A bio-inspired control system and a VRML Simulator for an Autonomous Humanoid Arm.

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Abstract. A hierarchical control architecture and a virtual model are under development on the basis of a biologically based analysis of manipulation. The control model has two levels: immediately over the effectors, the motoneurons give directly commands. Over it, the pattern generator and the inverse kinematic neural network transforms specifications of points to reach with the hand into joints values to actuate.The model of the virtual arm, integrated with the control model, helps to better understand the simulation results.

1 Introduction

A Humanoid Robot, in order to mimic the human morphology and functionality, needs a complex kinematic structure.

Since in the human body we have more than one hundred degrees of freedom, a humanoid robots needs in theory one hundred actuators at least, and a double number of sensors to sense position and force in each actuator. Moreover, it is extremely important in a humanoid robot to control the joint compliance in order to allow a safe collaboration with the human beings. In this situation classical control systems [1, 2], based on the accurate knowledge of the process dynamic model, are not so easy usable. This observation is more strong if the robot that we want to control is composed by light and high power to weight ratio actuators, like McKibben pneumatic artificial muscles or electroactive polymers fibers. This kind of devices tend to change their comportment when the number of working cycles increase, therefore a classical PID controller is not able to maintain the initial performance and an adaptable control system is needed.
The control system strategy and the arm model,proposed in this paper, have been designed for our prototypes of artificial hands, namely Blackfingers and Whitefingers, illustrated in Figure1. The first project was born at Politecnico di Milano three years ago, while the second derived from the collaboration between our AIRLAB Laboratory and the Intelligent Robotics Laboratory of the Portland State University, started with the aim to conduct coordinated experiments.
Both artificial hands were designed on the basis of anatomical studies of the human limb. Each hand is composed by five fingers with 4 mechanical degrees of freedom (DOF) each. In particular the first phalanx is provided by a spherical joint wraps by an elastic band that allow only two DOF. The joints between the first and the second phalanx and between the second and third phalanx are cylindrical, and they permit only the rotation respect the axial axis. In order to test our control system we have developed also a virtual model for the arm.
We used this model for the two following purposes:

– One is to graphically understand the macroscopic result of the controller on the hand. For this task the model will be moved by the values computed from the neural artificial system.
– The other is to verify, by animation, the best mechanical structure for the arm and its ability to reach specific positions in the work space.

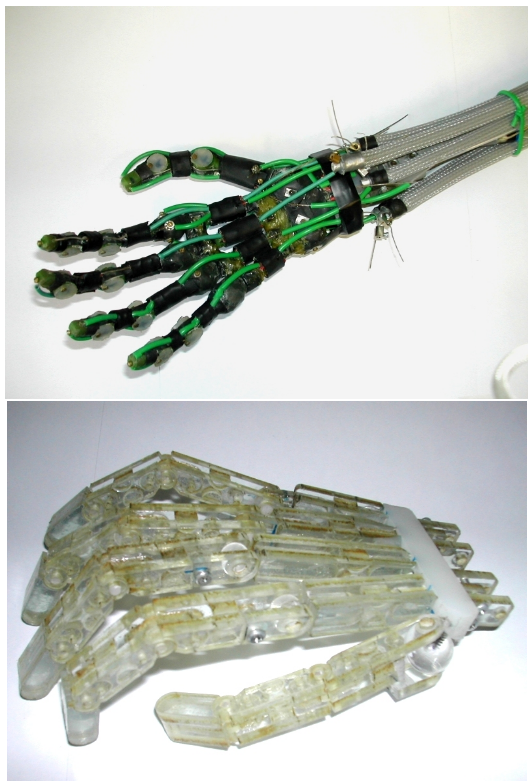

Fig. 1. Blackfingers and WhiteFingers Endoskeleton

We are not talking here about the classical approach to robot grasping that requires a dynamic analysis of the object and the hand : our hypothesis is that the Pattern generator and the inverse-kinematics model find the target for the joints positions, and that the target is reached by the low level controller in the robot. Our idea is to simulate, for instance, a process in which the hand reaches and grasp the object, after the vision system has located an object graspable inside the hand. This idea will be useful for systems based on imitation learning as well, a kind of learning that has not yet been applied to the complete hand.

2 Biologically Inspired Control

In the past most of the proposed artificial hands used a control system based on a complete mathematical model of the hand (actuators, joints and links) and of the manipulated object. In humanoid robotics instead the goal is to create a robot able to interact with people [3]using the same characteristics (dimensions, forces,) of the natural counterpart. The mechanical structure should be light, and the assumption that joints and links are rigid relaxed. The new structures of humanoid robots cannot be modelled as linear systems, and often their dynamic model is complex because the joints acts one on another. Moreover the light materials will degrade more rapidly, so an adaptive controller is needed to keep the system working. To build a biologically funded control we consider now 2 levels: the high level which is responsible for defining the motor patterns or primitives, and the low level which is based on the motoneurons and implements the reflexes. Both the levels can be constructed with some learning capability; however only the high level learning has been developed in modern artificial systems. Marr (1969) and Albus (1971) started this kind of research on the consideration that the cerebellum is responsible for coordination and temporization of the muscular activity to obtain the basic motions. The spinal system is able to learn the basic motion actions and to adapt them to the external conditions. This learning is basically context driven. Models developed after include [4]:

- CMAC (Cerebellar Model Articulation Controller): proposed by Albus (1975) [5] . It uses a table that keep the relationships between input and output, with connections weighted through learning.
- AGP (Adjustable Pattern-Generator): introduced by Hook , Barto et al (1989) [6], models the structure of the cerebellum and the connections to the motoneurons.
- Internal dynamic model: Kawato (1992) [7] from the evidence of neurophysiology experiments claims that the optimal control of the arm is based on an internal representation of the dynamic model of the skeleton and muscular systems. In fact the rapid movements (150-500 ms) are not compatible with the delay of the visual feedback (150-250 ms), moreover also the time of the reflexes (30-50 ms) are not short enough to integrate the sensory information in the control strategy. In conclusion, the inverse dynamic model is learned by the encephalon and is used to control the movements in a Feed Forward strategy.

The reflexes arcs are our low level controller. Hannaford et al.[8] have provided many results on this topic, and are able to reproduce the arc on an artificial device to maintain its position and control its stiffness. Another approach is proposed by Kawamura et al [9], to reproduce the 3 phases that characterize he muscular activity. Another way to produce a motor pattern uses recurrent neural networks as in Ogihara et al. (1999) [10]. A model that consider at the same time the dynamics of the reflex circuities, present in the spinal cords, and those one present in the cerebellum, was present by Grossberg et al [11].This model illustrates how a central pattern generator in the cortex , a neuromuscular force controller in spinal cord, and an adaptive cerebellum cooperate to reduce motor variability during multi-joint arm movements.

2.1 Biologically Inspired Control in Blackfingers

In this section we describe the control architecture that we have tested by simulation. In Figure 2 there are represented three main blocks:

Reflex Circuits These systems have the purpose to control the single joint position and stiffness.
Inverse Kinematic This system calculate the joints reference position receiving as input a specific object position in cartesian coordinates.
Pattern Generator It receive the sensorial information and in function of the task to perform it decide the trajectory in terms of instantaneous joint's position and stiffness.

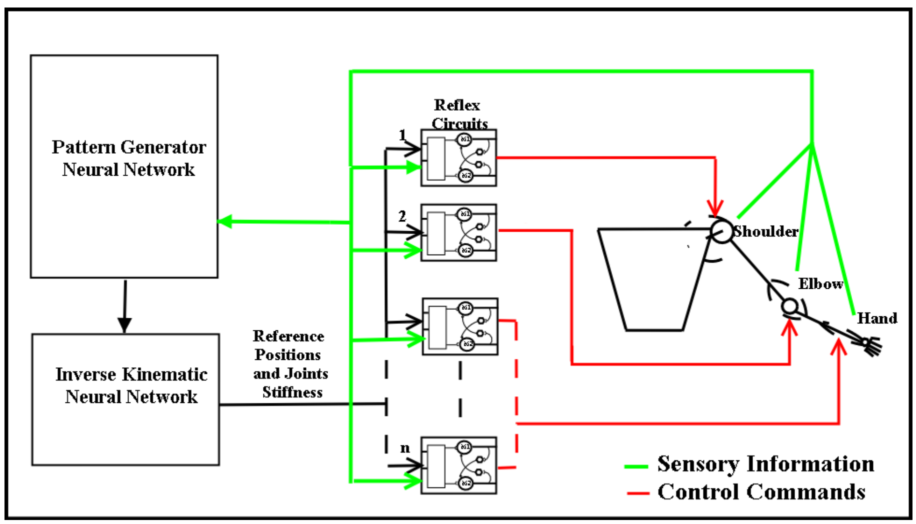

Fig. 2. Control Architecture

We have developed the reflex controller of our hand on the basis of different models. Dynamic models of the components (joints, actuators, sensors) and model of the reflex control system. Starting from the models proposed in Grossberg (1982), we defined dynamic neurones. The model incorporates also dynamic synapses based on a kind of habitant learning Hebb (1942) [12].

Equation 1 gives the general model of the dynamic neuron used in our reflex circuit. In this equation, P represents the action potential of the artificial neuron; its variation is proportional to the frequency of impulse inputs and their weights. The threshold function Th has a relay behavior: it assumes the value 'one' when the potential exceeds the upper limit l_1 and the value 'zero' when the potential is lower than the limit l_2; between l_1 and l_2 the value is equal to the previous state. x_1 and x_3 are the excitatory inputs, whereas x_2 is an inhibitory input; their values are weighted by w_1, w_3 and w_2 respectively. The parameters G_1,G_2,G_3 are loop gains, and theirs values can modify the dynamic neuron's response.

$$
\begin{array}{lll}
\dot{P} = G_1(w_1 x_1 - w_2 x_2 + w_3 x_3 - fP - G_2 Th(P)) & & \\
Y = G_3 Th(P) & & \\
 & & \\
Th(P) = 1 & if & P > l_1 \\
Th(P) = 0 & if & P < l_2 \\
Th(P) = previus\ value & if & l_2 \leq P \leq l_1
\end{array}
\tag{1}
$$

Like the natural one, the artificial neuron has a short-term memory, and the decay term $-fP$ in equation 1 determines the rate of "forgetting".

Our network architecture reproduces a simplified reflex arc and is comparable with the model of Hannaford (1996) [13]. The network is able of maintaining the position of the joint and of controlling its stiffness. The pattern generator, not already implemented, will be able to learn motion primitives, at the level involved in the cerebellum. It will use the representation of the motion system and of the external world, and this representation will be adaptable to the external stimulations. The representation will be able to generate a voluntary motor pattern in short times.

3 Arm and Hand Kinematic model

In this section we described the general direct kinematic model for a finger and the direct and inverse kinematic model for the arm.

3.1 Finger direct Kinematic

In Fig 3 we see a detailed view of the index finger.

It is possible formalize the direct kinematic of an hand's finger using the homogeneous coordinates. In particular we chose to work in relative coordinates and for this reason we used the matrixes post-multiplication. If we assume that the metacarpus structure is rigidly connected with the carpus articulation, we can pass from a Sdr_0 to Sdr_r using the matrix $T_{R\rightarrow 0}$ expressed by equation 2. Using this matrix we can calculate the orientation of the metacarpal link after a wrist rotation. It is implicit in this equation, that to calculate the wrist orientation we rotate first of an angle $alpha_0$ with respect the $X-axis$ and then of an angle $alpha_1$ with respect the $Z-axis$. The angles are positive in clockwise turns.

$$
T_{R\rightarrow 0} = \begin{pmatrix} \cos\alpha_0 & -\sin\alpha_0\cos\vartheta_0 & \sin\alpha_0\sin\vartheta_0 & a_1 \\ \sin\alpha_0 & \cos\alpha_0\cos\vartheta_0 & -\cos\alpha_0\sin\vartheta_0 & a_2 \\ 0 & \sin\vartheta_0 & \cos\vartheta_0 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{2}
$$

Now it is possible define the orientation of the first phalanx Sdr_1 relative to the Sdr_0, this is formalized by equation 3.

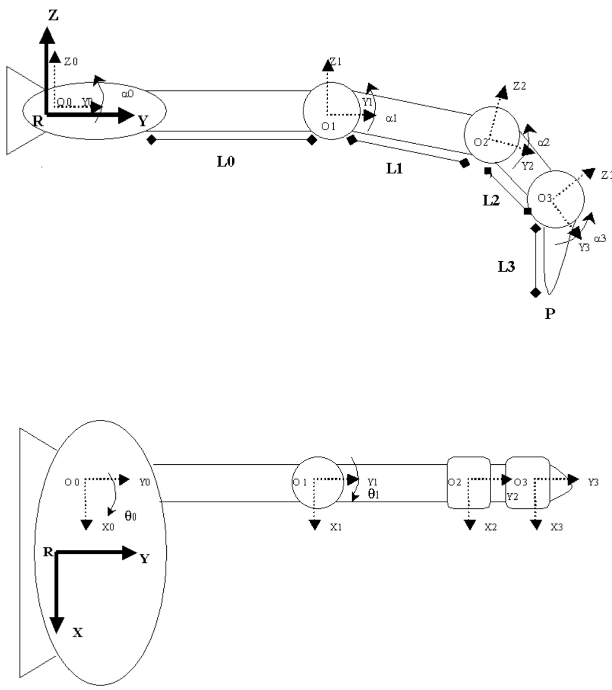

Fig. 3. Right hand index, in lateral view

$[R, X, Y, Z]$ reference system
$[O_0, X_0, Y_0, Z_0]$ carpus reference
$[O_1, X_1, Y_1, Z_1]$ joint1 reference
$[O_2, X_2, Y_2, Z_2]$ joint2 reference
$[O_3, X_3, Y_3, Z_3]$ joint3 reference
$[\alpha_0]$ flexion carpus - metacarpus
$[\theta_0]$ adduction-abduction carpus
$[\alpha_1]$ flexion first phalanx
$[\theta_1]$ adduction-abduction - metacarpus
$[\alpha_2]$ flexion second phalanx
$[\alpha_3]$ flection third phalanx
$[P]$ contact point of the index tip
$[L_0]$ length metacarpus
$[L_1, L_2, L_3]$ lengths of the phalanxes

Table 1.

$$T_{0\to 1} = \begin{pmatrix} \cos\alpha_1 & -\sin\alpha_1\cos\vartheta_1 & \sin\alpha_1\sin\vartheta_1 & 0 \\ \sin\alpha_1 & \cos\alpha_1\cos\vartheta_1 & -\cos\alpha_1\sin\vartheta_1 & L_0 \\ 0 & \sin\vartheta_1 & \cos\vartheta_1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \qquad (3)$$

The equation 4 represent the orientation of the Sdr_2 relative the Sdr_1, therefore the second phalanx orientation.

$$T_{1\to 2} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\alpha_2 & -\sin\alpha_2 & L_1 \\ 0 & \sin\alpha_2 & \cos\alpha_2 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{4}$$

The orientation of the third phalanx depend, in our prototype, from the orientation of the second phalanx, they are connected by a cross tendon (see Figure 4). This cross-tendon permit to actuate the last two phalanx using only 2 tendons. This is partially true also in the human hand, in fact common people are not able to control separately the second and the third phalanxes. The cross tendon is not present in the thumb and this provides to this finger an additional degrees of freedom.
In order to complete the direct kinematic we obtained the relationship between the last two finger phalanxes. This relationship is expressed by equation 5.

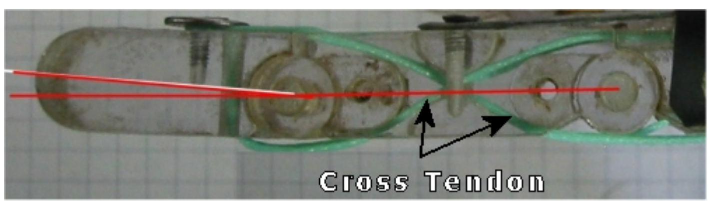

Fig. 4. The last two phalanx are connected by the cross tendon

$$\alpha_3 = \frac{\alpha_{2max}}{\alpha_{3max}}\alpha_2 \tag{5}$$

Now we can calculate the last matrix that express the orientation of the Sdr_3 respect Sdr_2.

$$T_{2\to 3} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos(\frac{\alpha_{2max}}{\alpha_{3max}}\alpha_2) & -\sin(\frac{\alpha_{2max}}{\alpha_{3max}}\alpha_2) & L_2 \\ 0 & \sin(\frac{\alpha_{2max}}{\alpha_{3max}}\alpha_2) & \cos(\frac{\alpha_{2max}}{\alpha_{3max}}\alpha_2) & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \tag{6}$$

If we know the coordinates of a point respect the Sdr_3, for example a fingertip's point, it is possible now calculate the coordinates of this point relative to the Sdr_R using the equation 7.

$$\mathbf{P_R} = T_{R\to 0}T_{0\to 1}T_{1\to 2}T_{2\to 3}\mathbf{P_3} \tag{7}$$

3.2 Arm direct and inverse Kinematic

The arm that we modelled has three degrees of freedom (see Figure 5) , two rotations in the shoulder and one rotation in the forearm. We denote with α the shoulder rotation respect the $x - axis$, with β the shoulder rotation respect the $y - axis$ and with φ the forearm rotation respect the $x - axis$.

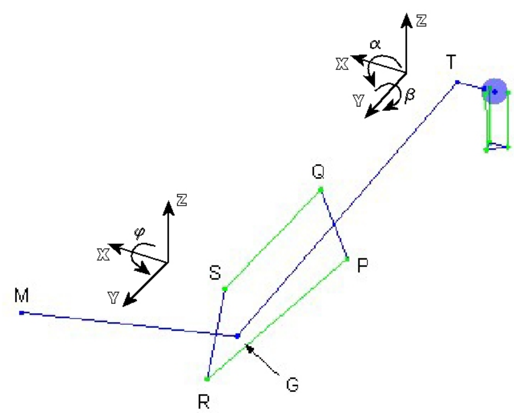

Fig. 5. Arm kinematic

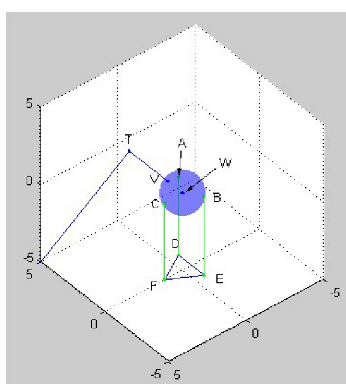

Fig. 6. Shoulder detail

The segments $\overline{SQ}$, $\overline{RP}$, $\overline{FC}$, $\overline{DA}$, $\overline{EB}$ (see Figures 5 and 6)represents the artificial muscle that actuate the arm. Again we can calculate the direct kinematic using the homogeneous coordinates, this is not so different from the fingers kinematic therefore is not reported here. Particular attention must be applied for the angles limits. In order to mimic the human shoulder mobility, we impose that α can variate from 0 to π radians, instead β from 0 to $\frac{\pi}{2}$. For the forearm angle φ the arm structure imposes that the extensor muscle $\overline{PR}$ does not overcome the elbow articulation G when the forearm is flexing. We can formalize this superior bound with equation 8.

$$\varphi_{max} = arccos \frac{ab - cd}{\sqrt{(b^2 + c^2)(a^2 + d^2)}} \tag{8}$$

Where parameters a,b,c,d are the arm dimension (see Figure 7).

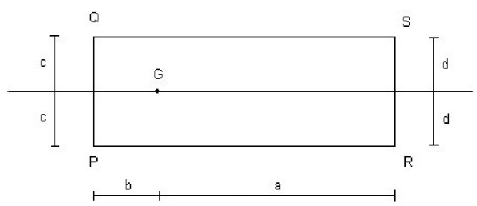

Fig. 7. Arm's dimensions

When the direct kinematic model is known, it is possible perform the inverse arm kinematic using a neural network with back-propagation learning algorithm. The advantages of using a neural network instead a classical inverse Kinematic algorithm, are many:

– Using a NN the calculation of the joints coordinates, when the position to reach is know, is faster than other methods that use algorithms or systems of equations.
– It is possible avoid the singularity configuration using attention during the NN training.
– It is possible to re-train periodically the NN off line in order to have an adaptive system, this using for example data coming from a visual system.

The third point is very interesting, in fact it is possible to think of saving the outputs generated by the on-line NN (the neural network that is currently calculating the inverse Kinematics in real time) and compare them with the final position goal. In this case we need a visual system able to identify the hand position into the cartesian space, or otherwise use the direct Kinematic model and the joints position sensors information. The first solution is preferable to the second one, this to bypass eventually errors introduced by the sensors or linkages degradation. When a sufficient amount of data are available , it is possible to calculate the average error generated by the on-line NN and decide if to star in background a new NN training.

In our simulation we do not have already implemented this system, so actually we have only a static NN for the calculation of the inverse Kinematics.

The network was trained using the hand coordinate as inputs and the arm angles as target. The training set was calculated using the arm direct kinematic, before the training, the input-output pairs were opportunely normalized between -1 and 1. In Figure 8 we can see a simulation result. The dashes line represent the desired trajectory, instead

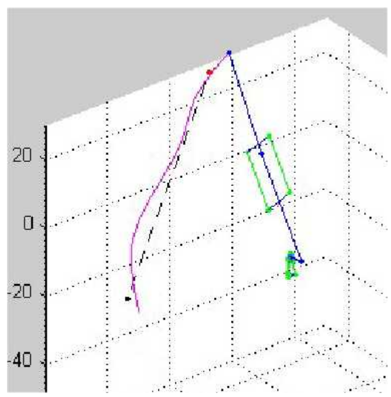

Fig. 8. Inverse Kinematic Results

the continue line is the result generated by the neural network. As it is possible see there is a big error especially during the last trajectory part. This is partially due to the fact that, in our simulation, the shoulder has only two degrees of freedom, instead in the human shoulder is allowed also the rotation respect the $z - axis$. We think also that more improvement can be made also during the training phase.

4 Virtual Model

In order to have a visual feedback of our simulation we have implemented a VRML model of our artificial arm-hand. This model was useful also for setting the real prototype specifications.

Our project develops through the following steps:

1. Development of the system of virtual reality, that demands of modelling the hand, the arm, and feasible movements (geometry, cinematic, force). For making the system portable on Internet VRLM2,0 is selected. The model replicates the geometric characteristics of the prototype.
2. Analysis and creation of the actuation model. This part is developed using Matlab.
3. Implementation of the collision detection in the VRML model; This will help the future simulations on path planning and generation of motor primitives.

The environment that we chose to integrate the vrml model and the control and kinematic-dynamic models is simulink that work on matlab. This permit us to connect the models in an easy way. Recently with the introduction of matlab release 13 is also possible to use the built in vrml browser.

4.1 State of the art and motivation for simulating fine manipulation

Many research areas in Computer Simulation and Robotics are converging to the common aim of building software systems able to simulate in real time the behavior of autonomous systems that exist in a real world, characterized by high structural complexity, and able to react to stimuli from the real, dynamic, environment. Such simulation systems have a graphical, active, 3D interface available also to remote operators. The classical off-line robot programming, where the long time of simulation was compatible with the off-line planning phase performed before the real execution, is now substituted by the real-time programming in virtual reality. The physical experiment is substituted by the virtual experiment. In the simulation area, animation methods able to respect the real behavior of the modelled systems are becoming central [14], opening the road to introducing virtual reality in tele-robotics [15]. In particular a new class of programming methodologies for robotics has originated; we call it ”manipulation through human remote control”. In this approach the human operator sends macro-commands to the robot, and the intelligence embedded in the robot expands those macro into motion programs. This offers also a solution to many tele-operation problems originated from the limited bandwidth available for communications. Moreover, the new research area defined as Computer Networked Robotics by [16], has indicated how it is possible to interconnect robots through the Internet. Such complex approach has not yet been fully developed for fine manipulation. Humans, due to the great flexibility of their hands, have abilities in interacting with objects in the real world far more advanced that the actual robots. Let consider as example how to check possibly dangerous objects in non destructive ways: for instance we can only destroy, with a remote command, a bag but we are not able to send a robot to open it, examine what is inside, and eventually detach a timer. To obtain this kind of manipulation ability we need robots more than mobile; they should have a manipulation system able to repeat almost the same movements of the human hand. Many difficulties arise both for the construction of such hands, to reproduce the compactness, compliance, and energy savings of the biological systems, and to govern it. We do not know the algorithms to program such complex machines to get the adaptability of the natural systems, but we can try to mimic the biological control.

Our project aims at developing a fine manipulation system for the humanoid hands already available, Blackfingers and Whitefingers, and to develop both the geometric virtual environment and the strategies to control the manipulation activities. Because of the difficulty in controlling such a complex system, we will use simulations and virtual reality to reach the target. Ideally the virtual system allows trying the movements (expressed as macro-commands) and a tele-control system enables the execution of the correct sequences on the real hand. To accomplish the manipulation we will need to add a planning system to generate trajectories (possibly not colliding with obstacles). Some methodological aspects are very important: 3D modelling, a good representation

of the environment is important in any computer controlled, real-time system. In many applications the robot should also be able to sense the environment and to change it by acting in real-time. For this kind of robotics systems it is very important to evaluate the characteristics and dexterity in the execution of tasks. The real robot must use its sensors to identify the elements in the working space. After the robot is operating in its environment, it must use sensors to identify the dynamic elements in its working space. The integration of knowledge obtained by the robot using exploration with a-priori knowledge and internal state information will allow planning the better strategy. The perception system of advanced robots should be multi-modal, to extend the inadequacy of each kind of perception. Specific manipulation strategy. Manipulation consists of a sequence of movements of grasping and translation in contact with the object. It can be defined as the application of forces from the hand to the object in order to accomplish the assigned task satisfying the constraints given by the geometric-mechanical structure of the hand. Input is the task to accomplish; output is the temporal variation of the hand positions and the forces exerted from actuators. From the control point of view the biological hand is a very hard task; we will consider how the degrees of freedom can be grouped into motor synergies, so to reduce the dimensions of the control space. Spatial and action planning: Planning is an essential component of any autonomous system. Integrated in the cycle from sensors reading to action, it should be performed in a time compatible with the dynamics of the environment For the human hand, which is highly redundant, generating trajectories is computationally expensive. Different solutions have been proposed, from purely reactive systems [17], to systems able to deduce the action on the basis of stimuli (deliberative systems) [18]). In our case, the planning will be manually performed using the concept of motor primitives as illustrated in the following.
Manipulation consists of a sequence of movements of grasping and translation in contact with the object. It can be defined as the application of forces from the hand to the object in order to accomplish the assigned task satisfying the constraints given by the geometric and mechanical structure of the hand. From the control point of view the biological hand is a very hard task, with 28 degrees of freedom and 39 muscles [19]. The high number of degrees of freedom allows for a great variety of movements and contributes to characterize the human specie. To solve the control problem we will consider that the degrees of freedom can be grouped into motor synergies, so to reduce the dimensions of the control space. Those synergies are in function of the task. The models integrated into a simulation environment (geometric and dynamic) for fine manipulation will give the user the opportunity to try macro-commands of grasping and manipulations of the humanoid hand in the virtual world.

4.2 Geometric Model and simulation of the Arm

We have developed a virtual model and a simulator able to receive input from a virtual console or from the control system, as we will illustrate in the next section. The robotic hand has been modelled with a realistic geometry, written in VRML, and is moved through the EAI (External Authoring Interface). The program for the animation is written in Visual C++, and interfaced to VRML through EAI. In Figure 9 we see the virtual model of the right hand, built with spherical and cylindrical joints, as the real prototype.

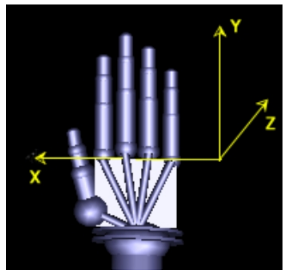

Fig. 9. The virtual hand

The hand is connected to the arm through a wrist. The possible movements of the wrist are extension and flexion, as shown in Figure 10, and adduction or abduction;

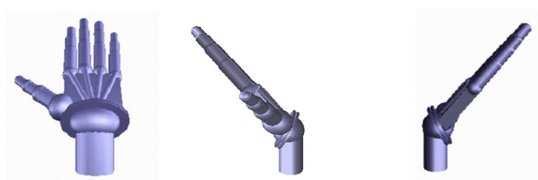

Fig. 10. Extension and flexion of the hand

The possible movements of the fingers are flexion of any phalanx, and adduction or abduction of the first phalanx .All the joints can move together as in the Figure 11.

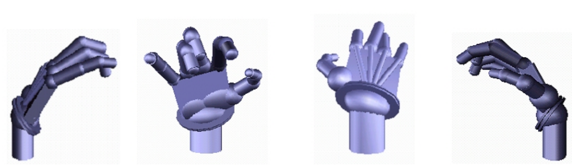

Fig. 11. Composite movements of fingers and wrist

To check the simulator ability in complex configurations, we have defined 4 specific positions: closed hand, pointing, ok, hook. We see them in Figure 12.

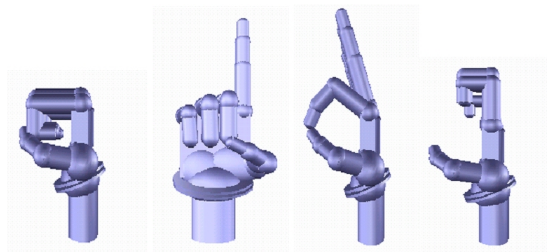

Fig. 12. Some predefined positions of the hand

The hand is attached to the virtual arm as we see in the following Figure 13, where the elbow is moved. The arm implements the basic bone structure of the human arm, and again is compatible in size and movements with the prototype arm.

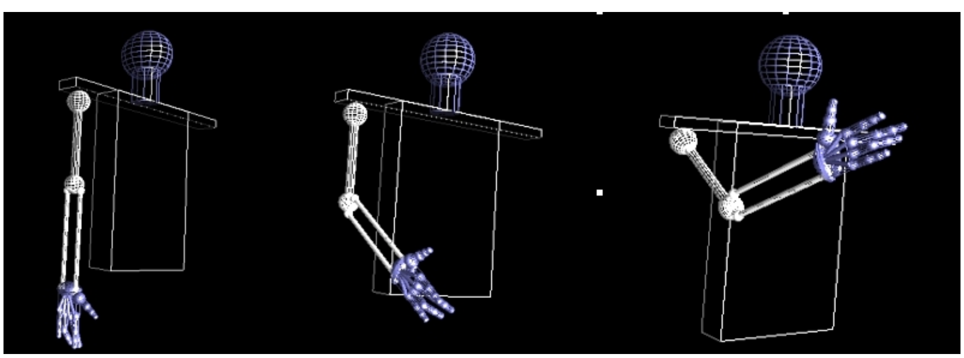

Fig. 13. The virtual right arm and hand

The main experiments done until now with the geometric and kinematics models of the simulator are to move the arm for gross reaching of a grasping position for the hand. The movements are visualized by the simulator in wire-frame or solid objects, as in the following views of Figure 14. We were able also to visualize the simulation results for the low level controller when an arm link was influenced by an external noise force.

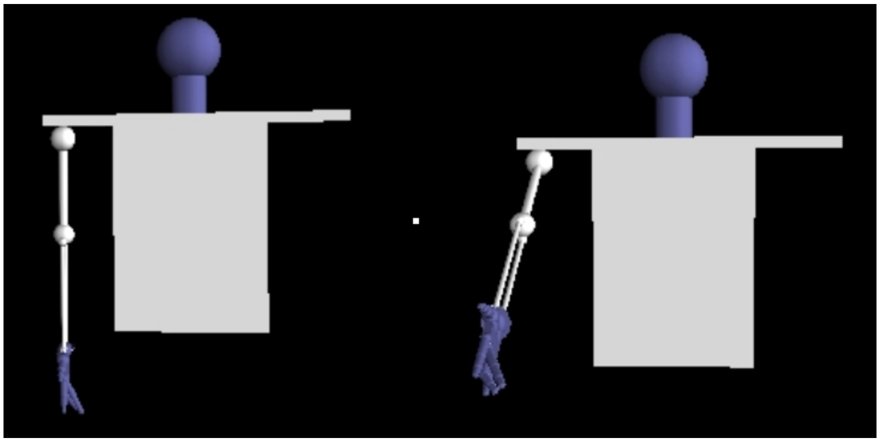

Fig. 14. Moving the shoulder

5 Conclusion and further work

In this paper we presented a possible control structure for an humanoid artificial arm. The control architecture is based on low level reflex controller that receive from the inverse kinematic neural network the reference position and from the high level control system the joint stiffness. The high level pattern generator, not already implemented, will emulate some cerebellum functions. It will receive the sensory information from the arm and the visual system and generate the trajectory in function of a task that has to be performed.

We presented here, also the advancements made in a virtual reality model that can be combined with a dynamic simulators to build a simulator system for fine manipulation. The system will also be the basis for a tele-programming system of the real arm. The choice of VRML is because it is currently de facto standard for web based 3D visualization. Some problems however will need more consideration. Although VRML supports collision handling between the user viewpoint and the objects in the scene, there is no collision detection object to object. However we will approach this problem in the future. Agents used only in simulation (as in artificial life) employ virtual sensors in order to sense and interact with the environment. Instead here we can connect directly the controller and the real sensors values to the model. Tele-presence is the future application for the simulator. While in VR the environment and the user are simulated, in tele-presence the environment is real and the user is represented by a robot, which acts accordingly to the user instructions and modifies the environment.

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