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PHOTOGRAMMETRIC MOTION CAPTURE SUBSYSTEM FOR CHANGE OF BODY POSITION ANALYSIS IN THE FRONTAL AND SAGITTAL PLANES

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ABSTRACT

Context. The increase in other orthopedic injuries, particularly among military personnel, requires new innovative solutions to assess posture changes and monitor rehabilitation effectiveness. Existing systems have limitations in terms of portability, cost, and flexibility of use, which necessitates the development of hybrid systems that combine computer vision and sensory analysis methods..

Objective. To assess the effectiveness of combining non-contact computer vision and accelerometric sensors for detecting changes in human posture under different lighting, background, and movement speeds

Method. The study implemented a photogrammetric subsystem that includes MediaPipe Holistic for markerless tracking of key body points and WitMotion WT9011DCL-BT50 accelerometers for analyzing inertial motion parameters. The system model was built in IDEF0 notation. The accuracy was assessed by comparing the obtained values of the blade inclination angle and the asymmetry coefficient with the specified norms

Results. The combined use of visual and sensory data made it possible to reduce the error to 5.05% under normal conditions and ensure the stability of the results under conditions of changes in the external environment. Image modification (contrast, noise filtering) increased the accuracy of computer vision. Threshold values of the asymmetry coefficient corresponding to normal, mild and severe postural disorders were determined.

Conclusions. The proposed system demonstrates high potential effectiveness in telemedical rehabilitation support for patients with musculoskeletal disorders. Its practical significance lies in the creation of an affordable, portable, and accurate diagnostic and monitoring tool suitable for further integration into personalized medicine systems with built-in artificial intelligence modules.

KEYWORDS: rehabilitative orthopedics, motion capture, computer vision, MediaPipe Holistic, inertial sensors, postural analysis, gait monitoring, telemedicine, accelerometer.

ABBREVIATIONS

AI is artificial intelligence;

CLAHE is a contrast limited adaptive histogram equalization;

CSV is a comma-separated values file;

CP is cerebral palsy;

CT is computed tomography;

IDEF0 is an Integration Definition for Function Modeling;

IMU is an inertial measurement unit;

IPR is an individual rehabilitation plan;

MRI is a magnetic resonance imaging.

SW is a software;

US is an ultrasound.

NOMENCLATURE

θ_i is a sensor orientation in space;

ω_a is a data acquisition frequency of the accelerometers;

ω_b is a frame rate of the video recording;

ω_i is an angular velocity;

a_i is a linear acceleration;

I_i is an input image at time t_i;

K_{asymm} is an asymmetry coefficient;

K_{kyphosys} is a scapula plane tilt angle relative to the vertical axis;

L is a tilt angle for the left side;

P is a set of key body points;

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P_a is a measurement error of the accelerometers;

P_b is an error of the markerless method;

P_{comb} is a combined measurement error;

p_j is a coordinate of the j-th key point;

R is a right side tilt angle;

t_i is a time moment corresponding to image I_i;

Y is a horizontal component of accelerometer position;

Z is a vertical component of the accelerometer position.

INTRODUCTION

Rehabilitation orthopedics is an important area of modern medicine that concerned with the treatment and restoration of musculoskeletal functions in patients who have suffered injuries or have either congenital or acquired orthopedic problems. The primary objective of rehabilitation orthopedics is to help the patient return to a normal lifestyle, reduce mobility restrictions and improve the quality of life [1]. In modern conditions, rehabilitation orthopedics faces challenges related to the accuracy of diagnostics, monitoring the progress of treatment and ensuring patient safety during therapy. One of the promising areas that can contribute to problem-solving is the implementation of computer vision systems and other machine learning methods [2].

As a result of computer vision techniques application in the practice of rehabilitation orthopedics, it becomes possible to ensure accurate monitoring of patient movements, analysis of their biomechanics and real-time feedback provision, which is important for rehabilitation processes [3]. In addition, the use of computer vision technologies can partially eliminate the physical presence of the orthopedic doctor, providing separate monitoring of the recovery process and supporting feedback to achieve optimal results in the recovery of patients [4].

Rehabilitation orthopedics is aimed at solving a wide range of musculoskeletal disorders (Table 1), each of which requirdfgdfes an individual approach and the use of different methods to achieve optimal results.

Table 1 – Key conditions addressed by rehabilitation orthopedics

Injury class	Injury example	Rehabilitation direction
1	2	3
Injuries to bones and joints	fractures, dislocations and sprains.	strengthening the muscles that support the joint.
Degenerative joint diseases	– osteoarthritis (arthrosis)$ – osteoporosis.	– improving mobility and muscle strength around the affected joint, physiotherapy, and reducing the load on the joint; – improving balance and coordination to reduce the risk of falls and injuries.
Spinal injuries and posture disorders.	– damage to the intervertebral discs (herniation, disc protrusion); – scoliosis, kyphosis, lordosis	– reduction of pain syndrome, restoring mobility and strengthening back muscles; – posture correction, strengthening the corset muscle and improving coordination.
Limb amputations	– rehabilitation after amputation; – complications prevention; – contracture.	– physical therapy and psychological support; – maintenance of joint mobility and limb functionality
Muscle and tendon injuries and diseases	– muscle tears and tendon injuries; – tendonitis and bursitis.	– restoring muscle strength, flexibility and endurance, which reduces the risk of reinjury; – stretching and strengthening of the affected areas exercises, as well as physiotherapy procedures.
Post-surgery rehabilitation	– rehabilitation after arthroplasty; – rehabilitation after osteosynthesis.	– restore limb functions, adapt to new movement conditions and return to an active life; – preserve the mobility of the surgical site and strengthen the surrounding muscles.
Neurological conditions with impaired musculoskeletal function	– strokes and paralysis – CP (cerebral palsy)	– coordination training, restoring balance and mobility, strengthening muscles and learning new movement skills; – rehabilitation of children with cerebral palsy includes special exercises to improve movement control and motility development.

Sadly, there is a need for affordable and effective rehabilitation tools in Ukraine, especially for combat veterans and people who have been injured as a result of military conflicts or accidents [5]. Computer vision systems allow for remote patient monitoring, which is important in conditions where many people do not have access to specialized rehabilitation centers. Therefore, the development and implementation of such technologies is not only relevant but also the most demanded task for the medical industry of Ukraine.

Thus, research in the field of computer vision for rehabilitation orthopedics is an extremely relevant and promising direction, especially for Ukraine [6–8]. The implementation of such systems can significantly improve the quality of rehabilitation, reduce the workload on doctors and facilitate the recovery process for patients.

The idea of developing medical care technology that can be applied at the rehabilitation stage of military personnel and civilians who received surgical pathologies because of military actions in our country is justified by the unfortunate statistics that show that the number of orthoprosthetic patients and those in need of prosthetics and further physical rehabilitation has increased significantly recently (as of June 2023, 58,852 people applied for rehabilitation aids, of which 20,737 people received prosthetics).

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Blast injuries, shrapnel and gunshot wounds are causes of surgical pathologies, which include pathologies of joints and bones that require surgical intervention (for example, joint endoprosthetics, orthoprosthetics of affected limbs) in order to restore the function of the affected limb and return the person to motor activity, improve the quality of life, psycho-emotional state, and become more independent in everyday life [9, 10].

A mandatory stage after such operations is rehabilitation and adaptation to the new “limb.” Rehabilitation is a long, continuous, multi-stage process [11].

A common rehabilitation algorithm is:

– initial examination and assessment of the condition, review of medical history;

– agreeing on the treatment strategy, prognosis and client expectations;

– composition and implementation of an individual rehabilitation plan (IRP);

– results monitoring and the IPR adjustments if necessary;

– after achieving maximum results – support and guidance during the post-rehabilitation period, which involves psychological and physical adaptation, and the patient’s return to a normal and quality life.

Despite the advantages, existing solutions still have such disadvantages as high cost, complexity in installation and use, focus on clinical settings, and limited data integration, which confirms the relevance and necessity of developing portable systems available for independent use, using the principles of telemedicine to monitor the rehabilitation process.

The aim of the work is to investigate the effectiveness of using a computer vision system in combination with electronic sensors in a photogrammetric motion capture subsystem for analyzing changes in body position relative to the frontal and sagittal planes in real time.

To achieve the objective, **the following tasks** must be solved:

– develop a prototype of a system that can track and analyze patient movements;

– to evaluate the effectiveness of using computer vision methods under different environmental conditions to determine the condition of joints during walking;

– to evaluate the effectiveness of using electronic sensors to determine the condition of joints during walking;

– develop a combined method for monitoring the position of the patient’s joints during gait.

1 PROBLEM STATEMENT

Considered the problem of determining deviations in the position of a human body relative to the frontal and sagittal planes during movement or in statics based on a combination of computer vision data and inertial sensors.

Let $I = \{I_1, I_2, ...I_n\}$ be an ordered set of input images, where each image I_i contains an image of the patient in motion or in a static pose. For each image, using computer vision algorithms, a set of coordinates of key body points $P_i = \{p_1, p_2, ...p_k\}$ is determined, where $p_j = (x_j, y_j) \in R^2$ is the projection of an anatomically significant point onto the image plane.

In parallel to each time point t_i corresponding to I_i, a vector of inertial sensor readings $S_i = (a_i, \omega_i, \theta_i)$, where $a_i \in R^3$ is the linear acceleration, $\omega_i \in R^3$ is the angular velocity, $\theta_i \in R^3$ is the sensor orientation in space, is received. Let $K_{\text{kyphosys}} \in R^3$ be the calculated angle of inclination of the scapula plane to the vertical axis in frame i, determined using the key points of the shoulder joints and the vertical vector. When $K_{\text{kyphosys}} \in [15^0, 30^0]$, the patient is considered to be in a normal state; exceeding this range is interpreted as the degree of kyphosis.

The asymmetry coefficient K_{asymm} is determined, which characterizes the deviation of the symmetry of the location of the joints of the upper or lower extremities at time t_i, as a function of the Euclidean distance between paired points, normalized to the anatomical width of the shoulders or pelvis. With values of $K_{\text{asymm}} < 5\%$, symmetry is considered normal; for $5\% \le K_{\text{asymm}} < 15\%$, a mild form of scoliosis is recorded; and with $K_{\text{asymm}} \ge 15\%$ – pronounced asymmetry requires clinical intervention. To increase the accuracy of determining the deviation of the body position from the norm, the work proposes a combination of the two aforementioned approaches – optical and based on inertial sensors, which involves the use of a weighted combination of errors of both sources of information P_{comb}.

Thus, the input variables of the problem are the coordinates of key points of the body obtained using a computer vision algorithm; acceleration and orientation vectors from inertial sensors (accelerometers); environmental parameters: lighting level, background type, speed of movement.

The output variables are the numerical values of body position deviations, which are determined by the angular inclination of the shoulder blades relative to the vertical axis – K_{kyphosys} and the asymmetry coefficient (degree of scoliosis) – K_{asymm} based on accelerometers and the error in detecting deviations of the musculoskeletal system from the norm based on the optical marker-free method and the combined method of monitoring the position of the patient’s joints during gait.

The problem has such limitations as fixed resolution and frame rate, a limited number of accelerometers, the presence of interference in the images, such as a change in lighting, the presence of a noisy background, and uneven gait.

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2 REVIEW OF THE LITERATURE

Today, there are several approaches of using innovative technologies and artificial intelligence methods in rehabilitation orthopedics in the world. Among the most common are:

– camera-based systems – this approach involves using cameras to read the patient's movements. Specialized software analyses the video and determines the movement parameters. Well-known examples are technologies using Microsoft Kinect cameras or motion capture systems, which are often used in sports rehabilitation [12, 13];

– sensor and accelerometer systems – this approach involves the use of special sensors that are attached to the patient's body and track his movements. This method is less sensitive to external interference, but requires specialized equipment [14];

– integrated systems using artificial intelligence (AI) – such systems use machine learning algorithms to analyze and predict patient movements, allowing for an individual rehabilitation approach. AI can quickly process large amounts of data and draw conclusions that contribute to improving the quality of therapy [15];

– rehabilitation simulators with feedback systems – in some cases, special simulators with built-in cameras or sensors are used, which provide feedback to the patient about the exercise's accuracy. This allows the patient's movements to be corrected in real-time [16].

Each of these approaches has its advantages and disadvantages, but they all aim to improve the rehabilitation process, increase diagnostic accuracy, and create individual programs for each patient (Table 2).

Table 2 – Table describing the advantages and disadvantages of the methods

Method	Advantages	Disadvantages
Optical methods	High accuracy in marker systems, contactless data collection in markerless	Dependence on lighting, space limitations
Inertial Measurement Unit (IMU)	Compact, independent of lighting, effective in large spaces	Error accumulates over time, especially with long-term tracking
Magnetic methods.	Visibility-independent, suitable for indoor environments	The occurrence of obstacles in the environment
Ultrasonic methods	High accuracy in small spaces, no need for cameras	Dependence on acoustic conditions, limitations in large rooms
Mechanical methods	Precision joint tracking, suitable for medical and industrial applications	Uncomfortable for prolonged use, restrict natural movements

Among optical methods, marker and markerless methods can be distinguished. Marker optical methods use reflective or active markers placed on the body of the object. Cameras record the position of the markers and transmit this data for further processing. Markerless optical methods use computer vision algorithms to recognize characteristic points on the body without markers, in particular in three-dimensional space, which is more convenient and does not depend on markers. They are used in rehabilitation, virtual reality and sports.

The combination of inertial sensors and optical methods provides a visual analysis of motor activity and biomechanics of movements. It helps determine acceleration, angular displacements and limb positions, transferring them to a computer to build an accurate movement model. This allows the system to be used both indoors and outdoors without restrictions. The advantages are independence from special lighting and premises, the possibility of real-time use in open spaces, and support for accurate capture of even complex body movements. The disadvantages are higher cost than in conventional systems based on optical methods alone.

Such systems can significantly facilitate the work of medical professionals, increasing the accuracy of diagnostic and rehabilitation procedures, as well as reducing the time and cost of treating patients.

The combination of various analysis and monitoring of gait and posture methods in a single system allows for the work's high diagnostic and prognostic value.

3 MATERIALS AND METHODS

To ensure a clear understanding of the research process, it is necessary to describe the model at a basic and detailed level, which will allow you to structure and divide the entire process into different stages for more detailed analysis. Describing the model in IDEF0 notation will help describe the resulting process in the form of a "black box" and a detailed sequence of sub-processes.
Consider the top level of the photogrammetric motion capture subsystem model for analyzing changes in body position relative to the frontal and sagittal planes (Fig. 1). This model takes into consideration aspects of input data, constraints and controlling influences, performers or participants, and output data.

The input data are video recordings of patients' body movements and accelerometer data on the patient's body during movement. The controlling influences and constraints are the evaluation rules for determining deviations from the norm and the external conditions of the experiment (lighting, background, patient's movement speed). The performer or participant of the process is the patient, and the output data or result is the patient receiving recommendations for correcting the deviation of one's musculoskeletal system. By decomposing the base-level model, we can obtain a detailed model level (Fig. 2), in which we can see that the primary process has been divided into four sub-processes, which will be elaborated in more detail.

The decomposed model of the photogrammetric motion capture subsystem for analyzing changes in body position relative to the frontal and sagittal planes includes the following modules:

– video processing module using MediaPipe Holistics, for which the patient is a participant, the controlling influences and constraints are external conditions (light-

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ing, background, walking speed) and numerical values for determining deviations between key points, the output data is the processed video recording with detected deviations or their absence.

– module for processing data from accelerometers, where the patient is a participant, the controlling influences and limitations are external conditions (gait speed and location of accelerometers) and numerical values for measuring deviations from the norm due to the difference in acceleration indicators from accelerometers, the initial data is a sample of data from the movement of points on the patient's body during movement with a conclusion as to whether there are deviations or not;

– the combined data analysis module uses processed video and accelerometer data to improve the accuracy of patient-participated experiment data; the governing influences and limitations are numerical values for the combined data comparison to detect abnormalities, the output is the final conclusion, whether the patient has musculoskeletal abnormalities;

– module for recommendations provision based on the obtained conclusion of the detected deviations from the patient's norm, if any were detected, the initial data is an expert conclusion with recommendations for further actions, which is built based on the obtained results of automatic analysis and expert analysis by a doctor.

It is important to note that within the framework of the study of the motion capture subsystem for analyzing changes in body position, only a specialist can provide an expert opinion and further recommendations. Therefore, the main goal will be to describe and investigate the first three subprocesses of the model.

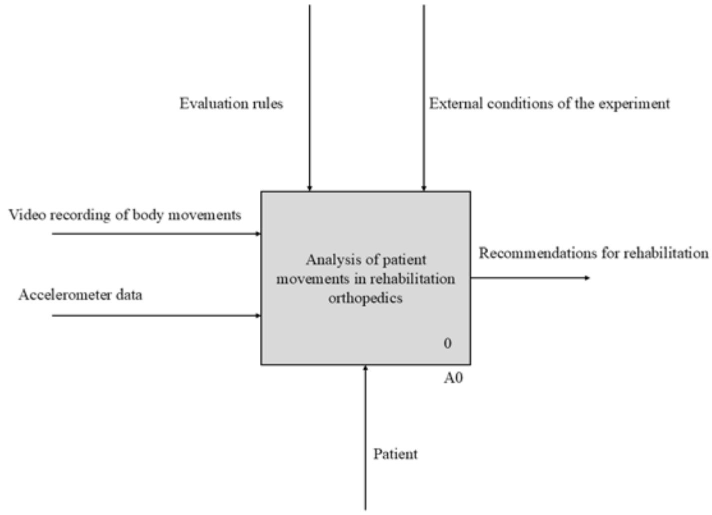

Figure 1 – Model of a photogrammetric motion capture subsystem for analyzing changes in body position relative to the frontal and sagittal planes. Top-Level (A-0)

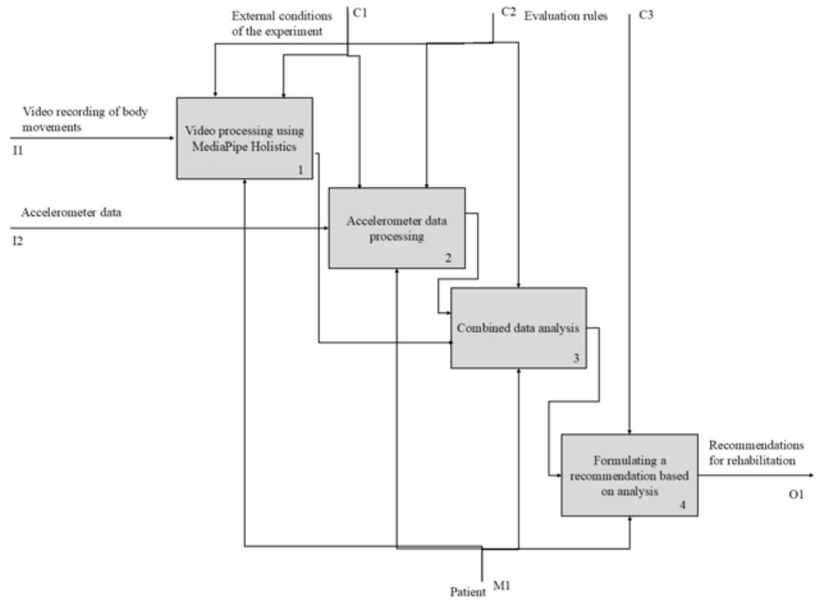

Figure 2 – Decomposition of the photogrammetric motion capture subsystem model for analyzing changes in body position relative to the frontal and sagittal planes (A-1)

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To detect deviations from the norm of the human musculoskeletal system using computer vision methods and accelerometers, it is necessary to determine key indicators by which deviations from a healthy state can be distinguished. As key indicators, you can use:

– displacement of the body's center of mass from the vertical (determined based on key points of the body and allows assessing the patient's stability during movement);

– the angle of inclination of the body, shoulder blades and hip joints (evaluating the angle of inclination relative to the horizontal for each group of joints allows you to identify asymmetries and incorrect posture);

– symmetry and smoothness of limb movements (measured by comparing the amplitudes of movements of the right and left limbs, determined by analyzing the trajectories of movement of key points).

When working with computer vision methods, external conditions are important factors that can affect the accuracy of assessing a person's musculoskeletal system. The study focused on the following external factors to determine their impact on assessing the state of the musculoskeletal system: lighting, background type, and walking speed.

The hypothesis of the study is that the combination of MediaPipe Holistics and accelerometers will help to achieve greater accuracy and reliability of the analysis, but for the correct interpretation of the data, the results need to be synchronized. Depending on whether the recording is real-time or previously prepared and data sampling from the accelerometers, a synchronization tool is needed that will work in both cases. A unified timestamp system can be used to reconcile the data both pre-recorded and when working in real time.

The general algorithm for determining deviations from the norm of the human musculoskeletal system can be depicted in the form of a flowchart (Fig. 3).

The studied methods for determining the degree of deviation of the body position from the norm of the human musculoskeletal system relative to the frontal and sagittal planes are:

– using a markerless method of motion analysis by means of computer vision;

– using accelerometers to monitor acceleration and body tilt during movement;

– the combination of the markerless method and the use of accelerometers to analyze changes in accuracy rates.

As part of the research on the markerless method, the main attention was focused on the accuracy of detecting deviations from the norm and the time of data processing under different environmental conditions. The patient's movements were analyzed to detect kyphosis or scoliosis; for each deviation, separate groups of experiments were conducted with different input environmental conditions.

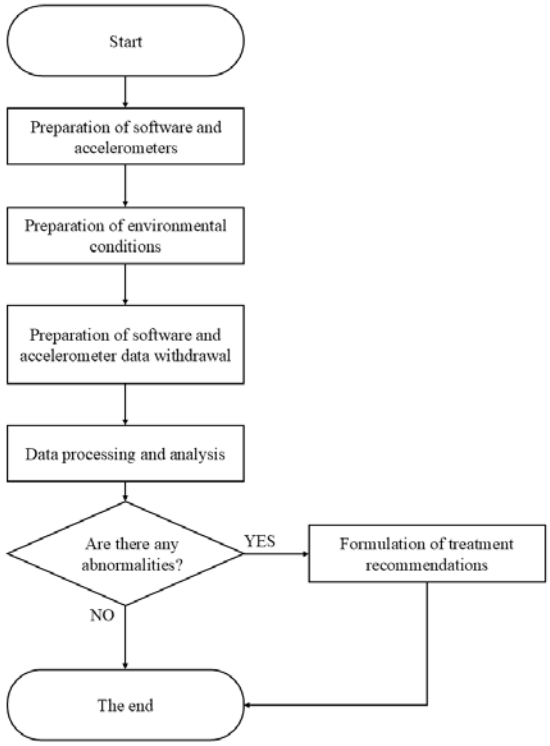

Figure 3 – Flowchart of the algorithm for determining musculoskeletal abnormalities

To determine the presence of kyphosis, it is necessary to find the angle of inclination of the shoulder blades (scapulas) relative to the vertical axis using the formula (1):

$$K_{\text{kyphosys}} = \arctan\left(\frac{Z}{Y}\right). \quad (1)$$

The normal angle of inclination is from 15 to 30 degrees; if the angle of inclination is greater, then different degrees of kyphosis are diagnosed.

The same accelerometer data will be used to conduct experiments to detect scoliosis, namely angle data that can be used to determine the degree of scoliosis or the asymmetry coefficient (2):

$$K_{\text{asymm}} = \frac{L-R}{\frac{L+R}{2}} \times 100\% . \quad (2)$$

For the joint use of the markerless method and accelerometers, it is necessary to synchronize the received data, which can be done using time information. The data set obtained from the accelerometers also contains data on the time of fixation of the indicators of each accelerometer, respectively, it is possible to bind to a specific frame of the shooting from this time data. Now you can calculate the error when using the combined analysis using the markerless method and the accelerometer (3):

$$P_{\text{comb}} = \frac{\omega_a \times P_a + \omega_b \times P_b}{\omega_a + \omega_b}. \quad (3)$$

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4 EXPERIMENTS

The work considers good and dim lighting:

– good lightning is from 300 lux or 300 lumens per m^2;

– dim lighting is up to 100 lux or 100 lumens per m^2.

The background is compared for uniformity:

– a solid background is an ideal condition for working with computer vision methods;

– a noisy background or a multi-colored background with high contrast can create interference when identifying key points of the body.

Walking speed – a variable condition that can affect the result in different ways, the following approximate indicators were chosen:

– slow, up to 50 steps per minute;

– fast, from 100 steps per minute.

It is also important to define metrics for evaluating the success and efficiency of the program, which will help to weigh in on the correct decisions for software implementation and successful conditions:

– error in detecting inclination angles relative to detected key points of the body;

– delay of data processing of one frame in milliseconds.

Using the selected indicators, you can not only qualitatively present the results, but also justify improvements to the program or process of identifying deviations from the norm of the human musculoskeletal system.

The research tool is a developed software application created using the Python programming language and the MediaPipe library for markerless movement analysis based on the identification of key points of the body and the WitMotion WT9011DCL-BT50 accelerometer (Fig. 4) together with software from manufacturers for collecting inertial data (Fig. 5).

The study used the MediaPipe Holistic model, which allows tracking key points of the body, hands, and face in real time.

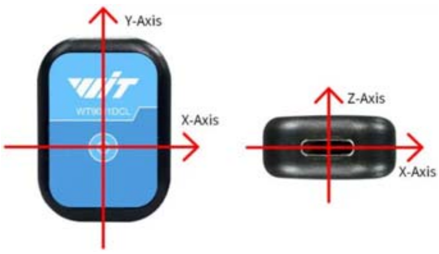

Figure 4 – WitMotion WT9011DCL-BT50 sensors

Figure 5 – Software from WitMotion

Accelerometers are attached to the patient's shoulder blades to monitor movements, and then WitMotion software is used for initial data recording in the form of a CSV file. The final stage is the analysis of the obtained data in a developed Python program.

The first stage is the preparation of software and configuration of equipment (camera, accelerometers) for data collection. Before the start of the experiments, the system was tested for the correctness of determining key points (Fig. 6) and the accelerometers were calibrated to obtain correct data (Fig. 5).

Figure 6 – Correctness of key point recognition test using MediaPipe Holistics

External conditions were adjusted to assess the accuracy of the methods in different scenarios:

– two lighting modes are organized: natural daylight and artificial light of varying intensity;

– a solid background is provided using a canvas and a noisy background with furniture, decorative elements and moving objects;

– speed measurement was performed using a metronome and stopwatch for patients' stable pace compliance.

To detect kyphosis in a patient, he needs to move from side to side with a normal gait so that the back is visible from the side (Fig. 7a, Fig. 7b). The results of the developed program for detecting kyphosis are presented in Figure 8a.

The results of this experiment indicate that poor lighting conditions do indeed negatively affect the accuracy of detecting musculoskeletal abnormalities.

Also, the results of studies on the detection of kyphosis based on optical markerless methods showed a large error in poor lighting and noisy background. With increasing patient movement speed, the error decreased but was too large to provide an accurate result. It is also worth noting that poor environmental conditions increase the time for processing one video frame, from which we can conclude that for a satisfactory analysis result and program speed, it is recommended to create conditions that will not interfere with data processing and reduce the overall error when detecting deviations from the norm.

For the scoliosis detection experiments, the input data did not change except for the patient's direction of movement; to detect scoliosis, the patient needs to move towards or away from the camera so that the back is in full view. The results of the developed scoliosis detection program (Fig. 7b) are presented in Figure 8a.

Good lighting and a solid background have the greatest impact on reducing the error in determining the deviation, which can be seen in Figures 8a and 8b.

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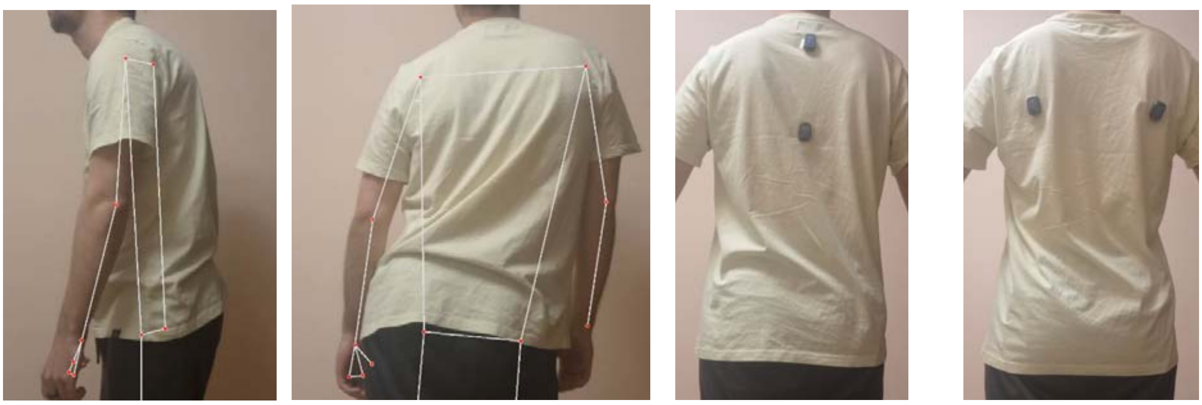
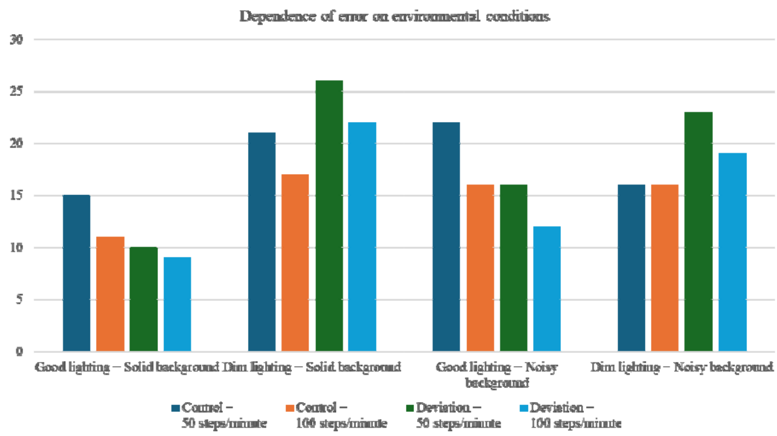
The results of studies using markerless methods have shown the ease of use and speed of analysis, but poor lighting and a non-uniform background with the presence of objects in the final frame increase the processing time of each frame and error in determining the presence of deviations from the norm in the patient. To reduce the error, it is necessary to improve image processing methods and/or use the markerless method together with others.

In the study of detecting musculoskeletal abnormalities using accelerometers, there are two parameters that affect the accuracy of identifying the degree of joint abnormalities: the placement of the accelerometers on the body and the patient's walking speed. The accelerometers will be placed at the beginning and middle of the thoracic vertebrae to detect kyphosis (Fig.7c), and symmetrically on each scapula to detect scoliosis (Fig. 7d).



a b c d

Figure 7 – Joint position and additional sensors to determine kyphosis and scoliosis:
a – the position of the back in which kyphosis is determined based on the optical markerless method, b – the position of the back in which scoliosis is detected based on the optical markerless method, c – placement of accelerometers to determine kyphosis, d – placement of accelerometers to determine scoliosis



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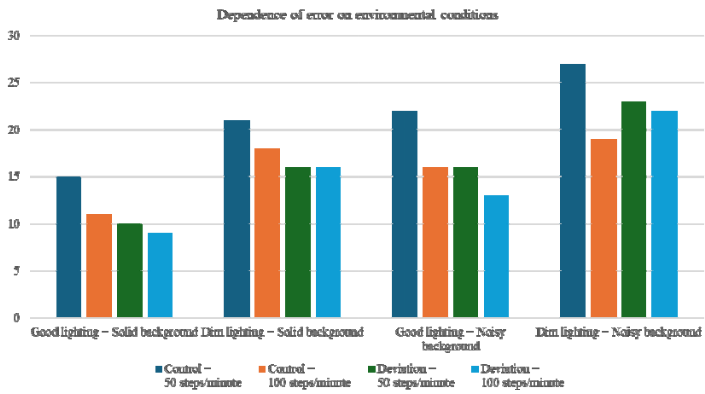

b

Figure 8 – Dependence graphs of the accuracy of determining the body position deviation on external conditions: a – dependence graph of the error in determining kyphosis on external conditions; b – dependence graph of the error in determining scoliosis on external conditions

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The results of processing data from accelerometers for determining kyphosis are given in Table 3.

Table 3 – Results of using accelerometers to detect kyphosis

	Angle of inclination	
	Walking speed up to 50 steps per minute	Walking speed up to 100 steps per minute
Control experiment (normal body position)	20º	30º
Experiment with deflection (with a case with a tilt)	41º	54º

The results of studies on detecting kyphosis using accelerometers show high accuracy rates in identifying the presence or absence of deviations in patients, as well as the dependence of the increase in the angle of inclination on the patient's movement speed, which must be considered when analyzing the data.

The results of processing data from accelerometers for determining scoliosis are given in Table 4.

Table 4 – Results of using accelerometers to detect scoliosis

	Asymmetry coefficient	
	Walking speed up to 50 steps per minute	Walking speed up to 100 steps per minute
Control experiment (normal body position)	1.5%	3%
Deflection experiment (with a tilted body)	8.2%	13.5%

From the presented results of studies on the detection of scoliosis, it is clear that the use of accelerometers determines with high accuracy whether a deviation is present or not. As in the experiments on the detection of kyphosis, the dependence of the resulting data on the speed of the patient's movement is visible, therefore, in future analysis, it is also necessary to take into account the increase in the asymmetry coefficient due to the speed of the patient's movement.

The use of accelerometers has shown that their use provides sufficiently accurate data with little dependence on environmental conditions, but to obtain such an analysis requires a number of conditions, namely: the presence of at least a pair of accelerometers, their precise installation at the specified points of the patient's body, preliminary data collection without the possibility of obtaining the result immediately. Despite the disadvantages of using accelerometers, the high accuracy of the obtained analysis allows it to be used not only as an independent method for detecting deviations of the musculoskeletal system in a patient, but also to increase the accuracy of the results of visual methods of data acquisition and analysis.

5 RESULTS

The results of the proposed combined method of monitoring the position of the patient`s joint during gait are presented in this section. As the research results showed (Fig. 8, Table 3, Table 4), each of the methods has its strengths and weaknesses, but the key features are fast processing in the markerless method and high accuracy in accelerometers, regardless of conditions such as lighting intensity and monotony of the video background. If these two methods are combined, this will ensure increased accuracy of measurement and analysis and resistance to external factors. But when used together, the final analysis can be obtained only after processing data from the video recording and accelerometers, which means the impossibility of obtaining a result in real time.

Returning to the results of the markerless method, we can see that the smallest error that was achieved was 9% (Fig. 8). Since the MediaPipe framework works with color images, in addition to improving the shooting conditions, you can use the methods of contrast enhancement (CLAHE) and noise filtering (Gaussian Blur). To check how much these modifications will improve the accuracy of the analysis, we will conduct an experiment in the best lighting conditions, a monochromatic background, at a patient speed of up to 100 steps per minute, the results of kyphosis detection are given in Table 5.

Table 5 – Results of using a modified markerless method for detecting kyphosis

	Processing time of one frame, ms	Number of correctly identified frames	Error
Control experiment	48	141	6%
Deflection experiment	48	142	6%

The results of experiments on determining scoliosis using the modified program are given in Table 6.

Table 6 – Results of using a modified markerless method for detecting scoliosis

	Processing time of one frame, ms	Number of correctly identified frames	Error
Control experiment	48	142	6%
Deflection experiment	48	140	6%

From the results of the experiments, the error in determining musculoskeletal abnormalities when using marker-free methods has decreased to 6%, which is a significant improvement from the previous best result.

Video recording was conducted at a frequency of 30 frames per second, data collection by accelerometers occurred on average every 140 milliseconds (7 samples per second). Accelerometers cannot work with 100% accuracy, so assuming that their error will be 1%, we can calculate the total error (4):

$$P_{\text{comb}} = \frac{7\times 1 + 30\times 6}{7+30} \approx 5.05\%. \qquad (4)$$

Thus, combining the use of a marker-free method and accelerometers allowed us to reduce the error in detecting deviations of the musculoskeletal system from the norm to 5%, increasing resistance to external factors.

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6 DISCUSSION

Thus, the combined approach demonstrates high efficiency for the analysis of movements in rehabilitation orthopedics, which allows for expanding the possibilities for both diagnostics and monitoring of the treatment process of patients. The results of the experiments confirm the feasibility of its further improvement and implementation in practice. However, the markerless method of analysis and the use of accelerometers may have a reasonable separate use due to their advantages (Table 7).

Table 7 – Substantiation of the effectiveness of combined processing of data on the condition of patients' joints

Method	Advantages	Disadvantages	Recommended usage
Markerless method	Does not require special equipment; Analysis speed; Minimal implementation costs.	High dependence on lighting and background.	For initial analysis in good lighting conditions.
Using accelerometers	High measurement accuracy; Independence from lighting and background.	Does not work in real time; Difficult to install and calibrate.	For monitoring movements in difficult conditions (poor lighting, noisy background).
Combined method	High measurement accuracy; High resistance to external factors. Comprehensive analysis of movements.	Does not work in real time; Difficulty in data synchronization.	For precise analysis of complex cases and creation of individual programs.

Re-examining the advantages and disadvantages of the methods for analyzing musculoskeletal abnormalities has allowed us to determine the conditions under which each of them can be used. The combined use of methods is most effective for rehabilitation orthopedics, which opens up opportunities for the development of complex systems for analyzing movements that can provide high diagnostic accuracy, adaptation to individual patient needs, and the possibility of remote monitoring. Further research can be aimed at implementing machine learning algorithms to automate the analysis and adapt the systems to work in real time.

CONCLUSIONS

The scientific novelty of the proposed study lies in the development of a hybrid method for real-time postural analysis using a combination of markerless computer vision (MediaPipe Holistic) and inertial accelerometric data. Within the framework of this work, a combined method for monitoring the position of the patient's joints during gait has been proposed, which includes error correction based on a weighted combination of optical and sensor-based approaches. For the first time, a formal definition of postural deviation metrics has been introduced, enabling the classification of symmetry states, including mild and pronounced scoliosis, based on an asymmetry coefficient.

The practical significance of the work consists in the creation of an affordable, portable, and customizable tool for remote rehabilitation diagnostics that can be used outside clinical settings. The system supports individualized monitoring of patients with musculoskeletal disorders, improves the accuracy of motion analysis, and enhances the quality of feedback for physiotherapists and healthcare professionals. It ensures accurate detection of postural disorders under varying external conditions, which is critically important for scalable telemedicine applications.

Prospects for further research include the implementation of machine learning algorithms for automatic classification and the generation of adaptive rehabilitation recommendations. Future system improvements will focus on real-time synchronization, integration with electromyographic sensors, and the personalization of recovery strategies based on long-term monitoring. Additionally, the expansion of functionality is planned through artificial intelligence modules for predictive analysis and anomaly detection in gait patterns.

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ФОТОГРАММЕТРИЧНА ПІДСИСТЕМА ЗАХОПЛЕННЯ РУХУ ДЛЯ АНАЛІЗУ ЗМІН ПОЛОЖЕННЯ ТІЛА ВІДНОСНО ФРОНТАЛЬНОЇ ТА САГІТАЛЬНОЇ ПЛОЩИН

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АНОТАЦІЯ

Актуальність. Зростання кількості ортопедичних травм, зокрема серед військовослужбовців, потребує нових інноваційних рішень для оцінки змін постави та моніторингу ефективності реабілітації. Існуючі системи мають обмеження щодо портативності, вартості та гнучкості у використанні, що зумовлює потребу в розробці гібридних систем, які поєднують методи комп’ютерного зору та сенсорного аналізу.

Мета роботи – оцінити ефективність поєднання безконтактного комп’ютерного зору та акселерометричних сенсорів для виявлення змін постави людини в умовах різного освітлення, фону та швидкості руху.

Метод. У дослідженні реалізовано фотограмметричну підсистему, що включає MediaPipe Holistic для безмаркерного відстеження ключових точок тіла та акселерометри WitMotion WT9011DCL-BT50 для аналізу інерційних параметрів руху. Модель системи побудовано у нотації IDEF0. Оцінку точності виконано шляхом порівняння отриманих значень кута нахилу лопаток та коефіцієнта асиметрії із заданими нормами.

Результати. Комбіноване використання візуальних і сенсорних даних дало змогу зменшити похибку до 5,05% при нормальних умовах та забезпечити стабільність результатів за умов змін зовнішнього середовища. Модифікація зображень (контраст, фільтрація шуму) підвищила точність комп’ютерного зору. Визначено порогові значення коефіцієнта асиметрії, що відповідають нормі, легким та важким порушенням постави.

Висновки. Запропонована система демонструє високу потенційну ефективність у телемедичному супроводі реабілітації пацієнтів із порушеннями опорно-рухового апарату. Її практична значущість полягає у створенні доступного, портативного та точного засобу діагностики та контролю, придатного до подальшої інтеграції у системи персоналізованої медицини з вбудованими модулями штучного інтелекту.

КЛЮЧОВІ СЛОВА: реабілітаційна ортопедія, захоплення руху, комп’ютерний зір, MediaPipe Holistic, інерційні сенсори, аналіз постави, моніторинг ходи, телемедицина, акселерометр.

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