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A neural network architecture to learn arm motion planning in grasping tasks with obstacle avoidance

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SUMMARY

A In this article, we present a learning model that can control the kinematics motion of a simulated anthropomorphic arm in reaching and grasping tasks of a static prototypic object placed behind an obstacle of varying position and size. The network, composed of two generic neural network modules, learns to combine multi-modal arm-related information (trajectory parameters) as well as obstacle-related information (obstacle size and location). We based our simulation on the Via Point notion, which postulates that the reach motion planning is divided into successive positions of the arm. In order to determine these particular positions, some specific parameters have been extracted from an experimental protocol and constitute the pertinent parameters to be integrated into the model. This net of neural net determines the total path able to reach and grasp the prototypic object while avoiding an obstacle.

KEYWORDS: Reach motion; Obstacle avoidance; Neural network; Via point.

I. INTRODUCTION

In the last twenty years, motion planning has become one of the most important research topics in the field of robotics. More especially, the learning of the reach-and-grasp of an object by a robot is particularly difficult when an obstacle is placed between them. However, although several studies have shown the coupling of arm and finger movements during prehension,[1–3] the reach motion planning system in a cluttered environment can be handled separately. Thus, in this study, we consider the kinematics motion planning of the arm avoiding obstacles.

Two main methods arise from the literature. The "global" method uses complete information about the workspace and considers the whole degrees of freedom of the robot manipulator. In this case, the collision avoidance algorithms can be classified into an "off-line" algorithm, where the motion planning is carried out before the robot motion. The second method called "local" uses only incomplete information of the environment, and, is usually implemented in "on-line" algorithms. In this case, the robot checks potential collisions during the robot motion and activates a matched strategy to avoid the obstacle. Several authors have worked on this path planning problem involving obstacles and propose a large number of methods, such as potential-field,[4–6] or the wall-following method[7] that continues to follow the obstacle's contours until it has passed by the obstacle, and the goal-oriented recursive path planning method.[8] Koren and all used the APF method and assumed that each object in the environment exerts a repulsive force on the mobile robot whereas the goal exerts an attractive force on it. The resulting force is then computed at each step and used to determine the direction of movement for the next step. Noorhosseini and all, in the GORP method, tried to find the longest straight-path segment with a predetermined clearance from the obstacles in the direction that takes the robot closer to the goal.

Concerning the off-line algorithm,[9] Latombe proposed of distance maps method whose principle is to divide the space by grids with equal distance.[10,11] On the intersection of the grids are nodes which are marked with number of collision inspection. Many solutions have been proposed in the literature. As example, we can note the differential-geometry method based on the kinematics set forth.[12,13] In this case, Chirikjian used "virtual tunnels" through which the multi-body system has to pass in order to avoid obstacles. Some authors proposed a method based on a potential function around the obstacles.[14–16] With this formulation, the motion of the manipulator of the multi-body system is planned in terms of minimum potential.

Another approach emerged at the beginning of the 1980's based on imitation learning idea. Inspired by artificial intelligence techniques, symbolic reasoning was commonly chosen to behavior mime. During a training phase, several sample movements were generated under manual robot control. Sensor recording as position and force were stored all along the experiment as well as the positions and orientations of the obstacles and the goal states.[17] More recently, new elements were included to use visual input of the teacher and to perform movement segmentation out of computer vision algorithm.[18–20] Other projects used data gloves,[21] or marker-based observation systems as input for imitation learning.[21]

In this paper, we present a learning model that can control a simulated anthropomorphic arm kinematics motion in order to reach and grasp a static prototypic object placed behind an obstacle of varying position and size. The network, composed of two generic neural network modules,[22] learns to combine multi-modal arm-related information such as trajectory parameters, as well as obstacle-related information such as obstacle size and location.

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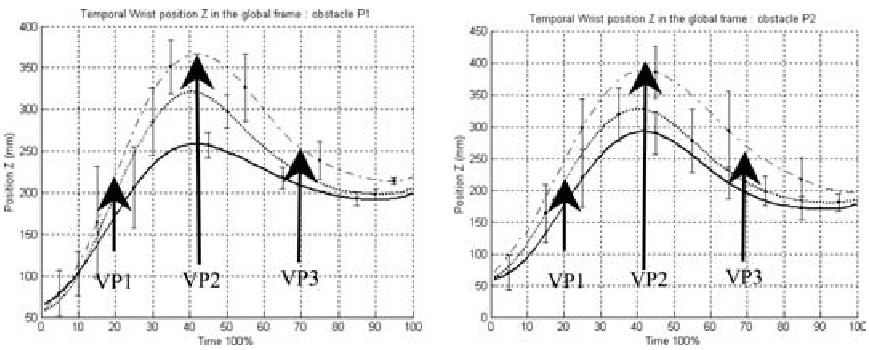

Fig. 1. Temporal wrist elevation and Via Point specification.

We based our simulation on the notion of Via Point, previously observed by Johansson,[23] which postulate that the reach motion planning is divided into some specifics successive position of the arm based on gaze information. In this study, deprived of gaze information, we assume that elbow and wrist positions characteristic in relation to the height of obstacle allow the impediment avoidance during the motion. For that, we present an experimental protocol which makes possible the extraction of several specific data to be integrated into the generic learning model. The neural network architecture is used to determine the total trajectory of the arm in reaching and grasping tasks while avoiding the obstacle. According to these studies, we propose an original method which takes into account the previous learning modules. The goal of this method is to determine the entire trajectory of the wrist in order to reach the object placed behind two successive obstacles.

This paper is organized as following. In section II, we present the method used to obtain the different required data. The third section is devoted to the presentation of the neural network architecture retained to perform the reach-and-grasp learning. In section IV, we present the learning and simulation results demonstrating the tools efficiency. Finally in section V, we present the neural network architecture and simulation results of the novel approach.

II. EXPERIMENTAL PROCEDURE

II.A. Materials and methods

Seventeen healthy subjects (age, 22–34 years), twelve males and five females, volunteered to participate. Subjects were seated in a chair facing a table and were instructed to reach for and grasp a prototypic object (box) placed behind an obstacle of varying position and size. The object to be grasped was a compact block ($8*8*8$ cm) placed at 50 cm from the wrist initial position Po. Three obstacles of different sizes ($10*35*10, 10*35*15, 10*35*20$ cm) were placed randomly at 25 (P 2 position) or 40 (P1 position) cm from Po. Then, subjects performed six different tasks.

Each subject executed all the randomized tasks. Movements were recording using the Vicon optoelectronic system which allow the record of markers placed on the shoulder, elbow and wrist articulations. With the help of a specific software, the trajectories of each marker can be reconstructed. Subjects were allowed to reach around the obstacle or to grasp the block from the top but only the last strategy was taken into account.

II.B. Results

II.B.1. Trajectory analysis: Via point underlining. The location of the obstacle between the initial hand position and the target object required the subjects to produce greater vertical elevation during the reach to avoid the obstacle. This phenomenon affects the wrist and the elbow trajectory. Figures 1 and 2 represent, respectively, the wrist and elbow trajectory in the six conditions (obstacle height (cm): 10, 15, 20, Position P1 and P2).

According to the trajectory description, we can notice that the maximum vertical height achieved by the wrist happened at $42 \pm 1\%$ times relative to the total time of the task independently of the obstacle location and size. This

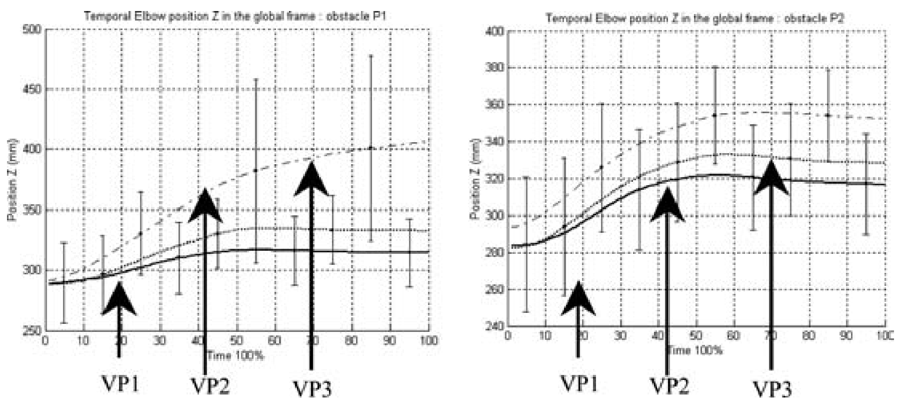

Fig. 2. Temporal elbow elevation and Via Point specification.

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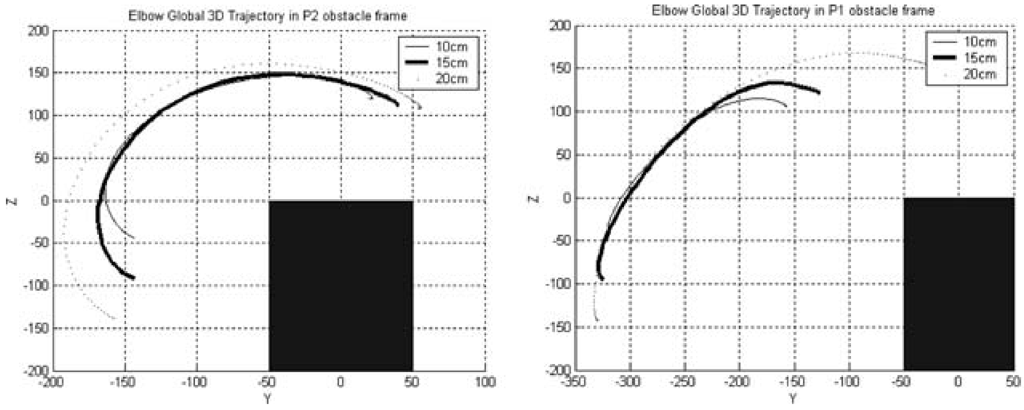

Fig. 3. Elbow trajectory in the obstacle frame.

trajectory parameter characteristic represents the first *Via point* position.

In order to take into account the reach path curve depending on the height of the obstacle, we determine the second and the third via point position respectively at 20% and 70% of the total task time (see figures 1 and 2). With these three characteristic positions, we can reproduce the experimental trajectories with the use of a spline interpolation.

Then, in relation with these time characteristics, we define the corresponding *Elbow Via Point* location as shown in figure 2.

II.B.2. Final position analysis. The data relative to the final position give some relevant information relative to the elbow and wrist position in relation to the obstacle position and size. In fact, we notice the existence of a safety distance between the elbow and the obstacle allowing the obstacle avoidance. Figure 3 represent the elbow trajectory in the obstacle frame and show that the final vertical distance between the elbow and the obstacle is invariant whatever the obstacle height:

$$\text{d\_safety} = 120 \pm 10\,\text{mm} \tag{1}$$

Then, the final elbow, like that the wrist position, can be determined according to the obstacle position and height. At this step, we have determined five characteristic positions (see Table I) of the upper limb for each condition which allow the path planning: the initial position, the first heuristic Via point, the Via point corresponding to the maximal height of the wrist, the second heuristic Via point and the final position.

In the next section, we present the neural network used to learn the final arm configuration and the generalization of the trajectory parameter determined in this paragraph.

Table I. Trajectory characteristic position.

Characteristical position	Initial position	Via point 1	Via point 2	Via point 3	final position
%time	0	20	43	70	100

III. NEURAL NETWORK MODEL

III.A. Architecture

The neural network learning algorithm is based on the Locally Weighted Projection Regression (LWPR), used for incremental learning of nonlinear functions.[24,25] It uses locally linear models, spanned by a small number of univariate regressions in selected directions in input space, to achieve a piecewise linear function approximation.

The region of validity, called a receptive field, of each linear model is computed from a Gaussian function:

$$w_k = \exp\left(-\frac{1}{2}(x - c_k)^T D_k (x - c_k)\right) \tag{2}$$

where c_k is the center of the kth linear model, and D_k corresponds to a distance metric that determines the size and shape of validity region of the linear model. Given a query point x, every linear model calculates a prediction $y_k(x)$. The total output of the learning system is the normalized weighted mean of all linear models:

$$y = \sum_{k=1}^{K} w_k y_k \Bigg/ \sum_{k=1}^{K} w_k. \tag{3}$$

The main capability of the generic neural network is to learn multi-modal sensory-motor relations independently of the specific nature of the sensory signals. In this paper, we focus on a net of two neural networks which is able to generate the entire trajectory avoiding collision relative to the position and size of the obstacle and the object data to grasp.

The first learning module is dedicated to the learning of the final upper limb configuration whereas the second module is devoted to the learning of the via point generating by the trajectory. Figure 4 illustrates the net of the neural network.

III.B. Learning of the final upper limb configuration

The arm configuration determination requires multiple steps. The first one concerns the end effectors position and orientation definition. In fact, the wrist position and orientation relative to the object has been pre-defined.

According to the study of Tolani,[26] we have computed a robust algorithm in order to solve the inverse kinematics and to deal with the redundancy problem. In fact, we can

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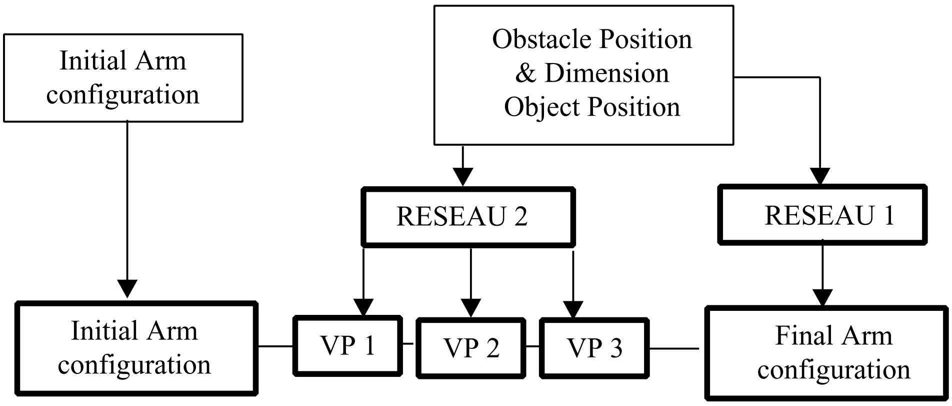

Fig. 4. Net of neural nets.

determine only one arm configuration imposing the elbow desired position such as a constraint. This desired position is provided by the experimental data as shown in section II. With these two conditions, the information of the final arm configuration avoiding the obstacle is determined and the learning can be performed. The following algorithm (Figure 5) explains the learning procedure.

In the next section, we present the results of the learning described in this paragraph and we illustrate the efficiency of the tool through some modelisation results.

III.C. Learning of the Via point generated trajectory

The generalization of the via point definition comes from the experimental data analysis. A training point matrix containing the Via point position and the corresponding obstacle height and position has been established. Then, the neural network learns to generalize the via point position. The algorithm related to the via point learning is shown in Figure 6.

IV. SIMULATION RESULTS

IV.A. Learning curve results: final arm configuration and Via Point

Here we present the simulation results that concern the learning of the arm configuration avoiding the obstacle and the learning of the trajectory parameters such as Via Point (see Figure 4 and 5). Figures 7a and 7b show, respectively, their learning curves (Mean Squared Error, MSE) over 6000 and 9000 training epochs.

To evaluate the efficiency of the neural network, we compute the mean positional error corresponding to the norm of the vector from the desired position to the actual position, with a test set of 5000 different configurations, after having specified the obstacle position and size. These mean error value are, respectively, 5.1 ± 1.0 mm and 7.2 ± 1.6 mm for the elbow and the wrist.

Moreover, the safety distance given by the predicted model is approximately equal to the one given by experimental data:

$$d\_safety\_predicted = d\_safety \pm 5\,\text{mm} \qquad (4)$$

IV.B. Efficiency of the tool

Figure 8a represents the wrist trajectory given by the predicted model and the experimental one for the three obstacles heights in P1 position. Figure 8b represents the predicted elbow trajectory in P2 position for the higher obstacle and an arbitrary case trajectory (Position: 0.3; Height: 0.16). The mean error value of the wrist position is equal to 20 ± 6 mm and 15.5 ± 3 mm for the elbow in the six conditions.

Figure 9a represents the wrist trajectory given by the predicted model and the experimental one for the higher

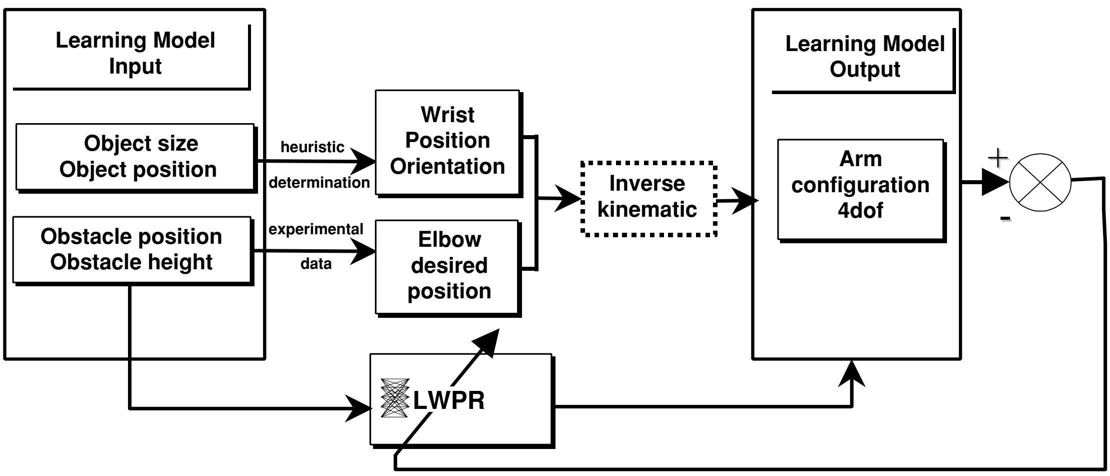

Fig. 5. Algorithm for the arm configuration learning.

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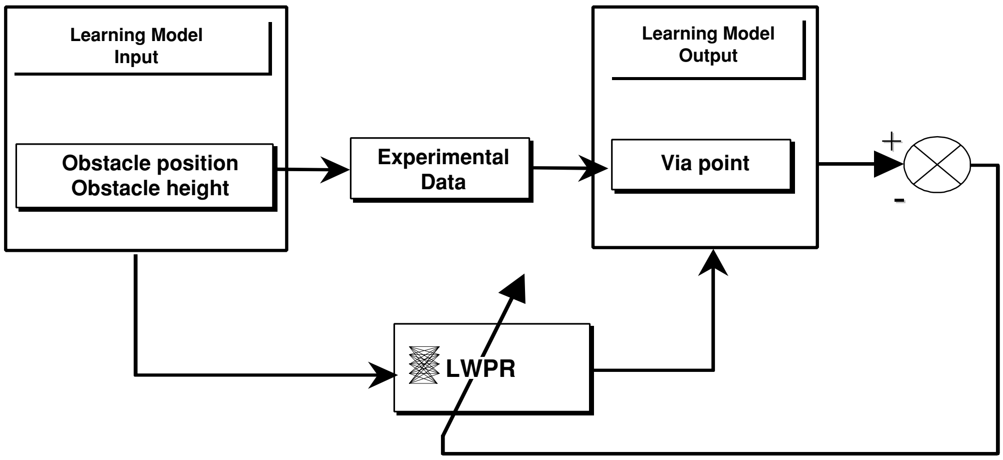

Fig. 6. Algorithm for the Via Point position learning.

obstacle height in P1 and P2 position. Figure 9b represents the predicted wrist trajectory for an arbitrary case (Position P: 0.33; Height: 0.11; 0.13; 0.16; 0.19 cm).

IV.C. Modelisation results

In order to illustrate the adaptability of the model, we present the anthropomorphic arm simulated. The 7 degrees of freedom (DoF) arm model is composed of two segments (arm and forearm) linked by three joints, as shown in Figure 10. The shoulder joint has 3 DoF (q_1, q_2, q_3), the elbow joint has 1 (q_4) and the wrist joint has 3 DoF (q_5, q_6, q_7).

Thus, the configuration of the arm is completely defined by the vector of the joint angles q $= (q_1, q_2, q_3, q_4, q_5, q_6, q_7)^T$.

These last figures illustrate the capability of our learning model. The hand shape and the wrist position and orientation relative to the object has been pre-defined. The inputs of the model are the obstacle position and height as well as the object position to be grasped. With the use of the two neural nets learned, the simulator is able to generate the entire trajectory which enables to avoid the obstacle. Figures 11a and 11b show the grasp performed once the trajectory is

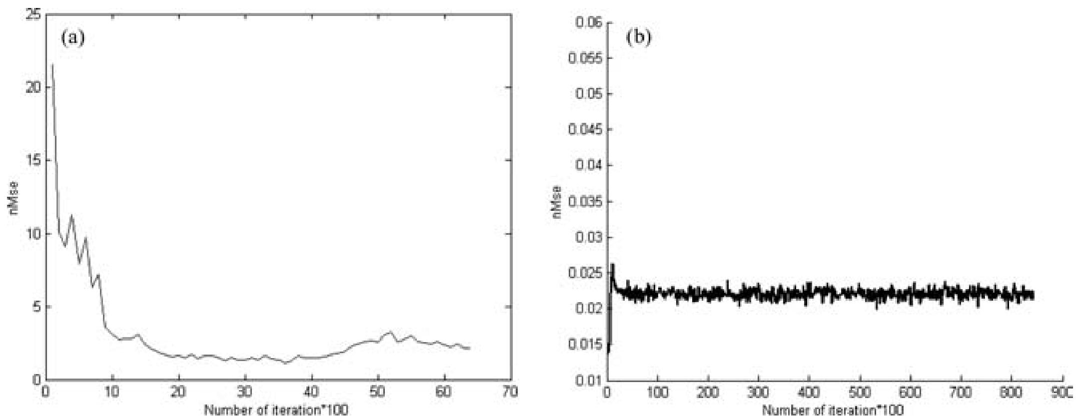

Fig. 7. Learning curves. (a) Final arm configuration. (b) Via point.

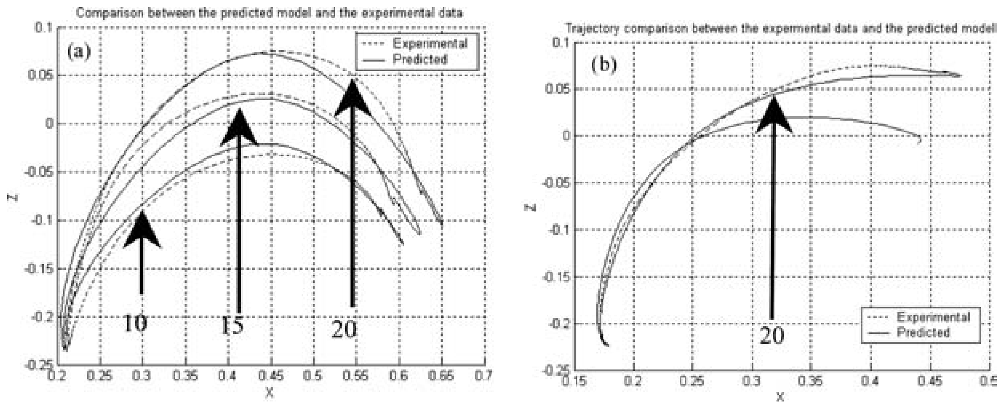

Fig. 8. Simulated trajectories. (a) Wrist. (b) Elbow.

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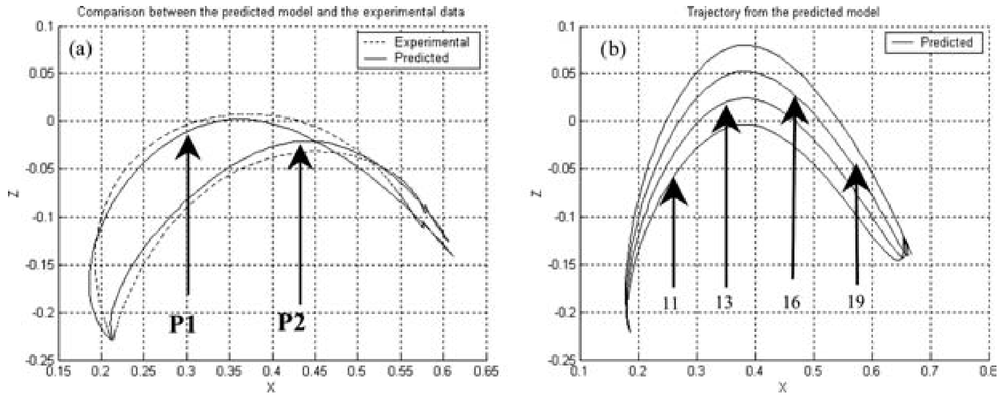

Fig. 9. Simulated trajectories. (a) Wrist. (b) Elbow.

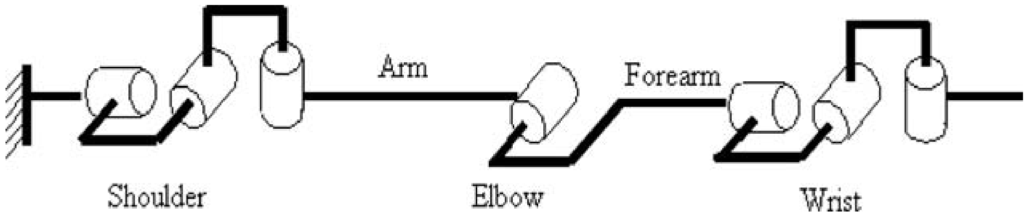

Fig. 10. Seven degrees of freedom arm model. (Shoulder: 3 DoF, Elbow: 1 DoF, Wrist: 3 DoF).

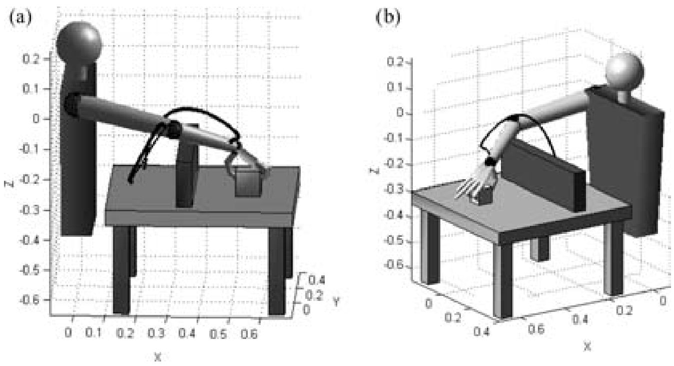

Fig. 11. Model illustration. (a) Wrist and Elbow trajectories. (b) Wrist trajectory.

performed. We have represented the elbow and wrist evolution in order to avoid the obstacle.

V. CONCLUSION

In this paper, we have presented an original approach that integrates several parameters from experimental data in a generic neural network in order to perform a path planning. According to the notion of Via point and obstacle-related information such as obstacle size and location, the entire trajectory is determined after learning in order to reach and grasp a static prototypic object placed behind an obstacle of varying position and size. The method uses a net of two neural networks. The first performs the learning of the final upper limb configuration avoiding the obstacle, whereas the second is devoted to the learning the trajectory parameters (Via Points). Both of these informations are provided by the experimental data analysis and integrated to the two different learning modules. Several results show the efficiency of the tool and allow us to think that the use of this net of generic neural network can treat more complex situation as the combination of the reach-and-grasp. In future works, we will integrate other learning modules as the determination of the hand shape and such as the wrist orientation and position relative to the object.

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