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Pattern Recognition Methods as a Tool to Build an Automatic System for Learning Coordinated Human Motions

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ABSTRACT There is great social and economic significance in the teaching and learning of motion activities. This is notably true for teaching the activities involved in rehabilitation, sports, and professional work. The possibility of engaging an automatic teaching system is highly significant. Nevertheless, building an effective system is an ongoing challenge. This article describes a general outline of the teaching system, which includes MEMS (micro-electro-mechanical systems) sensors, haptic actuators, and algorithms for signal classification applied to the online selection of an appropriate teaching method. The main goal of this paper was to prove that the system is able to teach fast and synchronized movements effectively. To this end, system performance was presented and discussed. The statistical tests revealed an efficiency of the proposed approach, especially for tasks of teaching fast and periodic movements. This result was the primary outcome of the presented paper. The described scheme can be utilized for building two types of motor learning systems. The first relates to the ''personal'' learning systems for rehabilitation and sports. The second type can perform the classification of complex movements of human body parts and may be used in teaching the remote control of machines and vehicles (excavators, cranes, search and rescue drones, etc.).

INDEX TERMS Haptic feedback, machine learning, MEMS sensors, motor learning, pattern recognition.

I. INTRODUCTION

A. THE LEARNING OF HUMAN MOTION ACTIVITY

As a term of motion activity, we understand an execution of a movement of certain parts of the body in order to achieve a defined aim. Learning a motion activity is called motor learning [1] and is of immense social and economic importance. This pertains to the acquisition of the skills necessary for professional work, sports, and the rehabilitation of patients with musculoskeletal disorders [2]–[7], [9], [11]–[13]. In the learning for many kinds of motion activity, the emphasis is placed on the speed, synchronicity, and accuracy of movements. This is especially relevant for teaching sports and professional tasks [13], [14]. Thus, the prospect of engaging an automatic system for teaching fast and coordinated motions is of great value.

Let us study a simplified chart of a general scheme of motor learning – Fig. 1. The learner as a whole can be regarded as an object of the control system. The teacher's instructions may be considered as input signals of this object, whereas the output signals are related to the learner's motion activities. The teacher (or an automatic controller) assesses these output signals and determines the means for correction of the taught activity. This constitutes a general feedback loop related to the process of teaching.

The learner can also be considered a subsystem that controls his or her own motion activity. This is done by several feedback loops (Fig. 1), in which the information processing varies from very fast (based on a spinal core response), through slower, but to some degree modifiable (motor cortex), to slow but corresponding to voluntary and fully learnable movements [1]. We will denote the above kinds of control loops by the symbols: M_1, M_2, and M_3, respectively (these simple indications relate to the broadly used naming of the classes of muscular responses [1]).

To depict essential aspects of the matter we will consider an example. Let us imagine an instructor attempting to teach a child the simplest way of turning in skis, called the

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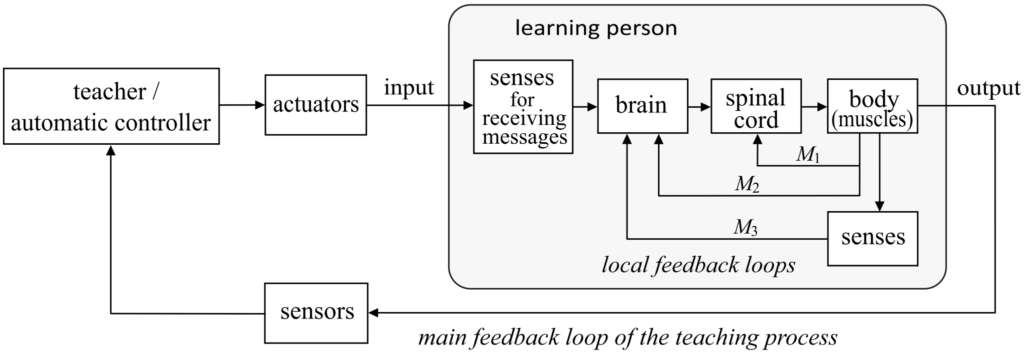

FIGURE 1. The general scheme of the motor learning. The human teacher or automatic controller assesses the performed movements and sends corrective signals to the learner (main feedback loop of the teaching process). The learner uses local feedbacks (M_1, M_2, M_3) to control the movements.

"snowplough" technique. The child is supposed to transfer its body weight to the appropriate leg. Unfortunately, the child has difficulties interpreting instructions in the form of calls: left leg!, outside leg! Often the child does not know which leg is the left or outside, or time is required to think things over. Usually, after this time the changing situation requires a different reaction of the pupil.

Fig. 2 illustrates a known communication method employed by ski instructors. This involves the instructor pointing, touching and even striking the tip of the relevant ski. On sensing the vibration the child is able to react instantly. The method is highly effective, with often only a dozen or so minutes being needed for the child to learn how to turn like a snowplough.

FIGURE 2. The snowplough technique being taught by the use of haptic stimuli.

After these preliminary considerations, let us return to the problem of building a teaching system. The system described in the paper is intended to teach periodical and mutually synchronized movements of specific parts of the body. These types of movements are performed in:

- activities involved professional tasks, such as driving, piloting, machinery operation (excavators, cranes), and remote controlling,

- the rehabilitation (in particular for patients with diseases of the musculoskeletal system of the limbs), and

- sports (e.g.: race walking, swimming, and snowboarding).

The above applications make it possible to articulate specific problems and system requirements, namely:

1. The problems of sensors and actuators. Considering the possible applications, the learning system should have the ability to work in outdoor environments using convenient systems of motion sensors and actuators [15], [16].

2. The communication problems. The communication between a teacher and a learner should be fast and unambiguous. Additionally, in order to focus a learner's attention on the other valid actions (sports, machine operating), the communication should not involve a high mental activity of the learner.

3. The teaching method problems. In order to modify the fast responses of the human motor system (Fig. 1), the messages should be sent to the learner in a suitable context (it refers to the appropriate moment in the period of movement and the corresponding arrangement of the learner body parts). Accordingly, the automatic system ought to recognize this context correctly.

In this study, we concentrated on the methodology of building an automatic system that is able to recognize aspects of the learning process to effectively teach synchronous movements. This problem has not yet been discussed in the literature. However, similar matters involving automatic motion teaching have been considered.

The article [5] (Zahradka, Behboodi, *et al.*) presented a system for neuromuscular rehabilitation of children. The signal analysis was limited to a gait phase detection. Feedback was provided using a functional electrical stimulation. Bark *et al.* [17] described a system to support rehabilitation after a stroke. With the use of haptic and visual feedback, the system was able to control the position of the patient's arm. The paper [6] (Bächlin, Förster, and Tröster) described an integrated environment that aided learning to swim.

TABLE 1. The main properties of selected teaching systems that apply diverse kinds of sensors, types of feedback, and ranges of motion analysis.

Article	Application field	Type of sensors	Feedback to learner	Analysis of motion signal
Taborri, Palermo et al. [18], 2019	sports, race walking	MEMS IMU	— (lack of feedback)	offline classification for judge or trainer
Alonso, Dieguez et al. [19], 2015	sports, volleyball	biometric sensors	—	online classification for trainer's analysis
Bächlin, Förster et al. [6], 2009	sports, swimming	MEMS IMU	acoustic, visual, haptic	trainer's online analysis, alarm generating
Stamm [11], 2018	sports, swimming	MEMS IMU	—	offline analysis for trainer
Zahradka, Behboodi et al. [5], 2019	neuromuscular rehabilitation of children	MEMS IMU	functional electrical stimulation	online detection of gait phase
Wójcik, Piekarczyk et al. [10], 2020	rehabilitation, sports, trajectory tracking	MEMS IMU	haptic	online classification of slow movements
Bark, Hyman et al. [17], 2015	rehabilitation after stroke	infrared camera	haptic, visual	preprocessing for position controlling
Żywicki, Zawadzki, Górski [20], 2017	work skills training (Industry 4.0)	MEMS IMU	haptic, visual	preprocessing for online production simulation

The system, using an array of motion sensors, calculated several parameters describing the movements. Nevertheless, their interpretation was performed by the trainer. The similar systems were proposed by Wang *et al.* [7] and Stamm [11]. The systems calculated the movement parameters, however, the feedback data was provided to the learner after performing the motion. The usage of real-time tactile instructions in a snowboard training system was presented in the work of Spelmezan *et al.* [8]. Similarly, another article [9] (Petermeijer, Abbink, Mulder, and de Winter) described various strategies for using haptic feedback in driver assistance systems. The authors of the last two papers suggested analyzing the current teaching context in order to change the teaching method accordingly (however, they did not propose specific methodologies). A system that used the results of the motion signal classification in the task of learning a trajectory, was described by Wójcik and Piekarczyk [10]. The authors concluded however, that, due to a problem with the system-learner communication, the proposed approach was not suitable for teaching fast movements. Examples of typical solutions used in motor learning systems are presented in Table 1.

B. MOVEMENT SENSORS AND ELEMENTS THAT TRANSFER INSTRUCTIONS TO THE LEARNER

Several types of sensors can be utilized in a subsystem of motion capture. For instance, we can use image sensors cooperating with image recognition software. These, however, require a prior prepared environment. This disadvantage does not apply to MEMS (micro-electro-mechanical systems) [16] sensors. A typical MEMS inertial sensor includes a triaxial accelerometer, gyroscope, and magnetometer. The sensor allows for determining the acceleration, as well as speed and position of body parts in a selected coordinate frame.

Communication from the teaching system to the learner may be realized by the use of senses of sight, hearing, touch, balance and proprioception. Considering the requirement of fast and ''intuitive'' (without cerebral involvement) conveying the messages, the sense of touch should be preferred. It may be supplemented by the use of auditory and visual senses. Vibrotactile and haptic sensations can be generated by many types of devices, for example, vibration motors, servomotors, and electrodynamic units [17], [21]. All the devices, regarding their role in the automatic system, should be named actuators or effectors [22].

C. LEARNING METHODS AND THE ROLE OF EXPERT KNOWLEDGE

The main objectives of the motor learning process should refer to the prospective consequences of teaching like improving athletic performance, person's health, or productivity of a machine being operated. Achieving these goals requires the use of the expert's knowledge and experience. Knowledge is also necessary to properly interpret motion signals, that are typically unstable and depend on the features of individual learners. Therefore, an online classification of the motion signals must be performed.

Many classification techniques can be utilized. For example, using the Bayesian classifier [23], [24], it is possible to estimate the probability of affiliation of the signals to prior defined classes. A probabilistic approach is also utilized in the Hidden Markov Model (HMM) [25]. Other widely applied methods use Artificial Neural Networks (ANNs) [3], [24], [26] or Support Vector Machine (SVM) [2], [18]. According to another methodology, the signals may be modeled and recognized by the use of an ontology [27]. A relatively simple idea is employed by a wide group of pattern recognition techniques named minimal distance methods. This involves the comparison, using a predefined metric function [28], of an unknown signal to several pattern signals, who are known to belong to previously defined classes [24], [29].

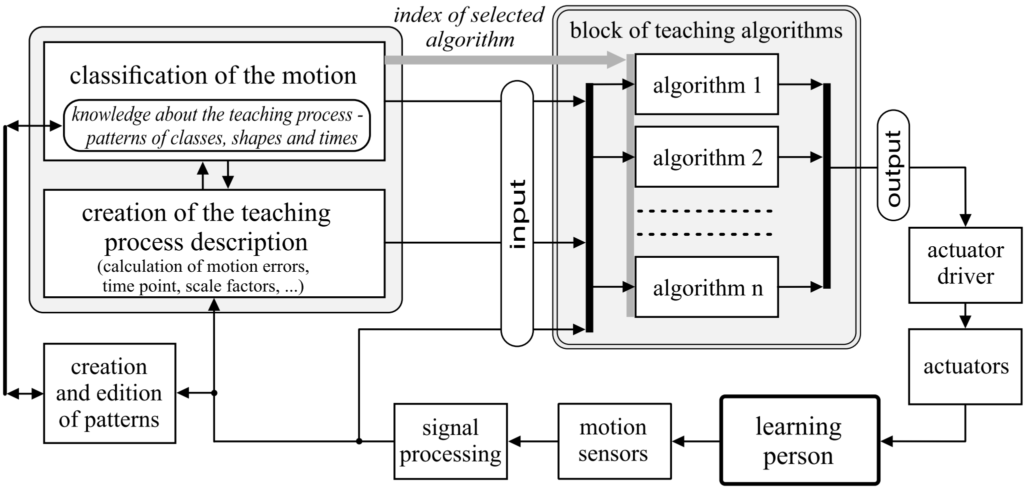

FIGURE 3. Diagram of the signal flow of the prototype teaching system. The thick gray arrow represents the output of the classification process that is used to select the teaching algorithm.

In order to conduct the classification task, a process of knowledge acquisition should be performed. We assume that this will be done with the participation of the teacher (expert). The expert can examine a set of exemplary motion signals (we will call them objects) and assign them to defined classes. As a result, a sequence of pairs: $(object, label\_of\_class)$ is created. Such a string, called a learning sequence, can be utilized in the process of ANN training, in tasks of creating pattern objects (in minimal distance methods), etc. [24], [28]. The expert contributes to building the learning sequence, however, he or she should also be able to modify the created classes in order to adapt them to changing conditions of the learning process. To do this, the representation of system data should be as simple as possible.

The creation of specialized learning algorithms is another important problem, which must be performed with the participation of experts [8], [10]. However, the experts might not necessarily perceive critical relationships between the aspects of the automatic teaching process, and generally may be unprepared for the challenges of creating new, unconventional algorithms of teaching. Therefore, the use of methods and tools supporting the construction of the automatic teaching system has an enormous significance.

D. THE AIM OF THIS STUDY

With a view of building a motor learning system, we have many essential questions to answer, e.g., What type of sensor and actuator subsystems should be used? Or, what signal processing methods have to be applied? However, as the above review showed, the key problems are the appropriate use of motion signal recognition methods and the proper utilization of expert knowledge. We believed that the expert aiming to build the effective motor learning system should utilize the extended description of the teaching process delivered by the classification procedures.

The main research question was formulated as follows: Can the classification methods be considered to be an effective tool to construct an automatic system for learning the synchronous motions?

A major goal of the article is to answer this question. To this end, the author of the paper designed and implemented a prototype motor learning system. During the initial test, certain variants of the methods were chosen. Then, using a selected motor task an interaction of the teaching system with the learning persons was tested. The tests were analyzed with the help of statistical methods. The result was positive; thus, we can answer in the affirmative to the main research question. This is an important contribution to the existing research.

With the aim of replicating the experiment, key elements of the built prototype system were described. This description may be regarded as an additional goal of the paper. However, due to the limited space, some issues were omitted. These mainly concerned the standard algorithms of signal processing.

The article is organized as follows. After the introduction, the main matters involving the classification task and teaching algorithms are presented (Section II). Section III presents results of testing the system work. Major outcomes of the article are summarized in Section IV.

II. THE AUTOMATIC TEACHING SYSTEM

Fig. 3 depicts a simplified signal flow diagram of the proposed automatic motor learning system. The general system structure from Fig. 1 was enriched by a block containing a number of teaching algorithms (surrounded by a double line) and by modules performing signal classification and producing a description of the teaching process. The system is a discrete control system [22], that operates in real time (the sampling rate is 100 Hz). In each cycle, the following major operations are performed: reading the signals of motion, signal preprocessing, classification, and the execution of the automatically chosen teaching algorithm. The normal system operation, i.e., the teaching of the human motion activity, is preceded by a stage of system learning in which the expert knowledge is used. The prototype of the system is implemented on a laptop computer ($I5$ processor, 2.4 GHz). The software was written in C++ language.

A. THE MOTION SENSORS

The teaching system should be able to work in an outdoor environment (see Subsection I-A). For this reason, the MEMS inertial sensors were applied (in the prototype system VN-100 sensors were used [30]). Each sensor, which is equipped with a microcontroller, sends motion signals to the main minicomputer of the system. The acceleration is sent as a vector $\mathbf{a}_s = [a_x \; a_y \; a_z]^T$ of real components. The rotation from the gyroscope is provided as a quaternion $\mathbf{q}_s = (v_x, v_y, v_z, k)$. It allows for the calculation of a rotation matrix, let it be denoted by $\mathbf{A}$, representing the sensor's orientation expressed in an Earth–fixed reference frame [31]:

$$\mathbf{A}=\begin{bmatrix} 2(k^2+v_x^2)-1 & 2(v_xv_y-kv_z) & 2(kv_y+v_xv_z) \\ 2(kv_z+v_xv_y) & 2(k^2+v_y^2)-1 & 2(v_yv_z-kv_x) \\ 2(v_xv_z-kv_y) & 2(kv_x+v_yv_z) & 2(k^2+v_z^2)-1 \end{bmatrix} \tag{1}$$

The Earth–fixed frame will be simplistically called an inertial frame. Note that the vector $\mathbf{a}_s$, obtained from the accelerometer, is expressed in its local frame. As a consequence, a calculated trajectory of the motion strongly depends on an accidental rotation of the body part to which the sensor is attached. Therefore, we should express the acceleration vector in the inertial frame. We can use the matrix $\mathbf{A}$ obtained from the gyroscope, that is:

$$\mathbf{a}_g = \mathbf{A}^{-1}\mathbf{a}_s \tag{2}$$

where $\mathbf{a}_g$ is the acceleration vector in the inertial frame.

After subtracting the constant value of the gravitational acceleration from the $\mathbf{a}_g$, we obtain an acceleration connected with the motion. Then, using an integration operation, we determine velocity and position vectors.

It should be emphasized here that the calculated values are strongly influenced by the noise of the accelerometer and gyroscope. In teaching system the motion signals are relatively slow, so the noise can be reduced using a low-pass filter (in the presented system, the IIR (Infinite Impulse Response) filter [31] was utilized). For the sake of limited space we must omit the description of other problems concerning the accuracy of the obtained motion signals [30], [31].

B. THE ACTUATORS

Considering the requirements for fast and intuitive information transfer, the vibrotactile effectors were implemented. Each actuator includes four miniature vibrotactile devices (units) containing a permanent magnet and moving coil. With the help of a small tappet, the vibrations are transmitted to the person's skin. The units are attached to the chosen parts of the body with an elastic hook–and–loop strip – see Fig. 4.a. The actuators are controlled by a specialized driver (based on the Atmega 128 microcontroller), that is connected to the main minicomputer. In typical cases, the actuator impulses should inform the learner about the needed direction of the corrective movement [17]. We assume that the corrective direction is an output of a particular algorithm of teaching. This output, corresponding to the ith actuator, can be expressed by a vector in the inertial reference frame:

$$\mathbf{g}_i = [g_{ix} \; g_{iy} \; g_{iz}]^T \tag{3}$$

The problem is how to select which unit in the actuator ought to be activated. First, vector $\mathbf{g}_i$ should be transformed to the actuator's frame. The actuators are rigidly mounted near the sensors; thus, using the sensor's rotation matrix we can calculate actuator vector $\mathbf{w}_i$, expressed in its local frame:

$$\mathbf{w}_i = \mathbf{A}\,\mathbf{g}_i \tag{4}$$

The actuator units are placed on a ring located on a certain plane p. It is perpendicular to some contractually defined axis of the given body part – see Fig. 4.b. Then, we can project vector $\mathbf{w}_i$ onto the plane p, receiving the vector:

$$\mathbf{o}_i = \mathbf{F}\,\mathbf{w}_i \tag{5}$$

where $\mathbf{o}_i$ is the actuator's vector on the plane p, and $\mathbf{F}$ is a 2×3 transformation matrix.

A direction of the vector $\mathbf{o}_i$ on the plane p determines the index of actuator's unit to be activated.

Let us note that the described way of installing the vibrotactile devices cannot stimulate motion in the normal direction of the plane p. This direction may be achieved by installing a supplementary actuator on a selected adjacent body part. For instance, suppose the additional actuator is installed on the arm, between the biceps and the elbow. Thus, the forearm (Fig. 4.b.) can be stimulated to move in parallel along its axis, that is, along the normal direction of the plane p.

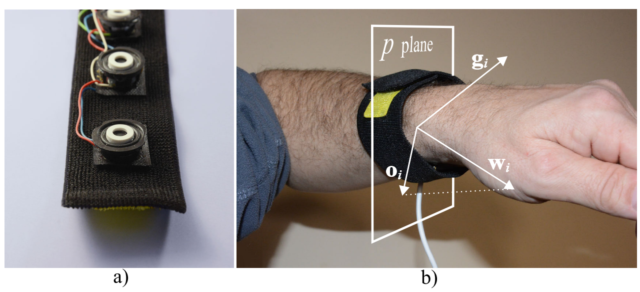

FIGURE 4. Actuator units (a) and an actuator band built using the elastic strip (b).

C. THE ANALYSIS OF MOTION SIGNALS

A wide range of methods for motion signal classification are depicted in Section I-C. The question on the choice of an adequate method is broadly discussed in the subject literature [2], [10], [18], [25], [32]. Regarding the character of the particular motion and the sensors used, the SVM, kNN, and HMM approaches are suggested. However, as we noted, the data utilized in the proposed system must be easy to interpret by the experts. This requirement prefers classification methods based on the minimal distance methodology. In the prototype system a version of "k-NNModel" method is used [29], [33]. It requires defining the generalized and non-redundant representation of pattern signals. But now, let us focus on the definition of the used motion signals.

We assume that the taught movements have a periodic character. Let us also assume that the expert, using the knowledge and experience, has suitably selected a number of motion signals for analysis. These signals (e.g., acceleration, speed, and position) refer to specified coordinates of individual sensors. Each chosen signal, denoted by S_i, is represented by a time sequence of samples:

$$S_i = (s_i^1, s_i^2, \ldots, s_i^n); \quad i \in \mathbf{K} \tag{6}$$

where i is a unique signal index, $\mathbf{K}$ is a set of indices of selected signals, s_i^k is the kth sample of the S_i signal (we assume that the upper index refers to the sample number in the sequence), and n is the number of samples in the signal.

The S_i sequence will be named a one-dimensional signal. We will call a set of one-dimensional signals a multi-dimensional signal:

$$\mathbf{S} = \{S_i : i \in \mathbf{K}\} \tag{7}$$

In an analogous way, we define the signal patterns that we use in the classification process. The one-dimensional pattern is defined as a certain generalized signal. Additionally, we assume that it refers to only one motion period:

$$P_i = (p_i^1, p_i^2, \ldots, p_i^w); \quad i \in \mathbf{K} \tag{8}$$

where P_i is the one-dimensional pattern, p_i^k is the kth sample of P_i, and w is the number of samples in the pattern (we assume that this is equal to the pattern's period).

The one-dimensional patterns are built on the basis of one-dimensional signals - see Subsection II-E. A set of one-dimensional patterns:

$$\mathbf{P} = \{P_i : i \in \mathbf{K}\} \tag{9}$$

will be named a multi-dimensional pattern.

Let us concentrate on the knowledge representation in the learning sequences (Subsection I-C). This should consist of pairs containing examples of objects and their class labels [24], [29]. We assume that the objects are represented by the multi-dimensional signals. Let us replace each multi-dimensional signal in the learning sequence with the multi-dimensional pattern that was created from this signal. As a result, we obtain a sequence:

$$\mathcal{P} = ((\mathbf{P}_1, \iota_1), (\mathbf{P}_2, \iota_2), \ldots, (\mathbf{P}_q, \iota_q)) \tag{10}$$

where $\mathbf{P}_u$ is the uth multi-dimensional pattern, and ι_u is a class label, $u = 1, 2, \ldots, q$.

Let us consider the $\mathbf{P}_u$ pattern from the sequence $\mathcal{P}$. As a rule, it is composed of several one-dimensional patterns. Let the symbol $P_{i,u}$ stand for a one-dimensional pattern that has been built from the ith signal ($i \in \mathbf{K}$), and that corresponds to the uth element of the sequence $\mathcal{P}$. Using this denotation, we can write:

$$\mathbf{P}_u = \{P_{i,u} : i \in \mathbf{K}\} \tag{11}$$

According to our general goal, we should perform the classification of a multi-dimensional signal that refers to the motion at the current moment. Let this current signal be denoted by $\widetilde{\mathbf{S}}$. It consists of many one-dimensional signals:

$$\widetilde{\mathbf{S}} = \{\widetilde{S}_i : i \in \mathbf{K}\} \tag{12}$$

where $\widetilde{S}_i = (s_i^1, s_i^2, \ldots, s_i^m)$ is a one-dimensional signal in which the m*th* sample refers to the last value from the sensor.

The classification of the $\widetilde{\mathbf{S}}$ will be performed by comparing it to defined patterns. At the beginning, values of a certain distance function between $\widetilde{\mathbf{S}}$ and all the multi-dimensional patterns belonging to the sequence $\mathcal{P}$ are calculated. From the sequence $\mathcal{P}$, we choose k elements that contain the closest patterns. Next, the set of chosen elements is split into subsets whose elements have identical class labels. Then, a subset having the greatest cardinality is selected. The class label of its elements indicates the final result of the classification.

An important problem in the described approach is the proper construction of generalized patterns (also called models) [33]. We will deal with this matter in Subsection II-E. Another problem is the appropriate definition of the distance (metric) function. Let it be denoted by $\hat{d}$. It is important that its output be easily interpreted by the experts and that its computation time not exceed a certain value, referring to the sampling interval of the control system. Arguments of the function $\hat{d}$ should be a multi-dimensional signal and a multi-dimensional pattern. They are finite sets consisting of one-dimensional signals and patterns. Thus, the $\hat{d}$ function can be constructed by the use of a prior defined distance function $\hat{h}$, between the one-dimensional signal and pattern. For example, we can apply a weighted average:

$$\hat{d}(\mathbf{P}_u, \widetilde{\mathbf{S}}) = \frac{1}{\sum_{i \in \mathbf{K}} w_i} \sum_{i \in \mathbf{K}} w_i \, \hat{h}(P_{i,u}, \widetilde{S}_i) \tag{13}$$

where $P_{i,u} \in \mathbf{P}_u$ is the one-dimensional pattern, $\widetilde{S}_i \in \widetilde{\mathbf{S}}$ is the one-dimensional signal, and w_i is the weight of the ith signal.

The function $\hat{h}(P_{i,u}, \widetilde{S}_i)$ is intended to measure a similarity between the one-dimensional pattern and the one-dimensional signal. It may be defined in many ways. However, its value should not be affected by linear scaling nor by a shift of the signals (the function should have a property of scale and translation invariance). This property ensures a consistency of the similarity estimation provided by the automatic system and the expert (teacher). Consequently, it allows experts to recognize key aspects of the system and supervise its work.

Let us focus on the way of defining the scaling and shift operation. The result is a transformed value of a sample of the one-dimensional pattern. For simplicity, the operation will be

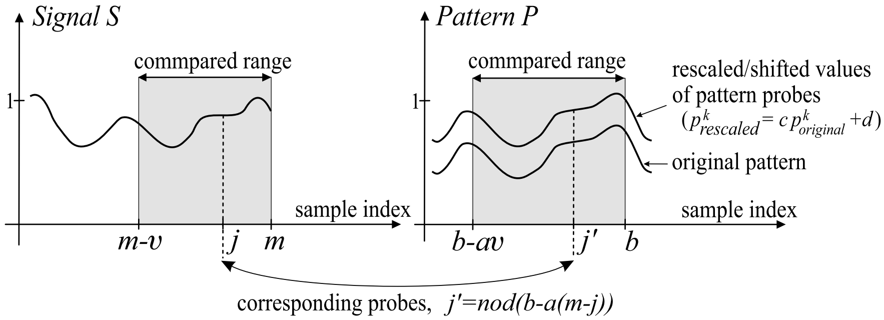

FIGURE 5. The comparison of the one-dimensional signal S and the pattern P using the function $\hat{g}$. In the presented example: $m = 300$, $\upsilon = 160$, $b = 240$, $a = 1.15$, $c = 1$, and $d = 0.2$. We assume that the depicted signals are dimensionless.

denoted by $\underset{a,b,c,d}{scal}(P, k)$ and defined as follows:

$$\underset{a,b,c,d}{scal}(P, k) = p^{\,nod(b-ak)}c + d \tag{14}$$

where $P = (p^1, p^2, \ldots, p^w)$ is the one-dimensional pattern, w is the number of elements of P, k is the input index of the sample (before transformation), a, b, c, and d are the values of the scaling/shift parameters that belong to the established sets $A, B, C, D \subset \mathbf{R}$, respectively, and nod is a function that performs a normalization of the sample index; the function converts its argument ($b-ak$ in our case) to the closest integer number and appropriately shifts it by the period value so that it belongs to $\langle 1, w\rangle$, in which the pattern is defined.

The parameters a and b refer to scaling and shift in the time domain (this relates to the transformation of the indices); whereas, c and d correspond to the scaling and shift of the sample value. The adopted way of defining the transformation allows for easy interpretation of the parameters a, b, c, d (Subsections II-F and II-G).

Using the scaling/shift operation, we define the function $\hat{g}$, which assesses the distance between the one-dimensional pattern P and signal S, after the linear transformation of the pattern samples. The function $\hat{g}$ applies the Euclidean metric:

$$\hat{g}(P, S, a, b, c, d) = \frac{1}{\upsilon}\left(\sum_{k=0}^{\upsilon-1}\left(\underset{a,b,c,d}{scal}(P, k) - s^{m-k}\right)^2\right)^{1/2} \tag{15}$$

where $P = (p^1, p^2, \ldots, p^w)$, $S = (s^1, s^2, \ldots, s^m)$ are one-dimensional pattern and signal, respectively, and υ is the number of matched samples; $\upsilon \leq w, m$.

The function $\hat{g}$ computes the differences between the signal samples, indexed by $m - k$ and the pattern samples having index $nod(b-ak)$ (14). Thus, in each difference, we take into account a certain jth signal sample and its equivalent in the pattern indexed by $nod(b-a(m-j))$. The way of calculating the function $\hat{g}$ is illustrated in Fig.5.

Finally, using $\hat{g}$, we can define the distance function $\hat{h}$ between the current one-dimensional signal $\widetilde{S}_i$ and the one-dimensional pattern $P_{i,u}$, after their matching:

$$\hat{h}(P_{i,u}, \widetilde{S}_i) = min_{\substack{a\in A,\, b\in B,\\ c\in C,\, d\in D}}\, \hat{g}(P_{i,u}, \widetilde{S}_i, a, b, c, d) \tag{16}$$

In order to calculate the $\hat{h}$ function we must establish the values of four parameters: a, b, c, and d that minimize $\hat{g}$. There are a number of methods to perform this minimization. Due to limited space, we can only outline two that have been successfully implemented in the prototype system.

The first refers to a simple exhaustive algorithm [28] that tests a certain number of values of the parameters a, b, c, d. Let us assume that the sets A, B, C, D (to which the parameters belong), are finite. The number of necessary computations of the $\hat{g}$ can be estimated by the product of the cardinality of these sets. In our case the number is on the order of 200 thousand. Nevertheless, by writing the program code in a time-optimized assembly language and by normalizing the signals, we can achieve a calculation time of the $\hat{h}$ function on the order of 0.8 ms (for a *I5* 2.4 GHz processor).

For many cases, this result is acceptable. However, when we compare many one-dimensional signals, we must use the faster method (e.g., for 10 signals the total computational time, which equals about 8 ms, is close to the sampling interval of the whole discrete system - 10 ms, see the beginning of this section). In this situation we use an effective, heuristic method [28] of calculating the minimum (16).

The analyzed signals are periodic. Moreover, we can find, in them, certain characteristic artifacts (objects) related to the signal extremes, the rapid decreases, etc. Let us consider an artifact in the current signal. Its calculated position, expressed by a signal index, is denoted by ζ_{signal}. Let us conjecture that this artifact corresponds to a certain artifact in the pattern, that has index $\zeta_{pattern}$. If some signal and pattern areas are to match each other, the expressions:

$\underset{a,b,c,d}{scal}(P, k) - s^{m-k}$, see (15), should have minimum values. Consequently, considering the method of scaling the signal and pattern indices (see the comments below (15)), the index of the artifact on the pattern should be: $\zeta_{pattern} = nod(b - a(m - \zeta_{signal}))$.

Let us assume that another artifact of the current signal also has its equivalent in the pattern. If the hypothesis regarding the mutual correspondence of two pairs of artifacts is true, we can correctly calculate the parameters a and b. In an analogous way, using the values of the artifacts, we can calculate the parameters c and d.

The genuineness of the hypothesis is easy to establish. It is sufficient to calculate the matching of the signals through the calculation of the function $\hat{g}$ for the values of the parameters a, b, c, and d associated with the given hypothesis. There exists a limited number of possible hypotheses that correspond to the combinations of artifacts (in our case, this number does not usually exceed 50). For every hypothesis, we calculate the value of the function $\hat{g}$, and select the hypothesis for which this value is the smallest. Using the described method, we achieve very short computational time of the $\hat{h}$ function, equal to approximately 0.015 ms.

However, there are situations in which the above method fails (e.g., the random appearance of an additional extremum). The fact that such situations arise can be revealed by comparing the value of the $\hat{h}$ for the best hypothesis with a certain established threshold. In these situations we can limit the number of compared signals and use the slower exhaustive algorithm.

D. CLASSIFICATION BASED ON A SEQUENCE OF RESULTS

The classification task is performed in each sampling interval of the discrete controller. Thus, we can derive an aggregate result of the process, based not only on the last cycle but also on the results gained in the earlier steps. The results obtained in successive cycles form a sequence:

$$\mathbf{\Lambda} = (\iota_1, \iota_2 \ldots, \iota_r) \tag{17}$$

where ι_i is the class label and r is the number of elements in the sequence.

For example, the $\mathbf{\Lambda}$ may contain elements: (1,2,0,0,2,2,2). The computation of an output, ''aggregate'' class label can be performed according to several strategies. We can point to a few general rules:

– the output should depend on the number of elements in the $\mathbf{\Lambda}$, that possess the specified class label,

– an impact of the individual element should be reduced over time,

– a validity of the element ought to be related to the value of the distance function calculated in the classification process.

One of the approaches that meets the above requirements is based on a certain semi–histogram function:

$$his(\kappa) = \sum_{i=1}^{r} q(\kappa, \iota_i) w_i; \quad q(\kappa, \iota_i) = \begin{cases} 1, & \text{if } \kappa = \iota_i \\ 0, & \text{otherwise} \end{cases} \tag{18}$$

where κ is an index of the class, ι_i is the ith element of $\mathbf{\Lambda}$, w_i is the weight of the ith individual result: $w_i = \frac{i}{r(\delta + \hat{d}_i^{out})}$, δ is a chosen small constant, and $\hat{d}_i^{out}$ is the value of the distance function $\hat{d}$, referring to the nearest pattern in the $\mathcal{P}$ sequence (10), and gained from the classification process in the ith cycle.

The choice of the output class is made according to the maximum semi–histogram value.

E. BUILDING OF PATTERNS

At the beginning of the pattern creation process, the learner performs a series of movements, which are recorded in the learning sequences. The teacher/expert establishes the class label of the conducted motions, but also manages the whole process in order to generate representative examples of classes.

Let us focus on a chosen one-dimensional signal from the signals recorded in the learning sequence. In the signal, we find fragments corresponding to periods of movement [35]. Then, using an arithmetic mean, an average signal shape is calculated. Next, a certain number of fragments that have the most distance (in terms of $\hat{h}$ function) to the average signal is rejected. The second averaging of the remaining fragments leads to the pattern creation. The above process refers to a simple clustering method [36]. The quality, denoted by Q_p, can be assessed by the mean distance between all the remaining fragments (again, the $\hat{h}$ function is used). We can apply the pattern creation process to several one-dimensional signals, as a result of which, a multi-dimensional pattern is created. It is important to notice that the expert can upgrade the system by constructing new patterns. Accordingly, the system can be adjusted to the time–varying process of teaching.

F. PATTERNS OF CLASS, SHAPE, AND TIME

We can distinguish several kinds of teaching algorithms that refer to controllers of position, speed, or motion accuracy [17]. Let us focus on a simple algorithm of the position control. An input of the algorithms is a motion error, which can be calculated as a difference between the motion signal at the current moment and the sample value corresponding to that moment, in a specific, one-dimensional pattern. Such kinds of patterns will be called shape patterns. Thus, we need to know an index of the sample in this pattern that refers to the present moment. This index will be designated by the term ''*time point*''. It may be calculated through the matching of the current signal to another specific one-dimensional pattern called a time pattern. The above process can be performed by the minimization of the $\hat{g}$ distance function. As a result, we obtain the set of fit parameters (a, b, c, d (16)). The parameter b can be interpreted as the index in the time pattern that refers to the present moment (see (15) and Fig.5, sample indices for $k = 0$). Accordingly, the b directly refers to the *time point*.

To sum up, we can define three kinds of patterns:

- **class patterns**: the earlier introduced patterns defining classes of motion signals,

- **shape patterns**: the patterns defining the correct signal, and

- **time patterns**: the patterns designated to determine the *time point*.

In an analogous way to the case of the class patterns, we can define multi-dimensional patterns of shape and time.

On the grounds of the multi-dimensional time pattern (i.e., a set of one-dimensional time patterns) we can establish a more reliable *time point* value, resistant to signal noise and accidental moving of the learner's body parts. First, we calculate *time point* values for all one-dimensional time patterns (by minimizing the $\hat{g}$, see above). Let the calculated individual results create a sequence: $(\tau_1, \tau_2, \ldots, \tau_\rho)$ where ρ is the number of time patterns. To obtain the value of the more reliable, aggregate *time point*, we can rank these results according to a certain reliability measure, or take a vote, etc.

Particularly, we can easily implement a method, in which a ranking criterion utilizes distance function $\hat{h}$ between the individual one-dimensional time pattern and the current signal. Let us consider a sequence of pairs containing the calculated values of *time points* and related values of distance function:

$$\Theta = ((\tau_1, \hat{h}_1), (\tau_2, \hat{h}_2), \ldots, (\tau_\rho, \hat{h}_\rho)) \tag{19}$$

The output, generalized value of *time point* is computed as a weighted average of certain number of the best results (the weight of the ith result is calculated as follows: $w_i = \frac{1}{\hat{h}_i + e}$ where e is a small constant).

G. CALCULATION OF THE ERROR SIGNAL

The value of the error can be calculated as the difference between the value of the current signal and the value of the corresponding sample in the shape pattern. This solution, however, is sensitive to disturbances and noise. To reduce their impact, we can calculate a mean value from a given number of samples. A similar effect is achieved by matching the final part of the signal and a relevant part of the pattern, using the minimization of the $\hat{g}$ function (analogously to the *time point* calculation). One of the results obtained is a value of parameter d, which can be treated as the error signal (15). An advantage of this method is the possibility to predict, to some extent, the error value. Using this method, we can compute the motion errors related to all defined one-dimensional shape patterns, obtaining an error vector:

$$\mathbf{e} = [e_1\ e_2\ \ldots\ e_\eta]^T \tag{20}$$

where η is the number of shape patterns.

The vector $\mathbf{e}$ is applied in particular algorithms of teaching (Subsection II-I).

H. A GENERAL DESCRIPTION OF THE TEACHING PROCESS

The match parameters ($a, b, c,$ and d), which have been computed in the classification process, can be utilized in the *time point* (parameter b), and errors (parameter d) calculation. Similarly, the parameter a, which determines the scaling in the time domain, can be used to control the proper pace of movements. Analogously, the c parameter can evaluate the range of the performed motions. In general, the parameters and other variables, e.g., speeds, positions, and values of the $\hat{h}$ function, calculated at successive stages of the analysis, provide concise information regarding the signals and the relationships between them. This information can be utilized to improve the classification process; however, it is also applied in particular algorithms of teaching. Therefore, we can regard this information as an extended input of the algorithms. In summary, the input of the teaching algorithms can be understood in the broad sense, referring not only to the error vector but also to any data structure produced by processes executed in the system (this property is exposed in Fig.3 by the generalized module ''creation of the teaching process description''). In this light, the whole system can be considered as a set of specialized units and tools utilized to construct the teaching algorithms.

I. ALGORITHMS OF MOTION TEACHING REFERRING TO DEFINED CLASSES

Before proposing the teaching algorithms, we should underline the limitations concerning the human responses to the actuator signals. The problems involve the proper reaction to signals generated by many effectors in a relatively short time. Particularly, during one period of motion (about 2–4 s), the learner is capable of correctly interpreting the messages from only one actuator. The messages from other effectors have a disturbing effect. Similarly, too frequent messages coming from one actuator are also unclear.

1) $\mathcal{A}_1$ ALGORITHM – SERVO–MECHANISM

We deal with an algorithm that controls the position of the selected body part. As an input of the algorithm, we consider the vector of error $\mathbf{e} = [e_1\ e_2\ \ldots\ e_\eta]^T$ (20), which was computed on the base of the current multi-dimensional signal and the multi-dimensional shape pattern (Subsection II-G). The output of the algorithm is related to the vector $\mathbf{g}_i = [g_{ix}\ g_{iy}\ g_{iz}]^T$ (3), which determines the way of activating the ith actuator. A relationship between the vectors $\mathbf{e}$ and $\mathbf{g}_i$ defines a character of the motion regulator; in the proposed algorithm this is defined by a linear transformation:

$$\mathbf{g}_i = \mathbf{Y}_i\,\mathbf{e} \tag{21}$$

where $\mathbf{Y}_i$ is a $3 \times \eta$ transformation matrix (η - number of shape patterns, (20)).

The matrix $\mathbf{Y}_i$ determines which one of the components of the $\mathbf{e}$ vector influences which component of the ith actuator. Typically, a component of the error signal obtained from a certain sensor affects the relevant component of a nearby actuator (see Subsection II-B). In this case, the transformation (21) becomes a scaling function, and, accordingly, the teaching algorithm has the character of a simple proportional servo–mechanism.

Having the $\mathbf{g}_i$ vector, we calculate the $\mathbf{w}_i$ (4) and $\mathbf{o}_i$ (5) vectors, and select the vibrotactile unit in the ith actuator to activate. To indicate the corrective direction of motion, a sequence of short impulses is generated (typically with the frequency of 20 Hz). Additionally, as previously noted, we must consider the human ability to interpret the actuator impulses. The described algorithm, in some cases, generates messages that force a quick change in the direction of corrective movements. Such rapid changes cannot be made by man. The problem is solved by setting a minimal interval (lag time) between successive messages (in the prototype system this interval equals 1.6 s).

2) $\mathcal{A}_2$ ALGORITHM – SYNCHRONIZATION OF PERIODIC MOVEMENTS

Information provided to the subject during the motion teaching can be regarded to be a temporal sequence of instructions describing the moves needed. Instructions delivered by haptic stimuli are often imprecise; this is especially true for poorly innervated body parts. However, a transfer of information regarding an exact moment at which the move should occur (e.g., a simple indication of this moment), can be fast and reliable. Let us use this property to design a regulator that has input and output corresponding to time moments.

Let us denote by $\mathtt{m}$, a certain move (e.g., an elbow flexion), which should be properly synchronized with the movements performed by other body parts. The appearance of the $\mathtt{m}$ can be detected by analyzing the specific features in the signal (e.g., a rapid increase in the signal value). Suppose, that the $\mathtt{m}$ is occurring in the present moment. Then, the current value of the *time point* (Subsection II-F), calculated according to the defined time pattern can be regarded as the position of the $\mathtt{m}$ in the current movement period. This position, let it be denoted by t_{cur}, is expressed by the index in the time pattern. Additionally, let t_{set} be a given by the expert moment when the move $\mathtt{m}$ should occur. A difference: $e_{ph} = t_{cur} - t_{set}$ we will define as a phase error.

This value can also be calculated by another method that does not require the determination of t_{cur} nor t_{set}. Let us assume that a certain one-dimensional signal in which the movement $\mathtt{m}$ is observable, is utilized to compute an ''individual'' *time point*. Simultaneously, we have, at our disposal, the reliable, general *time point* value (calculated on the base of other signals, Subsection II-F). The difference between these two *time points* can be considered as the phase error.

Let us define an additional valid point in time. This is a moment, denoted by t_{com}, when the corrective command should be sent to the learner (the t_{com} is also expressed by the index in the time pattern). A simplified example of the location of the defined moments is presented in Fig. 6.

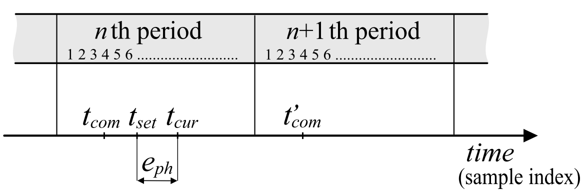

FIGURE 6. **Exemplary location of the moments defined in the phase regulator; t_{cur} is the moment of the performed movement, t_{set} is given by the expert moment in which the movement should occur, t_{com} is the calculated moment of sending the command, and t'_{com} is the moment of sending the command that refers to the next period of the motion.**

The moment of command sending t_{com} may either precede or follow the t_{cur}. However, there is a certain difficulty: the t_{com} may correspond to the ''past'' in relation to the t_{cur}. This problem can be solved by taking advantage of the periodic character of the motion. Sending the command (the moment t_{com}) can be performed in the next period of the move – see Fig. 6.

Let us relate the moment t_{com} to the phase error e_{ph} by a function:

$$t_{com} = f_{reg}(e_{ph}) \tag{22}$$

If the f_{reg} has a linear character, we obtain a proportional phase regulator. In many practical cases, we can use a simple strategy, in which the function f_{reg} has only two output values corresponding to two clear commands.

Similarly to the $\mathcal{A}_1$ algorithm, due to human limitations, the minimal time interval between sending successive commands is defined (it is equal 1.9 s).

III. TESTING OF THE SYSTEM

A. MAIN GOAL OF THE EXPERIMENT

The main aim of the conducted test was to evaluate the general idea of using an array of tools and methods to design a system for teaching synchronous motion. With this aim, two distinct approaches corresponding to two teaching methods were tested and compared. The first one, denoted by $\mathcal{M}_{class}$, was designed according to the idea described, and this approach used the results of the signal classification to online select the teaching algorithm. For simplicity, only two teaching algorithms (corresponding to $\mathcal{A}_1$ and $\mathcal{A}_2$) were automatically selected. The second method, utilized a single value of the e_{ph} phase error to select the proper algorithm ($\mathcal{A}_1$ and $\mathcal{A}_2$ were also utilized). The method will be denoted by $\mathcal{M}_{sgv}$ (single decision variable).

The details of the test are described in the following points, and now we depict its basic outline. A specific exercise was selected for testing both methods. It involved teaching a synchronization between the movements of the person's left hand and the right foot (the person was sitting on a chair). The hand moved according to a semi–ellipsoidal trajectory with a straight line at the bottom. The trajectory, projected on a vertical plane passing through the learner's shoulder blades, is illustrated in Fig. 7.a. At a precisely defined point in the motion period, the foot should perform a fast, short move up and down. The described exercise is an example of a broad class of synchronous movements taking place during the control of specific machines and mobile robots.

B. PARTICIPANTS

All participants of the experiment were volunteers; they were students of Automatics and Robotics from the Cracow University of Technology. The participants, 2 women, 14 men, aged 22—25 years, were healthy and were not aware of the test goals. There were three excluding criteria: left-handedness, declared neurological disorders, and abnormal motor control of the extremities. Prior to the experiment,

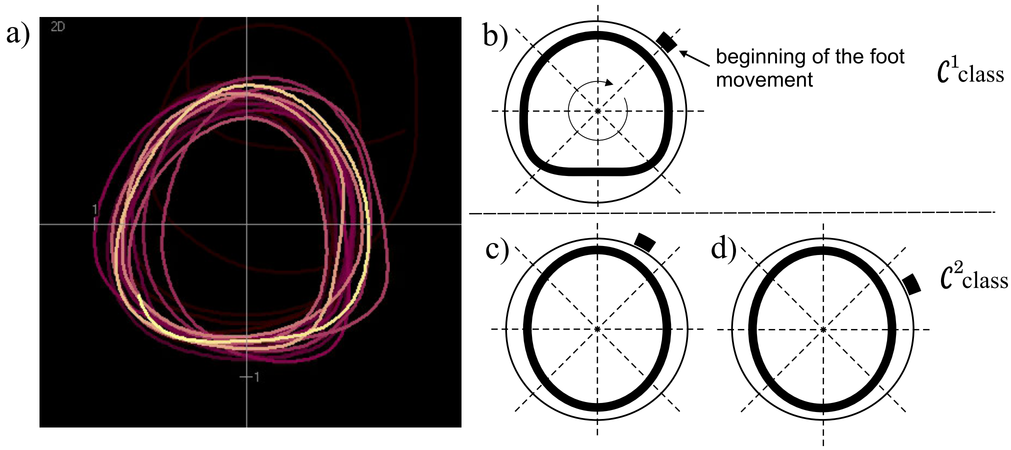

FIGURE 7. **The movement of the left wrist; (a) the movement that was utilized to build the pattern of the class $\mathcal{C}^1$, a disappearing trajectory color reflects the passage of time, the axes' units are 0.1 m; (b) the symbolic map of the pattern of the $\mathcal{C}^1$ class; (c),(d) symbolic maps of the patterns of the $\mathcal{C}^2$ class.**

the participants provided their informed consent. The subjects were divided at random into two equinumerous groups (each group contained one woman).

C. TESTED METHODS OF TEACHING

1) TEACHING METHOD $\mathcal{M}_{class}$

The $\mathcal{M}_{class}$ method of teaching used the results of the classification process. The expert, after a short preliminary test, created two classes of signals and ascribed them to the two teaching algorithms.

2) $\mathcal{C}^1$ CLASS OF MOVEMENTS

The first class, denoted by $\mathcal{C}^1$, corresponded to motions that refer to minor, irrelevant errors of hand movement (in respect to the defined trajectory), and correctable phase errors of the foot motion.

The $\mathcal{C}^1$ class was constructed on the basis of a single multi-dimensional pattern. Fig. 7.a illustrates the movement associated with this pattern (the depiction was created by the graphical interface of the system). Additionally, a symbolic chart of this pattern is shown in Fig. 7.b.

We assumed that when the current movement belonged to the class C^1, the more substantial error was the phase error e_{ph}, which can be successfully corrected by applying the $\mathcal{A}_2$ algorithm. The phase error e_{ph} was calculated using the vertical acceleration signal of the learner's right foot (the signal was provided by the VN-100 MEMS sensor). The calculation was based on the signal matching method, which used the value of the "individual" *time point*, Subsection II-I.

The phase regulator was defined by a simple function that had only two output values determining the moments of the actuator activation (see (22)). The specific values of parameters defining this function are given in Fig. 8. The generated impulses were directed to the actuator that was fixed to the foot of the learner.

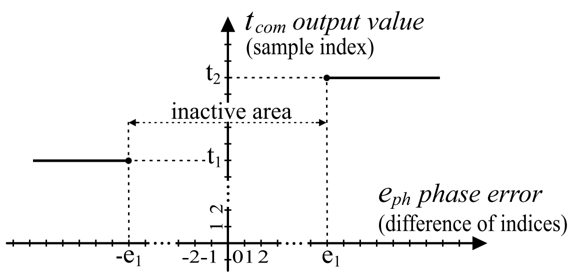

FIGURE 8. **The parameters defining the phase regulator, the range $(-e_1, e_1)$ refers to the inactive area (in which the actuators were not activated); $e_1 = 11$, $t_1 = 78$, $t_2 = 114$.**

3) $\mathcal{C}^2$ CLASS OF MOVEMENTS

The second class, which is denoted by $\mathcal{C}^2$, corresponded to the typical errors observed in the learners' movements. In the majority of cases, the improper movement was characterized by a lack of the straight section in the hand trajectory and a decrease in the hand's speed just before the moment of the foot movement. The hand errors coexisted with relatively great phase errors. The expert decided that the hand trajectory errors should first be corrected using the $\mathcal{A}_1$ algorithm ($\mathcal{A}_2$ was inactive).

The $\mathcal{C}^2$ class was constituted according to two patterns that are examples of the errors described. The patterns refer to premature and delayed foot movements in relation to the movements defined by the class $\mathcal{C}^1$ (the delays were of ± 0.3 s). All the defined patterns are presented in a symbolic manner in Fig. 7. The executed $\mathcal{A}_1$ algorithm utilized the VN-100 type sensor (it was attached to the learner's wrist) and the actuator indicating the desired direction of the motion (also mounted on the wrist, see Fig. 4).

At the end of this description, let us highlight the significant aspects of the system building. The expert who determined the classes and teaching algorithms was supported by the analysis of the motion parameters carried out during the preliminary test. In our case, these were: the peak acceleration of the hand, its speed (the expert can analyze graphs of patterns), the calculated period of the created patterns, and the values of the distance function $\hat{h}$ between the tested signals and patterns. The expert took into account the quality of the created patterns expressed by the parameter Q_p (see Subsection II-E). Further, the expert decided that the motion could be effectively taught by particular algorithms. He adjusted them and set their parameters (the parameters of the phase regulator were selected based on the phase errors observed in the tested movements). In summary, the system provided information and tools that could be used for its development.

4) TEACHING METHOD $\mathcal{M}_{sgv}$

The second method, $\mathcal{M}_{sgv}$, also used the algorithms $\mathcal{A}_1$ (trajectory control) and $\mathcal{A}_2$ (phase control). However, the method did not perform the signal classification. The choice between $\mathcal{A}_1$ and $\mathcal{A}_2$ was made according to the value of the phase error (this error was computed by the method of signal matching; it did not use the classification process). If the absolute value of the e_{ph} error exceeded an experimentally chosen threshold (equal to 17 sample intervals), the algorithm $\mathcal{A}_2$ was executed. Thus, when the trajectory and phase errors occurred simultaneously, only the phase errors were corrected.

D. TEST PROCEDURE

In order to only examine the transfer of learned skills, and not skill retention [1], [37], the test duration was reduced to a few minutes. The test procedure consisted of the following phases:

- *Phase 1.* Using the automatic system for motor learning. The first group of subjects was taught by the use of the $\mathcal{M}_{class}$ method; the second group was taught using the $\mathcal{M}_{sgv}$ method. This phase lasted 3 min.
- *Phase 2.* 1–minute break.
- *Phase 3.* Testing of the learned skills.
  The learned movements were repeated; however, the actuators were switched off. The duration of this stage was 2 min.

E. OUTCOME MEASURES

The motor learning efficiency should be evaluated by measuring the results of the performed motor task. That final assessment is typically approximated by a number of parameters, for instance: movement time, velocity, position matching errors, torques, and forces [1], [37]. Moreover, having at our disposal digital signals of motion (in the described system all signals were registered during the course of the test) we can easily compute the learning parameters defined in time and frequency domains (*RMSE* errors from selected signals, amplitudes corresponding to specified frequency bands, etc.) [37], [38].

In order to evaluate the $\mathcal{M}_{class}$ and $\mathcal{M}_{sgv}$ teaching methods, the accuracy of the motion synchronization may be assessed. Let us introduce a parameter, called $\mathcal{F}_{ph}$, that is based on the *RMSE* of a sequence of phase errors: e^i_{ph}; $i \in U$, relating to the foot motion. This sequence is defined using a string of indices U, that refer to the consecutive sampling intervals of the discrete system. We assume that the U corresponds to the signal range: $\langle 0.3\,n,\ 0.8\,n\rangle$, where n is the total length of the signal. We also assume that the sequence of errors is calculated during the third (test) phase of the experiment. The $\mathcal{F}_{ph}$ parameter is computed as follows:

$$\mathcal{F}_{ph} = RMSE_{i\in U}(e^i_{ph}) = \left(1/n \sum_{i\in U} (e^i_{ph})^2\right)^{1/2} \tag{23}$$

However, we should also evaluate the accuracy of the hand motion. We can calculate the hand's position errors in relation to the relevant shape patterns, obtaining the sequence of errors: e^i_{tr}; $i \in U$. Then, analogously to (23), the parameter assessing the accuracy of the hand trajectory can be defined as

$$\mathcal{F}_{tr} = RMSE_{i\in U}(e^i_{tr}) \tag{24}$$

Using a weighted average of the parameters $\mathcal{F}_{ph}$ and $\mathcal{F}_{tr}$ we can define the aggregate error of the movement. Nevertheless, in order to more precisely estimate the total errors we should calculate the *RMSE* value of a function that assesses a combined error in each individual sample of the signal. Accordingly, we define the parameter:

$$\mathcal{F} = RMSE_{i\in U}(\mu(\mathbf{e}^i)) \tag{25}$$

where $\mathbf{e}^i = [e^i_1 \ \ldots \ e^i_v]$ is the vector of error components corresponding to the ith moment, v is the number of vector components, and μ is the norm function that outputs the total error at the distinct moment.

We can define the function μ using *p-norm*: $\mu(\mathbf{e}^i) = \left(\sum_{k=1}^{v} |e^i_k|^p\right)^{1/p}$. By the choice of a suitable value of the constant p, we can establish the impact of the greatest vector's component on the output value of the norm.

In the performed tests, p was equal to 1 (this refers to the Manhattan norm, which emphasizes the influence of relatively small components). The argument of the norm μ was a vector having two components, referring to the phase (e^i_{ph}) and hand trajectory (e^i_{tr}) errors, i.e.,

$$\mathbf{e}^i = [\alpha e^i_{ph} \ \ \beta e^i_{tr}] \tag{26}$$

The scale factors α and β determined the influence of the e^i_{ph} and e^i_{tr} errors on the μ value, and consequently on the final $\mathcal{F}$ value. In order to illustrate this impact, the $\mathcal{F}$ was computed for two pairs of values: $\alpha = 1$, $\beta = 4$ and $\alpha = 1$, $\beta = 10$. These two obtained efficient parameters are denoted by $\mathcal{F}_4$ and $\mathcal{F}_{10}$, respectively.

F. DATA ANALYSIS

Table 2 presents the calculated values of the $\mathcal{F}_{ph}$, $\mathcal{F}_4$, $\mathcal{F}_{10}$, and $\mathcal{F}_{tr}$ learning efficiency parameters for two groups of subjects corresponding to two learning methods (the $\mathcal{F}_{ph}$ was expressed in seconds, reflecting the sampling rate = 100 Hz; the unit of $\mathcal{F}_{tr}$ is meter, re-scaled in the table to millimeters; $\mathcal{F}_4$ and $\mathcal{F}_{10}$ are considered dimensionless).

TABLE 2. The $\mathcal{F}_{ph}$, $\mathcal{F}_4$, $\mathcal{F}_{10}$, and $\mathcal{F}_{tr}$ parameters of teaching efficiency related to the teaching methods $\mathcal{M}_{class}$ and $\mathcal{M}_{sgv}$.

Parameter	Method	Mean	Dev.	Participant label (in the group)								
				1	2	3	4	5	6	7	8	9
$\mathcal{F}_{ph}$ (s)	$\mathcal{M}_{class}$	0.31	0.074	0.22	0.29	0.31	0.29	0.32	0.46	0.23	0.37	0.28
	$\mathcal{M}_{sgv}$	0.43	0.19	0.62	0.16	0.72	0.49	0.33	0.18	0.37	0.47	0.56
$\mathcal{F}_4$ (10^{-3})	$\mathcal{M}_{class}$	46	6.2	42	53	44	41	45	57	45	50	37
	$\mathcal{M}_{sgv}$	61	18	77	60	92	62	52	28	48	63	69
$\mathcal{F}_{10}$ (10^{-3})	$\mathcal{M}_{class}$	73	12	76	96	68	62	69	76	85	72	55
	$\mathcal{M}_{sgv}$	92	27	100	136	125	83	85	48	69	89	90
$\mathcal{F}_{tr}$ $(10^{-3}\,\mathrm{m})$	$\mathcal{M}_{class}$	48	15	59	74	41	39	43	34	69	41	34
	$\mathcal{M}_{sgv}$	54	28	46	127	57	39	60	35	38	45	40

The comparison of the groups of data will be conducted by the use of the Student's t-test (a two-sample location test). However, taking into account the fact that the data were the results of the discrete and nonlinear processes, we should check the conditions for using the t–test. Two groups of data should have a normal distribution and homogeneous variances. These requirements were verified by the Shapiro-Wilk and Levene's tests, respectively. Table 3 depicts computed values of statistics related to both tests, and their critical values that correspond to a confidence level 0.95 (in the case of Levene's test the value of statistic should be less than the critical value, in Shapiro-Wilk test - greater). According to the test results we can apply Student's t-test only for the parameters $\mathcal{F}_4$ and $\mathcal{F}_{10}$.

G. DISCUSSION

The calculated values of Student's t distribution, and the corresponding p-values are presented in Table 3. On the basis of Student's t-test, we rejected, with an error probability of 0.02 (p-value), the hypothesis claiming that the $\mathcal{F}_4$ efficiency of both teaching methods is equal, favoring a hypothesis stating that the efficiency of method $\mathcal{M}_{class}$ is greater. We can formulate the analogous statement for the efficiency parameter $\mathcal{F}_{10}$ (p-value $= 0.048$). The above results clearly indicate the effectiveness of the proposed tools for building the teaching system. This can be considered to be the main outcome of the performed experiment. Let us now discuss a few additional issues. We will organize them in the following points.

1) MOTION ERRORS, INADEQUATE MESSAGES, SYSTEM STABILITY, AND PROPER SELECTION OF THE TEACHING ALGORITHM

In both teaching methods, relatively great motion errors were observed. Particularly in the case of the phase error (parameter $\mathcal{F}_{ph}$) the mean error was equal to 0.31 s for the $\mathcal{M}_{class}$ method and 0.43 s for $\mathcal{M}_{sgv}$. Similarly, the mean errors of the hand trajectory (parameter $\mathcal{F}_{tr}$) were: 48 mm and 54 mm. The algorithms $\mathcal{A}_1$ and $\mathcal{A}_2$ utilized methods based on the signals matching (using the function $\hat{g}$ (15)). As a result, both the algorithms were sensitive not only to improper signal timing but also to irregular signal amplitudes. As a consequence, the output signals of the algorithms were often generated too early or too late. The incorrect, confusing instructions sent to the learner were equivalent to disturbance signals. Using the terms of the control theory, the incorrect output of the controller (see Fig. 3) can cause an instability of the whole learning system. This is particularly true for the objects being controlled, i.e., the humans, which have a delay time and generally a non-stationary character [22].

We can minimize these effects by using properly selected teaching algorithms. It seems, that the choice can be made according to the value of the phase error ($\mathcal{M}_{sgv}$ method). This simple decision-making does not take into account the many properties and relationships between the movements performed. For example, as the observations of the subjects showed, the delayed foot movement not only caused the phase error but also changed the trajectory of the hand. The expert can detect this situation, create a suitable motion pattern, and associate it to the proper algorithm.

The created patterns constituted an advanced description of the motion signals, which included non-obvious relationships and motion properties that were difficult to express and define in an analytical manner. The usage of this knowledge resulted in a less chaotic character of the learners' movements in response to the teaching system messages. This effect was visible in a lower value of standard deviation of all the parameters for the method $\mathcal{M}_{class}$ in comparison to the $\mathcal{M}_{sgv}$ (see Table 2, $\mathcal{M}_{class}$: 7.4, 6.2, 12, 15, $\mathcal{M}_{sgv}$: 19, 18, 27, 28).

2) DIFFICULT READING OF HAPTIC MESSAGES, PERIODIC NATURE OF MOVEMENTS, INSTANT CORRECTION OF MOTION, AND MOVEMENT SYNCHRONIZATION

Teaching fast motions required rapid messages from the vibrotactile effectors. However, sending messages too frequently had a disturbing effect (Subsection II-I). This was the main reason, in addition to the problems of generating inadequate messages, for observed incorrect student responses to the teaching system. The erroneous reactions were of a non-stationary nature, which caused the t-test for all efficiency parameters could not be used (see the values of the Levene's and Shapiro-Wilk statistics, Table 3).

The way to overcome this serious problem was to use lag times between successive messages. Their necessary values were relatively high (they were chosen by the expert who observed the learners; the lag times were 1.6 and 1.9 s, for $\mathcal{A}_1$ and $\mathcal{A}_2$ algorithms respectively, Subsection II-I). A high value of lag times can result in key messages not being sent. The question arises here, whether the length of the lag time should be automatically selected depending on the type of

TABLE 3. The calculated values of the statistics related to Levene's, Shapiro-Wilk, and Student's t-tests; the values correspond to particular parameters and methods.

Parameter	Method	Shapiro-Wilk (crit. value=0.829)	Levene (crit. value=4.5)	Student's t distribution	Student's t p–value
$\mathcal{F}_{ph}$	$\mathcal{M}_{class}$	0.91	7.9	— (not applicable)	—
	$\mathcal{M}_{sgv}$	0.95			
$\mathcal{F}_{4}$	$\mathcal{M}_{class}$	0.96	3.2	2.23	0.020
	$\mathcal{M}_{sgv}$	0.99			
$\mathcal{F}_{10}$	$\mathcal{M}_{class}$	0.97	2.6	1.77	0.048
	$\mathcal{M}_{sgv}$	0.97			
$\mathcal{F}_{tr}$	$\mathcal{M}_{class}$	0.83	0.6	—	—
	$\mathcal{M}_{sgv}$	0.66			

the movement? In this context, we can note that with the approach described in the article, it is possible to classify these movements (using additional classes) and adjust the lag time accordingly.

In the tested teaching system, the problem of adverse mutual influence of haptic messages was also minimized by simplifying the form of these messages ($\mathcal{A}_2$ algorithm). Additionally, the periodic nature of the movements allowed for repetition of the messages at a suitable moment of the period. This enabled almost instant correction of the taught movements. The forced quick reactions make it possible, to some degree, to modify motor programs stored in the human memory. The programs, described by Schmidt and Lee [1], are responsible for the very fast movements, and are crucial for learning the movement synchronization.

The problems of interpreting the messages may also be overcome by the use of additional senses, such as sight or hearing. However, this solution extends the human reaction time and engages the person's mental attention. Therefore, in the automatic learning system implemented for sports and machine operating tasks, it can be applied in a limited scope.

3) CALCULATION OF TEACHING EFFICIENCY PARAMETERS

The mean values of the parameter $\mathcal{F}_{ph}$ that assessed the phase error were about seven times greater than the trajectory parameter $\mathcal{F}_{tr}$ expressed in meters (Table 2). Therefore, using the values $\alpha = 1$ and $\beta = 10$ in the vector $\mathbf{e}^i = [\alpha e^i_{ph} \;\; \beta e^i_{tr}]$ (26) we obtained slightly higher relative impacts of the trajectory errors, in comparison with the phase errors, on the final $\mathcal{F}_{10}$ parameter. Analogously, the parameter $\mathcal{F}_4$, where $\alpha = 1, \beta = 4$, to a greater extent depended on the phase errors. Using several kinds of variables describing the motion, we were able to effortlessly construct and employ parameters that assessed the particular learning tasks.

4) EMBEDDED AND PERSONAL MOTOR LEARNING SYSTEMS

The described approach may be applied in two kinds of motor learning systems. The first uses several motion sensors and actuators, and performs classification of many signals. It can be implemented as an embedded system cooperating with control systems of several types of machines and vehicles. This makes it possible to acquire the system knowledge (patterns of proper movements) from experienced operators. In addition, the training of beginners can be performed in a real environment. The second type of system (which uses a limited number of sensors and actuators) relates to miniature "personal" teaching systems for rehabilitation and sports.

IV. CONCLUSION

Building an effective, automatic motor learning system for fast and synchronous movements is a serious challenge. However, as the author demonstrated using the results of the conducted test, this task may be accomplished by the application of several tools, particularly related to the classification methods. Consequently, the answer to the main research question: "Can the classification methods be considered to be an effective tool to construct an automatic system for learning the synchronous motions?" is affirmative.

The paper described key properties of the system and provided ways to achieve them. Their articulation can be treated as the important outcome. In this context let us itemize the most essential matters. The system was based on expert knowledge and experiences. The acquisition and application of this knowledge required a suitable communication between the expert and the system, with the use of several concepts that described learning process (e.g., class and shape patterns). The expert improved the teaching algorithms using an augmented description of the entire learning process, which was provided by the classification methods. The results of the classification process were utilized to select the teaching algorithms. Haptic messages were used to ensure the fast communication between the learner and the system.

Moreover, we can extend the last statement by a significant conclusion. The usage of haptic feedback in teaching very fast movements that refer to trajectory tracking is problematic. This is mainly caused by human limitations in detecting fast haptic signals. However, in the task of teaching the synchronization of movement, the impact of these limitations is reduced.

The general ideas presented in the paper can be utilized to create two types of motor learning systems. Considering the size of the system, both personal learning systems (for rehabilitation and sports) and embedded teaching systems (integrated with control systems of machines) can be built.

The conducted test of the prototype disclosed many problems and pointed to necessary future modifications. The essential enhancements should include creating teaching algorithms that minimize errors of reading the haptic messages and developing algorithms to edit the class and shape patterns in order to adapt them for the individual features of the learners. Another improvement ought to be the creation of a software repository containing the verified algorithms for specific learning tasks.

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