# LOWER MOTOR CONTROL MODELED BY NEURON WITH FUZZY SYNAPSES

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*Abstract*- **The paper presents a model of information flow through the sensors to muscle system in regard to the control of output. The model takes into account both the logical and emotional action components. The emotional components depend on the current needs of the organism. Actions resulting in a positive change in the emotional analysis of the world activate the reward component that enables the action of logical analysis of the situation. The principal component of the system, which provides input to most muscle fibers of human body, is called lower motor neuron (LMN). The control of LMN is modeled via a set of fuzzy rules. The principles of processing seem applicable to artificial systems.**
***Keywords* – Lower motor control, fuzzy control, fuzzy synapses**

## I. INTRODUCTION

Natural communication modeling - information coding and transmission in human body is useful for technical implementations as well in data communications as in other related fields as robotics.

## II. MUSCULAR CONTROL BY LOWER MOTOR NEURONS

The discharge activity of a motor unit is regulated by a complex interaction between excitatory and inhibitory inputs to the motor neuron. A major portion of the input comes from supraspinal motor centers, directly or through interneurons. Consequently, disorders of these centers can alter the motor unit discharge pattern as seen in parkinsonism, chorea, cerebellar disorders, and spasticity. In most cases, muscles work in opposing pairs: one muscle opens or extends a joint and the other closes or flexes it. This configuration is necessitated by the fact that muscles exert force in one direction only (i.e., contraction). Figure 1 demonstrates this arrangement for a typical joint. This diagram also shows some of the neural elements, which control the contraction of these muscles. The principal neuron of this system, which provides input to most muscle fibers, is called a lower motor neuron and is labeled L in figure 1. This type of neuron and the other neurons associated with it are located in the spinal cord, where they function as the final processing stage before output to the muscle. We shall refer to the lower motor neuron and its associated elements as a LMN system. This system is a good place to observe some of the principles of the brain's motor organization. There are a great many LMN systems in the spinal cord. Every muscle is composed of thousands to millions of fibers and in the case of muscles used for precise operations there may be an LMN system for each individual fiber. In other cases, a single LMN system may control many fibers of a muscle. Basically, an LMN system must accept and reconcile commands from a multitude of other systems, which desire control of the muscle in question. It must attend to these commands according to their priority, modify them on the basis of inputs from both the kinesthetic and vestibular systems and on the basis of status information from related LMN systems, provide an appropriate output to the muscle, and make its own status information available to other systems. In a practical robotics application, there is no reason why a single servo actuator and LMN processor for each joint would not suffice. There are reasons why a single processor for many joints is less practical, but before addressing this issue, let us examine the LMN system to see what it accomplishes.

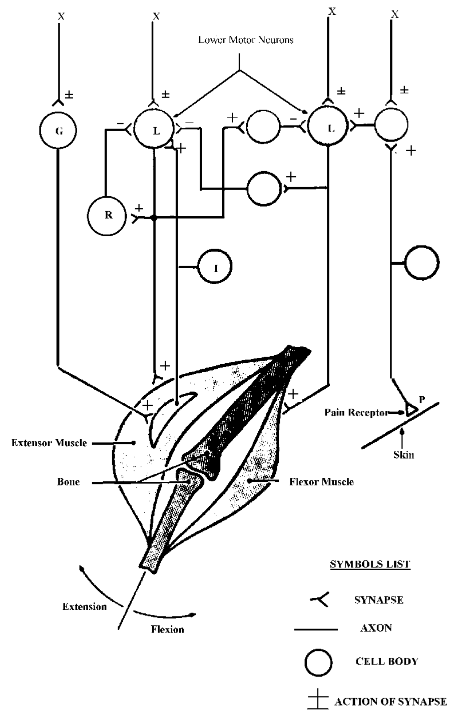


Figure 1. LMN circuitry has final control over muscular contractions, operating as a low level, closed-loop, feed-back system

In figure 1, for clarity, only a single LMN driving each muscle is shown. The degree of contraction of the muscle is proportional to the output pulse frequency of the LMN: the higher the frequency, the stronger the contraction. The circuit shown on the right illustrates the simplest type of protective spinal reflex: a pain receptor (nocioceptor) in the skin (P) fires a neuron in the LMN system, which in turn fires the LMN driving the flexor muscle.

This simple high-priority operation quickly removes the limb from danger. Inhibitory cross connections between the LMNs driving the two muscles insure that they do not act antagonistically; one muscle relaxes as the other contracts. This reciprocal, synergistic circuitry is generally active in all LMN operations, unless specifically overridden.

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## III. Information transmision through the sensors to muscle system

The motor output system appears to be responsible for a phenomenon called sensory neglect, in which animals simply cease to attend behaviorally to events in their environment. They will not even orient to novel stimuli. They must be force fed to survive and generally seem unable to initiate a response to any sensory stimulus. In terms of present model, this would result from the fact that no external stimulus would be able to serve as a means of disinhibiting the motor output system.

The function of the limbic system involves behavioral reactions of the individual toward the external environment as a result of receiving information through all the sensory modalities. In addition, the response may be influenced by the internal environment, which may alter the excitability of the nervous system (circulating levels of hormones, electrolytes, availability of glucose etc). It seems to operate in preserving the individual (feeding, fleeing or fighting) or the species (reproduction). These responses are mediated through lower centers of the diencephalon. Exactly how the emotional perceptual apparatus is connected is not yet well understood, but it appears that whatever the precise nature of its operation, it will not be very different in principle from the model described in this paper. In terms of behaviour, its general functional operation is established. For potential applications to robotics, the present model will adequately summarize these facts. The general scheme is presented in figure 2.

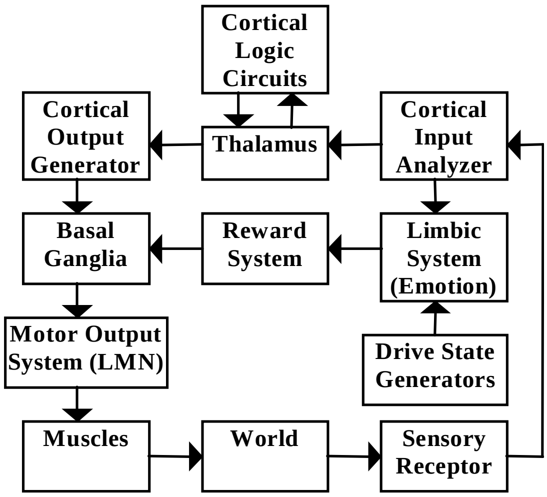


Figure 2. The general plan of information flow through the system in regard to the control of output by the goal-directing system

In this diagram, the data flow from the receptors follows two main routes. After preliminary analysis in the sensory cortex, the data are available both to the limbic system for motivation-relevant feature extraction processes and to the other areas of the cortex for logical analysis. The information, which is processed in the limbic system, can activate the reward mechanism if (1) the information decodes to features relevant to a drive state and (2) the limbic system elements, which decode it, are gated onto the reward system bus by activity of the appropriate drive state mechanism. When these conditions are met, the behavioral strategies developed by logical analysis of the sensory data can continue to be translated into motor patterns by the basal ganglia and other portions of the output system. There seems to be a large component of the reward value of positive stimuli, which is due to the rate of increase, or derivative, of the decoded stimulus rather than its absolute value; this feature seems to improve system response characteristics. In the case of escape and avoidance behaviours, the reduction of activation of certain stimulus elements serves to activate the reward mechanism, possibly through release of inhibitory elements.

In the figure 2, the input is analyzed for the generation of logical action schemes in the upper portion of the circuit, while the lower portion evaluates the same inputs for their emotional relevance. The emotional relevance depends on the current needs of the organism as reflected in the activity of the drive-state generators. Actions resulting in a positive change in the emotional analysis of the world activate the reward system, which permits the perpetuation of the action generated by the logical analysis of the situation. In the figure 2, are not shown the connections that enable the logical portion of the system to employ knowledge of the drive-state of the system in generating goals for directing the logical synthesis of action.

## IV. Neuron with fuzzy synapses

The use of fuzzy and neuro-fuzzy prediction of time series has recently become popular [1]. In this section, the use of a specific type of neuron, named neuron with fuzzy synapses (NFS) is shown. For a NFS having m inputs, x1-xm the output y is computed as a sum of nonlinear functions:

$$y = \sum_{i=1}^{m} f_i(x_i), \quad f_i : U_i \to R, U_i \subset R \qquad (1)$$

A function $f_i$ can be viewed as a synaptic transformation of its input $x_i$. Since every function $f$ is implemented using a particular class of neuro-fuzzy systems, we shall use the term fuzzy synapse (FS) to designate these particular synapses. The fuzzy synapse number $i$, implementing the NFS function $f_i$ from (1), uses a number of $N$ reference fuzzy sets, denoted with $A_{ir}$, $r = 1,2,...,N$. Every fuzzy set $A_{ir}$ is characterized by its membership function (MF) $\mu_{Air} : U_i \to [0,1]$.

The membership functions $\mu_{Air}$ have a triangular form, like in Figure 3. For a certain value $u_i$ of the input $x_i$, the truth degree (TD) $t_{ir}$, of the proposition ($x_i$ is $A_{ir}$), is equal with the value of MF $\mu_{Air}$ computed for $u_i$, $t_{ir} = \mu_{Air}(u_i)$. For every crisp input value, a number of $N$ truth degrees $t_{ir}$, $r = 1,2,...,N$, are computed. But, as one can see only two consecutive TDs are nonzero. Moreover, the sum of these TDs is 1, $t_{i,k} + t_{i,k+1} = 1$, where $k$ is the index of the first nonzero TD.

The fuzzy synapse has $N$ rules, $r = 1, 2, . . . , N$, of the form:

If $x_i$ is $A_{ir}$ then $y_{ir} = w_{i1r} t_{ir} + w_{i2r} t_{ir}^2 + ... + w_{iPr} t_{ir}^P$ (2)

where $y_{ir}$ is the output of the rule $r$, $w_{ijr}$, $j = 1, 2, \ldots, P$, are adaptive weights of the rule $r$, $t_{ir}$ is the truth degree of the rule premise ($x_i$ is $A_{ir}$), $t_{ir} = \mu_{Air}(x_i)$.

The function used for the rule output computation is a polynomial of degree $P$, having the variable $t_{ir}$ and the coefficients $w_{ijr}$. For $P = 1$, (2) defines the fuzzy rule of Yamakawa's neuron synapse. Despite its computational simplicity, Yamakawa's neuron provides good prediction performances for the tested series. For polynomials of degree $P > 1$, there is an increase in the computational complexity of the rule compared to the case $P = 1$, but the improved prediction performances justify the increase in computational complexity [1].

We present the prediction performances of predictor schemes based on neurons with fuzzy synapses of order $P = 3$ in tremor prediction applications. The rules of these particular synapses are, for the third-order fuzzy synapse:

Rule no. $r$ : If $x_i$ is $A_{ir}$ then $y_{ir} = w_{i1,r}\, t_{ir} + w_{i2,r}\, t_{ir}^2 + \ldots + w_{i3,r}\, t_{ir}^3$

The output of the fuzzy synapse, $y_i = f_i(x_i)$, is computed as the linear combination of the rule outputs $y_{ir}$

$$y_i = f_i(x_i) = \sum_{r=1}^{N} y_{ir} \Big/ \sum_{r=1}^{N} t_{ir} = \sum_{r=1}^{N} y_{ir} \Big/ \sum_{r=1}^{N} \mu_{ir}(x_i) \qquad (3)$$

where $y_{ir}$ is computed with (2), and $N$ the number of the synapse rules. The fuzzy synapse is a fuzzy system with a crisp input $x_i$ and a crisp output $y_i$, belonging to the category of Sugeno fuzzy systems. The parameters of the fuzzy synapse are the weights $w_{ijr}$ from (2). By adapting these weights, we can approximate a desired shape of the synapse function $f_i$. For every value belonging to the input domain $U_i$, only two adjacent rules have nonzero truth degree, and the sum of the truth degrees is equal to one. By denoting with $t_{ik} = \mu_{Aik}(x_i)$ and $t_{i,k+1} = \mu_{Ai,k+1}(x_i)$, these nonzero truth degrees, we can rewrite (3) as $y_i = y_{ik} + y_{i,k+1}$. Thus, for triangular MFs, the computation is drastically reduced. Since the computation complexity does not depend on the number of fuzzy rules $N$, one can use as many fuzzy reference sets as needed, for a satisfactory fuzzy partitioning of the input domain $U_i$. We denote $a_1 = x_{min}, a_2, \ldots, a_r, \ldots, a_N = x_{max}$, a1< a2 < . . < $a_r < a_N$, the points in the input domain $U_i$ where the triangular MFs are unitary, $\mu_{Air}(a_r) = 1$, $r = 1, 2, \ldots, N$. For Yamakawa's neuron, one can show that between any two successive points $a_r$ the synapse output $y_i$, computed with (3), has a linear variation with $x_i$, that is $y_i = c_{0r} + c_{1r}x_i$, for $x_i$ $[a_r, a_r + 1]$, $r = 1, 2, \ldots, N - 1$. For a third-order synapse, the synapse output $y_i$ has a third-order polynomial variation with the input $x_i$, on the intervals $[a_r, a_{r+1}]$. The nonlinear behavior of the higher (second and third)-order synapses allows us better prediction performances with respect to Yamakawa's neuron performances [1], with the expense of increased computational complexity.

The neuron output is the sum of all fuzzy synapses outputs. Thus, one can write the neuron output y, for a particular input vector ($u1$, $u2$,. . ., $u_m$), as:

$$y = \sum_{i=1}^{m} f_i(u_i) = \sum_{i=1}^{m}\sum_{r=1}^{N} y_{ir}(u_i) = \sum_{i=1}^{m}\sum_{r=1}^{N}\sum_{j=1}^{P} w_{ijr}\left[t_{ir}(u_i)\right]^j \qquad (4)$$

Since the TDs $t_{ir}$ are directly computed for a certain input value (4) represents a linear weighted sum of dimension $m$ x $N$ x $P$, having the weights $w_{ijr}$. Adapting these weights can approximate the desired behavior of the neuron synapses.

## V. Fuzzy rule bank for motor outputs (LMNs) having logical and emotional action component as input variables

For each action component, the logical and emotional outputs computed on a set of commonly real life situations are used to derive the membership functions for those input variables, by means of a simple fuzzy clustering method based on a Euclidean distance. The clustering algorithm is applied to obtain five clusters in the product input space, which, when projected on each input dimension, form the membership functions. Since, with fuzzy clustering techniques, redundancy occurs when the clusters are projected on the individual input variables, a simplification is made by merging similar fuzzy sets and by removing sets similar to the universal set (these fuzzy sets do not contribute to the rule base) [2]. As a result, five fuzzy sets have been obtained for the logical action variable, while only three fuzzy sets are sufficient for the emotional variable. For the output variable (muscle LMN control) three fuzzy sets, labeled by Low (L), Medium (M) and High (H) have been considered. Figures 3a, b and c show respectively the membership function for the input and output variables.

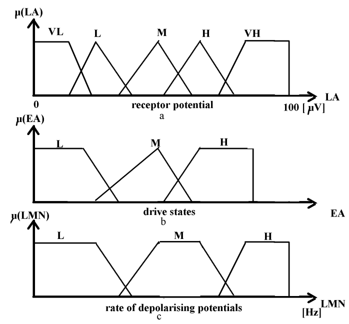


Figure 3 Membership functions for Logical Actions, LA, (a), Emotional Actions, EA, (b) and LMN control (c)

TABLE I
FUZZY RULE BANK FOR LMN MUSCLE OUTPUT CONTROL

| EA \ LA | VL | L | M | H | VH |
|---|---|---|---|---|---|
| L | L | L | L | M | H |
| M | L | L | M | M | H |
| H | L | M | M | H | L |

The rules have been independently defined but since the human sensorial system is not a perceptually uniform system, the Euclidean metrics are not significant in terms of perceived logical action an emotional inputs differences. Then the fuzzy rules are tuned by means of an off-line learning phase, based on the perceptive response of human operators and this response is used as an external reinforcement signal to adjust the initial rule bases. The result of this process is that we can use the same fuzzy rules for all input components of the same sensorial type as shown in Table 1.

## VI. The Fuzzy Integral and the Multisensorial Fusion Operation

The main function of a fusion operator is the reduction of the multidimensionality that the use of more than one sensor introduced in a multisensorial pattern recognition system. The selection of an appropriate fusion operator is the basic point for the attainment of the aims mentioned in the introduction of this section. The fuzzy integral, a non-linear fusion operator, which was first introduced with this name by Sugeno, [3], has showed its suitability for the integration of information. The use of the fuzzy integral in problems Multicriteria Decision Making [4], and Pattern Recognition [5], supports this affirmation. The favorable properties of the fuzzy integral regarding the qualitative aspect mentioned in the introduction are achieved through the fuzzy measures.

Fuzzy measures extend the concept of classical additive measures as probability measures by relaxing their additivity axiom. This kind of measures includes probability, possibility, belief and fuzzy measures. In the multisensorial fusion approach the fuzzy measures are used to characterize the weight of importance of the information sources. Not only treated individually, but also considering the importance of their possible coalitions. It is in this last aspect where the formerly named types of fuzzy measures show their differences. Intuitively, sub-additive fuzzy measures, as possibility measures, are only capable of characterizing redundancy between information sources. Super-additive measures, as belief and fuzzy measures, are useful for complementarity. Finally, independence of information sources is characterized by probability measures. This concept, presented in [6] for multicriteria decision making, can be extended to multisensorial pattern recognition. Thus, general fuzzy measures are the most appropriate for the achievement of the qualitative gain formerly mentioned. By not fixing the relationships between the coefficients of the individual sources and those of their coalitions, general fuzzy measures overcome the formal problem of considering only one type of interaction between information sources considered in other frameworks for multisensorial fusion, e.g. Bayesian classificators or Dempster-Schafer theory of belief. The fuzzy measures coefficients, also called fuzzy densities, are determined using a priori knowledge of the relevance of the information sources to be fused. The theoretical disadvantage of the general fuzzy measures is the increment of the number of coefficients to be calculated. Nevertheless, while considering two or three information sources as in the present framework this fact is not of significance.

There are basically two types of fuzzy integral, respectively known as Sugeno's integral ($S_\mu$):

$$S_\mu(x_1,\ldots,x_N)=\bigvee_{i=1}\left[x_{(i)}\wedge\mu(A_i)\right] \tag{5}$$

and Choquet's integral ($C_\mu$):

$$C_\mu(x_1,\ldots,x_N)=\sum_{i=1}^{N}\left[x_{(i)}-x_{(i-1)}\right]\mu\left(A_{(i)}\right) \tag{6}$$

The enclosed sub-index in the former expressions indicates a sorting in descending order operation prior to the calculation of the integral itself. As an example, in the case of three sources of information this ordering could be:

$x_1 \geq x_3 \geq x_2$ results in $x_{(1)} = x_1$, $x_{(2)} = x_3$, $x_{(3)} = x_2$

This data-driven operation confers to the fuzzy integral the property of varying the set of operating weights depending on the current data value since the operating fuzzy density varies in the form:

$$\mu\left(A_{(i)}\right)=\mu\left(\bigvee_{j=1}\left\{x_{(j)}\right\}\right) \tag{7}$$

In the here presented framework the selection of one or another type of fuzzy integral in the realization of different types of fusion is done heuristically case to case.

## V. Conclusion

The flexible performance of biological systems is based, among other reasons, on the parallel processing of different kinds of information. Parallel processing is understood to mean that different properties of the environment are analyzed concurrently, and, to some degree, independently. The goal of this parallel processing is the maximal exploitation of the information prior to its fusion. The parallel processing prior to the fusion of the embedded information is also found in higher cortical areas. The proposed model showed the validity of the independent processing of information previous and during the information fusion stage.

The multisensorial fusion of information is one of the key concepts for the intelligent exploitation of this powerful sensor development in pattern recognition systems.

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