland.ac.uk
E-mail: [Cornelius.Weber, Mark.Elshaw, Stefan.Wermter]@sunderland.ac.uk

Abstract— **Imitation learning offers a valuable approach for developing intelligent robot behaviour. We present an imitation approach based on an associator neural network inspired by brain modularity and mirror neurons. The model combines multimodal input based on higher-level vision, motor control and language so that a simulated student robot is able to learn from observing three behaviours which are performed by a teacher robot. The student robot associates these inputs to recognise the behaviour being performed or to perform behaviours by language instruction. With behaviour representations segregating into regions it models aspects of the mirror neuron system as similar patterns of neural activation are involved in recognition and performance.**

I. INTRODUCTION

Current robot applications rarely use neural networks, neuroscience inspired models or language instruction. Typically traditional methods for robot control have been historically wider spread than neural networks as such systems need to combine complex perception and motor skill to achieve non-trivial behaviour. Furthermore, many robot approaches fail to make full use of language to aid robot-human interaction. For instance, the tour-guide robot Rhino [3] does not interact via language. The Pearl robot to guide the elderly has a restricted number of possible spoken questions but uses also touch sensitive displays for interactions [14].

However, an approach that is inspired by the brain may offer an efficient approach to robot learning and behaviour. In response to this we propose a robot system that uses an associator neural network which models specific aspects of the brain in terms of a modular organisation and learning through imitation based on the concepts of the mirror neuron system [20].

In our approach a student robot learnt from a teacher robot how to perform three separate behaviours 'pick', 'lift' and 'go' based on multimodal inputs. These multimodal inputs were vision, language and motor condition whose combination enabled the student robot to learn to associate language instructions and the behaviour of another robot with its own behaviour. Once the student robot learnt by imitation it was able to predict which behaviour was being performed by the teacher and perform one of these behaviours based on a language instruction. The fusion of such multimodal inputs is critical for the common acceptance of service robot due to the need to instruct robots to perform actions in a natural way through language and visual demonstration [24].

One design motivation for our imitation robot approach is modularity in the brain. Brain modularity can be viewed as various distributed neural networks in diverse regions which perform processing in a parallel distributed manner to perform specific cognitive function [19]. In the brain complex tasks are split into smaller subtasks, with the uniqueness of the human brain not coming from the number of neurons but from structural complexity. Although, it is not fully understood why certain regions of the brain are associated with specific cognitive function, the performance achieved would not be possible without this type of modularity [23].

Research into the form that regional brain modularity takes has focused on brain lesion examination and brain imaging techniques. As with other higher cognitive functions, language and vision for instance have a modular processing structure with various theories available on the form that this modularity takes. Over 30 brain regions have been observed to be involved in the visual system alone [7]. Probably the earliest model of language process is one based on two main areas: Wernicke's and Broca's areas linked via the arcuate fasciculus [1].

A number of studies have observed further regions involved in language processing and so extended the modular model of language processing. For instance, Papke et al. 1999 [16] find increased activation for silent word generation in Broca's and Wernicke's areas and sections of the left frontal, temporal and partial lobes. In the visual system the middle temporal area determines the direction of visual motion and velocity [13] and colour stimulus processing is performed by areas of the ventral collateral cortex and in particular the collateral sulcus and lingual gyrus [21].

II. ROBOT IMITATION LEARNING BASED ON THE MIRROR NEURON SYSTEM

Imitation learning is common in everyday life and it speeds up the learning process [22]. Many forms of elaborate behaviour such as social interaction and tool manipulation are learnt by one generation through the imitation of the previous generation [18]. As a result of the role played by imitation learning in animal and human development there has been a great deal of interest from diverse fields such as neuroscience, robotics, computation and psychology. The degree of trial-by-error learning is reduced as a great deal of information can be gained from observing and imitating another robot or human teacher [6]. It is a useful approach for robots as it should allow them to learn to cope with complex environments and reduces the search space and the number of training examples compared with reinforcement learning [6].

Our robot imitation model using multimodal inputs makes use of concepts from the mirror neuron system [20] found in monkeys and later also in humans [8]. In the mirror neuron system a class of the neurons in the F5 area not only fire when performing an action but when seeing or hearing the action performed. The role of mirror neurons is to depict actions so they are understood or can be imitated based on the action goal [20]. The ability to understand others actions, beliefs, goals, expectations allows the observer to predict future actions and so determine if they are helpful or unhelpful [8].

It was found that there is increased excitation in the regions of the motor cortex that were responsible for performing a movement even when they were simply observing it. In humans the mirror neuron area in the brain includes the left superior temporal sulcus, the left inferior parietal lobule and the anterior region of Broca's area. The association of mirror neurons with a language region of the human brain according to Rizzolatti and Arbib 1998 [20] indicates the role played by the mirror neuron system in the evolution of language. The ability to recognise an action is required for the development of communication between members of a group and finally speech.

Previously the mirror neuron system has been used in other robot imitation approaches. For instance, Demiris and Hayes 2002 [6] used the concept of mirror neurons with an architecture containing behaviour and forward models. A behaviour model is given information on the current state and the goal and produces the required motor commands. Following which the forward model creates the expected next state based on the output from the behaviour model. Comparing the predicted state with the actual state of the demonstrator produces an error signal. This error signal is used to create a confidence value to establish the confidence by which a particular behaviour was identified. Two simulated robots are used in this approach, with an imitator robot reading the position of the demonstrator robot based on angles of the joints. The forward model produces forecasts for each joint in the demonstrator robot and compares them with the actual values at the next time step. Using a set of stored action orders the imitator robot increases the confidence value for the order that matches that of the demonstrator actions and reduces the others.

Billard and Matarić 2001 [2] also based an imitation robot approach on the mirror neuron system. This approach uses a hierarchy of neural networks and provides a depiction of the visuo-motor pathways. In doing so there is an examination of the ability to reproduce human arm movements. The model uses the temporal cortex to process visual information to identify the direction and orientation of the teacher's limbs with reference to the teacher's body. The motor control is based on a hierarchical model with a spinal cord module at the lower level. Learning of movement occurs in the pre-motor cortices and cerebellum modules. These modules make use of a Dynamic Recurrent Associative Memory Architecture which enables time series and spatio-temporal invariance to be learnt. The model is implemented on eight sets of arm movements and reproduces motions despite the noisy environment.

It should be noted that although the mirror neuron system in humans incorporates language processing neither of these imitation approaches consider language. Our model differs from existing imitation models by integrating language with vision and motor control and testing this model on a simulated robot platform.

III. EXPERIMENTAL METHOD

First, a robot simulator was produced with a teacher robot performing 'go', 'pick' and 'lift' actions continuously in an environment (Fig. 1). The student robot observed the teacher robot performing the behaviours and was trained by receiving multimodal inputs. These multimodal inputs were *(i)* higher-level visual inputs which were the x and y coordinates and the rotation angle φ of the teacher robot relative to the nearest wall, *(ii)* the motor directives of the robot (forward, backward, turn left and turn right) and *(iii)* a language description stating what the teacher was doing ('go', 'pick' or 'lift').

The coordinates x and φ are relevant to avoid a wall during the 'go' behaviour and x, y and φ are relevant for the 'pick' action. They are thus task-related and can theoretically be retrieved using a lower visual system by the agent. They were also designed in such a way that once the imitation system is implemented on a real robot all could be determined by the student robot when observing the teacher robot. The coordinate transformations that lead to this common representation of the teacher and the learner are however not a topic of this paper.

The simulated teacher robot performs the three behaviours in reoccurring loops and in the following order: the behaviour represented by the word 'go' involves moving around the environment until it reaches a wall and then turns away from the wall at a set angle. It switches to the behaviour represented by the word 'pick' if it comes close to the target at the top of the arena at x and y coordinates 0,0 and if it has a suitable angle of $-45^o < \varphi < 45^o$. This accounts for the object to be within the teacher's field of vision which is a condition to perform a "docking" procedure produced by a reinforcement approach as described by Weber et al. 2003 [26]. Hereby the robot moves in a way such that it arrives at the final 'pick'
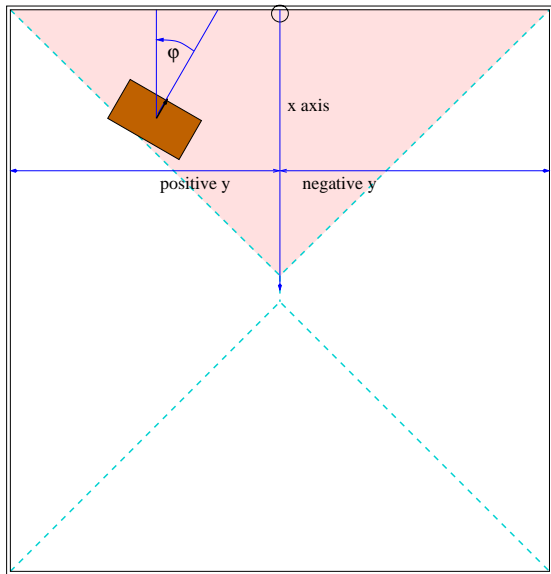
Fig. 1. The simulated environment containing the robot. The x,y and φ coordinates of the robot are taken with respect to the nearest wall. Dashed lines indicate the borders of areas "belonging" to a wall. The area belonging to the top wall is depicted in light grey.

position that was parallel to the table in front of the object. It follows the behaviour represented by the word 'lift' involving moving backward to leave the table and then turning around to face toward the middle of the arena. Then it goes into the next loop starting with another 'go' behaviour. All behaviours involve only body movements but no actual gripper actions.

When receiving the multimodal inputs the student robot was required to learn these behaviours so that it could recognise them in the future or perform them based on a language instruction. In doing so it was required to determine the appropriate next motor direction given the current rotation angle and x and y coordinates so as to achieve the goal of completing the behaviour.

The imitation model used an associator network based on the Helmholtz machine approach [5]. The Helmholtz machine generates representations of data using unsupervised learning. Bottom-up weights W^{bu} generate a hidden representation $\vec{r}$ of some input data $\vec{z}$. Conversely, top-down weights W^{td} reconstruct an approximation of the data $\tilde{z}$ from the hidden representation. Both sets of weights are trained by the unsupervised wake-sleep algorithm which uses the local delta rule. Parameterised by a sparse coding approach the Helmholtz machine creates biologically realistic edge detectors from natural images [25] and unlike a pure bottom-up recognition model [11] produces also the generative model of the data as neural connections. This is used during testing when we regard either the language area or the motor area as output.

The sparse coding paradigm leads to the extraction of independent components in the data which is not desired since many of these components would not span over multiple modalities. Therefore we augmented the sparsity toward a winner-take-all mechanism as used in Kohonen networks [11].

The modified learning algorithm is described in the following and consists of alternating wake- and sleep phases to train the top-down and the bottom-up weights, respectively.

In the wake phase, a full data point $\vec{z}$ is presented which consists of the full motor, language and higher-level visual components. The linear hidden representation $\vec{r} = W^{bu}\vec{z}$ is obtained from which a competitive version $\vec{r}^c$ is obtained by taking the winning unit of $\vec{r}$ (given by the strongest active unit) and assigning activation values under a Gaussian envelope to the units around the winner. Thus, $\vec{r}^c$ is effectively a smoothed localist code. The reconstruction of the data is obtained by $\tilde{z} = W^{td}\vec{r}^c$ and the top-down weights from units j to units i are modified according to

$$\Delta w_{ij}^{td} = \eta\, r_j^c \cdot (z_i - \tilde{z}_i)$$

with an empirically determined learning rate $\eta = 0.001$. The learning rate was increased 5-fold whenever the active motor unit of the teacher changed. This was critical during the 'go' behaviour when the robot turned for a while in front of a wall until it would do its first step forward. Without emphasising the 'forward' step, the student would learn only the 'turn' command which dominates this situation. Behaviour changes are significant events [10] and neuroscience evidence supports that the brain has a network of neurons that detect novel or significant behaviour to aid learning [12], [15].

In the sleep phase, a random hidden code $\vec{r}^s$ is produced by assigning activation values under a Gaussian envelope centred on a random position on the hidden layer. Its linear input representation $\vec{z}^s = W^{td}\vec{r}^s$ is obtained, and then the reconstructed hidden representation $\tilde{r}^s = W^{bu}\vec{z}^s$ is obtained from which a competitive version $\tilde{r}^c$ is obtained by assigning activation values under a Gaussian envelope centred around the winner. The bottom-up weights from units i to units j are modified according to

$$\Delta w_{ji}^{bu} = \epsilon\, (w_{ji}^{bu} - z_i^s) \cdot \tilde{r}_j^c$$

with an empirically determined learning rate $\epsilon = 0.01$. Learning rates η and ϵ were decreased linearly to zero during the last quarter of training in order to reduce noise. All weights W^{td} and W^{bu} were rectified to be non-negative at every learning step and the bottom-up weights W^{bu} of each hidden unit were normalised to unit length.

The hidden layer of the associator network in Fig. 2 that acted as the student robot's cortex had 16 by 48 units. In the wake phases of training it received multimodal inputs $\vec{z}$ based on observing the actions of the teacher robot performing the three behaviours.

These multimodal inputs included first the higher-level vision which represents the x and y coordinates and rotation angle φ of the teacher robot. The x, y and φ coordinates in the environment were represented by two arrays of 36 units and one array of 24 units, respectively. For a close distance of the robot to the nearest wall, the x position was a Gaussian of activation centred near the first unit while for a robot position near the middle of the arena the Gaussian was centred near the last unit of the first column of 36 units. The next column
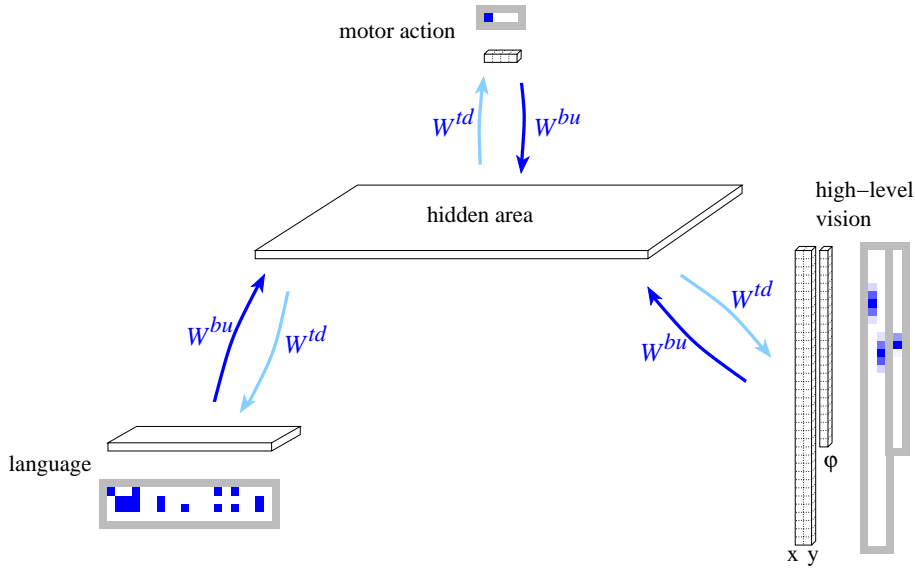
Fig. 2. The associator model for robot imitation learning. A stimulus example is shown near each of the three input areas.

of 36 units represented the y coordinates so that a Gaussian centred near the middle unit represented the robot to be in the centre of the environment along the y axis. Rotation angles φ from -180° to 180° were represented along 24 units with the Gaussian centred on the centre unit if $\varphi = 0^o$.

The second part of the multimodal inputs was the language region on which representations of phonemes were presented. This approach used a feature description of 46 English phonemes, as developed by partners in Cambridge based on the phonemes in the CELEX lexical databases (http://www.kun.nl/celex/). Each of the phonemes was represented by 20 phonetic features, which produced a different binary pattern of activation in the language input region for each phoneme. These features represent the phoneme sound properties for instance voiced or unvoiced so similar phonemes have similar structures. A region of 4 rows by 20 columns was used to represent the words with the first row representing the first phoneme and second row the second phoneme etc., so that the order in which they appear in the word is maintained. For words like 'go' that are described by less than four phonemes there was no active units in the language region for the rows not used, as displayed in Fig. 3. The coding of the language input has been agreed with collaboration partners working in linguistics and neuropsychology and also the words were taken from a commonly agreed restricted dictionary.

Fig. 3. The phonemes and the corresponding 4×20-dimensional vectors representing 'go', 'pick' and 'lift'.

As final part of the multimodal inputs the teacher robot motor directives were presented on the 4 motor units (forward, backward, turn right and turn left) one for each of the possible actions with only one active at a time. The activation values in all three input areas were between 0 and 1.

During training the student robot received all the inputs, however when testing, either the language area or the motor inputs were omitted. The language input was omitted when the student network was required to take the other inputs that would be gained from observing the teacher robot and recognise the behaviour that was performed. Recognition was verified by comparing the units which are activated on the language area via W^{td} (Fig. 2) with the activation pattern belonging to the verbal description of the corresponding behaviour. The motor input was omitted when the student robot was required to perform the learnt behaviours based on a language instruction. It then continuously received its own current x, y and φ coordinates and the language instruction of the behaviour to be performed. Without motor input it had to produce the appropriate motor activations via W^{td} which it had learnt from observing the teacher to produce the required behaviour.

IV. RESULTS AND DISCUSSION

The associator network imitation learning robot performed well when recognising the behaviour being performed by the teacher robot and performing the behaviour based on a language instruction. Recognition was tested by the network producing a phonological representation on the language area which was compared to the appropriate language instruction. As can be seen from Table I the associator model based robot recognised the 'go' behaviour 54.51% of time, the 'pick' behaviour 96.47% and the 'lift' behaviour 86.88%, while the teacher robot was looping between the three behaviours as done during training. The total count shows that the teacher spends most time with the 'go' behaviour. Its false recognition as 'pick' behaviour in 44.26% of time can be explained with the similarity of these two behaviours, but also with the

missing language input which would be strong compared to the motor input.

TABLE I

PERCENTAGES OF CORRECT RECOGNITION OF BEHAVIOURS.

Recognising:	'go'	'pick'	'lift'	Total Count
Performing 'go'	54.51%	44.26%	1.23%	746211
Performing 'pick'	3.08%	96.47%	0.45%	111495
Performing 'lift'	0.89%	12.23%	86.88%	142195

Furthermore, when considering if the trained student robot was able to produce a certain behaviour requested by a language input, the movement traces in Fig. 4 on the next page show that when positioned in the same location the robot performs these different behaviours successfully.

Fig. 5 indicates that the three behaviours are represented at three separate regions on the hidden area. In contrast, the four motor outputs are represented each at more scattered patches on the hidden area (Fig. 6). This indicates that language has been more dominant in the clustering process.

'go'   'pick'   'lift'   all

Fig. 5. Trained weights W^{td} to four selected language units of the student robot. Each rectangle denotes the hidden area, dark are strong connections from the corresponding regions. Each of the three first units is active only at one input, denoted above. The rightmost unit is active by all language words.

forward   backward   right   left

Fig. 6. The trained weights W^{td} to the four motor units of the student robot. As in Fig. 5 the regions from which strong connections originate in the hidden area are depicted dark.

The ability of the robot to both recognise an observed behaviour and perform the behaviour that it has learnt by imitating a teacher shows the model was able to recreate some concepts of the mirror neuron system. The student robot displays mirror neuron properties by producing similar regional unit activation patterns when observing the behaviour and performing it, as seen in Fig. 7. Furthermore, the achieved common "action understanding" between the teacher and student on the behaviour's meaning through language corresponds to findings in the human mirror neuron system whereby language would be allowed to emerge.

V. FUTURE WORK

We will consider two future directions for the associative imitation model. There is an intention to implement the model on our MIRA and LENA robots based on the PeopleBot platform (See Fig. 8). Our robots have on board PCs, microphones

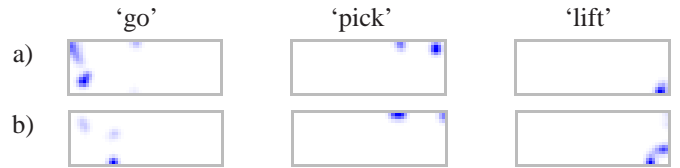
'go'   'pick'   'lift'

a)

b)

Fig. 7. Activations for the associator network summed up during short phases while the student robot **a)** correctly predicts the behaviours and **b)** performs them based on a language instruction.

and speakers and a PC104 audio board. They have adjustable 120-degree pan-tilt cameras, infrared sensors, sonars and 2-degree grippers that contain break-beam sensors. By training the neural network model on a simulator and then transferring it on to the student MIRA robot this allows the use of many more training examples than would have been possible had we gone straight onto the MIRA and LENA robots. As stated earlier the inputs selected are such that they can be obtained by the student MIRA robot observing the teacher LENA robot by using traditional or neural network based vision processing techniques.

Fig. 8. Our two PeopleBot robots, LENA and MIRA.

An additional future direction of this research is to expand the number of behaviours so that the student robot is able to perform more actions related to grasping. In doing so it is possible to expand on our previous work [27], [28] that recreated the neurocognitive evidence of Pulvermüller [17] on how the brain processes action verbs. Pulvermüller found through brain imaging techniques that networks of cell assemblies in the brain represent the word form and the semantic feature of the word in such a way that those actions performed by specific body parts share similar brain regions. By using such an approach it will be possible to incorporate into the model this knowledge on how the brain processes action verbs.

VI. CONCLUSIONS

In this paper we described a model for robot imitation based on the concepts of modularity in the brain and the mirror

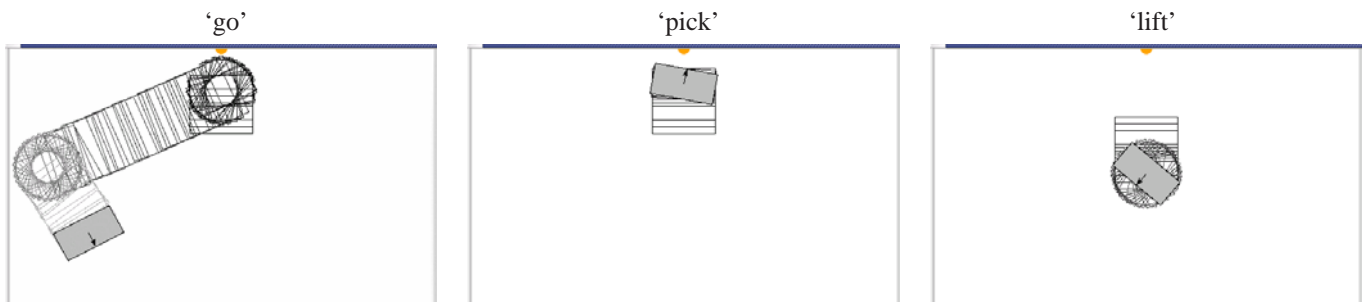| 'go'	'pick'	'lift'

Fig. 4. The simulated trained student robot performance when positioned at the same point in the environment but instructed with different language input. The robot was initially placed in the top middle of the arena facing upward. In the 'go' behaviour it moves around the arena; during 'pick' it approaches the middle of the top wall (target position) and then alternates between left- and right turns; during 'lift' it moves back and then keeps turning.

neuron system. The associator model combined multimodal visual, language and motor inputs and was able to predict the behaviour of the teacher robot and perform a behaviour based on language instruction. This associator network goes beyond previous imitation approaches that incorporate the concepts of the mirror neuron system by using language instruction and therefore integrating vision, language and motor control for the human mirror neuron system. Finally, the model made use of the concepts of modularity in the brain by different regions representing each of the three behaviours for prediction and performance.

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