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تصميم تمارين للذراع البشري للمساعدة في إعادة تأهيلة

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**مركز أبحاث العلوم التطبيقية والتكنولوجيا المتقدمة التابع للمعهد الوطني للفنون التطبيقية الموجود في كويريتارو، المكسيك
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الخلاصة

يقدم هذا البحث تصميم واختبار لتمارين الذراع البشري للمساعدة في إعاده تأهيلة. تم وصف الذراع البشري جنباً إلى جنب مع وصف مشكلة ضعف الحركة. وتم كذلك وصف مخطط مسار الحركة لأربعه تمارين للذراع مع جمع البيانات عن طريق اختبار هذه المسارات. تم توضيح تصميم مسارات مرجعية عن طريق تحليل الانحدار. تم التحقق من الاجراءات عن طريق النواتج الرقمية لاثبات نجاح إنشاء مسار حركي عن طريق تحليل مجموعه عينات من المسارات، وتم إنشاء المسارات المرجعية عن طريق تحليل اثنا عشر عينه من المسارات التي تم الحصول عليها من أربع تمارين مقترحه. يمكن استخدام المسارات المرجعية التي تم الحصول عليها للمساعده في العلاجات التقليدية لإعادة التأهيل باستخدام جهاز آلي.

Design of arm exercises for rehabilitation assistance

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ABSTRACT

This paper presents the design and testing of arm exercises for rehabilitation assistance. The description of the human arm is presented together with the arm motion impairments. The motion planning for four arm exercises and the experimental procedure for data collection are described. A procedure to generate reference trajectories by regression analysis is explained. The procedure is numerically validated to prove the successful generation of a representative trajectory for a set of trajectory samples. Reference trajectories are generated using the proposed procedure for four arm exercises through trajectory samples acquired from 12 subjects. The obtained reference trajectories can be used for rehabilitation assisting the traditional therapies using an automatized device.

Keywords: biomechanics; motion assistance; motion planning; regression analysis; rehabilitation exercises.

INTRODUCTION

The design of human motion can have several applications such as the functional evaluation of the extremities, the evaluation of the biomechanics of the human walking, and the motion assistance by using medical devices. Particularly, the characterization of the normal gait has been the most treated topic in this field. For example, in Varela *et al.* (2015), a process to characterize the human walking is presented, and several trajectories were acquired by using the Cassino Tracking System (CaTraSys). To compute an average over all the walking cycles, the time of the trajectories was normalized into a range from 0 to 100% of the cycle gait, and the positions were interpolated by using a spline interpolation. Thus, the mean trajectory can be used as a reference trajectory to evaluate the effects of different walking conditions. In Koopman *et al*. (2014), speed-dependent references for the normal gait were generated from trajectories acquired from healthy people. The trajectories were reconstructed by regression analysis and smoothed by splines. The references were generated depending on the velocities to assist the human walking.

On the other hand, in Ijspeert *et al*. (2001), trajectories from the human body motion have been acquired to generate references for a virtual trainer. The reference trajectories were successfully calculated by a recursive least squares regression. Therefore, the virtual trainer can teach body movements for rehabilitation therapy. In Chaparro-Rico *et al.* (2015), reference trajectories were generated for knee rehabilitation. Trajectories from a healthy person were acquired by using an image processing method. The trajectories were processed and adapted to different legs sizes, using anthropometric human dimensions. The references were used for an assistive device that performs the trajectories by using ranges of velocities and accelerations that are generally used in commercial devices for knee rehabilitation.

Since the human arm performs several activities of the daily life, its functionality can be affected by injuries or diseases. Therefore, the design of human arm motion is also an important topic for rehabilitation purposes. In Corona-Acosta & Castillo-Castaneda (2015), reference trajectories were generated for arm rehabilitation. Trajectories from healthy people were acquired by using image processing to reproduce them in a device for arm rehabilitation. The trajectories obtained from a person were transformed to different arm sizes. This method allows varying the trajectory according to patient sizes. However, the trajectory samples come from just one person. In Zadravec & Matjačić (2013), a model of the planar biomechanics of the arm was obtained. The model allows planning the arm trajectory to move from one point to another, including muscle tension. The model is based on healthy patients, and it can generate reference trajectories that can be used for postural training or prosthesis motion planning. However, the model cannot generate references trajectories for complex maneuvers as required in therapy (Ju *et al.*, 2005) such as the tracing of paths with different shapes. In Nef & Riener (2005), reference trajectories for arm therapy can be obtained by using samples from each patient. Arm positions are stored by ARMin, a device for arm rehabilitation , while the movement is performed by the patient with the help of an assisting therapist. The stored positions are used as path reference for the therapy by using different speeds. The device stores just one path and reproduces it. Thus, the movements could be wrong. The human motion is variable, and a reference should be obtained by using several samples (Billard *et al.,* 2008). In Martin & Reza-Emami (2014), geometric figures such as the circle or the right line were used as reference trajectories for arm rehabilitation. In addition, the therapist force was imitated and regulated by using a neurofuzzy control. However, an exercise for arm rehabilitation can be more complex than a typical geometric figure (Ju *et al.,* 2005).

In this paper, reference trajectories are obtained for four human arm exercises by using regression analysis. The samples have been acquired from 12 subjects by performing 12 cycles for each exercise. Since regression analysis required a known polynomial order to generate the polynomial that fits the trajectories, the proposed procedure has been designed to automatically select the polynomial order that best fits the trajectories by using an algorithm that has been designed by the authors. The relevance of the proposed approach is that it can automatically generate a reference trajectory using a set of samples from each subject. The procedure has been validated to demonstrate that it can successfully generate a reference trajectory of an arm exercise using several samples acquired from a subject.

ARM ANATOMY AND MOTION IMPAIRMENTS

The human arm is the upper limb of the human body and performs several activities of the daily life such as eating, writing, combing the hair, and driving, among others. The main function of the human arm is the manipulation of objects. Unfortunately, mobility and functionality of the upper limb may be affected by injuries or diseases. Therefore, a rehabilitation therapy is indispensable to restore the normal function of the limb, and the recovery of the range of motion. Several diseases can affect the arm motion, for example, neurological diseases such as polio, hemiplegia, paraplegia, and sclerosis; muscle diseases such as myelitis, immobilization syndrome, muscular dystrophies, spasticity, and muscle atrophy postural alterations; joint diseases such as osteoarthritis, arthritis, and periarthritis, among others that can also alter the arm capabilities as pointed out in Corona-Acosta (2015). On the other hand, the injuries that can alter the arm capabilities can occur during sport activities, falls, or impacts.

The human arm is composed of three principal parts, namely, upper arm, forearm, and hand. The arm is connected to the body trunk through the shoulder joint; the forearm is connected to the upper arm through the elbow joint; and the hand is connected to the forearm through the wrist joint. Figure 1 presents the motion axes of the human arm. The shoulder joint has three degrees of freedom (DOFs): two around the axes 2, 3 (flexion-extension) and one around axis 1 (abduction-adduction). The elbow joint has one DOF moving around axis 4 (flexion-extension), and the motion of the forearm around axis 7 (pronation-supination) adds another DOF to the elbow. The wrist joint has two DOFs around axis 5 (flexion-extension) and around axis 6 (abduction-adduction). However, also the pronation-supination (around axis 7) adds another DOF to the wrist joint (Kapandji, 2008).

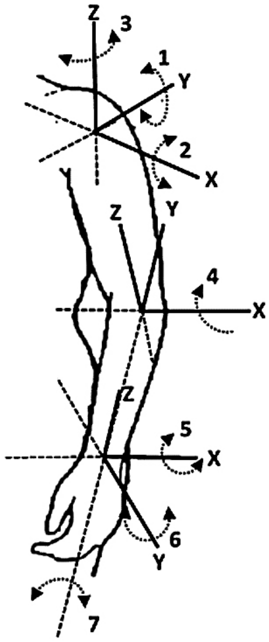

Figure 1. Motion axes of the human arm.

MOTION PLANNING FOR THERAPY EXERCISES

To design the arm exercises for rehabilitation assistance, three main stages have been considered for the procedure as seen in Figure 2. The first stage has been the motion planning consisting of selecting the therapy exercises and planning the experiment for data collection; the second stage has been the lab test for data collection; and the third stage has been the postprocessing of data collection to generate reference trajectories by regression analysis. The method for postprocessing is also explained in detail further on. In the first stage for the motion planning, four exercises that are generally used for therapy arm have been planned to treat the shoulder and elbow (Figure 3). The four exercises can be used in the rehabilitation therapy in several phases to recover capacities.

1. Motion planning → 2. Lab Test → 3. Post processing

Figure 2. Flowchart of the general procedure carried out in this work by three stages.

The selected exercises are commonly used by physiotherapists such as therapy specialists at CRIQ (Center of integral rehabilitation of Queretaro, Mexico) (Corona-Acosta & Castillo-Castaneda, 2015) who provided advice on arm rehabilitation therapies. In general, the exercises consist of tracing a predefined figure with a hand tracing point (TP), Fig. 3a, from an initial point A to an end point B. An exercise from a point A to a point B has been considered as a cycle. Every figure is defined by a path represented by dotted lines in Figure 3. The four exercises are performed on a horizontal plane by possible leaning with the upper limb on a table where the reference frame is defined as X and Y, Figure 3. The wrist keeps a constant posture during the execution of all exercises. It is important to mention that a skateboard is generally used as arm support when the selected exercises are performed by a patient with an injury or an illness. However, a healthy subject should be able to perform the exercises without arm support as seen in Figure 3.

The procedure for Exercise No. 1 consists of tracing a curve with the tracing point of the hand (TP) from the point A to the point B by performing horizontal flexion of shoulder, while the elbow keeps a constant posture, Fig. 3a. The procedure to perform the Exercise No. 2 consists of tracing a curve with the tracing point of the hand from the point A to the point B by carrying out flexion of elbow, while the shoulder keeps a constant posture, Fig. 3b. The procedure for Exercise No. 3 consists of tracing the figure of the number **8** with TP from the point A to point B by performing coordinated motions of shoulder and elbow, Fig. 3c. In Exercise No. 3, the point A is the same point B since the trajectory starts and finishes at the same point. The exercise for tracing the number **8** is more complex because it involves coordinated motions of the shoulder and the elbow, and the path to trace the number **8** has changes in directions. The number **8** is also used as reference trajectory to evaluate the performance in robots that imitate human tasks as indicated in Chatzis *et al.* (2012). The procedure for Exercise No. 4 consists of tracing the letter **L** with TP from the point A to the point B by performing coordinated motions of shoulder and elbow, Fig. 3d. The Exercise No. 4 has been selected to evaluate a trajectory that involves the combination of straight lines. The alphabet is commonly used as reference to evaluate the imitation skill of a robot when it traces a trajectory (Billard *et al.,* 2004).

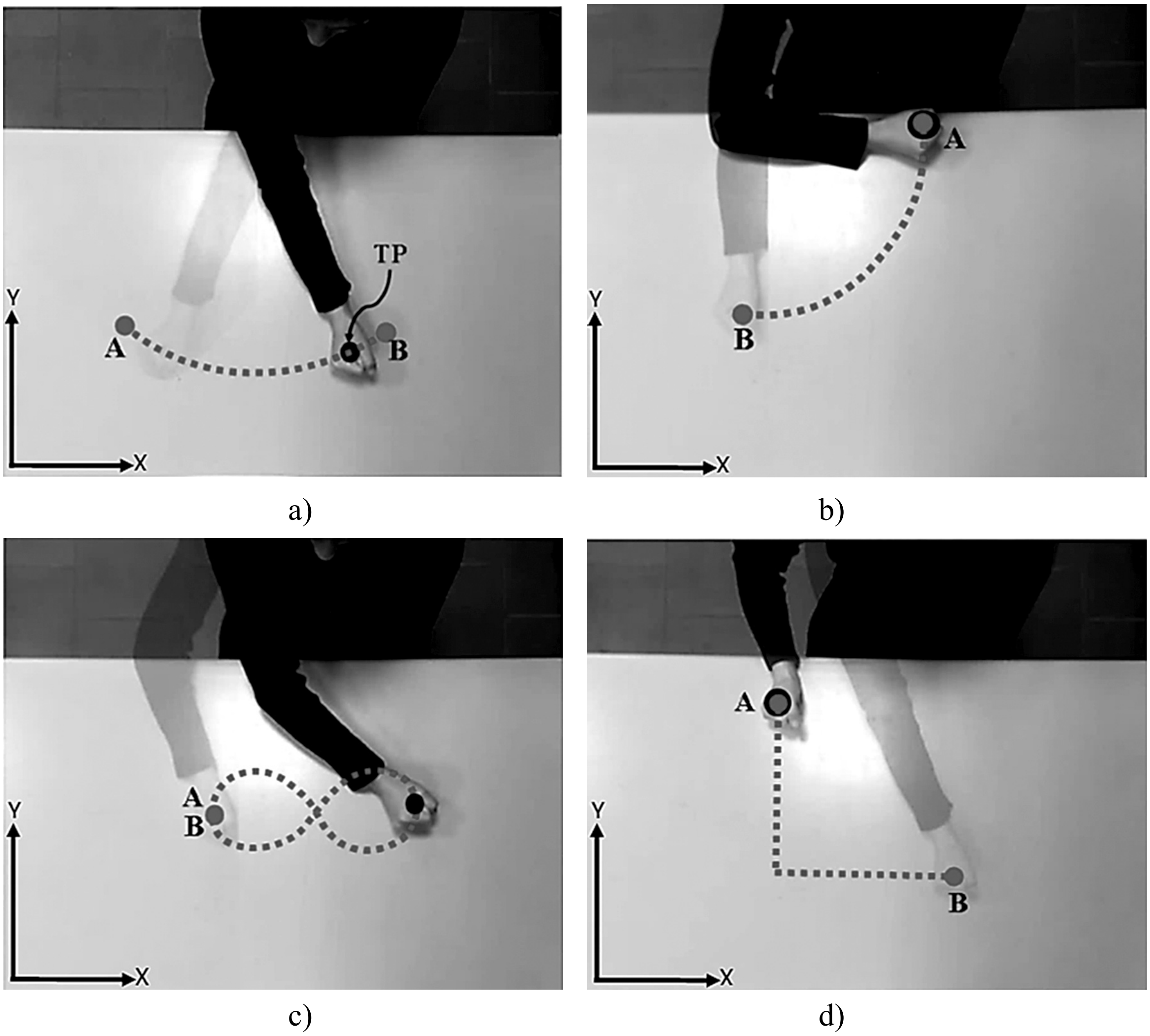

Figure 3. Snapshots of the exercises for arm therapy to trace a figure by a path (dotted line) of the hand point TP of from A to B: a) Exercise No. 1; b) Exercise No. 2; c) Exercise No. 3; d) Exercise No. 4.

Since the target of the exercises is to trace a figure with a point of the human hand, the parameters for designing the exercises are the obtained coordinates of a point of the human arm respect to a XY reference frame versus time during the exercise execution. Although the exercises involve the motion axes of shoulder and elbow, the path traced by a hand point is the parameter that can be used to assist the motion, while the subject tries to reach the target. Therefore, the coordinates as function of time are required to obtain the reference trajectories of the exercises by using regression analysis.

A Kinect vision system can be used for the data collection of the motion. It detects the human body motions by using a camera in combination with infrared sensors and a laser so that it can specifically measure the changes of position of the human hand. A flowchart in Figure 4 shows the proposed procedure for data collection of all the trajectories.

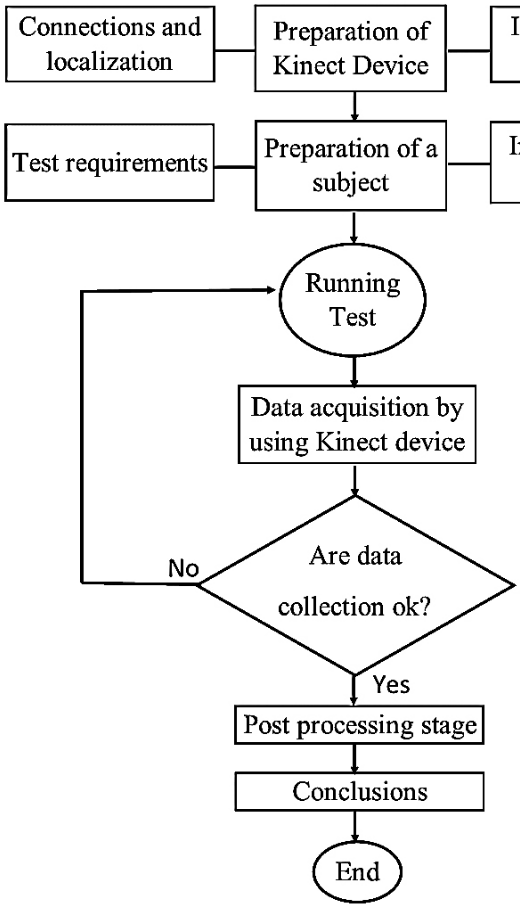

Figure 4. Flowchart of the proposed procedure for data collection.

As seen in Figure 4, the Kinect device is prepared by connecting and initializing a program to acquire and store the data. The Kinect device should be located so that the subject can be entirely seen by the device. The localization of the Kinect device defines the XY reference frame. Then, a subject receives instructions by a supervisor about the procedure to carry out during the test and the exercise performance. When the subject and the Kinect device are ready, the subject performs the procedure 12 times for each exercise as previously explained, while the test is running Kinect device acquires and stores the coordinates of a point on the human hand in a database w. If the collected data is not usable due to human errors during test execution, the test is repeated. If the data have been collected successfully so that the data is usable, the data collection is suitable for the postprocessing stage, and the procedure can be concluded. The proposed procedure was carried out by 12 subjects.

A METHOD TO OBTAIN A REFERENCE TRAJECTORY BY USING A SET OF TRAJECTORY SAMPLES

A trajectory during a human movement varies from one person to another due to individual physical characteristics. Furthermore, a human is not able to reproduce exactly positions during several cycles of a defined movement repeatedly. However, the essential components remain unchanged across the various cycles of a movement. Therefore, reference trajectories can be obtained by processing the samples that are acquired during several cycles of a human movement (Billard *et al.,* 2008; Delson & West, 1996).

Regression analysis has been a widely used method to obtain reference trajectories of a human motion by using several samples with successful results. Particularly, least squares regression is a simple method that can be used to design a human motion (Billard *et al.,* 2008). By using least squares regression, a reference trajectory can be generated by polynomials that are fitted to a set of cycles of a movement. Since the least squares regression analysis is a suitable method to obtain reference trajectories of a human motion, it has been implemented to generate reference trajectories for the selected exercises for arm motion assistance.

To fit a set of samples by using a polynomial, least squares regression method requires a known position data, a known time data, and a polynomial order that should be specified as a known input. Since the position data of the trajectories for arm exercises are composed by X and Y Cartesian components, a polynomial can be obtained for each one.

Figure 5 shows a flowchart to illustrate the inputs and outputs in the regression analysis process, where k is the total number of samples; the inputs $x_1, x_2, \ldots, x_k$ correspond to X components and $y_1, y_2, \ldots, y_k$ correspond to Y components; the inputs $tn_1, tn_2, \ldots, tn_k$ correspond to the normalized time data, where k corresponds to the last sample of the time vector. The time data are normalized for 0-100% of the exercise cycle to apply the regression analysis. Each normalized time sample has been represented by the notation tn_i, where i corresponds to the current sample. The outputs $p_1, p_2, \ldots, p_{N+1}$ correspond to the calculated coefficients that compose the polynomial to fit X components, where N is a predefined polynomial order that is expressed as

$$\hat{x}_i = p(tn_i) = p_1 tn_i^N + p_2 tn_i^{N-1} + \cdots + p_N tn_i + p_{N+1} \tag{1}$$

$c_1, c_2, \ldots, c_{M+1}$ correspond to the calculated coefficients that compose the polynomial to fit Y component, where M is a predefined polynomial order that is expressed as

$$\hat{y}_i = c(tn_i) = c_1 tn_i^M + c_2 tn_i^{M-1} + \cdots + c_M tn_i + c_{M+1} \tag{2}$$

The variables $\hat{x}_i$ and $\hat{y}_i$ are the fitted position outputs that are calculated by the polynomials, and these will define the reference trajectory.

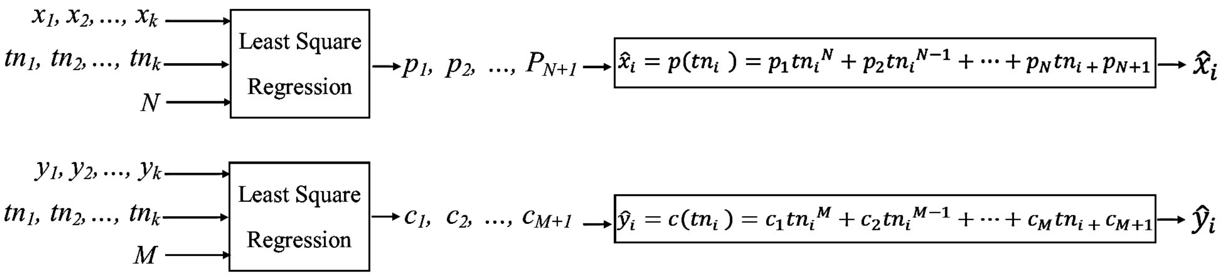

Figure 5. Flowchart to illustrate the regression analysis process.

The coefficients $p_1, p_2, \ldots, p_{N+1}$ and $c_1, c_2, \ldots, c_{M+1}$ can be fitted by calculating the error e_x and e_y, respectively, between the fitted position outputs $\hat{x}_i$ and $\hat{y}_i$ and the position inputs x_i and y_i under the minimum error criterion that can be expressed for each Cartesian component as (Bishop, 2006; Vijayakumar & Schaal, 2000 ; Calinon *et al.,* 2010)

$$e_x = \sum_{i=1}^{k} (\hat{x}_i - x_i)^2 \tag{3}$$

$$e_y = \sum_{i=1}^{k} (\hat{y}_i - y_i)^2 \tag{4}$$

Since the N and M orders are inputs that will be predefined to start the regression analysis, a process has been designed to select a feasible value for N and M automatically. Thus, the error between position data inputs (x_i, y_i) and the fitted position outputs $(\hat{x}_i, \hat{y}_i)$ is estimated for N and M values from 1 to 20. The error $(\hat{x}_i, \hat{y}_i)$ has been defined as the mean square of the residuals r_i between position input data (x_i, y_i) and the fitted position outputs $(\hat{x}, \hat{y}_i)$ as

$$e_{x,y} = \sqrt{\sum_{i=1}^{k} \frac{(r_i)^2}{k}} \tag{5}$$

where a residual r_i can be understood as the distance between a point $(\hat{x}, \hat{y}_i)$ and a point (x_i, y_i) that can be expressed as

$$r_i = \sqrt{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2} \tag{6}$$

where i identify the current evaluated point. A suitable algorithm selects a value for N and a value for M by discarding the polynomials when the error has a negligible reduction regarding the other polynomial, discarding the polynomials with larger error. This is accomplished by using the calculation of the slopes along the error curve. The algorithm selects a combination polynomial when the slope is less than 1.0 corresponding to error reduction value around 5%.

To test the regression method that includes the algorithm to select a suitable N and M polynomial order, 100 sets of 10 trajectories have been simulated by disturbing a predefined trajectory. The predefined trajectory has been named target trajectory, and each trajectory obtained by disturbing the target trajectory has been named simulated trajectory. Three disturbances have been applied. The disturbance 1 consists in adding or subtracting a determinate magnitude to the starting and the ending position values of the target trajectory so that the trajectory is scaled on their X and Y Cartesian components in function of the new starting and ending positions. The disturbance 2 consists in varying the run-time by adding or subtracting time to the period time of the target trajectory so that the temporal axis is scaled in function of the new run-time. The disturbance 3 consists in applying random noise to all point positions.

By applying the disturbance 1, the variations of the trajectories performed by a subject during the execution of an exercise for several cycles are simulated. By applying the disturbance 2, the run-time variations during the execution an exercise for several cycles are simulated. By applying the disturbance 3, possible noises during an acquisition data are simulated. Every set of simulated trajectories is processed by the regression method to rebuild the target trajectory so that an average of the simulated trajectories is calculated for each set by this method. The disturbances are controlled in order to test if the error $er_{x,y}$ (see Equation 7) between the average of the simulated trajectories and the target trajectory varies proportionally to the magnitude of the disturbances. If the error $er_{x,y}$ varies proportionally to the disturbances, the method that includes the algorithm for selection of the polynomial order can be considered feasible to calculate reference trajectories for arm exercises. The error $er_{x,y}$ can be expressed as

$$er_{x,y} = \pm \frac{\sum_{i=1}^{k}\left(\frac{|x_i - \hat{x}_i|}{x_i} * 100\right) + \sum_{i=1}^{k}\left(\frac{|y_i - \hat{y}_i|}{y_i} * 100\right)}{2k} \% \tag{6}$$

where x_i and y_i are the position points of target trajectory and $\hat{x}_i$ and $\hat{y}_i$ are the positions points average of the simulated trajectories. Fig. 6a shows an example of a set of 10 simulated trajectories, and Fig. 6b shows the given target trajectory versus the average of the simulated trajectories that has been obtained by using the proposed method. The error $er_{x,y}$ for the example in Fig. 6b is ± 0.3754%. In this example, the introduced method is able to reconstruct the trajectory with small error.

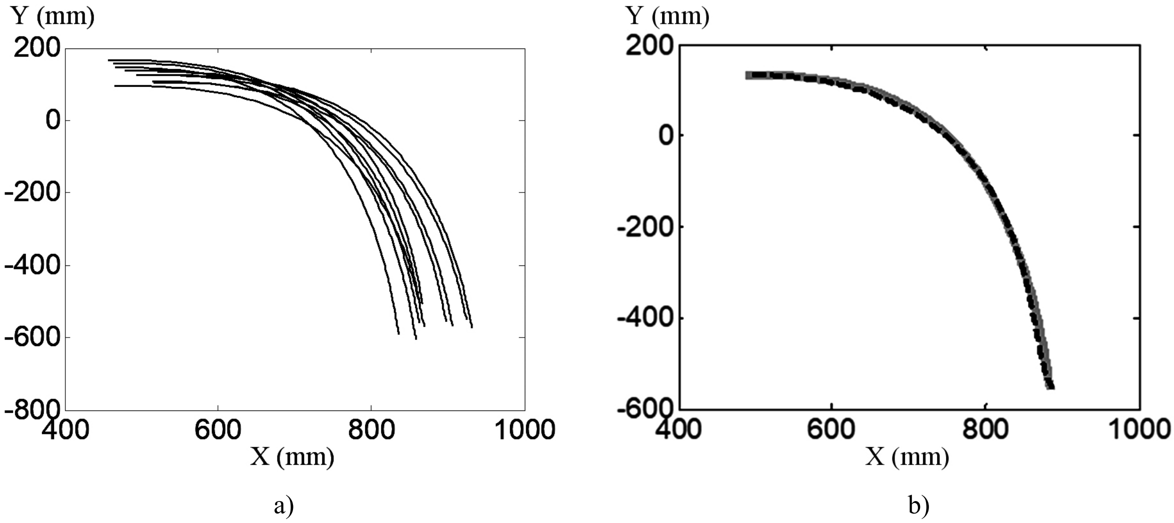

Figure 6. An example of a set of 10 simulated trajectories processed by using the proposed method: a) a set of 10 simulated trajectories; b) Target trajectory (in gray) versus the average curve obtained by applying the method (dotted line).

However, it is necessary to test if the error $er_{x,y}$ varies proportionally to the magnitude of the disturbances. Therefore, the error $er_{x,y}$ has been calculated for five cases, namely, *Cases I, II, III, IV*, *and V*, where the magnitude of the disturbances has been gradually increased starting with *Case I* and ending with Case V as seen in Table 1. Therefore, each case *(Cases I, II, III, IV*, *and V)* corresponds to different disturbance magnitudes where *Case I* corresponds to the range of smaller magnitudes and *Case V* corresponds to the range of larger magnitudes. In each case, 100 sets of 10 simulated trajectories have been processed using the proposed method. In Table 1, the error $er_{x,y}$ is listed as obtained for each case. The error $er_{x,y}$ calculated between the obtained average curve and the target trajectory increases proportionally to the magnitude of the disturbances in *Cases I, II, III, IV*, *and V.* Since the error $er_{x,y}$ is proportional to the disturbances, the method can be considered feasibly to process the human arm exercises. In particular, *Case I* gives the smallest error with a value of ± 0.949% since this proposed case has the smallest disturbance values of the used ones. *Case V* gives the highest error with a value of ± 2.932% since this proposed case has the highest disturbance values of the used ones.

The designed algorithm used for the trajectory fitting is based on a CAS (Computer Algebra System). The software has dedicated tools that allow the implementation of statistical modelling as regression analysis and other statistical methods. The trajectory fitting has been elaborated as off-the-shelf toolboxes using proper tools in CAS environment with algorithms designed by the authors.

Table 1. Ranges of the disturbances applied to the simulated trajectories for each evaluated case and the error $er_{x,y}$ calculated between the average trajectory obtained by applying the proposed method and the target trajectory.

Cases	Ranges of disturbance 1 (mm)	Ranges of disturbance 2 (ms)	Ranges of disturbance 3 (mm)	Error $er_{x,y}$ (%)
I	[-10 ,0] ,[0 ,10]	[-10 ,0] ,[0 ,10]	[-0.1 ,0] ,[0 ,0.1]	± 0.949
II	[-20 ,-10] ,[10 ,20]	[-20 ,-10] ,[10 ,20]	[-0.2 ,-0.1] ,[0.1 ,0.2]	± 1.160
III	[-30 ,-20] ,[20 ,30]	[-30 ,-20] ,[20 ,30]	[-0.3 ,-0.2] ,[0.2 ,0.3]	± 1.745
IV	[-40 ,-30] ,[30 ,40]	[-40 ,-30] ,[30 ,40]	[-0.4 ,-0.3] ,[0.3 ,0.4]	± 2.195
V	[-50 ,-40] ,[40 ,50]	[-50 ,-40] ,[40 ,50]	[-0.5 ,-0.4] ,[0.4 ,0.5]	± 2.932

LAB TESTS AND POST PROCESSING RESULTS

To carry out the proposed data collection procedure, experiments have been performed with 12 healthy subjects: five women and seven men. The subject ages range from 23 and 56 years, their heights from 1.53 m to 1.85 m, and their weights from 52 kg to 105 kg. A snapshot of a subject performing the exercises while a Kinect device stores the trajectories is shown in Fig. 7a. The snapshot in Fig. 7a has been captured during the experiment at LARM in Cassino, and the subject is one of the twelve participants in the experiment campaign. The environment captured by the Kinect while the subject in Fig. 7a is performing the exercises can be seen in Fig. 7b. As an example, Figure 8 shows X versus Y coordinates of the exercises that have been acquired during the experiment with the subject in Fig. 7a.

Figure 7. An experiment at LARM in Cassino: a) A subject performing the exercises while a Kinect device stores the trajectories; b) Environment captured by Kinect while the subject is performing the exercises.

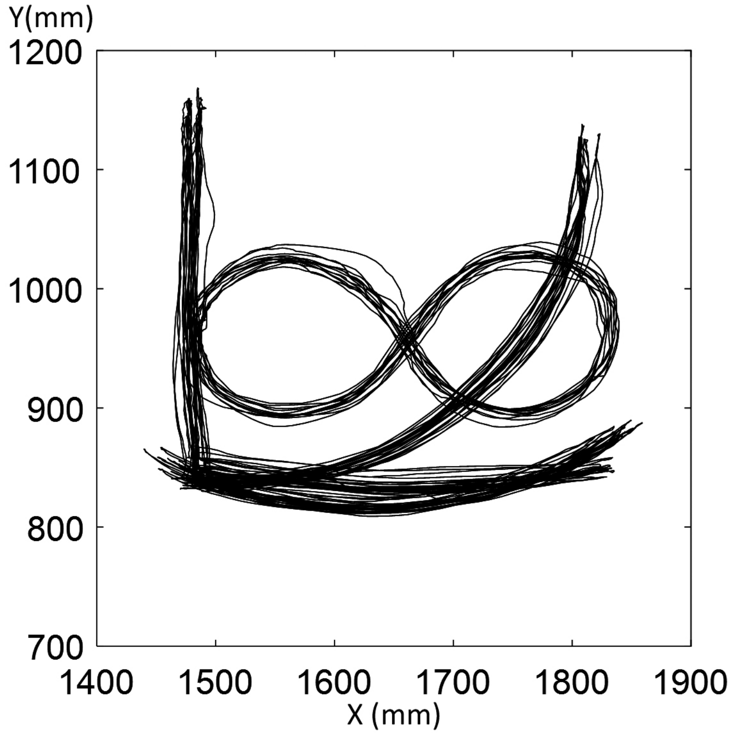

Figure 8. Trajectories of the four exercises during the experiment with the subject in Fig. 7a.

The trajectories acquired from the 12 subjects for the four exercises together with the average obtained using the proposed method are presented in Figure 9. Fig. 9a, Fig. 9b, Fig. 9c, and Fig. 9d show the trajectories for exercise No. 1, exercise No. 2, exercises No. 3, and exercise No. 4, respectively. As seen in Figure 9, the proposed method can successfully fit the shape of the exercises so that the average trajectories can be used as reference trajectories that describe the path of each exercise. Since the trajectories in Figure 9 are computed by X and Y coordinates, it is important to notice that each coordinate has been fitted by the proposed method as described in the previous section. To present the average trajectories for each coordinate, Figure 10 and Figure 11 show each fitted trajectory of X and Y Cartesian coordinates versus the % exercise cycle for the four exercises.

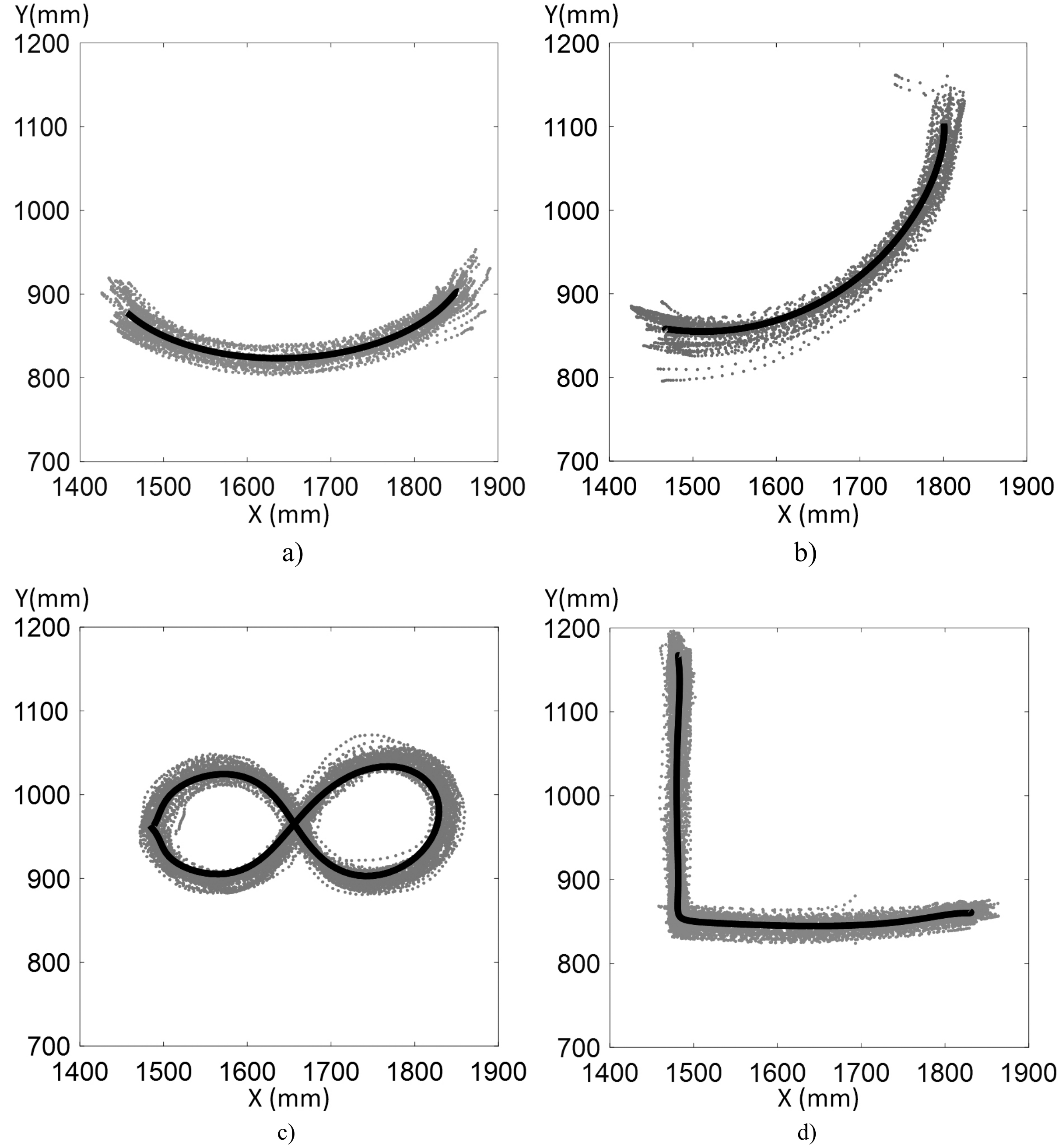

Figure 9. The four trajectories acquired from the 12 subjects (in gray) and the average trajectories (in black) obtained using the proposed method: a) Exercise No. 1; b) Exercise No. 2; c) Exercise No. 3; d) Exercise No. 4.

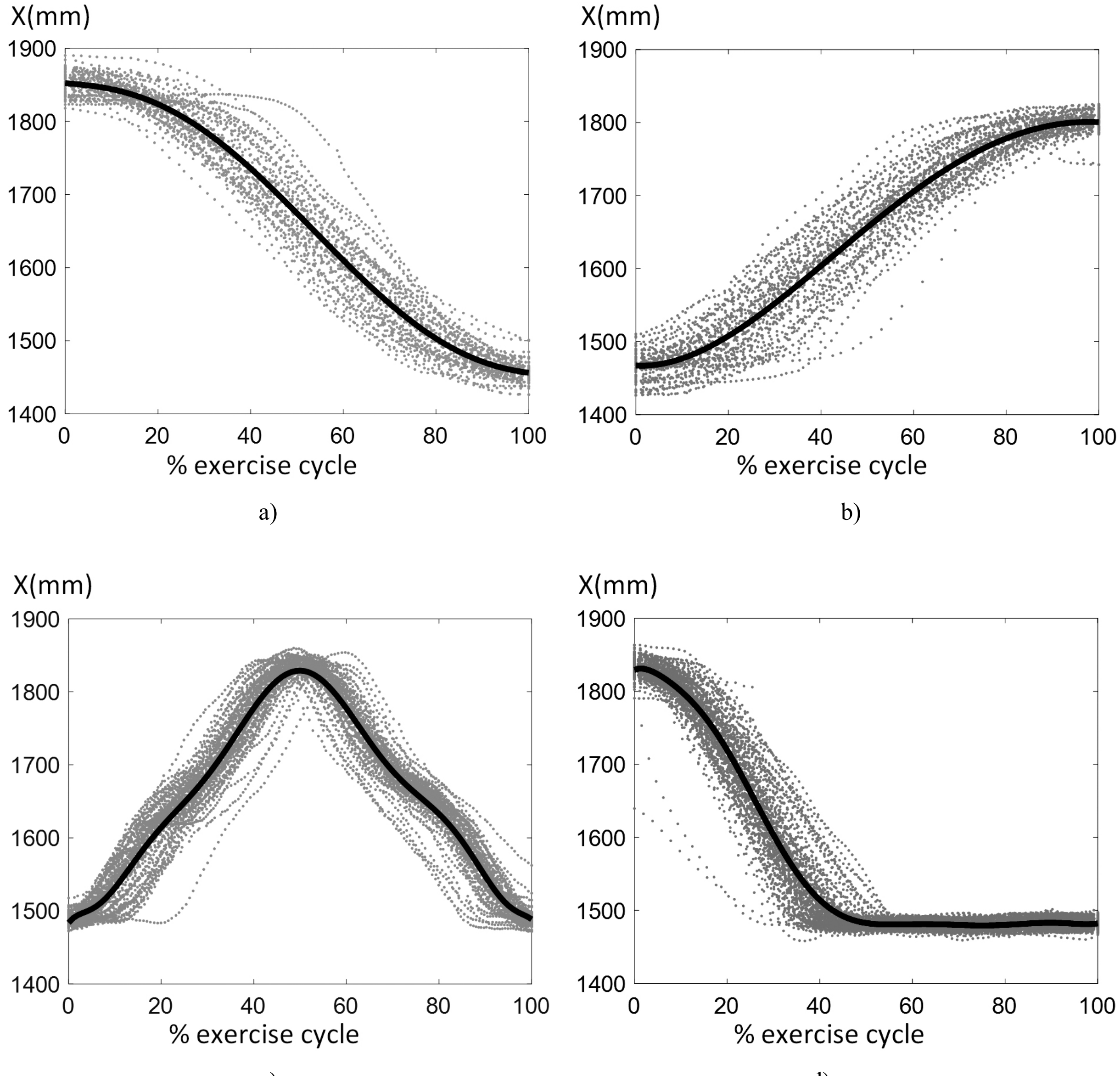

Figure 10. The obtained average trajectories (in black) and the X Cartesian components versus the % exercise cycle of the acquired trajectories (in gray): a) Exercise No. 1; b) exercise No. 2; c) Exercise No. 3; d) Exercise No. 4.

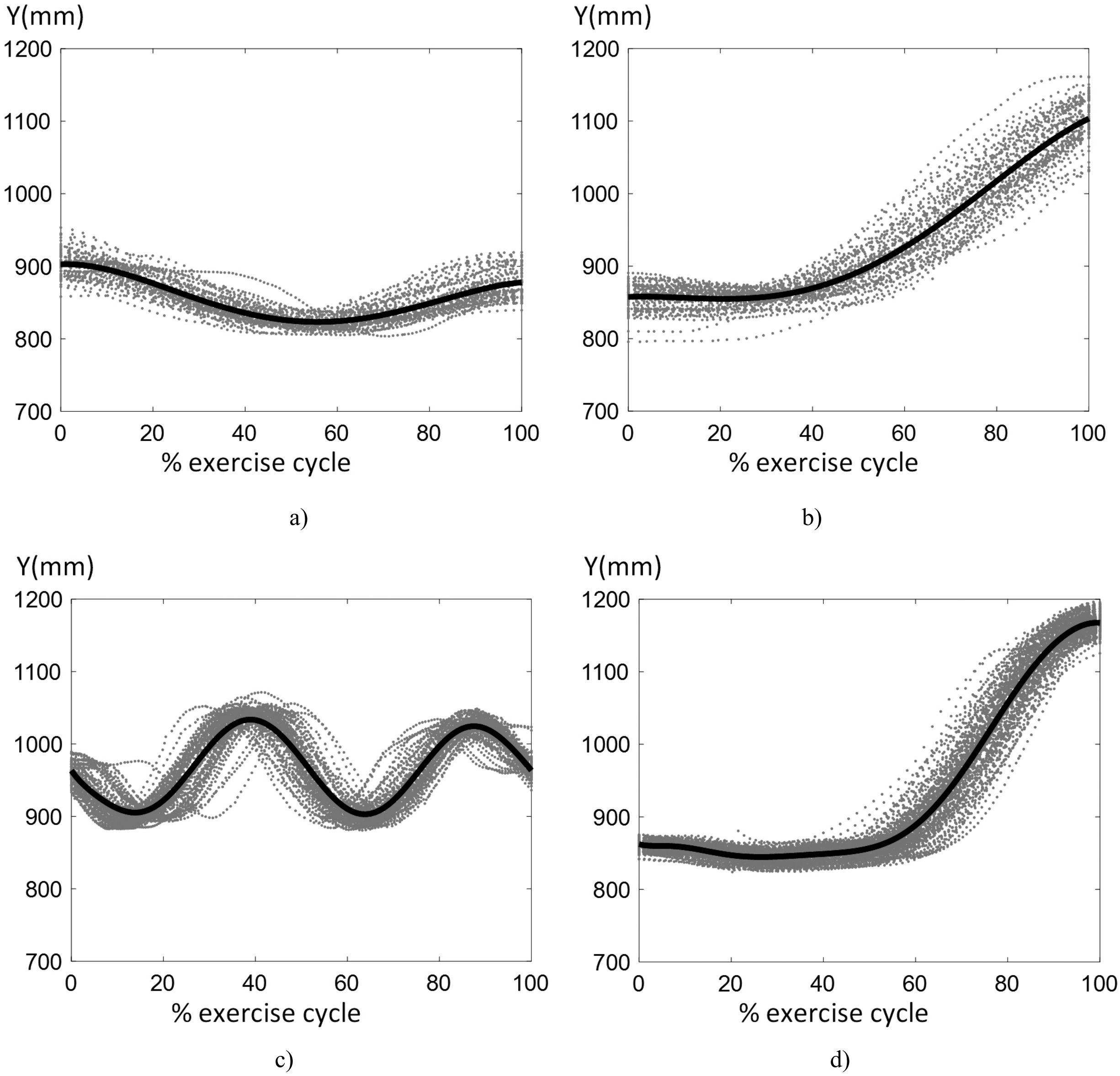

Figure 11. The obtained average trajectories (in black) and the Y Cartesian components versus the % exercise cycle of the acquired trajectories (in gray): a) Exercise No. 1; b) Exercise No. 2; c) Exercise No. 3; d) Exercise No. 4.

For the experimental results, the error $er_{x,y}$ has been calculated using Equation 7. In this case, the error $er_{x,y}$ is calculated between the trajectories from the 12 subjects and the average trajectories obtained by the method. Therefore, x_i and y_i are the cartesian components of the trajectories from the 12 subjects and $\hat{x}_i$ and $\hat{y}_i$ are the cartesian components of the average trajectories obtained using the proposed method. The polynomial order used to fit each trajectory coordinate for the four exercises and error $er_{x,y}$ are shown in Table 2. Although it is assumed that the subjects performed their best attempts during the experiment, it is important to notice that the error $er_{x,y}$ is proportional to the inherent disturbances in the acquired trajectories. Since the trajectories of exercises No. 3 and No. 4 are more complex than the trajectories of the exercises No. 1 and No. 2, they need higher polynomial orders to be fitted.

The reference trajectories have been successfully obtained for the arm exercises as seen in Figures 9, 10, and 11. The proposed method and the obtained reference trajectories have been useful to design and to test the performance behaviour of a device for arm motion assistance in Chaparro-Rico *et al.* (2017), and Chaparro-Rico *et al.* (2018), and Chaparro-Rico et al. (2020). The reference trajectories can be used to help the patients perform the exercises trajectories during a physical therapy.

Table 2. The identified polynomial order for the trajectory coordinates in the exercise examples in Figure 9.

Exercise	Trajectory coordinate	Used polynomial order	Error $er_{x,y}$ (%)
No. 1	X	5th	± 1.4422
	Y	4th	
No. 2	X	4th	± 1.8216
	Y	4th	
No. 3	X	10th	± 1.5606
	Y	9th	
No. 4	X	10th	± 1.2095
	Y	10th	

CONCLUSION

The motion of four arm exercises commonly used by physiotherapists has been planned by using the proposed procedure. An experiment has been proposed and successfully carried out for the data collection of the position trajectories for the four arm exercises. By the experiment procedure, usable trajectory samples of each arm exercise have been acquired from 12 subjects during 12 cycles using a Kinect device. A method to generate reference trajectories from the acquired trajectory samples has been proposed through regression analysis. The proposed method generates reference trajectories using different polynomial orders, and it selects the set of polynomial orders that best fit X and Y components of a trajectory samples set. The proposed method has been validated to prove that it can successfully generate a reference trajectory for a set of trajectory samples. It has been shown that the error is proportional to the disturbances of the trajectory samples so that the method can be considered feasible for obtaining reference trajectories. If trajectory samples with very small disturbances are simulated, a reference trajectory with error near to zero is obtained. The results can be affected by the quality of the trajectory samples. However, it is assumed that the subjects perform their best attempts during the experiment. In addition, the validation of the method proves that the method can fit successfully the shape of the trajectory samples. Since the trajectories of the exercise No. 3 and No. 4 are complex, they need high polynomial orders to be fitted. The four obtained reference trajectories are successfully fitted to the shape of the arm exercises. The obtained reference trajectories for the four arm exercises can be used for rehabilitation assistance or diagnosis purposes. As for future work, the proposed method can be adapted to generate reference trajectories for three-dimensional exercises. In addition, an alternative way to better quantify the similarity between the experimental data and the reconstructed trajectory can be studied.

REFERENCES

Billard, A., Epars, Y., Calinon, S., Schaal, S. & Cheng, G. 2004. Discovering optimal imitation strategies. Robotics and Autonomous systems. **47**(2-3): 69–77.

Billard, A., Calinon, S., Dillmann, R. & Schaal. 2008. Robot programming by demonstration. In: Bruno Siciliano & Oussama Khatib (Eds.). Handbook of Robotics. Pp. 1371-1394. Springer, Würzburg.

Bishop, C.M. 2006. Pattern Recognition and Machine Learning. Springer. Singapore. Pp. 563-565.

Calinon, S., D'halluin, F., Sauser, E.L., Caldwell, D.G. & Billard A.G. 2010. Learning and reproduction of gestures by imitation: An approach based on hidden Markov model and Gaussian mixture regression. IEEE Robotics & Automation Magazine. **17**(2): 44-54.

Chaparro-Rico, B.D.M., Castillo-Castaneda, E. & Maldonado-Echegoyen, R. 2015. Design of a Parallel Mechanism for Knee Rehabilitation. In: Ceccarelli M., Hernández Martinez E. (eds). Multibody Mechatronic Systems. Mechanisms and Machine Science 25. Pp. 501-510. Springer, Cham.

Chaparro-Rico, B., Cafolla D., Ceccarelli, M. & Castillo-Castaneda, E. 2017. Design and Simulation of an Assisting Mechanism for Arm Exercises. In: Boschetti G., Gasparetto A. (eds), Advances in Italian Mechanism Science. Mechanisms and Machine Science 47. Pp. 115-123. Springer, Cham.

Chaparro-Rico, B.D.M, Cafolla D., Ceccarelli, M. & Castillo-Castaneda, E. 2018. Experimental Characterization of NURSE, a Device for Arm Motion Guidance. Journal of Healthcare Engineering. 2018: 1-15. Article ID 9303282.

Chaparro-Rico, B.D.M, Cafolla, D., Ceccarelli, M., & Castillo-Castaneda, E. 2020. NURSE-2 DoF Device for Arm Motion Guidance: Kinematic, Dynamic, and FEM Analysis. Applied Sciences. 2020: 10(6), 2139; https://doi.org/10.3390/app10062139

Chatzis, S., Korkinof, D. & Demiris, Y. 2012. A Quantum-Statistical Approach Toward Robot Learning by demonstration. IEEE Transactions on Robotics. **28**(6): 1371-1381.

Corona-Acosta, I.P. & Castillo-Castaneda E. 2015. Dimensional Synthesis of a Planar Parallel Manipulator Applied to Upper Limb Rehabilitation. In: Ceccarelli M., Hernández Martinez E, editors. Multibody Mechatronic Systems. Mechanisms and Machine Science 25. Pp. 443-452. Springer, Cham.

Corona-Acosta, I. 2015. Development of a Mechatronic Device for Rehabilitation of Upper Extremity (shoulder, elbow, wrist). Instituto Politécnico Nacional, Queretaro. Pp. 21.

Delson, N. & West, H. 1996. Robot Programming by Human Demonstration: Adaptation and Inconsistency in Constrained Motion. Proceedings of IEEE International Conference on Robotics and Automation (ICRA). Minneapolis, MN. 1: 30-36.

Ijspeert, J.A., Nakanishi, J. & Schaal, S. 2001. Trajectory Formation for imitation whit non-linear dynamical systems. Proceedings of the 2001 IEEE/RSJ International Conference on Intelligent Robots and systems. Maui, HI. 2: 752-757.

Ju, M.S., Lin, C.C.K., Lin, D.H., Hwang, I.S. & Chen, S.M. 2005. A rehabilitation robot with force–position hybrid fuzzy controller: hybrid fuzzy control of rehabilitation robot. IEEE transactions on neural systems and rehabilitation engineering. **13**(3): 349-358.

Kapandji, I. 2008. The physiology of the joints: The upper limb. 6th ed. Churchill Livingstone, New York. 1: 4-102.

Koopman, B., van Asseldonk E.H.F. & van der Kooij, H. 2014. Speed-dependent reference joint trajectory generation for robotic gait support. Journal of Biomechanics 47: 1447-1458.

Martin, P. & Reza-Emami, M. 2014. A neuro-fuzzy approach to real-time trajectory generation for robotic rehabilitation. Robotics and Autonomous Systems 62: 568-578.

Nef, T. & Riener, R. 2005. ARMin-Design of a Novel Arm Rehabilitation Robot. Proceedings of the 2005 IEEE 9th International Conference on Rehabilitation Robotics. Chicago, USA. Pp. 57-60.

Varela, M.J., Ceccarelli, M. & Flores, P. 2015. A kinematic characterization of human walking by using CaTraSys. Machine and Machine Theory journal 86: 125-139.

Vijayakumar, S. & Schaal, S. 2000. Locally Weighted Projection Regression: An on Algorithm for Incremental Real Time Learning in High Dimensional Spaces. Proceedings in International Conference on Machine Learning (ICML). Stanford, CA. Pp. 288-293.

Zadravec, M. & Matjačić, Z. 2013. Planar arm movement trajectory formation: An optimization-based simulation study. Biocybernetics and Biomedical Engineering 33: 106-117.