A new neural architecture based on ART and AVITE models for anticipatory sensory-motor coordination in robotics

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Abstract. In this paper a novel sensory-motor neural controller applied to robotic systems for reaching and tracking targets is proposed. It is based on how the human system projects the sensorial stimulus over the motor joints, sending motor commands to each articulation and avoiding, in most phases of the movement, the feedback of the visual information. In this way, the proposed neural architecture autonomously generates a learning cells structure based on the adaptive resonance theory, together with a neural mapping of the sensory-motor coordinate systems in each cell of the arm workspace. It permits a fast open-loop control based on propioceptive information of a robot and a precise grasping position in each cell by mapping 3D spatial positions over redundant joints. The proposed architecture has been trained, implemented and tested in a visuo-motor robotic platform. Robustness, precision and velocity characteristics have been validated.

1 Introduction

One of the topics in robotics is the problem of solving the inverse kinematics of redundant visuo-motor systems for reaching applications in real time. Most of the proposed solutions are based on close-loop control systems. They are highly dependent on the vision system and also need to track the entire robot arm end-effector trajectory. Although these control systems are continuously employed in robotic and good results are obtained [1], the sensory-motor coordination human system does not require the visual tracking of the joints whose propioceptive information is learning [2] during action-perception cycles, mainly during the child phase.

The main objective of this work is to give a solution for solving the inverse kinematics of robots, without the knowledge of the internal physical properties of the robot arm, such as joint lengths and rotation and translation thresholds of each joints. One algorithm giving that solution has the advantage of avoiding the continuous calibration of the system and simultaneously to be independent from the considered robotic platform. The information propiocetive will need to be learned by mapping the end-effector 3D spatial position, given by the vision system, and the joint positions configuration, given directly by the motor encoders.

One of the difficulties in this work was the necessity to have a totally well-mapped spatial-motor and motor-spatial information [3], using previous learnt information for anticipatory planning an action program. In this way, the actions are produced quickly without a close-loop. The final workspace of the robot arm is autonomously divided in small structures like learning cells. The proposed model aims at the idea of solving the accuracy sensory-motor coordination by means of two neural networks whose interconnection allows the anticipatory behaviour of the model. This interconnection is based on the self-organizing Adaptive Resonance Theory (ART algorithm) for discrete processes [4], and the AVITE model (Adaptive Vector Integration to End Point) [5]. The ART algorithm is a self-organizing neural network which has the ability of solving the stability–plasticity dilemma for the competitive learning phase. Uses of this algorithm to the proposed architecture will permit to carry out the described anticipatory behaviour. In the other hand the AVITE neural model, based on supervised learning, permits to map the spatial-motor positions in each learning cells. As results, the proposed work is capable to combine visual, spatial, and motor information for reaching objects by using a robot arm, tracking a trajectory in which the close-loop control is only carried out in each learning cell of the workspace. The proposed architecture has been implemented in an industrial robot arm and capabilities of robustness, adaptability, speedy, accuracy have been demonstrated for reaching tasks, including perturbations in the objective position.

2 Neural Model Structure: Self-organizing and Fast Mapping

The proposed architecture is based on two interconnected neural models that sequentially project the 3D final position (sensorial information) of the object to be grasped over the joint positions (spatial information) of the robot arm end-effector. This task is made in a predictive way by means of adaptive distribution of the workspace. The base of the control scheme is to generate random movements of the robot arm, whose end-effector position is detected and computed by a vision system and then the robot arm 3D workspace is divided into small cells in whose centres the precise position of the robot joints are well known, by means of the propioceptive information and one previous learning phase. It produces, in the operation phase, an anticipatory movement of the robot toward the centre of the cell in which the target is located. The supervised neural model based on the ART algorithm includes a vigilance parameter controlling the competitive learning and the final position and dimension of each cell. By means of a second learning phase, one neural weight map is obtained for each cell. Due to the lineal nature of the AVITE model, the spatial-motor projection is quickly computed and few steps close-loop control are required for accurate reaching tasks. The AVITE model projects the difference vector (*DV*), in visual coordinates between the current and desired position of the end-effector, over the incremental angular positions of the robot arm. Thus, the 3D visual distance inside the winner cell is reduced with high precision and fast operation. The general performance of the proposed model is represented in the scheme of the Fig.1.

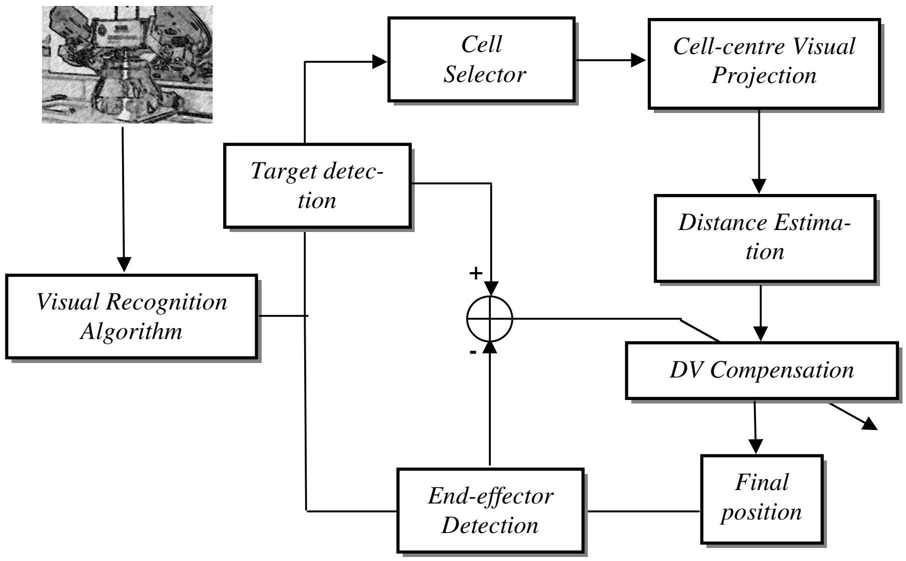


Fig. 1. General scheme of the neurocontroller. It is formed by two interconnected neural models to map the 3D workspace (non-supervised model) and to compensate the spatial error between the current and desired final spatial position (supervised AVITE model).

In this neural model, the vision system of the stereohead detects the position of the object to be grasped. The internal representation of that position will be the input to the cell selector module. By means of a competitive algorithm, this module calculates the cell in whose workspace is located the target. The projection of the visual position of the centre of the cell over the arm joint positions is achieved by the *cell-centre visual projection module*. Once the AVITE model has been executed, the difference between the centre of the cell and the desired position, in visual coordinates (*DV*), is estimated by means of the *distance estimator module*. Then, the *DV compensation* module reduces that distance by means of few robot arm movements and lineal projections. Finally, the produced error is used to update the neuron weights of the AVITE model. It will permit to detect if an unexpected situation happens or if a mechanical blocking in some joints of the robot arm is produced. In order to validate the behaviour of the proposed architecture operating in dynamic environments, perturbations to the target position have been considered and the performance of cells commutation when tracking moving objects is tested. The obtained results emphasize the emulations of human biological behaviour for the proposed architecture. In a human system the majority of the time for reaching objects is dedicated to the movement compensation due to possible perturbations in the measurements of both sensors: visual and propioceptive. The associative maps which are generated by the AVITE algorithm, permits to learn the gesture of the robots, including the mechanical faults of the robot system.

3 Non-Supervised Adaptive Generation of Learning Cells

The non-supervised neural model implemented in the proposed architecture is based on the ART2 model developed by Carpenter, et al. [4]. It is focused to the workspace division in spatial coordinates and to supply the anticipatory behaviour to the neural architecture. Each 3D region will be different and characterized by the position of its centroids and the Voronoi frontiers, implying the configuration of the final dimension of each cell. How the cellular structure is defined in the spatial frame, it will determine the number of steps and the precision or final error of the neural model for reaching tasks. The structure of the ART model allows to control the final cell configuration by means of one vigilance parameter and the learning trial number. The structure of the ART neural network is represented in Fig.2.

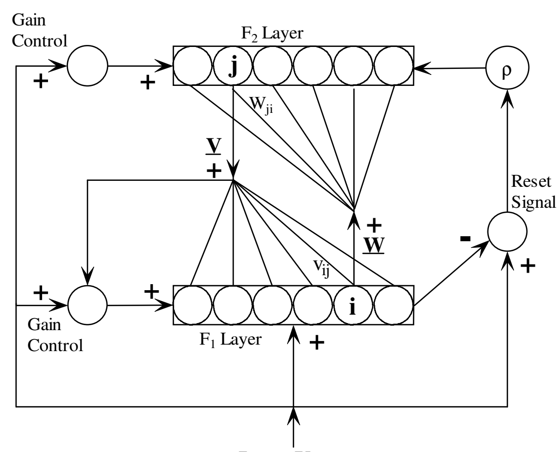


Fig. 2. ART structure for adaptive generation of learning cells. The input layer F_1 has the same dimension like the input vector; The neurons (centroids) of the output layer F_2 are the patterns to be classified; W_{ji} are the feed-forward connection weights; V_{ij} are the feedback connection weights; The *Gain Control* is used to get network stability by inhibition of activation control of the F_1 and F_2 layers; The *Reset Signal* is used to control the membership level of a pattern to the winner neuron in F_2 layer and, finally, ρ is the vigilance parameter.

In the learning phase, initially one random posture for the robot arm is generated and both end-effector spatial positions and target, referred to the robot arm coordinate frame, are computed by the vision system. Taking *D* the number of d.o.f. of the robot, each position is represented by the θ_v vector (*1xD* dimension) while its corresponding end-effector position is represented by P_{xyz} vector (*1x3* dimension). A ρ parameter permits to control the adaptive generation in every k learning step. In each trial, the P_{xyz} vector is the input to the network. The winner centroid wij^* is selected by the nearest to end-effector position in terms of Euclidean distance. Then, the value of each weight associated to these centroids will be updated by means of equation (1), starting from random initial values:

$$w_{ji}(k+1) = v_{ij}(k) = \frac{e_i(k) + w_{ji}(k) \times N_j(k)}{N_j(k)+1} \quad \textbf{(1)}$$

where $e_i(k)$ is the ith component of the input vector P_{xyz}; N_j represents the times that jth neuron of F_2 layer has been winner.

The process will be repeated until the convergence of the neuron weights of the ART map is reached. The ρ parameter will be compared, in each iteration, with the Euclidean distance between the new patron position and the winner cell centroid. This comparison will determine the generation of new cells or the updating of computed centroids. In the operation phase, when a target position is detected, the network selects the winner cell. Then, it will project that sensorial over the spatial position of the robot arm, by means of the learnt propioceptive information.

The next step will be to compensate the *DV* between the calculated current position of the robot arm and the desired position in sensorial coordinates. The cell generation permits to know the most favourable posture of the robot arm whose end-effector position is the nearest to the target. By adding the ART algorithm to the neural structure is possible its implementation in any robotic platform with independence of their internal dynamic models.

4 Neural Associative Maps for Sensory-Motor Transformation

The second neural model is dedicated to compensate the error in each cell. Every cell has an independent behaviour for the others, that is, if one cell is excited the others are inhibited. All the cells implement the spatial–rotation transformation. In order to control the robot arm, the neurocontroller must obtain the propioceptive data from the joints and visual information also according to the AVITE learning model from which is inspired. Fig.3. shows the scheme of the learning system, where *TPVs* is the desired spatial position of the arm; *PPVs* is the spatial position of the cell centre; *PPVm* is the angular position of robot arm joints; *DVs* is the difference between *TPVs* and *PPVs*; and *DVm* is the result of the transformation between spatial and rotation increments.

When a cell is excited, the centre of the cell applies its content into PPVm and *PPVs* vector. The *DVs* vector calculates the difference between the centre of the cell and the desired position. The *DVs* is transformed into the *DVm* through a set of neurons. The resulting increments are modulated by a *Go(k)* signal and the results integrated into the *PPVm*.

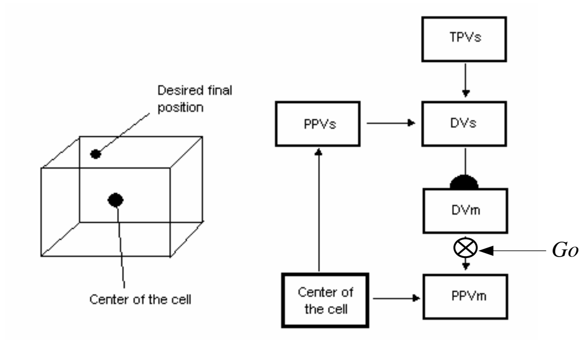


Fig. 3. Structure of the sensory-motor transformation in each learning cell, based on the AVITE fast mapping in spatial (visual) coordinates. The centre of the cell stores the spatial coordinates and the motor coordinates in that point.

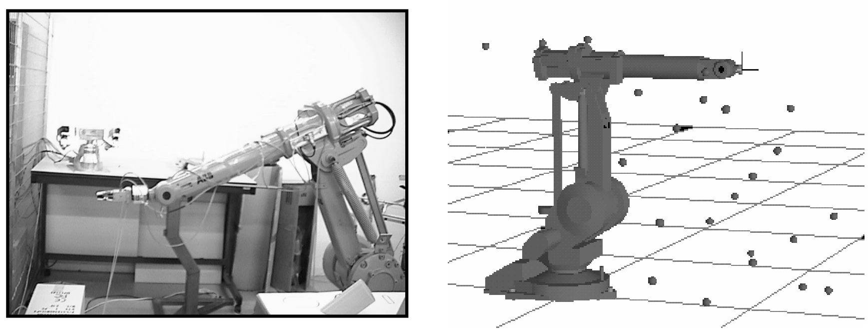
The learning phase is based in the knowledge acquired in action-reaction cycles. During this phase, random increments are introduced in the *DVm* vector, the system produces these movements and its spatial effect is taken over the *DVs* vector. In this way, the neuron weights, given by ***W*** matrix, are updated by means of the Gradient Descent optimization algorithm. The compensation of the position error produced by the *DV* will be made by the expression (2):

$$\Delta\overline{\theta} = W \cdot \Delta\overline{S} \tag{2}$$

where $\boldsymbol{\Delta\theta}$ vector computes the incremental values to be added to the current position of the robot arm in spatial coordinates, and $\boldsymbol{\Delta S}$ stores the *DV* in visual coordinates. Each cell generates a neuron weight matrix with a dimension equal to the size of sensorial coordinates (x, y, z) multiplied by the size of spatial coordinates (number of degrees of freedom of the robot arm). Thus, the dimension of ***W*** matrix will be *3xD* for each N^{th} cell, being *N*, the number of the learning cells, and *D* the robot arm d.o.f. The linearity of the equation (4) has the advantage of the easy implementation over a hardware device like *DSP* or *FPGA* and the fast computation of the spatial projection over the motor commands.

5 Results

The implementation of the proposed system has been carried out in a real robotic installation, as Fig.4a shown, formed by an industrial robot arm and the LINCE anthropomorphic stereohead with two colour cameras to simultaneously detect the objective (a small red sphere) and the end-effector robot arm (green label over the gripper). The implementation of the proposed neural architecture has been focused on robotic applications for reaching and tracking targets. The base, elbow and shoulder joints have been considered for the experimentation. Firstly, the generation of cells inside the robot workspace has been carried out based on the described ART neural algorithm. Fig.4b shows a graphical representation of the results for 600 trials and ρ=0.18 over the simulation software developed by DISA, Spain [6]



a) *b)*

Fig. 4. Robotic installation. (a) Visuo-motor robotic system formed by LINCE stereohead and one ABB-1400 robot arm. (b) Simulation of the centroid distribution by the ART algorithm is shown. For ρ = 0.18, 24 centroids have been autonomously generated.

To test the proposed model for reaching applications without perturbations several experiments have been carried out. In Table 1, the most relevant results are shown. In it, the behaviour of the model is compared with the number of generated cells and the final error reached, which is given by (3):

$$E(k) = \sqrt{\sum_{i=1}^{3} \left(T\arg et_i(k) - CurrentPosition_i(k)\right)} \quad (mm.) \tag{3}$$

Table 1. Experimental scenarios for reaching tasks. Different ρ parameters, target positions and desired errors have been considered. In all cases Go=1; The end-effector initial position was {900,100,400} and the target positions were T1={100;900;1000} and T2={300;-900,800}. The influence of the ρ parameter in the final precision and in the time-to-reach can be observed

ρ	error (mm)	target (mm)	cells	time (sec.)	ρ	error (mm)	target (mm.)	end-effector final position (mm.)	Time (sec.)
0,12	8,6	T_1	53	3,4	0,13	<1	T_1	{100,5; 900,1;1000,6}	6,0
0,16	7,5	T_1	27	3,4	0,13	<5	T_1	{102,3; 900,5;1002,9}	5,2
0,18	9,4	T_1	21	3,5	0,13	<10	T_1	{104,9; 901,1;1006,2}	4,8
0,12	6,7	T_2	53	3,3	0,13	<1	T_2	{299,6;- 900,0;800,3}	3,2
0,16	7,0	T_2	27	5,5	0,13	<5	T_2	{301,5;- 900,7;799,2}	2,9
0,18	5,9	T_2	21	4,5	0,13	<10	T_2	{294,0;- 900,2;804,1}	2,9

The obtained results for reaching tasks have been compared with other close-loop neural architectures in the same platform [7]. In this case, times to reach the object are reduced about 60%.

To test the behaviour of this architecture when unexpected variations in the target position are produced, experiments with instantaneous displacements of the object have been carried out from $P_1=\{1000;500;900\}$ to $P_2=\{700;-900;400\}$. The results are shown in Fig. 6 and 7. In this case, the object position varies from cell Nº3 to Nº35. Thus, the cell commutation procedure is achieved and the movement compensation inside the second cell is computed by means of the learnt inverse Jacobian matrix which was learnt for that cell.

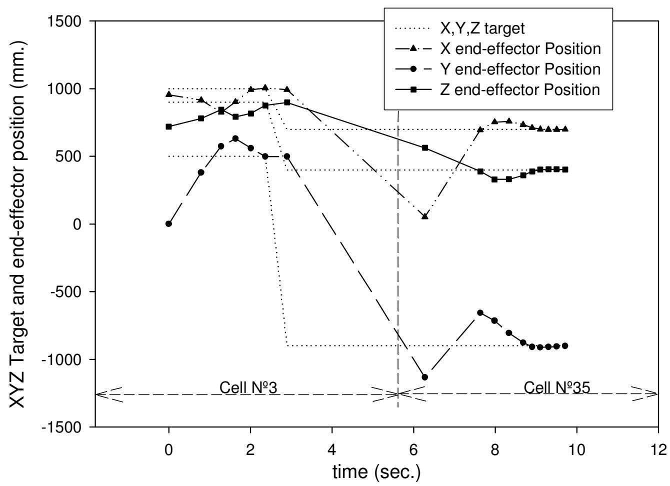
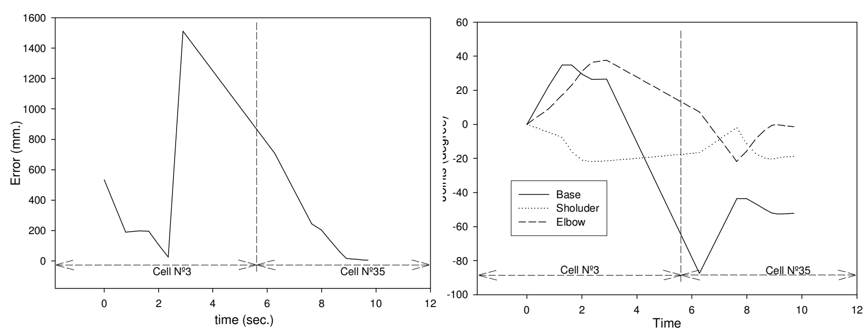


Fig. 6. Evolution of the robot arm end-effector to reach the object with perturbations



a) *b)*

Fig. 7. Evolution of (a) the error and (b) the robot arm joint positions. Because the proposed architecture allows to control the cell commutation when perturbations happen, the error is quickly decreased by means of the open-loop positioning in the centre of every cell, the specific neural weight matrix for each cell and the lineal characteristics of the AVITE model.

Finally, to test the capabilities of the proposed architecture for tracking tasks, constant movements of the object have been generated and the algorithm has been executed. Normally in this case, several commutations of cells are produced and small movement compensations are generated inside each cell of the 3D spatial trajectory. An appropriated filtering in the space of the joints allows to smooth abrupt variations of the end-effector position. Fig. 8 and 9 show the obtained results for tracking tasks.

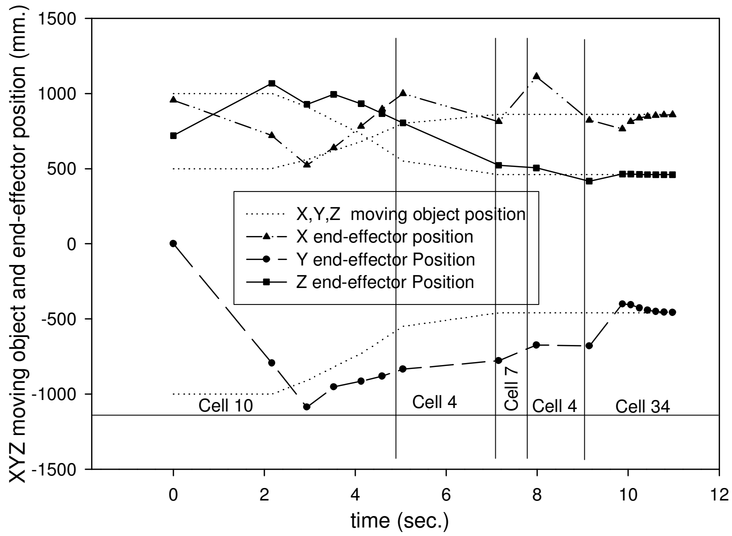
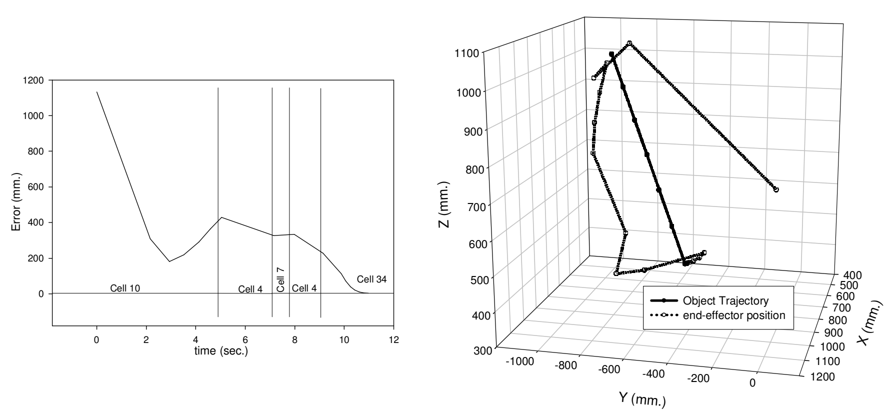


Fig. 8. Evolution of the 3D end-effector position for tracking an object which is moving with constant velocity of 7,6 cm/sec. Five changes of cells are produced and the proposed architecture, quickly compute the next position by means of the associated weight matrix.



a) *b)*

Fig. 9. Evolution of (a) the error in spatial coordinates and (b) the 3D trajectory of the robot arm end-effector and the moving object.

6 Conclusions

In this paper a neural architecture based on human biological behaviour has been presented and the obtained results have been analysed for robotic reaching and tracking applications with a head-arm system. The 3D spatial division of the robot arm workspace in learning cells is proposed and is solved by means of a self-organizing neural algorithm based on the ART2 model. Indeed, in this process the propioceptive information is learnt. The produced error by the discrepancy between each cell-centre and the target position is compensated by means of an AVITE (*Vector Associative Map*) adaptive architecture. It projects the difference vector of visual position over incremental joint positions of the robot arm. The obtained results over a robotic platform have demonstrated that final error in reaching applications can be very low, taking into account the robustness and fast operation of the model.

Acknowledgments

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