Sensory-motor control scheme based on Kohonen Maps and AVITE model

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Abstract. In this paper a control scheme is proposed for anticipatory and discrete event sensory motor driven. The control system elaborates a sensory-motor program based on its internal data and a high level objective. The global system implements several biological models in each one of its subsystems. One of the novelties of this work is the structure of the sensory-motor algorithms which are based on cell distributions of the sensorial spaces. Indeed, the correspondence between cells and the sensorial spaces is distributed by Kohonen maps. This control scheme has been tested on a robotic platform constituted by an industrial robot and a stereohead. More relevant results are presented and analyzed in this paper.

1 Introduction

Today, a lot of work has been made to achieve the performance of movement, and skills of the humans in reaching, grasping and manipulation tasks. It is important to emphasize the models of the control system in humans developed by Grossberg [1], Bullock [2], Greve [3] and Guenther [4]. These models were adapted by Guerrero-González, Pedreño-Molina and Lopez-Coronado [5], for robotics platforms formed by a robotic hand, arm and a stereohead. Flexibility, adaptability, real time response and learning capabilities were demonstrated with that platform. Initially, these authors implemented the DIRECT model for spatial positioning. This model is characterized for several control loops, based on visual information and propioceptive information. One of the difficulties in this work was the necessity to have a totally well-mapped spatial-motor and motor-spatial information, also the close-loops produce slow responses in the positioning tasks. So the proposed model uses previous learned information for anticipatory planning an action program. In this way, the actions are produced quickly without a close-loop, and after the movement, an assessment of the task is made which permits to update the learning information of the neural controllers.

2 Characteristics and Benefits of the Proposed Control Scheme

The proposed controller implement several neuro-biological models proposed in the CNS research group of the Boston University, which are the base of the real time control system proposed. This controller, also implements Kohonen maps for autonomous organization of the neural structures of the neurocontroller. This control architecture for reaching carries out the cinematic control of a redundant robot arm guided by the visual information given by acquisition system of the LINCE[1] stereohead. The most important characteristic is that the neurocontroller does not need the robotic model of the experimental platform, and therefore, does not need to calibrate the system. All the necessary knowledge of the robotic platform is learned by means of action – reaction cycles from visual-motor trials. This neural architecture has been developed integrating a set of neural networks of some discovered biological functions carried out by the animal neural system. This architecture is characterized by:

- *Integration of multiple algorithms*. This architecture integrates different algorithms which execute concrete tasks. The consistency of the communication between these algorithms warrants the global robustness of the architecture.
- *Parallel*. The architecture is able to execute multiple algorithms, and simultaneously each algorithm is executed in parallel.
- *Relocation of resources*, dynamically. With the purpose of facilitating the image processing, the system is able to lead the visual sensors in order to find a better point of view which alleviates the visual processing load.
- *Active*. The global system has active perception capability.
- *Reactive*. It means the capability to be data-driven by environment changes.
- *Predictive behaviour*. The final position is reached in one anticipatory movement.

In the structure of neurocontroller, several real-time concurrent processes are developed for the performance of the different tasks intervening in the final reaching operation. This architecture contains three main modules, shown in figure 1, which correspond with the interconnected processes: spatial internal representation module, stereohead controller and robot arm controller.

3 Sensory-Motor Coordination Neural Structure

The structure of the proposed model is based on two interconnected neural models which in a sequential way, 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. The base of the control scheme is to discretize with random positions the 3D workspace of the robot arm in small cells in whose centre the precise position of the robot joints are well known, by means of the propioceptive information and a previous learning phase. Then, the non-

[1] LINCE Stereohead has been entirely developed by NEUROCOR Research Group, Spain

supervised neural model based on Kohonen maps starts a competitive algorithm to select the winner cell and so to obtain, in this first step, the nearest position of the arm in which the reaching error is minimum. That is the centre of the winner cell.

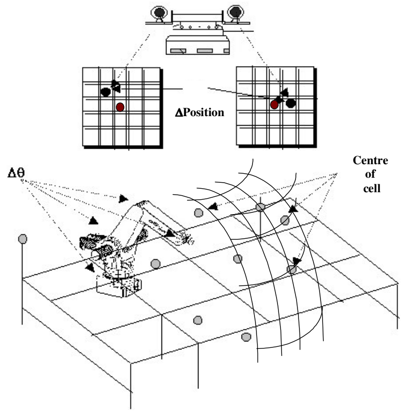

Fig 1. This scheme shows the scene for the control system. The 3D space is divided into small learning cells. So, the system obtains several sensorial-motor coordination maps in order to achieve precise reaching operations in open-loop mode.

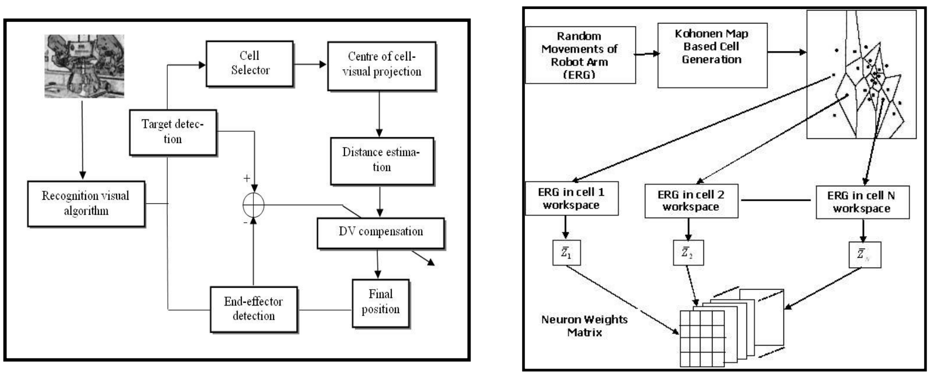

Fig. 2. The scheme of the neurocontroller (left) is formed by two interconnected neural models for mapping the 3D workspace (non-supervised model) and for compensating the spatial error between the current and desired final spatial position (supervised AVITE model). In the scheme of neurocontroller learning phase (right) a multi-dimension neuron weights matrix is generated by means of the contribution of the sensory-motor associative maps generated in each cell of the Kohonen map.

By means of a second learning phase, one neural weight map is obtained for each cell. It'll permit a fast projection of 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. Once the centre of the cell has been reached, a supervised neural model based on AVITE (*Adaptive Vector Integration To End Point*) architecture is executed in order to reduce the 3D visual distance inside that cell with high precision and fast operation. The general performance of the proposed neural model and block scheme of the learning module are represented in figure 2.

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, the target is located. The projection of the visual position of the centre of the cell, over the arm joint positions is achieved with the centre of cell visual projection module. Once the non-supervised 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 distance reduction by means of robot arm movements is made by the *DV compensation* module. Finally, the produced error is used to update the neuron weights of the AVITE model. It'll permits to detect if an unexpected situation happens or if a block in some joint of the robot arm is produced.

In a first learning level, an ERG (*Endogenous Random Generator*) module carries out movements of the robot arm along the 3D workspace. The non-supervised neural model creates non-uniform cells by means of the displacement of initial positions of centroids toward final positions in which the possibility distribution of robot arm position is higher. Then, the final neuron weights are obtained from each cell bay means of a new ERG phase but, in this case, it is only carried out inside the workspace of each cell. Each cell generates a neuron weights matrix with a dimension equal to the size of sensorial coordinates (x, y, z) by the size of spatial coordinates (number of degrees of freedom of the robot arm). So, the dimension of W matrix will be Nx3xD, being N, the number of the Kohonen map cells and D, the robot arm d.o.f.

3.1 Non-supervise Generation of Cells

The non-supervised neural model implemented in the proposed architecture is based on Kohonen maps and it is oriented to workspace discretization. Each 3D region will be different and will be characterized by the position of its centroid and the Voronoi frontiers. For learning sequence initially, *N* centroids w_{ijk} are placed in random positions.Then, the robot arm movements from the ERG module gives, by means of the visual detection algorithm, the 3D position of the end-effector in each movement. It'll be represented by θv vector. Taking *D* the number of d.o.f. of the robot, each position will be represented by the vector $(\theta_1, \theta_2, \ldots. \theta_D)$. In each trial, the winner centroid *wijk** is selected. It'll correspond to the nearest to end-effector position. Then, the value of each weight associated to that centroids, will be updated by means of next expression:

$$w_{ijk}(t+1) = w_{ijk}(t) + \frac{1}{t} \cdot \left[\theta_v(t) - w_{ijk^*}(t)\right] \qquad \textbf{(1)}$$

The process will be repeated *T* times until the convergence of the neuron weights of the Kohonen map was reached. The accuracy inverse cinematic of the robot in the centre of the cells is calculated by and adjusting algorithm. It moves the calculated neuron weights toward the nearest position of the training phase in which the joint position is known. Finally, the 3D Voronoi frontiers are generated over the map. In the operation phase, when a target position is detected, the algorithm calculates by computing the minimal distance, the cell in which it is placed. Then it'll project that sensorial position over the spatial position of the robot arm, by means of the propioceptive information learned by the ERG module. The next step will be to compensate the DV between the calculated current position of the robot arm and the desired position is sensorial coordinates.

3.2 Neural Associative Maps for Sensory-Motor Transformation

The second neural model is dedicated to make that error compensation. Each cell has an independent behaviour of the others, that is, if one cell is excited the others are inhibits. Each cell implements 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. Figure 3 shows the scheme of learning system.

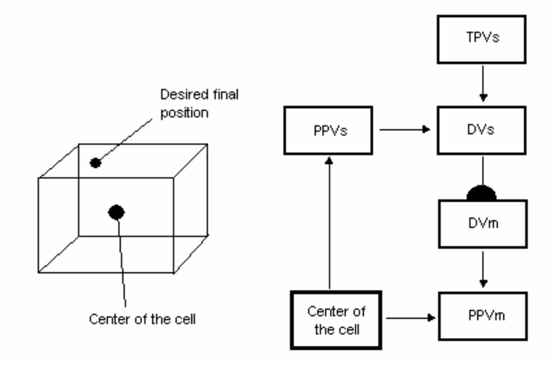

Fig. 3. Learning cell algorithm. The elements of the cell learning algorithm are: TPVs (desired spatial position of the arm), PPVs (spatial position of the cell centre), PPVm (angular position of robot arm joints), DVs (difference between TPVs and PPVs) and DVm (result of the transformation between spatial and rotation increments). The centre of the cell stores the spatial coordinates and the motor coordinates in that point.

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 integrated into the PPVm. 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, updating the neuron weights by:

$$z_{ijk}[n+1] = z_{ijk}[n] + \mu \cdot \left(DVm_i - \sum_j Z_{ijk}[n+1] \cdot DVs_j \right) \cdot DVs_j \qquad (2)$$

The expression for error position compensation produced by the DV will be:

$$\Delta\overline{\theta} = \overline{Z} \cdot \Delta\overline{S} \qquad (3)$$

where $\Delta\theta$ vector computes the incremental values to be added to the current position of the robot arm in spatial coordinates, and ΔS stores the DV in visual coordinates. The final reaching operation is separated in two movements. The *gross process* is carried out by means of mapping of three-dimensional spatial positions of prefixed points (centres of cells) and the end-effector position of the arm. The *fine approximation* is carried out by means of implemented AVITE model for learning the mapping between increments of arm joints and difference of position between present position (end-effector position) and desired position (target visual position).

4 Robotic Installation and Experimental Results

The implementation of the proposed system has been carried out in both simulation and real robotic installation, formed by the LINCE stereohead and a commercial ABB robot arm. In order to verify the capabilities of the proposed neural algorithm, the results have been analyzed.

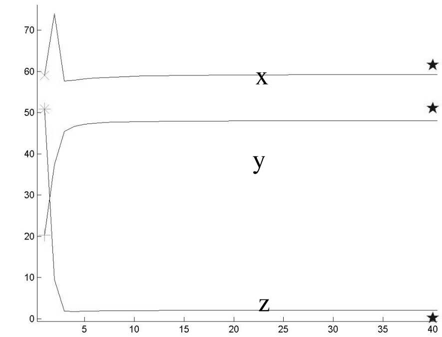

Fig. 4. This picture shows the iteration number of the non-supervised algorithm when the 3D centroid weight reach the convergence of final value of a random cell for 500 trials of learning position of the robot arm and 40 for the iterations of the non-supervised algorithm. Star symbols at the end of the training indicate the corrected position of the weight in order to give the nearest position in which the inverse cinematic is known.

The first set of trials has been focused to the generation of the 3D cells with different learning parameters. Figure 4 shows the evolution of the neuron weights of one random cell and figure 5 shows the 3D Voronoi regions projected over XY and XZ planes.

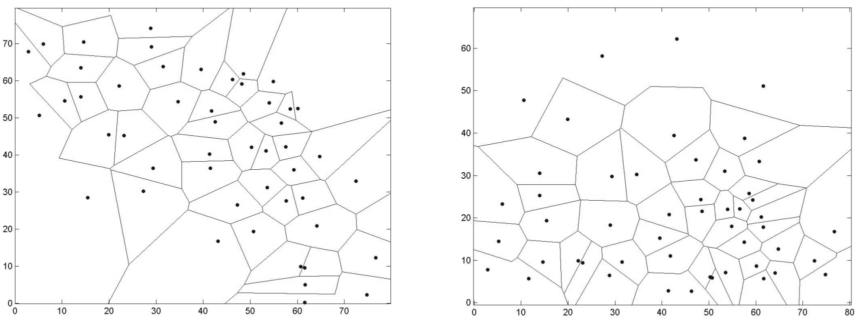

Fig. 5. Results of the implemented algorithm for 3D Voronoi regions generation, represented by 2D projections: XY for right picture and XZ for the left one. The selected parameters have been N=20 and 500 learning positions of the robot arm. The number of cells is greater in spatial coordinates where the robot arm has a higher possibility of being configured.

The implemented neural model for cells generation starts from an initial parameter *N* indicating the final number of cells in which the workspace will be segmented. This parameter in no critical for the accuracy of a reaching operation. However, a high value for N implies a greater time for the computing of the Kohonen map, but the number of cells which will have the same value for some neuron weights will be higher. To test the performance of the AVITE supervised algorithm for compensating the DV in visual coordinates by means of calculating the incremental position for the motor commands, a learning phase in each cell is carried out. The result will be a 3x5 matrix of neuron weights Z for each cell. In the real experiments, a 5 d.o.f configuration for the robot arm has been selected.

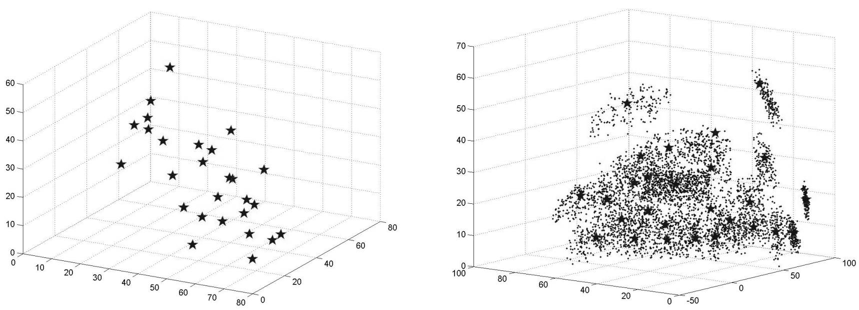

Fig. 6. On the left, the final position distribution of the centroids of the Kohonen map is represented. On the right the results for the AVITE learning phase is shown.

Figure 6 shows the final position of the centre of the cells and the end-effector spatial points resulting from the learning phase. Finally, results obtained from real platform have show errors about 2% in visual coordinates in cells near the normal workspace of the robot arm. The final position for the robot arm is obtained in two steps but executed in only one. For each cell, random movements of the robot arm joint positions are generated inside the Voronoi region of the cell. The weights matrix is obtained from the mapping between the incremental spatial positions and the produced incremental visual positions.

4 Conclusions

In this paper a neural architecture based on human biological behaviour has been presented and the obtained results have been analyzed for robotic reaching applications with a head-arm system. Open-loop behaviour for reaching operations allows to carry out precise and fast reaching operations and the possibility of remote execution, due to it needn't visual feedback during the reaching movement. The 3D spatial segmentation of the robot arm workspace is solved by means of a non-supervised neural algorithm based on Kohonen maps. In the same process of cells generation the propioceptive information is learned. The produced error in the reaching operation using the position of the cells is compensated by means of an AVITE (*Vector Associative Map*) adaptive architecture which projects the difference vector of visual position into incremental joint positions of the robot arm. The obtained results have demonstrated that final error in reaching applications can be very low, taking into account the robustness and fast operation of the model.

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