Determination of the Relationship Between EMG Signals and Hand Grips Using a Commercial Myo Armband

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Abstract:

The work discusses the construction of a measurement system for determining the relationship between EMG signals and hand grip movements. The relationship is necessary for the synthesis of control of the hand bioprosthesis. The measurement system is based on commercial Myo armband with EMG signals sensors and sensory glove with bend and pressure sensors. There are presented possibilities, advantages and disadvantages of such approach.

Keywords: *EMG signals, electromyography, pattern recognition, hand bioprosthesis control*

1. Introduction

The progress of medicine is inseparably linked with the development of technology, especially in such fields as mechatronics, computer science and robotics. A good example is advanced hand bioprostheses whose control is based on recognizing the patient's intent of guiding the prosthesis by registering biosignals from his limb stump, and recognizing the patterns contained in them. The result of such recognition is the decision controlling the movement of the bioprosthesis. The idea of such a control is illustrated in Figure 2, included together with the description in Chapter 2.

The basis for the synthesis of the recognition system is the knowledge of the relationship between the measured biosignals and the patient's intention regarding the movement of the prosthesis. Such a relationship can be determined (with a good approximation) on the basis of the examination of a healthy person, by recording biosignals generated in the muscles of the forearm during the performance of specific manipulative-grasping movements (movements from specific classes). The desired relationship can then be expressed by labeling the recorded biosignals with the classes of performed grips (types of finger movements) and its parameters (movement speed, strength and points of contact of the object with the hand).

The labeling can be performed automatically by the measuring system based on information on the type of motion provided by the vision system or sensory glove or by the operator participating in the experiment [12, 13]. The paper presents the latter approach.

The quality of bioprosthesis control is characterized essentially by two parameters:

- the size of repertoire of manipulative-grasping movements, and
- the reliability of recognition of intentions of these movements' realization.

Due to the disturbances accompanying the process of biosignal registration, which reduce the information contained in biosignals, the recognition error is usually greater than zero. Additionally, this error increases naturally with the number of prosthesis movements.

Hence, when determining the relationship between the biosignals and the intent of prosthesis movement (also later, while controlling), the key issue is the quality of biosignal registration which depends directly on the measuring system and the registration procedure applied.

The paper presents the course and the results of measurement experiments conducted with the commercial measuring band called the Myo (equipped with electromyographic sensors [6, 7, 15] and accelerometer), and the sensory glove developed by the authors (equipped with bend and pressure sensors, Fig. 5). As the quality criterion of the obtained measurement data, the level of reliability of the recorded signals class recognition has been accepted (or alternatively the recognition error). To verify the quality of the acquired data, the tests to recognize the recorded signals were carried out. These tests together with the applied algorithms of extraction and classification of features are described in Chapter 4.

The quality of the recorded signals was compared with the Biosignal Measurement System developed in the Mobile Robots & BioControl Laboratory, Faculty of Electronics, Wroclaw University of Science and Technology [14]. The comparison was made on the basis of the signal recognition results.

Fig. 1. The set of gestures proposed by the Myo armband's manufacturer [1]

In contrast to similar studies using the Myo armband [3, 5, 8], the authors introduce a new element, i.e. the registration of hand and object interaction based on the use of pressure sensors to identify the moment of contact with the object being grabbed, as well as the measurement of the existing pressure forces (end of the motion). Also, the repertoire of 11 gripping movements chosen for the study definitely exceeds the modest set of movement classes proposed by the manufacturer of the measuring band (Fig. 1) [1]. The adopted repertoire of movements is described in Chapter 4.

2. Recognition Process With Feedback

As it has been mentioned, registered bio-signals, after recognition of the patterns contained in them, can be used to control the machine, for example, a biomanipulator or bio-prosthesis of the hand. The scheme of the recognition process is shown in Figure 2. It includes the following stages:

signal acquisition – The process of collecting the raw measurement data and saving them in digital form.

The information obtained at this stage may be redundant and contain interference. In a multichannel measuring system, an improper location of measuring electrodes may lead to repetition of some information in different signals. In turn, the most common sources of interference are, among others, own noise of measuring electronic devices and overlapping external noise from power devices. These disturbances can be substantially reduced by constructing appropriately the measuring circuits (differential measurement, measuring amplifier directly by the electrodes, etc.). Another source of noise at the stage of determining the biosignals-the intention of prosthesis movement relationship, is the poor repeatability of movements performed (for each class). This source of interference can be significantly reduced by applying the appropriate registration procedure.

extraction – The measurement data processing stage. The registered signal is subjected to the process of feature extraction.

By means of appropriate extraction algorithms, the features characterizing the interesting (for the recognition process) information contained in the signal are determined. Extraction algorithms can operate in the time domain (determining such parameters as: rms, mav, number of passes through zero, etc.) [2], in the frequency domain (Fourier Transform, STFT, etc.) [9, 10] or time and frequency domain (for example: Wavelet Transform [4]). You can also combine features obtained by different methods. After combining the features of signals from all measuring channels (for a single measurement), a feature vector is created that uniquely characterizes a given class of signals.

selection – Stage of selecting a set of features best describing a given movement.

At this stage, redundant data as well as data related to interference are deleted. This is done by experimentally removing superfluous features from the vector of features or by manipulating the components of the vector to minimize intra-class dispersion and at the same time maximize the interclass dispersion. Examples of algorithms are: SBS, SFS [12].

classification – The last step of the classic recognition scheme.

At this stage, the feature vector representing the recognized signal is assigned to the best matching class. Examples of algorithms are e.g. neural networks NN [16], decision tree [11], or applied in the work K nearest neighbors (KNN) [17].

control command – The step of translating the classification result into a control signal.

The recognized signal class can be treated as a signal initiating a specific movement of the prosthesis.

feedback – An additional step in the classic recognition process.

It provides information about the course of the signal generation process. In the case under consideration, it is a sensory signal from the measuring glove informing about hand posture changes (bend sensors) and pressure forces of individual hand elements (resistive sensors).

Bio-signal recognition is a flexible process in terms of the type of different data. It is possible to use all biological signals mentioned at the outset after bringing them to the digital representation in the form of a vector of features of finite size. [2]

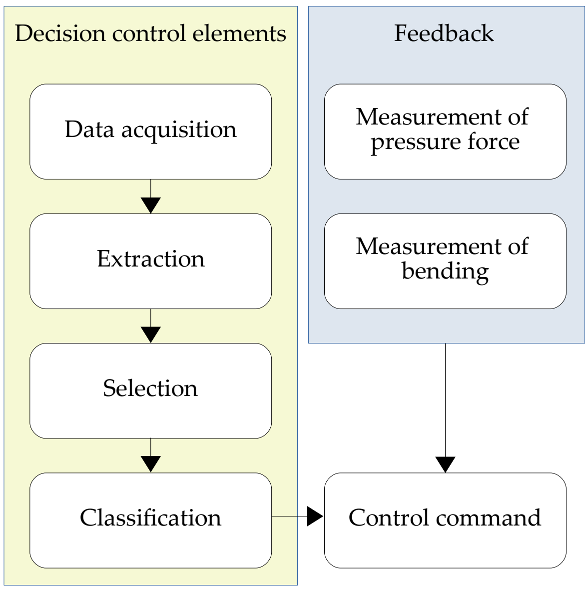

Fig. 2. Diagram of the recognition process

3. Measurement Stand

Muscle movements are accompanied by changes in the electrical potential appearing on the membrane of their cells (myocytes / muscle fibers). These changes propagate into the surrounding tissues reaching the skin surface. On the surface of the skin, changes in potentials from various cells, various muscles currently active, create a superposition that can be recorded as a surface EMG signal. Therefore, EMG signals recorded on the skin of the forearm, above the muscles moving fingers of the hand, represent these movements.

For obvious reasons, the highest percentages in the EMG signal measured have potentials from the closest muscle. Therefore, due to the efficiency of recognizing the movement class, the individual measurement points should be located successively over the muscles we are interested in. This arrangement is facilitated by the construction of the Myo armband by Thalmic Labs.

The proposed measuring stand consists of the Myo measuring armband (Fig. 4) and the measuring glove (Fig. 5). The band, due to its construction, allows the signal to be measured only in eight places evenly distributed on the ring surrounding the forearm. On the other hand, the sensory glove registers such parameters as the pressure force on individual areas of the anterior of the hand and flexion of the fingers. Diagram 3 shows the entire measurement system. The master device is in this case the central unit connecting all peripheral devices.

The measuring band connects to the computer via the Bluetooth 4.0 protocol. Unmodified, raw data is sent at 1 Mb / s. The limitation in this case is the micro controller located directly on the band that samples at 200 Hz. [1]

On the other hand, the sensor glove uses a 64-channel Advantech PCI-1747u measuring card that samples at a frequency of up to 250 kHz. In order to ensure a uniform measuring data frame, the frequency has been limited to 200 Hz.

3.1. Measurement Band

The used Myo measuring band (Figure 4) is a tool that is widely used in many areas. Starting from the simple control of computer applications, ending with the control of complex prosthetic systems.

The distribution of electrodes mounted on the band ensures repeatability of measurement conditions. Assuming that the band is always put on the same height of the forearm, the position of the electrodes in the subsequent tests does not differ significantly. Plates with sensors are connected by flexible joints which expand evenly with the extension of the band. The whole is a stable construction.

Apart from the positive impact on repeatability of measurements between subsequent tests, the construction significantly limits the measuring area to only a small area of the forearm. Covering additional muscle with EMG sensors requires the fusion of more bands working in parallel. Unfortunately there is no possibility of re-using rejected channels in the case of

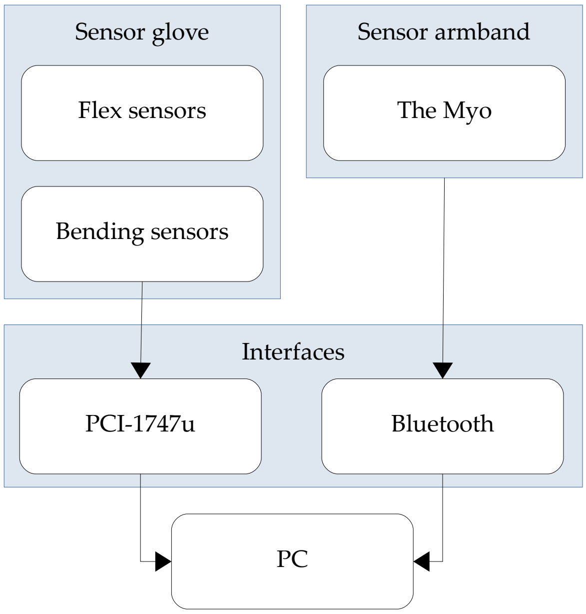

Fig. 3. Diagram of the measurement system

omission of individual channels in the process of feature selection.

Fig. 4. The Myo armband

3.2. Sensor Glove

The applied sensor glove (Fig. 6) is an alternative and at the same time an extended version for the commercial *Motion Capture Data Glove* solution. It was built as part of the didactic project at the Wroclaw University of Science and Technology.

The elaborated solution consists of 24 independently operating sensors, including:

- 18 pressure sensors located on the anterior of the hand palm, successively on the fingertips, the proximal finger segments and the metacarpal. These sensors were built in a technology using a polymer film with variable resistance under the influence of pressure and bending forces. They give information about the pressure on individual parts of the hand;
- 6 standard 2.2 inch bend sensors. One sensor for each finger and one additional thumb sensor to examine the bending of its base (Fig. 6). They were

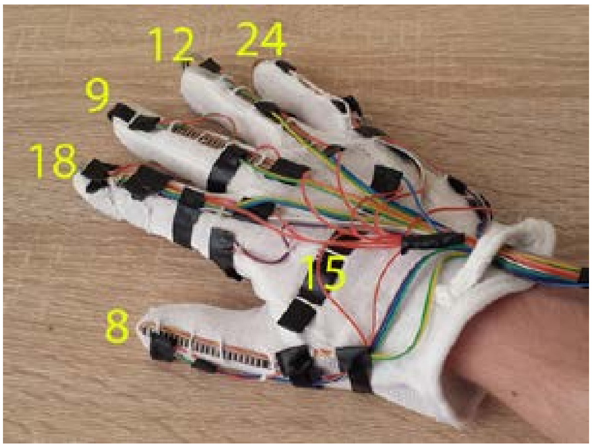

Fig. 5. Sensor glove – posterior

Fig. 6. Sensor glove – anterior

made in the ink technology and inform about the posture of the fingers.

The glove communicates with the system via a measuring card with an AC converter.

3.3. Force Sensor

Table 1 shows the voltage values which were measured on selected pressure sensors for five weight values [g]: 0, 50, 100, 500 and 1000. The test was carried out at 5 [V] supply voltage.

Tab. 1. Voltage characteristics of selected force sensors (on the fingertips)

Position	Voltage value [V] at sensor load [g]				
	0	50	100	500	1000
Thumb	0.2	1.4	2.6	3.9	4.3
Index	0.5	1	1.5	2.6	3
Middle	0.6	2	2.8	4.1	4.5
Ring	0.4	1.4	2.2	3.5	4
Pinky	0.7	1	1.7	3	3.6

As expected, with the increase of the pressure force on the sensor, its resistance decreases. It leads to a reduction in voltage drop.

An example signal recorded on a force sensor is presented in Figure 7. In accordance with the sensors

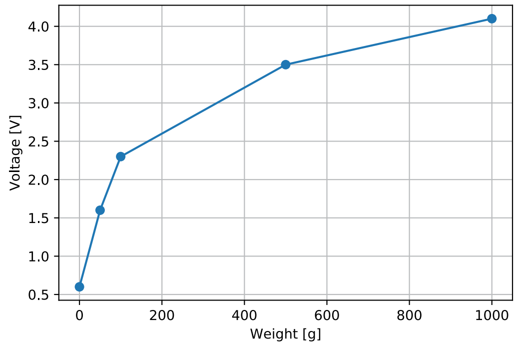

Fig. 7. Voltage characteristics of the force sensor

characteristic (Tab. 1 and Fig. 7) in the initial phase of movement, when there was no contact with any object from the environment, the voltage value measured on the sensor is contained in the range of 0 [V] to 0.5 [V]. In the second of movement occurs a contact and the voltage increases sharply to around 2 [V]. Then it gently falls and grows again, stabilizing in the range between 1.5[V] and 1.75[V].

The data coming from the pressure sensors not only inform about the existence of the contact with the obstacle, but also about the force exerted on the object during the grip itself. For example, it can be read from the graph that the sensor has a force of about 0.981 Newton in accordance with the formula:

$$F = ma \quad (1)$$

Where *m* is the mass value read from Diagram 7 for voltage equal to the instantaneous voltage in $\frac{3}{4}$ seconds and amounts to $2[V]$, *a* is the value of gravitational acceleration and is assumed to be $9.81[\frac{m}{s^2}]$.

$$F = \frac{1}{10} \times 9.81 = 0.981[N] \quad (2)$$

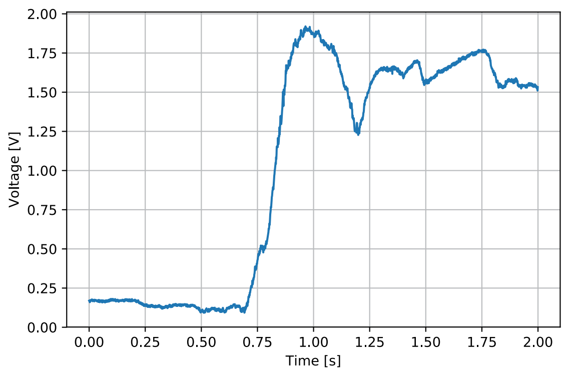

Fig. 8. Example signal of force sensor

3.4. Bend Sensor

The properties of standard bend sensors are presented in Table 2. According to the presented data, along with the progressive bending of the sensor from 0^0 to 90^0, its resistance increases and the voltage decreases.

The averaged values for all three positions are presented in Diagram 9. Analyzing the data contained therein, it can be stated that in the examined range the voltage characteristics of the sensor are linear.

Tab. 2. Voltage characteristics of bend sensors

Position	Voltage value [V] at the sensor bends [^{0}]		
	0	45	90
Thumb	3	2.5	2
Index	2.6	2.1	1.8
Middle	3.3	2.9	2.6
Ring	2.4	1.9	1.5
Pinky	3.1	2.5	2

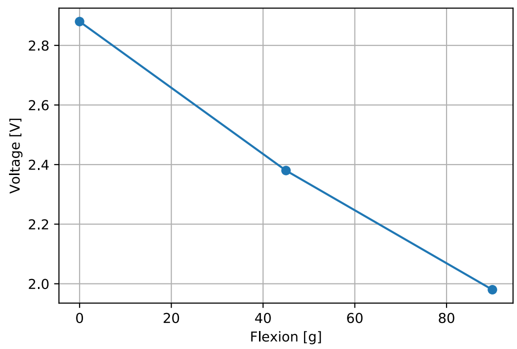

Fig. 9. Voltage characteristics of the bend sensor

The data contained in Diagram 10 shows the electrical signal from the bend sensor. As in the previous case, the registration took 2 seconds. Comparing the data with the voltage characteristic (Figure 2) of the sensor, it can be stated that in the initial phase of movement the finger with the sensor was bent by 45^0. Then in $\frac{1}{2}$ seconds it was straightened and bent again in the of the first second of movement.

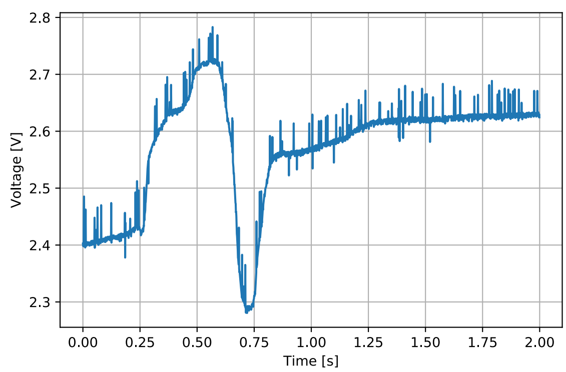

Fig. 10. Example signal of bend sensor

4. Tests

The carried out research aimed at illustrating the possibilities of the measuring stand in terms of the interpretation of electromyographic data from the Myo

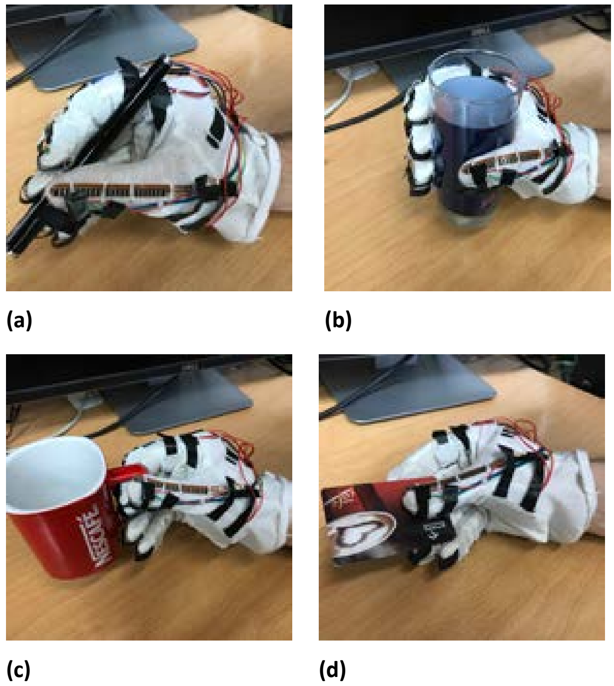

Fig. 11. Example classes of movements

measuring band for the purpose of recognizing the intention of making a movement. The authors' intention is also to maximize the number of correct identifiers (input data $\rightarrow$ movement class) and aspiration to completely eliminate false matches for three different algorithms: standard deviation, wavelet form, energy of signal. The KNN algorithm was used as the classifier with parameter of neighbors number equal to 3. According to the studies, it is the optimal parameter value for the problem of classifying the time features of electromyographic signals [12].

4.1. The Run of the Experiments

The selected set of movement classes consists of 11 different grasps. This set has been presented in the paper on an innovative measurement system developed at the Wroclaw University of Science and Technology [14]. It consists of movements during which everyday objects are captured: a pen (Fig. 11a), a screw, a potentiometer, a glass without handle (Fig. 11b), a glass with handle (Fig. 11c), a kettle, an ATM card (Fig. 11d), a mobile phone with rotary movement, a computer mouse, a mobile phone without rotary movement, a suitcase.

The process of data acquisition took place in two stages. First, proper movement was performed for 2 seconds. Then, again for 2 seconds, a rest period took place during which the user had time to put away the object and return to the starting position. The measuring application has been equipped with two progress bars that fill in alternately and inform about the remaining time.

For each of the 11 classes, 200 measurements were taken. Then, for each move, a 100-element subset was selected for teaching the classifier. The rest of the measurements were used to assess the quality of classifications. As a result of subsequent tests, tables of truths and a percentage of recognition of the tested measurements are presented.

The succeeding lines of the truth table contain information about single, examined classes of movements. For each of them, the numbers in the following columns describe the percentage recognition of a given movement as another class. The numbers lying on the diagonal are the values of the correct recognition of the next move by the classifier. All other values greater than 0 indicate an erroneous assignment of the classed measurement.

4.2. Results

Standard deviation (SD)

The standard deviation algorithm belongs to the group of classical, time algorithms of character extraction.

$$X_{sd} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - x_0)^2} \tag{3}$$

The calculations were carried out for the standard deviation and the KNN classifier.

Tab. 3. Truth table for standard deviation

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1.	92	2	1	1	3	0	1	0	0	0	0
2.	0	89	2	0	7	0	2	0	0	0	0
3.	2	3	92	0	2	0	1	0	0	0	0
4.	0	0	1	99	0	0	0	0	0	0	0
5.	2	8	5	1	83	0	1	0	0	0	0
6.	1	0	0	0	0	99	0	0	0	0	0
7.	6	0	0	0	1	0	91	0	2	0	0
8.	0	0	0	0	0	0	0	93	0	7	0
9.	0	0	1	0	1	0	0	0	98	0	0
10.	0	0	3	0	0	0	0	5	0	91	1
11.	0	1	0	0	0	0	0	0	1	0	98

Table 3 shows the results of the classification for a set of 11 grabs. The selected row 5 contains elements from columns 1 to 11. The values contained in them indicate successively the number of classifications 10 for classes from 1 to 11. In the example shown, class 5 was recognized 83 times correctly and 17 times incorrectly: 3 times as class 1, 7 times as class 2, twice as class 3 and once as class 7.

The sum of values on the diagonal of the truth table in relation to the total amount of classed measurements gives the percentage value of the classification of the movements studied.

$$X_{sk} : 93\% \tag{4}$$

Wavelet form (WL)

Wavelet form algorithm from the group of time algorithms. The value of the feature determined by this method is calculated as the sum of absolute values from the differences of the subsequent amplitudes of the signal.

$$X_W = \sum_{k=2}^{N} |\Delta x_k| \tag{5}$$

$$\Delta x_k = x_k - x_{k-1} \tag{6}$$

The calculations were carried out for the wavelet form and the KNN classifier.

Tab. 4. Truth table for wavelet length

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.
1.	93	1	1	1	4	0	0	0	0	0	0
2.	1	91	0	0	5	0	2	0	0	0	1
3.	5	0	91	0	3	0	0	0	0	1	0
4.	0	0	0	99	0	1	0	0	0	0	0
5.	0	6	5	0	89	0	0	0	0	0	0
6.	0	0	0	0	0	99	1	0	0	0	0
7.	0	0	2	1	5	0	91	0	1	0	0
8.	0	0	0	0	0	0	0	93	0	7	0
9.	0	0	1	0	1	0	2	0	96	0	0
10.	0	0	0	0	0	0	0	1	0	98	1
11.	0	0	0	2	0	0	1	0	0	0	97

$$X_W : 94\% \tag{7}$$

From table 4, you can read the class that was most often incorrectly recognized. Class 5 has been mistakenly identified 11 times.

Energy (En)

Another classic algorithm of character extraction is the algorithm for calculating Energy of a signal.

$$X_{En} = \sum_{k=1}^{N} |x_k|^2 \tag{8}$$

The calculations were carried out for the Energy of signal and the KNN classifier.

Tab. 5. Truth table for energy

1.	86	2	2	1	6	0	3	0	0	0	0
2.	2	80	4	0	13	0	1	0	0	0	0
3.	7	7	81	0	1	0	2	2	0	0	0
4.	4	0	0	89	0	2	2	0	0	3	0
5.	2	14	6	0	78	0	0	0	0	0	0
6.	2	0	0	0	0	98	0	0	0	0	0
7.	8	0	3	0	3	0	83	0	3	0	0
8.	0	0	0	0	0	0	0	89	0	11	0
9.	0	0	2	0	2	0	2	1	93	0	0
10.	1	1	6	5	2	0	0	10	0	74	1
11.	1	2	0	0	0	0	1	1	0	2	93

$$X_{En} : 84\% \tag{9}$$

Again analyzing truth table 5, the class that is most often wrongly recognized can be easily found. In this case, it is class 10 with 26% of the samples incorrectly recognized.

4.3. The Comparison of Measurement Systems

In the next step of the research, the results of experiments were compiled and the measurement data obtained with the Myo armband and a professional measuring system [14] developed at the Wrocław University of Technology and Science were compared. In both cases, the tests (both data acquisition as well as digital processing) were proceeded with the same measurement methodology. In the case of a measurement system from the Wroclaw University of Technology and Science, data acquisition took place on 16 channels, 8 of them were electromyographic signals and the remaining 8 mechanomyografic signals. The results of the experiments were presented in Table 6 and in Figure 12.

Tab. 6. Accurate classifications for the Myo and Lab 06 systems

	The algorithm used to extract features		
	SD	WL	En
The Myo	93%	94%	84%
Lab 06 EMG	82%	86%	74%
Lab 06 MMG	67%	76%	64%
Lab 06 EMG + MMG	89%	93%	77%

The average value of correct classifications was in each case the highest for the system using the Myo.

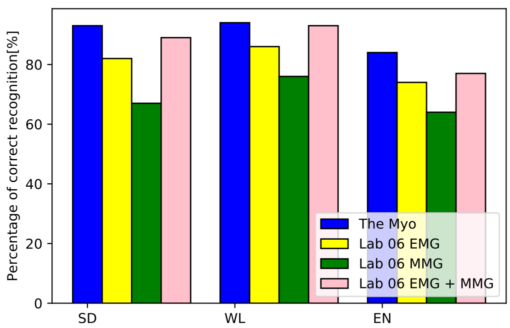

Fig. 12. Comparison of the Myo and Lab 06 systems

5. Conclusions

The paper presents the concept of the system construction for the simultaneous measurement of the bioelectric signal and pressure force on the prosthesis's fingers during motion. When the system was compared to a professional measuring system, the parameters of a commercial measuring band appear to be sufficient in terms of the quality of the received signal. In addition, the commercial system also allows the registration of the signal from the mounted accelerometer and gyroscope which extends the existing capabilities of traditional measurement systems [14].

The use of a measuring glove with bend and pressure sensors gives additional information about the hand posture (bend sensors) during motion as well as interaction with the surrounding world (touch sensors). Thanks to this information, it is possible to accurately describe the condition of the hand and forearm at any time during the movement. Additionally, thanks to bend and pressure signals, it is possible to control the prosthesis in such a way that the interaction with the surrounding world is as non-invasive and realistic as possible so that the manipulated objects and the prosthesis themselves will not be damaged due to the movement.

The presented concept of the measurement system gives new possibilities due to the study of algorithms for the recognition of biological signals. In contrast to the current classical approach, the input vector contains signals from four different sources. Starting from the electrical signal ending with a mechanical signal, which gives the ability to recognize intentions based on different sources of signal, and thus carrying different information.

The results of experiments in Chapter 4 show that the quality of recorded signals is satisfactory. The use of simple algorithms for extraction of features, operating on the temporal properties of signals, is sufficient to achieve high recognition values. These results can be the starting point for further research on the algorithms for recognizing biological patterns. The next stage of work should be the expansion of the controller by a part of the event controller reacting to contact with an obstacle from the environment.

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