ADAPTIVE REFLEX CONTROL FOR AN ARTIFICIAL HAND

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Abstract: In this paper we illustrate the properties and the morphology of a human like neural reflex controller, used to set the stiffness and joint positions of an anthropomorphic artificial hand. In particular we explain, by simulations results, its ability to emulate the myotatic human reflex, and its capacity to learn in real time the best control strategy. We also present the dynamic model of the joints and of the artificial muscles used in Blackfingers, our artificial hand.

Keywords: Reflex Control, Neural Control, Artificial Hand, Humanoid Robot

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 so as to mimic the human control system. At MIT, Matsuoka (Matsuoka 1995) in her Master thesis has developed different learning strategies. However, that hand which was developed for the Cog robot 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, backpropagation algorithm and reinforcement learning strategies. Interesting in the work of Matsuoka is the implementation of a reflex control. Another interesting project is under development at the Vanderbilt University (K. Kawamura and Rogers 2000). Their robotic system, ISAC, is targeted to aid elderly or disabled people in their homes. ISAC's 6DOF arms thus require anthropomorphic hands. The current implementation utilizes a

Watt 6-Bar Linkage for coupling actuator motion for both the distal and proximal joints of a single finger. 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 underway in Neural Computation (M. Kawamura 1999), which attempts to combine knowledge from biology with knowledge from physics and engineering, with the goal of discovering new technologies by studying the principles of natural behavior. Using this approach we have designed the hand control proposed in this paper. In the following Section 2 we illustrate our prototype of an artificial hand. In Section 3 we discuss the functional aspects of the muscle control in natural systems, while in Section 4 we present the control strategy based on emulating the reflexes. Section 5 discusses the model description for the

artificial hand, while Section 6 develops the models of neurons. In Section 7 we present and discuss the simulation results of a single joint actuated by two artificial muscles. Section 8 gives conclusions and proposes further research.

2. OUR ARTIFICIAL HAND

As already underlined, the first step of our design was a good understanding of the human hand. After the study of the natural hand, both in bones and muscles organization, we illustrate here the construction of the artificial hand Blackfingers (Figure1).
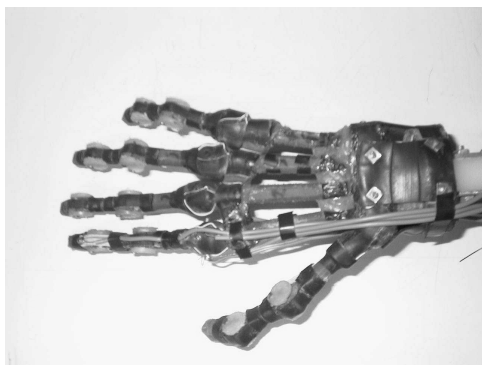

Fig. 1. Blackfingers

As in the human hand, the joints of Blackfingers (M. Folgheraiter 2000) are of two kinds: the spherical ones connect metacarpi to the first phalanxes (and provide 2 d.o.f), the cylindrical ones provide rotation. In our hand all the joints have been made from Nyloil using a special cutting technique that replicates the natural shapes of of the bone structures. The ligaments were obtained from elastic bands that connect joints, thus allowing them limited movement. The tendons are obtained with iron cables covered with 0.5mm of Teflon. To connect tendons with the artificial bones plastic bands have been applied. In our prototype each finger is moved by the combined action of six tendons. For actuating the total of 18 degrees of freedom of the hand (3 in each finger and 3 in the wrist), we needed 36 actuators that must be inserted in the forearm. To solve this problem we have studied and experimented with a new version of McKibben actuators, that we have built using light and resistant materials. All components were built using a polymer material and aluminum alloy; the total weight is only 20 g, with a good reduction with respect to the 170 g of a traditional pneumatic cylinder. Also the dimensions are half with respect to the classical pneumatic actuators, but the advantage is that we can maintain the same force and dynamic performance. With this new actuation system we can give the full motion at every hand joint. Currently, we are working on 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 wires in the joints deteriorate with use due to joint movement and friction. After this short presentation of the prototype construction, we are able to introduce the control problem.

3. NATURAL REFLEX CONTROL

The most important human interoceptive reflex is the myotatic 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. Its principal function is maintaining the joint position fixed and compensating external noise forces. The other reflex, present in the human beings, is the myotatic inverse reflex; it starts from the Golgi tendon organs and has the main function to inhibit the motoneurons of the given muscle when the strength exceeds dangerous values (Atsushi 1991).

In most cases muscles work in opposing pairs: one muscle opens a joint and the other closes it. This configuration is necessitated by the fact that muscles exert force in one direction only. We can see in Figure 2 the model of a typical joint with the two antagonist muscles, the spindle inside, the lower motor neurons (LMN), the gamma neuron, and the interaction between them.
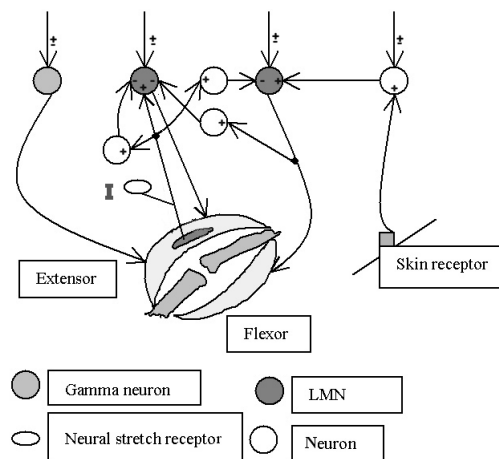

Fig. 2. Schema of a joint with the principal neurons involved in the reflex control

The principal neuron of this system is called the lower motor neuron (LMN). All the neurons illustrated are in the spinal cord, and there are LMN for each fiber or one for the muscle. In figure 2 we see only one LMN for a muscle. An LMN system must accept commands from many other systems which desire control of the muscle. The degree of contraction of a muscle is proportional to the output pulse frequency of

the LMN. The part on the right illustrates the simplest type of spinal reflex: a pain receptor in the skin fires a neuron in the LMN system, which in turn fires the LMN driving the flexor muscle. This operation removes the limb from danger. Inhibitory cross connections between the LMNs driving the two muscles insure that they act in concert. This reciprocal synergistic circuitry is generally active in all LMN operations. Higher level inputs to the LMN system may request such actions as holding a particular position or moving to a specific position. Suppose that the higher nervous center wishes the LMN to maintain a joint at a particular angle. This command reaches a set of constant inputs to the LMN and to the gamma neuron. Now suppose that a load is applied to the finger. This will tend to flex the joint, causing the extensor muscle to be stretched, causing the spindle to be stretched too. Finally, this will increase the output of neuron I, which increases the output of LMN. The resulting increase in the contractive force of the muscle will compensate for the increased load. This kind of local feedback allows the higher system to ignore the fluctuation in contraction required to maintain a certain joint extension. To develop a neural control for the myotatic reflex we started the construction of a simulator to set the parameters of the reflex control.

4. STRUCTURE AND STRATEGY FOR OUR CONTROLLER

In figure 3 we can see the general control structure for a single finger of the artificial hand. We can recognize 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 observe in the human body. In particular, in this paper we presented the simulation of the myotatic reflex. The last block in figure 3 represents the dynamic model for the finger and for the actuation system.

4.1 Reflex control

In this control block we can find all the components necessary for the position and moment control of the joint (see top at right of Figure 3). The real position is subtracted from the reference

position supplied by the finger dynamic model; in this manner the position error is obtained. This value is sent to position receptors for the extensor and flexor actuators. Artificial receptor converts the analog value into a neural impulse signal appropriate for 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 comes from the Low Level Task Control. Another task of the auxiliary neuron is to emulate the inverse myotatic reflex (M. Folgheraiter 2001), which is based on the two artificial force receptors. As long as the force developed by the actuators is under a threshold, the force-receptor potential is at a low level and consequently it does not fire. However, when the force exceeds the threshold, its potential increases, and so does its firing frequency. This action inhibits the motoneuron and in turn diminishes the actuator force and 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 damaging the tendons, actuators and mechanical structure of the finger. It is important to note also the partial motoneuron inhibition due to the output of the antagonist motoneuron ; this circuit ensures that when an actuator is contracted, the other is automatically released.

5. MODEL OF THE ARTIFICIAL FINGER

The model has been configured to replicate the finger dynamic of the artificial hand. First, we have empirically obtained the dynamic constants that characterize the dynamics of the real system: elastic constants, friction, inertia, mass, etc. Then we have built the dynamic mathematical model and represented it with the Simulink library.

5.1 Model of the artificial muscle

This system reproduces the dynamics of the actuation system that is utilized in our artificial hand prototype Blackfinger. It is a modified version of McKibben actuators. Tondu and Lopez have proposed a good dynamic model for this type of actuators, for more details about the model see (B. Tondu 2000) and (M. Folgheraiter 2001).

5.2 Model of the finger joint

The model in equation 1 represents the dynamics of the Blackfinger phalanx joint. The model has been defined using the Newton-Euler formulation of dynamics. Like the actuator model, the joint
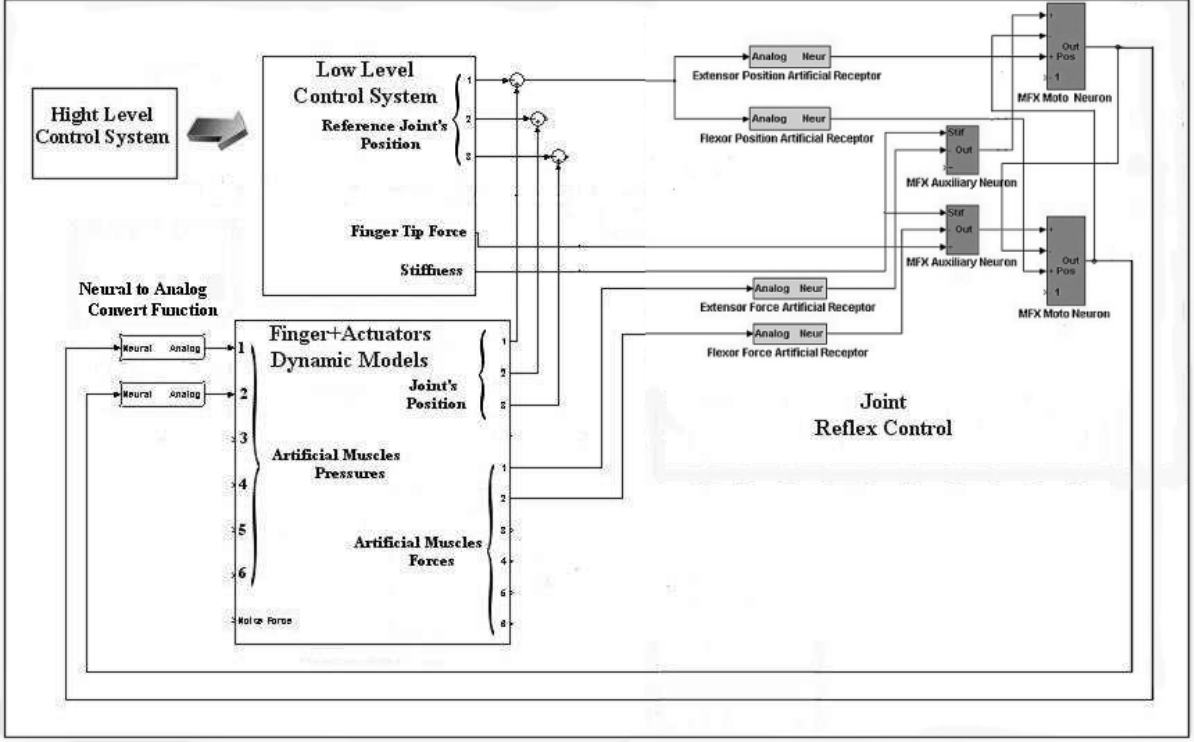
Fig. 3. Low Level Control General Schema

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 (Atsushi 1991), we keep the nonlinear system and develop a neural control as illustrated in the following section.

$$J\ddot{\theta} = -K_e\theta - F_d l + \frac{1}{2}mlg\cos\theta + (F_1 - F_2)R \quad (1)$$

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

6. MODEL OF THE ARTIFICIAL NEURON

The dynamic neuron model will reproduce the impulse behavior of a natural neuron and is based on the Hodgkin model (Hodgkin and Huxley 1952), (M. Scholles 1993). Equation 2 gives the general model of the dynamic neuron. 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.

$$\dot{P} = G_1(w_1x_1 - w_2x_2 + w_3x_3 - fP - G_2Th(P))$$
$$Y = G_3Th(P)$$

$$
\begin{array}{lll}
Th(P) = 1 & if & P > l_1 \\
Th(P) = 0 & if & P < l_2 \\
Th(P) = previus\ value & if & l_2 \le P \le l_1
\end{array}
$$
$$(2)$$

Like the natural one, the artificial neuron has a short-term memory, and the decay term $-fP$ in equation 2 determines the rate of "forgetting". Similar to the input, the output is a sequence of impulses that have the same duration but variable frequency which is a function of the inputs and of the weight values.

6.1 Neuron Learning Ability

The reflex neural network must be able to adapt to the dynamic characteristics of the system that needs to be controlled. In order to perform this behavior, neuron weights have to be changed during the system operation. Their values will change until they reach the optimal solution for the control. This means that the error must decrease as

fast as possible, and no overshoot can be present in the system response.

In supervised learning, the adjustment of neuron weights happens in concomitance with function minimization; that is significant for the control problem in question. Instead, in unsupervised learning, the neural network improves its performance using a task-independent measure of the control quality. However, this process usually is difficult to perform in real time, especially if the network has to learn and control the system at the same time. What we have tried to do in our neuron model is to use dynamic input weighting. In this specific case, the weight W is also a dynamic system, and the model is presented by the equations 3.

$$
\begin{aligned}
&\dot{w}(t) = K_1 x(t) - K_2 w(t) \\
&w(t_0) = 0 \\
&W = Lim(w(t)) \\
\\
&Lim(V) = V \quad if \quad 0 \leq V \leq 1 \\
&Lim(V) = 0 \quad if \quad V < 0 \\
&Lim(V) = 1 \quad if \quad V > 1
\end{aligned}
\tag{3}
$$

In equations 3 the function Lim is an output limitation, and it regulates the internal status of the weight $w(t)$. K_1 is the learning constant and K_2 is the forgetting constant, these are conveniently chosen to set the "correct" learning and forgetting rate. For example, if K_1 is too high, the weight saturates rapidly at the maximum value permitted. It is possible to set these two values empirically; let's suppose that the neuron input $x(t)$ weighted by W has the maximum frequency, we want that, in these initial conditions, the weight increases and reaches the maximum value admissible (one) in one second. This specification is sufficient to set the K_1 value. In the same mode we can set the K_2 value, but this time we have to consider a null $x(t)$ input signal and choose the period of time that the weight status $w(t)$ needs to pass from the high value to the low admissible value (zero).

The weight behavior differs from the Hebbian learning rule(Hebb 1949), because it does not take into account the correlation between the presynaptic and postsynaptic neuron activity. In fact here, we can think about this learning rule as a local observer: the weight is reinforced if the input neuron is stimulated, and weakened otherwise.

6.2 Artificial Receptor

Artificial receptor is able to convert an analog signal into impulse signals that are appropriate to stimulate the neurons. Its formula is expressed by the equation 4.

$$
\begin{aligned}
&Y = Th(v) \\
&\dot{v} = x[1 - (Th(v)\frac{1}{x} + Th(v))]
\end{aligned}
\tag{4}
$$

v is an internal state, x is the input signal, and the threshold function is the same as in (4). When the state v is lower than a preset value l_2, v gets the value of the integration of the input signal x, and Y remains at zero value. If v overcomes the l_1 limit, the threshold function assumes the value of one, and so does the output Y. The impulse duration is a constant independent from the input signal; the impulse frequency instead is proportional to the input intensity. In this manner, we are able to have an impulse signal that has a frequency directly proportional to the analog input value.

6.3 Neural to analog function

With this function it is possible to convert an impulse neural signal into a continuous analog signal. The formula that describes this function is expressed by equation 5 in the Laplace transform domain.

$$
Y(S) = G\frac{1}{0.08S + 1}
\tag{5}
$$

In this function, the choice of pole frequency is very critical; 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 impulse behavior.

7. 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 chose Euler integration method with a integration step of $10\mu s$, this to guaranty the correct spiking neuron behavior. We have simulated the tracking of reference position for a finger joint. The results of simulation are presented in figure 4. In the figure, at the bottom, we can see the reference position (radians) that changes like a square wave whose amplitude is 1 radian and period is 1 s. As can be seen at the top of the figure 4, the real position in the beginning of simulation does not follow the reference very well. This is due to the fact that initially there is no cross neurons inhibition. However after two second the two inhibition weights are converged to an optimal value (Figure 5) and the real joint position reaches the reference in 0.25 seconds.

This result is good considering the global system characteristics, in particular recalling that the finger joint model and the actuators model are
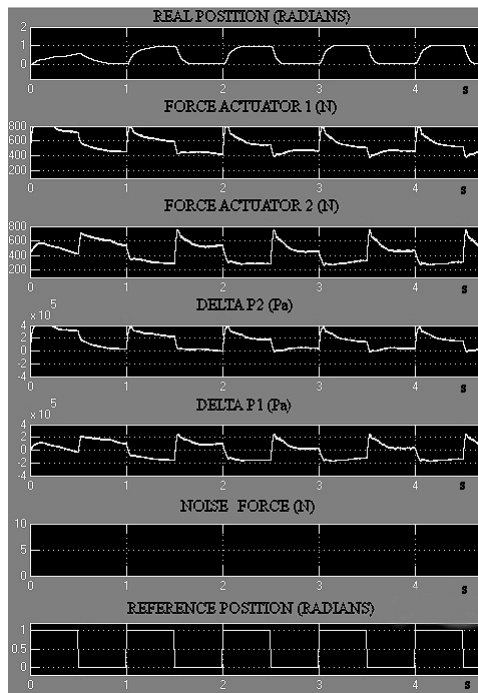
Fig. 4. Myotatic Reflex Test

highly non linear. It is also possible to appreciate a gradual improvement of the response. The other quantities represented in the graphic output are the forces and the inner pressures of the actuators. As is possible to see in figure 5 the two weights converge to two different values, this probably is due to the fact that gravity and elastic force are positive in a flexion rotation and negative in a extension movements.
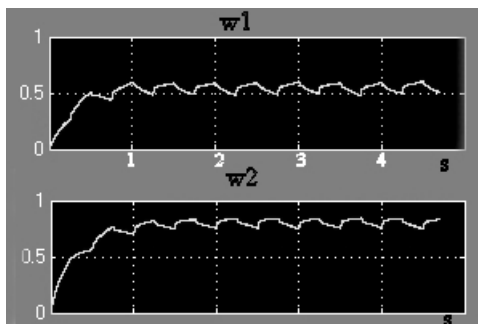

Fig. 5. Myotatic Reflex Test

8. CONCLUSIONS

The simulation results show that the artificial myotatic reflex control is able to emulate the human reflex even if it is applied to an artificial system like Blackfingers. We have also demonstrated, by simulation,the importance of the cross inhibitions in the reflex control, and its ability to learn the best control strategy in real time. With respect to 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 work (L. Yong 1996), we have demonstrated that the myotatic reflex control is applicable to McKibben 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 more human-like response.

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