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RESEARCH ARTICLE

Limb Movement Tracking Technologies Used to Obtain an Objective Assessment of their Functional State

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ABSTRACT

Acute cerebral circulatory disorders are currently the leading cause of disability. The main task of rehabilitation in this case is to restore upper-extremity motor function, which is observed in only 5% of patients. The assessment of motor functions and the dynamics of their recovery is currently focused on the use of subjective clinical scales administered by experienced medical specialists, including the Fugl-Meyer scale. Their alternative may be hardware and software complexes, the result of which will provide us with objective criteria for assessing limb condition. As a result of the research conducted, two main technological approaches to this have been identified. The first approach involves the use of optical motion capture systems, which have the disadvantages of complex deployment and expensive equipment. The second approach involves working with arrays of wearable sensors, which are compact and accessible but slightly less accurate at registering complex movements. The most promising, according to the authors, are systems that combine several technologies. For example, using inertial measurement modules and surface electromyography. Data processing by such complexes using machine learning methods enables an accuracy of 80-97% when evaluating the performance of a number of exercises on the Fugl–Meyer scale compared with expert opinion. However, there is also the problem of compensatory movements that distort the received data. To solve this problem, it is important to train machine learning models on extensive datasets that cover the full range of possible movements. The use of such systems will automate the objective assessment of the course of rehabilitation measures, both in the clinic and at home, thereby increasing the effectiveness of therapy and motivating patients through visual representation.

INTRODUCTION

One of the leading causes of long-term disability worldwide is the effect of acute cerebrovascular accident (ACVA) (De Diego-Alonso et al., 2023). The key factors contributing to the recovery of patients are their early return to their usual social life and physical activity (English et al., 2013). Here, special attention is paid to motor disorders of the upper extremities, which occur in half of the cases and the patients fully recover in only 5% of them (Kayerova et al., 2021). The basis for successful recovery is the competent planning of all stages of rehabilitation, which should follow each other, in order to consolidate and enhance the effect achieved at the previous stage (Karaseva et al., 2024). An important role is assigned not only to the organization of rehabilitation measures in hospital or outpatient departments, but also at home. Considering the psychoemotional problems faced by patients after a stroke, an objective presentation of the effectiveness of rehabilitation treatment is an important aspect (Gordeev et al., 2024). Currently, objective assessment is achieved using various scales and tests that allow a medical specialist to obtain a general idea of the injured limb's current condition. The patient, performing exercises at home, lacks a medical assessment and focuses only on their own feelings.

Modern research shows the effectiveness of rehabilitation and a positive effect on the restoration of upper-extremity motor function when using wearable devices (Lin et al., 2018; Song et al., 2024). These include robotic devices equipped with tactile sensors, sensors for limb-part position, and sensors that measure joint flexion (Cordella et al., 2020; Jha, Chakraborty, 2018). Furthermore, they can be equipped with additional systems that perform muscle stimulation and use augmented reality technologies (Condino et al., 2019; Laver et al., 2011). Depending on their purpose and composition, such devices allow the performance of standard exercises, support the patient in performing daily tasks, or implement specialized rehabilitation programs (Turk et al., 2022).

According to a study by L. Santisteban et al. (2016), the most commonly used scale for assessing upper-limb function in stroke survivors is the Fugl-Meyer Assessment (FMA) (Deakin et al., 2003; Fugl-Meyer et al., 1975). This is also confirmed by Samantha Rozevink in her dissertation (Rozevink, 2023). When studying the effects of specific methods for restoring upper-limb function in stroke patients, she showed that the FMA provides a more comprehensive assessment than the ARAT (Action Research Arm Test). Working with the FMA requires a doctor's presence, but the result depends on the doctor's clinical experience, making it impossible for the patient to use it at home. It should also be noted that comprehensive testing, including a full protocol, requires significant time, from 20 to 35 minutes, depending on the degree of damage (Poole, Whitney, 2001). Several existing studies aim to adapt the scale to reduce time, simplify procedures, and perform exercises suitable for processing in the context of remote interaction with the patient while automating the assessment (Lee et al., 2024; Lin et al., 2021; Pérez-Robledo et al., 2022). An example is the work of F. Pérez-Robledo (Pérez-Robledo et al., 2022), who proposed to remove subsections 1 (Reflexes) and 6 (Reflex activity) from the Upper limb section, flexion /extension in different positions (angle of the elbow joint 90°, shoulder 0°; angle of the elbow joint 90°, shoulder 30°) from subsection 7 (Stability), remove the items corresponding to the gripping of objects from subsection 8 (Flexion of all fingers), and the Tremor and Dysmetria items from subsection 9 (Coordination during the finger-nose test). The result was a maximum of 42 points out of 66 in the original version of the scale. Y. W. Hsieh et al. (2007) suggested using 12 points from the original scale (6 for the upper and 6 for the lower extremities). Gong-Hong Lin proposed a version of FMA (Lin et al., 2021) consisting of 10 points (5 points each for the upper and lower extremities). The authors claim to have achieved psychometric properties comparable to those of other versions of the FMA (full, 37-point, and 12-point).

Based on these results, we suggested that formalizing requirements for the sequence of actions and the positions of individual limb elements enables the creation of tools that yield objective indicators and allow an accurate assessment of the condition of the damaged limb, for use both in the hospital and at home. These tools should be designed as compact hardware-software complexes, easily mounted on a limb, with an intuitive operating algorithm that eliminates errors when performing the required actions. The fulfillment of such requirements largely depends on the set of technologies used to obtain an objective assessment of the condition of damaged limbs. For example, when using the optical method to track the movements of a limb, to obtain accurate movement trajectories, it will be necessary to use an array of at least three video cameras positioned in different areas of the room. This will impose restrictions on working conditions and will require the use of expensive equipment to analyze the information received. The use of sensors located on the surface of a limb to record its movements also requires the development of methods for their placement, recording techniques, and resource-intensive algorithms to solve classification and regression problems to objectify the assessment. The paper presents results obtained by us during the initial stage of developing a device designed to record and analyze limb movements. Processing the arrays of data received from this device will allow us to obtain an objective assessment of the patient's limb's functional state. The purpose of the work carried out was to identify and substantiate a set of key technologies whose application will create a technical solution suitable for use both in the hospital and at home. The main focus in obtaining the stated results was the analysis of studies in the literature that present data comparing the results with the expert opinions of specialists.

MATERIALS AND METHODS

The search for scientific and technical information during the research was conducted using bibliographic databases in Russian (eLibrary, CyberLeninka) and English (Web of Science, Google Scholar, PubMed); the search depth was set to 10 years. The search queries included the following keywords: adaptation of the FMA scale, automation of the rehabilitation process of upper limbs after stroke, automation of rehabilitation assessment using the FMA, and Mocap system for upper-limb rehabilitation. Publications describing the results of studies on the automated assessment of rehabilitation in patients after stroke were reviewed. The main focus was on publications examining combinations of hardware that work independently or complement each other to solve motion-capture problems and assess the condition of damaged upper limbs. In addition, information was analyzed to compare the results obtained with the expert opinions of specialists, without reference to the methods used to obtain them. The priority was given to works using the FMA scale to objectify the assessment (Deakin et al., 2003; Fugl-Meyer et al., 1975; Santisteban et al., 2016).

RESULTS AND DISCUSSION

During the research, two conditional groups of devices were identified that can be used to objectify the assessment of the functional state of patients' limbs: motion capture systems using optical sensors and systems built using one or more groups of sensors (inertial measurement, electromyography (EMG), electroencephalography (EEG), etc.).

The optical capture method is the gold standard and is used when it is necessary to register and reproduce movements with high accuracy. For this purpose, three-dimensional optical motion capture (OMC) systems are used. They are large, expensive laboratory complexes that include systems with one or more cameras and suits fitted with specialized markers on anatomical landmarks. These are passive (for example, colored or reflective) or active markers, such as inertial measurement units (IMU) or LEDs (McGinley et al., 2008). When working with such systems, the need for specialized equipment to process data sets is considered. To simplify working with them, the number of optical sensors is reduced, or smartphone cameras available to the average user are used (Zamin et al., 2023). At the same time, studies are underway to explore the use of OMC systems to assess upper-extremity mobility in patients using FMA. An example is the work of W. S. Kim et al. (2016), in which a Kinect sensor was used to capture movement and transmit depth data in addition to infrared images. The study involved 41 patients with hemiplegic stroke, each of them performed 13 exercises from the FMA protocol: shoulder abduction, shoulder lift, external shoulder rotation, elbow flexion, forearm supination, shoulder reduction and internal rotation, elbow extension, forearm pronation, voluntary movement combining dynamic synergy of flexors and extensors and arbitrary movement with little or no dependence on synergy (shoulder abduction from 0° to 90°, shoulder flexion from 90° to 180°). The exercises and the evaluation of their results were carried out under the supervision of a therapist with 2 years of experience. The accuracy of obtaining points (accuracy metric) ranged from 65% to 87%. Movements such as supination of the forearm, bringing the arm to the lumbar spine, shoulder abduction from 0° to 90°, and shoulder flexion from 90° to 180° showed a prediction accuracy of 60% to 70%. The low prediction accuracy is associated with occlusions of body parts during video recording, as well as with the inability to capture the full range of upper-limb movements due to the use of a single Kinect sensor at a predetermined viewing angle. To solve the problem, the authors of the study (Zamin et al., 2023) proposed supplementing the developed system with additional sensors, such as the Leap Motion sensor (Bizyukin, Majkov, 2016), which is designed to digitize finger and hand movements.

Currently, researchers' attention has turned to hardware solutions, the analysis of whose data will allow the reproduction of limb movement trajectories, the accuracy of which is comparable to that of OMC systems. Such solutions include IMU and sensors that register electrical potentials (for example, EMG). The possibility of obtaining accurate limb movement trajectories was evaluated in (Bonfiglio et al., 2024; Hughes et al., 2019, 2022; Li et al., 2017; Robert-Lachaine et al., 2016; Stival et al., 2018; Tran et al., 2022). In this case, the comparison of the obtained trajectories with those from reference methods served as the accuracy criterion. A summary of the results of these studies is presented in Table 1.

Table 1: Results of the study aimed at finding methods for recording the trajectory of limb movements

Source	Sensor type	Sensor position	Recorded movements	Accuracy metric
Hughes et al., 2019, 2022; Tran et al., 2022	IMU	1 wrist sensor	Hand movements	RMSE: from 1.24-2.7 Mean absolute error (MAE): from 1-2.26 R2: 0.734-0.891
Robert-Lachaine et al., 2016	IMU	17 sensors located on all parts of the body	Movement of individual parts of the body	RMSE = 5°
Bonfiglio et al., 2024	IMU	3 sensors on the hand, elbow, shoulder. 1 reference sensor on the chest	Movement of individual parts of the limb	RMSE: 10.26°±8.94°
Stival et al., 2018	IMU+EMG	22 IMU sensors on the hand, 12 EMG sensors on the forearm	Separate and joint movements of the fingers of the hand	Correlation coefficient: 0.7659-0.8634
Li et al. , 2017	IMU+EMG	2 IMU sensors (forearm: at the wrist, shoulder: next to the elbow joint). 8 EMG sensors on the forearm, 2 EMG sensors on the shoulder.	Movement of individual parts of the limb	The Pearson correlation coefficient for IMU with EMG is 0.8780; for EMG 0.6672; for IMU 0.8736

As shown in Table 1, no specific metric is used by teams of authors exploring the use of technologies other than OMC systems to track limb movement trajectories. Thus, M. L. Hughes et al. (2019, 2022; Tran et al., 2022) used a set of metrics that determine the deviation of the obtained trajectory of the hand movement, on which one IMU sensor was fixed, from the trajectory obtained using reference equipment, which was the Vicon motion system, which includes eight optical sensors. The plotting was carried out using calculated trajectories of velocity changes when performing, for example, a finger-nose test. X. Robert-Lachaine et al. (2016) used the Root Mean Square Error (RMSE) metric to compare the movement trajectories of individual body parts obtained during actions performed within a limited space. To obtain a reference trajectory of movement, the OptoTrak Certus OMC system was used. The movement trajectory using the IMU was captured by the Xsens system, covering the entire subject's body. A. Bonfiglio et al. (2024) presented the results of a study, in which OptoTrak Certus was also used to obtain a reference trajectory of movement. The system under study consisted of IMU sensors mounted on the subject's hand, forearm, shoulder, and chest. The RMSE metric was also used to assess differences between data from the reference and studied systems. As can be seen from the Table, the systems used showed fairly good results relative to the reference ones, indicating the possibility of using them to obtain information about the movement of the whole limb or its individual parts. Based on the results described, it can be assumed that improving the accuracy of shaping the trajectories of individual parts or limbs as a whole can be achieved by combining information from IMU sensors with information about the start and end of movements. Thus, F. Stival et al. (2018), in their study, attempted to combine data from IMU and EMG sensors to construct the trajectory of the hand and fingers of the upper limb. For this study, the NinaPro dataset was used, which includes jointly recorded data from two types of sensors when performing the most common movement patterns (Atzori et al., 2012). To construct the trajectories of the hand movement, a regression model was used, with input provided by the coefficients of a discrete wavelet transform (core: Daubechies wavelets). The trajectories were constructed only from EMG sensor data and from the combined use of two sensor types. The results obtained by the team (Stival et al., 2018) were comparable in accuracy to the correlation coefficients for the trajectory presented in the dataset.

Currently, two groups of devices are also used to objectively present the assessment of a patient's limb functional state. Thus, Saed A. Zamin et al. (2023) used video sequences captured with a smartphone camera positioned 3 to 5 meters from the patient to obtain an FMA score. Practitioners also participated in this work and conducted the annotation of the obtained images. To obtain the estimate, 21 joint coordinates detected by a neural network with the YOLO V3 architecture were used. To obtain the score value, a convolutional neural network was used, achieving an accuracy (RMSE metric) of 82.7± 1.6%. Won-Seok Kim et al. (2016) also used an OMC system (a Kinect sensor positioned in front of the patient) in conjunction with their own neural network to register movements and obtain an FMA score. Here, only 13 points of the scale were implemented. The classification task was solved (each point is one class) with a resulting accuracy (accuracy metric) from 65% to 87%, depending on the type of exercise performed. Systems that include one or more types of sensors are also used to conduct research aimed at objectively assessing the functional state of a patient's limb. For example, Jiping Wang et al. (2024), using two IMU sensors located on the patient's shoulder and wrist and their own dataset (FMA exercises), obtained an accuracy (F1-score metric) of 97.3%. Brandon Oubre and Sunghoon Ivan Lee, in their study (Oubre, Lee, 2022, 2023), also showed the possibility of using data from IMU sensors attached to patients' wrists. The recorded data were converted into logarithms of average velocity and displacement, and segmentation was carried out along the axes at the points of intersection with the zero level. The FMA score was calculated using a random forest model (regression, metric R2 = 0.75) and a neural network with two convolutional layers (R2 = 0.72). Yusuke Ueyama et al. (2023) positioned Noraxon Myomotion IMU sensors on the spinal column, shoulder, forearm, and hand of patients. During the work, the authors recorded movements according to 23 FMA exercises. At the same time, despite the stated error of ±0.4°, the accuracy metric of assessing the condition of the upper limb for 16 exercises was 80%, and for the remaining 7, from 64.4% to 75.6%. The authors of (Ueyama et al., 2023) associate such a change in accuracy with movements involving rotation of the forearm and back flexion of the hand, which leads to a significant distortion of the data based on which the assessment is carried out. In this case, compensatory movements such as shoulder reduction/withdrawal, trunk flexion, and extension can also be performed. The results of the review work carried out by Hao Xu and Anbin Xiong (2021) showed that the best way to account for such movements is the joint use of several technologies (IMU, EMG registration, and the use of OMC systems). This approach makes it possible to compensate for the disadvantages of each method.

Summing up the research results, it can be concluded that at the current level of technology development, the task of objectively presenting the assessment of the functional state of the upper limb can be solved using specialized software and hardware complexes. They should be used both inside medical institutions and at home. The need to assess the functional state of patients' limbs at home is supported by results indicating that rehabilitation methods within a medical institution are less effective at improving patients' quality of life outside it (Waddell et al., 2016). At the same time, several authors (Ghorai, 2023; Rozevink, 2023; Rozevink et al., 2021; Sethy et al., 2023, 2024) have shown that training exercises simulating the solution of patients' everyday tasks improve the function of the affected limbs. This suggests that providing patients not only with assistance during training but also with the opportunity to form an objective assessment of their results in a familiar environment will increase the effectiveness of therapy by visually representing positive progress. To implement such software and hardware complexes, technologies are used to track the movement of the affected limb and to record electrical potentials from the surface of its muscles. Both OMC systems and IMU sensors can be used to register movements.

The use of OMC systems provides high accuracy in obtaining estimates (up to 87%); however, their use requires expensive computing equipment and the maintenance of the necessary sensor arrangement. In addition, the conditions for image registration are important, as are occlusions that occur when the patient's limb and body move during exercise. This is especially important when reducing the number or quality of sensors, for example, when using a smartphone camera, as evidenced by the decrease in accuracy reported in (Zamin et al., 2023). Machine learning methods are used to obtain an objective assessment of OMC system use, enabling the detection of key points (joints) and the sequence of their spatial arrangement to assess the quality of the exercises performed. To assign a score on the FMA scale, the classification problem is solved, with classes ranging from 0 to 2 points.

Using IMU sensors allows one to build systems with simple hardware components. To analyze the information recorded by such sensors, both raw data and their derivatives are used (the coefficients of the wavelet transform, the sensor's movement speed, the results of logarithmization (Atzori et al., 2012; Bonfiglio et al., 2024; Hughes et al., 2019, 2022; Li et al., 2017; Oubre, Lee, 2022, 2023; Robert-Lachaine et al., 2016; Rozevink et al., 2021; Sethy et al., 2024; Stival et al., 2018; Tran et al., 2022; Ueyama et al., 2023; Waddell et al., 2016; Wang et al., 2024; Xu, Xiong, 2021), etc.). At the same time, approaches are used that involve both comparing the trajectories of healthy and paretic limbs of patients and using machine learning methods to solve regression or classification problems when obtaining the score for the performed FMA exercise. The need to use machine learning models, as well as in OMC systems, implies the inclusion of high-performance central or graphics processors in the complexes. However, when they are integrated into telemedicine systems or web services, the amount of data transmitted for calculations will be significantly reduced compared with OMC systems. The calculations will be carried out centrally on the server. Besides, when using such systems, the likelihood of occlusions that distort machine learning model results is significantly reduced.

Surface EMG data are used by different authors both to form the trajectory of movement (Stival et al., 2018) and to recognize the types of movements performed by a limb. At the same time, researchers pay special attention to detecting compensatory movements, which can introduce distortions both during operation with OMC systems and with arrays of IMU sensors (Ueyama et al., 2023; Xu, Xiong, 2021). In addition, EMG is used by several authors to assess the degree of patient participation in exercise. For example, in (Osborn et al., 2021; Pareek et al., 2019a, b), when using the MyoTrack development, it was shown that the patient's participation in rehabilitation activities was characterized by higher EMG activity. Differences in prediction or classification accuracy for exercises, as reflected in the final scores, can be explained by differences in the sets of exercises used, as well as by the small sizes of the training and validation datasets for the proposed algorithmic software. In addition, during patient-based testing, data registration is affected by changes in the registration environment and deviations in the patient's action sequence when performing the specified exercises.

CONCLUSION

The results of the studies conducted have shown the feasibility of implementing technology to objectify the assessment of the functional state of the paretic limb in stroke patients during FMA-included exercises. The technology can be implemented in the form factor of a wearable device designed for home use. An array of IMU sensors can be used to record data on limb movement. EMG data can be used to assess the degree of patient involvement in performing exercises and to correct IMU-recorded data during, for example, forearm rotation. The preliminary processing of the received data can be carried out using standard approaches, depending on their initial characteristics. Further analysis should be carried out using machine learning models that address related tasks within the exercise framework: detecting a specific type of movement and determining the score value according to the FMA scale. The training of models should be based on data recorded during a specific exercise, considering all possible variations in its performance, including compensatory movements of the patient's body.

CONTRIBUTION OF THE AUTHORS

D. Zhdanov: definition of the concept, leading the research, first draft of the manuscript.

E. Golobokova: definition of the concept, data analysis, first draft of the manuscript.

Ya. Kosteley: validation, revision and editing of the manuscript.

A. Tonkoshkurova: validation, revision and editing of the manuscript.

N. Miryutova: validation, revision and editing of the manuscript.

All authors have approved the manuscript (the version for publication) and have also agreed to be responsible for all aspects of this work, ensuring proper consideration and resolution of issues related to the accuracy and integrity of any part of it.

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DISCLOSURE OF INTERESTS

The authors declare that there is no conflict of interest.

A STATEMENT OF ORIGINALITY

When conducting the research and creating this work, the authors did not use previously published information (text, illustrations, data).

ACCESS TO DATA

The editorial policy regarding data sharing is not applicable to this work.

GENERATIVE ARTIFICIAL INTELLIGENCE

No generative artificial intelligence technologies were used in the creation of this paper.

PEER REVIEW

This paper has been submitted to the journal on the authors' own initiative.

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