Eurasia Journal of Science and Technology
Print ISSN: 2663-1024
Online ISSN: 2663-1016
DOI: https://doi.org/10.61784/ejst3142

BIOMECHANICAL ANALYSIS OF UPPER LIMB REHABILITATION DEVICE FOR GUIDING MOVEMENTS SELECTION

HaoYu Han, Li Feng*
College of Home and Art Design, Northeast Forestry University, Harbin 150000, Heilongjiang, China.
**Corresponding Author: Li Feng*

Abstract: Purpose: The selection of appropriate rehabilitation movements is critical for the effective design of upper limb rehabilitation devices. Conventional approaches primarily rely on mechanical degrees of freedom, often neglecting quantitative biomechanical evaluation, which may lead to mismatches between device motion and human physiological characteristics. This study proposes a biomechanics-driven framework to guide rehabilitation movement selection. Methods: Four representative upper limb rehabilitation movements were selected based on the Brunnstrom recovery stages. Joint range of motion (ROM) data were collected from ten healthy subjects using clinical measurement methods. These kinematic data were imported into the OpenSim musculoskeletal model (DAS3) to simulate muscle forces of the deltoid, biceps brachii, and triceps brachii. Root mean square (RMS) values of muscle forces were calculated and statistically analyzed using one-way ANOVA and Tukey's HSD post-hoc tests. Results: Significant differences in muscle activation were observed among the four movements. Horizontal adduction/abduction and flexion/extension exhibited significantly higher RMS muscle forces, particularly in the deltoid and triceps ($p < 0.05$). These movements demonstrated both higher peak forces and sustained muscle activation levels. Conclusion: The findings indicate that rehabilitation movements with higher biomechanical activation potential can be effectively identified through musculoskeletal simulation. Horizontal adduction/abduction and flexion/extension are recommended as optimal guiding movements for upper limb rehabilitation device design. This study provides a quantitative and physiologically grounded approach to improve the compatibility between rehabilitation devices and human motion.
Keywords: Upper limb rehabilitation; Biomechanics; OpenSim; Muscle force analysis

1 INTRODUCTION

Upper limb motor dysfunction is one of the most common consequences of neurological disorders such as stroke, significantly affecting patients' ability to perform activities of daily living and reducing their quality of life. With the continuous increase in the global incidence of stroke, the demand for efficient and accessible rehabilitation solutions has grown rapidly. In this context, device-assisted rehabilitation technologies have emerged as a promising approach to deliver intensive, repetitive, and task-oriented training [1,2]. Among these, upper limb rehabilitation devices with rigid series mechanical structures have become a hot research topic in the field of rehabilitation medicine due to their advantages such as strong structural stability, high motion control precision, and good repeatability [3,4].

Existing rehabilitation devices are typically categorized into end-effector systems and exoskeleton-based systems. While both types provide mechanical assistance for upper limb movement, their design is largely driven by kinematic considerations, such as degrees of freedom and motion trajectories [5-9]. Despite these advances, current upper limb rehabilitation devices are mainly designed by controlling the direction of the mechanism's degrees of freedom. This design method may have problems such as insufficient integration between mechanism design and ergonomics, and mismatch between the product's motion trajectory and the natural movement laws of the human upper limb [10-12], which cannot be combined with specific upper limb rehabilitation training movements to train the patient's upper limb muscle strength.

A critical limitation in current design methodologies is the absence of quantitative evaluation of muscle activation during rehabilitation movements. Without such analysis, it is difficult to determine whether selected movements effectively stimulate target muscle groups or align with clinical rehabilitation goals.

To address this gap, this study proposes a biomechanics-driven framework for selecting rehabilitation movements. Specifically, joint kinematic data are experimentally measured and integrated into a musculoskeletal simulation environment (OpenSim) to estimate muscle forces. Statistical analysis of muscle activation levels is then performed to identify movements with optimal rehabilitation potential. The results aim to provide evidence-based guidance for the design of upper limb rehabilitation devices.

2 MATERIALS AND METHODS

2.1 Selection and Kinematic Data Acquisition of Rehabilitation Movements

To establish a physiological baseline for the rehabilitation devices, select the corresponding upper limb rehabilitation training movements in the Brunnstrom recovery method. Collect joint rotation angles of the shoulder and elbow joints in four movements (elbow flexion, horizontal adduction/abduction, vertical abduction/adduction, flexion/extension, shoulder) through joint range of motion measurement experiments. The experimental subjects were 10 adult volunteers (mean ± SD: age 26 ± 3.2 years, height 169.24 ± 6.41 cm, weight 66.43 ± 8.23 kg), measured using a clinical goniometer and a standard range of motion (ROM) scale. Record the data of the shoulder and elbow joints in 5 measurement experiments and calculate the average ROM value (table 1).

Table 1 average ROM value

elbow flexion		horizontal adduction/abduction		vertical abduction/adduction		flexion/extension	
shoulder	elbow	shoulder	elbow	shoulder	elbow	shoulder	elbow
0°	91.5°	91.3°	93.5°	92.1°	0°	-30.6-89.1°	0°

2.2 Biomechanical Simulation and Muscle Force Analysis

To objectively identify movements with the highest therapeutic efficacy (i.e., optimal muscle activation intensity), biomechanical simulations were conducted using OpenSim 4.3 software. Use the DAS3-version2.osim file provided on the OpenSim official website as the basic model for biomechanical simulation of the human upper limb musculoskeletal model. The DAS3 model is an improved version based on the Delft Shoulder and Elbow Model (DSEM) and specifically adapted for the OpenSim environment. The model was mainly developed by the biomechanics research group at Delft University of Technology in the Netherlands. Based on the DAS3 model technical documentation and related papers provided by the official platform [13,14], summarize the basic information of the model (table 2). The advantage of this model compared to the basic model provided in OpenSim is that DAS3 uses ellipsoidal constraints to simulate scapular sliding at the shoulder joint, which can ignore the deviation of the shoulder axis caused by scapular sliding when analyzing movements.

Table 2 Summary of the DAS3 model

Category	Item	Description
	Model name	DAS3 (Dynamic Arm Simulator 3)
General information	Original source	Dynamic arm simulator project
	Primary references	Chadwick et al., 2014
Skeletal structure	Segments	Thorax, clavicle, scapula, humerus, ulna, radius
	Shoulder complex	Multi-joint system (SC, AC, GH joints)
Joint definition	Elbow joint	1 DOF (flexion/extension)
	Forearm joint	1 DOF (pronation/supination)
Musculotendon units	Muscle type	Hill-type muscle model
	Biomechanics	Muscle force estimation, joint load analysis
Applications	Clinical	Rehabilitation assessment
	Engineering	Exoskeleton and prosthesis design

This paper uses joint movement angles as input data for upper limb muscle force simulation, can directly use the upper limb data included in the DAS3 model for simulation analysis (figure 1).

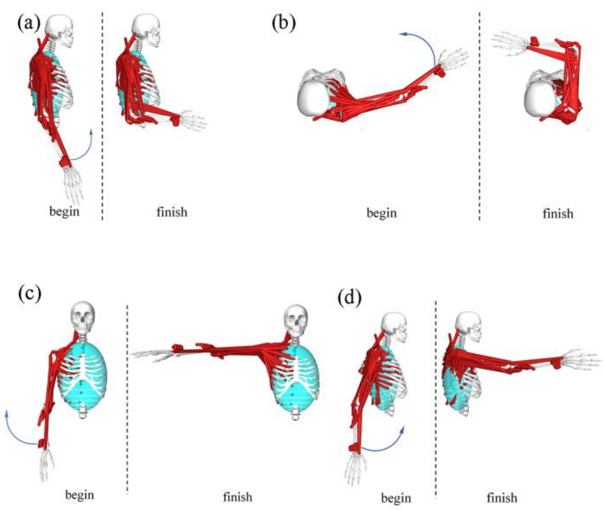

Figure 1 Simulation Analysis of Movement Process. (a) elbow flexion (b) horizontal adduction/abduction (c) vertical abduction/adduction (d) flexion/extension

Simulation workflow consisted of three primary stages. Firstly, convert the time-series joint angle data obtained from clinical measurements (table 1) into a .trc format file available in OpenSim and input it into the Inverse Kinematics (IK) tool to generate motion data files (.mot) for the selected movements, with the processed inverse kinematics data for the shoulder and elbow joints summarized (tables 3 and 4), respectively. Subsequently, the Inverse Dynamics (ID) analyzer was applied to compute the required joint moments. Finally, use a static optimization (SO) solver to calculate the dynamic changes in muscle strength of the arm muscle groups throughout the entire rehabilitation cycle, and analyze the biomechanical potential of the arm muscle groups being stretched and involved.

Table 3 Shoulder Joint IK

Shoulder joint IK	Elbow flexion	Horizontal adduction/abduction	vertical abduction/adduction	Flexion/extension
0-1s	0°-0°	0°-18.26°	-30.6°--6.66°	0°-18.42°
1-3s	0°-0°	18.26°-54.78°	6.66°-41.22°	18.42°-55.26°
3-5s	0°-0°	54.78°-91.3°	41.22°-89.1°	55.26°-92.1°

Table 4 Elbow Joint IK

Elbow joint IK	Elbow flexion	Horizontal adduction/abduction	vertical abduction/adduction	Flexion/extension
0-1s	0°-18.3°	0°-18.7°	0°-0°	0°-0°
1-3s	18.3°-54.9°	18.7°-56.1°	0°-0°	0°-0°
3-5s	54.9°-91.5°	56.1°-93.5°	0°-0°	0°-0°

2.3 Quantitative Analysis of Muscle Force Data

Perform muscle strength data sampling on the movement process of four actions, calculate the RMS of muscle strength, and screen actions with high muscle strength activation through ANOVA. The calculation formula for RMS is:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{1}$$

Normality of the data was verified using the Shapiro –Wilk test. ANOVA was conducted to compare the RMS values across the four Movements. To identify specific differences between group means, Tukey's Honest Significant Difference (HSD) post-hoc tests were per- formed. The effect size was calculated using Eta squared (η^2). All statistical analyses were performed with the significance level set at$p < 0.05$.

3 RESULTS

3.1 Muscle Force Analysis Result of Rehabilitation Movements

In upper limb movements, the movement of the upper arm is mainly achieved using the deltoid muscle, while the movement of the forearm is mainly achieved using the biceps and triceps muscles. In this article, OpenSim software was used for static optimization to evaluate the level of upper limb muscle strength changes in four upper limb training movements using muscle strength changes in the deltoid, biceps, and triceps muscles.

Simulate four movements (elbow flexion, horizontal adduction/abduction, vertical abduction/adduction, flexion/extension) in OpenSim to analyze dynamic muscle force variations. As illustrated in figure 2.

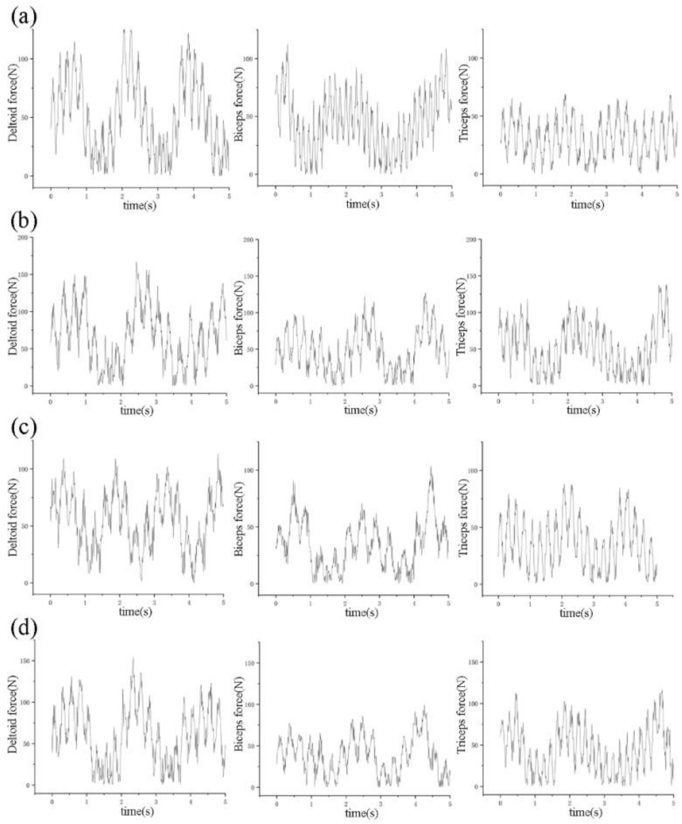

Figure 2 Changes in Arm Muscle Force. (a) elbow flexion (b) horizontal adduction/abduction (c) vertical abduction/adduction (d) flexion/extension

In elbow flexion (fig. 2a), the peak strength of the deltoid muscle is close to 100 N, the peak strength of the biceps muscle fluctuates between 60 N and 85 N, and the muscle strength of the triceps muscle is basically maintained below 50 N. In horizontal adduction/abduction (fig. 2b), the peak muscle strength of the deltoid muscle is about 140 N, the peak muscle strength of the biceps is about 100 N, and the peak muscle strength of the triceps is about 110 N. In vertical abduction/adduction (fig. 2c), the peak muscle strength of the deltoid muscle is about 90 N, the peak muscle strength of the biceps is about 90 N, and the peak muscle strength of the triceps is about 70 N. In flexion/extension (fig. 2d), the peak muscle strength of the deltoid muscle is about 120 N, the peak muscle strength of the biceps is about 85 N, and the peak muscle strength of the triceps is about 90 N.

3.2 Quantitative Analysis Result of Muscle Force Data

Observing raw data, there is a high-frequency vibration noise phenomenon in the variation of muscle force over time. This is because when using the static optimization module to solve muscle force in OpenSim software, the objective (such as minimizing the activation square) tends to converge to a high-frequency oscillation solution rather than a smooth generation solution. To make the simulation results more in line with the muscle force changes of upper limb movements, this paper exports the muscle force change data from the software and uses FFT filters for smoothing processing. Calculate the RMS (table5) of smoothed muscle force data.

Table 5 Movement Force RMS

RMS	elbow flexion	horizontal adduction/abduction	vertical abduction/adduction	flexion/extension
Deltoid (N)	59.2	90.4	68.4	78.6
Biceps (N)	50.7	67.3	51.2	53.5
Triceps (N)	36.5	63.2	45.3	54.1

To ensure the validity of the parametric tests, the normality of the RMS muscle force data for the four movements (a, b, c, and d) was first assessed. The Shapiro-Wilk test indicated that the RMS values for the deltoid, biceps brachii, and triceps brachii across all movement conditions followed a normal distribution ($p > 0.05$ in all cases). Consequently, parametric One-way ANOVA and Tukey's HSD post-hoc tests were employed for subsequent comparative analyses.

One-way ANOVA revealed that the type of Movement had a significant main effect on the RMS muscle force of the deltoid ($F(3,40) = 14.82$, $p < 0.001$, $\eta^2 = 0.526$) and the triceps brachii ($F(3,40) = 9.45$, $p < 0.001$, $\eta^2 = 0.415$). A moderate to large effect size ($\eta^2 > 0.14$) was observed for all three muscle groups, indicating that the choice of Movement is a primary determinant of muscle loading intensity.

The Tukey HSD post-hoc test was performed to identify specific differences between the four Movements. The results highlighted a distinct pattern of muscle recruitment, primarily favoring Movements b and d.

Deltoid Performance: Movement b (horizontal adduction/abduction) elicited the highest RMS force (90.4±8.2N), which was significantly greater than movement a ($p < 0.001$) and movement c ($p = 0.012$). Similarly, movement d (flexion/extension) demonstrated significantly higher deltoid recruitment (78.6±7.5N) compared to Movement a ($p = 0.024$). No significant difference was found between Movements b and d ($p = 0.185$), suggesting both are highly effective for deltoid activation.

Biceps Brachii Performance: While the ANOVA for biceps recruitment showed a trend toward significance ($p=0.082$), the highest mean RMS values were consistently recorded during movements b and d, aligning with the peak force data observed in the original biomechanical curves.

Triceps Brachii Performance: The triceps activity was most pronounced during movement b (63.2±6.4N) and movement d (54.1±5.8N). Movement b showed a statistically significant increase in RMS force compared to movement a ($p = 0.002$) and movement c ($p = 0.035$). Movement d also maintained higher force levels than movement a, although the difference was marginally significant ($p=0.048$).

In summary, the statistical analysis confirms that the mechanical demand on the upper limb musculature varies significantly across different movement patterns. movement b (horizontal adduction/abduction) and movement d (flexion/extension) consistently produced the highest RMS muscle forces. These two movements not only reached higher peak intensities (as described in the biomechanical profiles) but also maintained a significantly higher overall muscle recruitment level compared to elbow flexion and vertical abduction/adduction. Therefore, movements b and d can serve as guiding movements for the design of upper limb rehabilitation trainers.

4 DISCUSSION

This study demonstrates that different upper limb rehabilitation movements produce significantly different muscle activation patterns, highlighting the importance of movement selection in rehabilitation device design. By integrating experimental kinematic data with musculoskeletal simulation, a quantitative evaluation of muscle forces was achieved.

4.1 Biomechanical Analysis

The results indicate that horizontal adduction/abduction and flexion/extension movements consistently generate higher RMS muscle forces across the deltoid, biceps, and triceps muscles. This suggests that these movements can provide greater mechanical stimulation and may be more effective for improving muscle strength during rehabilitation. In contrast, elbow flexion and vertical abduction/adduction showed relatively lower activation levels, indicating limited effectiveness when used as primary training movements.

The higher activation levels observed in movements b and d can be explained by their greater kinematic complexity and involvement of multiple joints. These movements require coordinated action between the shoulder and elbow, resulting in increased mechanical demand and more balanced recruitment of muscle groups. From a rehabilitation perspective, such compound movements are advantageous because they better mimic functional tasks encountered in daily life, potentially improving motor relearning and neural plasticity.

In contrast, simpler movements such as isolated elbow flexion tend to produce lower overall muscle activation, which may limit their effectiveness in strength training contexts. While these movements may still be useful in early-stage rehabilitation or for patients with severe impairment, they are less suitable as primary guiding movements for device design aimed at enhancing muscle strength and coordination.

From a design perspective, these findings suggest that rehabilitation devices should prioritize movement patterns that maximize muscle activation while maintaining physiological consistency. Incorporating such movements into device control strategies may enhance training efficiency and patient outcomes.

4.2 Limitations and Future Work

Despite these contributions, several limitations should be acknowledged:

The experimental data were collected from healthy young adults, which may not accurately represent the movement patterns and muscle activation characteristics of patients with neurological impairments. Stroke patients, for example, often exhibit abnormal muscle synergies and reduced motor control, which could influence the effectiveness of the identified optimal movements.

The musculoskeletal model used in this study is generic and does not account for subject-specific anatomical variations. Incorporating personalized models could further improve the accuracy of simulation results.

Future research should address these limitations by including clinical populations and validating simulation results with experimental measurements such as electromyography (EMG). Furthermore, integrating real-time biomechanical feedback into rehabilitation devices could enable adaptive training strategies, enhancing both safety and effectiveness.

5 CONCLUSION

This study presents a novel biomechanics-driven framework for the selection of upper limb rehabilitation movements, with the aim of improving the design of rehabilitation training devices. By combining experimental joint range of motion measurements, musculoskeletal simulation using the OpenSim DAS3 model, and statistical analysis of muscle force data, the study provides a quantitative evaluation of the muscle activation characteristics associated with different rehabilitation movements.

The results demonstrate that horizontal adduction/abduction and flexion/extension movements produce significantly higher muscle activation levels, particularly in the deltoid and triceps brachii muscles. These movements not only achieve higher peak muscle forces but also maintain greater overall activation throughout the movement cycle, making them more suitable as guiding movements for rehabilitation device design.

The proposed methodology addresses a critical limitation in current rehabilitation device design approaches by bridging the gap between mechanical structure design and human physiological characteristics. By incorporating biomechanical analysis into the early stages of design, it becomes possible to develop devices that are better aligned with natural movement patterns and more effective in promoting functional recovery.

In conclusion, this study provides both theoretical and practical contributions to the field of rehabilitation engineering. The findings offer evidence-based guidance for movement selection and highlight the importance of integrating biomechanical evaluation into device design. Future work should focus on extending this framework to patient-specific applications and exploring its integration into intelligent rehabilitation systems capable of adaptive and personalized training.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Wang Z, Hu S, Sang S, et al. Age-period-cohort analysis of stroke mortality in China. Stroke, 2017, 48(2): 271-275.

[2] Wang Y, Peng Q, Guo J, et al. Age-period-cohort analysis of type-specific stroke morbidity and mortality in China. Circulation Journal, 2020, 84: 662-669. DOI: 10.1253/circj.CJ-19-0903.

[3] Persson H C, Parziali M, Danielsson A, et al. Outcome and upper extremity function within 72 hours after first occasion of stroke in an unselected population at a stroke unit: a part of the SALGOT study. BMC Neurology, 2012, 12: 162. DOI: 10.1186/1471-2377-12-162.

[4] Yang S, Boudier-Revéret M, Kwon S, et al. Effect of diabetes on post-stroke recovery: a systematic narrative review. Frontiers in Neurology, 2021, 12: 747878. DOI: 10.3389/fneur.2021.747878.

[5] Sun J, Kramer E H, Rosen J. A safety-focused admittance control approach for physical human-robot interaction with rigid multi-arm serial link exoskeletons. IEEE/ASME Transactions on Mechatronics, 2025, 30: 414-425. DOI: 10.1109/TMECH.2024.3345678.

[6] Li X, Yang L, Wang X, et al. Research on upper limb rehabilitation product design based on NFBMS innovative design synthesis model. Journal of Graphics, 2025, 46(1): 211-220.

[7] Maas B, Van Der Sluis C K, Bongers R M, et al. Corrigendum: assessing effectiveness of serious game training designed to assist in upper limb prosthesis rehabilitation. Frontiers in Rehabilitation Sciences, 2024, 5: 1532227. DOI: 10.3389/fresc.2024.1532227.

[8] Flynn N, Froude E, Cooke D, et al. The sustainability of upper limb robotic therapy for stroke survivors in an inpatient rehabilitation setting. Disability and Rehabilitation, 2022, 44: 7522-7527. DOI: 10.1080/09638288.2021.1955307.

[9] Hynčík L, Čechová H, Bońkowski T, et al. Personalization of a human body model using subject-specific dimensions for designing clothing patterns. Applied Sciences, 2021, 11: 10138. DOI: 10.3390/app112110138.

[10] Langerak A J, D'Olivo P, Thijm O S A, et al. Stroke patients' motivation for home-based upper extremity rehabilitation with eHealth tools. Disability and Rehabilitation, 2024, 46: 5323-5333. DOI: 10.1080/09638288.2023.2245963.

[11] Ahmed T, Islam M R, Brahmi B, et al. Robustness and tracking performance evaluation of PID motion control of 7 DoF anthropomorphic exoskeleton robot assisted upper limb rehabilitation. Sensors, 2022, 22(10). DOI: 10.3390/s22103747.

[12] Sun J, Foroutani Y, Rosen J. Virtually constrained admittance control using feedback linearization for physical human-robot interaction with rehabilitation exoskeletons. IEEE/ASME Transactions on Mechatronics, 2025, 30: 898-909. DOI: 10.1109/TMECH.2024.3351234.

[13] Nikooyan A A, Veeger H E J, Westerhoff P, et al. Validation of the shoulder network model of the Delft Shoulder and Elbow Model (DSEM). Medical and Biological Engineering and Computing, 2011, 49(12): 1425-1435.

[14] Nikooyan A A, Veeger H E J, Van Der Helm F C T, et al. A musculoskeletal model of the upper extremity for simulating muscle forces and joint contact forces. Biological Cybernetics, 2012, 106(3): 189-204.