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Article

Improvement of the Classification Algorithms of Postures for Non-Marker Systems of Human Motion Capture

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Abstract: The rapid development of algorithms for skeleton detection with relatively inexpensive contactless systems and cameras opens the possibility of virtual exercise therapy for patients with different complications. However, evaluation and confirmation of posture classifications is still needed. The purpose of this study was therefore to find the most accurate algorithm for automatic classification of human exercise movement. A Kinect V2 with 25 joints identification was used to record movements for data analysis. A total of 10 subjects volunteered for this study. Four algorithms were tested for the classification of different postures in Matlab. These were based on: total error of vector lengths, total error of angles, multiplication of these two parameters and simultaneous analysis of the first and second parameters. A base of 13 exercises was then created to test the recognition of postures by the algorithm, and to analyse subject performance. The best results for posture classification was shown by the second algorithm with an accuracy of 94.9%. The average correctness of exercises among the 10 participants was 94.2% (SD1.8%). The algorithms tested in this study therefore proved to be effective and could potentially form the basis for developing a system for remote monitoring of rehabilitation involving exercise.

Keywords: exercise classification; motion capture; virtual rehabilitation

1. Introduction

Demographic ageing in humans means that to date, 12% of the global population are aged over 60 years and this number is likely to double in a few decades [1]. Ageing leads to a higher prevalence of complications that may benefit from exercise therapy. Such an increase in ageing will mean that rapid development of science and medicine, as well as the introduction of new technologies and methodologies utilised by health systems will be needed. More knowledge has been gained regarding new treatment regimes for a growing number of chronic diseases and traumas; with consequential increases in social and economic costs [2]. It is well-known that rehabilitation forms an important part of a typical overall treatment plan, which can be delivered, for instance, by utilising therapeutic exercise (physiotherapy). The performance of physical activity has many advantages in older people with dementia and can positively affect the preservation of cognitive abilities [3]. Stroke patents may also benefit from physical activities which can result in improved recovery rates.

However, the success of rehabilitation largely depends on keeping the patient interested and motivated in the continuation of treatment. Factors influencing adherence to the continuation of physical education depend on whether people continue to receive professional assistance and

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counselling, after the completion of the initial training [4]. Among the main reasons for the termination of continued professional assistance and counselling are forgetfulness, lack of further supervision and motivation, and time restrains (for example in getting to the rehabilitation centre).

The use of exercise therapy delivered by a physiotherapist via the telephone for knee osteoarthritis (OA) patients has demonstrated interesting results [5]. Although patients with OA may be sceptical about receiving such exercise therapy via the telephone, the overall effect has been shown to be positive. Participants have highlighted that they feel more confident doing their exercise programs without anyone watching them and it helped them to increase muscular strength, improve pain, and improve their ability to complete tasks that they had not been previously been able to do. There is therefore emerging evidence that remote monitoring can have a positive impact on the enablement of patients to perform exercise and their willingness to continue training.

Traditionally, exercise therapy consists of demonstrating exercises, observation and evaluation by a health professional, which in turn requires special training and significant face-to-face contact with a patient. However, modern computer and sensor technologies could be utilised to augment (or where appropriate replace) direct intervention by health professionals. The capability of motion capture systems have advanced significantly and have become more effective and accessible. They allow the kinematics of the human body to be measured and recorded with high accuracy, and this data could help in assessing the patient's condition and in forming future treatment options.

Two main types of motion capture systems are widely used; those which use markers, and those which estimate joint and limb segment parameters based on neural network training from marker systems. The first requires use of a special suit or a removable system of sensors (active or passive markers) attached to the human body. The second type, such as those provided by Microsoft Kinect, Intel RealSense and others, use colour and depth data as well as image recognition algorithms to retrieve the data. These systems can record kinematic data and perform analysis of the human body movements in real time.

In addition, the development and availability of these sensors opens more opportunities, as it makes it possible to create bespoke rehabilitation courses and monitor their implementation [6-11]. Similar applications have been developed for different patient groups, but the most widely represented software has been designed for post-stroke patients [12-16]. Software has also been designed for people with neurological diseases [17], including cerebral palsy [18], multiple sclerosis[19] and traumatic brain injury [20].

However, the algorithms used by these systems to estimate the accuracy of execution of movements by such patients, are not fully described in the literature. Two of those algorithms can, however, be distinguished by their differing mode of operation. The first is based on the use of dynamic time warping (DTW) along with fuzzy logic [7], and the other on the recognition of different body segment postures and trajectories [21]. However, the use of a home-based system using virtual rehabilitation offers the possibility of communication with a doctor, is more convenient for the patient, and also allows the rehabilitation course to be altered by adding new exercises if necessary. DTW is however, difficult to apply when compared to posture estimation algorithms. Anton et al. utilised the recognition of postures and recognition of postures together with trajectories, which resulted in accuracy of posture estimation by 91.9% and detection of movements by 95.16% [21].

The aim of this research was therefore to find the most accurate algorithm for posture and exercise movement estimation. It was performed by using four different algorithms.

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2. Materials and Methods

2.1 Posture Description

A 3D Sensor (Microsoft Kinect V2) was used to record movement, as it is able to recognise different subjects, track their movement, and create a skeleton consisting of 25 points (Fig. 1); which may be described by three-dimensional coordinates (i.e. by using X, Y and Z planes of motion).

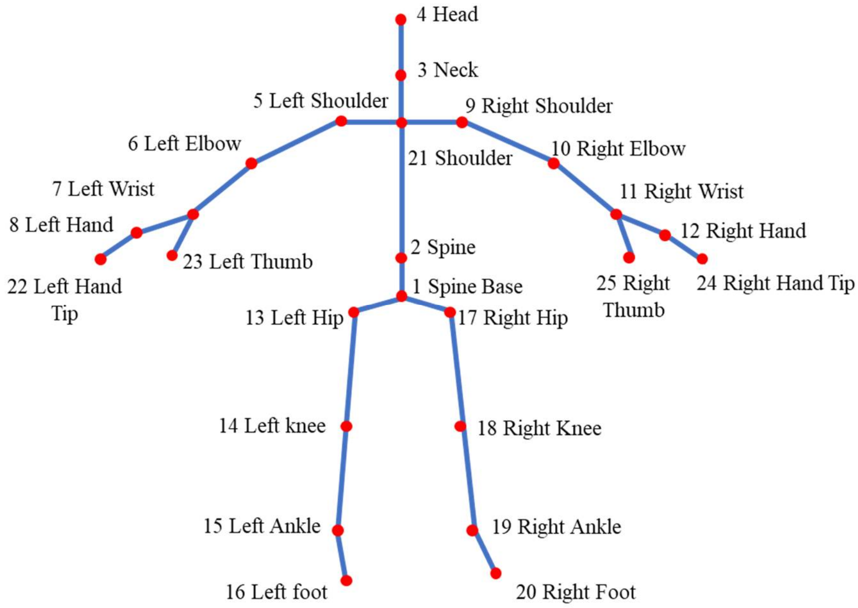

Figure 1. Diagram of connection of points received from the sensor.

Any movement consists of a series of postures. Eighteen joints were used to describe a posture in a series of volunteer subjects. It was decided to exclude such joints as numbers: 16, 20, 21, 22, 23, 24 and 25 (Figure 1) from algorithms as they demonstrated high inconsistency in tracking accuracy. A total of 40 parameters were therefore calculated based on 18 points: 17 were vector lengths, and 23 were angles.

The vector lengths were calculated relative to a position on the centreline of the torso (please see point "2", Figure 1), as it had minimal error in tracking. As each subject had a different body shape, which meant lengths between joints were not consistent, it was decided to normalise them using the participants' heights using the following formula [22]:

$$D_{vector} = \sqrt{\frac{(x-x_0)^2+(y-y_0)^2+(z-z_0)^2}{height}}, \tag{1}$$

where $x_0$and $z_0$represent coordinates of the midpoint of the back, and x, y, z are the coordinates of the point for which the distance is calculated.

Eleven angles were used in algorithms to describe postures and movements as shown in Figure 2 and Table 1. For all 11 joints, angles were between two vectors in 3D space. However, for the shoulder, hip and knee, angles were calculated in frontal and sagittal planes only.

Table 1. Angles used to describe postures.

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№	Angle	Vector Directions by Points
1	Neck tilt	[4 3] [21 3]
2	Right elbow	[9 10] [11 10]
3	Left elbow	[5 6] [7 6]
4	Right shoulder	[2 21] [10 9]
5	Left shoulder	[2 21] [6 5]
6	Right thigh	[1 2] [18 17]
7	Left thigh	[1 2] [14 13]
8	Right knee	[17 18] [19 18]
9	Left knee	[13 14] [16 14]
10	Inclination of the back to the right thigh	[2 1] [17 1]
11	Inclination of the back to the left thigh	[2 1] [13 1]

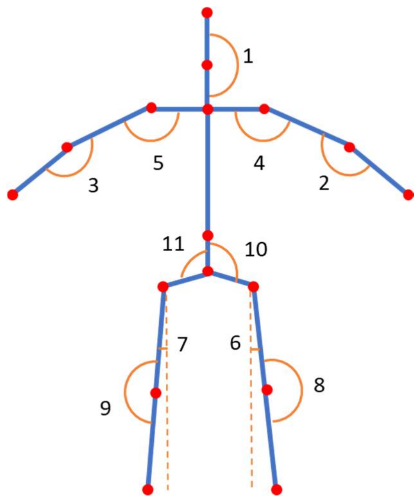

Figure 2. Angles used in describing poses.

The angles were calculated as the angle between two 3D vectors:

$$D_{angle} = \arccos\left(\frac{x_1x_2+y_1y_2+z_1z_2}{\sqrt{x_1^2+y_1^2+z_1^2}\sqrt{x_2^2+y_2^2+z_2^2}}\right), \quad (2)$$

where $x_1, y_1, z_1, x_2, y_2, z_2$ are coordinates of the first and second vector respectively.

2.2 Postures and exercises

A database of 12 postures was created to validate the algorithms containing poses and exercise movements (Table 2, Figures 3-4).

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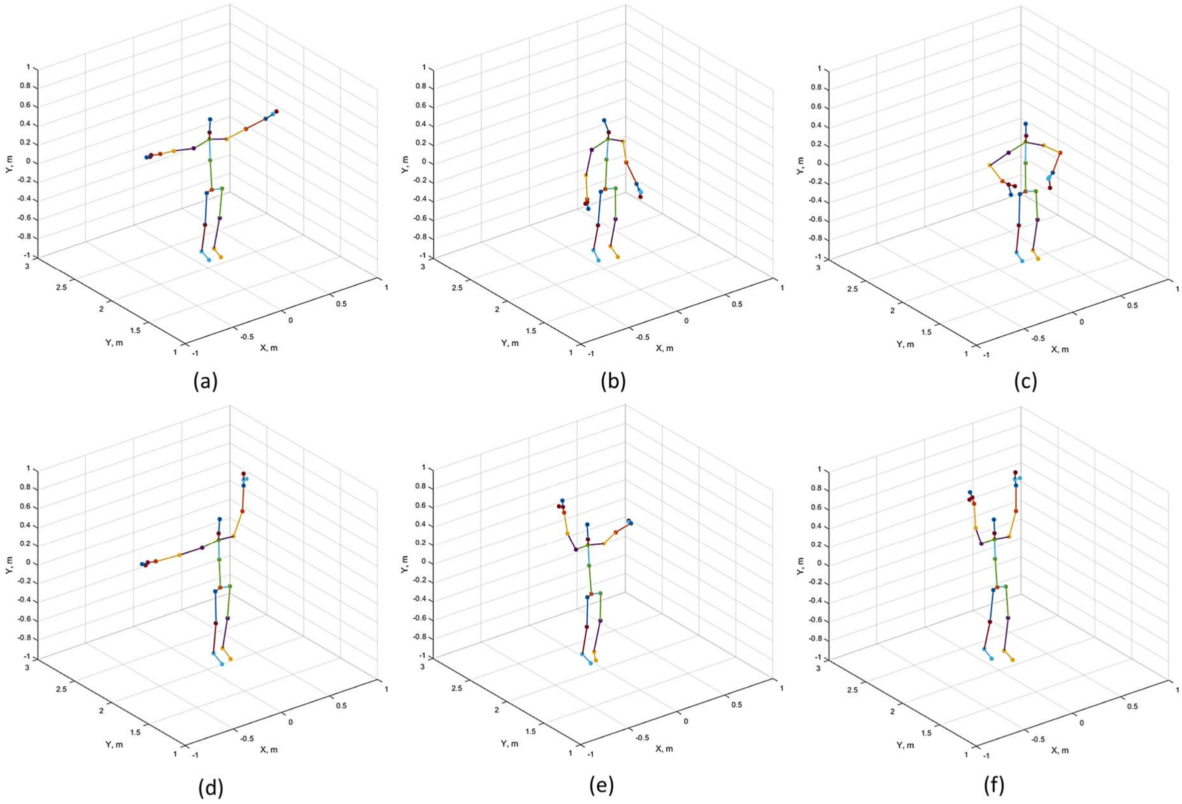

Figure 3. Postures: (a) hands outstretched; (b) hands down; (c) hands on the waist; (d) left hand up; (e) right hand up; (f) both hands up.

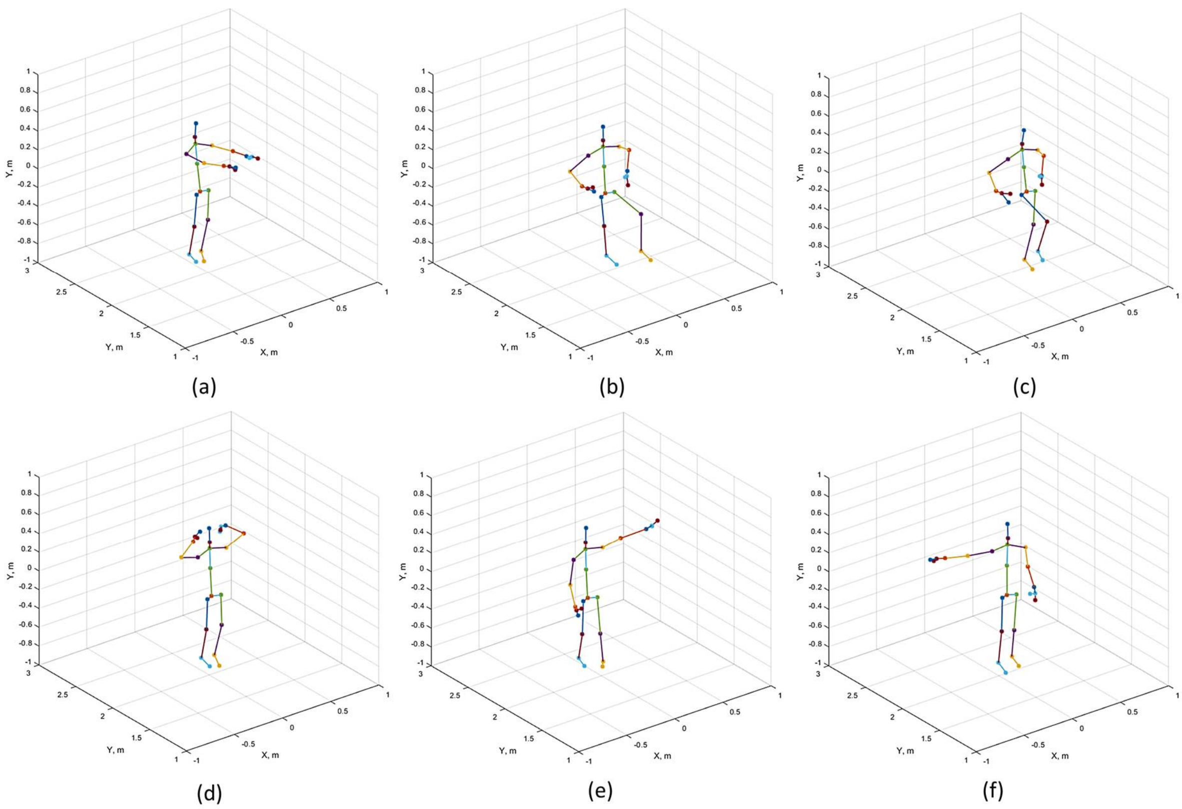

Figure 4. Postures: (a) hands forward; (b) left knee up; (c) right knee up; (d) both hands to the head; (e) left hand to the side; (f) right hand to the side.

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Table 2. Postures analysed.

	Posture
1	Hand outstretched
2	Hands down (neutral posture)
3	Hands on waist
4	Right hand up
5	Left hand up
6	Both hands up
7	Hands forward
8	Right knee up (hands on waist)
9	Left knee up (hands on waist)
10	Both hands to the head
11	Right hand to the side
12	Left hand to the side

The movement exercises were described as a sequence of postures. The simplest movement was described by the start and the end position. However, in some cases there were more complex sequences of movements where the middle phase movement had several postures mixed. A total of thirteen different exercise test movements were eventually used in the study as shown in Table 3.

Table 3. Test exercises.

№	Posture Exercises (initial posture-final posture)
1	Hands down – hands outstretched
2	Hands down – hands up
3	Hands at the sides – right hand up
4	Hands at the sides – left hand up
5	Hands at the sides – hands to the head
6	Hands on the belt – right knee up
7	Hands on the belt – left knee up
8	Hands at the sides – hands forward
9	Hands down – hands forward
10	Hands up-hands forward
11	Hands forward – right hand to the side
12	Hands forward – left hand to the side
13	Hands down – hands forward – hands up – hands outstretched

2.3 Accuracy evaluation of postures and movement exercises

Classification of postures was made by comparing recording posture descriptors (D_i) with a reference database (D_j). The distance between the reference and reordered posture could be calculated as:

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$$Er_i = dist(D_i, D_j), \tag{3}$$

A descriptor is composed of two parameters (angles and vectors) and therefore two types of errors were calculated: the total error of the length of vectors and the total error of angles.

The first was calculated using absolute differences between them:

$$ErVec_i = \sum_{k=1}^{17} \left| D_i(k) - D_j(k) \right|, \tag{4}$$

where $D_i(k)$, k = between 1 and 17 – Parameters that are responsible for the length of the vectors. The total error angles were calculated using the formula:

$$ErAngle_i = \sum_{k=18}^{28} \left| D_i(k) - D_j(k) \right|, \tag{5}$$

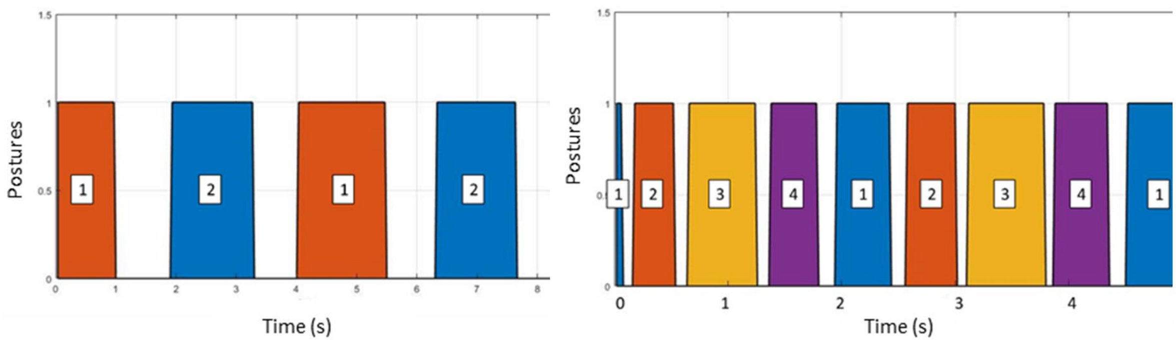
where is $D_i(k)$, k = between 18 and 40 – Parameters responsible for values of angles.

Based on those types of errors four algorithms for posture classifications assessment were presented. To classify the posture the results should be equal to the reference database. However, that was not always possible and therefore the threshold level was set for algorithms:

- Algorithm 1: vector length error
- Algorithm 2: angle error
- Algorithm 3: multiplication of angle errors by vector errors
- Algorithm 4: errors of vector lengths and angles (simultaneous fulfilment of conditions)

To evaluate the most accurate algorithm for posture detection, the classification database was made with descriptions of either "correct" or "incorrect" postures.

To justify the accuracy of exercise movement classification, the database, with a set of sequence postures in the correct order was made as shown in the examples in Figures 5.



(a) (b)

Figure 5. Example of a movement exercise: (a) Combination of two postures; (b) A more complex movement exercise with a set of postures in a sequence order.

2.4 Experimental protocol

Ten healthy subjects aged between 20 and 35 were recruited in the study. All participants read the information sheet before the experiment. Each exercise was repeated at least 25 times with a short rest between them. After completing all the exercises, participants were asked to randomly repeat a

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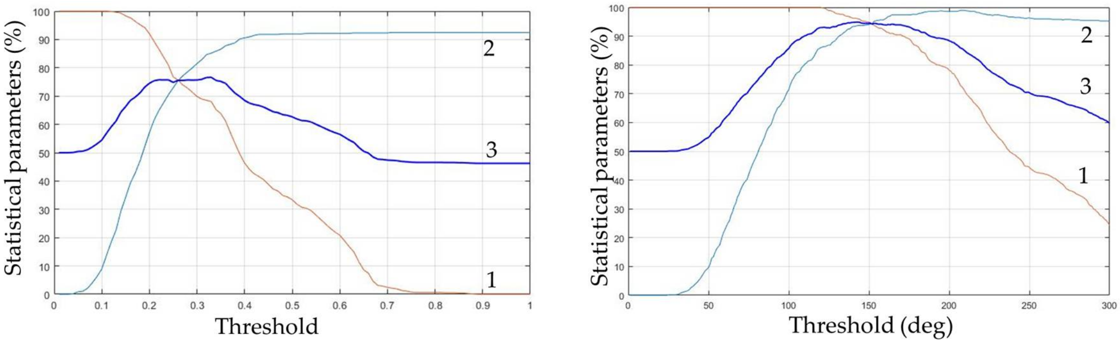
few more exercise movements 15 times. Postures were also recorded. Matlab was used for data collection and analysis.

3. Results

3.1 Classification algorithms

To find the most accurate classification algorithm, a database was created from the descriptions of the 573 known postures as shown in the table 2 and 903 postures which were not related to them. Using this database four algorithms were tested for which sensitivity, specificity and accuracy values were obtained (Figure 6-7).



(a) (b)

Figure 6. Relationship between specificity (1), sensitivity (2) and accuracy (3) and threshold for: (a) Algorithm 1; (b) Algorithm 2.

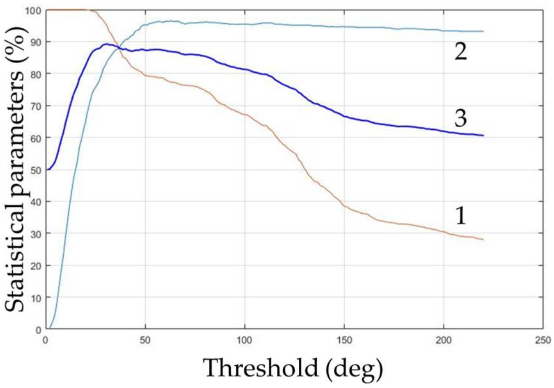


Figure 7. Relationship between specificity (1), sensitivity (2) and accuracy (3) and threshold for the algorithm 3

The mean sensitivity for the first algorithm was 92.5%, for the second 98.95%, for the third 96.5% and for the fourth 98.95%.

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Table 4. Statistical results.

Algorithm	Mean sensitivity, %	Intersection of sensitivity and specificity, %	Mean accuracy, %
Total vector error	92.5	75.7	76.6
Total angle error	98.95	94.1	94.9
Multiplication of vector errors by angle errors)	96.5	87.7	89.3
Total error of vectors and angles	98.95	94.1	88.7

The mean intersection of sensitivity and specificity for the first algorithm was 75.7%, for the second 94.1%, for the third 87.7%, and for the fourth 94.1%.
The mean accuracy for the first algorithm 76.6%, for the second 94.9%, for the third 89.3%, and for the fourth 88.7%.

3.2 Number of exercises performed by participants

Each participant performed at least 390 exercises in total. Table 5 demonstrates a detailed information on the number of exercises performed by each participant.

Table 5. Number of exercises performed by each participant.

	№	Exercise number													Total
		1	2	3	4	5	6	7	8	9	10	11	12	13	
Participants	1	25	25	35	35	25	40	40	25	25	25	35	35	40	410
	2	35	25	25	25	25	40	40	25	35	25	35	35	40	410
	3	25	25	25	25	25	40	40	25	25	25	35	35	40	390
	4	35	25	25	25	25	40	40	35	25	35	35	35	40	420
	5	25	25	25	25	25	40	40	25	25	25	35	35	40	390
	6	25	25	25	25	25	40	40	25	25	25	35	35	40	**390**
	7	25	25	35	35	25	40	40	25	25	35	35	35	40	**420**
	8	40	25	35	35	25	40	40	25	25	25	35	35	40	**425**
	9	25	25	35	35	25	40	40	40	25	25	35	35	40	**425**
	10	25	35	25	25	25	35	35	25	25	40	35	35	40	**405**

Figure 8 shows movement classification accuracy performed by participants.

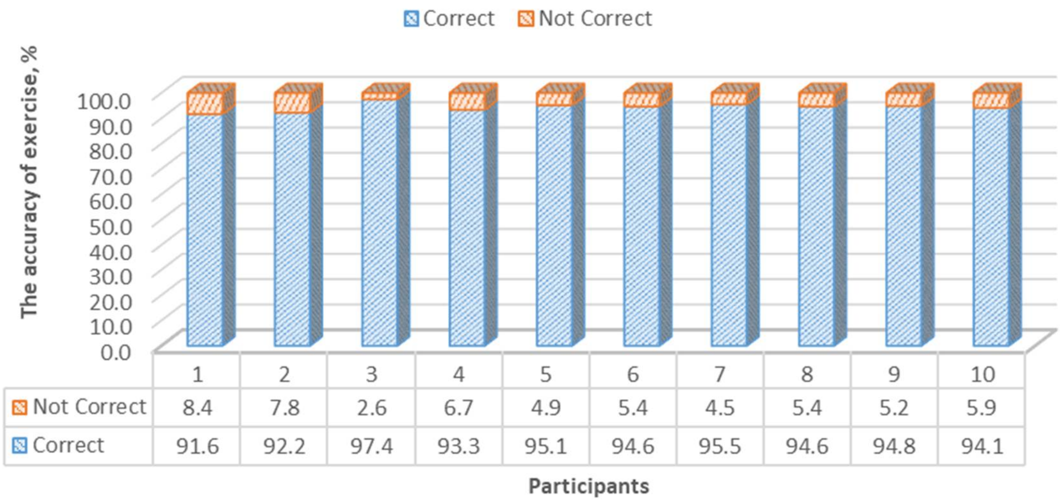

Figure 8. The accuracy of exercises.

Figure 9 shows the percentage ratio of the correct and incorrect for each exercise.

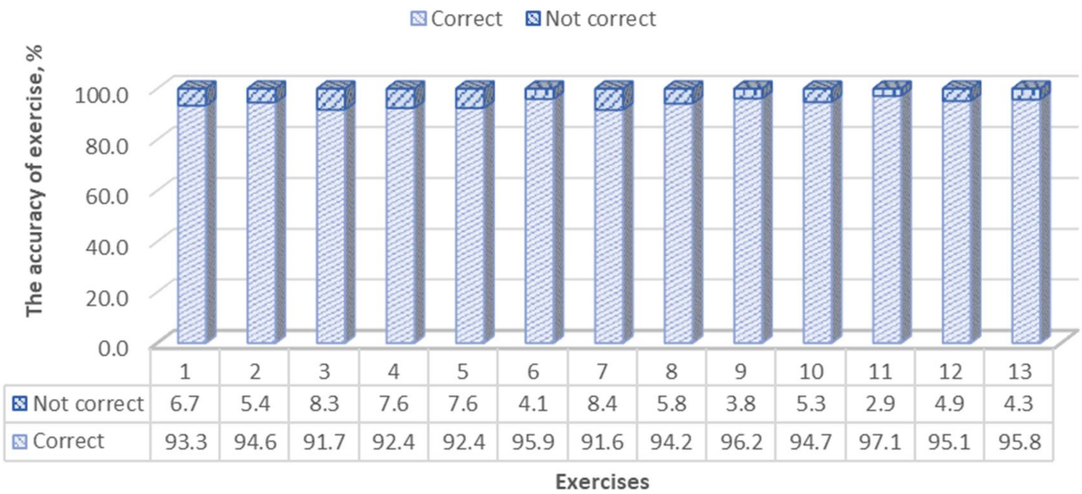

Figure 9. Correct execution of exercises.

The average accuracy of movement classification among participants was 94.3% (SD 1.7 %). The average accuracy of exercises was 94.2 %(SD 1.8 %).

4. Discussion

Authors should discuss the results and how they can be interpreted in perspective of previous studies and of the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

The aim of this study was to determine accurate posture and exercise classification algorithms with low-cost sensors such as Microsoft Kinect, which has also led to the development of different virtual rehabilitation programs [13,23]. Use of such sensors can have many advantages. Firstly, they highlight interactivity and motivation, and they can also be used at home. This is important for people who live in remote areas, where there may not be experts locally available. In addition, the technique can be adapted to the needs of any patient group [24].

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The comparison of this sensor with a professional optical motion capture system has demonstrated that it has the accuracy sufficient for both the tasks and data generation capability needed by specialists in the field of rehabilitation [8].

However, the question of how to evaluate the correctness of the exercise is still not certain, as the literature is represented by only a limited number of articles [7,21]. The previous research has demonstrated a most accurate posture classification of 91.9% and that for movement of 95.16% [21]. This study demonstrated a slight increase in the accuracy by using four different algorithms and by setting up a threshold level for total error of vector lengths, total error of angles, multiplication of vectors errors by angles errors (as in [21]) as well as total error of vectors and angles. Calculating sensitivity and specificity, the classification accuracy of the algorithms was obtained, with the best result shown by the algorithm using the total error of angles (94.9%). This algorithm showed better results when compared with previous research based on multiplication of total errors algorithm. This new algorithm also requires considerably less parameters for classification of postures and exercise movements.

In our study, when evaluating the classification accuracy of the exercises, we used results, such that the average accuracy for each participant and the average accuracy of the exercises, which were 94.3% (SD 1.7%) and 94.2 % (SD 1.8 %) respectively. Those results are close to that of the previous research which used a different algorithm [21]. It proved difficult to improve those results in this study, and this may be related to the number of participants, environmental effects and technical specification of the sensor such as frequency of recording, sensor resolution, or the accuracy of the joints detection algorithm.

More advanced marker-based motion capture systems can be used to improve the classification accuracy of the algorithms. Previous research has demonstrated that static error of tracking passive markers with Oqus (Qualisys) cameras was 0.15 mm and dynamic 0.26 mm [25] with much higher frequencies than that used by the Kinect v2 sensor.

The definition of human posture can be applied not only for the creation of applications for rehabilitation, but also for monitoring the life of older people- for instance in the recording of a sudden fall. According to statistics, 28-35% of people over 65 years of age experience a fall [26], and often after that they need a period of rehabilitation. Such a monitoring system, could detect a posture of a person and alert relatives, neighbours or close friends in cases if a person had a heart attack, stroke or other complication and lying down on the floor. The time factor in such situation is very crucial and it will be directly correlated to recovery of a person.

5. Conclusions

Virtual or home rehabilitation using modern technologies can improve health and quality of life for many people. The algorithm for posture and movement classification used in this study demonstrated good results using a sensor. Those algorithms may be also applied in other motion capture systems and improve the accuracy.

This posture and movement classification algorithm may also be used to monitor incidental falls in the elderly population that can be associated with a heart failure or a stroke and initiate a call for a help

Author Contributions: Tatiana Klishkovskaia writing—original draft preparation, collecting data and analysis in Matlab; Andrey Aksenov was supervising, writing in English original draft, preparing the final paper.

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Conflicts of Interest: The authors declare no conflict of interest.

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