A New Approach to Artificial Neural Networks

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***Abstract*— A novel approach to artificial neural networks is presented. The philosophy of this approach is based on two aspects: the design of task-specific networks, and a new neuron model with multiple synapses. The synapses' connective strengths are modified through selective and cumulative processes conducted by axo-axonic connections from a feedforward circuit. This new concept was applied to the position control of a planar two-link manipulator exhibiting excellent results on learning capability and generalization when compared with a conventional feedforward network. In the present paper, the example shows only a network developed from a neuronal reflexive circuit with some useful artifices, nevertheless without the intention of covering all possibilities devised.**

***Index Terms*— Control systems, manipulator position-control, neural-network architecture.**

I. Introduction

THE DESIGN of control systems requires the use of mathematical models and analytical techniques to derive control laws. It also requires the knowledge of the dynamic response of the processes involved. When the processes are complex, massive computing or experimental research is necessary. In spite of this, when the amount of uncertainty is large, one cannot assure that classical control will provide the desirable robustness, then other control techniques are required. Biological control systems have been quite successful at dealing with that kind of problem. In this context, adaptive control techniques have been developed, including the artificial neural networks (ANN's).

The purpose of this paper is to present the results of an innovation in the field of ANN's, and beginning the exploration of these innovating ideas for control purposes. The paper consists of six sections. Section I is this introduction. Section II gives a brief history and reviews some efforts in the field of ANN's. Section III shows the new concept derived from the neural science. Section IV presents an example of application in a robotics arm control. Section V is devoted to present some results and a comparison with a feedforward network. Section VI is a summary of conclusions with the new perspectives opened.

II. Artificial Neural Networks Review

Researchers of different fields have developed the field of ANN's. In this paper, a few of them will be referred to only show some basis to this new approach.

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Inspired from neuroscience, the theory of ANN has been developed based on the knowledge of neurobiology, mathematics, and physics. Since 1943, when McCulloch and Pitts [1] proposed a model of a neuron as a binary threshold unit, the research on neural networks had passed through periods of enthusiasm and criticism. Around the 1960's Rosenblatt [2] introduced the Perceptron rule and Widrow and Hoff [3] the ADALINE. As Hertz *et al.* related [4], these contributions gave rise to a cycle of development. Few years later, Minsky and Papert felt doubt that a multilayer learning algorithm could be invented, and their book *Perceptrons* [5], published in 1969, caused the slowing down on that enthusiasm. In 1974 Werbos [6] presented the backpropagation algorithm which was not well disseminated. In 1982 Parker [7] reinvented this algorithm which was once again reinvented by Rumelhart *et al.* [8] in 1985. Since then, a lot of work was done on that basis.

The theory of ANN's considers regular arrays of units (representing neurons) interconnected by single connections with linking weights (representing synapses). Because of this, the signaling in ANN's is composed basically by linear amplification or attenuation of input signals in each unit, a summation of all incoming signals and a scaling by a transfer function.

Concerning the transfer functions in ANN's one can note that simplification is the emphasis, with the hypothesis that nonlinearity is essential, but not its specific form [4]. Many experts also say that phase does not play a significant role and asynchronous updating is not usual. Because of all these concepts, the learning task is focused on single connections conductance and is treated almost apart from the action network.

In the last seven years ANN's researchers have focused on the limitations of this approach, and many interesting works have been produced. In 1991, Kolen and Goel [9] reported the results of a set of experiments to identify the power and limitations of the backpropagation algorithm. They concluded that: first, *the experiment on learning suggests that the computational efficiency depends on the initial weights in the network;* second, *the information content of what is learned is dependent on the initial abstractions in the network* and third, *the learning task addressed by connectionist methods is computationally intractable.* In addition, their results indicate that current connectionist methods may be too limited for the task of learning they seek to solve, and they propose that the development of task-specific connectionist methods may enhance the power of neural networks.

With these preliminary considerations we settled two main paradigms: 1) ANN's have been seen mainly as regular arrays of units interconnected by single connections with linking

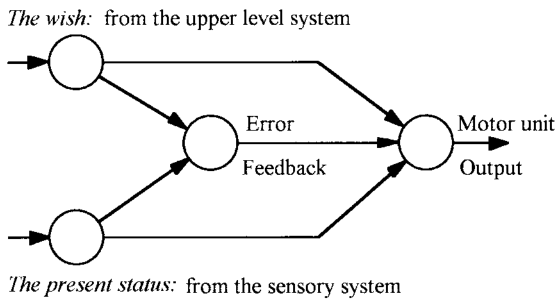

Fig. 1. Basic structure of a control unit.

weights (synaptic conductance) and 2) the learning task focus on single connections conductance and, in general, is treated apart from the action network. These paradigms may show that the whole basic nature of brain's evolution was not applied to the many designs of ANN's. At this point we must emphasize that the development of a new approach should be based on the logical that, if ANN's were inspired from neuroscience, they should be harmonious with the knowledge from this field.

These points let us with the following principles: 1) an ANN design shall be based on biological systems to take the profit of their evolutionary nature; 2) it shall represent what it knows and what is to learn and it must have capabilities to generalization, therefore it must have different regions specialized for different functions; 3) it must be robust to missing information, incorrect data, and unit removal or malfunction; 4) the learning task shall be done in realtime while functioning and shall be independent on the initial unit strength; and 5) the process of learning and functioning must be computationally efficient without limiting the power of connection's transfer functions to obtain higher classes of input-to-output functions.

To develop a new concept able to follow at least some of the above principles, the first step is to conduct a search program on biological neural systems. This search was focused on the following items: 1) architectural design and flow of information in the brain; 2) neuronal signaling; and 3) learning and memory mechanisms.

III. The New Concepts

This item presents the results of the search that followed the itemization given in the last item, showing the association between biological functions and the network equivalent components. The first source of information to this task was the book of Kandel *et al.* [10], which presents general information and references.

A. Architectural Design and Flow of Information

The functional, organizational, and developmental principles of neuronal circuits, that make the principles of parallel processing, suggests that a control circuit must have two separated pathways, one for the upper level control commands: *the wish*—like a target position; and, the second for the sensory signals: *the present status*—as the present position. Such circuits should also have convergent pathways from the upper level and sensory systems to the motor units. Fig. 1 resumes these main ideas with 1) error feedback (to maintain or correct posture); 2) separated pathways for upper level control signals and sensory signals; and 3) convergence to the motor units.

B. Neuronal Signaling

This topic is devoted to the neuronal signaling processes and models.

1) The Unit Transfer Function: The unit transfer function within a neuron is the composition of the processes of integration the incoming signals, generation of an action potential, and its conduction to other cells. The neuron's transfer function in biological systems is simple and can be generalized regardless of its size or shape. Because of this biological peculiarity, the evolutional process had to build expert systems to represent specific functions over extended ranges. The work of Akazawa and Kato [11] shows a good example of this proposal. They presented a model to investigate neural mechanisms of force control based on the "size principle of motor unit." This example, associated with the "common drive hypothesis" of DeLuca *et al.* [12], shows that besides the number of units has important roles in terms of robustness it is also essential to the *meaning of the signals.*

ANN's do not have the same constraints of biological systems. The unit transfer function improvement reduces the number of units and consequently decreases computation usage. In most cases it is enough a single unit, with a transfer function in a scaled positive–negative domain to emulate agonist and antagonist circuits, making use of the benefits of the size principle of motor units. The transfer function chose is the modified hyperbolic tangent function expressed in (1)

$$O = T_N \tanh(\alpha \Sigma S) \tag{1}$$

where O is the output signal; T_N represents the "size" of the unit; α is a gain; and ΣS is the summation of all synaptic input to that unit. The "size" can be set to convenient values to improve the linearity in the range of interest or to amplify or reduce the input to output relation.

2) Synaptic Transmission Modeling: Synaptic transmission depends on several processes in the nerve terminals that are even important for the cell survival. An average neuron forms about 1000 synaptic connections and receives even more; a motor neuron may have 10 000 different presynaptic endings and a Purkinje cell receives around 150 000 contacts—about 10^{14} synaptic connections are formed in the brain [13]. This observation brings us with the idea of improving the ANN concepts with the *multiple synapses model.* The multiplicity of synapses can improve the overall transfer function capability, by increasing the connective complexity but reducing the overall network complexity by reducing the overall number of units.

In the biological synaptic contacts, chemical synapses predominate. With this kind of synapses the most remarkable activities of the brain such as learning and memory are associated. In chemical synapses, the signaling is processed by transmitters released from the presynaptic terminal as a function of incoming flow of action potentials. The amount of transmitters released acts on a large number of ions' channels,

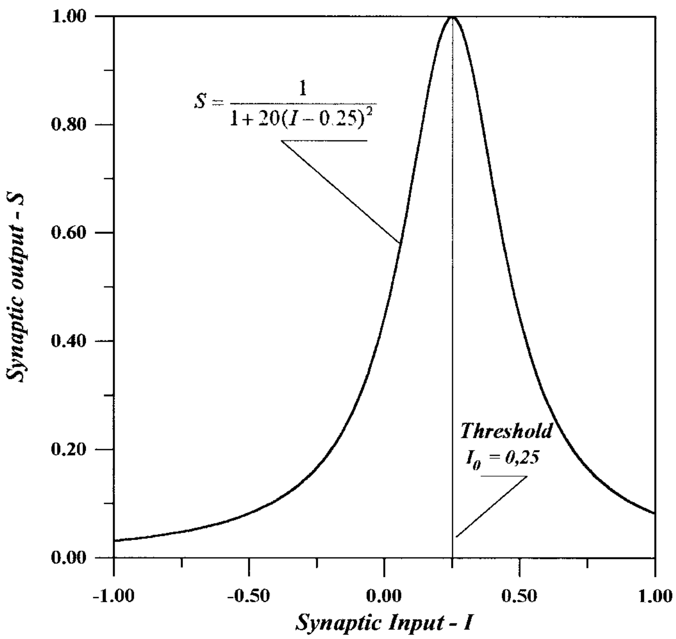

Fig. 2. Synaptic transfer function.

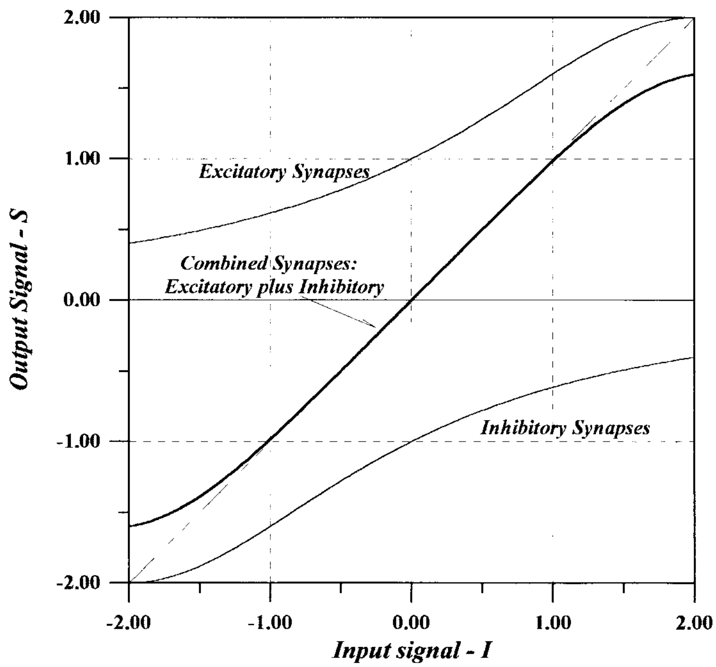

Fig. 3. Synaptic approximation $S = I$.

the receptors of the target cell. The number of activated channels opened during the synaptic potential is limited by the amount of neurotransmitter available. The chemical transmission also shows the property of amplification.

After many trials, a Gaussian like function of the type expressed on (2), and exemplified in Fig. 2, was found to be suitable to represent the neural synaptic transmission process

$$S = \frac{T}{1 + a(I - I_0)^2} \tag{2}$$

where T is the "strength" of the synapse, which can be set as any positive value (excitatory) or as any negative value (inhibitory); a is a constant that can be adequately choose to produce smooth functions according to the number of synapses; I is the signal value that pass through the axon; and, I_0 is the value of I, which is called here "threshold," that maximizes S, the output value to the target cell.

The function of (2) permits amplification and selective response, as would occur during synaptic formation according to the resonance hypothesis of Paul Weiss [14]. Also, this function enhances the whole unit transfer function capability and mimics the stochastic process of transmitter release through the numerous ion channels present in the synaptic contacts. This function is much simpler than sigmoidal functions in terms of computation time.

With convenient strengths and thresholds, a set of functions like that of (2) can produce any kind of continuous function. For example, fixed linear transfer functions can be provided to the regions that must remain unchanged. Equation (3) and Fig. 3 show the approximation of $S = I$, by a set of excitatory and inhibitory synapses, in the interval -1 to $+1$

$$S = \frac{1}{N}\sum_{j=1}^{N}\left(\frac{2}{1+0.25(I-2)^2} + \frac{-2}{1+0.25(I+2)^2}\right)_j \tag{3}$$

where N is the number of redundant units used to improve reliability. With no synaptic fail the results are independent from N and in the event of a synapse failure the effect in the results depends on the number of synaptic contacts and on the level of an incoming signal.

C. Learning and Memory Mechanisms

Learning is the process of acquiring knowledge about the world and memory is the storage of this knowledge. The study of the memory mechanisms provides the fundamentals to implement a learning process based on biological processes. The search should be focused on reflexive memory, which is the kind of memory that accumulates slowly through repetition over many trials. In this topic, some aspects of the *learning processes* and some *physical mechanisms* of memory are reviewed.

1) Learning Processes: A single set of synapses can participate in different forms of learning: they can be depressed by habituation or enhanced by sensitization. More complex forms of learning are classical conditioning and practice.

Detailed studies of these processes [15]–[17] suggests the design of a specific circuit to implement the learning process based on the reflexive memory mechanisms. The circuit, shown in Fig. 4, scales the error signal via one facilitating interunit, that is connected to the output unit synaptic terminals through axoaxonic connections, where the changes are to be affected. The sign of this error dependent signal decides if the process is a presynaptic facilitation or presynaptic inhibition, which will increase or decrease the synaptic strength.

2) Mechanisms of Memory Storage: The change of the synaptic strength due to the learning process can be outfitted by a plasticity model, based on memory storage mechanisms. Memory storage does not depend on *dynamic changes* in

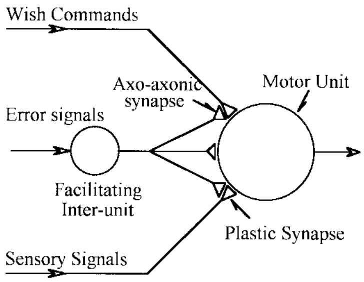

Fig. 4. Synaptic array for the learning process.

a closed chain of neurons, but on *plastic changes* in the strength of preexisting connections. These plastic changes are not a feature of all synapses. Some synaptic connections in the nervous system do not change their strength at all with repeated activation. Reflexive learning does not depend on specialized memory neurons either, but instead memory storage results from changes in neurons that are integral components of a normal reflex pathway.

At synapses related with learning, such as the connections between the sensory and the motor neurons as well as some of the interneuronal connections, a relatively small amount of training can produce large and enduring changes in the synaptic strength.

Cellular studies indicate that a long-term storage process appears to be a graded extension of short-term processes. Furthermore, the type of contact determines the function of the synaptic connections, and this is essential to the learning mechanisms—there are three main types of contact between cells: axo-axonic, axosomatic, and axodendritic. Axo-axonic synapses play an important role because they can depress or enhance transmitter release through presynaptic inhibition or presynaptic facilitation—by the regulation of free Ca^{++} concentration in the presynaptic terminal. This is the basis for a variety of mechanisms that give plasticity to chemical synapses. Aside from a modulatory influence on voltage-gated ion channels, the intracellular concentration of Ca^{++} triggers biochemical and morphological changes in the possynaptic cell.

The action of the facilitating interunit (the presynaptic cell), over the presynaptic contact of the motor unit (the learning cell) is to increase a source term—as the Ca^{++} concentration in real cells—that acts on the long-term plasticity. This can be done through a cumulative process, expressed by (4), where the governing term is proportional to the incoming signal (the training signal δ) and its decay rate

$$\frac{dC}{dt} = T_c\delta - \lambda C \tag{4}$$

where C is the long-term change's trigger factor; δ is the output signal of the facilitating interunit; λ is a decay constant; and, T_c is the strength of the facilitating synapse (that controls the rate of change).

According to (4) the long-term change's trigger factor (C) can grow in a rate proportional to the learning signal (δ), up to an equilibrium value. This makes the change in the synapses strength faster or slower. If the incoming learning signal decreases to zero the long-term change's trigger factor will also decrease to zero, according to the rate established by the decay constant (λ). This means that after a reasonable period of training, when there are no error and no excessive movement, there will be no need to further changes, thus making the process inherently stable.

To complete this idea, it is necessary to set an artifice that makes the changes occurring mainly in the convenient synapses, i.e., in the synapses where the threshold (i_0) is closer to the incoming desired values, like in the resonance hypothesis of Weiss [14]. This novel characteristic makes the correct synaptic selection. Equation (5) shows a model in which the strength rate of change of the motor unit synapses [parameter T in (2)] is a function of the long-term change's trigger factor and of the synaptic threshold

$$\frac{dT_j}{dt} = \frac{C}{1 + a_s(I - I_j^0)^2} \tag{5}$$

where T_j is the strength of the jth synapse of the motor unit; a_s is the constant of the Gaussian like function of the facilitating synapse; I is the signal value that comes from the upper control level (the Wish); and, I_j^0 is the threshold of the synapse.

In summary, (4) emulates the process of Ca^{++} accumulation within the synaptic terminal generating a source term that is the trigger of the long term changes, and (5) selects the correct synaptic terminal *(as in the resonance hypothesis of Weiss)* and generates the rate of change of the synaptic strength. This process acts on all synaptic contacts in the target unit but, with a higher strength growing rate in the synapses that have the threshold closer to the input desired signal $(I \approx I_J^0)$.

D. Motor Control Unit Concept

With the above considerations the network's main structure of Fig. 1 is improved to reach the structure represented in Fig. 5. This figure defines a "motor control unit," which summarizes the new concepts applied to control purposes.

In Fig. 5 the input pathway from the upper level system ("the wish"-$\boldsymbol{I_c}$) and that from the sensory system ("the actual condition"-$\boldsymbol{I_s}$) converge to the unit responsible for sensing the actual error (ϵ). These signals are linked to the error sense unit with rigid connections that will not change with training. These connections are modeled to make the error unit to sense the actual condition from the sensory system with the opposite sign of the wish signal, i.e., $\epsilon = I_c - I_s$. The schema of multiple branches of synaptic terminals improves the reliability as long as it allows the increase in the number of terminals, what can make a more fail-proof system. Equations (6)–(9), which model the terminal types' S_{e+}, S_{e-}, S_{i+}**e**S_{i-}, indicated in Fig. 5, are based on (3)

$$S_{e+} = \frac{1}{N}\left(\frac{2}{1 + 0.25(I - 2)^2}\right) \tag{6}$$

$$S_{e-} = \frac{1}{N}\left(\frac{2}{1 + 0.25(I + 2)^2}\right) \tag{7}$$

$$S_{i+} = \frac{1}{N}\left(\frac{-2}{1 + 0.25(I + 2)^2}\right) \tag{8}$$

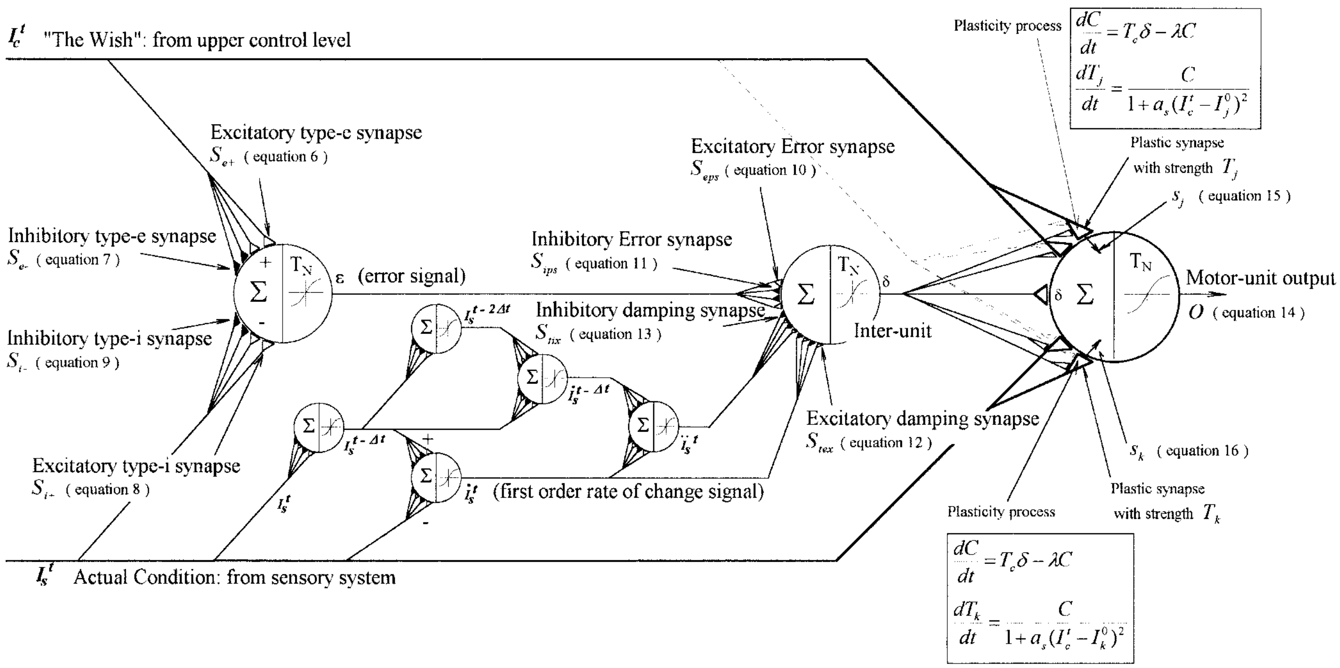

Fig. 5. Motor control unit concept.

$$S_{i-} = \frac{1}{N}\left(\frac{-2}{1+0.25(I-2)^2}\right) \tag{9}$$

where N is the number of redundancies, which does not modify the net result, the subscript e refers to the excitatory synapses, and the subscript i refers to the inhibitory synapses.

To avoid feeding the network with the rate of change of the sensory signals, an artifice is used to sense these rates within the network. Sensing differences between signals from units in different layers implement this. The interunits responsible for this function are presented between the error signal and the actual condition signal of Fig. 5. These units are coupled with rigid connections (which do not change during training) like that of the error unit defined previously. The output signals of these units in the several levels represent the rates of change of sensory signals. These signals are equivalent to the rate of change of the error signal when the desired value is constant. These signals are combined to the error signal into one intermediate unit that makes the connections with the output unit. This signal combination represents the system dynamics as an analogy to the summation of $\boldsymbol{a}_0\epsilon + \boldsymbol{a}_1 \boldsymbol{d\epsilon/dt} + \boldsymbol{a}_2 \boldsymbol{d^2\epsilon/dt^2} + \cdots$. The coefficient $\boldsymbol{a}_0$ of the error was implemented by the synaptic functions of (10) and (11) that result in a linear transfer function

$$S_{\text{eps}} = \frac{1}{N}\left(\frac{T_\varepsilon}{1+0.25(I-2)^2}\right) \tag{10}$$

$$S_{\text{ips}} = \frac{1}{N}\left(\frac{-T_\varepsilon}{1+0.25(I+2)^2}\right) \tag{11}$$

where T_ϵ is the strength of the error synapse.

The synaptic transfer functions for the connections of the rate of change's with the interunit were modeled with damping characteristics of the type of $x|x|$. This was necessary to attenuate oscillations and to make the process stable even in the presence of high rates of change. Equations (12) and (13) implement the coefficients a_i according to that characteristic. This damping is biologically plausible because we have neurons and muscle cells with damping characteristics

$$S_{\text{tex}} = \frac{1}{N}\left(\frac{T_r}{1+11(I-1)^2}\right) \tag{12}$$

$$S_{\text{tix}} = \frac{1}{N}\left(\frac{-T_r}{1+11(I+1)^2}\right) \tag{13}$$

where T_r is the strength of the rate of change synapses.

The sensory and upper level signals, and the error and dynamic sensory signals converge to the output unit, whose output signal (O) will be the input to the actuator's drives. Then the output unit receives sensory information, upper level commands, and a combination of error and rates of change of the signals, and generates the output signal according to (14)

$$O = T_N \tanh[\alpha(\delta + \Sigma S_j + \Sigma S_k)] \tag{14}$$

where S_j and S_k are the outputs of the upper level and sensory motor unit synapses, respectively, and δ is the signal generated in the interunit as a function of the error and rates of change.

The sensory and upper level signals are transmitted through two symmetrical (in terms of threshold and strength) sets of synapses, which are the synapses with plasticity that will be adjusted by learning. Equations (15) and (16) represent these plastic synapses. This solution adopted in the present model maintains similitude with the mechanisms of sensitization, habituation and classical conditioning.

$$S_j = \frac{T_j}{1+a(I_c - I_j^0)^2} \tag{15}$$

$$S_k = \frac{T_k}{1+a(I_s - I_k^0)^2} \tag{16}$$

where $T_{j/k}$ is the strength of the jth or of the kth synapse.

Before any training the plastic synapses have no strength, i.e., $T_{j/k} = 0$. The existence of an error signal ϵ yields a δ signal different from zero that acts to increase or to decrease the long-term trigger factor C given by (4). The plastic changes, responsible for the learning process, takes place in the motor unit synapses. The synapse's strength change according to (5), modified as follows:

$$\frac{dT_{j/k}}{dt} = \frac{C}{1 + a_s(I_c^t - I_{j/k}^0)^2}. \qquad (5').$$

The dotted line in Fig. 5 indicates that I_c is used to provide the selective characteristic of the learning process. Thus, the wish signal is used to control the plastic change of the both motor unit synapse sets to guarantee the symmetry between them.

Fig. 5 and the above explanation summarize what could be defined as the "new approach to a learning algorithm." This learning algorithm consists of an unsupervised learning method in which only the synaptic strength's T_j and T_k are updated.

IV. Control Modeling

This new philosophy is applied to the position control of a planar two-link manipulator. Simulations of this controller are undertaken to check its performance in terms of control and dexterity learning to reach desired targets. A feedforward backpropagation network is also implemented for the position control of the two-link planar manipulator with the purpose of comparison between the two different approaches.

A. Dynamic Process Modeling

The planar two-link manipulator is a nonlinear, two-degree-of-freedom problem. The variables considered in the manipulator model are shown in Fig. 6. The dynamics of this 2-D system is represented by (17) and (18), as follows:

$$\tau_1 = H_{11}\ddot{\theta}_1 + H_{12}\ddot{\theta}_2 + h_{122}\dot{\theta}_2^2 + h_{121}\dot{\theta}_1\dot{\theta}_2 + G_1 \qquad (17)$$
$$\tau_2 = H_{22}\ddot{\theta}_2 + H_{12}\ddot{\theta}_1 + h_{211}\dot{\theta}_1^2 + G_2 \qquad (18)$$

where

$$H_{11} = m_1 l_{c1}^2 + I_1 + [m_2(l_1^2 + l_{c2}^2 + 2l_1 l_{c2}\cos\theta_2) + I_2]$$
$$H_{12} = m_2 l_1 l_{c2}\cos\theta_2 + m_2 l_{c2}^2 + I_2]$$
$$H_{22} = m_2 l_{c2}^2 + I_2$$
$$h_{122} = -m_2 l_1 l_{c2}\sin\theta_2$$
$$h_{121} = -2m_2 l_1 l_{c2}\sin\theta_2$$
$$h_{211} = m_2 l_1 l_{c2}\sin\theta_2$$
$$G_1 = m_1 g l_{c1}\cos\theta_1 + m_2 g(l_1\cos\theta_1 + l_{c2}\cos(\theta_1+\theta_2))$$
$$G_2 = m_2 g l_{c2}\cos(\theta_1+\theta_2)$$

the subscripts 1 and 2 refer to the ith manipulator segment with mass m_i, total length l_i, distance from the link to the mass center l_{ci} and moment of inertia I_i; g is the gravitational acceleration; θ_1 is the angle between the first segment and the x-axis; θ_2 is the angle between the second and first segments; and, τ_1 and τ_2 are the joint torques 1 and 2, respectively.

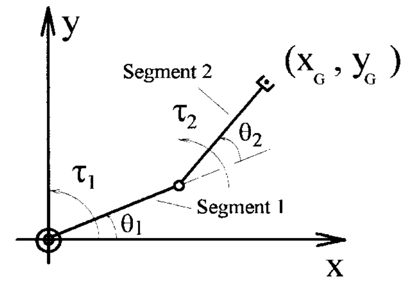

Fig. 6. Two-link manipulator model.

The dynamics of each electric motor coupled with the manipulator is governed by (19)

$$J_M\frac{dn}{dt} = \tau_M - \tau - \tau_{PM} \qquad (19)$$

where J_M is the polar moment of inertia of the rotor, n is the rotor speed, τ_M is the motor torque, τ_{PM} is the torque of losses, and τ is the load torque, which is given by (17) and (18).

The motor torque is

$$\tau_M = K_T O \qquad (20)$$

where K_T is the motor/drive torque gain, and O is the output of the attached neural controller.

The torque of losses, τ_{PM}, is composed of two parts: the bearing (τ_{LB}) and the motor losses (τ_{LM}). To describe the bearing friction losses, static and viscous friction are considered. This is represented by (20)

$$\tau_{LB} = K_{LB}\mu \qquad (21)$$

where K_{LB} is a constant, proportional to the contact pressure, and μ is the friction factor. This torque can be correlated from data presented in [19].

It was assumed that the motor torque of loss is proportional to the square of the motor speed as expressed by (22)

$$\tau_{LM} = K_{LM}\omega^2 \qquad (22)$$

where K_{LM} is a constant, function of the motor type.

B. Position Control with the New Proposed Neural Network

Since in the manipulator process there are two actuating devices (the two electric motors) at least two motor control units are necessary. This is similar to the biological systems where there are pools of motor neurons, each one associated with one muscle bundle. To the purpose of demonstration, the input signals to these control units were restricted to the desired and actual angles θ_1 and θ_2. Observe that the joint angular speeds are not necessary because the interunits sense the rate of change of the joint angles. Also note that in this demonstration the end effector position is treated as a result and not as an objective just to avoid the need of other layers to convert the target end effector position to desired and actual join angles.

It is important to say that another system could have been designed, in which each electric motor is controlled by an independent network with all possible combinations of inputs (e.g., θ_1, θ_2, and $\theta_1 + \theta_2$). In this case the networks should

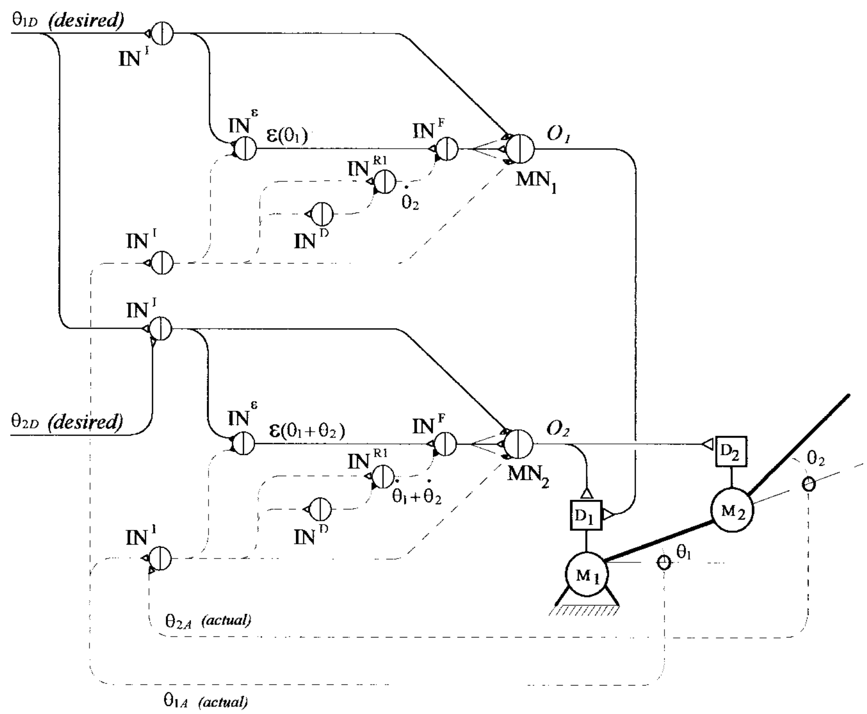

Fig. 7. Simplified outline of the network for the manipulator's control.

learn which of these inputs are important. But as long as it was decided to design task-specific networks and one can take the profit of its knowledge about the process and how biological systems can deal with it, some simplifications that can improve computer usage are implemented. Considering that the second segment position affects the load on the first segment, the driver of the first motor should be fed with the sum of the outputs of the two controllers. Taking into account that the angle θ_2 is relative to the first segment direction, θ_1 and θ_2 are summed to feed the second controller.

Fig. 7 shows the network that represents the two control units coupled with the process. In this figure, sensory pathways are represented by dotted lines; while upper level signals and solid lines represent intermediate pathways. It can be seen that input interunits (IN^I) have been added to perform the operation of input summations. In Fig. 7 θ_{1D} and θ_{2D} represent the wish commands (the desired angles), O_1 and O_2 are the output signals from the motor-units that feed the two motor drives D_1 and D_2, IN^ϵ are the interunits responsible for sensing the error, IN^{R1} are the interunits responsible for sensing the first-order rate of change (in this example higher orders are not needed), IN^F are the learning facilitating interunits, and IN^D are interunits to generate delayed signals needed to evaluate the rate of change of the signals.

The simulating parameters, training process, and performance evaluation of this approach are presented and discussed in Section V.

C. Position Control with a Feedforward Neural Network

Different types of neural networks can be used to solve highly nonlinear control problems like the two-link planar manipulator problem. This problem can be solved using hierarchical neural networks with inverse-dynamics systems, following the work by Kawato *et al.* [20]. Kung and Hwang [21] identify another variety of neural networks for robotic applications. Nguyen and Widrow [22] proposed a system where multilayered neural network simulates the system's dynamics while another multilayered neural network performs the control action. This approach must be implemented in two stages. They concluded that a two-layer neural network was able to represent the process dynamics. Controlling the nonlinear kinematics of the process required another two-layer neural network. They say that thousands of learning cycles were necessary to train these networks, requiring several hours on a workstation. Handelman *et al.* [23] present a methodology that integrates a knowledge-based system with an ANN in such a way that enables the acquisition of robotic skills. They concluded that, although neural networks have been shown to be efficient at learning from experience, in general an outside operator who must closely supervise the learning process must supply training.

Fig. 8 presents a general outline of the method proposed by Nguyen and Widrow [22]. It can be observed from Fig. 8 that the complexity of the process network is greater than the control network. This is because the process behavior depends not only on the two control signals—*one for each motor*—but also on the previous position and angular speed of each one of the segments. It also requires four output units representing the present positions and angular speeds that will generate the error signals for the training. Besides this, a conventional controller (PID) is necessary in the first stage to generate the control signal to allow the training of the process network.

For the exclusive objective of complexity, computational time, and performance comparison, it is not necessary to

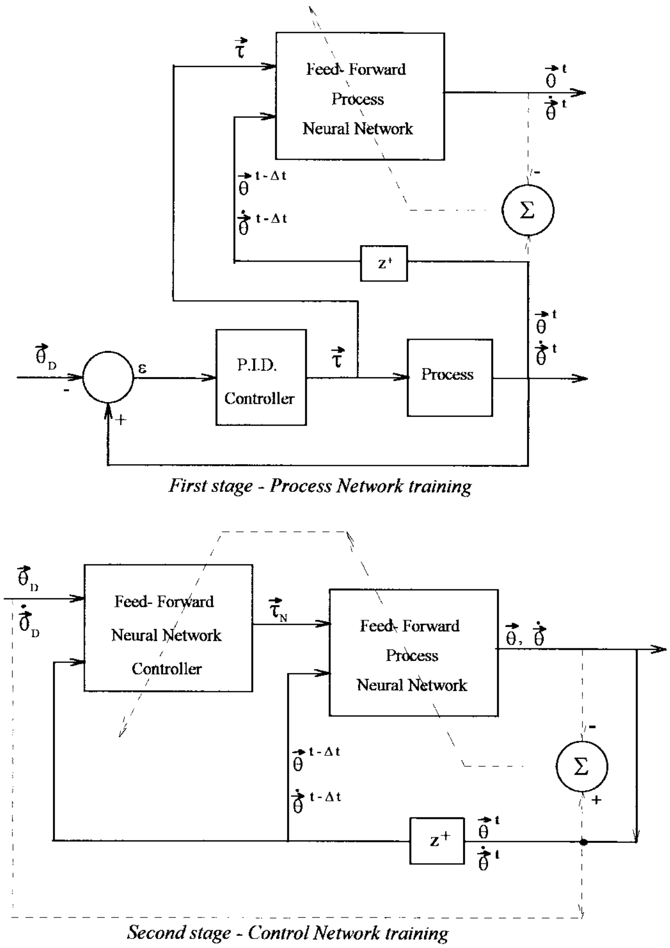

Fig. 8. General outline for a backpropagation FF network solution.

follow this two-stage procedure. Since a conventional PID controller is necessary anyway, the process network is dispensed and the training of the control network is performed using only the signals of a PID controller (in a similar way to that proposed by Handelman *et al.* [23]). Fig. 9 shows the schematic diagram of the solution adopted. This procedure simplifies the solution and allows, without favoring the new proposed neural network, the comparison of the new network concept with the feedforward control network. The results are detailed in next section.

V. Results and Discussion

Table I presents the numeric parameters used to simulate the two-link planar manipulator of Fig. 6. The main parameters of the new neural-network components are given in Table II. Table III presents the feedforward backpropagation network parameters.

1) Training and Evaluation of the New Neural-Network Approach: In the proposed approach, the training is performed on-line, i.e., during the performance of some commands of the wish. Changing the wish command following the sequence of positions numbered as shown in Fig. 10 performs the unsupervised learning process. A set of 28 target positions was used for training. The stretched manipulator starts from the resting position ($-90°$), goes clockwise to the $-185°$ position, returns to the resting position, and goes counterclockwise to the $+185°$ position and returns again to the resting position. This set of target positions was repeated six times (*six trials*). The targets pursue duration t in each trial were as follows: first and second trials, $t = 5$ s; third and fourth, $t = 10$ s; and, fifth and sixth, $t = 20$ s.

After repeating the set of commands six times the system was able to reach all the target positions with reasonable precision and the strengths of the two sets of motor unit synapses, initially zero, grew to that of Fig. 11. This "training-phase" lasts 1960 s of simulated time and only 85 s of CPU time in a 166-MHz Pentium Microcomputer with 64 MB of RAM memory. This is much faster than human capabilities and may indicate that the learning process is computationally efficient.

With those synaptic strengths, the next step was to check the response of the network to any kind of input. Thus the plasticity model was blocked [setting $T_c = 0$ in (4)] to avoid any new strength update in order to observe the generalization capability of the network. Tests were performed over the complete domain of θ_{1D} and θ_{2D} with excellent results. Tests were also performed without blocking the plasticity model, allowing the observation of its stable performance.

Fig. 12 exhibits the results of one of these tests, showing the manipulator end effector trajectory to five targets, each one defined by a different wish maintained during 6 s. In this example two positions were also presented in the training set (points 2 and 4) and three positions were not present in the training set (points 3, 5, and 6). The last target is at a greater distance from the anterior position to observe the network stability with large errors and rates of change. The evolution of the end effector distance from the desired position is presented in Fig. 13, which shows the five spikes that represent the transition of the wish commands, which is done in steps. Observe that, even for targets distant more than 2000 mm from the current position, the desired position is almost unwavering reached in less than 5 s. In this example the motor units have only 15 synapses per side, with a total of 60 plastic contacts in the two control units. With only 28 "training points" and 70 s of training time at each point, the maximum distance error reached during the performance tests was smaller than 5 mm.

Fig. 14 shows the equivalent evolution of the angular error for each link and Fig. 15 shows the evolution of the motor torques. Fig. 15 shows a maximum torque of 160 Nm at the joint 1, which is equivalent to the torque needed to maintain a mass of 11.5 kg at rest in the horizontal position. Observe that no restriction were imposed to the joint torques.

Although this neural network was not built with the intention of representing human arms control, nor optimizing movements or trajectories, it is interesting to see its performance as compared with the human behavior. Fig. 16 shows manipulator position's flashes, in intervals of 0.2 s, during a movement from the resting to a target position that requires arm angles $\theta_1 = 0°$ and $\theta_2 = 90°$. Observe that the arm movement was not mechanically precise, it passed the desired point before converging to it. This was expected due to the fact that the wish command was set to a constant value without

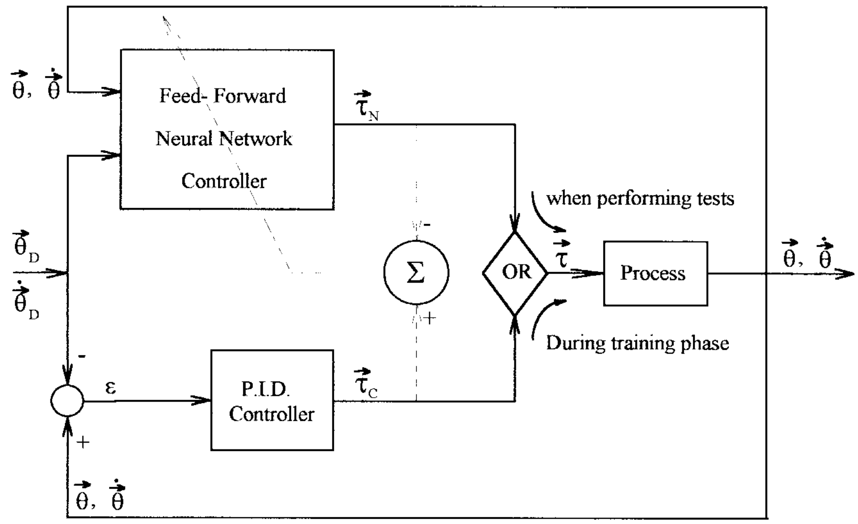

Fig. 9. Schematic diagram of the solution adopted.

TABLE I
PARAMETERS FOR THE TWO-LINK MANIPULATOR

Parameter	Segment	
	1	*2*
Length - L (mm)	707	707
Mass - m (kg)	3.0	2.0
Moment of Inertia - I (kg m^2)	0.041	0.027
Motor Torque Gain - K_T (N M)	60	30
Rotor moment of inertia - J_M (kg m^2)	0.0013	0.0013
Bearing loss constant - K_{LB}	1.0	1.0
Motor loss constant - K_{LM}	25.1	25.1

TABLE II
PARAMETERS FOR THE NEW APPROACH NETWORK

Parameter	Value
Unit's size - T_N (eq. 1)	2.1
Units gain constant - α (eqs. 1,14)	0.5
Plastic synapse's constant - a (eq. 15)	28.8
Plastic synapses: sensory to output unit - *kk*	15
Plastic synapses: "wish" to output unit - *jj*	15
Consecutive thresholds interval ($I_j^0 - I_{j+1}^0$)	0.1667
Strength of *error synapses* - $T\varepsilon$ (eqs. 10,11)	2.5
Strength of *rates synapses* - Tr (eqs. 12,13)	0.09
Strength of *facilitating synapses* - Tc (Fig. 5)	0.1
Synaptic strength decay constant - λ (eq. 4)	10.0
Plastic synapse's *plastic constant* - a_s (eq. 5)	144.0

TABLE III
PARAMETERS FOR THE FF BACKPROPAGATION NETWORK

Number of Hidden Layers	2
Number of Inputs	6
Units in the 1st Hidden Layer	6
Units in the 2nd Hidden Layer	60
Units in the Output Layer	2
Learning Rate - η	0.02 - 0.05
Coefficient - β [$tanh(\beta x)$]	1

any trajectory correction. Fig. 17, which presents the distance from the end effector to the target position, shows that in 1.4 s the end effector runs from a distance of 2236 mm to a distance of 137 mm to the target position. This represented an average velocity of 1500 mm/s. In the next 1.4 s the distance was reduced to 6 mm of the target position, with an average velocity of 90 mm/s. Finally, in the next 1.4 s the distance reached 4.8 mm of the target position, with an average velocity of 0.9 mm/s. This behavior was qualitatively compared with the human behavior showing great similitude.

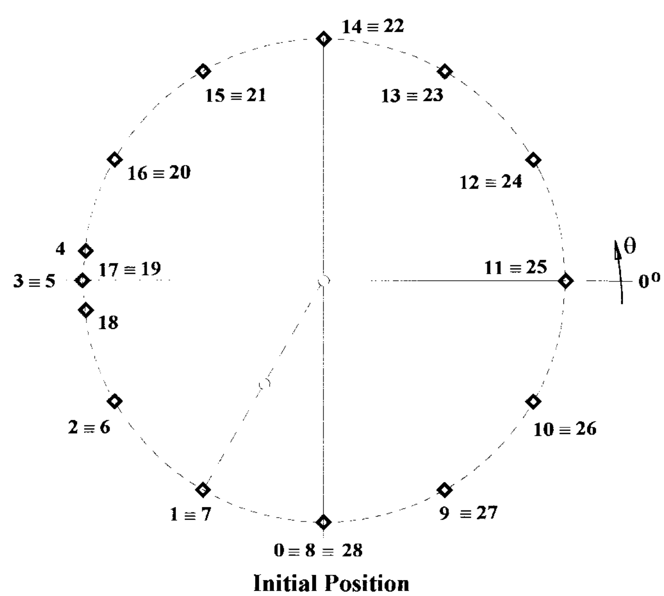

Fig. 10. Training positions set.

2) Training and Evaluation of the Feedforward Backpropagation Neural Network: As it can be imagined, in the case of the feedforward neural network, a good solution was not found in the first attempt. After several attempts, the most appropriate network architecture had three layers. The first layer contains six units, the second layer contains 60 units, and the third layer consisted of the two output units. A very detailed parameterization was not accomplished, having just been considered networks with ten, 20, 30, 40, 60, and 80 units in the second hidden layer. A number smaller than 60 units

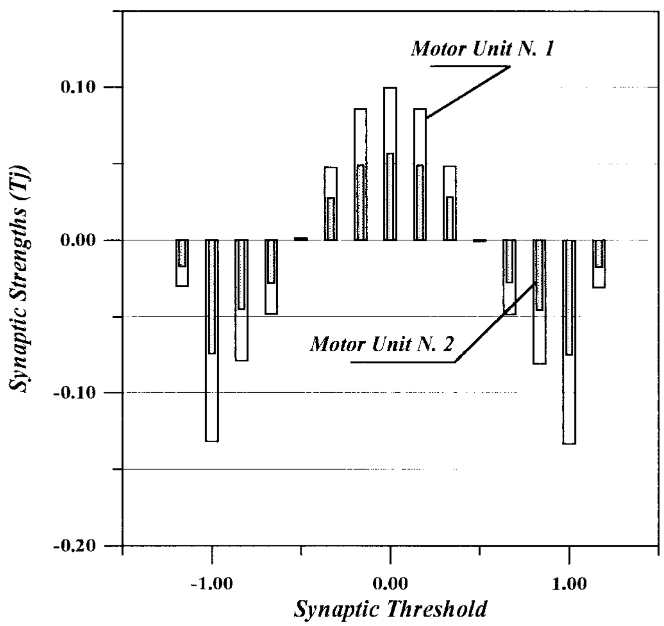

Fig. 11. Synaptic strengths after training.

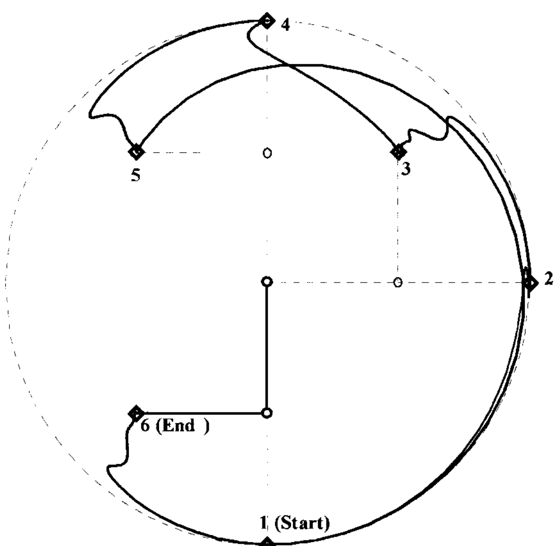

Fig. 12. Manipulator end effector's trajectory.

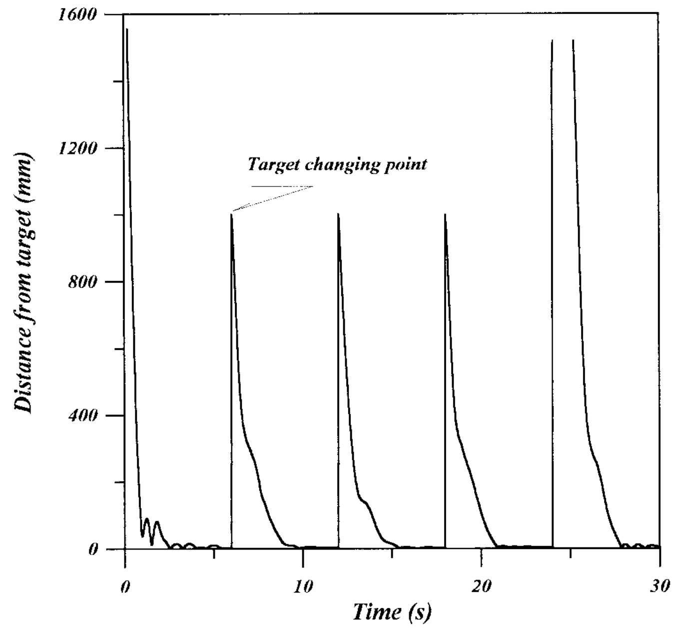

Fig. 13. End effector distance from target position.

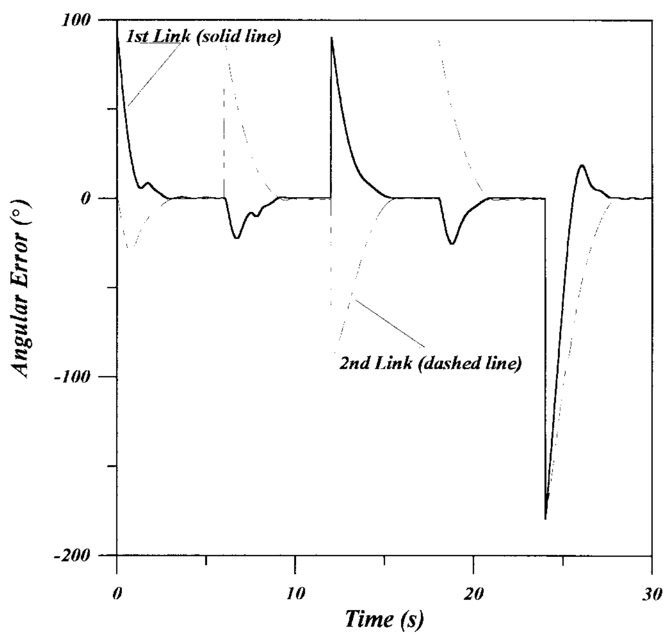

Fig. 14. Angular error evolution per link.

did not provide acceptable results, while a larger number of units did not result in improvement of the overall performance. Observe that the new approach, discussed in Section V-A, used a total of only 30 plastic synapses and 16 units in the two control units.

The network was trained with the same points, shown in Fig. 10, used for training the new proposed network. The learning rate was initially set to $\eta = 0.02$ and later on increased to 0.05 to improve the learning progress. The set of 28 target positions was repeated 146 times. Six s of simulated time was granted for each position. A time step of 0.003 s was used. Since at each time step a new desired pattern (O_1 and O_2) was presented to the network, a total of 8 176 000 examples and associated back propagation operations were processed in this training phase. Fig. 18 shows the evolution of one of the weights in the third layer with the only purpose of illustrating the convergence process. Each point in the graph of Fig. 18 corresponds to a target point commanded to the conventional controller.

The training with the points of Fig. 10 was not enough for the feedforward network to be able to perform the test presented in the diagram of the Fig. 12. Therefore, a new phase of training was done, but this time with the same points of Fig. 12 and in the same sequence that would be requested later on. However, only after more 288 000 backpropagation operations the feedforward network was ready to go through the test of Fig. 12, but yet presenting a poor performance

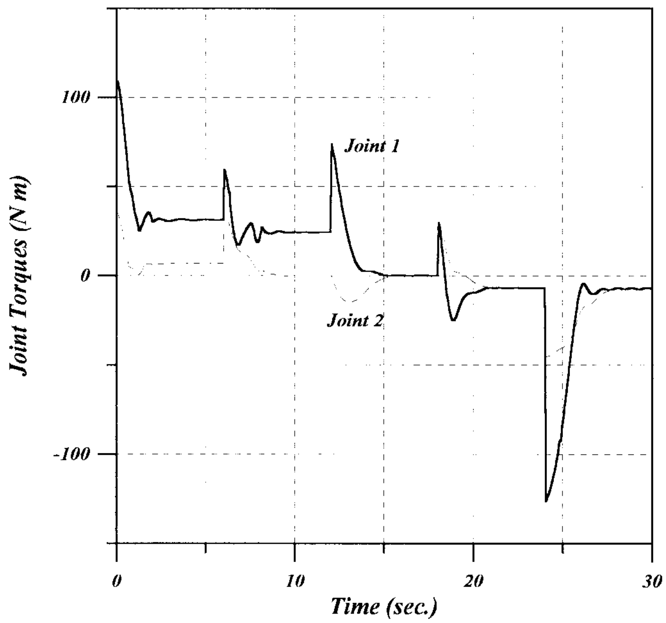

Fig. 15. Resultant torque in the motors.

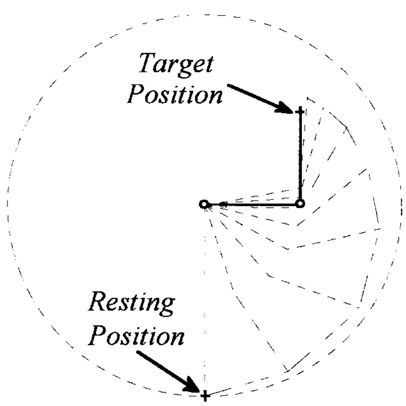

Fig. 16. Manipulator's position flashes.

as shown in Figs. 19 and 20. The trajectory followed by the manipulator's end effector during the sequence of test commands is exhibited in Fig. 19. From this figure, the enormous difficulty in stabilizing the manipulator and the great end effector positioning error can be observed mainly for target points 2–4. Fig. 20 presents the evolution of this error in terms of distance from the target, which reaches a maximum value of 450 mm for the point 3. The feedforward network was not able to follow the PID controller performance even after several hours of training.

3) Comparison of the New Approach with the Feedforward Backpropagation Network: The new approach proposed seems to be more complex than a conventional feedforward network because of the multiple synapses concept. However its general architecture is not complex and its numerical implementation is easier because there is nothing similar to the backpropagation algorithm. The additional complexity due to the presence of several synapses is compensated by the reduction in the number of units with expensive sigmoidal functions and by the distinction of specialized regions.

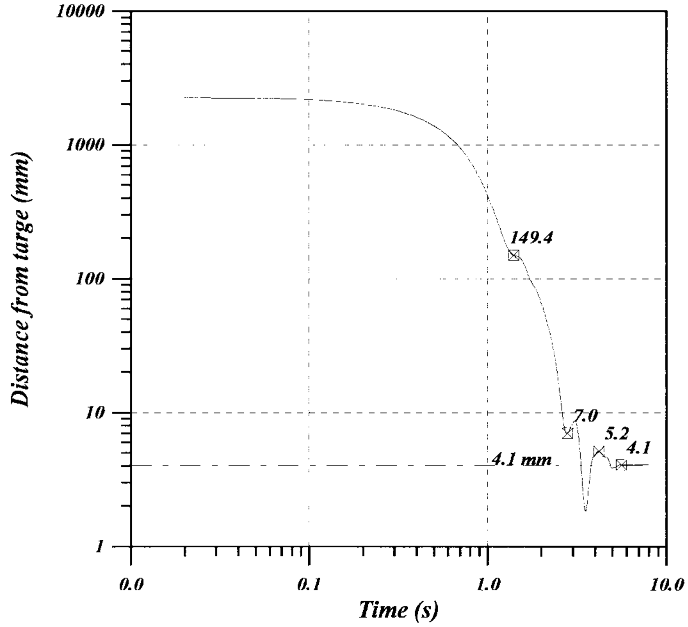

Fig. 17. Target distance evolution for the test of Fig. 16.

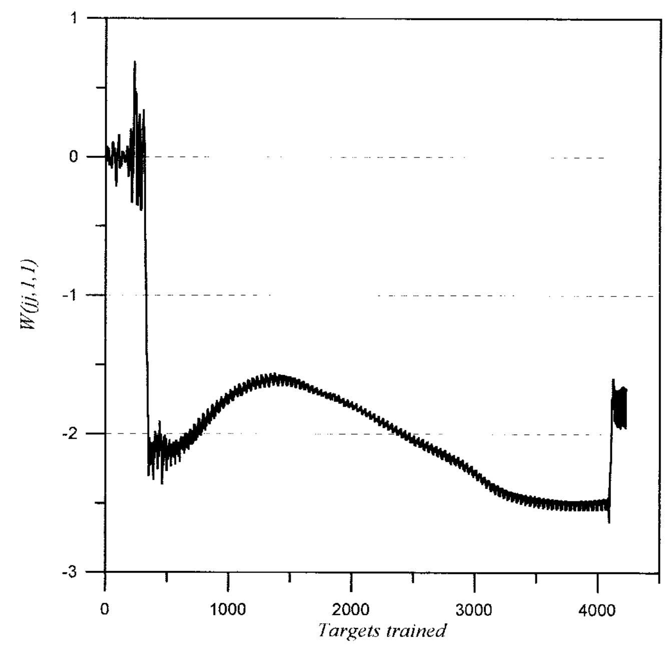

Fig. 18. Transient behavior of third-layer weight.

In the learning task, the performance of the new network was 200 times faster than the backpropagation algorithm associated with the feedforward network. It took only 85 s of CPU time for the training of the new approach network while it took 5 h of CPU time for the training of the feedforward network with backpropagation.

The generalization capability of the new approach was much better because its architecture was designed to the task of the manipulator control. For the new proposed network it was not necessary any kind of additional training after the training phase with the arm stretched, while for the backpropagation network it was necessary 144 additional training sessions.

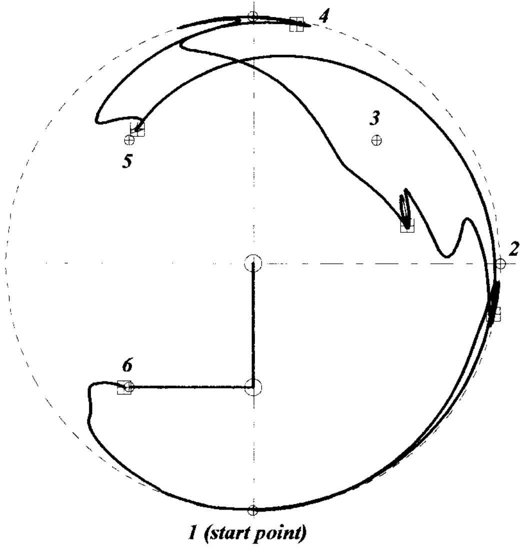

Fig. 19. FF Network results in the end effector's trajectory.

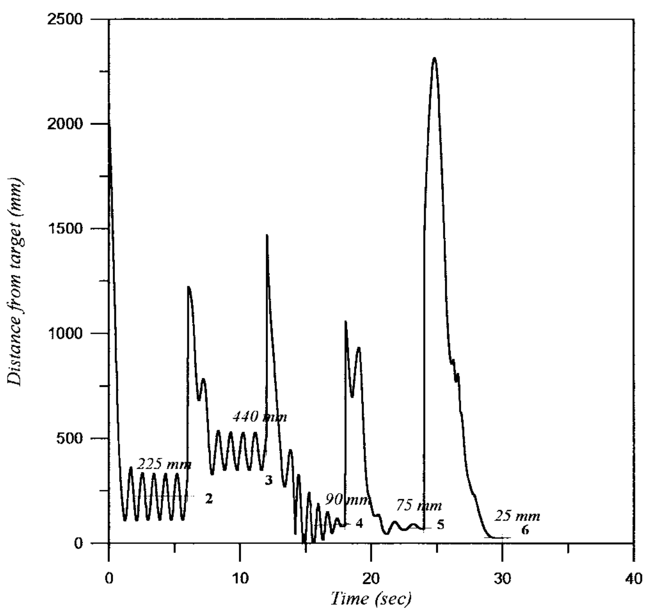

Fig. 20. FF network end effector positioning error.

The performance of the two approaches in the goal of positioning can be compared in the graphics of Fig. 21. During the test phase, the maximum end effector position error for the new approach was smaller than 5 mm, while for the backpropagation network the smaller error was 25 mm besides it reached values up to 440 mm.

VI. Summary of Conclusions

The performance of the novel ANN proposed for the position control of the planar two-link manipulator shows that the option of task-specific networks seems to be a resourcefully way to solve some problems of control.

The similarity with biological systems in terms of connection's complexity provides an additional strength to ANN's. The use of multiple contacts in each axon terminal increases the integration capability of each unit. Higher classes of

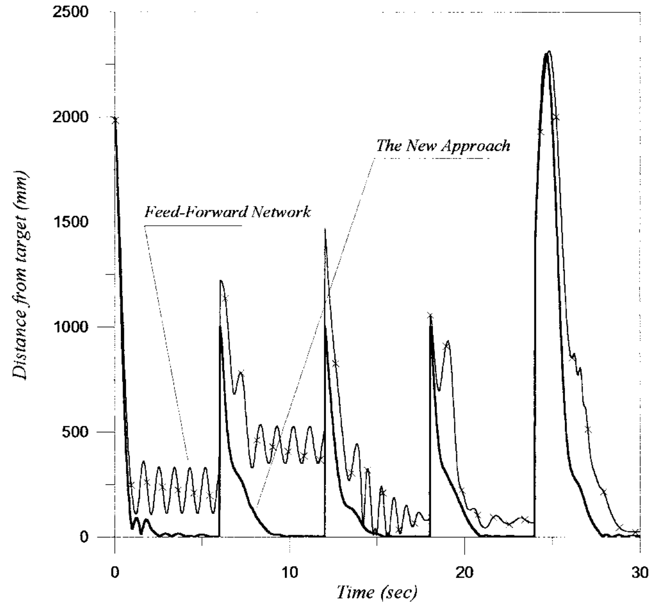

Fig. 21. Comparison of the two approaches positioning error.

connection's transfer functions improve the input-to-output relation, allowing a reduction in the total number of units with expensive sigmoidal functions; synaptic functions are less expensive.

The training task can be done on-line during the execution of desired commands, according to an unsupervised learning approach. The limited training time and the few targets needed to learn, associated with the good results obtained in the task of positioning over an extended domain, show a remarkable ability of this novel ANN of generalization and for the control of the planar two-link manipulator problem. This new approach implements artificial mechanisms resembling habituation or sensitization, provided by facilitating units. The use of a single plasticity model in the synapses enables real-time learning while functioning without any physically unexplained mathematical algorithm.

The clear display the elements and of the different regions responsible to different functions, like biological systems, is another advantage of this new concept, which allows easier diagnosis in the event of failures.

The model presented is more complex than conventional multilayered backpropagation networks in terms of synaptic arrays and transfer functions but it has the advantage of reducing the total number of units. As the transfer function of the neuron units is more complex than that of the synapses there is a net gain in terms of performance as demonstrated in Section V. We believe that it is still too early to affirm that this novel ANN is better or worst than the conventional ones. However, as the performance of learning and acting showed in the example was better than that of the feedforward backpropagation network, this is certainly a promising concept.

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