



Estimation of Limbs Angles Amplitudes During the Use of the Five Minute Shaper Device Using Artificial Neural Networks

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Abstract. Biomechanical studies are essential in health research areas, such as rehabilitation, kinesiology, orthopedics, and sports. For example, they provide information to elaborate on patients' diagnostics or improve athletes' performance. In recent years, deep learning and other computational methods have started to be used to quantify new biomechanical parameters or perform deeper data analysis. Motion capture is one of the methods commonly used in biomechanical studies. For this method, video-based and marker-based systems are the gold standards; nevertheless, those systems are typically quite expensive. Moreover, experimental errors in data capture are frequently related to the occlusion of the markers during motion capture. Data missed is solved by increasing the number of cameras to cover more angles or by using predetermined interpolation algorithms. However, the last method could fail to predict all the marker data missed, and both options increase the cost of the data analysis. For solving those kinds of problems, novel computational methods could be used. This study aims to implement an artificial neural network (ANN) to estimate the limb angle amplitude during the execution of a movement from a single axis (X-axis). For training and validating the ANN model, the data and features from the Five-Minute Shaper machine (a physical conditioning device) are used. The obtained results include RMSE values smaller than 3.2 (Minimum RMSE of 0.96) and CC values close to 0.99. The predicted values are very close to the experimental amplitude angles, and, according to the Two-sample Kolmogorov-Smirnov test, the experimental and the estimated amplitude angles follow the same continuous distribution (p - value > 0.05). It is shown that these methods could help researchers in biomechanics to perform accurate analysis, reducing the number of needed cameras and avoid problems due to occlusion by only needing information from a specific axis.

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1 Introduction

Biomechanical movement analyses have been essential for the management of neurological and orthopedic pathologies, where different kinematic and kinetic studies provide vital information for health professionals and even show the evolution of treatment, especially in real-time [4,10]. According to the above, several biomechanical systems have been introduced (diversified scales, low and high-cost tools): electromyography, dynamometry, weight platforms, among others [1].

The latest decades have increased the use of computational intelligence in the evaluation and analysis of biomechanics information. In this way, Artificial Neural Networks (ANN) has been used in biomechanics analysis due to their potential to classify and predict new data at different fields and situations [2]. In addition, the ANN has the capacity of generalizing the information, tolerate noisy inputs, removing redundancies in the input data, and dealing with different types [16,18]. Among the applications in biomechanics, it is important to highlight its use to predict joint amplitudes and moments [9,12], improve the data acquisition [15], determinate biomechanical postures [7] and others [14,17]. These applications impact daily exercises as gait, running, and devices to improve physical conditions.

Deep learning has also been applied in the field of kinematic motion with the aim of generating tools to improve biomechanical analysis [3,11,16]. For example, in [19], neural networks have been used for estimating the amplitude angles in the squat exercise by using electromyography (EMG) signals. As a result, the Root Mean Square Error (RMSE) and Pearson correlation coefficient (CC) were estimated. An average of five (5) for the RMSE and 0.99 for the CC were obtained.

There are several types of physical conditioning devices in the market, and, among them, the Five Minutes Shaper (FMS) that use the subject's weight to muscle toning, principally in the abdominal area. The FMS is a device that activates several muscles in the body in different proportions and involves the wrist, elbow, and knee joints. The principal activated joint is the knee due to the lower limbs are displaced by the knee following the machine's support to generate the movement. In addition, the most activated joint amplitude is the hip due to it acts as the center for stabilizing the trunk in the device [5].

Markers occlusion, when acquiring data in biomechanical laboratories, can cause problems with the data integrity and generated false diagnostics [8]. One solution to improve the acquisition and reduce the occlusion is to put more cameras in the biomechanical laboratories. However, these cameras have a high price in the market due to the kind of features used in data acquisition. Another method to fix the tracking failure is by using temporal continuity of a point trajectory, assuming rigid bodies of the volunteers' segments and manually digitizing the correct position [13].

There are new researches about using new devices to improve the study of kinematics parameters in the physical condition and the problems with the marker occlusion. This study aimed to estimate, through an Artificial Neural Network (ANN), the angle of amplitude of two joints around the upper and lower limbs when the subjects use the FMS device in the easy level from just one axis information. For this, features obtained of only X-axis kinematics information and some anthropometric features of ten (10) subjects were used as input of the ANN.

The neural network correctly estimated these angles with Root-Mean Squared Error (RMSE) between 0.5 and 2 and Correlation Coefficient (CC) close to 0.99. A Two-sample Kolmogorov-Smirnov test analysis shows that the amplitude angles estimation models do not have a significant difference ($p - value > 0.05$) compared to the gold standard information. This tool allows the reduction of cameras and diminishes the occlusion problem by only needing information from one specific axis.

This article is organized as follows: Section 2 presents the experimental methods, Section 3 presents the results obtained for each model. Finally, the last section presents the discussion, conclusions, contribution of the results, and futures works.

2 Experimental Methods

2.1 Five Minutes Shaper Device

The Five Minutes Shaper (FMS) is a fitness device used for total body workouts. This device has six different levels adjustable through the inclination angle to the floor. These levels are cataloged in easy, intermediate, medium, difficult, hard, and extreme, as shown in Fig. 1. The FMS is commonly used for muscle toning in the abdominal area and increases physical conditioning due to its use of the subject's weight to performs the exercises. The subjects moved the lower limbs through the knee machine's support until reaching the maximum limit located to 65 cm from the knee support and then return to the initial position. In this study, only the easy level with an inclination of 15 degrees is considered.

2.2 Data Collection

In this study, the experimental protocol consisted of registering ten healthy volunteers (five men and five women) who used the Five Minutes Shaper device (FMS) at the easy level of around 30 s. Table 1 shows the anthropometric parameters of each subject and the average values.

The FMS places the subjects in ventral decubitus posture by supporting the arms and knees on the device. The outline of the implemented protocol is presented in the Fig. 2. Each participant performed a survey to know the fracture history, surgical procedures, frequency in physical activity development, and physical conditioning level. This survey was taken as an indicator to establish the

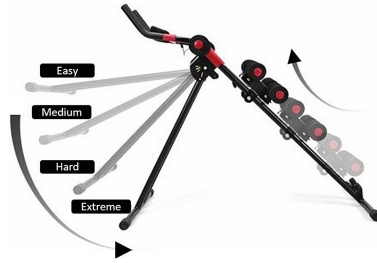


Fig. 1. An image of the Five Minutes Shaper Device used in the experimental protocol.

inclusion criteria, which is healthy subjects and without physical conditioning. The subjects were selected if they practice physical training routines less than once a month. In addition, each one signed an informed consent considering the recommendations established in the Helsinki declaration.

Table 1. Anthropometric parameters of each subject

Subjects	Weight (kg)	Height (m)	Age (years)
Man 1	75	1.80	22
Man 2	65	1.71	21
Man 3	59	1.68	19
Man 4	88	1.82	18
Man 5	62	1.69	20
Woman 1	55	1.57	18
Woman 2	68	1.75	19
Woman 3	50	1.50	19
Woman 4	55	1.67	18
Woman 5	62	1.66	20
Average	63.9 ± 11.1	1.7 ± 0.1	19.4 ± 1.4

Markers were placed on the left side of the subjects following the International Society of Biomechanics (ISB) recommendations for registering the biomechanical activity. The selected joints were the wrist, elbow, shoulder, hip, and knee and were labeled as follows: LW, LE, LS, LH, and LK, respectively, as shown in the Fig. 2. In addition, the used markers have a diameter of approximately 2 cm. The 2D video recording was in the sagittal plane to quantify the joints amplitude. For this, a Basler AG sCA640-70gc high-speed camera system with a capture frequency of 70 fps located 2 m distance from the subjects is used. For extracting the position of markers, the free software Kinovea (software for biomechanical analysis) is used. A single trial is registered for each subject, i.e., a cycle where the subject goes up and down. Nevertheless, the cycle for the analysis is extracted where the movement nature is noted for each subject.

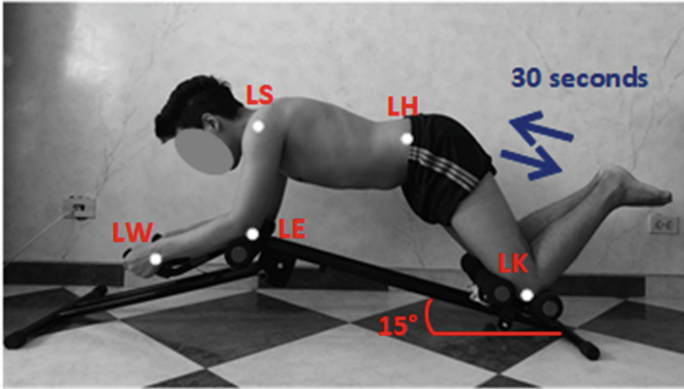


Fig. 2. Experimental protocol for collecting data. The FMS device is configured at the easy level.

2.3 Processing Signals

According to the experimental design, the continuous data were segmented into one cycle per person when the subject normally executed the movement. The markers' positions are stored as signals in a $10 \times M$ matrix. The rows correspond to the X and Y axis positions of the five markers, and M stands for the number of samples. In this work, 801 samples were used.

Subsequently, the matrix was reduced by using only the information of the axis with more variance (for this movement, Y -axis information was discarded), and thus the main extracted features consisted of the difference between the position of the markers of interest (LK, LH, LS, and LE), whose angles between them correspond to the joint amplitude of the movement (upper and lower joint amplitude), and a reference marker, corresponding to the one with less movement (LW). Model 1 was trained and evaluated only with features extracted from markers. For models 2–6, these features were complemented with data from subjects such as weight, sex, height, age, and anthropometric segment length (see Table 2).

Table 2. Features used to train and test the different ANN models

Features Models	LK-LW	LH-LW	LS-LW	LE-LW	Height	Sex	Weight	Age	Segment Length
Model 1	X	X	X	X					
Model 2	X	X	X	X	X				
Model 3	X	X	X	X		X			
Model 4	X	X	X	X			X		
Model 5	X	X	X	X				X	
Model 6	X	X	X	X					X

Finally, the true outputs correspond to the upper limb angle, calculated through the X and Y position of the LE-LS-LH markers, and the lower limb angle, calculated through the X and Y position of the LS-LH-LK markers. These angles were quantified following the Eq. 1, where α corresponds to the angle of limb amplitude either lower or upper, a is the vector formed between LS and LE for the upper limb, and LS-LH for the lower limb, and b is the vector formed between LS and LH for the upper limb and LH-LK for the lower limb, respectively.

$$\alpha = \cos^{-1} \left(\frac{\bar{a} \cdot \bar{b}}{|\bar{a}| \cdot |\bar{b}|} \right), \tag{1}$$

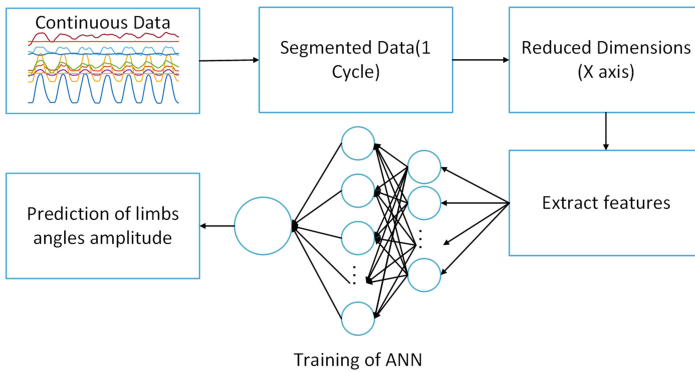


Fig. 3. Block Diagram of the processing of signals, feature extraction, and training of ANN for prediction of limbs angles amplitude

2.4 Neural Network Structure

The processed input features were given to a three-layer feed-forward neural network whose schematic view is shown in Fig. 3. The Levenberg–Marquardt algorithm was used for network training because the gradient descent algorithm may fall into a local optimum, and network outputs may never converge towards the targets. All the estimated results by the proposed model have been performed using the Leave-one-out cross-validation. The sigmoid function was selected as the network transfer function from the input layer to the hidden layers [19]. The output layer corresponds to the estimated limb amplitude angle. Ten (10) neural network structures were evaluated with different number of iterations in order to choose an optimal neural network for this study. For this purpose, only the input data corresponding to biomechanical variables (Model 1) and an output corresponding to the inferior angle were used. The different configurations were: 3 configurations with 1 Hidden Layer of 2, 5 and 10 respectively (C_1 – C_3), 3

Configurations with 2 Hidden Layers: 5×5 , 10×5 and 5×10 respectively (C_4 – C_6), and 4 configurations with 3 hidden layers: $5 \times 5 \times 5$, $10 \times 5 \times 5$, $5 \times 10 \times 5$ and $5 \times 5 \times 10$ respectively (C_7 – C_{10}). The different structures were compared and evaluated through the RMSE metric (see Eq. 2) and all processing was implemented in MATLAB software (version 2020a, MathWorks, Inc).

2.5 Metrics

The Root Mean Square Error (RMSE) and Pearson Correlation coefficient (CC) were used to evaluate the neural network estimation. Equations 2 and 3 define the metrics, where $\hat{\theta}_i$ is the estimated limb amplitude angle, θ_i is the actual limb angle amplitude angle at the sampling time i , and N is the length of the data for the angle amplitude.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (\hat{\theta}_i - \theta_i)^2}{N}} \quad (2)$$

$$CC = \frac{\sum_{i=1}^N (\theta_i - \bar{\theta})(\hat{\theta}_i - \bar{\hat{\theta}})}{\sqrt{\sum_{i=1}^N (\theta_i - \bar{\theta})^2} \sqrt{\sum_{i=1}^N (\hat{\theta}_i - \bar{\hat{\theta}})^2}} \quad (3)$$

2.6 Statistical Analysis

The statistical analysis evaluates which estimation method has a significantly lower error than the others. First, a Kolmogorov-Smirnov analysis was performed to confirm that the behavior of the data has a high probability of having a normal distribution. Subsequently, a Two-sample Kolmogorov-Smirnov test was performed. The null hypothesis is that the estimated amplitude angles and the true value of the amplitude angles follow the same continuous distribution. On the other hand, the alternative hypothesis is that they follow different continuous distributions. The analysis was performed in Matlab with the function *kstest2* where the criterion for the significant analysis was a p-value of 0.05 [6].

3 Results

In the Table 3 is possible to see the RMSE for the different configurations of Neural Network using biomechanical features and the lower limb amplitude angle, with this information is possible to choose a optimal configuration for this study. The C_3 (1 Hidden Layer with 10 neurons) with 400 iterations was selected to perform the analysis, because this configuration had less error than the others.

Table 3. RMSE for the different configurations of Neural Network using biomechanical features and the lower amplitude angle.

\Configurations Number of Iterations	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇	C ₈	C ₉	C ₁₀
100	2.82	1.82	1.25	3.06	3.68	1.89	5.79	5.55	5.48	4.61
200	2.73	1.67	1.18	3.48	3.59	1.78	5.61	5.34	5.41	4.33
300	2.91	1.72	1.24	3.36	3.57	1.81	5.33	5.16	5.46	4.24
400	2.88	1.67	1.12	3.11	3.25	1.96	5.36	5.08	5.34	4.10
500	2.77	1.68	1.12	3.17	3.22	1.71	5.24	5.37	5.42	4.32

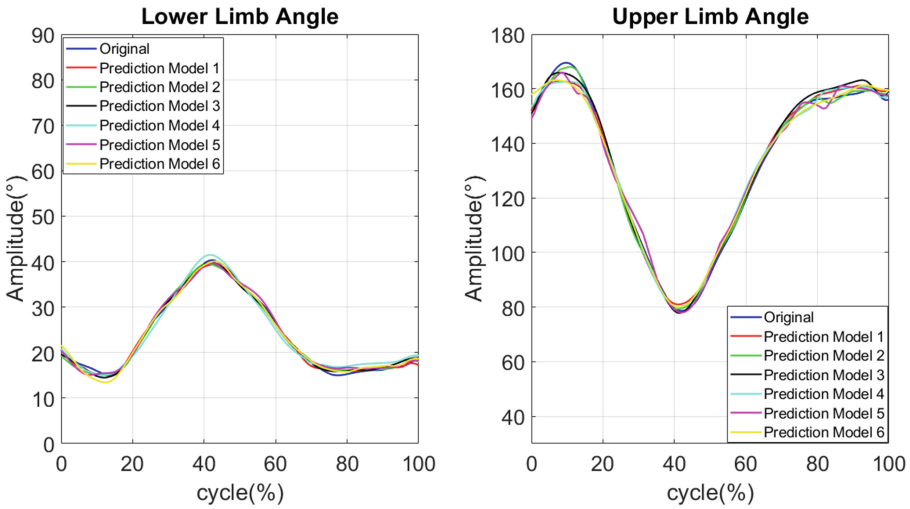


Fig. 4. Experimental upper and lower limb amplitude angle versus neural network estimation of each model for a female subject

Figures 4 and 5 show the results of estimating the upper and lower limb angles of two subjects (female and male) who performed the exercise in the Five Minute Shaper. In these figures, the blue line indicates the original limb angles; the red line indicates the angle estimated by the ANN model 1; and so on, as indicated in the figures' legends.

Figures 4 and 5 show that the estimated angles, using ANNs, are quite similar to the original limb angle during the movement of the exercise in the Five Minute Shaper. These facts can also be verified by the Table 4, in the Figs. 6 and 7 that show the calculated RMSE metric through the Eq. 2. On the other hand, the table 4 shows the calculated CC through the Eq. 3 for all the trained estimation models.

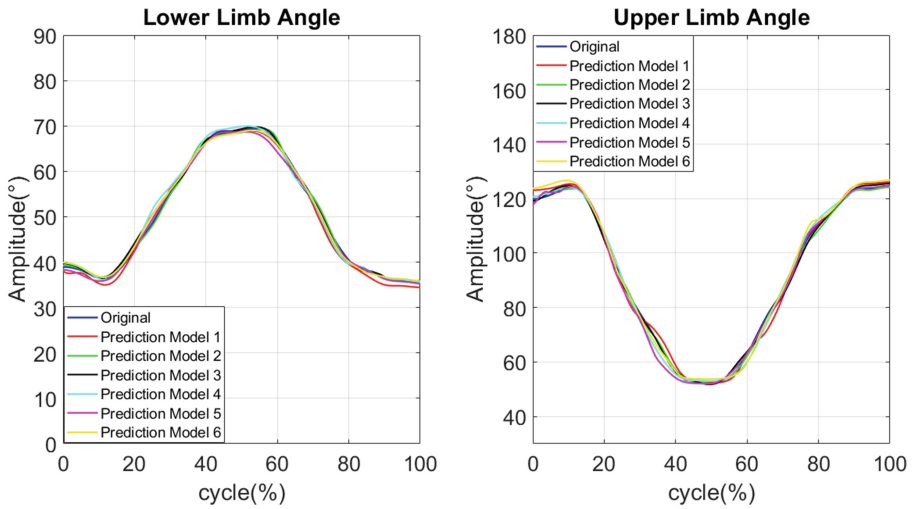


Fig. 5. Experimental upper and lower limb amplitude angle versus neural network estimation of each model for a male subject

Table 4. Estimated RMSE and CC metrics for the six models used for predicting the angles of the limbs

Lower limb angle			Upper limb angle		
Model	RMSE	CC	Model	RMSE	CC
1	1.2531	0.9885	1	3.1820	0.9857
2	1.0948	0.9915	2	2.6268	0.9883
3	0.9587	0.9936	3	2.4291	0.9916
4	1.1655	0.9918	4	2.6461	0.9895
5	1.0299	0.9948	5	2.7423	0.9855
6	1.1811	0.9861	6	2.6719	0.9906

The Kolmogorov-Smirnov statistical analysis for a sample showed that the behavior of the models has a high probability of having a normal distribution. When performing the Two-sample Kolmogorov-Smirnov test analysis between the amplitude angle estimated and the True amplitude angles, it is verified, for all models, that they follow the same continuous distribution ($p - value > 0.05$).

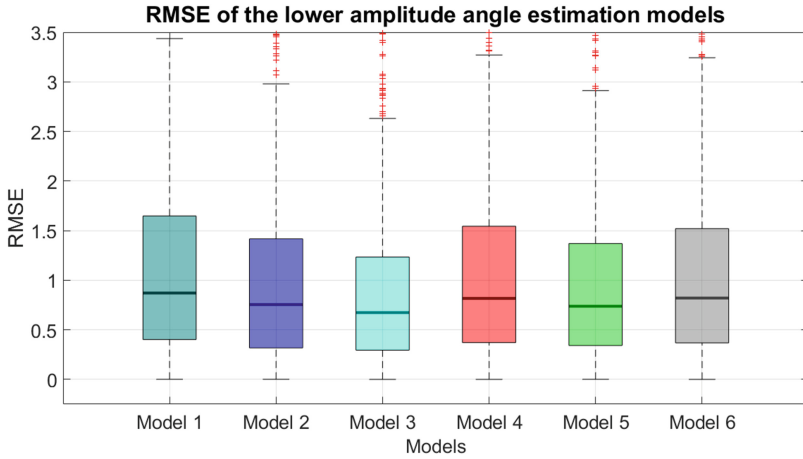


Fig. 6. Boxplot of the RMSE of the lower amplitude angle estimation models

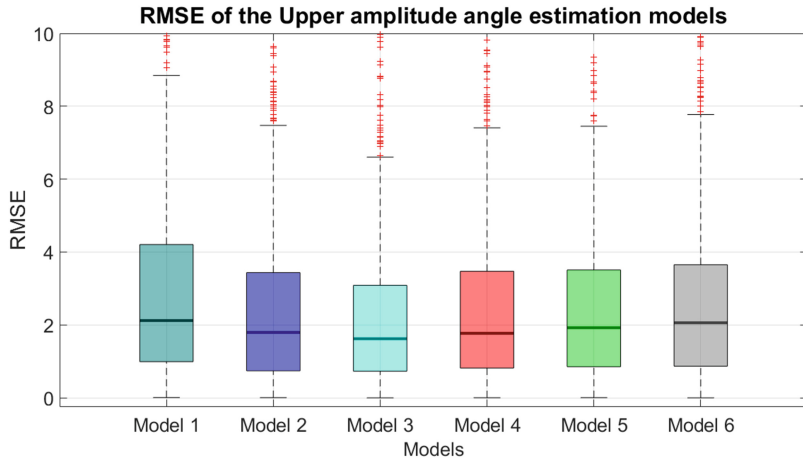


Fig. 7. Boxplot of the RMSE of the upper amplitude angle estimation models

4 Discussion and Conclusion

There are several computational methods for fixing missed data from markers' failures. This work shows that using neural networks is a promising way to evaluate the tracking results and improve data analysis in biomechanics.

It is possible to conclude, through the Table 4, that the models have quite acceptable performance for the estimation of the amplitude angles of the upper and lower limbs during the execution of the exercise in the Five Minute Shaper. Model 3 showed the best performance with an RMSE of 0.9587 and CC of 0.9936 and RMSE of 2.4291 with CC of 0.9916 for lower and upper limb amplitude, respectively. Model 1 had the worst performance with RMSE of 1.2531 and CC

of 0.9885 for lower limb amplitude and RMSE of 3.1820 and CC of 0.9857 for upper limb amplitude, respectively. The results support the conclusion that the physical variable related to sex may have a greater influence on the estimation of the angle, so it is recommended to investigate this variable further. Although the models have different behaviors from each other, it is highlighted that the six proposed models can be applied for estimating the upper and lower limb amplitude angle. The statistical analysis verified that the estimated values and the true samples of angle follow the same continuous distribution ($p - value > 0.05$).

This study demonstrated that a multilayer neural network with a simple structure could estimate the limb angle while performing a simple athletic movement through features obtained in a single axis of interest even though the movement is registered in two dimensions. This approach can be used in real-time biomechanical analysis. It allows decreasing physical resources such as the number of cameras, reducing the marker occlusion problem and acquiring biomechanical information without requiring a controlled environment. To our knowledge, kinematic estimation of human motion using artificial intelligence during multi-limb tasks in the real-load situation has not been fully studied.

This study is preliminary work and thus requires further examination. For example, in future studies, several athletic tasks with more participants can increase the generalizability of the network. In addition, future studies can use simpler models of refreshment that allow the estimation of the angles of the limbs, use less computationally expensive algorithms, and the option of using these models with other types of movements, possibly in 3D-type acquisition.

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