Online Learning of Visuo-Motor Coordination in a Humanoid Robot. A Biologically Inspired Model.

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***Abstract*—Coordinating vision with movements of the body is a fundamental prerequisite for the development of complex motor and cognitive skills. From a neuroscience perspective, visuo-motor coordination relies on neural processes that map spatial vision onto patterns of muscular activation.**

In this paper, we investigate the formation and the coupling of sensory and motor maps in the humanoid robot Aldebaran Nao. We propose a biologically inspired model for coding internal representations of sensorimotor experience that can be fed with data coming from different motor and sensory modalities, such as visual, auditory and tactile. The model is inspired by the self-organising properties of areas in the human brain, whose topologies are structured by the information produced through the interaction of the individual with the external world. In particular, Dynamic Self-Organising Maps (DSOMs) proposed by Rougier et al. [1] have been adopted together with a Hebbian paradigm for on-line and continuous learning on both static and dynamic data distributions, with the aim of simulating cortical plasticity.

Results show how the humanoid robot improves the quality of its visuo-motor coordination over time, starting from an initial configuration where no knowledge about how to visually follow its arm movements is present. Moreover, plasticity of the proposed model is tested. At a certain point during the developmental timeline, a damage in the system is simulated by adding a perturbation to the motor command used for training the model. Consequently, the performance of the visuo-motor coordination is affected by an initial degradation, followed by a new improvement as the proposed model adapts to the new sensorimotor mapping.

I. Introduction

Coordinating vision with movements of the body is a fundamental prerequisite for the development of complex motor and cognitive skills. In early developmental stages, infants progressively bootstrap their attention capabilities towards a growing number of salient events in their environment, such as moving objects, their own body, external objects and other individuals [2]. Developmental studies showed an early coupling between visual and motor systems in infants [3] and suggested a correlation between hand-eye coordination, learning capabilities and social skills [4].

Related work can be found in the developmental robotics literature. Metta [5] implemented an adaptive control system inspired by biological development of visuo-motor coordination for the acquisition of orienting and reaching behaviours on a humanoid robot. Following a developmental paradigm, the system starts with moving the eyes only. At this point, control is a mixture of random and goal-directed movements. The development proceeds with the acquisition of closed loop gains, reflex-like modules controlling the arm sub-system, acquisition of an eye-head coordination and of a head-arm coordination map.

Saegusa et al. [6] studied self-body perception in a humanoid robot based on the coherence of visual and proprioceptive sensory feedback. A robot has been programmed to generate random arm movements and to store image cues in a visuomotor base together with joint angles information. Correlations between visual and physical movements have been used to predict the location of the robot's body in the visual input, and recognise it.

In recent publications [7] [8], we showed how a humanoid robot acquires hand-eye coordination and reaching skills by exploring its movement capabilities through body babbling and by using a biologically inspired model consisting of Self-Organising Maps (SOMs [9]). Such a behaviour led to the development of pointing gestures. The model architecture is inspired by the Epigenetic Robotics Architecture [10], where a structured association of multiple SOMs has been adopted for mapping different sensorimotor modalities in a humanoid robot. We also showed how a robot can deal with tool-use when equipped with self-exploration behaviours and with the capability to execute internal simulations of sensorimotor cycles [11] [12].

From a neuroscience perspective, visuo-motor coordination relies on neural processes that map spatial vision onto patterns of muscular contraction. Such a mapping would be acquired over time through the physical interaction of the infant with its surrounding, with a gradual formation of internal representations already during the early stages of development [14]. Moreover, it is through interacting that topographic maps would form in the sensory and motor areas of the brain.

Topographic maps can be seen as projections of sensory

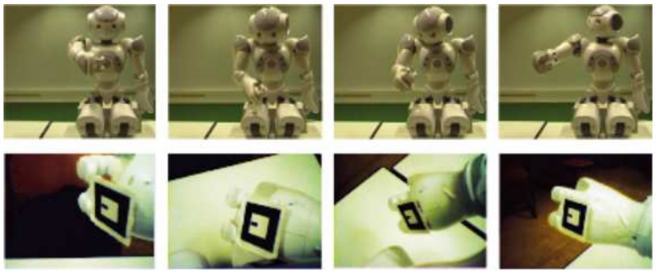

Fig. 1. Babbling sequence on the humanoid robot Aldebaran Nao. The picture has been taken from [13]. Real robot pictures are shown for the sake of clarification, since a simulated robot (Webots simulator) has been used for the experiment presented here. In the exploration behaviour presented in [13] and [7], head movements have been hard-coded to follow the movements of the hand. In the experiment presented here, instead, head movements result from the sensorimotor mapping learned by the proposed model.

receptors or of effector systems into structured areas of the brain. These maps self-organise throughout the brain development in a way that adjacent regions process spatially close sensory parts of the body. Several studies show the existence of such maps in the visual, auditory, olfactory and somatosensory systems, as well as in parts of the motor brain areas [15].

In this paper, we investigate the formation and the coupling of sensory and motor maps in the humanoid robot Aldebaran Nao. We propose a biologically inspired model for coding internal representations of sensorimotor experience that can be fed with data coming from different motor and sensory modalities, such as visual, auditory and tactile. The model is inspired by the self-organising properties of areas in the human brain, whose topology is structured by the sensory information produced by the interaction of the individual with the external world.

Already in 1990, Martinetz et al. [16] proposed an extension of Kohonen's self-organizing mapping for learning visuo-motor coordination in a simulated robot arm with fixed cameras. The authors used a network with three-dimensional topology matched to the work space of the robot arm. The system extracted the position of an object to reach from the visual input and fed the 3D-lattice of neurons with its coordinates. An output vector representing the arm posture was associated to each neuron of the map. A training session has been run for mapping sequences of input-output relations, to learn the required transformations for visuo-motor coordination of a robot arm [16]. However, as Arras and colleagues [17] pointed out, the approach proposed by Martinetz and collegues [16] was based on a time-dependent learning rate. While the model worked well for the initial learning, it then kept the learning rate at a constant level, which was insufficient for allowing the network to adapt to changes in the robot's environment. Thus, Arras et al. extended the algorithm by coupling the learning rate to the arm positioning error estimated from the continuous camera feedback, thus allowing for adaptation to drastic changes in the robots work environment [17]. However, both the approaches addressed learning of visuo-motor coordination of a robot arm with fixed cameras, with using a model consisting of a three-dimensional map whose nodes contain both visual input and motor output information [16] [17].

In this paper, Dynamic Self-Organising Maps (DSOMs) proposed by Rougier et al. [1] have been adopted as topology preserving maps. Similarly to the algorithm presented in [17], DSOMs allow for on-line and continuous learning on both static and dynamic data distributions, thus simulating cortical plasticity as a dynamic coupling between the environment and the model. In the experiment presented here, we address visuo-motor coordination in a humanoid robot with moving arm and camera, with using two DSOMs for coding the posture of the arm and the posture of the neck of the robot. The two DSOMs are associated through Hebbian learning modulated from the visual input through the interaction of the robotic agent with its surrounding, thus simulating the neural processes that map visual inputs onto patterns of muscular contraction in the human brain.

This paper is structured as follows. Section II introduces the DSOM algorithm proposed by Rougier et al. [1]; section III describes the main experiment on learning visuo-motor coordination in the humanoid robot Aldebaran Nao using DSOMs and a Hebbian learning paradigm; section IV presents the results and the performances of the system; we conclude the paper with a discussion in section V.

II. Dynamic Self-Organising Maps

Classical Self-Organising Map algorithms implement decaying adaptation parameters for tracking data distribution. Thus, self-organisation depends heavily on time-dependent decreasing learning rate and neighbourhood function. Once the adaptation strength has decayed, the network is unable to react to subsequent changes in the signal distribution [18]. Such an approach can not be used for simulating cortical plasticity, the capability of the cortex of re-organise itself in face of lesions and deficits [1] [19].

Models such as Growing Neural Gas (GNG) have been proposed for online and lifelong learning, that can also adapt to dynamic distributions [20]. GNGs have no parameters that change over time and they allow for continuous learning, adding units and connections, until a performance criterion has been met [20]. Similarly, Evolving Self-Organising Maps (ESOMs) [21] implement incremental networks that create nodes dynamically based on the distance of the winner node to the input data.

Rougier et al. [1] proposed the Dynamic Self-Organising Map (DSOM), a modified SOM algorithm where learning rule and neighbourhood function do not depend on time. The authors demonstrated how the model dynamically adapts to changing environments, or data distributions, as well as stabilises over stationary distributions. They also reported DSOM to perform better than classical SOM and Neural Gas in a simulated scenario [1].

DSOM is a structured neural map composed of neurons with fixed positions p_i in $\mathbf{R}^q$ in the lattice, where q is the dimension of the lattice (in our experiment $q = 2$). Each neuron i has a weight w_i that is updated according to the input data pattern v through a learning function and a neighbourhood function. For each input pattern v, a winner s is determined as the closest neuron in the DSOM to v using an Euclidean distance. All codes w_i are thus shifted towards v according to:

$$\Delta w_i = \epsilon \|v - w_i\|_\Omega h_\eta(i, s, v)(v - w_i) \tag{1}$$

where ϵ is a constant learning rate, Ω is the set of codes in the codebook (the weights of the neurons) and $h_\eta(i, s, v)$ is a neighbourhood function of the form:

$$h_\eta(i, s, v) = e^{-\frac{1}{\eta^2}\frac{\|p_i - p_s\|^2}{\|v - w_i\|_\Omega^2}} \tag{2}$$

where η is the *elasticity* or *plasticity* parameter, p_i is the position of the neuron i in the lattice, p_s is the position of the winner neuron in the lattice. If $v = w_i$, then $h_\eta(i, s, v) = 0$. The rationale behind such equations is that if a neuron is close enough to the data, there is no need for other neurons to learn anything, since the winner can represent the data. If there is no neuron close enough to the data, any neuron learns the data according to its own distance to the data [1].

However, the DSOM algorithm is not parameter free: the elasticity parameter modulates the strength of the coupling between neurons. If elasticity is too high, neurons cannot span the whole space and the DSOM algorithm does not converge. If elasticity is too low, coupling between neurons is weak and may prevent self-organisation to occur [1]. The effect of the elasticity, as reported by the authors, not only depends on the size of the network and the size of the support but also on the initial conditions. To reduce the dependency on the elasticity, the initial configuration of the network should cover as much as possible the entire support [1].

Nonetheless, DSOMs allow for dynamic neighbourhood and lead to a qualitatively different self-organisation that can be controlled using the elasticity parameter. DSOMs map the structure or support of the distribution rather than its density, as many other Vector Quantisation algorithms do.

III. Learning Visuo-Motor Coordination

We implemented a biologically inspired model for learning visuo-motor coordination in the Nao robot. The model consists of two bi-dimensional DSOMs encoding the arm postures and the head postures of the robot, respectively. Arm postures consist of 4-dimensional vectors containing the angle positions of the following joints of the robot: shoulder pitch, shoulder roll, elbow yaw, elbow roll. Head postures consist of 2-dimensional vectors containing the angle positions of the neck joints of the robot: head yaw, head pitch.

The two DSOMs are associated through Hebbian links. In particular, each node of the first DSOM is connected to each node of the second DSOM, where the connection is characterised by a weight. The weight is updated according to a positive Hebbian rule that simulates synaptic plasticity of the brain: the connection between a pre-synaptic neuron (a node in the first DSOM) and a post-synaptic neuron (a node in the second DSOM) increases if the two neurons activate simultaneously. Thus, the model consists of two DSOMs and a Hebbian table containing the weights of the links connecting the two DSOMs. The table has a size equal to the number of neurons of the first DSOM multiplied with the number of neurons of the second DSOM.

Learning consists of two parallel processes. The robot executes random body babbling of its arm, that is, it executes random motor commands of its arm sampled from uniform random distributions within its arm joints ranges. The first learning process consists in training the two DSOMs as follows. Instant by instant, the current positions of the joints of the arm have been used as input data vector for the learning rule of the arm DSOM (equations (1) and (2)). At the same time, a motor command is sent to the neck joints as follows:

- search for the winner neuron of the arm DSOM (the closest node in the arm DSOM to the input vector represented by the current arm joints configuration);
- select the winner neuron in the Head DSOM as the one that has the highest connection weight to the winner neuron in the arm DSOM. If there is more than one winner neuron (that is, multiple connections with the same weight), then choose a random one from the group of winners;
- send a motor command to the joints of the neck equal to the weight of the winning neuron.

The Head DSOM is also updated using equations 1 and 2, with using the current angle positions of the neck joints as input data vector.

In parallel to the first learning process, a second learning process based on a Hebbian learning paradigm is run. The Hebbian learning paradigm describes an associative connection between activities of two connected neurons [7]. Here, when the end-effector of the robot is visible from the visual input, the connection between the winner nodes of the two DSOMs is strengthened. The hand of the robot has been tagged with a fiducial marker and its position in image coordinates has been estimated using the ARToolkit (www.hitl.washington.edu/artoolkit). The bottom camera of the Aldebaran Nao robot has been used for grabbing visual input.

Thus, visuo-motor coordination can be considered as successful if the marker tagging the end-effector of the robot is visible from the visual input. In this case, the Hebbian learning process updates the Hebbian table connecting the two DSOMs as follows. If a marker is visible:

- select the pre-synaptic neuron (winner neuron) as the closest neuron i in the arm DSOM to the current arm joint configuration $\mathbf{x}$;
- select the post-synaptic neuron (winner neuron) as the closest neuron j in the Head DSOM to the current neck joint configuration $\mathbf{y}$;
- strengthen the connection w_{ij} between the pre- and post-synaptic neurons according to the modified positive Hebbian rule:

$$\Delta w_{ij} = \eta A_i(\mathbf{x}) A_j(\mathbf{y}) f_c \tag{3}$$

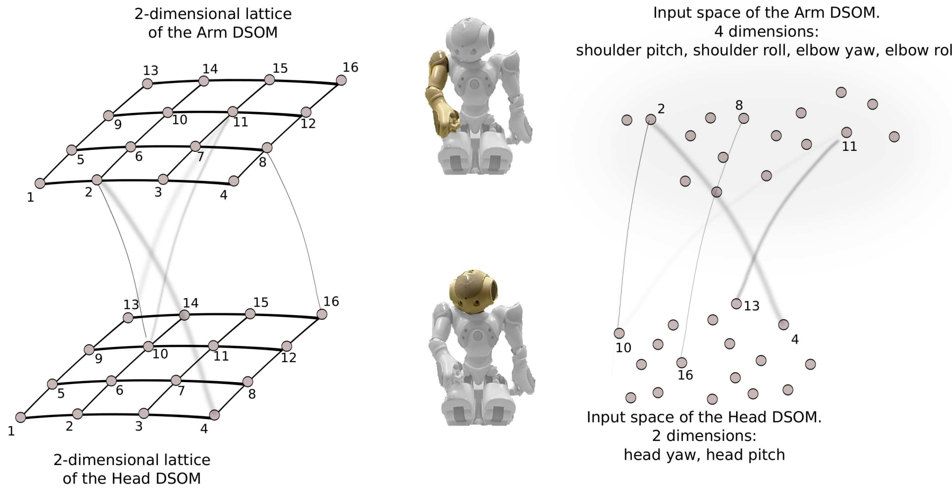

Fig. 2. Illustration of the proposed model. On the left side, the 2-dimensional lattices of the two DSOMs (arm and head) are shown. The DSOMs can be also represented in the input space, where neurons are positioned according to their weights (right side). Lines connecting the two DSOMs represent Hebbian links, with weights $w \neq 0$. Thicker lines correspond to stronger Hebbian links.

where $A_i(\mathbf{x})$ is the activation function of the neuron i over the Euclidean distance between the neural weights and the data pattern x, η is a scaling factor for slowing down the growth of the weights (in this experiments it is initialised with 0.01), and f_c is a multiplying factor related to the distance between the perceived position of the hand (marker) in image coordinates to the center of the image grabbed from the robot camera (image size: 320×240). f_c ranges from 1 (hand at the center of the image) to 0 (hand at the corner of the image) and it is used to make the system choose head positions that result in the hand being close to the center of the image.

As in Kajic et al. [7], the activation function of a neuron, $A(\mathbf{x})$ is computed over the Euclidean distance between the neural weights and the input vector, denoted with $\mathbf{x}$:

$$A(\mathbf{x}) = \frac{1}{1 + \tanh(\mathbf{x})} \tag{4}$$

All weights between two SOMs are set initially to zero allowing for an activity-dependent role of structural growth in neural networks [7].

Figure 2 shows an illustration of the proposed model, which consists of two DSOMs connected by Hebbian links.

IV. Results

The experiment was run on the Cyberbotics Webots robot simulator. As described in the previous section, two DSOMs, namely arm DSOM and Head DSOM, have been trained with data generated through motor babbling. Each DSOM consisted of 30×30 neurons, or nodes. Associated with each node of the arm DSOM is a weight vector of four dimensions, representing the positions of the following joints: shoulder pitch, shoulder roll, elbow yaw and elbow roll. Similarly, each node of the Head DSOM is associated with a weight vector of two dimensions, representing the following joint positions: head yaw and head pitch. Weights of the neurons of both the two DSOMs have been randomly initialised within the ranges of the corresponding joints, to reduce the effect of elasticity dependency. As pointed out by Rougier et al. [1], the initial configuration of the DSOM network should cover the entire support as much as possible to reduce elasticity dependency.

The experiment was run for around 3 hours and 20 minutes (197.58 minutes). It consisted in the robot generating random arm movements and moving its head accordingly to the current visuo-motor coordination skills. Learning was performed online, in parallel to the execution of the movements. It consisted in updating the DSOMs based model with training data represented by the current positions of the joints of the arm and those of the head. Instant by instant, the current arm joint configuration is used as input pattern for the arm DSOM update rule, as described by equation (1). Similarly, the current head joint configuration is used as input pattern for the Head DSOM update rule. Frequency of the updates matched the frame rate of the visual input, namely 15 frames per second. During 197.58 minutes, the DSOMs have been updated with input training patterns 177.823 times. In parallel to the DSOM updates, the Hebbian table connecting the two DSOMs has been updated with the positive Hebbian rule described by equation 3, only when the end-effector of the robot was visible in the visual input. During the 197.58 minutes, the hand of the robot was detected 91.658 times and, correspondingly, the Hebbian table was updated.

The quality of visuo-motor coordination has been measured as the number of times the end-effector of the robot has been detected from the visual input during a time window of 5 minutes. This measurement was repeated every 5 minutes for the entire duration of the learning session (197.58 minutes). A linear regression computed on the collected measurements showed a positive trend (slope 12.147, intercept 2175.176), demonstrating that the quality of visuo-motor coordination improves over time. In other words, the mapping between arm and head joints is learned over time, resulting in an improvement of the precision of the head movements in following the sight of the end-effector.

In addition to this analysis, we wanted to test the plasticity of the proposed model. After the first learning session, a damage in the system is simulated by adding a perturbation to the motor command used for training the model. In particular, arm movements have been randomly generated as in the first learning session but the vector representing the current arm joint configuration has been affected by a perturbation. The perturbation consisted in translating the vector of the arm motor command. The perturbation has been initialised as random, but then it has been kept constant. In this experiment, the following perturbation has been added to the arm joints: 0.1265 radians to the shoulder pitch joint, 1.1411 radians to the shoulder roll joint, 1.2295 radians to the elbow yaw joint and -0.2242 radians to the elbow roll joint.

A new learning process started after the first learning session. In particular, 96.049 new input patterns (around 106.72 minutes) containing the perturbation have been used for the on-line update of the models. The hand-detection rate has been measured over 5 minutes, as during the first learning session. A linear regression computed on the collected measurements during the first 35 minutes of learning affected by perturbation showed a negative trend (slope: -80.286, intercept: 2685.857). In other words, performance of the visuo-motor coordination degraded, probably due to the fact that the arm DSOM and the Hebbian table needed to re-adapt to the new input data. However, a new improvement in the visuo-motor coordination has been reported during the following 71.72 minutes, as confirmed by the positive trend of the linear regression (slope: 1.2154, intercept: 2255.264). This demonstrates that the proposed model is able to deal with the unexpected change in the input signal.

Figures 3 shows the trends of the quality of visuo-motor coordination. The three blue segments show the linear regressions of: the initial learning phase (without perturbation), the first degradation phase after the perturbation and the final phase characterised by a new improvement. These results confirm that the proposed model implements brain-like plasticity.

Figure 4 and 5 also show the trends of the distortion measurement of the arm DSOM and of the Head DSOM. Distortion is a popular criterion for assessing the quality of a Kohonen map [9]. It is computed as follows. For each input pattern:

- Update the DSOM using the input pattern;
- Compute the distance between the input pattern and the winner neuron (the closest DSOM neuron to the input)

Distortion is computed as the sum of the calculated distances, divided by the number of input patterns. Since we are dealing with on-line learning mechanisms, not the entire set of processed input data is used for computing the distortion error. Rather, at each instant, only the previous 1.800 observations (corresponding to two minutes of exploration) have been used for computing the error. Figure 4 shows a decreasing distortion error for the arm DSOM during the first 5 minutes of learning, followed by a quasi-stationary error until the moment when the perturbation is added to the arm command (around instant

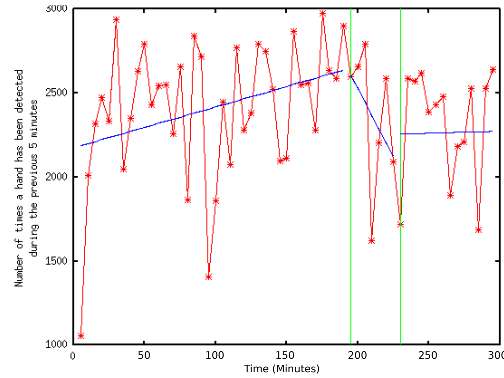

Fig. 3. The quality of visuo-motor coordination was measured as the number of times the end-effector of the robot was detected from the visual input during a time window of 5 minutes. This measurement (red line in the figure) was repeated every 5 minutes for the entire duration of the learning session. Blue lines show linear regressions. First learning phase: slope 12.147, intercept 2175.176; second learning phase (after perturbation marked by the first vertical green line): slope -80.286, intercept 2685.857; third learning phase (re-adaptation to the new data distribution): slope 1.2154, intercept 2255.264.

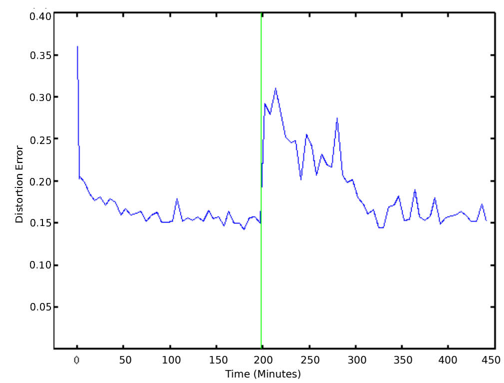

Fig. 4. Distortion error of the arm DSOM. The green vertical line marks the time instant (39.51, or 197.58 minutes) from when a perturbation is added to the arm commands. Errors are computed over a moving window of 1.800 input samples (2 minutes, considering the update frequency of 15 frames per second).

40 in the x-axis, or 197.58 minutes). Thus, an increase of the distortion error is reported, most probably due to the change in the distribution where the data is sampled from. Once the DSOM adapts to the new distribution, the distortion error starts to decrease and to stabilise.

The Head DSOM is not affected by the perturbation, in the current experiment. In fact, as shown in Figure 5, no significant jumps in the distortion error signal are reported.

V. Conclusion

We investigated the formation and the coupling of sensory and motor maps in the humanoid robot Aldebaran Nao. In particular, we proposed a biologically inspired model for on-line and continuous learning of visuo-motor coordination. The model is able to represent sensorimotor experience and, thus, can be extended to different motor and sensory modalities, such as visual, auditory and tactile.

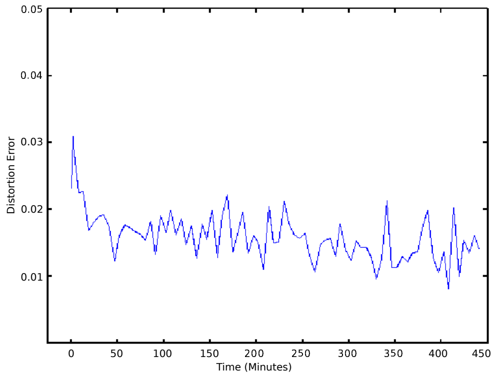

Fig. 5. Distortion error of the Head DSOM. Errors are computed over a moving window of 1.800 input samples (2 minutes, considering the update frequency of 15 frames per second). After the first 10 minutes of learning, the distortion error stays stable between 0.01 and 0.02, since the underlying data distribution is not changing.

The model consists of two Dynamic Self-Organising Maps associated through Hebbian links, which allow on-line learning of sensorimotor mappings, a fundamental prerequisite for the development of motor and cognitive skills. Moreover, results demonstrate that the model possess an adequate level of plasticity, since it is able to adapt to dynamic data distributions.

In particular, the aim of the experiment presented here is to make the robot able to learn how to follow the movements of its hand, while generating random motor commands to its arm joints. During the random movement generation, namely motor babbling, arm and head postures are used for updating the corresponding DSOMs on-line, while they are associated through Hebbian learning whenever the end effector of the robot is visible in the visual input. Head movements are generated as outputs of the proposed model. The quality of the head movements depends on how well the DSOMs encode the data distribution where the arm and neck postures are sampled from, and on how well they are associated through Hebbian learning.

Using the proposed model, the humanoid robot improves the quality of its visuo-motor coordination over time, starting from a random configuration where no knowledge about how to visually follow its arm movements is present. Moreover, plasticity of the proposed model is tested. At a certain point during the developmental timeline, a damage in the system is simulated by adding a perturbation to the motor command used for training the model, resulting in translating the original data distribution. Consequently, the performance of the visuo-motor coordination is affected by an initial degradation, followed by a new improvement as the Arm DSOM adapts to the new data distribution and the Hebbian connections between the Arm DSOM and the Head DSOM adapt to the new mapping.

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