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Fuzzy Deductive Inference Scheme Application in Solving the Problem of Modelling Movements of the Hand Prosthesis

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***Abstract* – The decision-making model with basic fuzzy rule modus ponens is suggested in this paper to control the hand prosthesis. The hand movements are described by angles of finger and wrist flexion. Electromyogram (EMG) of hand muscles was used as a source of the input data. Software was developed to implement the decision-making model with fuzzy rule modus ponens. In particular, the software receives EMG data, executes calculations and visualises the output data. The key advantage of the model is smoothness of output data changes; this way a maximum approach to natural hand movements is reached.**

***Keywords* – Electromyogram, fuzzy inference, hand prosthesis, modus ponens.**

I. Introduction

Over the past three decades, there is a topical problem in medicine of recovery the full functionality of the patient after amputation using different prosthetic techniques [1], [2]. Today the market offers different types of limb prosthesis [3]. One of the most effective in use and interesting in development and construction are prostheses with a biometric control. Control signals could be extracted from the electromyogram (EMG), which is read by the electrodes attached to the nearby muscles [4]. The main aim of this article is to develop a model of the movement of the hand prosthesis, controlled by the forearm muscles. Biometric prostheses usually have one major drawback. Although modern biopotential- controlled prostheses are highly accurate in detecting the EMG signals and execution of the movement, they are faced with a significant problem – discrete motion output [5]. The paper proposes a model of the hand prosthesis movement based on the methods of decision making using fuzzy inference [6], [7]. It was decided to use the decision-making model modus ponens, which is based on the degree of truth of the fuzzy rule to determine the output movement [8].

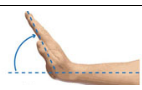
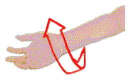
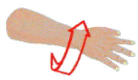
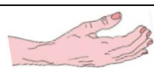
II. Problem

This paper considers the control system of biometric upper forearm prosthesis. The input data in this case are the EMG signals and the output data are the angles of flexion of the phalanges of fingers and wrist. To construct the control system we will use the EMG obtained in the analysis of muscle activity of the forearm. Electrode arrangement for measuring EMG is presented in Fig. 1. It includes 8 measuring electrodes and 1 reference electrode.

The experiment was held, where a person made several times each movement from Table I. The output data for each movement are EMG readings measured with each electrode. The acquired data are divided into two groups: the basic one, which we will use as expert information about gestures; and the test one, which we will use to test the model.

TABLE I

Examined Movements

Index	Movement	Image
1	Hand Open	
2	Hand Close	
3	Wrist Flexion	
4	Wrist Extension	
5	Supination	
6	Pronation	
7	Rest	

In order to classify the EMG signals, we used RMS (root mean square of the amplitude of the EMG potential) as a feature of a signal. It is calculated using (1):

$$RMS = \sqrt{\frac{\sum_{i=1}^{n} x_i^2}{n}}, \quad (1)$$

where x_i is the amplitude of EMG sample, n is the number of EMG signals of considered gesture.

Based on the foregoing, we had a problem of identifying the gesture of prosthesis using input RMS values of EMG of upper forearm. A fuzzy rule modus ponens was suggested as a decision-making method to solve this problem.

III. Basic Concepts and Definitions

A logical and linguistic description of the relationship of the input and the output control parameters is formed to construct a decision making model (DM). The generation of linguistic models is carried out using a set of rules such as <if ... then..>, which form a basis of the knowledge base of DM.

Deductive rule *modus ponens* has a great significance, which is presented below:

$$\frac{\begin{array}{c} P_1: < if\ A\ is\ a\ \ then\ B\ is\ \ b > ; \\ P_2: < A\ is\ a > -\ true; \end{array}}{< B\ is\ b > -\ true.}$$

According to this rule, if there is information in the form of statements P_1 and there is a fact in the form of statements P_2, the decision is made, that <*B is b*>. If statement P_2 does not match the premise of statement P_1 (for example, statement P_2 has form <*A is a'*>,), then the modus ponens rule cannot be applied. However, L. Zadeh extended the *modus ponens* rule, supposing that, if concepts *a*, *b*, and *a'* of statements P_1 and P_2 are modeled with fuzzy sets, then fuzzy conclusion <*B is b'*> can be inferred [6].

As a result, the main problems are:

- Task of composing and justification of a mechanism of a fuzzy inference, according to which a conclusion about fuzzy values of an input control parameter is made using fuzzy knowledge P_1 and input parameter P_2.
- Task of defuzzification, i.e. the task of converting a resulting fuzzy set into the exact value of the output control parameter.

Let A and B be the sets of input and output parameters of process PR. Let β_A and β_B be linguistic variables defined on sets A and B with basic values $T_A = \{\alpha_{A_j}\}, j = \overline{1,m},$ and $T_B = \{\alpha_{B_i}\}, i = \overline{1,n}$, respectively. Here, α_{A_j} and α_{B_i} are fuzzy variables. Let us present fuzzy expert information as System 2 of fuzzy conditional statements (2):

$$\tilde{L} = \{\tilde{L}_i : < if\ \tilde{A}_i\ then\ \tilde{B}_i > \},\ i = \overline{1,n}. \qquad (2)$$

Here $\tilde{A}_i$ and $\tilde{B}_i$ are fuzzy statements $< \beta_A is \alpha_{A_i} >, \alpha_{A_i} \in T_A$ and $< \beta_B is \alpha_{B_i} >, \alpha_{B_i} \in T_B$, respectively.

In general, the inference mechanism includes four stages [7], [9]: fuzzification; fuzzy inference; composition; defuzzification. There are various models of the fuzzy inference. The most important ones are the model of Mamdani and the model of Sugeno [10], [11].

Traditionally, the fuzzy inference of System 2 is presented as a maximin composition and as an interpretation of a conditional statement in the form of Mamdani's implication operation. This approach defines the membership function $\mu_B^*(b) = \underset{i=1,n}{\vee}(\mu_{A_i}(a^*) \,\&\, \mu_{B_i}(b))$. Here, μ_{A_i} and μ_{B_i} are the membership functions corresponding to fuzzy variables $\alpha_{A_i} \in T_A$ and $\alpha_{B_i} \in T_B$.

Solving the defuzzification problem, exact nonfuzzy value b_0 of output parameter B is defined on the basis of the analysis of membership function $\mu_B^*(b)$. There are different methods of defuzzification, but all of them are derivatives of two basic methods. The first approach determines the value of b_0 analysing entire membership function μ_B^*. The second approach uses the extreme values of membership function μ_B^*.

A typical representative of the first approach is a method of finding the centre of gravity of figure b_0, which is limited by the membership function $\mu_B^*(b)$.

The considered fuzzy inference has a significant disadvantage [12], [13]: the range of variation of the output parameter is part of the total control range.

A typical representative of the second approach is a method of the middle maximum. In particular, if there is an extremum of function μ_B in every point on interval $[b_1, b_2] \in B$, then value b_0 is naturally defined as the midpoint of interval $b_0 = \frac{b_1 + b_2}{2}$. The usage of the middle maximum method is problematic at the defuzzification stage, since function μ_B does not have the quasi-concavity property.

IV. Decision- Making Based on the Degree of Truth of the Rule Modus Ponens

The idea of the truth degree of the fuzzy rule *modus ponens* for inference Scheme 3 was introduced in the works [8], [14]:

$$\frac{\begin{array}{c} \tilde{L}; \\ A^* -\ true; \end{array}}{B - true.} \qquad (3)$$

The values with maximum degree of truth $T_{m.p.}$ are suggested as a solution. The definition of $T_{m.p.}$ is given in (4).

$$T_{m.p.}(a^*, b) = \underset{i=1,n}{\&}(T(A^*/\tilde{A}_i) \to T(B/\tilde{B}_i)). \qquad (4)$$

In 4) values $T(A^*/\tilde{A}_i)$ and $T(B/\tilde{B}_i)$ are the degrees of truth of nonfuzzy statements A^*: $< \beta_A\ is\ a^* >$ and B: $< \beta_B\ is\ b >$ relative to fuzzy statements $\tilde{A}_i$ and $\tilde{B}_i$, respectively. These values are defined as $T(A^*/\tilde{A}_i) = \mu_{A_i}(a^*)$ and $T(B/\tilde{B}_i) = \mu_{A_i}(b)$. Here, operation & is a t-norm, and operation $\longrightarrow$ is an operation of the fuzzy implication [15], [16].

In [14] it has been shown that if

1) the membership functions of the basic values of output linguistic variable β_B are quasi-concave continuous functions;

2) the operation of the fuzzy implication has properties of continuity and $0 \to \textit{в} = 1$ (false implies all);

3) the *min* operation is used as a *t*-norm,

then the truth of the fuzzy rule *modus ponens* for inference Schemes 3 is a quasi-concave continuous function. Thus, the truth degree reaches its maximum value either at one point or at a certain interval. Therefore, the method of the middle peak is natural to use in the defuzzification step. Furthermore, in (4) as an implication operation has been selected by operation of Lukasiewicz implication:

$$x \to y = \min(1 - x + y, 1).$$

Besides, if the rule base $\tilde{L}$ has properties of linguistic completeness and consistency [9] in inference Scheme (3), the output parameter *b*, which is defined the way described above, is a continuous function.

Basic samples, as well as all acquired data, consist of a set of 8 parameters, which are computed using (1), and a set of angles, by which phalanges of the fingers and the wrist rotate to form the movement. Statistic was made as a mean value over every sample for each parameter and for each movement.

In Fig. 2 the statistics are given for the RMS of the signal coming from the 3rd electrode for each considered movement.

Analysing the graph, we can divide the 3rd input parameter value into two groups: "big" – for the 4th movement and "small" – for the other movements. Similarly, composing and analysing statistics for each input parameter, we can make linguistic description for it. Thus we can assign a set of fuzzy variables to the movement. Conducting analysis of the fuzzy description, we can identify superfluity of the input data. In other words, we can use the 3rd, the 5th and the 6th electrode to identify the movement. This way we reduce the number of the input parameters, and the problem is simplified.

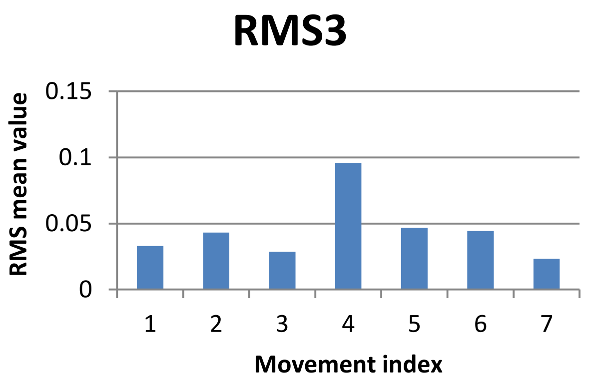


Fig. 2. Statistics over samples for the 3rd electrode.

Fuzzy values of 3 input parameters for each movement are given in Table II.

Summing it all up, fuzzy values for the 3rd parameter are $\tilde{A} = \{\tilde{A}_1, \tilde{A}_2\}$, where $\tilde{A}_1$ = "Small", $\tilde{A}_2$ = "Big"; for the 5th – $\tilde{B} = \{\tilde{B}_1, \tilde{B}_2, \tilde{B}_3\}$, where $\tilde{B}_1$ = "Small", $\tilde{B}_2$ = "Medium", $\tilde{B}_3$ = "Big"; for the 6th – $\tilde{C} = \{\tilde{C}_1, \tilde{C}_2\}$, where $\tilde{C}_1$ = "Small" and $\tilde{C}_2$ = "Big".

TABLE II
LINGUISTIC CODE FOR INPUT PARAMETERS

Movement index	RMS index		
	3	5	6
1	Small	Big	Big
2	Small	Medium	Small
3	Small	Big	Small
4	Big	Small	Big
5	Small	Medium	Big
6	Small	Small	Big
7	Small	Small	Small

The assignment of a membership function for fuzzy variables $\tilde{A}_1$ and $\tilde{A}_2$ is explained in example:

Example 1: mean RMS of movements 1, 2, 3, 4, 6 and 7 satisfies the linguistic variable "Small". Let us calculate *x* as a mean value of RMS of these 6 movements or

$$x_{small} = \sum_{i,j} RMS_{i,j}, \forall i, j : \tilde{RMS}_{i,j} = \text{"small"}, \tag{5}$$

where $RMS_{i,j}$ is value *i* for movement *j* (we have several samples for each movement).

Let $\mu^*_{\tilde{A}_1}(x) = 1$, so x_{small} is the abscissa of a membership function peak. Let us assume that the membership function equals 1, when the input parameter has a value between 0 and the peak. Using expert knowledge about membership function "Small", we can mark a point, where the function first equals 0. Thus, the function decreases from the peak till that point.

The same way, we can calculate a peak of membership function "Big" and find a point, when it first equals 0.

In Fig. 3, normalised membership functions "Small" and "Big" for the 3rd parameter are presented.

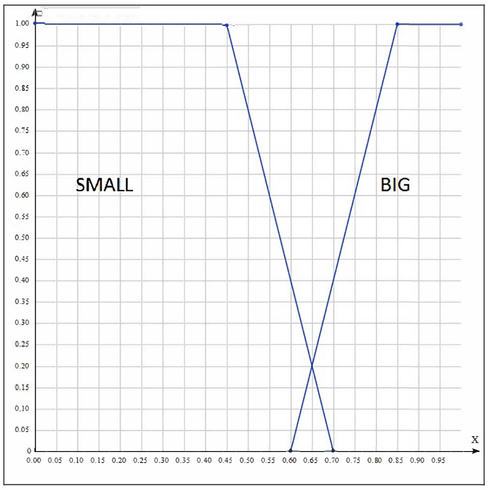


Fig. 3. Membership functions for the 3rd parameter.

The same way we can form membershipfunctions for all the parameters.

V. Output Data Analysis

We have to receive a certain position of the hand as output data. The hand position can be described with angles by which phalanges of the fingers and the wrist rotate. Angle values for each considered movement are given in Table III.

The angles of phalanges of the fingers are the same in each movement, so we can describe these angles with one variable. The values of the 1st and the 3rd phalanges are constant throughout all movements and are not output variables.

Making fuzzyfication of output parameters, finally we have the following fuzzy variables:

$\tilde{Y}_1$ = {near 0°, near 90°} – angle of the finger phalanges;

$\tilde{Y}_2$ = {near 0°, near 15°} – angle of the thumb phalange 2;

$\tilde{Y}_3$ = {near 0°, near 90°, near 180°} – angle of the wrist *α*;

$\tilde{Y}_4$ = {near −45°, near 0°, near 45°} – angle of the wrist *β*.

TABLE III

Values of Angles in Each Movement

Movement index	Fingers			Thumb			Angle of the wrist α	Angle of the wrist β
	Phalange 1	Phalange 2	Phalange 3	Phalange 1	Phalange 2	Phalange 3		
1	0	0	0	0	0	0	180	0
2	90	90	90	0	15	0	180	0
3	0	0	0	0	0	0	0	−45
4	0	0	0	0	0	0	0	45
5	0	0	0	0	0	0	180	0
6	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	90	0

Construction of membership functions for variables $\tilde{Y}_i$ was based on expert knowledge. For example, the membership function for $\tilde{Y}_1$ is graphically presented in Fig. 4.

We have transformed input and output data to the values of membership functions for linguistic variables. This way, we can now use the decision making model, using fuzzy expression based on the expert data. We can infer these data from Table II and Table III and compose fuzzy expressions.

For example, the fuzzy expression for a rotation angle of phalanges of fingers $\tilde{Y}_1$ will look like:

IF “ $\tilde{A}$ small & $\tilde{B}$ small & $\tilde{C}$ small” → “ $\tilde{Y}_1$ near 0”,

where $\tilde{A}$, $\tilde{B}$ and $\tilde{C}$ are the fuzzy variables, describing the values of RMS of input signals.

This way, we can compose expressions for each output parameter for each movement. As a result we have a set of fuzzy expressions.

Software was implemented to test the solution of the problem. Several C++ classes were implemented like “FuzzyFunction” and “FuzzyLogic”. The first one embeds fuzzy functions and their attributes into the software. The second one presents fuzzy logic, necessary to operate with fuzzy functions.

The application has also a graphical interface. The interface is divided into two parts: the right side of the window has input boxes for values of RMS of the signal and a push button to confirm the input data and start classification; the left side of the window has an OpenGL Widget depicting graphical representation of the output data [17]. In other words, it shows the schematic movement of the prosthesis.

As it was described above, a set of RMS values is input and the output parameters are viewed in the console and in the application window as a graphical movement.

Fig. 5 presents a few screenshots of the application, which shows several movements after a set of input data has been assigned.

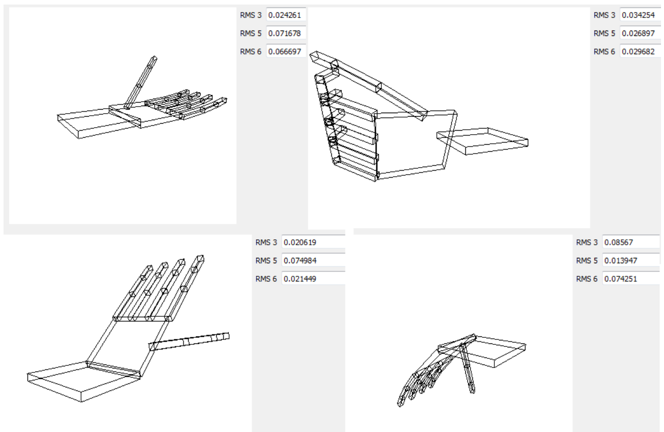


Fig. 5. Software implementation of the decision making model.

VI. Conclusion

The performed study is the basis for further research in the field of movement modelling of bioelectric prostheses. Next steps of the research include development of a model of the prosthesis with independent movements of the fingers. In particular, the hardware implementation of the prosthesis, which is based on the suggested decision-making model, is of a paramount interest

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