# CONTROL THEORY APPLIED TO NEURAL NETWORKS OF THE TRANSECTED HUMAN SPINAL CORD

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#### SUMMARY

This paper discusses the problems in modelling the interneurone system of the transected spinal cord in man. It is shown that at least 24 parameters would have to be identified to build even a simplified model. Due to complexity of the system simultaneous determination of all parameters is practically impossible. It is suggested that a self-adaptive control algorithm would be an optimal solution to the system.

The transected spinal cord of man contains a system of interneurones which behaves as a set of neural networks. If we wish to control this system externally for purposes of study and treatment, it is an essential step to build a model of the system as faithfully as possible and identify its parameters. The purpose of this paper is to consider such a design model based on current neurophysiological data.

To determine the relationship between the input and the output has been the objective of both neurophysiological as well as cybernetic investigations. The spinal interneurone system can be defined as a system with a multitude of input channels which are processed and translated into a multitude of output channels. The advantage of studying the isolated interneurone system of the transected spinal cord is obviously in the smaller number of the input channels. Neurophysiological methods have been designed with which it is possible to study only a limited part of the interneurone system. In such a part we can define the input multitude of impulses as I. The elements of the input multitude I are the impulses arriving from the periphery, as well as those arriving from other parts of the interneurone system. The output of the interneurone system can be defined as a multitude of responses R. A general model of the interneurone system would then be:

## N: I ---> R ...... 1

We are interested in the properties of the translating process within the interneurone system N. Unfortunately not all the elements of the multitude I nor of the multitude R are accessible to analysis, which implies that the properties of translation cannot be identified. The task is made even more difficult by the fact that the properties of the interneurone system are not stationary, but are the function of time and history of the system.

In the most sophisticated experiments so far carried out in attempts to control this system, the multitude of input functions has been reduced to two electrical stimuli and one mechanical stimulus, each employing a separate snatomical input pathway, while the multitude of output functions has been reduced to the amount of EMG response in a part of one muscle. A simplified model of this system is shown in Figure 1.

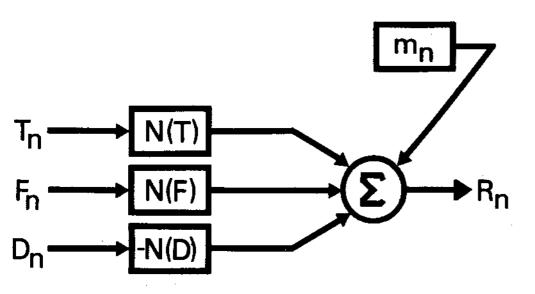


Figure 1

We can write the following equation:

where:

T is strength of the mechanical stimulus;

 ${\bf F}$  is strength of the electrical stimulus facilitating the  ${\tt EMG}$  response;

D is strength of the electrical stimulus depressing (or inhibiting) the EMG response;

Rn is EMG response to the n-th stimulus;

N(T) is function of the EMG response, when only the mechanical stimulus is presented to the system;

N(F) is function of the EMG response to the mechanical stimulus, when the facilitatory stimulus is also presented;

N(D) is function of the EMG response to the mechanical stimulus, when the depressionary stimulus is also presented;

 $\mathbf{m}_{\hat{\mathbf{n}}}$  is the contribution to the EMG response from other inputs to the system

The most important disadvantage of this description of the system is that it does not account for the memory of the system, i.e., the residual effect of preceding stimuli and responses. This can be partly compensated for by introducing the remaining inputs to the system which are the result of the preceding stimuli, at least for the input functions F and D which affect a more potent part of the interneurone system (Figure 2).

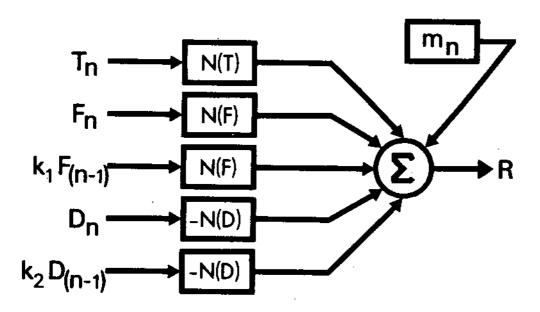


Figure 2

Another disadvantage of the model is that it implies simple additive relationships. This is sufficient only as the first approximation, and it depends on the possibility of measuring the effect of the individual inputs in the absence of other inputs.

The first approximation of response functions N is the so-called "piecewise" linear approximation. The strength of the stimulus is divided into three ranges. In the lowest range, the stimulus strength is subthreshold, in the intermediate range we suppose a linear relationship between the stimulus and the response, and in the upper range the system is oversaturated or "latched" (Figure 3).

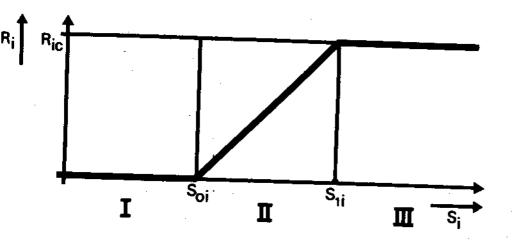


Figure 3

Such a function can be described with three parameters:  $S_0$ ,  $S_1$  and  $R_1$ , which must be identified. In our system altogether 9 parameters have to be identified for the functions N(T), N(F) and N(D).

On the assumption that the function m is random with a Gaussian distribution and zero mean value, that function can be described with only a single parameter  $\mathfrak{S}_m$ .

The parameters  $k_1$  and  $k_2$  can be obtained from the ratio of cross correlation coefficients obtained in random stimulation (1).

The described 12 parameters would describe the system, if it were stationary. Unfortunately it is not, due to a phenomenon of habituation, which is gradual decrease of effectiveness of stimulation, regarded as adaptivity of the interneurone system. This changes the parameters with a function of time and stimulus presentation, also depending on stimulus strength. It has been shown that this phenomenon can be approximated with an exponential function (2). The following equation is valid for responses to constant stimulation:

$$R_n = R_0 e^{-cn} + R_s$$
 ..... 4

Where Rn is response to the n-th stimulus,

 ${\bf R}_{{\bf O}}$  is a constant representing the mean value of initial responses,

c is index of habituation, identified with the method of minimal quadratic error.

 $R_{\rm s}$  is the mean response when habituation has reached its extreme.

Figure 4 shows an example where the parameters  $R_{\rm O}$ , c and  $R_{\rm g}$  are identified. Thus we have altogether 24 parameters to be identified.

The methods for identification of the individual parameters have already been designed. However, it must be emphasized that, due to constant interference of the function m and variability of responses, it is not possible to find out the exact values of the individual parameters, but only their estimates. These, of course, are closer to true values, as the number of samples used in the identification process is increased.

A very complex measurement would be needed in order to obtain all the 24 parameters required for the model, and that model is still rather simplified. We may suppose that the errors due to simplification and errors due to inaccurate estimates of the individual parameters would in combination so seriously affect the regulation algorithm based on the model that the final result would probably be worse than with other known algorithms. Another difficulty complicates the recognition of the momentary state of the system. In many actual experiments it can be seen that the nonstationarity of the system is not always a continuous function as assumed by equation 3, but is

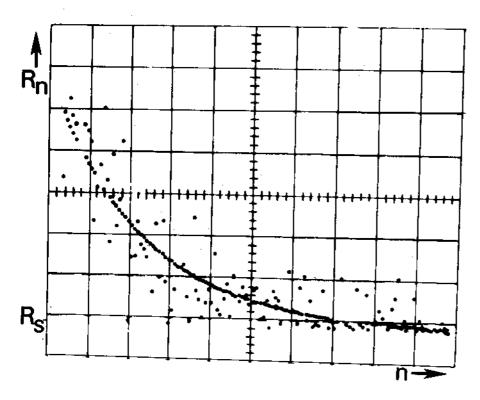


Figure 4

frequently interrupted by the process of dishabituation due to any sufficiently strong inputs. Dishabituation makes the course of the properties of the system discontinuous, and sometimes produces exceedingly strong excitation of the system (spasm), which is a momentary unstable condition; the condition to follow this disturbance is unfortunately unpredictable.

Systematic observations of the properties of the interneurone system made in our laboratories in the past years indicate the following conclusions:

- By using rather complex methods it is possible to estimate individual parameters of the system, however simultaneous determination of all the parameters is so difficult that it cannot be carried out at our present state of knowledge and technology.
- For this reason, we cannot expect to obtain in the near future an optimal control algorithm based on the knowledge of all essential properties of the system.

3. The described properties of the system can be approximated with an "intuitive" approach, thus avoiding the identification of all parameters. Such an algorithm is based on prediction of the following response from the past responses, it considers the mean error, is adaptive, and contains protective mechanisms against overcorrection and nonstability at sudden change of the condition of the system. Such an algorithm is described in the following paper.

## REFERENCES

- (1) Dimitrijević, M.R., Gyergyek, L. and Trontelj, J.K., "Stochastic Stimulation Used to Study Spinal Interneuronal System in Man", Progress of Cybernetics, Proceedings of the First International Congress of Cybernetics, London, Gordon and Breach, 1970, volume 1, 353-357.
- (2) Trontelj, J.K., "A Study of Properties of the Central Nervous System in Man by Cybernetic Methods", Thesis, University of Ljubljana, 1971.

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