Intelligent models for movement detection and physical evolution of patients with hip surgery

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Abstract

This paper develops computational models to monitor patients with hip replacement surgery. The Kinect camera (Xbox One) is used to capture the movements of patients who are performing rehabilitation exercises with both lower limbs, specifically, 'side step' and 'knee lift' with each leg. The information is measured at 25 body points with their respective coordinates. Features selection algorithms are applied to the 75 attributes of the initial and final position vector of each rehab exercise. Different classification techniques have been tested and Bayesian networks, supervised classifier system and genetic algorithm with neural network have been selected and jointly applied to identify the correct and incorrect movements during the execution of the rehabilitation exercises. Besides, prediction models of the evolution of a patient are developed based on the average values of some motion related variables (opening leg angle, head movement, hip movement and execution speed). These models can help to fasten the recovery of these patients.

Keywords: Computational intelligence, hybrid system, detection, prediction, rehabilitation, hip surgery, health monitoring.

1 Introduction

The use of online assistance systems is currently having a significant impact on different areas of knowledge. Health has been one of the most benefitted fields, where the rehabilitation of patients in real time greatly helps the recovery of patients' physical conditions [2, 3, 22, 23]. It also helps to alleviate some possible problems that may delay the recovery. In addition, it can be applied to several patients at the same time and at much less cost than having a specialist per patient or transporting them to the physiotherapist's office.

In this work, computational models are obtained to monitor and fasten the recovery of patients that have had a hip arthroplasty surgery. This orthopedic procedure involves people who need a postoperative functional rehabilitation program to recover strength and joint mobility.

The Kinect camera (Xbox One) is used to capture the movements of patients while executing rehabilitation exercises with both lower limbs, specifically, 'side step' and 'knee lift' exercises with each leg. The information is measured at 25 body points with their respective coordinates. Features selection algorithms are applied to the 75 attributes of the initial and final position vector of each rehab exercise.

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This work has a twofold objective. On the one hand, different intelligent classification techniques have been tested; among them, Bayesian networks, supervised classifier system (UCS) and genetic algorithm with neural network (GANN-C) have been selected and jointly applied to identify the correct and incorrect movements during the execution of the rehabilitation exercises. This is important since the incorrect execution of some rehab exercises can cause delays in the recovery or even new injuries.

Besides, prediction models of the evolution of a patient are developed based on the average values of some motion related variables (opening leg angle, head movement, hip movement and execution speed). It is quite common that after a hip replacement surgery and once discharged from the hospital, the pace of recovery of a patient is not as expected or desired. Even more, complications may be developed in other body joints (neck, back and ankles) as a result of compensatory movements. These models can assess the correct evolution of the patient recovery.

The article is organized as follows. In Section 2, related works are presented. In Section 3, the database obtained with the Kinect camera from patients undergoing rehabilitation is described. The computational intelligent methods used are detailed. In Section 4, the development of the body movement detection model using Bayesian networks, GANN-C and UCS is explained. The model for predicting the evolution of patients is also described. Section 5 discusses the results of the experiments. The paper ends with the conclusions and future works.

2 Related works

Tele-rehabilitation systems try to temporarily replace physical therapy units, developing a safe and adequate environment adapted to the location and schedule of the patients. A large number of patients can then have access to these systems simultaneously, which benefits their physical health. The use of technology allows the application of dynamic tools to treat various disabilities and control them remotely, as it has also been shown with robot rehabilitation [18].

Rehabilitation assistance systems have been studied in the last decades. The work of Lloréns *et al.* [15] details a tele-rehabilitation system that applies virtual reality to improve the balance in patients with hemiparesis (cerebrovascular accident). They use a Microsoft Kinect v2 camera. This system was clinically evaluated in the outpatients of the neuro-rehabilitation unit of a large metropolitan hospital. When compared with the traditional methodology, it resulted in a reacquisition of the locomotor skills associated with balance in the same way as an in-clinic intervention does but at a much lower cost.

Another example with patients with cerebrovascular lesions is presented in Macko *et al.* [16], with interactive video exercise tele-rehabilitation (IVET) technology, based on the web. The IVET uses a smart linked device to offer personalized rehabilitation exercises. The system was tested in 27 Jamaican adult patients with pan-vascular disease. The study analysed the neurological and cardiopulmonary capacities of each individual where the frequency and duration of the exercise performed by the patient was identified. The exercise was adjusted to produce a measured aerobic intensity that improved cardiovascular health. The results of this study showed that it is an excellent option for countries with low resources and limited access to technology. In Rojas-Lertxundi *et al.* [27], some low-cost motion capture devices were also described.

The work by Piotrowicz *et al.* [26] sums up some of the available computer tools for telemonitoring in order to improve patients' health. This work describes characteristics, applicability and effectiveness of these platforms. It highlights their benefits due to their psychological and physical adaptability to the patients.

Robotics has also been applied to tele-rehabilitation [8], using home-based robot tele-rehabilitation. This article analysed the functional results, access, utilization, cost, satisfaction and quality of life of patients that use this method. This study was conducted with 20 survivors of cerebrovascular diseases with excellent results, over a period of 3 months.

A highly frequent physical lesion in rehabilitation patients is the frozen shoulder, which is quite painful and affects the normal development of a patient's daily life. An example of a tele-rehabilitation system for this disease is the one described by Ongvisatepaiboon *et al.* [21], where a smartphone and multiple sensors are used, such as accelerometer, gyroscope and magnetic field, to determine the patient's movement during their rehabilitation session. This study identified the arm angle of rotation and determined if the patient did it correctly. The results obtained show that reasonable accuracy can be achieved with accessible equipment and that patients can improve their physical treatment in a better way.

Body movements and human behaviour prediction have been a common topic in medicine in recent years. The study carried out by Xiong *et al.* [31] selected a series of data points of the lower extremities and applied an artificial neural network to these data points to predict the movements of a patient during a walk. The method was tested on eight healthy patients on a treadmill at speeds of 2–5 km/h. The results had a precision of 96.33% with five or six variables, which showed the good performance of the model. In Majeed *et al.* [17], the authors conducted an experiment using patients with stroke on a treadmill. The information was collected over 3 weeks. A prediction model was applied to identify the evolution of the patients during the self-rehabilitation.

Another relevant work on rehab prediction is presented in Zhang *et al.* [32]. The article proposes a method based on the measurement of muscle activity using surface electromyography, which registers the activation level of skeleton muscles and is a more accurate method for determining the force exerted. The prediction was calculated from a musculoskeletal model using a Bayesian linear regression algorithm. In addition, a haptic device (Phantom Premium) was used to represent the predicted force. The results were quite acceptable and verified the effectiveness of the tele-rehabilitation system.

In Ayed *et al.* [6], it was demonstrated that the Microsoft Kinect device is reliable and adequate for therapeutic prevention of falls. Its usefulness was shown for patients who perform the rehabilitation treatment at home and every so often receive a visit from a physiotherapist. With this kind of device, a physiotherapist can assess the balance with a standard test without having to go to the home of a patient with other measuring instruments.

This work is an extension of the research presented in Guevara *et al.* [13], where real-time detection of movements during rehabilitation exercises was addressed in a preliminary and simpler way. With the inspiration of these examples of rehabilitation assistance systems, a new approach has been here proposed.

3 Materials and methods

3.1. Dataset description

To carry out this study, a database of four patients who had undergone hip replacement surgery was used. These patients agreed to be monitored by the Kinect 2 camera while performing the rehabilitation exercises along 10 physiotherapy sessions (once per week). The correctness of the rehab exercises was performed by a physiotherapist.

During the performance of the rehabilitation exercises, the Kinect 2 camera captured the space coordinates (x, y, z) at 25 body points (Figure 1), which means 75 attributes for each body position.

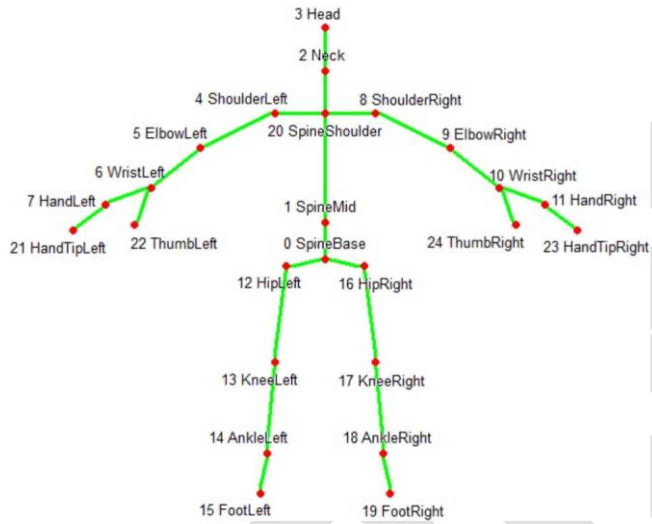

FIGURE 1. Body skeleton with body points detected by the XBOX One Microsoft Kinect 2.

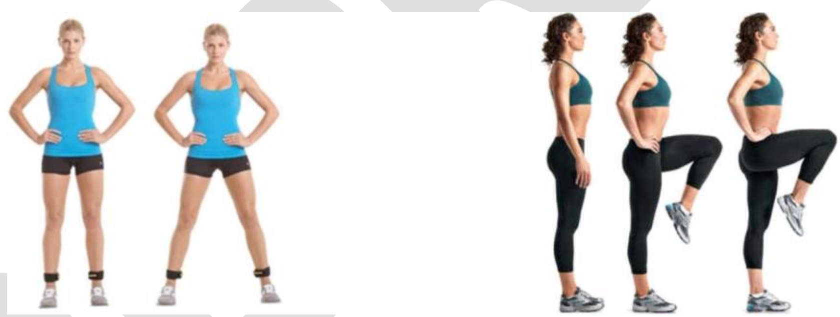

FIGURE 2. Rehabilitation exercises ‘side-step’ (left) and ‘knee-lift’ (right).

The rehabilitation exercises chosen in this study are the ‘side-step’ (lateral leg displacement) and ‘knee-lift’ (knee flexion) with both legs (Figure 2, left and right, respectively).

The Kinect camera records all the movements during the exercise (sampling rate, 16 kHz) but we are only interested in the initial and final position vector of the movement, and in the total time the exercise requires, to calculate the speed and the angle.

The rehabilitation sessions are planned by the physiotherapist. They are composed of a set of exercises. Each one of the four patients attends 10 rehabilitation sessions. Table 1 shows the number of series of exercises per session. Over the 10 weeks, a patient does an increasing number of exercises (from 64 to 104) of each type of the two exercises with each leg. For example, the first week the patient does 8 series of 8 exercises of each type of rehab exercise. That is, 64 exercises of knee lift with the right leg, 64 with the left leg and 64 side-step exercises with each leg. That means 256 exercises the first session. The second week the patients does the same number of exercises, but this number increases along the sessions. The last 2 weeks the patient does 104 exercises of each type with each limb (16 series of 8 exercises).

TABLE 1. Series of rehabilitation exercises each session (10 weeks) of each type and for each limb.

Week	1	2	3	4	5	6	7	8	9	10
No. series	8	8	8	8	8	8	8	8	8	8
No. exercises/series	8	8	9	9	10	10	11	12	13	13
Total no. exercises	64	64	72	72	80	80	88	96	104	104

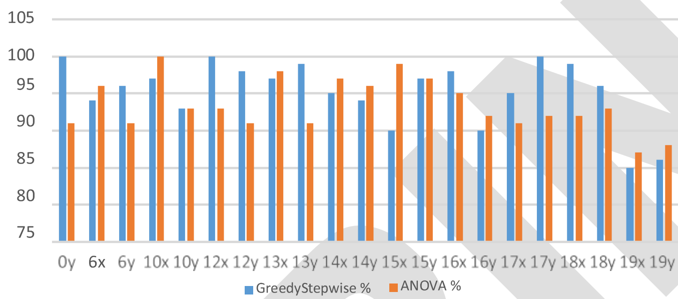

FIGURE 3. Features selection with Greedy Stepwise (blue, left) and ANOVA (red, right) algorithms (over threshold).

Hence, the first week a patient does 64 exercises of each type with each leg, i.e. 256 exercises. Along the 10 sessions, a patient does 3296 exercises that are recorder by the Kinect camera, 824 exercises of each type with each limb.

4.1.1 Attributes selection To generate the movement detection model and in order to reduce the database, it is necessary to identify which are the most relevant attributes [12]. Note that the Data Base consists of 3296 exercises for each patient, i.e. the four patients do a total of 13184 exercises along the 10 sessions. The Kinect camera records all the body position during the execution of the exercises but we will only use the initial and final position vector of each exercise. Still, these vectors have 75 attributes each. That is why it is necessary to reduce the number of features to work with.

Thus, the Analysis of Variane (ANOVA) and Greedy Stepwise [28,29] feature selection algorithms have been applied to the 75 attributes (25 body points captured by the Kinect camera, three coordinates; Figure 1) of the initial and final position of each exercise (13184 exercises).

As it is a supervised system, the correct values of those attributes are known. ANOVA compares each feature vs the rest by computing the ratio between the mean square for treatment and the mean square for error. We have used the mathematical function of the software Orange Python that calculates it. Besides, the Greedy Stepwise algorithm available with Weka software was also applied. It iteratively evaluates a candidate subset of features, then modifies the subset and evaluates if the new subset is an improvement over the old.

The relevant attributes were selected setting a threshold (85%) on the values obtained by the ANOVA and Greedy Stepwise feature selection algorithms. In practice, the values almost coincide with both methods. Out of the 75 features available, 54 were below that threshold, and they were discarded as they do not give useful information to discriminate the correctness of the rehab exercises, or the information was redundant. The 21 attributes chosen are shown in Figure 3.

In addition, the results were confirmed by the physiotherapist who has been working with us. Indeed, this expert, Dr. Yves Rybarczyk, is the one who properly assessed the correctness of the human's motion for all the exercises. In [28], a similar set of features is obtained. The body coordinates finally selected are the following: 0y, 6x, 6y, 10x, 10y, 12x, 12y, 13x, 13y, 14x, 14y, 15x, 15y, 16x, 16y, 17x, 17y, 18x, 18y, 19x and 19y. As it can be seen, these attributes mainly identify the movement of the patients' lower extremities and only the coordinates (x, y).

4.1.2 Description of the variables We are going to work with some variables related to the body movement. These variables will help us to assess if the rehab exercises are correctly performed. These variables are calculated from the 21 selected position attributes measured by the Kinect camera and the time spent in performing the rehab exercise.

The four decision variables are the opening angle between the legs (degrees), hip movement (cm), head movement (cm) and execution speed (cm/s), of each of the exercises.

The working angle, α (°), is obtained from the measured coordinates 0y, 15x, 15y, 19x and 19y. It is calculated by (1) from the triangle between the positions of the feet and the spine base.

$$\cos \propto = \frac{B(X_i) * C(X_i) + B(X_j) * C(X_j)}{\sqrt{(B(X_i))^2 * B(X_j)^2} * \sqrt{(C(X_i))^2 * C(X_j)^2}} \tag{1}$$

The head movement, δ (cm), is obtained by applying the Euclidean distance (2) between the initial and final positions of the head, $Q_i(x_i, y_i)$ and $Q_f(x_f, y_f)$, using the skeleton points 3x, 3y, 2x and 2y.

$$\delta = \sqrt{(Q_i + Q_f)^2 + (Q_i + Q_f)^2} \tag{2}$$

The hip movement, μ (cm), is calculated as the distance between the initial and final positions of the hip, $P_i(x_i, y_i)$ and $P_f(x_f, y_f)$, using the body coordinates 12x, 12y, 16x, and 16y (3).

$$\mu = \sqrt{(x_i + x_f)^2 + (y_i + y_f)^2} \tag{3}$$

The speed, ρ (cm/s), is calculated as the displacement of the movement (skeleton points 0y, 15x, 15y, 19x and 19y), divided by the time t that the completion of the exercise requires (4),

$$\rho = \frac{\sqrt{(x_i + x_f)^2 + (y_i + y_f)^2}}{t} \tag{4}$$

According to the physiotherapist, if the value of the variable is within a range set by these experts (Table 2), the rehab exercise is well done or at least the evolution seems to be positive. The labels 'low', 'well' and 'high' establish an envelope between two values that indicates the correctness of the exercise. The 'low' label means the values of the variables are below the appropriate completion of the exercise. This is usually due to the pain the patient suffers when stretching the limbs. The label 'well' means a correct execution of the exercise (healthy people would do it so), within the adequate range, and the 'high' label means too fast or too much displacement of the limbs.

Typically, an adequate evolution of a patient starts with movements in the 'low' range and improves until the patient remains in the good range of values. However, sometimes due to lack of physical therapy assistance and for the pressure to hasten the recovery, the patient can go to the 'high' range or stay in the 'low' one.

TABLE 2. Range of values of the rehabilitation exercise variables.

	Low		Well		High	
	Min	Max	Min	Max	Min	Max
Angle of legs α	0	24	25	45	46	90
Hip movement μ	-	-	0	10	11	20
Head movements δ	-	-	0	10	11	20
Execution speed ρ	1	9	10	20	21	30

TABLE 3. Movement detection with different algorithms, correctly (CC) and incorrectly classified (IC).

	Training (%)		Tests (%)	
Algorithm	CC	IC	CC	IC
Bayesian networks	100	0	99.99	0.01
UCS	99.98	0.02	98.17	1.83
C4.5	99.64	0.36	96.47	3.53
GANN-C	99.71	0.29	96.44	3.56
FURIA	99.87	0.13	98.78	0.12

3.2 Artificial intelligent techniques

The intelligent techniques that were tested for the classification of the rehabilitation exercises as correct or incorrect are brief ly presented in this subsection. Among them, we selected the most suitable ones for this particular application.

Bayesian networks

A Bayesian network is a probabilistic graphical model that represents a set of random variables and their conditional dependencies through a directed acyclic graph. The nodes represent random variables, which can be observable quantities, latent variables, unknown parameters or hypotheses. The edges describe the conditional dependencies, where each node has an associated probability function that takes as input a particular set of values of the parent variables of the node and returns the probability of the variable represented by the node [7].

UCS

The UCS is a learning classifier system (LCS) derived from XCS. An LCS is an adaptive method with reinforcement learning. In the supervised learning classifier, the correct action is only determined after the action is chosen [1]. The basic function of UCS is to generate the learning model and check the accuracy of that model. The population of a UCS is based on rules that have a condition and an action of the classifiers, but it requires a set of parameters to be configured [30].

Decision Tree C4.5

Decision tree is one of the most widely used classification methods, especially with unbalanced datasets. The C4.5 decision tree algorithm was developed by Quinlan. Decision trees are models whose structures have some similarities to f low diagrams. They continuously generate partitions of the initial dataset until they contain elements of a single class [11, 14].

FURIA

Fuzzy unordered rule induction algorithm (FURIA) is a relatively novel rule-based classification method, based on the well-known RIPPER algorithm (Cohen, 1995). The FURIA algorithm learns

TABLE 4. Classification algorithms performance for each rehab exercise.

	Side-step			Knee-lift		
	Right leg	Hip	Left leg	Right leg	Hip	Left leg
Bayesian network	97,02%	96,65%	99,03%	98,56%	98,00%	99,11%
UCS	98,64%	98,10%	98,69%	98,91%	97,34%	98,77%
GANN-C	96,45%	98,12%	98,78%	97,90%	98,67%	97,79%

fuzzy rules instead of conventional rules and unordered rule sets instead of rule lists. Experimental results have shown that FURIA significantly outperforms the original RIPPER algorithm, as well as other classifiers, in terms of classification accuracy [5, 24].

GANN-C

GANN-C is a search-based algorithm based on natural selection and genetic evolution. Indeed, GANN-C is part of evolutionary computation [4], [25]. This algorithm was first presented by Miller (1989).

4 Movement detection and rehab exercises classification

Some preliminary results of the outcomes of these five different classification algorithms are presented in Table 3. In order to select most suitable ones for this application, these algorithms were applied to two patients doing the knee-lift exercise with the right leg for the training, and they were tested on a third patient doing the same exercise.

The physiotherapist assesses if an exercise is correctly or incorrectly performed. The classifiers are then applied (only for that particular exercise) and the confusion matrix is obtained. Results of Table 3 indicates the hits (%), confirmed by the expert. This has helped us to select some techniques that are more appropriate for this specific application.

Practically, all the algorithms initially tested gave good results (Table 3). So we decided to select those that had better performance or were more f lexible to be used in combination with other. Thus, Bayesian, UCS and GANN-C techniques were chosen.

Those three algorithms were now applied to the same two patients and tested with the third one, this time for the two types of exercises (side-step and knee-lift) with both legs, to see if there was any difference in the results. The correctness of the results was again assessed by the physiotherapist.

According to Table 4, although the difference is very small, apparently GANN-C is the most suitable technique for the hip variable, regardless of the type of exercise; Bayesian networks is the best one for the left leg and UCS gives the best outcome for the right leg. So we decided to use the algorithm that gave best results for each limb and for each type of rehab exercise.

The correctness detection system was then implemented joining those three techniques. It is a supervised system. Once trained, it was applied to both types of rehab exercises. The dataset contains incorrectly and correctly performed ones, assessed as such by the physiotherapist. Each technique (Bayesian network, UCS and GANN-C) was applied to a specific limb or to the hip, according to Table 4. Results are shown in Table 5.

The Bayesian network works well for any exercise with the right leg, giving a true positive rate (TPR) of 98.9% and false positive rate (FPR) of 0.9% for the side-step rehab exercise and TPR = 98.7% and FPR = 1.2% for the knee-lift exercise. The UCS gives the ratios TPR = 99.9% and

TABLE 5. Classification results of correctness of exercises (% hits).

Side-step/right leg	Side-step/ left leg	Side-step/hip	Knee-lift/right leg	Knee-lift/ left leg	Knee-lift/ hip
Bayesian network 98,91	UCS 99,95	GANN-C 97,08	Bayesian network 98,66	UCS 100	GANN-C 99,90

FPR =0.24% for the side-step exercise and TPR= 99.9% and FPR=0.12 for knee-lift rehabilitation exercise. Finally, GANN-C reaches TPR= 97.1% and FPR = 2.9% for the side-step exercise and TPR =98.9% and FPR 1.0=9% for knee-lift rehab exercise.

The two exercises considered in this study have a similar difficulty level; both the side-step and knee-lift are simple exercises. This could explain the good and similar results obtained in the confusion matrix for both rehabilitation exercises.

Overall, the outcome of the algorithms matches over 98% with the assessment made by the physiotherapist.

5 Prediction of rehabilitation evolution

A predictive model was also developed based on the values of the four variables described in Table 2. The values of these variables were obtained during the 10 weeks of physiotherapy treatment (Table 1). The exercises were supervised by a specialist who confirmed when the movements were correct and also what values were considered outside the appropriate range. The main objective of this approach is to identify if a patient's evolution is adequate and thus the patient can successfully complete the rehabilitation; otherwise, it may be necessary to modify the exercise sessions or to change the way of performing it.

For each of the four variables (working angle, hip movement, head movement and speed), the correctness of the performance is given by the range of values of Table 2. This sets a maximum and a minimum. Our proposal is to determine a bounding envelope between the maximum and minimum values that are allowed for these four variables, i.e. to generate two curves (upper and lower bounds) as in [9]. The right evolution of the patient must fit that interval. The average curve shows a correct rehabilitation evolution, even if keeping the values of the variables within the rage is enough. That is, the first sessions the patient are probably within the 'low' range of values but still its evolution can be good if the trend is appropriate.

The average of the values of the variable for each series of exercises during a session is represented. That is, the series with the minimum average value and the series with the maximum average value. As those series of exercises has been monitored by a physiotherapist, supposedly these values represent a correct evolution of the patient, taking into account that all the four variables must be within the right interval at least during the last sessions. Low-order polynomial models are obtained for those data and they can be considered a good trend of the evolution of the patient, ever if at the beginning the values are out the correct range.

Figures 4–7 show the values of the four variables (angle, hip, head and speed) along the 10 sessions for a patient doing a series of one type of exercise. At each session, the average value of the variable during all the series for each type of exercise is represented (black line), with the maximum (green line) and minimum (red line) values. The ranges that indicate the exercise is correct are represented as dashed orange lines ('good' range; Table 2).

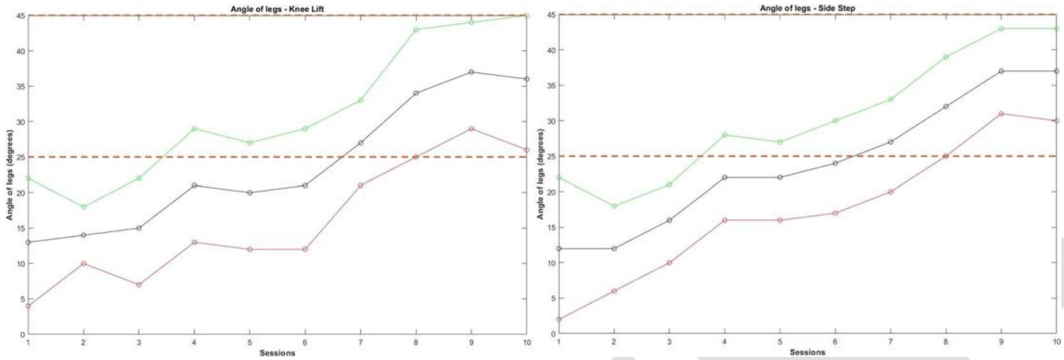

FIGURE 4. **Opening** angle values along the 10 sessions, maximum (green), minimum (red) and average (black). Knee-lift exercise (left) and side-step exercise (right).

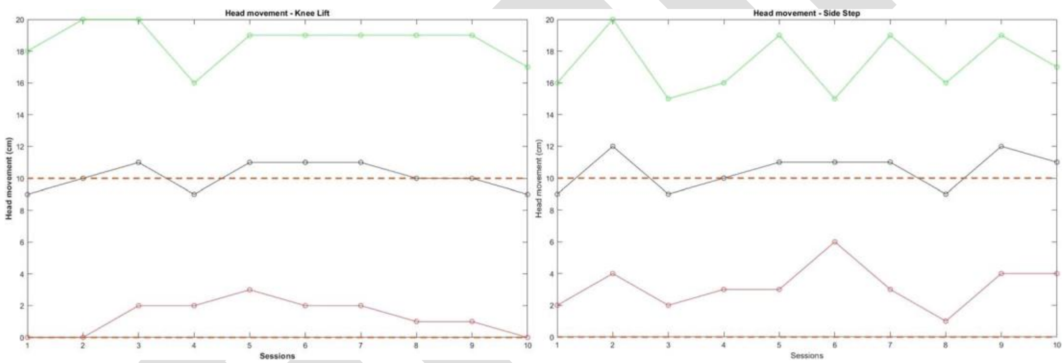

FIGURE 5. Head movement values along the 10 sessions, maximum (green), minimum (red) and average (black). Knee-lift exercise (left) and side-step exercise (right).

For instance, Figure 4 (left) shows the average of the 16 values of the angle between legs for the knee-lift exercise, with both limbs. In Figure 4, right, the same results are represented but now for the side-step exercise with both legs. At another session, the same average, maximum and minimum values are obtained for the exercises done during that session.

The same values has been obtained and represented for the head movement (Figure 5), hip movement (Figure 6) and speed (Figure 7). The corresponding polynomial models of each variable are also calculated.

As it is possible to see in Figure 4, the evolution starts with values below the low range but it ends in the correct range, according to Table 2. That means that during the last sessions, the patient did all the series of exercises correctly. Indeed, in the last two sessions, even the maximum and minimum angles are within the good range.

The polynomial model of the average values of this variable is given by the following equation: $F_{angle}(x) = p1x^4 + p_2x^3 + p_3x^2 + p_4x + p5$, $p_1 = 0.00278$, $p_2 = 0.56964$, $p_3 = -3.6304$, $p_4 = 10.302$, $p_5 = 5.0833$.

In Figure 5, the head movement along the sessions is shown. In this case, the movement was not correct for all the exercises. In fact, the average values are at some sessions below the correct

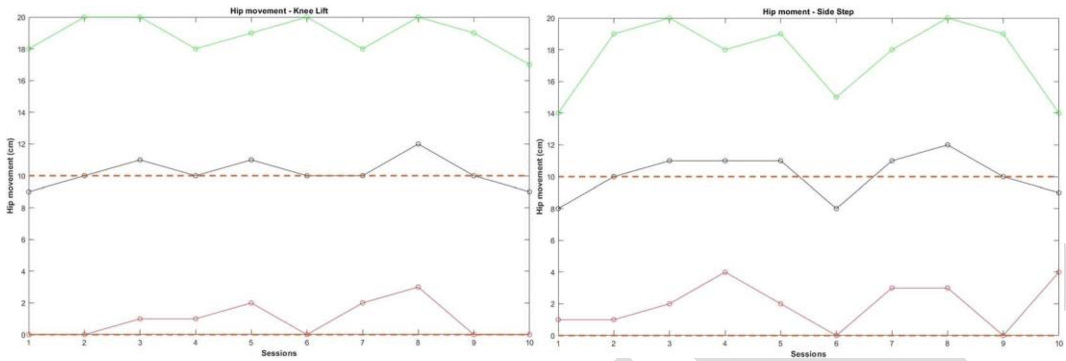

FIGURE 6. Hip movement values along the 10 sessions, maximum (green), minimum (red) and average (black). Knee-lift exercise (left) and side-step exercise (right).

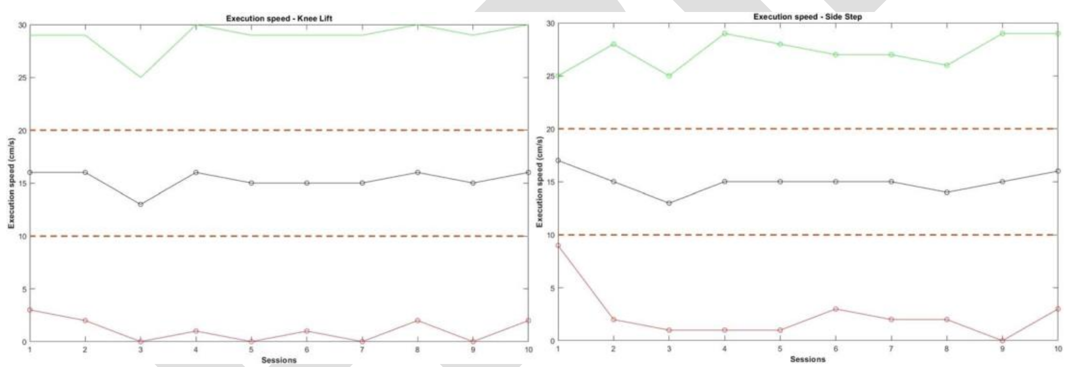

FIGURE 7. Speed values along the 10 sessions, maximum (green), minimum (red) and average (black). Knee-lift exercise (left) and side-step exercise (right).

threshold. However, according to the expert, there is a tolerance regarding this value as it is difficult to get it accurately and the variation is very small. Note that this variable is important for the balance. Anyway, the average values are within the right interval during most of the sessions.

$F_{head}(x) = p_1x^4 + p_2x^3 + p_3x^2 + p_4x + p_5$, $p_1 = 0.0042$, $p_2 = -0.0865$, $p_3 = 0.44945$, $p_4 = 0.0099$, $p_5 = -0.5833$.

Figure 6 shows the hip movement along the sessions. Again, the average movement is in the high range at some sessions because the range is very small.

$F_{hip}(x) = p_1x^5 + p_2x^4 + p_3x^3 + p_4x^2 + p_5x + p_6$, $p_1 = 0.0012821$, $p_2 = 0.029429$, $p_3 = 0.25758$, $p_4 = -1.1687$, $p_5 = 3.0279$, $p_6 = -1.333$.

Finally, in Figure 7, the speed of the execution of the rehab exercises is shown for the 10 sessions. The average values are always in the right range along the sessions; this may due to the fact the physiotherapist sets the pace of the performing of the rehab exercises.

$F_{speed}(x) = p_1x^5+p_2x^4+p_3x^3+p_4x^2+p_5x+p_6$, $p_1 = 0.0024359$, $p_2 = -0.062179$, $p_3 = 0.55554$, $p_4 = -1.9374$, $p_5 = 1.5334$ and $p_6 = 2.9333$.

TABLE 6. Prediction results of the rehabilitation evolution of the patients.

	Maximum	Minimum	Mean
	Accuracy	Accuracy	Accuracy
Angle of legs	86,56	87,71	87,11
Hip movement	85,67	86,55	86,43
Head movements	86,34	84,75	87,70
Execution speed	87,01	87,22	87,12
Mean	86,45	86,89	87,12

5.1 Results of the rehabilitation evolution prediction models

These polynomial models that fit the average values of each decision variable (working angle, movement speed, head movement and hip movement) along the physiotherapy sessions are used as prediction models of the evolution of the patient. Those variables are measured by the camera during the rehab exercise. With the values of a patient during the first sessions, the prediction model is applied to check if at a subsequent session the value of that variable will be within the correct range of values, i.e. if it will end within the envelope of the correct movements.

This way, the current recovery state of a patient at any physiotherapy session can be assessed. For instance, if according to the opening angle of the legs at a particular session, let us say, the third session, the angle at the six or seven session that results of applying the model is out of the correct range, some action should be taken to improve the recovery because the patient is not evolving properly. At that stage, according to the model, it should have a different value in order to end reaching the right value. Then, the therapist could make a decision for the next session, e.g. to improve the flexibility somehow or to do any other complementary exercise that will help the patient to evolve better and to obtain an adequate recovery.

After training the system with three patients, the system was tested with a patient who has not been used in the learning process and with another one included in the training set. The data of the first three sessions were used to calculate the values of the variables for the subsequent sessions. If the output of the algorithm matches the value of that variable for that patient, it is a hit, otherwise it is incorrect. The results obtained with these models are satisfactory (Table 6).

So, it is possible to predict the physical evolution of each patient and to take the proper action for the next physiotherapy sessions. The physiotherapist knows in advance what actions should be taken to improve the mobility of the patient (i.e. perform other therapeutic exercises, etc.).

These results can be very useful, but still it is necessary to take into account the different recovery speeds of the patients and the large number of external variables that can affect their physical conditions.

6 Conclusions and future works

In this work, a model for the real-time detection of correct and incorrect movements during the execution of rehabilitation exercises of patients who have undergone hip surgery has been developed. Body movement measurements captured with a Kinect camera of four patients in rehabilitation sessions were used. They performed two exercises over a period of 10 weeks.

An intelligent hybrid system that combines Bayesian networks, GANN-C and UCS algorithms was developed. Identification results of the correctness of the movements were quite satisfactory.

It has also been shown that models of the physical evolution of patients in rehabilitation can be obtained in a simple way. Low-order polynomial models allow the prediction of whether the evolution of a patient is correct, based on a small number of variables. This allows one to take preventive actions to improve the recovery, by changing the exercises or with the monitoring and correction of a specialist.

As future works, we propose applying other sensors to detect more efficiently the movements of the patients. The use of a different distance measure has been proved a critical factor in pattern recognition application [20] and may improve the identification results as the application of deep learning if a large database is available.

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