

A McKibben Muscle Arm Learning Equilibrium Postures

Paolo Tommasino and Daniele Caligiore and Valerio Sperati and Gianluca Baldassarre

Abstract—In designing artificial systems for studying motor control in humans and other organisms a key point to consider is the complexity reached by brain and body in their developmental stages. An artificial system whose brain and body complexity is shaped according to developmental stages might allow understanding weather, for example, newborn infants, infants, and adults use different neural mechanisms to cope with the same motor control problems. This article proposes an artificial system which aims at becoming a tool to study this type of problems. The system has a brain and body endowed with a set of *minimal bio-mimetic features*: (a) neural maps activated by receptive fields; (b) connections plasticity changed by Hebbian rule; (c) robotic arm actuated by a McKibben muscle. The arm autonomously learns to reach specific positions in space under the effect of gravity and for different load conditions. The results suggest that a fast and *incremental goal-action mapping formation* could constitute the computational mechanism underlying the neural growth and plasticity of an early developed brain at the onset of reaching. The same mechanism also allows a first approximate solution for load compensation avoiding the use of more sophisticated internal models (developed in further brain and body developmental stages). This paper aims to be a preliminary study on the feasibility of this approach.

Index Terms—compliant arm, hebb rule, load compensation, neural-networks, one-shot learning, reaching, receptive fields, stiffness modulation

I. INTRODUCTION

It is increasingly recognized that behaviour of humans and other animals arises through the *interactions* of brain neural activity, body features and environmental context [1][2]. This is particularly true in the field of motor control where limb geometry and muscle properties can influence the pattern of neural activities which determines movements [3][4]. This “neuroethological approach” [1][3] can crucially support collaborations and cross-fertilizations among experts of different disciplines. Roboticians and engineers can be inspired by neurological and psychological studies to design artificial systems which incorporate aspects of organism’s biomechanics and neural control to improve their agility and robustness for a given task [5]. On the other side, neurologist and psychologists can better understand biological systems, analyzing results coming from experiments run on the models [6].

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In this framework a critical point which is weakly addressed regards the role played by the *ontogenetic* factors in the emergence of motor control strategies [7][8]. Brain and body constraints change during life and these changes have a critical effect in how brain, body and environment interact.

Brain changes are present from the birth. Infants are not born with all the interconnections already formed in their brains and some cortical areas (e.g. the prefrontal cortex) are less developed [9]. *After birth*, there is a *period of rapid synapse formation* in the infant’s brain, and the “plasticity” of the brain allows different parts to develop and mature at different rates. Beneficial effects on brain connectivity and growth have been shown when newborn infants have been reared in an *enriched environment* [10].

The motor control strategies also depend on changes in body constraints management. Bernstein proposed that when organisms first learn a skill they restrict the degrees of freedom (DOFs) that they use [11]. In this way organisms simplify the dynamics of the effector and reduce the size of the search space. Once the organisms got some initial proficiency, the restrictions on the DOFs is gradually relaxed so that a skilled actor will be able to use the full power of the effectors. Similar behaviours have been observed in infant learning to reach [12] and to walk [13]. This evidence on brain and body constraints changes suggests that motor control strategies adopted by an infant’s brain which interacts with an infant’s body could be different by the ones adopted by an adult’s brain which interacts with an adult’s body.

This ontogenetic perspective suggests that in building *artificial systems to study human motor behaviour* it is crucial to consider the *cross-influence* among brain, body and environment *in relation to the degree of development* reached by the brain and body. Artificial systems whose brain and body complexity is shaped consistently with the complexity of the brain and body of the real organism might highlight alternative mechanisms by which, for example, newborn infants, infants, and adults cope with the same motor control problem. In this way, the limitations often encountered explaining and interpreting the data on infants motor behaviour based on the knowledge on data about adults motor behaviour (cf. [14]) might be overcome.

This article presents a preliminary study on the feasibility of this approach. More in details, it illustrates an experiment to study the motor behaviour which emerges endowing the brain and body of an artificial system with a set of minimal bio-mimetic features: (a) neural maps activated by overlapped *Receptive Fields* (RFs); (b) connections plasticity changed by an associative Hebbian rule; (c) an artificial arm actuated by a McKibben muscle.

The experiment demonstrates that an artificial system endowed with these minimal features is capable of capturing crucial aspects of motor behaviour of real organisms whose brain and body are early developed. First, a fast and computationally cheap learning (through one-shot learning) allows the system to autonomously acquire motor skills through self-exploration of the environment (similarly to the infants motor babbling [15][16]). Second, the overlapped RFs, fast learning rule and biceps compliance allows the system to quickly learn a load compensation and generalization avoiding to use sophisticated methods [3][17]. Finally, the *incremental* goal-action mapping formation (see Sec. II-B) during reaching acquisition, might shed light about the computational strategies adopted by the brain of real organisms at the beginning of their developmental history, when a limited set of resources are available [10].

The rest of the paper is organized as follows. Sec. I-A presents the main bio-mimetic features of the artificial system. Sec. II presents the artificial arm and the task used to test the neural controller and explains the functioning and the learning mechanisms of this. Sec. III shows the results obtained by testing the system. Sec. IV draws the conclusions and suggests future work.

A. Biomimetic constraints used to build the system

1) *Arm actuated by a McKibben muscle*: The body of the artificial system is formed by a single joint arm actuated by a McKibben muscle (Sec. II for details). McKibben artificial muscles are the most representative pneumatic air actuators used as a main motion power source in bio-mimetic robotics and in biomedical applications [18][19]. Thanks to their high power-to-weight and power-to-volume ratios they have an high level of functional analogy with human skeletal muscles. One of the major attractions of these actuators regards the *inherent compliant behavior* they show [20]. Compliance is due to the compressibility of air and can be influenced by controlling the operating pressure. Thanks to compliance a soft touch and safe interaction can be obtained. Hydraulic and electric drives, in contrast, have a very rigid behavior and can only be made to act in a compliant manner through the use of relatively complex feedback control strategies [21].

On the other side, the *compressibility* of air and *friction* are the main factors to the *nonlinearities* in the system that make these actuators *difficult to control* (this issue is common of all pneumatic air actuators [21]). In addition, since McKibben muscles are mainly used to actuate bio-mimetic robots which operate in unstructured and highly noisy environments, there are a series of nonlinear and time varying factors to take into account in designing a control strategy (e.g. changing in load force due to unexpected variation of environment conditions). All these factors make difficult and potentially inefficient adopting traditional control theories strategies for McKibben muscles. In this respect, interesting results have been obtained using supervised neural networks [22] or hybrid solutions which combine traditional controllers (e.g. PID) with neural networks [23][24].

2) *One-shot Hebbian learning and overlapped Receptive Fields (RFs)*: The proposed learning algorithm (Sec. II-B) aims at capturing two *basic ingredients* underlying motor learning mechanisms of real brain: fast learning and generalization. The human brain supports one-shot *fast learning* processes which are mainly implemented by one of the oldest sub-cortical area, the Hippocampus (Hip) [25]. Generalization mechanisms are instead mainly supported by the cortical regions [26][25].

The one-shot Hebbian rule used in the present paper reproduces the computational mechanisms underlying fast learning processes implemented by Hip. The overlapped RFs are instead used to mimic the computational mechanisms underlying the generalization processes developed within the cortical regions. In general, information processing based on RFs is an ubiquitous organizational principle in neurobiology which offers interesting computational opportunities [27].

Importantly, the neural controller proposed here is able to deal with the intrinsic non-linearities of the McKibben actuator (see Sec. III). However, it does not aim to overtake the performance of the controllers already proposed in literature for control of McKibben muscle systems [23][24]. Rather, it aims at demonstrating that one-shot Hebbian rule and overlapping RFs might represent low cost computational mechanisms used by a non-fully developed brain (as the newborn infants' brain is) to learn basic motor strategies (cf. [28][16]). The resultant motor behaviour might be further refined involving other functions to get more sophisticated motor control skills (e.g. action selection through basal ganglia and cortical loops [25] or motor adaptation exploiting cerebellar functions to create internal models of the world [14]).

II. METHODS

A. The Artificial Arm and the Task

Figure 1 shows the artificial arm and the environment. The arm has one DOF corresponding to the elbow joint. The dimensions of humerus and forearm (both wooden made), are comparable to the human arm, being respectively 30cm and 27cm long. The arm is actuated by a McKibben pneumatic muscle mimicking the action of biceps. The muscle has been built in our lab¹ using a simple air balloon inserted in an expandable braided sleeving clamped at the extremities (Figure 2).

The biceps muscle contributes to the elbow flexion allowing to lift and balance the forearm against gravity. From a physics point of view the forearm is a pendulum whose equation, under static condition, can be expressed as: $u(P, \epsilon) = -m \cdot g \cdot r \cdot \sin(\theta)$ (parameters were not constrained with real data because not necessary for the present work), where u is the joint torque due to the artificial muscle that mainly depends on its pressure P and its contraction ratio ϵ [29], m is the mass applied to the center of mass, g is the

¹<http://www.istc.cnr.it/group/locen>. We aimed at building a low cost and easy to maintain system. The total cost of the whole hardware (arm, sensors, actuators, microcontroller) has been about 350 euros.

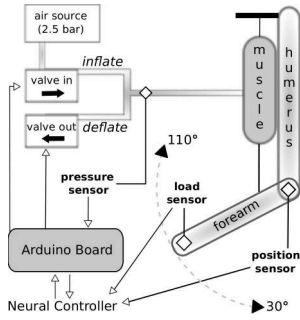


Fig. 1. Schematic of artificial arm and environment. Two solenoid valves (PVQ31, from SMC) regulate the quantity of air present into the muscle, determining the current pressure. The pressure sensor (ASDX015D44D, from Honeywell) detects the current pressure into the biceps. These devices are managed by a microcontroller Arduino Mega 2560, which interfaces with the neural controller. The position sensor (implemented through a webcam and a computer vision algorithm), detects the current elbow angle. For now the load sensor is virtual, and its value is manually set in the software by the experimenter, according with the load put on the hand (i.e. the forearm tip). In future, these last two sensors will be replaced respectively with an encoder and a load cell, both connected with the microcontroller, in order to enhance the autonomy of the system.

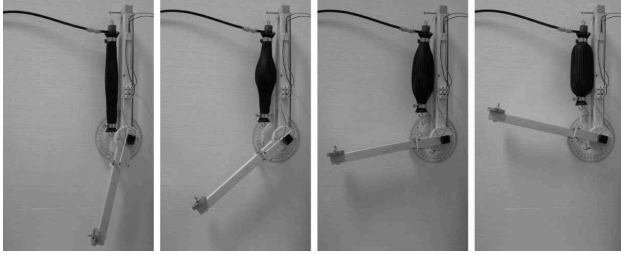


Fig. 2. The artificial arm during motion. At rest the muscle is 22cm long, and lets the forearm extended at 10° (first pic on left). When air is inflated, it slowly shrinks to about 17cm, corresponding to a 110° forearm flexion (last pic on right). Given the used materials, the muscle inner pressure never exceeds an increment of 0.7bar with respect to atmospheric pressure.

gravity force, r is the distance between the elbow joint and center of mass, and θ the elbow angle.

The task requires that the neural controller (Sec. II-B) learns to control the muscle allowing the arm to reach several positions in the workspace with its “hand” by starting from different positions and with different loads carried by its “hand”. Despite the high simplicity of the system the task is rather challenging for several reasons if one would solve it with standard robotic methods. First, it is strongly non-linear. The joint torque u depends in a non-linear manner on the pressure P , the contraction ratio ϵ and the load that influences the task in a sinusoidal manner. Second, the task requires *stiffness modulation* because the same posture could be associated to different pressures (and hence different forces) due to the presence or not of the load. Third, the neural controller requires to generalize for *unexperienced* desired postures and loads without using dynamic internal models of body and environment.

B. Neural controller and Learning Mechanisms

Different powerful machine learning techniques, like gaussian processes (GP) or support vector machines (SVM) [30],

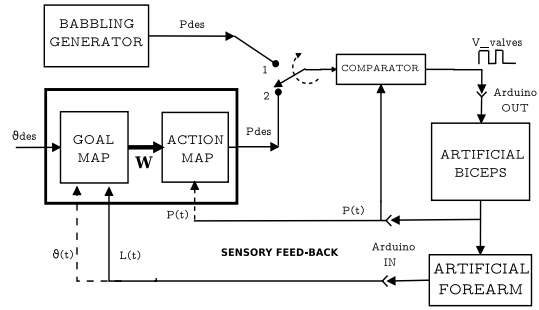


Fig. 3. The neural architecture (bold frame) and its connections. Each map receives sensory feedback from the arm by the Arduino Board. Dashed arrows are connected only during the “Incremental Goal Action Mapping Formation Phase”. The bold line W represents the connection weights formed during learning of reaching.

address the question of incremental learning with kernel basis functions. These algorithms rely on statistical techniques and are far from brain computational mechanisms. In contrast, the algorithm that we developed, even if it is less powerful compared with GP and SVM, allows using Hebbian learning and investigating the relationship between different neural maps that are linked with synapses. We will use the term fast learning or *one-shot learning* to mean that the algorithm needs only one training epoch to output the right response either on the training data set or the generalization set. Figure 3 shows the neural architecture of the model and its connections with the other components. The neural controller is formed by two interacting neural maps: the *Goal Map* (GM) and the *Action Map* (AM). The GM is activated by elbow angles and load stimuli and abstracts the brain areas (such as parietal region cf.[31]) that are involved with motor planning and where external stimuli are translated into motor goals. AM is activated by the pressure stimuli and abstracts the brain motor areas (such as premotor and motor regions cf. [31]) mainly involved in generating motor command sent to muscle accomplishing the planned goal encoded by GM. The motor command used to control the muscle is pressure.

Before training, both the maps have no RFs and there are no connections linking them. The aim of the training phase is to *incrementally* create and associate neural representations (i.e. RFs) of the elbow and load stimuli in the GM, to the representations of the pressure stimuli in AM. More in details, during training 9 elbow equilibrium postures (ranging from 30° to 110° , with a step of 10°) are associated with the corresponding 9 biceps pressures without a load on the hand and when a load of 100g is set on the hand.

The resultant neural growth process during the training phase depends on the motor experience arising from the interaction with the environment and mimics the neural growth mechanism present in the brain in the early stage of life [10]. Even if several works have addressed incremental perception formation [32], only few of them have considered simultaneously incremental formation of both perception and motor actions [33].

After the training phase, setting a desired goal \mathbf{x}^d in the GM, which means setting a desired elbow angle θ_{des}

while sensing the load $L(t)$ acting on the hand, the AM supplies the desired pressure P_{des} to achieve the goal. AM is directly connected with a comparator which gradually increases the current pressure P_t (acting on the voltage of valves) to reach P_{des} . The comparator is turned-off as soon as $P_t = P_{des} \pm 0.0025bar$. The next two subsections explain the computational details underlying these processes.

1) Incremental Goal-Action Mapping Formation Phase:

During this phase the babbling generator (switched on 1 in fig. 3) sets several desired pressures P_{des} that the muscle reaches thanks to the comparator. When $P_{des} = P(t)$ the information (normalized in $[0, 1]$) about the current elbow angle $\theta(t)$ and the current load $L(t)$ carried by the hand is used to decide if creating or not a RF in the GM. The information about the $P(t)$ is used to decide if creating or not a RF in the AM (see below the RFs trashold constraints).

In both maps the activation of the RFs are computed according to a population code (cf. [27]). Each neuron has a Gaussian activation when exposed to a stimuli \mathbf{x} :

$$a_i(\mathbf{x}) = e^{-(\mathbf{x}-\mathbf{c}_i)^T \cdot \Sigma^{-1} \cdot (\mathbf{x}-\mathbf{c}_i)} \quad (1)$$

hence a RF is completely defined given its center position $\mathbf{c}_i \in \mathbf{R}^n$ and its covariance matrix $\Sigma \in \mathbf{R}^{[n \times n]}$. The center \mathbf{c}_i represents the stimuli vector \mathbf{x} which maximally activates the RF. The covariance matrix Σ regulates *region-of-influence* of RFs over the input (GM) and output (AM) spaces. Each RF belonging to the GM has a constant diagonal Σ whose elements are set to $5 \cdot 10^{-4}$ and 0.1 for angle and load respectively allowing the formation of a new RF at each 10° and $100g$. For AM Σ is a scalar whose element is set to 10^{-5} allowing to insert a new RF at each $0.07bar$. Since the algorithm estimates the centers of the AM, *the higher the number of RFs, the higher the resolution of the estimation*.

A new RF is added in the map if $\sum_i a_i(\mathbf{x}) < a_{tr}$, where $a_{tr} = 0.001$ represents a threshold that measures “how far” the current stimuli are from those experienced during previous experiences and hence regulates both the RFs growing and the estimation accuracy. The values of covariance matrixes Σ allowed to allocate 18 different RFs (9 with the load and 9 without it) in both maps while preserving the *generalization* capability for the intermediate angles and loads *thanks to the overlapping of RFs* (Sec. III).

When a new RF is allocated in a map, synaptic connections are formed between the novel RF and the RFs belonging to the other map. The strength of the synapse (w_{ij}), initialized to zero, is incremented with the following Hebbian rule [16]:

$$\Delta w_{ij} = b_j^{GMmax}(\mathbf{x}) \cdot b_i^{AMmax}(\mathbf{y}) \cdot (1 - w_{ij}) \quad (2)$$

where b_j^{GMmax} and b_i^{AMmax} are the maximum softmax activations (obtained by normalizing $a_i(\mathbf{x})$ with respect to $\sum_i a_i$) of the GM and AM respectively, given the current stimuli $\mathbf{x} = [\theta(t), L(t)]$ and $\mathbf{y} = [P(t)]$. The term $(1 - w_{ij})$ avoids that synapses connections assume values beyond one if the architecture is subject to more training epochs (a condition that we do not test in our experiments).

2) *Goal Planning and Action Recalling*: During the functioning of the system the babbling generator is kept out (switched on 2 in fig. 3). Given a desired goal \mathbf{x}^d , the architecture estimates the P_{des} to achieve that goal by computing the reading-out of AM as follows:

$$\mathbf{h} = \mathbf{W} \cdot \mathbf{a}^G(\mathbf{x}^d); \quad P_{goal} = \frac{\sum_i h_i \cdot c_{pi}}{\sum_i h_i} \quad (3)$$

where \mathbf{W} represents the synaptic weights matrix, $\mathbf{a}^G(\mathbf{x}^d)$ are the activations of the RFs in the GM exposed to the stimuli \mathbf{x}^d . The internal activation \mathbf{h} is used to compute a weighted mean of the centers of the AM (c_p) to estimate P_{des} . P_{des} is then sent to the comparator to control the muscle as explained before (Sec. II-B.1). Importantly, the Eq.II-B.3 allows the computation of a *voting mechanism* involving the population of neurons of GM and their *synaptic relations* to select the pressure neurons of the AM. Similar voting processes are implemented by real brain structures involving, for example, the basal ganglia [25].

III. RESULTS

The performance of the artificial system is tested setting several desired equilibrium postures ranging from 30° to 110° with an incremental step of 5° to test both the learning of training set and the generalization capability. The generalization is also tested by applying a never-experienced load of $50g$ and the same postures. The average reaching error computed on training set is $1.03^\circ \pm 0.89^\circ$ while the average reaching error computed on the generalizations set is $1.84^\circ \pm 0.98^\circ$. The entity of these errors is largely acceptable for the aim of the work (cf. Sec. I-A.2).

During the test each desired goal \mathbf{x}^d in GM causes an activation of a corresponding P_{des} in AM. The corresponding desired pressures-desired angles curve is showed in Figure 4. The figure shows that, given a posture, a higher pressure is needed due to the load presence. Moreover, higher pressures are required to reach higher desired angles.

By abstracting the artificial muscle as a linear spring we have that the contraction force is directly proportional to its stiffness K and to the displacement between the spring equilibrium posture θ_{des} and the current posture $\theta(t)$: $F_{spring} = K(\theta_{des} - \theta(t))$. As a result a specific contraction force can be obtained by setting θ_{des} or by modulating the stiffness K . In this respect, Figure 4 shows that the neural architecture is able to express both mechanisms. In particular, different θ_{des} are modulated when the muscle moves along one curve, while “jumping” from the no load curve to the load curve, the neural architecture increases the biceps stiffness and therefore it balances a higher force with respect to the same equilibrium posture θ_{des} .

The performance of the system depends by the RFs mapping and by the choice of pressure as a control variable. In this respect, Figure 6 shows what happens within the GM and AM during the incremental goal-action mapping formation (cf. Sec. II-B.1) as well as during goal-action recalling (cf. Sec. II-B.2), for different desired angles and load conditions. Each Goal RF has a preferred Action RF

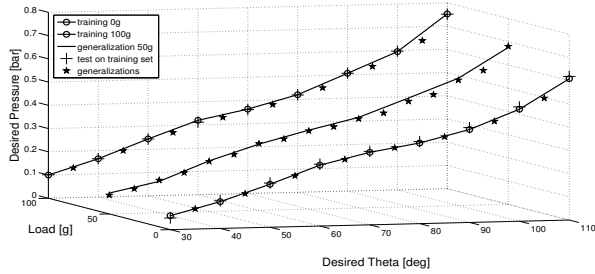


Fig. 4. Desired pressures (P_{des}) generated by desired angles (θ_{des}). Solid lines relative to $L(t) = 0g$ and $L(t) = 100g$ are obtained by interpolating the training pairs. Crosses represent P_{des} estimated by AM when θ_{des} belonging to the training set activate GM. Stars represent P_{des} estimated when θ_{des} belonging to the generalization test (not previously experienced) activate GM. The middle curve is relative to a never experienced load of 50g and it is obtained by interpolating pressure and desired postures (those of the training set) before the training started. Therefore, stars on it are relative to a further generalization test. The curves are approximately linear until 70° after that they assume an exponential variation. This is mainly due to the gravity effect (which acts maximally at 90°) and to the non-linear expandability of the braided sleeving and the balloon which increases further the slope of the curves over 100° .

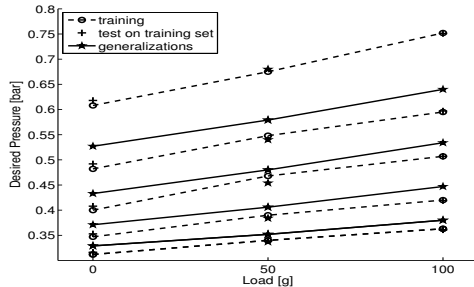


Fig. 5. This plot highlights the architecture performances by showing the relation between pressure and load for θ spanning the range between 70° (lower lines), and 110° (top lines). Dashed lines, crosses, and continuous lines concern respectively the training set, the test on the training set, and the generalization tests. The plot shows that the 100g condition increases the desired pressure of $\sim 0.05bar$ until 100° , and more than $0.1bar$ at 110° . Even if such increment can appear negligible, data not reported here have shown that without a further training with the 100g load, the architecture produces reaching errors above 5° .

and hence by moving horizontally in the GM the architecture modulates the muscle force, by estimating P_{des} (AM) in proportion to the displacement between the current sensed angle and the desired one. On the other hand by moving vertically through the GM the architecture modulates, through P_{des} (AM), the stiffness of the biceps and hence allows balancing different loads when the same equilibrium posture is specified.

The overlapping of the RFs and the voting mechanism (Eq.II-B.3) also allows getting a good pressure estimation when the GM is activated with unexperienced desired angle and sensed load which are between the previously learned ones. In other words, the angle overlapping regulates over its region-of-influence the slope of the curve in fig. 4 while the load overlapping allows to insert local biases on the curve allowing good estimation also for the *unexperienced* object whose weight is 50g.

IV. CONCLUSIONS AND FUTURE WORK

The artificial system proposed in this paper presents a number of interesting aspects with respect to both robotics and biology. From a robotic perspective several key features are apparent. First, combining one-shot Hebbian rule and overlapped RFs make the learning of simple reaching movements and the generalization to new postures and loads faster and computationally cheaper. In this respect, it was critical to set the minimal region of influence of RFs so to guarantee that the overlapping of RFs avoided that only one goal RF in GM was associated with several P_{des} RF in AM (e.g. this could happen in the case of learning redundant sensory-motor mappings). A possible solution could be to progressively reduce the covariance of the most active RF until a new RF is required, and then add a new RF on GM. Another solution could be to increase the number of inputs of GM using a covariance Hebbian rule (cf. [16]) to better disentangle the RFs. All these possible solutions are issues for further investigation.

Second, the combination of a fast learning algorithm for goal-action mapping with a compliant arm allows the system to autonomously acquire motor skills through *self* and *safe* exploration of the environment quickly learning load compensations. Using traditional robotic humanoid approaches would make it more difficult to obtain autonomous safe body-environment interactions and load compensation without using sophisticated control systems [3][17].

Even if the controller proposed here acts on a single joint arm the RF approach could be scaled to many DOFs system [33]. One way to use the algorithm proposed here to learn reaching movements to control redundant DOFs could be to modulate the learning rate of the Hebbian rule (Eq.II-B.2) according to the pressure costs of the McKibbens in order to have that low learning rates postures reach high values of pressures. In this way, the “low-pressure postures” could be strongly learned and hence be used more likely (cf. Eq.II-B.3). This solution could be further tested in future work.

The artificial system proposed here is also a valuable tool to investigate developmental phenomena related to the onset of reaching. In this respect, the experiments suggest that the incremental formation of RFs through Hebbian learning could constitute the computational mechanism underlying the neural growth and plasticity of early developed brain [10]. In addition, the organization of RFs is reminiscent of the possible organization of organisms motor behaviour on the basis of motor-primitives [34].

Remarkably, the results also suggest that these two computational mechanisms allow a first gross solution to cope with load compensation. In this respect, the role of the sensed load is to *passively modulate* the *biceps compliance* avoiding the use of more complicated solutions based for example on internal models which could be developed by the organism in further developmental stages [35].

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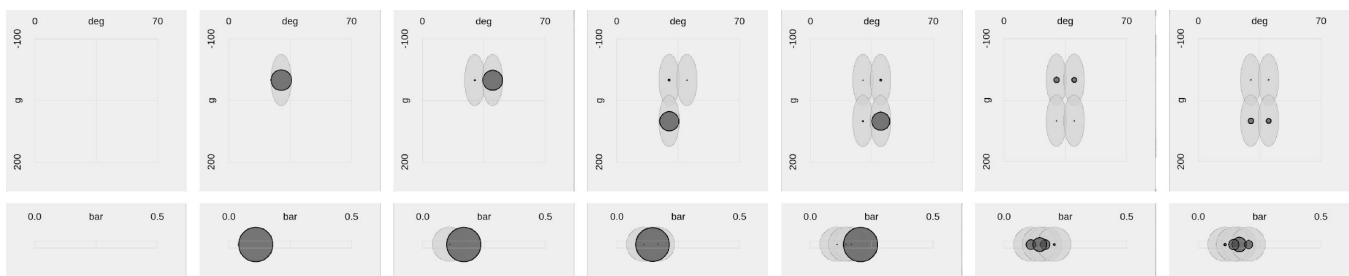


Fig. 6. Example of activation of GM RFs (top row of graphs) and AM RFs (bottom row). In all graphs, the light gray ellipses represent the region of influence of RFs, while dark gray circles represent the current neurons activations. Upper row, from left to right: graph 1 shows the GM when training has to start. Graphs 2-5: the RFs are incrementally allocated when input is respectively $[40^\circ, 0g]$, $[50^\circ, 0g]$, $[40^\circ, 100g]$, $[50^\circ, 100g]$. Graphs 6-7: generalisation test, when the requested position is 45° , respectively with $0g$ and $100g$. Note that in this case the overlapping of RFs (due to the previous training), partially activate several GM neurons determining a cluster of active AM neurons used to estimate the desired pressure.

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