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The method of automated filling of the database with descriptions of human physical exercises

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ABSTRACT

Presently, human-computer interaction employs infrared cameras equipped with motion tracking capabilities, facilitating the automatic generation of spatial descriptions for multiple human joints. The use of such cameras allows for the creation of active computer games, where the player can control the game process by performing physical exercises or specific gestures. The study examined support systems for computer games with physical exercises and identified the lack of an ability to modify the description of physical exercises in a separate database. The authors created a prototype for a computer game that incorporates physical exercises, storing them in the database as a series of gestures. However, the experiments revealed several drawbacks: the requirement for a specialist to independently populate the database with physical exercise descriptions, the potential for errors in the analysis of physical exercises, and the labor-intensive process of database filling. Therefore, the goal of this work was to reduce the time required to populate the database for identifying human physical exercises based on the spatial description of multiple joints formed by the infrared camera. To achieve this goal, the authors proposed the creation of a visual constructor for physical exercises and a method for automating the database's recognition of physical exercises. The practical significance of the work is as follows, the authors developed software, that includes the following steps: saving the states of joint positions over a specified period, processing the obtained joint state data from the spatial description, determining the logical relationships between the joints (greater, less, or equal), removing duplicate descriptions, identifying errors by the specialist using the visual constructor for physical exercises, and populating the database. The article examined the labor intensity of manually populating the database and the proposed method using physical exercises containing three, five, seven, and ten gestures. The results of the analysis showed a reduction in the labor intensity of populating the database using the proposed method by two point six to three point six times, depending on the complexity and specifics of the physical exercise. All experiments in the work were conducted using the Microsoft Kinect 2, which has been discontinued, but this does not affect the relevance of the work, as Microsoft encourages developers to continue using the existing Kinect Developer Kit programming environment for the Femto Bolt and Femto Mega infrared cameras from Orbex.

Keywords: Computer game; infrared camera; pattern recognition; database, spatial description of human joints; physical exercise

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INTRODUCTION, FORMULATION OF THE PROBLEM

Video games are becoming an integral part of occupational therapy in emergency care and rehabilitation [1]. The design of computer games in rehabilitation is based on a list of fundamental principles, such as reward, goals, challenge, and "meaningful play". "Meaningful play" arises from the relationship between the player's action and the system's result, which is evident to the player through visual, physical, and audio feedback [2].

Patients feel more involved in the gaming environment and less isolated in the doctor's office when interacting in virtual reality [3].

In medical centers, patients are offered rehabilitation exercises using computer games, for example, the following hardware and software systems: DoctorKinetic, Jintronix, VAST, Rehab, Evolv, SaeboVR, ReviMotion, Mirarehab. All systems utilize an infrared camera as a motion sensor, providing computer games with exercise-specific scenarios. However, these systems do not allow for changing game scenarios, nor do they allow for changing the list of movements by which the patient will control the game's characters.

ExerGame technologies ("exercise" + "game" = a game with physical exercise) utilize hardware and software to facilitate interaction between a person and a computer [4, 5]. These technologies recognize natural human movements, such as the head, upper, and lower limbs of the body, and allow you to control virtual world events based on these movements. This allows you to combine ordinary physical exercises or special sports exercises with computer game development. ExerGame technologies can utilize non-contact motion control sensors. For instance, the Microsoft Xbox 360/One gaming console includes an infrared camera known as MS Kinect, while the Nintendo gaming console features an infrared camera in the Wii system [6]. The following games were included in the Kinect Sport series of sports games: tennis, table tennis, golf, skiing, baseball, soccer, basketball, boxing, track and field (sprint, javelin, discus, long jump, and hurdles). However, a fixed set of scripts and predefined human movements for controlling the game character limit these games, making expansion difficult without professional programmers' assistance.

Most hardware and software systems provide only a fixed list of computer games without the possibility of adapting them to scenario preferences or physical limitations of users, which determines the relevance of further research in this direction.

1. LITERATURE REVIEW

The principles of operation for software and hardware solutions that track human movements are based on infrared cameras.

Fig. 1 illustrates examples of such infrared cameras for monitoring human movements.

Fig. 1. **Infrared cameras monitoring human movements**
***Source:* compiled by the authors**

The article [7] evaluates the accuracy of three popular cameras, MS Azure Kinect, MS Kinect 2.0, and Orbbec Astra, for tracking kinematic gait patterns while walking on a treadmill under five camera viewing angles. The article [15] presents an overview of MS Kinect 2.0 camera applications for human gesture control to further evaluate individual feature extraction and gesture recognition methods, recommendations for camera distance, and signal delay.

Fig. 2 shows the main stages of data transformation for creating a model of the skeleton of human joints using an infrared camera.

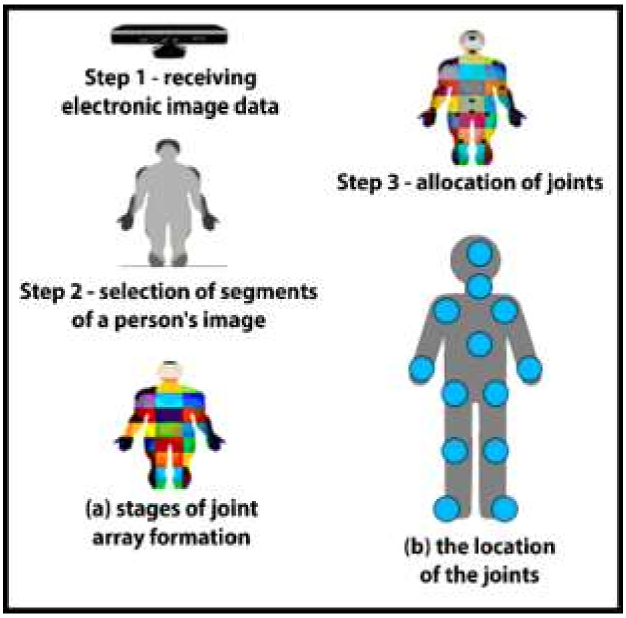

Fig. 2. **The main stages of creating a model of human skeletal joints based on the action of an infrared camera**
***Source:* compiled by the authors**

The set of joints of the human skeleton that are programmatically accessible when using the MS Kinect 2.0 camera is presented in Fig. 3.

There are various methods for recognizing human movements, one of which is the skeleton-based approach [9]. Systems implement these methods to monitor the accuracy of movements during sports competitions. For instance, the article [10] discusses a method for assessing Wushu movements that gathers data about human joints using the MS Kinect camera.

The article [11] presents a physical rehabilitation system that utilizes the MS Kinect camera to help patients with movement disorders carry out Tai Chi exercises at home. The system compares the patient's movements with the trainer's pre-recorded moves.

The article [13] investigates the effect of using the MS Kinect camera to assist young judokas' motor training by simulating pre-recorded performances of three master-level techniques.

The article [17] suggests recognizing the initial seven movements of Karate Kata 1 (Hein Shodan).

The article [18] presents a system for evaluating Taekwondo students' movements by comparing them to previously saved trainer movements.

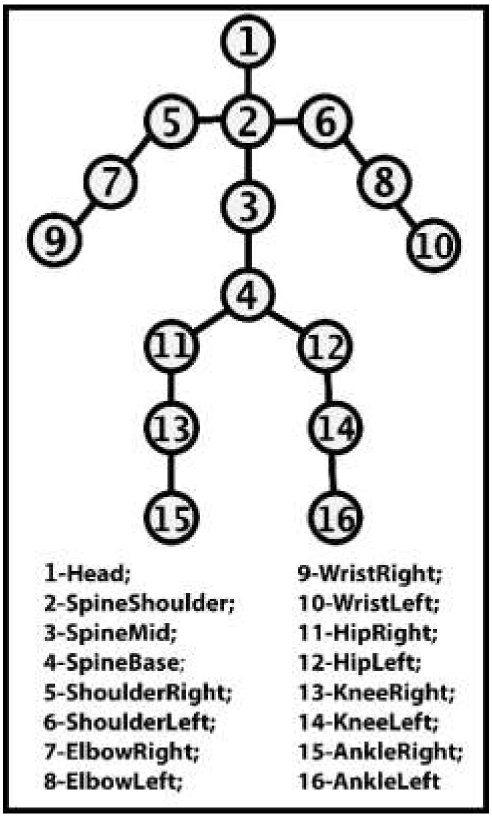

Fig. 3. **Human skeleton joint set for MS Kinect 2.0**
Source: **compiled by the authors**

The article [20] presents a system for monitoring the status of a fencing match using skeleton points obtained from the camera's video stream.

The article [14] proposed the Exergaming method, which controls human movement in sports computer games to increase the level of physical activity of students in online classes. This method is based on an open-access repository of computer programs in the Scratch block language, which includes 47 games for 28 summer species sports and 16 games for 10 winter sports. It recognizes movements using the PoseNet neural network.

Other examples of motor activity and gestures also use motion recognition techniques. For example, the article [16] presents a method for recognizing different dance poses. The paper [19] examines a new computer vision-based transformation model for human pose estimation and proposes a game that allows users to learn yoga practices.

The article [23] talks about a way to sort and classify gestures captured by the MS Kinect camera. It involves using a well-known dictionary of gestures to break down the classification of gestures in the edited data stream, finding and classifying gestures in an unedited stream that also includes random movements, and using rules to get rid of movements that weren't meant to be gestures but still look like gestures in the dictionary. The article [8] proposed a method that enhances the virtuality of training exercises with a ball, utilizing the MS Kinect camera. It also analyzed games from the LumoPlay and MotionMagix systems, encompassing logic, sports, entertainment, and relaxation genres while incorporating special effects.

This article [12] looks at 18 specially made motor “game” educational programs for the MS Kinect camera based on five factors: (1) how well they work with special needs students; (2) the types of educational goals they have (academic, social, cognitive, emotional, motor, sensory, and academic); and (3) the different ways they can be changed (“content adaptability” for academic or cognitive goals; “gestural adaptability” for predefined body movements and gestures; and “game adaptability” for the number of lives or a timer).

Computer games also implement movement recognition methods to support the rehabilitation of patients with motor activity limitations. The article [21] presents a special program for displaying human movement from the MS Kinect 1.0 and 2.0 cameras in Scratch v.1.4 touch blocks, which allowed the authors to quickly create several games with different scenarios for the rehabilitation of stroke patients by controlling left and right body movements by raising the hands above the head, moving the head up or down, and joining the palms.

The article [22] proposed the concept of a flexible and adaptive process focused on the patient's needs when creating serious games for physical rehabilitation, taking into account user-centered design and gamification elements that allow turning obstacles into positive and fun reinforcement, thereby encouraging patients in the rehabilitation process.

In 2023, Microsoft discontinued the MS Azure Kinect but offered developers to continue using the Kinect Developer Kit programming environment for Orbex's Femto Bolt and Femto Mega infrared cameras.

To carry out their experiments with the recognition of physical exercises in computer games, the authors of the work modified the script of the well-known computer game “Flappy Birds” in which the player must control the movement of the bird through the obstacles of the maze using special physical exercises. We used the C# programming language, Unity game engine, MySql DBMS, MS Kinect V 2.0 infrared camera, and LightBuzz software library for processing signals from the infrared camera to create the game. After filling in the database of descriptions of physical exercises for sports swimming styles “Breaststroke”, “Butterfly” and “Crawl”, a series of natural experiments were conducted. Fig. 4 shows a photo of the game process.

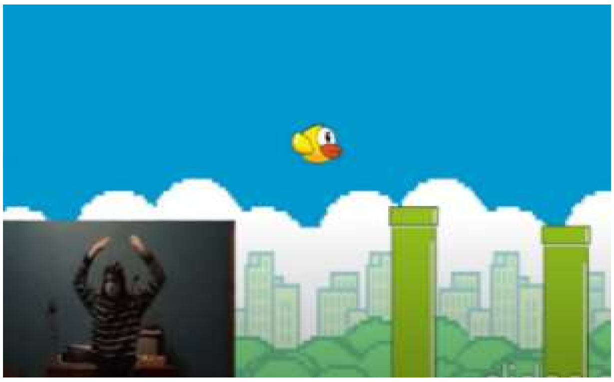

Fig. 4. **Photo of the game process**
Source: **compiled by the authors**

The analysis of the process of filling out the physical exercise description database revealed the following shortcomings that limit the use of the computer game:

– there is a need for a specialist who will fill in the database describing physical exercises;

– the human factor, such as the fallacy of the choices made when analyzing physical exercises and filling out the database;

– the database filling process has a high labor intensity.

2. PROBLEM STATEMENT AND GOAL OF THE STUDY

In the reviewed commercial systems supporting computer games with ExerGame technologies, there is no ability to change the description of physical exercises without the intervention of a programmer. In the reviewed works with prototypes of computer games, the authors did not find examples of software constructors that allow quick modification of physical exercise descriptions. The primary issue with the authors' developed method is the time lag during database filling.

Taking this drawback into account, the goal of this work is to reduce the time required to fill the database for identifying human physical exercises based on the spatial description of multiple joints. To achieve this goal, the authors propose the creation of a visual constructor for physical exercises and a method for automating the database's recognition of physical exercises.

3. THE METHOD OF AUTOMATED FILLING OF THE DATABASE WITH DESCRIPTIONS OF HUMAN PHYSICAL EXERCISES

3.1. Description of static and dynamic gestures in human physical exercises

A gesture is a body movement that contains gesture recognition information and is the basis for designing programs to use natural user interfaces to support actions such as navigation, data entry, multitasking, and more.

In the MS Kinect system, gestures are defined as specific positions of body joints relative to each other during a certain number of frames.

Any part of the body can perform different gestures. We determine each gesture by tracking specific positions of specific body parts at specific times.

Gestures can be static and consist of one state; for example, raise your hand or point to something with your hand. People perceive gestures as a sequence of several static gestures, which can also be dynamic.

Physical exercise is a correctly performed sequence of static gestures.

Fig. 5 shows the physical exercise “Brass” in the form of a sequence of three static gestures. When constructing gestures, the following methods can be considered.

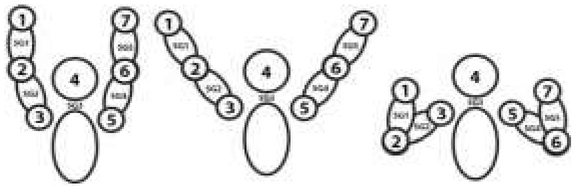

Fig. 5. **Physical exercise “Brass”**
Source: **compiled by the authors**

3.2. Gesture construction methods

Consider existing methods for constructing physical exercises, some of them are used for motion tracking, body position recognition, and data analysis.

Computer vision or depth sensors track human movement using the landmark-based method. The basic idea is that the system determines the position and movement of reference points on the human body to recognize and analyze movements, gestures, and physical exercises.

Key anatomical points or markers, known as anchor points, are easily identifiable on the human body. These points can include structural elements such as the head, shoulders, elbows, wrists, knees, ankles, etc. Each reference point has its own unique coordinates that can be tracked over time for motion analysis.

To perform recognition using the anchor point method, the following steps are usually used.

Step 1. Detection of reference points – the image or video is passed through computer vision algorithms that detect and identify reference points on the human body. This may include the use of face detection techniques, key point detectors, or body contour detection techniques.

Step 2. Track reference points – using computer vision or depth sensors, the system tracks the movement of reference points over time. This allows you to determine the trajectory and speed of movement of each point.

Step 3. Motion analysis and recognition – based on data about the movement of reference points, the system can analyze movements, gestures, and physical exercises. This can include posture detection, gesture recognition, exercise classification, or unusual movement detection.

The pivot point method is a powerful tool for real-time human motion analysis. It has found applications in many fields, including sports, rehabilitation, and virtual reality. However, the method is sensitive to noise, and requires accurate determination of reference points and the processing of a large volume of data [24].

The pivot point method presents the following challenges:

– point inconsistency problem – depending on lighting conditions, weights, or obstacles, points on the body can be difficult or impossible to track with high accuracy, which can lead to inaccuracies and incorrect reproduction of movement;

– the problem of estimating body orientation – the method of reference points cannot always accurately determine the orientation of the body in space, which can be a problem for accurate tracking and analysis of movements.

The method of skeletal models (the skeleton-based method) is one of the approaches to the analysis of human movement using computer vision or sensors. The main idea is to model the human skeletal structure by reproducing a set of joints and interconnected bones [25].

Typically, the following steps are used to use the skeleton model method.

Step 1. Joint Detection and Tracking – Images or videos are passed through computer vision algorithms that detect and track joints in the human body. This may include the use of face detection, body contour recognition, or key point detectors.

Step 2. Modeling of the skeletal structure - with the help of the received data on the joints, the system builds a skeletal model that displays a set of joints and their connections. Each joint has coordinates and orientation, which allows us to represent human movement in the form of a skeletal structure.

Step 3. Motion analysis and recognition – based on the skeletal model, the system can analyze movements, gestures, and physical exercises. This may include posture detection, motion classification, unusual motion detection, or gesture recognition.

The skeletal model method presents the following issues:

– the problem of lack of detail – the method of skeletal models does not always allow for the reproduction of all the details of body movement since the model is based on the approximation of the human body by the skeleton;

– the problem of the interaction of the body with the surrounding environment - the method of skeletal models can face the problem of tracking the movements of the body when it interacts with the surrounding objects or the surface, which can cause inaccuracies in determining the movement and position of the joints.

Both methods use computer vision or depth sensors to analyze human movement, but as previously mentioned, they differ in a number of criteria.

3.3. The method of automated filling of the database for the recognition of human physical exercises

3.3.1. Description of the steps of the method

Given the use of computer vision as a data collection method, determining the number of frames captured per second is necessary. At the same time, it is necessary to take into account that the more frames captured per second, the greater the value of the location of the joints will be for processing and building an associative array of gestures. Additionally, this can enhance the accuracy and quality of the exercise, thereby reducing the likelihood of incorrect analysis or static gestures. It is also important to consider the possibility of errors and noise, which can affect the quality of the data.

Applying filtering or other processing techniques can help reduce the impact of noise on data analysis.

We propose the following problem statement for the algorithm that automates the filling of the database with human physical exercises using the MS Kinect camera.

We read the input data set from a JSON file, which stores the associative array of human joint locations in space; if the file doesn't exist, we write the data instead. The task involves processing and analyzing the received data, converting it into a precise and understandable sequence of static gestures, creating a physical exercise, and finally entering all the data into the database tables.

Within the context of this problem formulation, we propose an automated method for populating a database with descriptions of physical exercises, utilizing a model of human joints from an infrared camera.

This method follows a specific sequence of steps:

– data on the location of human joints obtained from an infrared camera is saved in JSON format;

– the definition of physical exercise pertains to a subset of joints;

– the process involves forming a set of descriptions of static gestures based on the analysis of a subset of joints, taking into account the discreteness of the change in the state of these gestures;

– to remove duplicate elements from the set of descriptions of static gestures, we compare the properties of neighboring elements;

– filling out the database;

– the evaluation process involves the completion, correction, or re-execution of previous stages.

We need to provide additional explanations for the upcoming steps, specifically:

– record data on human joint positioning in space using the MS Kinect infrared motion sensor and saving it in a JSON file;

– select the joints that a specialist will be monitoring;

– compare the monitored joints based on coordinate values and remove unnecessary array elements.

As we elucidate the primary steps of the suggested methodology, we will concentrate more on the following characteristics of specific steps:

– recording joint positions, set recording settings, and adjust the frame rate and recording time, this step allows you to set the parameters for recording joint positions during movements, the specialist can set the frame rate, which dictates the frequency of updating joint position data, additionally, the specialist can adjust the recording time to determine the duration of the recording, which helps control the accuracy and detail of the movement recording as well as the amount of occupied space;

– during movement monitoring, a specialist can select specific joints to monitor, enabling them to concentrate on specific body parts or joints of interest, for instance, to monitor arm movements, the specialist can select the shoulder, elbow, and wrist joints;

– comparing the monitored joints with the nearest ones is crucial, after observing the positions of joints, it is important to compare them with known values or baseline indicators, this enables the evaluation of the joints' adherence to normal movement or the detection of any anomalies, algorithms or previous motion recordings can perform the comparison;

– filtering an existing associative array of static gestures: when recognizing static gestures such as hand poses, finger positions, etc., it may be necessary to filter the associative array, this involves removing unnecessary or incorrect gestures and retaining only meaningful information, filtering may include applying algorithms or rules to determine which gestures are considered correct and should be considered for further analysis.

3.3.2. Recording joint locations and recording settings

The speed at which gestures are recorded is a crucial indicator in the recognition process. Slow or small positional changes in gestures may allow for a lower frame capture rate without compromising clarity. However, for more complex and fast movements that involve many details, higher frame rates may be neces. When determining the optimal number of frames to capture per second, keep in mind that capturing more frames per second yields more accurate and detailed information about the joint position, enabling the construction of an associative array of gestures. uilt. However, this also leads to an increase in data volume and computational load. We chose default values as experimental values.

Before recording movements, the specialist can adjust the frame rate and capture duration, making it much easier to work with the data later. Every 0.3

seconds, the average speed of human exercise performance determines the capture of the joint positions description. The corresponding associative array JointPosition records this data, containing the following elements: jointName, the joint's name; xPosition, the x-coordinate; yPosition, the y-coordinate; and zPosition, the z-coordinate. We then convert the array into a JSON file, taking into account future software implementations of the processing algorithm. Fig. 6 shows the saved data structure in the form of a JSON file (jointName: joints, xPosition: yPosition, zPosition: spatial positions with corresponding coordinates; the values are normalized).

```
"Skeleton1": "ElbowLeft",
"Skeleton2": "ShoulderLeft",
"Condition_X": "=",
"Condition_Y": "<",
"Condition_Z": "="
```

Fig. 6. **Data structure in the form of a JSON file**
Source: **compiled by the authors**

3.3.3. Selection of joints for observation by a specialist

Depending on the physical exercises, the following factors may determine which joint to monitor. The exercise's purpose:

The exercise will select a specific joint for monitoring if its goal is to assess the movement of that body part or joint. For example, if the exercise involves standing or sitting positions, it may be important to monitor the leg joints, such as the knees or hips.

Importance for exercise performance: We may choose to monitor a specific joint if it's crucial for the proper execution of the exercise or needs special attention. For example, in balancing exercises, it may be important to monitor the joints of the foot or knee. The exercise's context, such as the type of movement, direction, or complexity, can also influence the choice of joint for monitoring.

Before automation takes place, the specialist configures the system in a certain way, taking into account the aforementioned factors. Experiments show that not all joints are well recognized by infrared cameras, and not all coordinates are available for them. Noise prevents infrared cameras from simultaneously assessing human movement from all angles, leading to these results.

The specialist selects the joints for monitoring in advance, taking into account the logic of performing the physical exercise, the authority of the trainer, and their knowledge and competence in the specific exercise under analysis. It is also possible to analyze all joints simultaneously, but this may lead to excessive data collection.

Fig. 7 shows the performance of the physical exercise 'Butterfly'.

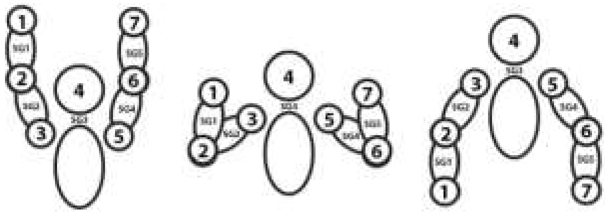

Fig. 7. **Performance of the physical exercise "Butterfly"**
Source: **compiled by the authors**

Fig. 8 shows the joints selected for monitoring by the specialist, highlighted in green. The specialist marks inactive joints in red and those suitable for comparison in pink.

The algorithm will automatically filter the data and monitor only those joints specified by the specialist.

This approach will reduce the program's processing time and avoid excessive descriptions of joint positions in space and their comparison with other joints.

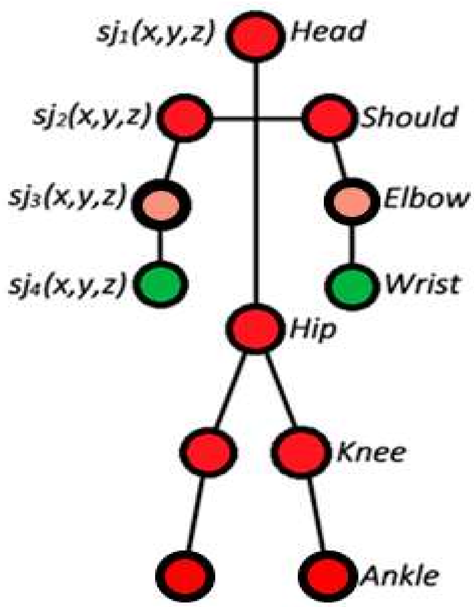

Fig. 8. **Joints of observation and joints of comparison**
Source: **compiled by the authors**

3.3.4. Comparison of observation joints with the axis of rotation

After obtaining data from the JSON file and the specialist's selection of joints for monitoring, their comparison with the axis of rotation for all three coordinates (X, Y, Z) takes place.

The axis of rotation is an imaginary line or point around which an object rotates. It can be a straight line around which the object rotates, or it can be an imaginary axis that passes through the object's center and rotates around it. For example, in physics, the axis of rotation is frequently used to explain the movement of bodies in space, such as the rotation of planets around their axes or the rotation of a wheel.

The coordinate values (xPosition, yPosition, zPosition) of the monitored joint Skeleton1 are compared with the coordinates of the nearest joint Skeleton2.

For each coordinate (q), we execute the following steps:

Step 1. The coordinate is selected.

Step 2. A variable Condition is set, indicating the comparison of coordinate values: Condition = {>, <, =}, where ">" means that the value of coordinate Skeleton1.qPosition is greater than the value of coordinate Skeleton2.qPosition, "<" means less, and "=" means equal.

Step 3. The specialist adjusts the allowable error range for the position by comparing the difference diff with it. If the difference diff falls within this range, they assign the value "=" to the variable (coordinateX, coordinateY, coordinateZ); if not, they retain the value from the previous comparison.

Step 4. The received data is recorded into a new associative array called Gesture:

- skeleton1 – the name of the observed joint;
- skeleton2 – the name of the nearest joint;
- coordinateX – the X-coordinate that was compared;
- coordinateY – the Y-coordinate that was compared;
- coordinateZ – the Z-coordinate that was compared.

We repeat this process for every observed joint Skeleton1 in the associative array JointPosition, leading to the creation of the associative array Gestion.

Additionally, the sequence of data in the associative array JointPosition automatically determines the position number OrderPosition.

The obtained associative array, known as the Gesture, contains all the necessary information about comparing the observed joints with the nearest joints by coordinates, and it also indicates the comparison result (Condition).

We repeat this process for each entry in the JSON file JointPosition until we process all the data. Each iteration of the loop processes one entry, computes the static gesture description parameters, and adds this description to the GestureList. The loop completes, yielding a complete list of descriptions.

3.3.5. Filtering an array of static gestures

Filtering an existing associative array of static gestures involves the process of excluding unnecessary or incorrect gestures to preserve only meaningful information for further analysis. Various algorithms or rules can achieve filtering by determining which gestures are considered correct and worth considering.

Below is a detailed description of the steps involved in filtering an associative array of static gestures:

- definition of filtration criteria: The first step involves defining the criteria for filtering gestures. We can establish these criteria based on domain knowledge, expert opinion, or the results of previous analysis. For instance, we can utilize criteria that take into account joint positions, degree of movement, and time constraints;
- the next step involves implementing the filtering algorithm or filtering rules, which consider the established criteria. This may involve the use of conditional operators, value comparisons, and logical operations, among other methods. For example, if the filtering criterion is a time limit, then gestures lasting less than a given period can be filtered;
- applying filtering to the associative array: filtering must be applied to each element of the associative array of static gestures, which means going through each element of the array and checking whether it satisfies the set filtering criteria. gestures that do not meet the criteria will be filtered out, and gestures that meet the criteria will be saved for further analysis;
- preservation of meaningful information: By filtering the associative array of static gestures, we can create a new list or an updated initial list that solely includes meaningful information. This list can be used for further analysis, classification, or other tasks related to static gesture recognition;

– filtering of the associative array of static gestures allows efficient processing and analysis of only correct and meaningful gestures, improving the accuracy and reliability of the recognition system. The implementation of the filtering algorithm may depend on the specific needs and requirements of the gesture recognition system.

The system modifies the gesture indexes and their corresponding positions in physical exercises after removing extraneous details. The server then receives the data in JSON format, which enables the automatic populating of the database tables.

Fig. 9 illustrates a relational model of the database detailing human physical exercises, while Fig. 10 provides examples of populated database tables.

Fig. 9. **Relational database model for describing human physical exercises**
Source: **compiled by the authors**

An example of the table contents Gesture

id	Skeleton1	Skeleton2	X	Y	Z
1	WristLeft	ElbowLeft	>	>	>
2	WristLeft	ElbowLeft	<	>	>

An example of the table contents Exercise

id	Name	Description
1	Breaststroke	Swimming style

An example of the table contents Exercise-Gesture

id_gesture	id_exercise	OrderPosition
1	1	1
2	1	2

Fig. 10. **Examples of contents of tables of a relational database of human exercise descriptions**
Source: **compiled by the authors**

3.3.6. Development of a skeleton constructor for visualization and correction of the obtained physical exercises

We have developed a visual skeletal exercise constructor to investigate the proposed methodology. This tool enables the user or a healthcare professional to import previously recorded exercises. Then, the user or a healthcare professional can observe how the physical exercise is performed or begin editing the gestures in this exercise by changing their sequence, deleting them, or adjusting the positions of joints. Update the exercise after making any modifications. Additionally, users can delete existing exercises, change their names, and create new physical exercises using the constructor. The constructor operates according to an algorithm that creates gestures and adds them to the physical exercise. As you adjust the sliders, the system compares the joint positions in space with each other, updating the recording in the gesture array accordingly. Overall, the implementation bears similarities to the algorithm for creating physical exercises, but it involves the user adjusting sliders interactively instead of automating the process.

Fig. 11 depicts the visual skeletal exercise constructor.

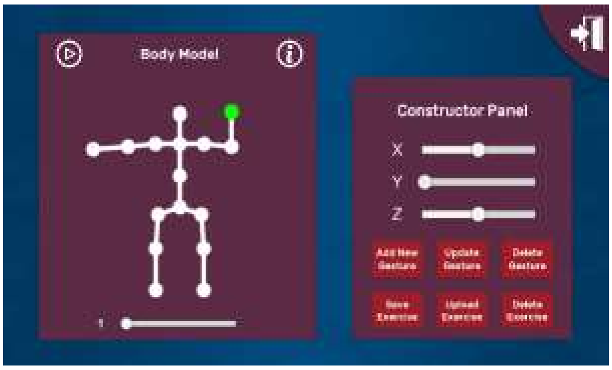

Fig. 11. **Visual skeletal constructor of physical exercises**
Source: **compiled by the authors**

For testing the skeleton constructor, 14 types of exercises used in Olympic sports were chosen: badminton, basketball, boxing, freestyle wrestling, volleyball, handball, judo, athletics long jump, athletics javelin throw, swimming, tennis, table tennis, fencing, and football [14].

The exercises under consideration incorporate the following number of gestures: 2 gestures – fencing, volleyball, handball, swimming, tennis, table tennis; 3 gestures – other exercises.

4. EXPERIMENTAL RESULTS

We conducted experiments on manually constructing physical exercises and applying the methodology to confirm the achievement of the research goal.

During these experiments, the person's movement was subject to the following constraints:

– taking into account the viewing angle from the MS Kinect sensor, the area of human movement does not exceed two m2, when some active movements, for example, moving in all directions with more than two steps, running, jumping, must be replaced by other alternative movements that take this limitation into account;

– taking into account the two-dimensional location of the image points (planes along the X and Y axes) provided by the MS Kinect camera, the direction of human movements is more appropriate in the direction perpendicular to the plane of the location of the camera to reduce the probability of movements in depth (the plane along the Z axis).

Exercises used to test the skeleton designer's operation include only two or three gestures.

Therefore, the proposal suggested conducting experiments with alternative exercises, where the distribution of gestures would be significantly higher:

Breast Stroke – 3 gestures; Crawl – 5 gestures; Abstract Exercise 1-7 gestures; Abstract Exercise 2–10 gestures.

We selected varying numbers of gestures to illustrate the differences in workload between manually filling the database and the automated approach. We conducted an analysis to compare the time costs of automated and manual database filling using gestures during human physical exercises.

Table 1 presented the results, incorporating special columns:

– tam – time for gesture analysis in the case of manual filling;

– taa – time for gesture analysis in the case of automated filling;

– tea – time for error correction (exists only for automated filling);

– tia – time for automated filling, tim – time for manual filling;

– ta – total time for automated filling, tm – total time for manual filling.

We present the experiment results as a series of graphs to evaluate the effectiveness of the suggested methodology:

– dependence of the tam / taa, ratio (y axis) on the number of gestures (axis x);

– dependence of tea / ta ratio (axis y) on the number of gestures (axis x);

– dependence of the avg tim / tam ratio (axis y) on the number of gestures (axis x);

– dependence of the avg tim / taa ratio (axis y) on the number of gestures (axis x).

Fig. 12 shows the dependence of the ratio tam / taa, tea / ta, avg tim / tam та avg tim / taa.

Based on the analysis of the presented graphs, conclusions can be drawn regarding the effectiveness of automated versus manual data entry depending on the number of gestures and the complexity of the gestures themselves. Overall, the graphs indicate that automated database population is faster than manual data entry, which is particularly noticeable in Fig. 12.

The experiment results demonstrate that automated data entry outperforms manual entry in terms of processing speed ratios:

– with 3 gestures – 2.6 times faster;
– with 5 gestures – 2.4 times faster;
– with 7 gestures – 2.9 times faster;
– with 10 gestures – 3.6 times faster.

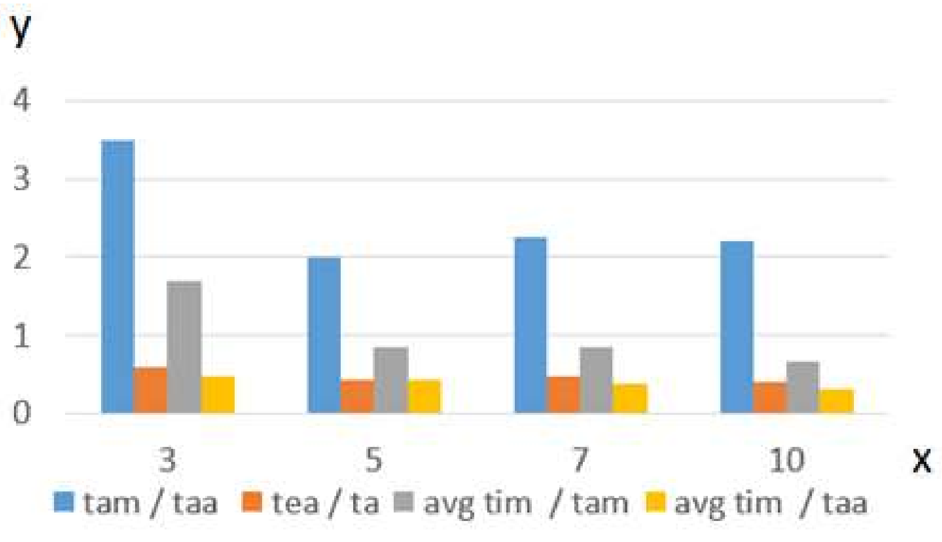

Fig. 12. **Dependence of the ratio ta_m / ta_a , te_a / t_a, avg ti_m / ta_m and avg ti_m / ta_a**

Source: **compiled by the authors**

Table 1. **Analysis of time cost estimation for automated and manual filling of human gesture database with physical activities**

Name of the exercise	Number Gestures	Time to analyze the picture, s		Gesture description	Time to fill, s		Time to correct mistakes, s	Total time, s	
		ta_a	ta_m		ti_a	ti_m	te_a	t_a	t_m
Breast Stroke	3	10	35	Hands down	1	17	20	33	87
				Hands up	1	18			
				Hands to sides	1	17			
Crawl	5	20	40	Hands down	1	17	20	45	111
				Left hand up	1	11			
				Left hand forward	1	12			
				Right hand up, left hand down	1	19			
				Right hand forward	1	12			
Abstract Exercise 1	7	20	45	Hands down	1	17	25	52	159
				Hands up	1	15			
				Hands to sides	1	17			
				Hands up	1	16			
				Hands to sides	1	15			
				Hands down	1	18			
				Hands up	1	16			
Abstract Exercise 2	10	25	55	Hands down	1	17	25	60	220
				Hands up	1	15			
				Hands to sides	1	17			
				Hands up	1	16			
				Hands to sides	1	15			
				Hands down	1	18			
				Hands up	1	16			
				Hands down	1	18			
				Hands up	1	16			
				Hands down	1	17			
				Hands to sides	1	17			

Source: **compiled by the authors**

CONCLUSIONS

The article delves into the intricacies of automating the population of a database containing human physical exercises. It presents a methodology comprising specific steps aimed at automating this process effectively:

We are recording data on the location of human joints in space through the MS Kinect infrared motion sensor and storing them in a JSON file.

A specialist selects the joints for observation. The study compares observation joints based on coordinate values.

Add the description of the associative array to the list.

The array's redundant elements were removed. filling the database tables.

We created and tested a visual skeletal exercise constructor for 14 types of Olympic sports exercises to verify the proposed methodology. The experiments on populating the database for four types of exercises revealed that the time required for populating the database using the methodology decreased by a factor ranging from 2.6 to 3.6, depending on the complexity of the exercise. The results showed that the automated database population saves more time than manually creating rules for static gestures and filling the gesture table with physical exercises. Thus, the research objective was achieved. The authors performed all experiments using MS Kinect 2.0. Despite the discontinuation of MS Kinect 2.0 in 2016 and MS Azure Kinect in 2023, Microsoft continues to offer developers the Kinect Developer Kit programming environment for infrared Femto Bolt and Femto Mega cameras from the Orbex company.

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Методика автоматизованого заповнення бази даних опису фізичних вправ людини

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АНОТАЦІЯ

Одним із прикладів людино-комп'ютерної взаємодії є інфрачервоні камери із відстеження руху людини та автоматичним створенням просторового опису множини суглобів людини. Використання таких камер дозволяє створювати активні комп'ютерні ігри, коли гравець виконанням фізичних вправ чи при виконанні того чи іншого жесту може керувати ігровим процесом. У роботі розглянуто системи підтримки комп'ютерних ігор з використанням фізичним вправ та виявлено відсутність можливості зміни опису фізичних вправ в окремій базі даних з метою швидкої зміни описів. Авторами було розроблено прототип комп'ютерної гри з використанням фізичним вправ, який у базі даних зберігає фізичні вправи як послідовності жестів. Але після проведення експериментів виявлено наступні недоліки: наявність фахівця, який зможе самостійно заповнювати базу даних опису фізичних вправ, можливі помилки під час аналізу фізичних вправ та трудомісткість процесу заповнення бази даних. Тому метою цієї роботи стало зменшення часу на заповнення бази даних про ідентифікацію фізичних вправ людини на основі просторового опису множини суглобів, які формуються інфрачервоною камерою. Для досягнення мети авторами запропоновано створити візуальний конструктор фізичних вправ та методику автоматизованого заповнення бази даних із розпізнавання фізичних вправ, яка містить наступні кроки: збереження станів розташування суглобів за визначенний проміжок часу, обробка отриманних даних станів суглобів просторового опису та визначення логічних співвідношень між суглобами (більше, менше або дорівнює), видалення описів-дублікатів, визначення помилок зі сторони специалиста з використанням візуального конструктору фізичних вправ, заповнення бази даних. В статті було проведено аналіз трудомісткості заповнення бази даних вручну та запропонованою методикою на прикладі фізичних вправ, які містять три, п’ять, сім та десять жестів. Результати аналізу показали зменшення трудомісткості заповнення бази даних при використанні запропонованого методу від двох цілих шість десятих до трьох цілих шість десятих разів залежно від складності та специфіки фізичної вправи. Всі експерименти в роботі автори проводили з використанням інфрачервоної камери Microsoft Kinect другої версії, яка вже знята з виробництва, але це не впливає на актуальність роботи, оскільки компанія Microsoft пропонує розробникам продовжити використовувати існуюче середовище програмування Kinect Developer Kit для інфрачервоної камери Femto Bolt та Femto Mega від компанії Orbex.

Ключові слова: комп'ютерна гра; інфрачервона камера; розпізнавання шаблонів; база даних, просторовий опис суглобів людини; фізичні вправи

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