Adaptative Reaching Model for Visual-Motor Mapping Applied to Redundant Robotic Arms

Juan Luis Pedreño-Molina[1], Antonio Guerrero-González[2], Juan López-Coronado[2], and Cecilia Laschi[3]

[1] Department of Information Technologies and Communications, Technical University of Cartagena, Campus Muralla del Mar s/n, 30.202 Cartagena, Spain.
Juan.Pmolina@upct.es

[2] Department of System Engineering and Automatic, Technical University of Cartagena, Campus Muralla del Mar, s/n, 30.202 Cartagena, Spain
{antonio.guerrero , jl.coronado}@upct.es

[3] Scuola Superiore Sant'Anna, Via G.Carducci, 40
56127, Pisa, Italy
c.laschi@mail-arts.sssup.it

Abstract. Most of control algorithms for robotic reaching and grasping tasks, from visual and motor perception systems, are based on feedbacked systems. It supposes a limitation for the performance of remote reaching applications and for the robustness of the system. In this paper, a very robust learning-based model for visual-motor coordination is presented. This architecture is based on how the human system projects the sensorial stimulus onto motor joints and how it sends motor commands to each arm in open-loop mode, starting from initial visual and propioceptive information. The self-organizing characteristics of this model have allowed to obtain good results on robustness, flexibility and adaptability in both simulation and real robotic platforms. Coordination of the information from different spatial representations is based on VAM (*Vector Associative Maps*) algorithms, developed in CNS (Boston University). Indeed, compatibility requirements and system adaptation capability, give a solution for control of redundant systems.

1 Introduction

Motor equivalence computations allow humans and other animal to flexibly employ an arm with more degrees of freedom than the space in which it moves to carry out reaching tasks under conditions that may require novel joint configurations. Any three-dimensional point can typically be reached by one arm using multiple motor means. Psychophysical studies of reaching, handwriting and drawing have shown that the spatial trajectory is more invariant that the joint rotations, or than force-time patterns [1], [3].

The need for spatial representation in the control of motor-equivalent behaviors is not merely a matter of defining target movements with respect to an external 3D space. Manly it concerns in how internal representations of 3D space can be used to control motor equivalent actions. These internal representations are expressed in both head-centered coordinates and body-centered coordinates since the eyes move within the head, whereas the head, arm, and legs move with respect to the body. Several researches of CNS (Cognitive and Neural Systems) of Boston University, have proposed different models of human neural structures, involved in target reaching tasks. These models are based on VAM (Vector Associative Maps) architectures and explain how the visual-motor system projects the sensorial stimuli onto motor commands in redundant systems. One of these architectures is named AVITE (Adaptative Vector Integration To End Point). In [2], a model for visuo-tactile-motor integration in robotic reaching and grasping task, using AVITE models is described.

The goal of this work is to design a system which is capable of autonomously learning to combine visual, spatial, and motor information in a way that supports motor equivalent reaching behaviors. In particular, it can learn an inverse kinematic transformation from directions in 3-D space to joint rotations that are capable of moving the arm in these spatial directions. In order to increase the capabilities of robustness, adaptability and flexibility, as well as to reach the target in an open-loop way, an adaptative process based on learning cells has been designed. These characteristics give to the system the capability of remote operation for precise reaching tasks.

2 Characteristics and Description of Propose Neurocontroller

The neurocontroller implemented on the robotic platform follows neuro-biological models proposed in the CNS (*Cognitive and Neural Systems*) research group of the Boston University. Grossberg, Bullock and others, proposed some models of the animal neural system related with the reaching process. Adaptation of these models to redundant robotic platforms has permitted to develop a neural control architecture for reaching tasks which integrates several perception systems (visual, tactile and propioceptive).

The relationship between both representation spaces is carried out by means of VAM (Vector Associative Maps) adaptative algorithms. It consists of a self-organizing neural model that quickly projects sensorial onto motor information in robust mode. 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 neuro-controller 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 form visual-motor trials. This neural architecture has been developed integrating a set of neural network of some discovered biological function carries out by the animal neural system. This architecture is characterised by the following capabilities:

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

- *Integration of multiple algorithms*. This architecture integrates different algorithms which execute concrete task. 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 simultaneously in parallel.
- *Relocation of resources, dynamically*. With the purpose of facilitated 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 the active perception capability.
- *Reactive*, meaning the capability to be data-driven by environment changes.

In the structure of neuro-controller, 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, which correspond with the interconnected processes: spatial internal representation module, stereohead controller and robot arm controller.

2.1. Spatial Internal Representation Module

This module carries out an internal representation on two reference frames, a head-centred and a body-centred frame, of the position of visually selected objective (robotic arm end-effector or object). It captures the images, processes the data based on colour parameters and transmits the selected information by means of visual algorithm and visual system.

This algorithmic module has been developed, starting from neural network models of how the brain learns spatial representation, with which to control sensory-guided and memory-guided eye and limb movements. These spatial representations are expressed in both head-centred coordinates and body-centred coordinates, because the eyes move within the head, whereas the head, arms, and legs move with respect to the body. The structure of this spatial representation module is based on biological models, which explain how animals do this representation. In a binocular system, it is possible to represent the position of an objective from the geometrical properties of the head: version, vergence and elevation.

2.2. Stereohead controller

This module implements a visuo-motor control for the stereohead ocular joints. This controller moves the neck and ocular joints of the stereohead. It positions the stereohead in a situation of symmetric vergence, which is the most favourable position for visual processing and position representation.

For the control of the ocular joints a AVITE algorithm has been used. Figure 1 summarises the main components of the neural head controller.

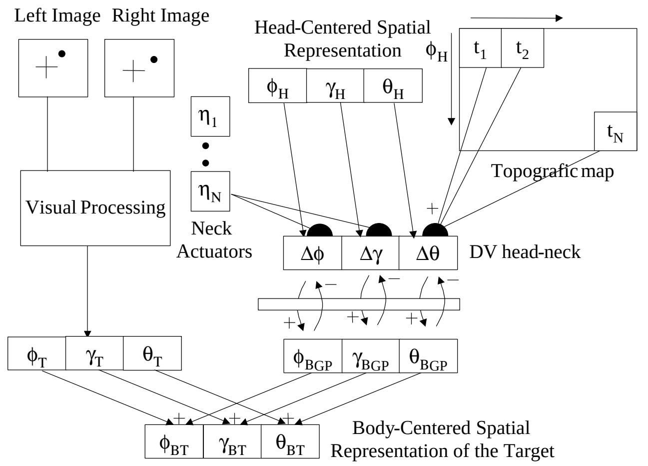

Fig. 2. Implementation scheme of neuro-controller. In this figure the blocks into the controller are shown, including the real-time processes that have been implemented

The TPV vector (*Target Position Vector*) represents the desired final position of the head. When an action of foveation is carried out, the Body-Centered Spatial Representation vector of the target point is charged in the TPV. The PPV vector (*Present Position Vector*) represents the real position of the head, this vector is charged with the Body-Centered Spatial Representation vector of the gaze point. The difference vector, ΔV_T, continuously compute the discrepancy between present position vector and the desired target position vector. The output of the difference vector is converted into commands to the ocular joints. This conversion is carried out in a transformation with fixed weights. The neck controller has the function of maintaining the head structure in the best position in order to perform the visualization of the targets. The optimal position is that in which the head has zero version angle and zero elevation angle. To resolve this problem, a self-organizing neural network based on VITE model has been used. The mapping between version variable (ϕ_H) and a neck compensation variable (α_{pan}) is established by means of an adaptative weight.

$$\Delta a_{pan} = z_{pan} \cdot \Delta f_H \quad \textbf{(1)}$$

In the learning phase, ERG (*Endogenous Random Generator*) module achieves panoramic movements with random values of incremental rotation angles. Then, the ocular controller module fix the target and the spatial representation module calculates the new incremental values for ($\Delta\phi_H$) with respect to reference situation (ϕ_H=0).

2.3. Robot Arm Controller

This module carries out the positioning of the arm over a point marked by the stereo-head. This algorithm receives the absolute internal representation of the end-effector position and the absolute internal representation of the point marked by the stereohead, and determinates in one step the angular commands to the arm joints to reach the desired point.

A neural controller the visual positioning of a robot manipulator has been developed. This neural controller is based in the biologically inspired AVITE model, which gives an explication of how animals do the control of their limbs. The resulting controller gives a solution to the motor equivalence problem and has the adaptation capability to the lose of degrees of freedom maintaining its performance in spice of a suddenly internal change. Also, this neural control algorithm has the capability to perform without additional learning, reaching tasks with tools of variable lengths, with distortions of visual input, and also has the capability to perform blind reaches. All the workspace of the robot arm has been divided in cells. A scheme of this algorithm is shown in figure 2.

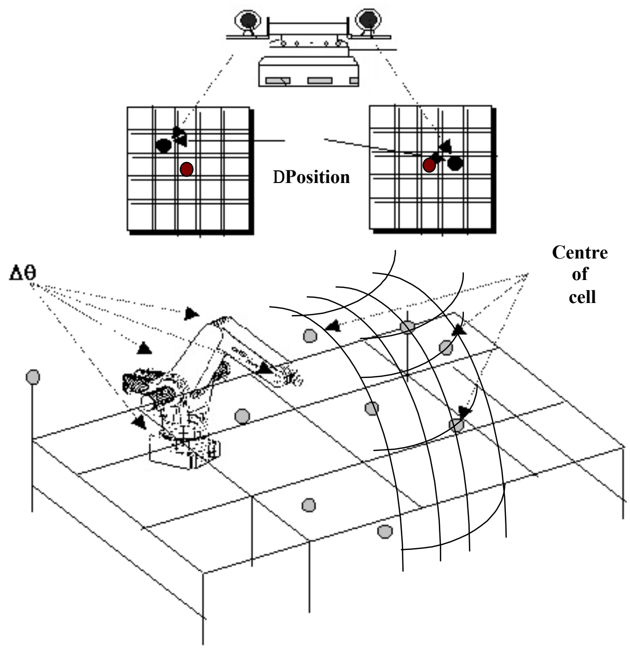

Fig. 2. This scheme shows the scene for learning process. The 3D space is divided into small learning cells. So, the system obtains several sensorial-motor coordination maps in order to achieve precise reaching operations in open-loop mode.

3 Sensorial-Motor Coordination based on Learning Cells

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 arm/hand subsystem, the neuro-controller must obtain the propioceptive data from the joints and visual information also according to the VAM learning model from which is inspired. Figure 3 shows the scheme of learning system.

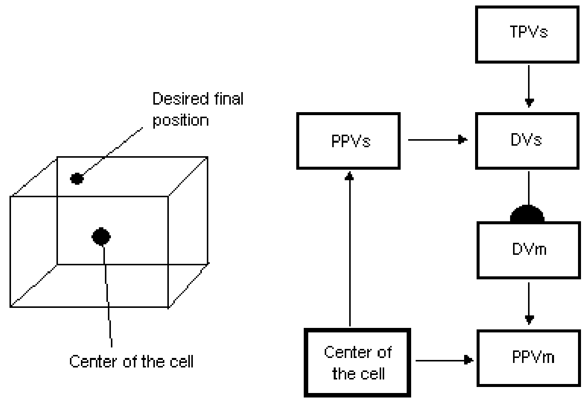

Fig. 3. Learning cell algorithm. The elements of the cell algorithm are: TPVs (desired spatial position of the arm), PPVs (spatial position of the cell center), PPVm (angular position of robot arm joints), DVs (different between TPVs and PPVs) and DVm (result of the transformation between spatial and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

When a cell is excited, the center of the cell applies its content into PPVm and PPVs vector. The DVs vector calculates the difference between the center 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. In this way, the neuron weights are updated by the equation:

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

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 VAM 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). The specifications of this neuro-controller depend strongly of the number of cells that are prefixed, the dimension of each cell and the learning trials.

4 Experimental Results

The implementation of the proposed system has been carried out in both simulation and real robotic installation. Simulation results - figure 4 -have allowed to verify the capability of the system for being applied to different redundant robotic systems.

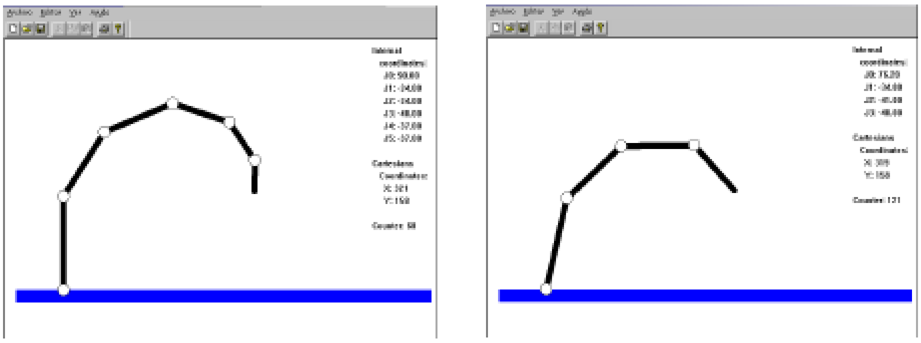

Fig. 4. Simulation processes in redundants platforms for reaching one prefixed spatial point

The experimental tasks were developed in a real robotic installation - figure 5-, formed by LINCE stereohead (5 d.o.f), robotic DEXTER[2] (7 d.o.f) arm and MARCUS hand (2 d.o.f). Initially, vision system detects the specified object and the end-effector, based on colour information. Then, the spatial representation of both points is calculated. Finally, the neuro-controller projects that information over motor joints and plans the gross and fine movement, in order to reach and grasp the object

Fig. 5. This picture shows the robotic installation. The communication between neuro-controller, vision system and robotic arm-hand is based on TCP/IP protocol

[2] DEXTER and MARCUS robots belong to ARTS Laboratory (Pisa, Italy)

The experiments have been focused to evaluate the characteristics of the neuro-controller about *robustness* (repeatability and affordability), adaptability, a*daptability* (the same task with different objects) and *flexibility* (the same task in variable environment conditions). Next tables show the obtained results in each category.

Table 1. Robustness

Object Position [cm]			Hand Position [cm]			Pos.error [cm]	Result
x	y	z	x	y	z		
67,99	-15,84	-3,45	67,53	-13,74	1,29	2,15	Success
67,99	-15,84	-3,45	68,04	-13,72	1,68	2,12	Success
67,99	-15,84	-3,45	67,88	-13,76	1,74	2,08	Success
67,99	-15,84	-3,45	67,96	-13,72	1,72	2,12	Success
67,99	-15,84	-3,45	67,82	-13,8	1,69	2,06	Success

Table 2. Adaptability. Reaching and grasping of objects with different shaps and dimmensions, in the same place

Trial	Object	Object Position [cm]			Hand Position [cm]			Result	Pos. Error [cm]
		x	y	z	x	y	z		
1	Big Cylinder	67,99	-15,84	-3,45	68,039	-15,451	2,035	Success	0,39
2	Big Parallelepiped	67,99	-15,84	-3,45	68,867	-12,776	1,844	Success	3,19
3	Big Cube	67,99	-15,84	-3,45	70,281	-10,906	0,22	Fail	5,44
4	Little Cylinder	67,99	-15,84	-3,45	68,094	-12,279	1,412	Success	3,56
5	Little Sfere	67,99	-15,84	-3,45	66,954	-13,684	0,64	Fail	2,39
6	Little Cube	67,99	-15,84	-3,45	67,079	-13,768	0,555	Success	2,26

Table 3. Adaptability. Reaching and grasping the same object in different places of the same learning cell, evaluating the error in positioning the arm.

Trial	Object Position [cm]			Hand Position [cm]			Result	pos. Error [cm]
	x	y	z	x	y	z		
P1	78,6	5,35	-4,32	81,66	4,22	-0,6	Success	3,26
P2	79,03	13,06	-2,92	81,05	12,41	-0,26	Success	2,12
P3	78,4	0,95	-3,24	81,42	-1,79	-0,18	Fail	4,08
P4	85,92	4,75	-5,44	86,62	1,1	-2,12	Success	3,72
P5	72,15	6,2	-4,67	75,91	5,27	0,86	Success	3,87
							Average	3,41
							Variance	0,78

Table 4. Adaptability. Reaching and graspin the same object, moving the object from a cell to another cell, after a learning phase of 10 positions

Trial	Cell	Object Position [cm]			Hand Position [cm]			Result	Pos.error [cm]
		x	y	z	x	y	z		
1	First Cell	79,9	6,78	-4,32	80,77	3,7	-0,23	Success	3,20
2	First Cell	79,9	6,78	-4,32	80,48	4,04	0,25	Success	2,80
3	First Cell	79,9	6,78	-4,32	80,54	3,86	0,34	Success	2,99
4	Second Cell	76,4	33,97	-3,65	76,33	32,27	1,79	Success	1,70
5	Second Cell	76,4	33,97	-3,65	76,7	32,67	1,89	Success	1,33
6	Second Cell	76,4	33,97	-3,65	76,58	32,58	1,59	Success	1,40
								Mean Variance	2,24 0,85

Table 5. Flexibility. Evaluationg the system performance, moving the LINCE stereohead to another position and after a previous learning phase. This new srelative situation between robotic head and hand/arm is showed in figure 6.

Trial	Object Position [cm]			Hand Position [cm]			Error Position	Result
	x	y	z	x	y	z		
1	77,4	0,85	-3,12	79,18	-0,21	0,94	2,07	Success
2	77,4	0,85	-3,12	78,62	-0,33	0,94	1,70	Success
3	77,4	0,85	-3,12	79,28	-0,43	0,94	2,27	Success
4	77,4	0,85	-3,12	79,34	-0,35	0,94	2,28	Success
5	77,4	0,85	-3,12	78,88	-0,42	0,94	1,95	Success

Fig. 6. This control system is independent of the relative position between the robotic head and the robotic ar,m-hand. The obtained results demonstrate the flexibility of the system

6 Conclusions

In this paper the used methodology and techniques in the integration of the all HW and SW modules into a system for reaching tasks has been presented. It includes sensorial devices, actuator devices and a neuro-controller, implementing a biologically inspired model of sensory-motor coordination in reaching operations.

This multisensorial architecture can be applied to any redundant robotic system, starting from visual and propioceptive perception systems. The implemented algorithm is based on neurophisiological models, developed in CNS (Boston University) explaining how human behaviour is learning bay means of action-perception cycles. Indeed, the open-loop behaviour for reaching operations allows remote reaching applications.

The design specifications of the system have allowed to obtain good results in reaching and grasping tasks. In this way, the characteristics of robustness, flexibility and adaptability have been quantified and analyzed.

Finally, the implementation of this model in both simulation and real robotic installations, have demonstrated the capability of the system to be applied to any redundant system, given a solution for the equivalence motor problem in robotic platforms.

References

1 Bullock, D. and Grossberg, S. "Adaptive neural networks for control of movement trajectories invariant under speed and force rescaling," Human Movement Science, vol. 10, 1991, pp. 3-35.

2 López-Coronado, J., Pedreo-Molina, J.L., Guerrero-González, A. and Gorce, P. "A neural model for visual-tactile-motor integration in robotic reaching and grasping tasks". Volume 20, Issue 01. January 2002. pp23-31

3 Morasso, P. "Trajectory formation", In P. Morasso and V. Tagliasco (Eds.), Human movement understanding, Amsterdam: North Holland, 1986.