The application of the brain-computer interface (BCI), as well as robots (orthoses, exoskeletons), in neurorehabilitation is a new and vigorously developing field of research. The discovery of plastic alterations in the functional topography of the primary motor cortex as a result of training is one of the impulses for such development [1]. It was shown quite quickly that movement can be recovered even several years after a stroke [2, 3]. This offered new possibilities for neurorehabilitation: the principles of intense, regular, and motivated movement training have been developed [4]. Exoskeletons proved to be ideal technical devices for the implementation of these principles. Different kinds of exoskeletons have actively been used in clinical settings, and the number of developments has been exponentially increasing for the past decade [5].

There are several examples of exoskeletons successfully used for neurorehabilitation: ARM-Guide (Assistant Rehabilitation and Measurement Guide), which can facilitate (or prevent) movements at the elbow and shoulder [6]; MIME (Mirror-Image Movement Enabler), by means of which it is possible to control the forearm and hand movements with signals from a healthy arm [7]; BI Manu Track, which stimulates hand flexion—extension and pronation—supination of the right and left forearms [8]; NeRobot (Neuro Rehabilitation Robot), which allows movements with three degrees of freedom at the shoulder and with two degrees of freedom at the elbow [9]; Haptic Master, which does not impose the correct movement but only correctes deviations from it [10]; and T-WREX (Therapy Wilmington Robotic Exoskeleton), which blocks unnecessary (for one or other therapeutic exercise) degrees of extremity mobility [11].

Exoskeletons are often coupled with a computer game where the cursor reflects the movement of the hand’s working point (a joystick in a patient’s hand). The patient is able to solve computer game tasks by means of visual feedback. A passive spring mechanism unloading the controlled arm is used in the joints of some exoskeletons. In other exoskeletons, active control of the joints is used: their drives perform the correct movement. Certain rehabilitation protocols provide for the formation of the correct movement in the course of a computer game with adjusted parameters. In other protocols, the doctor performs movements with the patient’s passive arm; these movements are recorded for reproduction by means of the exoskeleton.

Two aspects are noted in the reviews of the principles of action of exoskeletons: the first principle, indisputably positive, is the effective use of exoskeletons in the practice of poststroke rehabilitation; the other consists of the fact that the progress in the development of more sophisticated exoskeletons is interfered with by the lack of understanding of the principles of motor control by the central nervous system (CNS) [12]. However, even the known principles of motor control in the living body have been little used in the development of the system of exoskeleton control.
Here, we describe three of these principles: (1) the control of an external device (in particular, the exoskeleton) using the signals directly generated by the brain bypassing the natural activity of muscles and peripheral nerves; (2) the formation of motor synergies, i.e., coordination of articular angles and the moments of forces at the joints in movements of the multijoint extremity; and (3) the feedback control of the moment of muscular forces at a joint from the articular angle.

BRAIN–COMPUTER INTERFACE

General principles. The general BCI scheme is shown in Fig. 1. It includes the system of obtaining the brain activity signals, their input into the computer, the real-time data classification, the system of coupling with an external device, and the feedback system (visual or proprioceptive) supplying information about the results of command execution. Two types of brain activity are used for BCI creation: electrophysiological and hemodynamic.

The electrophysiological activity is determined by the electrochemical processes connected with the information transfer between the brain’s neurons. It is recorded in electro-(EEG) and magnetoencephalography (MEG) where the sensors of signals are placed outside the head; in electrocorticography where the sensors are placed on the surface but not deep in the brain; and in the intracortical recording of the activity of individual neurons. The hemodynamic activity is determined by the increased rate of oxygen supply to active brain regions compared to inactive regions. This leads to local changes in the oxyhemoglobin to deoxyhemoglobin concentration ratio. The ratio changes can be recorded by functional magnetic resonance imaging or near-infrared spectroscopy. In contrast to the methods for recording electrophysiological activity, these methods indirectly reflect alterations in the neuronal activity in connection with the performance of mental tasks.

Although the first BCI was created back in the early 1970s [13, 14], the idea of decoding human thoughts and intentions from the brain’s signals seemed to be practicable only in the remote future, if at all, because of the high variability and low resolving power of these signals. In addition, BCIs require real-time analysis of the brain signals, and until recently, the relevant technologies were either absent or too expensive. However, the situation has radically changed over the past 20 years. While only three research groups were involved in BCI development 20 ago and eight groups, 10 years ago, at present, their number exceeds 100. Accordingly, the number of publications pertinent to this subject have exponentially increased from 10 in 1993–1995 to approximately 500 in 2008–2010 [15, 16]. The greatest number of studies concerns the use of electrical signals. To record MEG, bulky and costly devices are required. The same applies to the use of hemodynamic activity.
Therefore, only the BCIs based on the use of electrical brain signals are discussed below.

Numerous investigations have identified the brain’s activity patterns characteristic of movement performance and motor imagery [17–19], as well as of the performance of different types of mental tasks [20–22]. Thus, the indicators of electrical brain activity potentially suitable for BCIs have been identified.

Classification of BCI types. BCIs differ in the type of the recorded brain signals and the modes of their transformation into commands exercising control over an external device. The BCIs based on the use of the multiple activity of separate neurons are invasive, because this activity is recorded with the system of microelectrodes implanted in the brain tissue. It should be noted that, despite the obvious encouraging results of the application of invasive BCIs, their mass-scale clinical application is unlikely to happen in the near future. The main obstacles are (1) the short time of their effective functioning because the recording electrodes are overgrown with connective tissue, which results in the loss of their electrical contact with the brain tissue and (2) the possibility of infection through the trephine aperture for the cables. This is the reason why it is noninvasive BCIs that are expected to be used on a large-scale basis in the near future.

BCIs are also subdivided into gradual and discrete BCIs. In a gradual BCI, the new sensorimotor coordination connecting the brain’s activity with the direction of movement to the target by continuous transformation is learnt. A typical protocol of the experiment with a gradual BCI based on EEG analysis instructs the subject to shift the cursor towards a voluntary target on the computer screen with a mental effort [23]. After several weeks of training, the subjects are taught to shift the cursor from the initial voluntary position towards a voluntary target for 2–5 s.

In the case of an invasive BCI based on recording the activity of individual neurons, the cursor control task is facilitated, because the neuronal activity of the cerebral motor cortex and the desirable direction of movement are initially related [24]. Note that each neuron has a preferable direction of movement at the peak of its activity. With a different direction of movement, the neuronal activity is proportional to the cosine of the angle between this direction and the preferable one. Recording the activity of several neurons and having predetermined their preferable directions, we can easily calculate by their current activity which direction of movement is desirable. Gradual invasive BCIs based on recording the activity of individual neurons are typically used in experiments on monkeys [25].

In contrast to gradual BCIs, discrete BCIs are capable of sending only a limited set of commands to the external device. An example of a binary BCI is the interface based on recording the P300 component of the potential evoked in response to an unexpected, rarely presented significant stimulus (presented, e.g., with a probability of 0.2) when it appears among frequently presented insignificant stimuli [26, 27]. P300 appears approximately 300 ms after presentation of the significant stimulus; its duration is about 300–400 ms and the positive amplitude is 5–15 μV. The more rarely the significant stimulus is presented the higher the P300 amplitude. The first efficient P300-based BCI was described by Farwell and Donchin [28]; and its slight modification, by Donchin et al. [29].

Another type of discrete BCIs is based on the recognition of the EEG spatiotemporal patterns corresponding to different types of mental activity. The idea of such a BCI was first put forward by Millan et al. [30]. In most studies, the spatial distribution of the amplitudes with different EEG rhythms on the surface of the head, whose reorganization is known to reflect the dominance of one or another cognitive process, is studied as an EEG spatiotemporal pattern.

The logic of the application of the EEG patterns corresponding to different mental tasks is the following. At first, the subject is instructed to perform several types of mental tasks. It is determined using an adaptive classifier what types of tasks can be classified with maximum accuracy. After that, by agreement with the subject, each of these tasks is associated with a certain command controlling the external device. In order to perform a voluntary command, the subject then solves the corresponding mental task in the mind. The number of mental tasks and, consequently, the number of commands sent to the external device in such a BCI are not formally limited. The main thing is that the corresponding patterns could be easily differentiated. If the command to the external device is to perform a certain movement, it is psychologically convenient to relate the command to motor imagery. For example, turning an invalid’s wheelchair to the left is easily associated with the left-arm movement imaging; and to the right, with the right-arm movement imaging.

Figure 2 exemplifies the results of our experiments [31–34] assessing the accuracy of the EEG patterns corresponding to the performance of three mental tasks with the use of motor and visual imagery. For motor tasks, the left and right arm movements and their resting state were imagined. For visual tasks, the images of a house, a bench, and a blank computer screen were formed in the mind. In the figure, the subjects are ranged according to the quality of recognition of their EEG patterns. The level of random recognition for the three tasks is 1/3. The results are given for day 5 of training. The EEG patterns were recognized by a simple Bayesian classifier [31–35].

As shown in Fig. 2, the quality of recognition surpasses the random level for both types of tasks; however, it is much higher on average for performing motor tasks. The quality of recognition by different subjects is also highly variable. The proportion of the correct motor task recognition for approximately 15% of the subjects is more than 80%; and it hardly exceeds the random level for approximately 20% of them. However, the continuation of training normally allows the quality of rec-
ognition to be substantially improved. Since the BCIs based on motor imagery are mainly used for motor rehabilitation, we will further consider only this type of BCIs.

**Neurophysiological prerequisites for the development of BCIs based on motor imagery.** The movement or preparation for the movement of a certain executive organ is usually accompanied by the μ- and β-rhythm decreasing in the cortical representations of this organ. This decrease is called event-related desynchronization (ERD) [17, 19]. The μ-rhythm increase, i.e., event-related synchronization (ERS), is observed in the brain’s regions that represent the organs not connected with the performance of the given movement [17].

BCIs based on motor imagery is so effective because the ERD and ERS responses are also observed in motor imagery. Visual and kinesthetic motor imaginations should be differentiated. In the former case, the subjects visually imagine their own movement as if seen from the outside. In the latter case, they create kinesthetic motor perceptions. It has been shown that kinesthetic motor imagery activates the same brain regions as a real movement, while visual imagery mainly activates visual divisions of the brain [36–38]; therefore, the ERD and ERS appear in response to kinesthetic motor imagery. Representations of the executive organs are sufficiently widely distributed on the cortical surface [39]. That is why the motor imagery of different organs creates a different distribution of activity on the surface of the cortex and, accordingly, different EEG spatial patterns, which facilitates the tasks of the BCI classifier.

The source of electrical activity of the brain that is most important for the functioning of the BCIs based on the arm motor imagery was pinpointed by Frolov et al. [35]. The experiments were made according to the standard protocol. Each experimental series consisted of four sequential sessions: preliminary, teaching, and two testing series. The preliminary session data were later used for removal of the oculomotor artifacts and identification of the occipital α-rhythm. The teaching and testing sessions served for preliminarily adjusting the BCI classifier and its testing, respectively. The subject carried out one of three instructions: to relax and to imagine the left or right arm movements. As an arm movement imaging, the subject was instructed to imagine slowly clenching the fist or bending his separate fingers. According to the instruction to relax (rest), the subject was to sit quietly and to look at the center of the screen. Each 15-s motor imagery instruction was preceded by a 7-s instruction to relax. Four such rest–movement pairs presented in a random order formed a unit. The teaching sessions consisted of two units; and the testing sessions, of four units.

During the classifier testing, the results of recognition of mental task performance were presented to the subject by visual feedback: the gaze-fixing mark at the center of the screen changed to a green color if the classifier recognized the task corresponding to the motor instruction presented and remained white if a different task was recognized. During presentation of the relaxation instruction, the mark turned white, irrespective of the recognition result.

The EEG was recorded using 24 electrodes uniformly arranged on the head surface. The EEG signals were filtered in the frequency band from 5 to 30 Hz. During the testing session, the EEG patterns were analyzed in the real-time mode. The classification was carried out with the Bayesian classifier mentioned earlier using a 1-s segment that was moved with a pitch of 250 ms. Cohen’s kappa index [40] accepted for BCI investigations was used as an indicator of the classification accuracy.

To search for the sources of electrical activity accompanying motor imagery, we used independent component analysis (ICA), widely used in recent years for examining multichannel EEG recordings in general and for analyzing the experimental BCI in particular [41]. To decompose the initial signal into independent components, we employed the RUNICA method presented in the EEGLab software package in the MATLAB medium [42]. RUNICA ensures the identification of independent components by maximizing the difference of their distribution from the normal one [43].

Three independent components ensuring the best recognition of the performed mental tasks by the kappa index were identified for each subject on each experimental day. Figure 3 shows the identified components for one of the subjects. The first two components designated as μ1 and μ2 were identified in this subject regularly on every experimental day. They demonstrate ERD and ERS responses to arm motor imagery. The activity of the μ1 component in the bands 8–13 and 20–25 Hz is inhibited during the left arm motor imagery and increased during the right arm motor imagery. The foci of this component are located in the right hemisphere, where the left arm sensorimotor regions are represented. For the μ2 component, the ERD and ERS responses are the opposite. It should be noted that the ERD and ERS responses are much stronger for these
components than in the case where they are recorded from individual electrodes. For example, for the subject whose data are shown in Fig. 3, the signal spectral density in the band 8–13 Hz decreased approximately five-fold during the ERD response, whereas it decreased only by 30% when recorded from the central electrodes $C_3$ and $C_4$, where it is at the strongest.

The identified sources of $\mu_1$ and $\mu_2$ electrical activity were localized by the method of solving the inverse problem of encephalography [35]. Their foci appeared to be located in the $3\alpha$ regions in the depth of the central sulcus, where the proprioceptive sensitivity of the palms of the hands and the fingers is represented. Hence, in the state of motor relaxation, the source of the $\mu$-rhythm source is located in the somatosensory cortex rather than in the motor cortex. This agrees with the data on the localization of the $\mu$-rhythm in cats [44].

Thus, the ERD and ERS responses, i.e., inhibition of the resting $\mu$-rhythm in the region of representation of the proprioceptive sensitivity of the arm whose movement is imagined and its enhancement in the region of representation of the contralateral arm, are a neurophysiological prerequisite of the high quality of the operation of BCIs based on motor imagery.

**CONTROL OF THE MOMENT OF MUSCULAR FORCES IN THE JOINT**

In the BCI paradigm, the brain activity signals connected with motor imagery are processed in the real-time mode for the components most significantly reflecting human intentions to be identified. For task-oriented arm movements, this intention can be formalized in the form of the arm’s working point trajectory, e.g., the hand trajectory for taking a certain object or the fingertip trajectory for reaching a certain point (Fig. 4a).

The problem of transformation of the working point trajectory into rotation at the joints does not have a
unique solution due to the kinematic redundancy of the human arm. This transformation is formed during the motor learning process; one of the possible neural network models of such learning is cited by Frolov et al. [45]. The result of the transformation of the working point trajectory into the desirable articular angle changes is strictly individual and is related to the individual biomechanical properties rather than to differences in control [46]. In this section, we present the experimental and simulation data enabling us to propose a biologically plausible model of control of the moment of muscular forces at the joint.

The experimental physiological studies showed that the PD controller (Proportional-Derivative Controller) equivalent to a viscoelastic spring with adjustable parameters—equilibrium length, stiffness, and viscosity—is such a model [47–49]. The equilibrium length of the spring modeling the articular moment corresponds to the desirable articular angle value and is preset by supraspinal CNS levels. The spring stiffness and viscosity are determined by the interaction of three different physiological mechanisms: the viscoelastic properties of muscular fibers and tendons, the spinal stretching reflex loop, and the feedback loops passing through the brain [50]. As distinct from the first mechanism, the second and third mechanisms have significant delays in action. For the stretching reflex loop, this delay is 50 ms; and for the second loop, up to 150 ms [50–52]. The effective delay used in the PD-controller model is determined by the contributions of the three mechanisms mentioned above. The time delay imposes limitations on the feedback parameters determining stable control. These limitations manifest themselves in the fact that the spring stiffness and viscosity values should be limited from both above and below [53].

The viscoelastic nature of the articular moment combined with low articular stiffness values was formulated by N.A. Bernstein as one of the main difficulties of motor control by the CNS. This difficulty is overcome by feedback control and multiple repetition of movement in the process of motor learning [54]. Since the arm joint stiffness is rather low (according to the data in the literature, from 2 to 100 N m at the elbow and from 10 to 70 N m at the shoulder), the tight control of the joint during the fulfillment of the preset kinematics, which is often used in modern exoskeletons, is perceived by many patients as uncomfortable. The biologically plausible control of the articular moment necessitates the feedback from the articular angle and the low exoskeleton joint stiffness values habitual for patients.

The stiffness and viscosity of the joints in task-oriented movements are experimentally determined by means of short random mechanical disturbances of the extremity links. It is reasonable to suggest that the CNS does not have enough time to respond to these disturbances, and, therefore, stiffness and viscosity can be calculated using the linear regression model of the dependence of the articular moments of force on the articular angles and angular velocities caused by disturbance [52, 55].

In order to use this method, it is necessary to record the kinematics of movement and to calculate the total moments of muscular forces at the joints. Goniometers [46], optic systems [56], or electromagnetic [57] systems are used for movement recording. In our investigations, movements are recorded by the electromagnetic systems, such as Spatial Tracking System (Fastrack Polhemus), Flock of Birds, MiniBirds, and TrakSTAR (Ascension Technology Corp.). When movements are recorded, the sensors are fixed to the human extremity links or to the trunk. In the data analysis, these links are considered to be solids bound by ideal hinges. In the process of movement, the sensor coordinates and orientation relative to the stationary coordinate system connected with the magnetic field source (base) are recorded (Fig. 4a). Thus, the movement of each link is described by six parameters as a movement of a free solid. This description is redundant: for example, there are 24 parameters of four sensors fixed to the arm links—the hand, the lower arm, the upper arm, and the scapula—to describe seven degrees of freedom of the human arm (two each at the wrist and elbow and three at the shoulder joint) (Fig. 4a). This enables us to apply different optimization methods for calculating the position of the axes and the joint rotation centers, as well as for calculation of the articular angles in the process of arm movement [58, 59].

The total moments of muscular forces are calculated based on the kinematics of movement (temporal changes in the articular angles, angular velocities, and angular accelerations) by solving the inverse dynamic problem [60].

The controlling forces are preset by the PD controller with a time delay whose action in our studies is described by the following equation:

$$\Pi_\lambda(t) = \Pi_\lambda(t - \tau) + S_{\lambda\mu}[(\eta^\mu(t) - \eta^\mu(t - \tau)]$$

$$+ V_{\lambda\mu}[(\dot{\eta}^\mu(t) - \dot{\eta}^\mu(t - \tau)),$$

where $\lambda, \mu = 1, 2, ..., 7$ (the number of the arm degrees of freedom); summation over repeated indices is implied; $S_{\lambda\mu}$ is the stiffness matrix; $V_{\lambda\mu}$ is the viscosity matrix; $\eta^\mu(t)$ and $\dot{\eta}^\mu(t)$ are the articular angles and the angular velocities at the moment $t$, $\eta^\mu(t)$ and $\dot{\eta}^\mu(t)$ are the desirable articular angle and angular velocity values; and $\tau$ is the time delay. The articular angles $\eta^\mu(t)$, the angular velocities $\dot{\eta}^\mu(t)$, and the angular accelerations $\ddot{\eta}^\mu(t)$ are calculated according to the movement recording data [58, 59]. The articular moments $\Pi_\lambda$ are calculated from the preset kinematics of movement (i.e., by $\eta^\mu(t)$, $\dot{\eta}^\mu(t)$, and $\ddot{\eta}^\mu(t)$) by solving the inverse dynamic problem. The link’s inertia masses and moments are determined for each subject individually using the anthropometric tables [61]. The viscoelastic
The plausibility of the above model of control of the moment of muscular forces at the joint was shown for control of the elbow during unexpected and controlled forearm unloading [62]; the arm joints during its task-oriented movements [52]; and the movements of the hip, knee, and ankle joints during upper trunk bending in the sagittal plane [53, 63]. The $PD$-controller model (1) was also successfully used in the development of the method for the early diagnosis of diseases of the hip joint [64].

**FORMATION OF MOTOR SYNERGIES**

The so-called synergies, i.e., co-ordinated movements in the extremity joints controlled by a unifying command are formed in the process of motor learning [54]. Motor synergies manifest themselves in co-ordinated changes in the articular angles $\eta^\mu(t)$ (kinematic synergies) and articular moments $\Pi^\mu(t)$ (dynamic synergies). The relationship between kinematic and dynamic synergies is determined by the complex dynamic interaction between the biomechanical chain links. The movement of each segment affects the movement of all others, and the activation of any muscle involves the movement of all the segments (not only those to which the muscle is attached). As a consequence, the simplicity of the kinematic pattern does not give evidence of the simplicity of the dynamic pattern or the simplicity of the controlling command. The fact that synchronous changes in the articular angles are not accompanied by synchronous changes in the moments of muscular forces at the joints was shown, e.g., for the thumb and the index finger movements during the precision grip movement [46].

The control of the multilink biomechanical system would be considerably simpler if there existed such classes of movements for which kinematic synergy occurred simultaneously with dynamic synergy. Such movements could constitute the repertoire of the motor control modules. As it was shown by Alexandrov et al. [53, 63, 65], for upper trunk bending in different motor perturbations, the movements corresponding to the eigenvectors of the linear dynamic equations of the multilink system meet these conditions: for them, the dynamic synergy of articular moments involves the kinematic synergy of articular angles. For these movements, the interrelated dynamic equations become independent, which considerably facilitates the motor control of the multilink system.

The calculation of such movements was carried out for the human arm model, including all its main degrees of mobility: three at the shoulder joint (flexion—extension, abduction—adduction, and rotation relative to the longitudinal axis); two at the elbow (flexion—extension of the forearm relative to the upper arm and pronation—supination of the forearm relative to its longitudinal axis); and two at the wrist (flexion—extension and abduction—adduction) (Fig. 4b).

The eigenvectors of the linearized dynamic equations of the arm model are shown in the table. These vectors determine the contributions of the arm’s degrees of freedom to its eigen movements. For example, the degrees of freedom of the wrist make a contribution in first three eigen movements; in the fifth eigen movement, the forearm pronation is added to them; in the sixth movement, the degrees of freedom of the elbow and the shoulder joint (except for abduction—adduction); the fourth eigen movement is mainly determined by rotation of the shoulder joint relative to its longitudinal axis and by flexion at the elbow; the seventh movement, by abduction at the shoulder joint (table).

In order to determine the eigen movements corresponding to the eigenvectors shown in the table, it is necessary to solve the direct dynamic problem, i.e., to integrate the dynamic equations whose members on the right side represent the $PD$-controller described by Eq. (1). The $PD$-controller parameters, the stiffness and viscosity matrices, are calculated from the

<table>
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<tr>
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<td>$w_1^\mu$</td>
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<tr>
<td>Shoulder joint</td>
<td>Rotation $Rots$</td>
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<td></td>
<td>Abduction—adduction $Ab$—$Ads$</td>
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<td>Flexion—extension $F$—$Es$</td>
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<td>Elbow</td>
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<td>Wrist</td>
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conditions of stability of the initial arm position: the values of their elements are to afford the maximal velocity of return to the equilibrium position after perturbation [66]. The calculated values are in the range of the results cited in the literature pertinent to the viscoelastic properties of the arm joints.

The periodic movement at the joints with the amplitudes proportional to the eigenvector elements is preset as a desirable movement:

\[ \eta_{k\mu}^{d}(t) = A\omega_{k}^{\mu}\sin\omega t, \]

where \( k = 1, 2, \ldots, 7 \) is the eigenvector number; \( \mu = 1, 2, \ldots, 7 \) is the articular angle number; and \( A = 0.1 \text{ rad}, \omega = 1 \text{ Hz} \).

The movements obtained as a result of integrating the dynamic equations are close to the desirable movements (Fig. 5). Thus, the PD controller ensures stable control of the arm model.

The movement along the eigenvector in the space of articular angles, namely, eigen movement, is referred to as natural synergy [67]. In studies on the control of bending in the sagittal plane [53, 63, 65], a hypothesis was proposed that natural synergies are not simply a formal assumption for a convenient description of movement, but they play the role of independent motor control units that serve for the solution of functionally different behavioral tasks. The following data support this hypothesis:

1. The division of the coupled system of dynamic equations into independent equations for each of the eigen movements is in agreement with the principle of minimal interaction, the fundamental principle of motor synergies organization [68]. The presence of an independent equation for each of the eigen movements is indicative of the possibility of independent control of these movements as integral units of motor control.

2. In each of the eigen movements, the articular angles and the moments of forces at the joints are changed synchronously. Thus, the kinematics and dynamics of these movements have a relatively simple organization in the form of unidimensional temporal evolvement with certain inertia. Any other arm movement may be represented in the form of the superposition of eigen movements with different inertias. As a consequence, it requires more complex controlling signals with significantly different temporal characteristics.
(3) The analysis of the adaptation of movements to changes in the conditions of their performance showed that modification of the temporal characteristics of the eigen movements is a much more difficult task for the subject than modification of the amplitude characteristics of these movements [67]. If the motor pattern remains invariant despite the fact that its reorganization would be functionally useful, then this movement represents a basic neural behavioral unit [69], i.e., an integral motor control unit.

We note that the solution of the problem of redundancy through identification of natural synergies is not generally accepted. Several authors believe that in order to overcome the redundancy of the skeletal and neuromuscular apparatuses, the nervous system solves a certain optimization problem [49]. For a living system, this suggestion, quite logical in designing a robot, seems to be too artificial. In a biologically plausible system of control of the human arm’s exoskeleton, the possibility of feedback control of natural synergies should be provided for.

CLINICAL APPLICATIONS OF AN EXOSKELETON CONTROLLED BY BCI SIGNALS

Modern methods of the recovery of motor functions are aimed at stimulating natural mechanisms of the plasticity of the brain by compensating its defect [70–73]. It was shown that repeated active purposive movements help to restore the motor functions. Practically, this approach has been used for the past 10 years in some methods, such as feedback motor training under virtual reality [74, 75] and robot-based training used as a therapeutic tool [76, 77]. This approach is based on the ability of a patient to perform active movements using his or her affected arm or leg and, consequently, requires partial preservation of the motor functions. If these functions are lost, the promising method for stimulating brain plasticity is only motor imagery. As shown in many studies [37, 78, 79], motor imagery is subject to the same principles as the control of real movements and, therefore, can stimulate the same plastic mechanisms [80].

However, this concerns only kinesthetic motor imagery. It is important to stimulate in patients the imagery that can be controlled as described above by the dynamics of the sensorimotor rhythm. It is for this reason why the BCI technology, permitting the feedback control of the sensorimotor rhythm and, hence, the targeted stimulation of plastic reorganizations in the brain related to the execution of movement, seems to be promising for neurorehabilitation.

Two strategies of the application of BCIs for the recovery of movement are discussed in the literature [81]. The first strategy allows us to teach the patient to stimulate a more stable pattern of brain activity corresponding to the intention to perform a certain movement. It is suggested that multiple repetition of this pattern will reinforce the relation between intention and
the corresponding activity of the brain, thereby improving motor control. The second strategy assumes that, in addition to the identification of the specific brain activity, it is necessary to stimulate the corresponding movement. This is implemented with a mechanical manipulator (exoskeleton) or by electrical stimulation of muscles. Such a movement ensures the proprioceptive stimulation of the sensorimotor regions of the brain, which additionally activates their plasticity.

The results of the experiments in the first strategy are encouraging [82–84]. The studies show that EEG normalization occurs in parallel with the restoration of the motor functions. The same result was obtained by us in the rehabilitative experiments with poststroke patients. Hope for the efficacy of the second strategy is supported by the fact that the performance or even observation of a movement that is maximally approximated to normal can improve the motor function [85–87] and contribute to sprouting of new axons in the brain’s regions that are involved [88]. If a normal movement is impossible after a stroke, it is necessary to reproduce it artificially. It has been shown that, when it is reproduced by electrical stimulation of the corresponding muscles, it is possible to significantly improve the motor function in patients affected moderately or severely after a stroke [89, 90]. The same is observed in the case when the exoskeleton helps perform a normal movement [91]. In the studies cited, a movement was reproduced without the help of BCIs, which requires very meticulous and laborious work of the personnel. The BCI technology allows us to automate the reproduction of movements.

In order to investigate the rehabilitative effect of the use of a BCI-controlled exoskeleton, we propose to begin with the simplest hand exoskeleton with one degree of freedom (allowing the patient to clench/unclench the fist, Fig. 6a).

Hand movements are more difficult to restore after a stroke and brain injury, and the application of a BCI in this case may be especially beneficial. In order to control such an exoskeleton, it is sufficient to use a discrete BCI based on motor imagery and described in the previous sections.

For further progress in the studies of the potentialities of the rehabilitative procedures using the control of an external BCI-based device, a human arm exoskeleton with seven degrees of freedom is being developed in projects nos. 11-04-12025 ofi-m-2011 and 11-04-12067 ofi-m-2011 of the Russian Foundation for Basic Research. The prototype of such an exoskeleton with four degrees of freedom (flexion–extension at the shoulder joint, flexion–extension and pronation–supination at the elbow, and the hand grip movement (adduction of fingers to the palm)) has already been developed (Fig. 6b) and is undergoing a model trial. This exoskeleton will be controlled by both the signals from invasive and noninvasive BCIs using the biologically plausible methods described above. Its application is not limited to poststroke rehabilitation; it can be used for restoration of the motor functions in patients with disorders of different etiology, not only central but also peripheral.

CONCLUSIONS

The use of BCIs seems to be the most promising for the creation of a new channel of communication between completely paralyzed patients and the environment instead of the natural channel lost by them and requiring activation of muscles. The data on the successful application of BCIs to the solution of this task stimulate, in addition to the elaboration of the BCI themselves, the development of anthropomorphic prostheses and exoskeletons whose control would draw...
upon the biologically plausible principles, including the feedback control of natural synergies from the articular angle.

The use of these principles in the development of an arm exoskeleton, as well as coupling of the system of the exoskeleton’s control with the BCI, is a promising avenue of investigation and is at the frontline of developments of robot-based technical systems of neurorehabilitation.

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REFERENCES


