Human-Like Hierarchical Reflex Control for an Artificial Hand

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Abstract.

We illustrate the low level reflex control used to govern an anthropomorphic artificial hand. The paper develops the position and force control strategy based on dynamic artificial neurons able to simulate the natural neurons found in the human reflex control. The controller has a hierarchical structure. At the lowest level there are the receptors able to convert the analogical signal into a neural impulsive signal appropriate to govern the reflex control neurons. Immediately upon it, the artificial motoneurons set the actuators inner pressure to control the finger joint position and moment. Other auxiliary neurons in combination with the motoneurons are able to set the finger stiffness and emulate the inverse miotatic reflex control. Stiffness modulation is important both to save energy during task execution, and to manage objects made of different materials. The inverse miotatic reflex is able to protect the hand from possible harmful external actions. The paper also presents the dynamic model of the joints and of the artificial muscles inserted in Blackfingers, our artificial hand. This new type of neural control has been simulated on the Blackfingers model; the results indicate that the developed control is very flexible and efficient for all kind of joints present in the humanoid hand.

Keywords
Artificial Hand, Humanoid Robot, Multi-body Dynamics, Neural Control.

1. Introduction

Our target is development of a “human-like” control system for an artificial hand. Very few projects have so far investigated the problem of controlling a humanoid hand in a manner to mimic the human control system.

At MIT, the Master thesis of Matsuoka [1], has developed different learning strategies. However the hand there developed for Cog is not human like but much simpler, with three fingers and a thumb. It is self-contained having four motors and 36 exteroceptor and proprioceptor sensors controlled by an on-palm microcontroller. Primitive manipulation is learned from sensory inputs using competitive learning, back-propagation algorithm and reinforcement learning strategies. Interesting in the work of Matsuoka is the implementation of a reflex control. A curling reflex, which allows the fingers to curl when the inner surface palm is touched, and a releasing reflex when an intolerable amount of stimulus is applied. In the implementation a simple threshold is used for both. When the inner skin in weakly stimulated all the fingers curl; in the other case when the signal on the force-sensing resistor is higher than a threshold the fingers move in the opposite direction of the stimulus.

Another interesting project is under development at the Vanderbilt University [2]. Their robotic system, ISAC, is targeted to aid elderly or disabled people in their home. ISAC's 6DOF arms will thus need anthropomorphic hands. The hand utilizes a Watt 6-Bar Linkage for coupling actuator motion for both the distal and proximal joints of a single finger. This allows one actuator to emulate the joint ranges of the proximal and distal joints of the human phalange. The hand has five force sensitive resistors (FSRs). Each finger's inside distal pad will contain an FSR that varies its resistance based on the force exerted on its

“*Proceedings of the IEEE-RAS International Conference on Humanoid Robots*

surface. Additionally, one FSR will reside in the palm. The backside of the palm will contain the circuitry for the FSRs.

A grasping behavior based on the first grasping patterns of the neonates, as seen before, is implemented. Force-Based Grasping is a high level behavior used to grasp objects based on a priori knowledge. A grasping force and a simple Boolean command are given to this behavior. If the fingers close at the given grasping force without registering any forces, this behavior issues an error message for the upper control level.

Other relevant work is under way in Neural Computation, which attempts to combine knowledge from biology with knowledge from physics and engineering, with the goal to discover new technologies by studying the principles of biological behavior.

Movement coordination requires some form of planning: every degree-of-freedom needs to be supplied with appropriate motor commands at every moment in time. Due to the numerous degrees of freedom in humanoids, and the almost infinite number of possibilities to use them over time, there exist an infinite number of possible movement plans for any given task, making learning quite intractable. Thus, research on trajectory planning as been focussing on an alternative method by requiring that movements are built from movement primitives defined by speed and amplitude parameters; then learning finely tunes the parameters to improve the movement [3].

Again inspiration from biology motivates another project. A common feature in the brain is to employ topographic maps as basic representation of sensory signals. Such maps can be built with various neural network approaches and learning motor control with topographic maps can follow [4].

None of the above mentioned methods are so far used for the hand control.

In the following Section 2 we illustrate our prototype of artificial hand.

In Section 3 we present the control strategy. Section 4 discusses the model description for the artificial hand, while Section 5 develops the models of neurons.

In Section 6 we present and discuss the simulation results of a single joint actuated by two artificial muscles. Section 7 gives conclusions and proposes further research.

2. Our Artificial Hand

In this paper we describe the low level control strategy for our prototype of artificial hand Blackfingers (Figure 1).

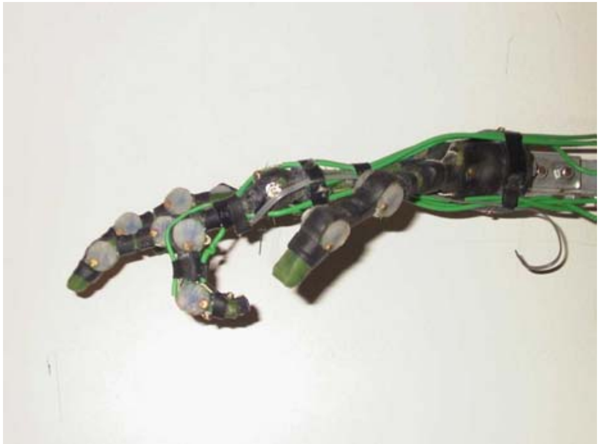

Figure1: Blackfingers

As in the human hand the joints of Blackfingers[5] are of two kinds: the spherical ones connect metacarpi to the first phalanxes (and provide 2 d.o.f), the cylindrical ones provide a rotation. In our hand all the joints have been obtained with a special cutting of the bone structure, which replicates the natural shapes of the contact parts.

The *ligaments* are obtained with elastic bands that connect joints allowing them a limited movement. The *tendons* are obtained with iron cables covered with 0.5 mm of Teflon. To make the tendons connected with bones, plastic bands have been applied. In our prototype each finger is moved by the combined action of six tendons.

In the first version of the prototype we built a hybrid hydraulic-pneumatic propulsion system using as actuators 6 cylinders for each finger .

The precision of the system was good as well as its strength. Nevertheless for actuating the total 18 degrees of freedom of the hand (3 in each finger and 3 in the wrist), we needed 36 actuators that we were not able to insert all in the forearm.

So during this year we have studied and experimented a new version of the McKibben actuators, that we have built using light and resistant materials, as in Figure 2.

All components are build using a plastic polymer and aluminum alloy, as we can see in figure 2; the total weight is only 20 g, with a good reduction with respect to the 170 g of a traditional pneumatic cylinder.

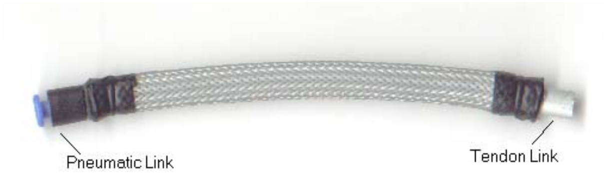

Figure 2: Actuator

Also the dimensions are half with respect to the classical actuators but the advantage is that we can maintain the same force and dynamic performance.

With this new system we can pack about 40 actuators in a space of only $60mm \times 60mm \times 200mm$, and give the full motion at every hand joint.

Actually we are working for implementing the position and force sensors directly inside the actuator, to save space and to reduce the wire connections with the control system. This aspect is very important because the electric wire in the joint suffer of deterioration due to the joint movement and friction.

After this short presentation of the prototype construction, we are able to introduce the control problem.

The control problem of the finger joints is approached here using a biologically based approach and is developed through simulation.

In all vertebrates, the motion control is distributed in many centers. A muscle receives nervous pulses from nervous fibers of the motoneurons. Pulses are regulated both by signals from peripheral receptors (reflex) and by the brain motor.

Reflex actions depend only on the spinal cord. The simplest biological control system is the reflex arc, which does not involve the encephalon activity, and which presents characteristics as:

- reflex time: from 0.5 to 1.5 ms.
- reflex threshold: the minimum value of the stimulus to activate the reflex.
- reflex inhibition: some neurons are able to inhibit the reflex; for instance when flexing a finger, the extensors are inhibited.

According to the receptor involved, reflexes are esteroceptive as well as enteroceptive. The most important enteroceptive reflex is the miotatic reflex, which originates from the neuro-muscular fibers. This reflex is characterized by two phases; a rapid contraction followed by a lower and longer contraction that stabilizes the muscle to a given length. The miotatic inverse reflex starts from the Golgi organs, go to the spinal centers, and inhibit the motoneurones of the given muscle that is relaxed back [6].

To develop a neural control for the miotatic reflex. we started the construction of a simulator to set the parameters of the reflex control.

3. Control Strategy

In figure 3 we can see the general control structure for a single finger of the artificial hand.

We can individuate three main blocks: the low-level task control, the reflex control and the dynamic model for the finger and for the actuation system.

The *low-level task control* receives the high level command from the hand control manager and converts it into a sequence of joint position and force specifications. This control is able also to set the finger stiffness; in this manner it is possible to save energy to maintain a determinate joint position and at the same time execute a specific task.

The *reflex control* block is able to simulate two reflexes that we can find out in the human body. In particular we have simulated the miotatic reflex control and the inverse miotatic reflex control.

The last block in figure 3 represents the *dynamic model* for the finger and for the actuation system.

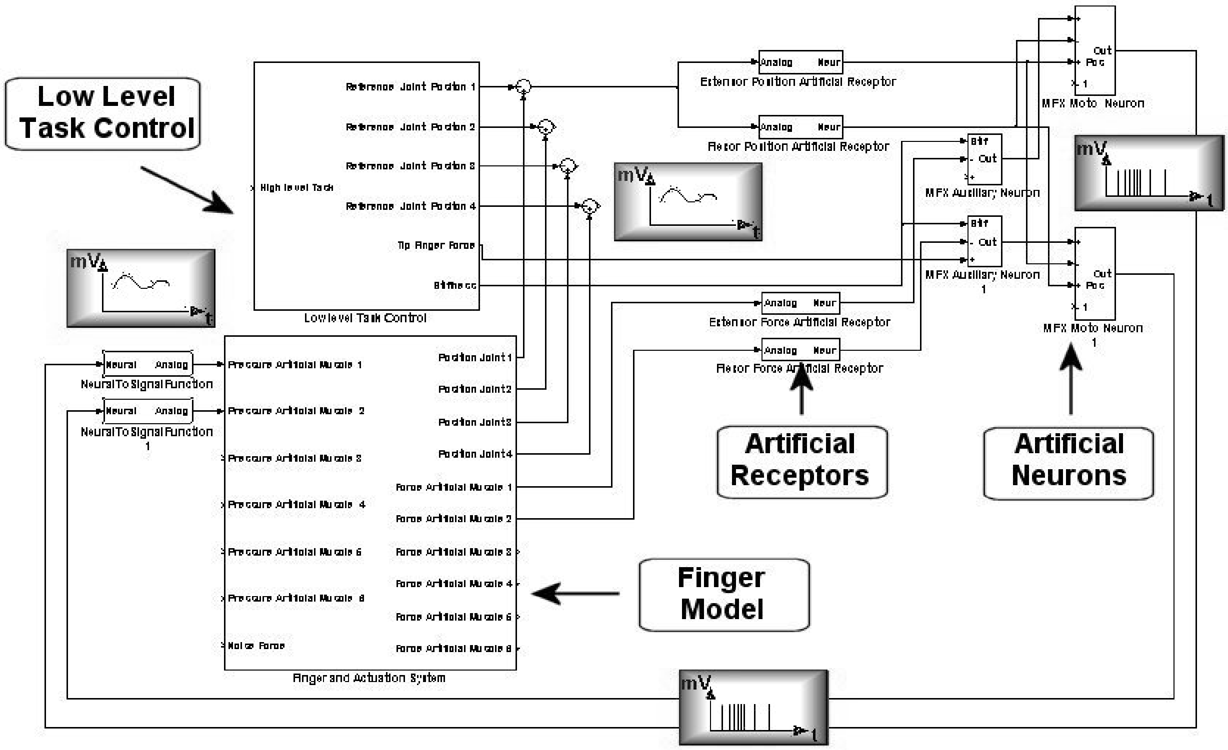

Figure 3: Low Level Control General Schema

3.1 Reflex control

In this control block we can find all the components necessary to the position and moment control for the joint (figure 4).

The real position is subtracted from the reference position supplied from the finger dynamic model; in this manner the error position is obtained. This value feeds the position receptors for the extensor and flexor actuators [7].

By the artificial receptor the analog value is converted into a neural impulsive signal appropriate to feed the motoneurons.

Another motoneuron input comes from an auxiliary neuron whose task is to set the joint stiffness.

Even if the position error is null, this motoneuron fires with a frequency proportional to the stiffness value that come from the Low Level Task Control.

Another task of the auxiliary neuron is to emulate the inverse miotatic reflex, which is based on the two force artificial receptors.

As far as the force developed by the actuators is under a threshold, the force-receptor potential is at low level and consequently it does not fire.

However, when the force exceeds the threshold, its potential increases and so its firing frequency.

The force receptor output, in its turn, feeds an inhibitory input of the auxiliary neuron, so when it starts firing at high frequency the auxiliary neuron potential decreases, and so its firing frequency.

This action inhibits the motoneuron that diminishes the actuators force and so the tensions in the flexor and extensor tendons. At this point the joint is free to move under the external action. This behavior avoids the possibility of damages at the tendons, actuators and mechanical finger's structure.

4. Models for the artificial hand

The model has been configured to replicate the finger dynamic of our artificial hand.

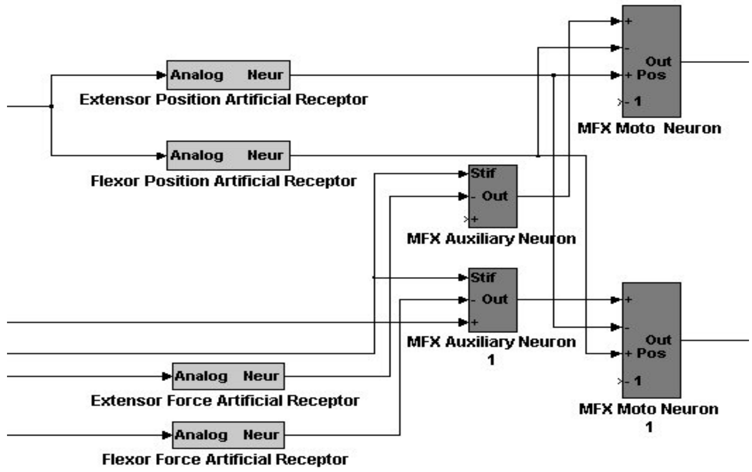

Figure 4: Artificial Miotatic and Inverse Miotatic Reflex Control

First we have experimentally obtained the dynamic constants that characterize the dynamic of the real system, like elastic constants, friction, inertia, mass etc. Then we have built the dynamic mathematical model and represented it with the Simulink library. Finally after simulations we have set the parameters that characterize the dynamic behavior of the reflex control.

4.1 Model of the artificial muscle

This system reproduces the dynamic of the actuation system that equip our artificial hand prototype Blackfinger. It is a modified version of Mc Kibben actuators.

Tondu and Lopez [8] have proposed a good dynamic model for this type of actuators, as in the equations (1) and (2).

$$F_i = \pi r_0^2 P_i \left[a(1 - K\varepsilon_i)^2 - b \right] + \\ - \left[f_k + (f_s - f_k) e^{-\frac{\dot{x}}{\dot{x}_s}} \right] \frac{1}{n} Sco \cdot P_i sign(\dot{x}) \qquad (1)$$

$$Sco = 2\pi r_0 \ell_0 \frac{sen\alpha_0}{(1 - K\varepsilon)\sqrt{1 - \cos^2 \alpha_0 (1 - K\varepsilon_i)^2}} \qquad (2)$$

F is the force generated from the artificial muscle; P is the pressure that feeds the actuator, r_0 and ℓ_0 are the initial radius and length of the muscle, x is the muscle position, and a, b, ε, f_k, f_s are other parameters that characterize the muscle structure and the dynamic friction.

4.2 Model of the finger joint

The model in equation (3) represents the dynamics of the Blackfinger phalanx joint.

The model has been defined using the Newton-Euler formulation of dynamics.

$$J\ddot{\theta} = -K_e \theta - F_d \ell + \frac{1}{2} m \ell g \cos\theta + (F_1 - F_2) R \qquad (3)$$

J	Phalanx inertia moment
K_e	Ligament elastic constant
m	Phalanx mass
F_d	Noise force
F_1, F_2	Artificial muscles forces
ℓ	Phalanx length
R	Joint radius

Like the actuators model, the joint model isn't linear, making it difficult to apply the classic control theories.

Instead of working to transform the system into a linear formulation, as in [6] we keep the nonlinear system and develop a neural control as illustrated in the following section.

5. Model of Artificial Neuron

The dynamic neuron model will reproduce the impulsive behavior of a natural neuron [9, 10].
Equation (4) gives the general model of the dynamic neuron.

$$\dot{P} = G_1\left(w_1 x_1 - w_2 x2 + w_3 x3 - fP - G_2 threshold(P)\right)$$
$$Y = G_3 threshold(P)$$

$$threshold(P) = 1 \qquad \text{If} \qquad P > l_1$$
$$threshold(P) = 0 \qquad \text{If} \qquad P < l_2 \tag{4}$$

In the above equation P represents the action potential of the artificial neuron; its variation is proportional to the impulsive inputs frequency opportunely weighted.

The threshold function has a relay behavior; it assumes the value 'one' when the potential exceed 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 with w_1, w_2 w_3.

The parameter G_1 is a loop gain and its value can modify the dynamic neuron's response.

As the natural one the artificial neuron has a short-term memory, and the decay term *–fP* in (4) determines the rating of forgetting.

As for the input, the output is a sequence of impulses that have the same duration but a frequency variable in function of the inputs and of the weights values.

In figure 5 we can see an application of the artificial neuron implementing a motoneuron.

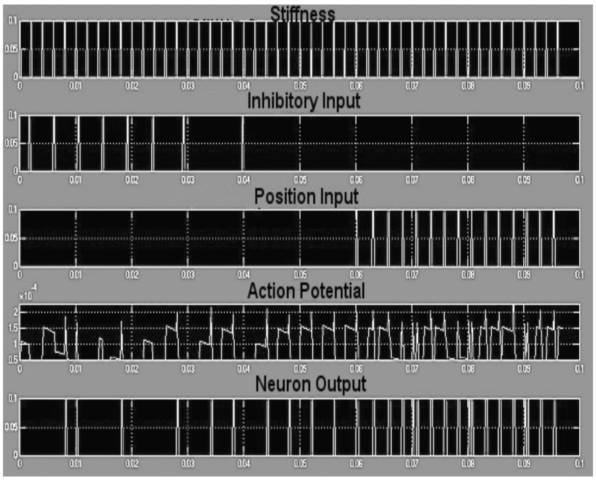

Figure 5: Neuron response

5.1. Artificial Receptor

This function is able to convert analogical signal in impulsive signal that are appropriate to stimulate the neurons.

Its formula is expressed by equation (5).

$$\dot{S} = x\left[1 - \left(threshold(S)\frac{1}{x} + threshold(S)\right)\right]$$

$$Y = threshold\,(S) \tag{5}$$

S is an internal state, x is the input signal, and the threshold function is the same as in (4).

When the state S is lower than a preset value l_1, S will assume the integration of the input signal x and Y remains at zero value.
If S outranges the l_1 limit the threshold function assumes the value one and so the output Y.

The impulse duration is a constant independent from input signal; the impulse frequency instead is proportional to the input intensity.

In this manner we are able to have an impulsive signal that has a frequency directly proportional to the input analogical value.

5.2 **Neural to analogical function**

With this function it is possible to convert an impulsive neural signal into a continuous analogical signal.

The formula that describes this function is expressed by (6) in the dominium of *L*aplace transform.

$$Y(s) = G\frac{1}{0.08s+1}x(s) \quad (6)$$

In this function is very critical the choice of polo frequency; if it is too high there is no integration of the input signal, while if it is too low the output will not be continuous but will have an impulsive aspect.

6. Computer Control Simulation

To test our control system we have used the Simulink software. Simulation is performed on AMD Athlon 1GHz computer, equipped with 256 Mbytes of RAM.

We have simulated two types of control behavior: the tracking of reference position for a finger joint and the response to a harmful force.

We can see the results of our first experiment in figure 6.

In the figure, at the bottom, we can see the reference position (radians) that changes like a square wave whose amplitude is 1 radiant and period is 0.5 s.

At the top there is the real joint finger position that follows with an appreciable precision the reference position. This result is good considered the global system characteristics, in particular recalling that the finger joint model and the actuators model are highly non linear.

The other quantities represented in the graphic output are the forces and the inner pressures of the actuators.

The actuator inner pressure is set by the output of the neural to analogical function.

The other experiment , illustrated in figure 7, was for testing the artificial inverse miotatic reflex. To do that we have fixed the position of the medial and distal finger joints, then we have flexed the first phalanx of 0.5 radians.

In this condition we have applied at the fingertip a noise force of 80N, that generated a moment dangerous for the hand, especially for the tendons that are designed to support only fixed maximum loads.

In the first 1.5 seconds of test the joint reaches the settled position at 1 radian (57.2 degrees), at this point the noise force acts at the fingertip.

As a consequence the force of the actuator connected with the flexor tendon increase as long as the max value of 800N. In this condition the artificial force receptor connected with the actuators starts firing at high frequency.

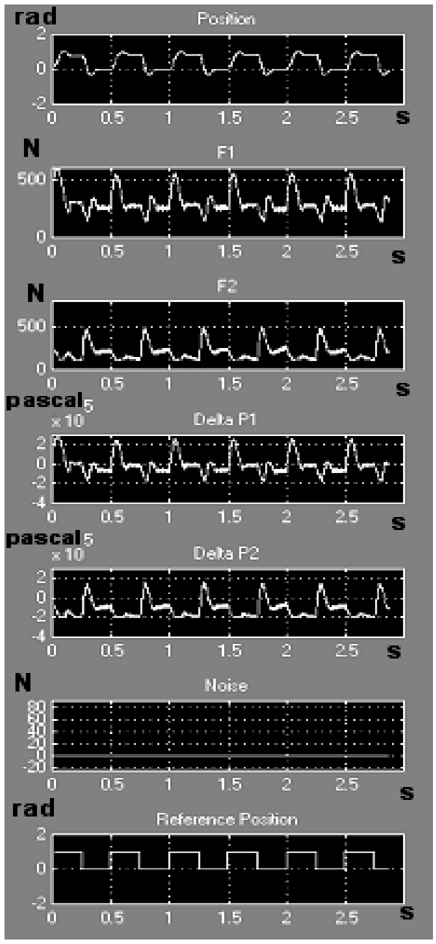

Figure 6: Miotatic Reflex Test

This action inhibits the auxiliary neuron and so the motoneuron that controls the force in this actuator.

After the effect of the artificial inverse miotatic reflex the force is lowered to 600N that is acceptable for the flexor tendon.

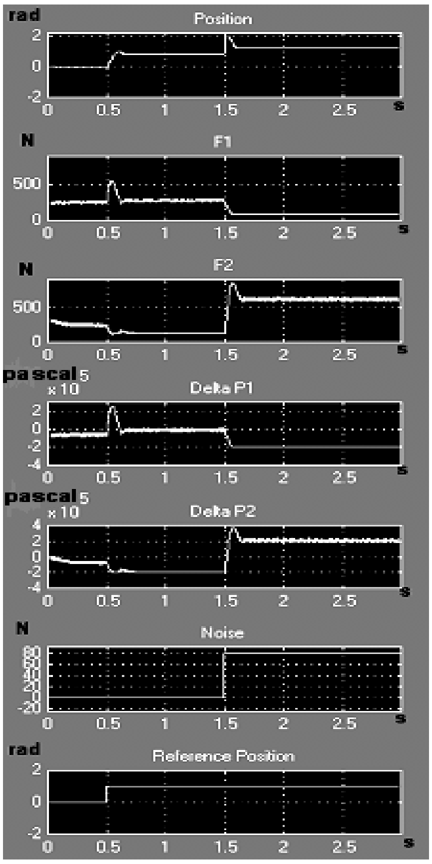

Figure 7: Inverse Miotatic Reflex Test

7. Conclusion

The simulation results show that the artificial miotatic and inverse miotatic reflex controls are able to emulate the human reflex even if they are applied to an artificial system like Blackfingers.

With respect to the classical control systems; the reflex control is more easily configurable. This is very important especially if the system that we want to control is highly non-linear.

In comparison with L. Yong et al [11], we have demonstrated that the miotatic reflex control is applicable to Mc Kibben actuation system, and in the specific case to our prototype of artificial hand.

Moreover, in our research, we have developed a specific type of dynamic artificial neuron that has a response more human like.

The next step of our work is to test our control system on the real prototype.

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