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Control of Dexterous Bio-Prosthetic Hand via Sequential Recognition of EMG Signals Using Fuzzy Relations

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Abstract. The paper presents a concept of bio-prosthesis control via recognition of user intent on the basis of myopotentials acquired of his body. We assume that in the control process each prosthesis operation consists of specific sequence of elementary actions. The contextual (sequential) recognition is considered in which the fuzzy relation approach is applied to the construction of a classifying algorithm. Experimental investigations of the proposed algorithm for real data are performed and results are discussed.

Keywords. bio-prosthesis, EMG signal, pattern recognition, fuzzy relation

1. Introduction

The muscle activity of living organisms is reflected in characteristic biosignals, which can be measured. Some of them can be exploited to control the work of technical devices. Electrical potentials corresponding to the movement of skeletal muscles are an example of such biosignals. They can be detected and registered on the skin surface as EMG signals. The profile of EMG signals depends critically on the relative proximity of activated motor units to sensor-contact locations on the skin surface (spatial filtration effect). In particular, distinct finger movements correspond to distinct EMG features. The features depend on the type of actual movements made or on the imagined movements (in the case of amputees). Consequently, the user's intentions (with regard to limb movement) can be inferred from EMG features [1–7]. Bio-prostheses can utilize these features to control the actuators of artificial hands, fingers, knees and feet, or even the wheels of a wheelchair.

The paper presents the concept of a bio-prosthesis control system which in principle consists in the recognition of a prosthesis user's intention (i.e., patient's intention) based on adequately selected parameters of EMG signal and then on the realization of the control procedure which had previously been unambiguously determined by a recognized state. The paper arrangement is as follows. Section 2 includes the concept of prosthesis control system based on the recognition of patient intention and provides an insight into sequential classification method. Section 3 presents the key recognition algorithm based on the fuzzy relation approach. Section 4 in turn describes experimental investigations of proposed algorithm and discusses their results.

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2. Control System of Bio-Prosthesis

The design of the considered control system is based on the assumption that every prosthesis action (irrespective of prosthesis type) consists of a specific sequence of *elementary actions*. User *intention* is equated with the *will to perform* a particular elementary action [8]. Thus prosthesis control is modeled as a discrete process. At the n-th stage of the process the following steps are performed consecutively:

- a *measurement* is made of EMG signal parameters x_n ($x_n \in \mathcal{X}$), which represent patient's will j_n ($j_n \in \mathcal{M} = \{1,2,...,M\}$) (in this paper, the will of the patient means the intention to take a particular action),
- the *recognition* of this intention (the result of recognition at the *n*-th stage will be denoted by $i_n \in \mathcal{M}$),
- the *realization* of an elementary action $a_n \in \mathcal{A}$, uniquely defined as a recognized intention.

In other words, it is assumed that there is total number *M* number of elementary actions $\mathcal{A} = \{a^{(1)} a^{(2)},...,a^{(M)}\}$ (an example of how the notion of elementary action can be interpreted in the context of a dexterous prosthetic hand is described in section 4).

In order to define the algorithm responsible for identifying patient intent, we shall apply the concept of the so-called sequence recognition. In the context considered here, the essence of sequence recognition is the assumption that patient intent at a given stage is dependent upon earlier intentions. This assumption seems entirely natural, since a sequence of consecutive elementary actions performed by a prosthetic limb must make up a well-defined, complete action. Not every sequence of elementary actions is admissible, but only those sequences which make up actions chosen for a prosthetic device. Examples of such actions (admissible sequences of elementary actions) are presented in section 4.

Since a patient's current intention depends on past history, in full generally the decision (recognition) algorithm should take into account the whole sequence of the preceding feature values (parameters of EMG signal), $\bar{x}_n = (x_1, x_2, ...x_n)$ [9]. It must be stressed, however, that sometimes it may be difficult to include all the available data, especially for large *n*. In such cases we have to allow various simplifications (e.g., make allowance for only *k* recent values in the vectors).

For the recognition algorithm to work, we need information about the associations between decisions (i.e., the will of the patient) and features (i.e., parameters of the EMG signal). Henceforth we assume that these correlations are provided by a *training set*, which in our case consists of *training sequences* of the following form:

$$S = \{S_1, S_2, ..., S_N\} \tag{1}$$

were:

$$S_m = \{(x_{1,m}, j_{1,m}), (x_{2,m}, j_{2,m}) ... (x_{L,m}, j_{L,m})\} \tag{2}$$

denotes a single-patient sequence of prosthesis activity that comprises *L* EMG signal observation instants, and the patient's intentions. In practical situations acquisition of learning set is rather difficult task. An appropriate procedure requires simultaneously (synchronic) measurement of EMG signal (usually in multi channel mode) and observation of finger posture and hand movement which define elementary action.

3. Algorithm of Sequential Recognition Using Fuzzy Relation

The proposed algorithm, which includes *k*-instant-backwards-dependence ($k<L$), i.e., the decision at the *n*-th instant is made by considering the *k* most recent feature vectors:

$$\bar{x}_n^{(k)} = (x_{n-k}, x_{n-k+1}, \ldots, x_{n-1}, x_n) \tag{3}$$

can be presented according to the following points:

1. Cover the space $\mathcal{X}^{(l)}$ of the individual feature $x^{(l)}$ ($l = 1,2,\ldots,d$) by overlapping fuzzy sets corresponding to the linguistic "values" of this feature (e.g., *small*, *medium*, *big*, etc.). For each fuzzy set define its membership function. Obtained fuzzy sets state fuzzified feature space $\mathcal{X}_F^{(l)}$ of individual features. Create fuzzified feature space as a product $\mathcal{X}_F = \mathcal{X}_F^{(1)} \times \mathcal{X}_F^{(2)} \times \ldots \times \mathcal{X}_F^{(d)}$. Let its cardinality be equal to d_F.
2. Determine observation matrix $O^{(k)}$ i.e., fuzzy relation in the space $\mathcal{X}_F^{k} = \mathcal{X}_F \times \mathcal{X}_F \times \ldots \times \mathcal{X}_F$ (*k* times) and learning subset $S^{(k)}$ containing sequences of (*k*+1) learning patterns from S. The *i*-th row of observation matrix contains membership degrees of features $\bar{x}^{(k)}$ of *i*-th learning sequence from $S^{(k)}$ to the fuzzy sets of space $\mathcal{X}_F^{k}$.
3. Determine decision matrix $D^{(k)}$, i.e., relation defined on product of learning sequences $S^{(k)}$ and the set of decisions (classes) $\mathcal{M}$. For the training data, where the classification is exactly known, the *i*-th row is a fuzzy singleton set at the place corresponding to the last class number of *i*-th sequence in the set $S^{(k)}$.
4. Find matrix $E^{(k)}$ as a solution of so-called *fuzzy relational equation* [10], or – in approximate way – so as to minimize criterion $\rho(O^{(k)} \circ E^{(k)}, D^{(k)})$. Criterion $\rho(A,B)$ evaluates difference between matrices *A* and *B*, i.e., $\rho(A,B) \geq 0$ and $\rho(A,B) = 0$ if $A = B$. Operator $\circ$ denotes here *max-min*-norm composition of relations, i.e., multiplication of matrices *O* and *E* with $\times$ and + operators replaced by *min* and *max* operators (more general by *t*-norm and *s*-norm operators) [11]. In the further experiments we decided to select the method of determination of matrix *E*, adopting $\rho(A,B) = \sum_{i,j}(a_{ij} - b_{ij})^2$ and applying as an optimization procedure real-coded genetic algorithm [12].

To classify a new pattern x_n at the *n*-th step of sequential recognition, first the row-matrix of fuzzy observation $O(\bar{x}_n^{(k)})$ is calculated from known sequence of feature observations (3). Then matrix $E^{(k)}$ is applied to compute an output row-matrix called *target vector* [10]:

$$O(\bar{x}_n^{(k)}) \circ E^{(k)} = T(\bar{x}_n^{(k)}) = [t_1(\bar{x}_n^{(k)}), t_2(\bar{x}_n^{(k)}), \ldots, t_M(\bar{x}_n^{(k)})], \tag{4}$$

which gives a fuzzy classification in terms of membership degrees $t_i(x)$ of the pattern *x* to the given classes $i = 1,2,\ldots,M$. When a crisp decision is required, defuzzification has to be applied, typically according to the maximum rule.

4. Experimental Investigations

4.1. Description of Experiments

In order to study the performance of the proposed method of sequential recognition of patient intent, some computer experiments were made. In the control process of the grasping of 6 types of objects (a pen, a credit card (standing in a container), a computer mouse, a cell phone (laying on the table), a kettle and a tube (standing on the table)) were considered. In the process of grasping with a hand 7 types of macro-actions were distinguished [8]: rest position, grasp preparation, grasp closing, grabbing, maintaining the grasp, releasing the grasp and transition to the rest position – it gave in total 25 different elementary actions (or pattern classes).

Fundamental testing of the recognition algorithm depended on the learning sequences containing pairs of the form (x_i, j_i), (2). The set S, as stated in equation (1), was determined from the data taken from the synchronous registration of finger/hand movements (using a camera) and EMG signals (using surface electrodes). For the purpose of the experiment, a special measurement system was set up [13]. It comprises of the PC computer, equipped with EMG and video-signal acquisition circuits, together with software which performs the following consecutive tasks:

(a) synchronous registration of both EMG and video signals,
(b) signal segmentation with regard to defined elementary actions (resulting in pairs of the form: EMG signal segment/class of elementary action,
(c) compilation of feature vectors for specific signal segments (the result of this are pairs of the form (x_i, j_i), as stated in Eq. (2).

In the investigations the EMG signals were registered using 3 electrodes located on a forearm of a healthy man. The electrodes were respectively located above the following muscles: *extensor carpi radialis brevis*, (*flexor carpi ulnaris*) and *extensor pollicis brevis*. For the purpose of simplifying of experiments, the constant time of 250 ms for each action was adopted. The *rms* values for 3 selected intervals of EMG signal spectrum were taken as the feature of each signal segment. Eventually vector x has a form:

$$x_i = (\tilde{x}^{I}_{i,1}, \tilde{x}^{II}_{i,1}, \tilde{x}^{III}_{i,1}, \tilde{x}^{I}_{i,2}, \tilde{x}^{II}_{i,2}, \tilde{x}^{III}_{i,2}, \tilde{x}^{I}_{i,3}, \tilde{x}^{II}_{i,3}, \tilde{x}^{III}_{i,3}) \tag{5}$$

were the features $\tilde{x}^{I}, \tilde{x}^{II}, \tilde{x}^{III}$ were calculated for the intervals: $R0/RI$ = (10–60Hz), RI/RII = (60–200Hz), $RII/RIII$ = (200–500Hz), according to the following formulae:

$$\tilde{x}^{I}_{i,j} = \frac{1}{\tilde{x}^{0}_{i.j}}\sqrt{\frac{1}{2}\sum_{k=R0}^{RI-1} X_k^2}\ ,\ \tilde{x}^{II}_{i,j} = \frac{1}{\tilde{x}^{0}_{i,j}}\sqrt{\frac{1}{2}\sum_{k=RI}^{RII-1} X_k^2}\ ,\ \tilde{x}^{III}_{i,j} = \frac{1}{\tilde{x}^{0}_{i,j}}\sqrt{\frac{1}{2}\sum_{k=RII}^{RIII} X_k^2}\ ,\ \tilde{x}^{0}_{i,j} = \sqrt{\frac{1}{2}\sum_{k=R0}^{RIII} X_k^2} \tag{6}$$

The algorithm was constructed on the basis of the collected learning sequences (2) of the length 7 elementary actions (assigned to successive macro-actions). The tests were conducted on 100 subsequent sequences.

4.2. Results and Conclusions

The proposed sequential algorithm with fuzzy relations (Fuzzy) was compared with appropriate algorithm for single classification (Fuzzy 0) ([9, 10]) and with two algorithms based on the probabilistic model: naive Bayes classifier (Bayes) [14] and sequential algorithm with Markov dependences (Markov) [9]. The outcome is shown in

Table 1. It includes the frequency of correct decisions for the investigated algorithms depending on the number of training sets.

Table 1. Frequency of correct classification (in per cent) versus the number of learning sets for various algorithms (the names are explained in the text)

Algorithm	50	75	100	125	150
Fuzzy	75.7	79.4	83.4	86.1	88.6
Fuzzy 0	55.5	59.9	65.2	68.5	70.9
Markov	83.2	86.3	89.1	90.5	92.4
Bayes	64.2	70.1	71.0	72.8	73.6

There occurs a common effect within each algorithm group: algorithms that do not include the inter-state dependences and treat the sequence of intentions as independent objects (Fuzzy 0 and Bayes) are always worse than those that were purposefully designed for the sequential decision task (Fuzzy, Markov), even for the least effective selection of input data. This confirms the effectiveness and usefulness of the concepts and algorithm construction principles presented above for the needs of sequential recognition of patient intent in the bio-prosthesis control system.

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