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Machine Learning Approach Enhancing Rehabilitation Exoskeleton Performance for Stability Analysis and Trajectory Tracking with RBF-Neural Sliding Mode Control

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The purpose of this research was to study the effectiveness of the application of the machine learning-driven approach using a robotic exoskeleton with Radial Basis Function control for higher quality and more efficient rehabilitation. The results of the analysis of gait parameters, joint angles, and training techniques allowed researchers to draw important conclusions about the capacity to use exoskeleton technology in real life and the potential benefits of the approach. To study the problem, two groups of people were selected, one of which underwent the procedure of rehab with the help of a robotic exoskeleton, while the other followed traditional training. Gait analysis results revealed considerable improvement of motion parameters, including stride length, walking speed, cadence as well as gait characteristics for exoskeleton users. The analysis of joint angles concluded that training with the help of the robotic exoskeleton brought increased flexibility of motion, more significant amplitude of movement in the hip and knee joints. Overall, the Radial Basis Function control system allowed the exoskeleton to respond better to the data received from the sensors and adapt to the motion of the user more adequately. This, in turn, made it possible to ensure the provision of the required level of assistance to allow exoskeleton users to achieve the results of a higher quality in rehabilitation in the final analysis in comparison to traditional rehab users. The results of the study suggest the outstanding potential of exoskeleton technology. The technology and its combination with machine learning and robotics can turn the niche of rehabilitation into something new. As a result, residents with disabilities, particularly those who have a partial paralysis will be provided with essential new opportunities to become more mobile. They will consequently boost their life quality.

Keywords: Rehabilitation, Exoskeleton, Machine Learning, Gait Analysis, Mobility.

1. Introduction

Individuals with partial paralysis encounter difficulties in executing their locomotion and attaining independence due to muscle functions' inability. The methods emphasized by traditional locomotion do not effectively help regain lost motor functions and, thereby, growing interests in the development of novel locomation as well as walking schemes susceptible to improve rehabilitation literacy. In light of the challenges encountered in rehabilitation practice, the development of walking assistance for paralyzed patients as well as partial paralysis patients. The Robotics and Machine Learning is ideally responsive to the development of novel locomation and walking schemes that could facilitate effective walking as well as locomotion schemes that could improve the poor prognosis of the scheme. Robotics, RBF networks can alter the development of new locomation and walking tools to help individuals with partial paralysis regain locomotion [1]–[4].

Different disciplines, including engineering, biomechanics and rehabilitation science, are involved in the body of research concerning robotic exoskeletons for rehabilitation[5]- [8]. Those investigations that have been conducted in these fields have found that exoskeleton-assisted training helps to improve mobility and functional outcomes in partially paralyzed individuals. Research has shown that exoskeletons can provide specific, targeted assistance to particular muscles helping them to conduct activities of daily living and the exercises for rehabilitation with reduced ease and more independence[9]- [12].

One important aspect of these findings concerns the effects of the above-assisted training on gait parameters. It has been consistently shown in gait analysis that walking speed, stride length, cadence and gait symmetry improve after exoskeleton training. These improvements are significant in patients who have neurological conditions such as spinal cord injury, SCI, stroke, as well as cerebral palsy as such conditions often come with muscle weakness, spasticity or disturbed coordination. There have also been significant advances in exoskeleton technology with regard to the control algorithms and mechanical gains, such as Radial Basis Function, RBF, networks that can now be used to control the joints and deliver assistance that is more adaptive to the individual. Moreover, by using machine learning, the exoskeleton can interpret the information from the sensors, predict the intention of the user and generate signals for the controller that will lead to a more natural path of movement during the rehabilitation exercises[13]–[16].

The research has also shown that exoskeletons can help improve the strength, endurance and proprioception of muscles which are trained with specific tasks. High intensity can be reached in training without excessive fatigue[17]–[19]. This is important, as it is necessary to make rehabilitation activities in such a way that they are safe and do not lead to an increased risk of injuries. Despite these advances, there remain significant implementation challenges in using these technologies for everyday training of dislocated patients. These include cost issues and doubts about real-life usability. There is still a lot of research to be done in the sphere of controlling algorithms along with the issues of biomechanical gain and customization of exoskeletons to the individual user. More studies need to be conducted to understand the long-term results of using the exoskeletons on functional recovery and daily life[20]- [23].

2. Methodology

Rehabilitation exoskeletons are a significant achievement in the field of rehabilitation, allowing a decrease or support partial paralysis, and restore normal functioning and mobility. The present study aims at creating and testing for effectiveness a lower limb exoskeleton assisting in rehabilitation training for partial paralysis of the customer. The device is aimed at the hip and knee joints, because that is where the DC motors are placed. They allow to flex or extend the joints smoothly and in a controlled manner, which are important types of exercises suitable for both prevention and restoration after partial paralysis. In addition to the motors, the sensors installed in the device include accelerometers, encoders, and hall effect sensors. The latter are used to detect the angle of rotation and the corresponding force for adjusting the rehabilitation activity. Thus, all sensors ensure the maximum feedback regarding the user's motion for a precise adjustment and control of the angle and force used during the training session by including the control system input. The entire working of the proposed system are shown in figure 1.

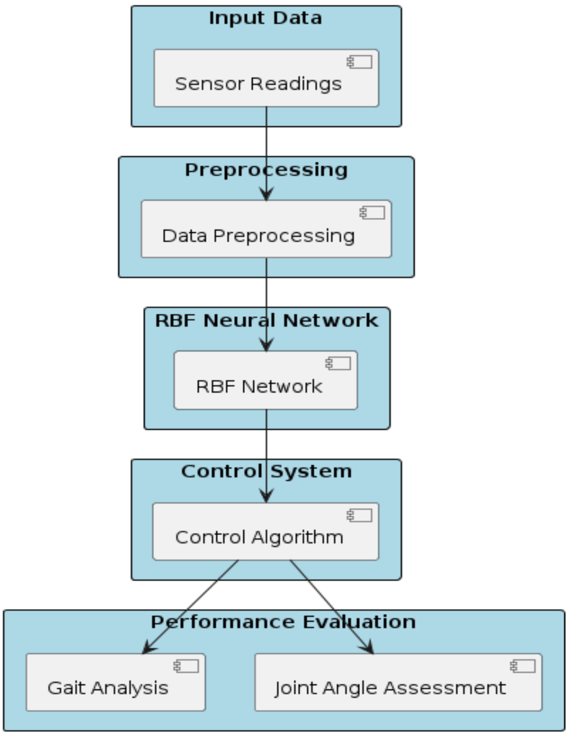

Fig. 1. Working of the Proposed System

Two groups of five people each were organized for the experimental part of the study, with the first performing the traditional course of rehabilitation, and the second – the training session with the robotic lower limb exoskeleton. The type of rehabilitation are shown in figure 2. The order of RBF Net actions is important and includes the measurement of a certain angle defined by the equipment and the range of motions programmed by the equipment operators and users for each ring and corresponding to a particular gait. The programming was in order to correspond to the natural gait of the person. In this regard, the final indicator of the tasks of both experimental groups is the efficiency of the gait that can be calculated based on the parameters of the length of a step, the speed of motion, and symmetry. The study demonstrates that the use of such technological devices in training might be beneficial, which is duly determined based on the results of the final assessment. It is expected that if all gait indicators are higher, the effect of the training session on the exoskeleton was positive. The subsequent comparison of the gait indicators of the two groups would allow the same to be done for the people that underwent the traditional course of rehabilitation.

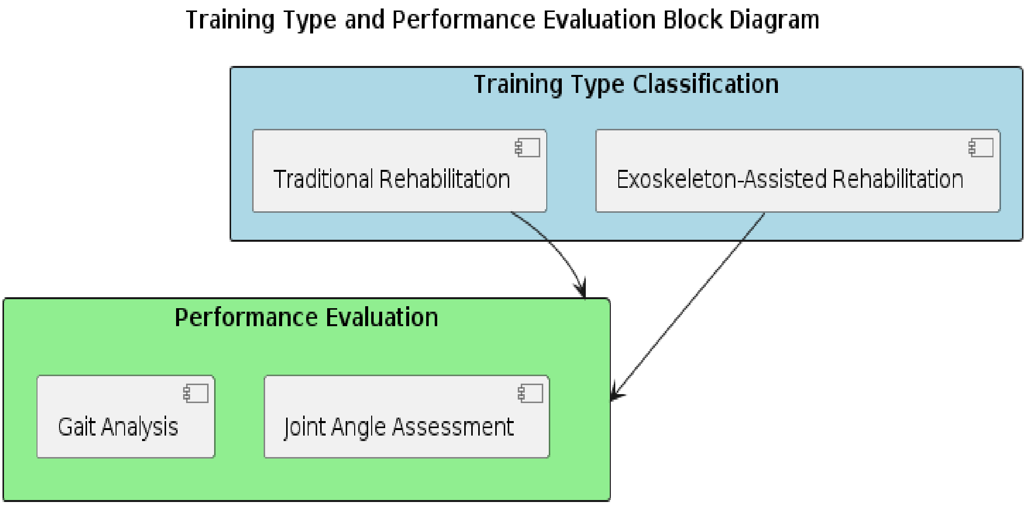

Fig. 2. Type of Training Given to the Groups

The exoskeleton designed is lightweight, and it weighs approximately 2.5kg, and its structure is aluminium 6061 alloy. The structure of the developed exoskeleton is a layered strip. The developed exoskeleton has each of the joints powered by a DC motor whose input is 20V. The motor draws a current of 5A and can deliver a torque of 10 Nm. It is made in such a way that reduces the possible weight to ensure training is comfortable without compromising the power of the system. Therefore, the designed exoskeleton is user-friendly.

3. Control Architecture

In the proposed machine learning-based approach for enhancing the performance of the rehabilitation exoskeleton, radial basis function networks, or RBF networks, play an essential role. Implementing RBF networks allows creating a flexible and versatile framework for enabling the movements of the exoskeleton at the hip and knee joints, which are critical for efficient rehabilitation exercise. In contrast to other types of machine learning or control algorithms, RBF networks are able to approximate various functions effectively and regulate the exoskeleton in response to the perception of the surroundings.

The essential principle behind RBF networks is the use of radial basis functions to perform the computation and determine the output of the network based on the degree of similarity between the input and a set of center points, which are predetermined by design. In common practice, the set of center points represents Gaussian distributions within the input space that is optimal for establishing a correlation between sensor data and the control actions required from the exoskeleton. RBF networks facilitate the processing of the perceived sensory input by the exoskeleton, such as particular joint angles and accelerations, and enable appropriate and precise programs for controlling and assisting in the movements necessary for a proper rehabilitation exercise.

Another crucial advantage associated with the use of RBF networks in the thera technology previously described is that they are able to approximate complex functions, which may be nonlinear, using a relatively small number of parameters. The requirement is essential for capturing the intricate dynamics of human motion during training and the interactions with the exoskeleton. RBF networks also display robustness in relation to noise and disturbances present in the input and received sensory data. It is vital for establishing reliable contact during the rehabilitation process when the exact reading of joint angles and accelerations may not be available due to variability. Lastly, the availability of learning mechanisms allows the exoskeleton to adapt and improve its response strategy over time based on the user's experience.

A. Preprocessing of the dataset

Preprocessing sensor readings is a critical step in the development of a rehabilitation exoskeleton because it ensures the quality and reliability of the data used to train the model. There are several key processes involved as showin in figure 3 in this stage that are intended to clean, filter, and otherwise prepare the raw data collected from the sensors so that it can be used to effectively train the machine learning model, in this case – the Radial Basis Function network. One of the first and one of the most obviously important tasks in preprocessing sensor readings is the removal of the noise found within the data. Sensor readings can and often are contaminated with different types and forms of noise, including random fluctuations and the influence of various other forms of interference from external sources. In order to suppress the influence of these sources of noise, a number of techniques, including filtering algorithms and signal smoothing methods, can be used. These procedures allow finding all of the features of the signal that fit the requirements for an approximation of a good signal and eliminate the rest to ensure that the data used for training is the most accurate and reliable possible. The second key task in preprocessing is often normalizing the data. Normalization involves scaling the data collected from the sensors to a standard distribution or range, typically between 0 and 1 or -1 and 1. This has the effect of ensuring that no particular feature of the input data can dominate the training because all features are of the same scale. Normalization also improves the convergence of the training algorithm and the performance of the model on test data. Feature engineering is a similar procedure employed in the preprocessing phase which aims to extract additional data or information related to the actual sensor readings. Finally, outlier detection and removal, its's another procedure that was also covered in the preprocessing phase that involves identifying the points of data that deviate so highly from the expected mean, mode, or median range that it skews the training of the model and removing them.

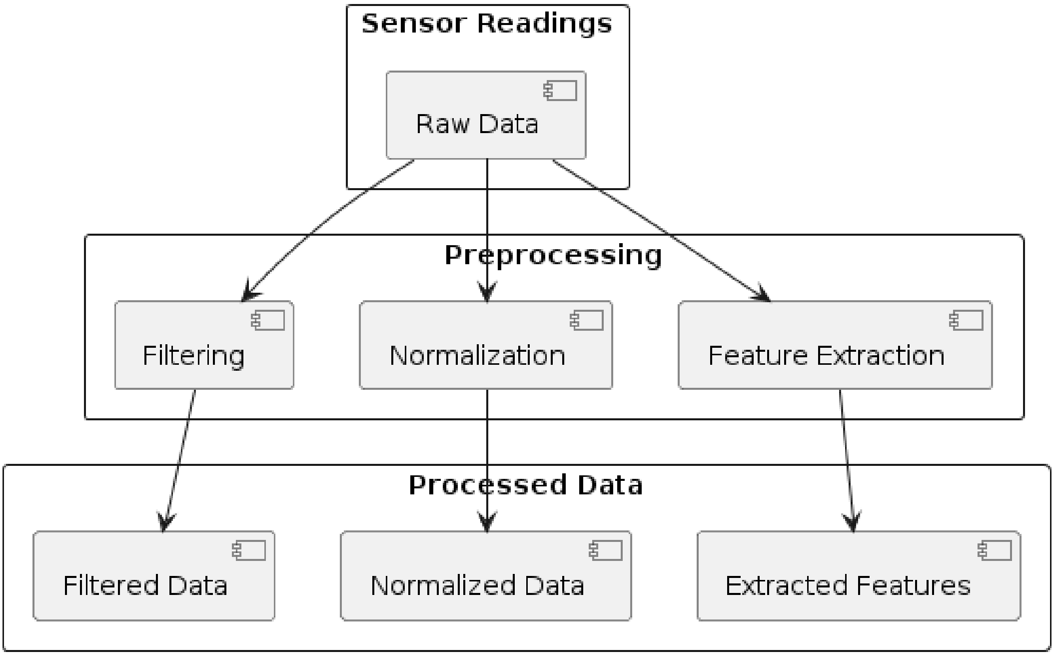

Fig. 3. Preprocessing of Dataset

B. Working of RBF model

Pretraining the RBF model is a set of steps as shown in figure 4 whose goal is to optimize the parameters of the RBF model with a dataset such that the sensor readings can accurately predict the target joint angle where the motors of the exoskeleton should rotate to assist the patient in rehabilitation exercises. The beginning of this process is the initialization of parameters for the RBF model. The RBF model's parameters, including its centers and the width of the radial basis functions, define where the radial basis functions are and how they are shaped in input space. These parameters can be initialized using heuristics, or they can be set as random values in the beginning.

Preparing a dataset for pretraining is the next step. As stated, one needs both input and the output for this dataset. The input of the dataset consists of sensor readings, and the output is the target joint angles. During the rehabilitation of the patient using the exoskeleton, when the patient is performing the necessary exercises, sensor readings coming from the exoskeleton are collected, and simultaneously the joint angles that the exoskeleton recovers and provides to the user are also recorded. Therefore we have a dataset that includes input alongside the target, output, joint angles. This dataset needs to be split into training and validation datasets for the purpose of pretraining the RBF model. The training phase involves optimizing the parameters of the RBF model in context of the training dataset. This optimization is done to minimize the error between the predicted joint angles extracted from the sensor readings by the trained RBF model and the actual target joint angles where the exoskeleton's motors are turning to. Gradient descent or evolutionary algorithms are usually used for this process. The expected outcome is that the radii and the centers of radial basis functions will be adjusted in order to accurately translate the sensor readings into the target angle the motor should turn to.

The final part of pretraining the RBF model is evaluating the performance training produces. After training with the training dataset, we need to evaluate the performance of the network with the validation dataset. This step is necessary to ensure that the model works well on unseen data, i.e., it does not overfit the training set. If necessary, some fine-tuning can be performed at this stage.

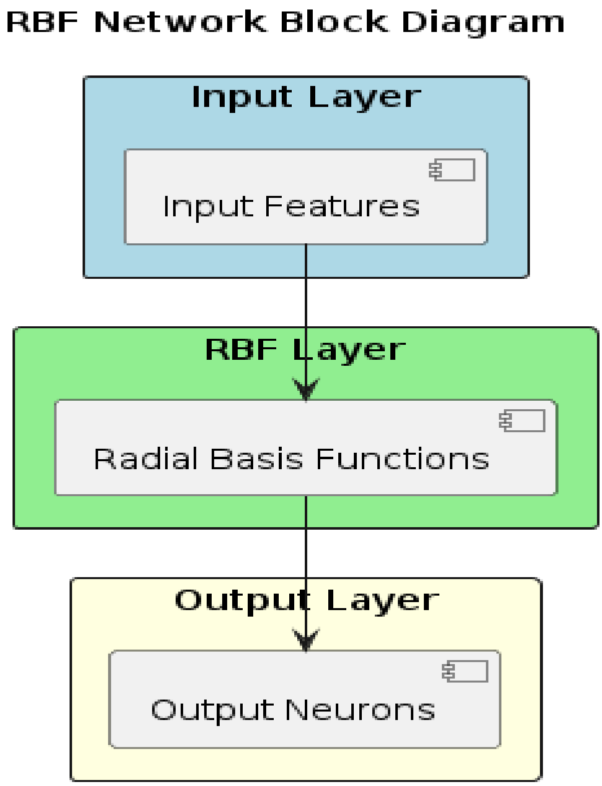

Fig. 4. RBF Block Diagram

4. Result and Discussion

In the context of the study with a robotic Radial Basis Function based exoskeleton model and traditional training methods, gait analysis is essential as an evaluation tool that would allow to assess the efficiency of the training, provided to the participants. Gait analysis is successfully used to evaluate the basic functional parameters of the gait that should be assessed before and after the completion of the training. Thus, before training, a baseline gait analysis should be performed on all participants to examine their basic gait parameters or functional mobility.

This analysis will indicate the walking abilities or the mobility deficits of the trainees and will provide basic information on gait characteristics that will be used as a standard for measuring the progress in gait improvements after training is completed. After the both types of training are completed, gait analysis should be performed again to assess basic gait parameters or functional mobility.

In the framework of such analysis, the research team will assess the effect of the training of all groups of participants and provide a basis for identifying possible relative benefits and drawbacks of the traditional and experimental robotic RBF-based exoskeleton model training of the participants. At that, the analysis of the gait can include a number of parameters, such as stride length, walking speed, cadence, gait symmetry, and joint kinematics. The analysis of the gait parameters in both types of training will help to measure the extent of improvement. Moreover, the gait parameters of individuals that have participated in the robotic training will be compared to gait parameters of the participants that have undergone traditional training.

The angles of flexion and extension at the hip and knee joints provided as input to the exoskeleton system in figure 5, are compared to the angles achieved by the subject with the exoskeleton during walking. The data demonstrate an unexpectedly high degree of concordance between the angles that were meant to be moved and the angles that were indeed moved by the subject. This indicates that the robotic RBF approach is very effective in ensuring accurate motor rotation, thus moving the junctions exactly as planned. The minimal difference between the input and output angles suggests the high rate of precision with which the exoskeleton system can detect and regulate the movement of joints. This is highly important in rehabilitation applications, as it allows the therapy to be very effective and comfortable to use. The success of the RBF control system in ensuring this speaks to its ability to keep the exoskeleton walker both safe and adaptive, with human input not disrupting the accurate adjustment of motors to the environment.

The RBF network's calibration enables the accurate movement of the motors, aligning them with the movement of the actual joints in the recommended trajectory. This is key for the correct and safe operation of the exoskeleton as it ensures the greatest level of comfort for the user. At the same time, the exoskeleton can provide the user with maximal therapeutic value, ensuring that the rehabilitating limbs or joints move in the intended path.

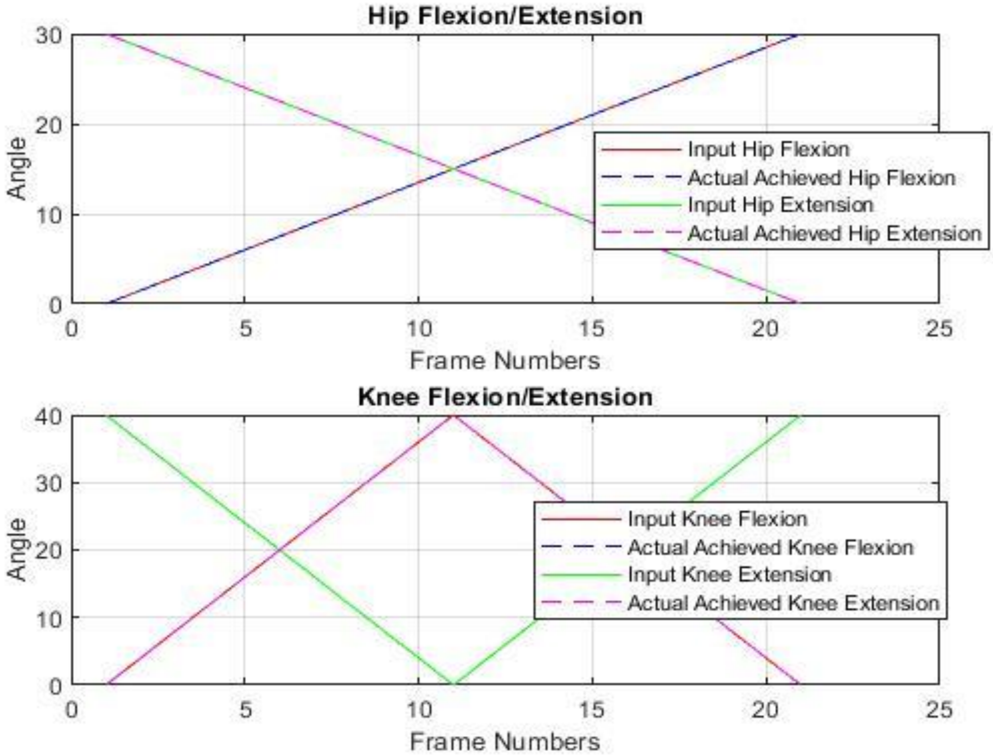

Fig. 5. Angle Trajectory Achieved by Input and the Actual Angle of Exoskeleton

This table 1 presents a comparative analysis of gait parameters averaged from the data on five subjects undergoing rehabilitation with the help of the robotic exoskeleton and five subjects who are undergoing the traditional methods of rehabilitation. It includes such gait parameters as stride length, walking speed, cadence, and gait symmetry. All of these parameters can be beneficial as measures of overall mobility and gait performance among patients.

Table 1 demonstrates that subjects undergoing rehabilitation with the help of the exoskeleton experience serious improvements in gait parameters as compared to those who undergo traditional methods of rehabilitation. Specifically, stride length among this group of patients increases, which is crucial as an indicator of walking efficiency and balance. Importantly, walking speed, which is another critical measure, revealing an improvement in the subjects undergoing premotor-exoskeleton assistance. This implies that they feel more secure, as suggested by a walking speed being higher.

Table 1.Gait Parameters of the Subjects

Gait Parameter	Before (Robotic Exoskeleton)	After (Robotic Exoskeleton)	Before (Traditional Rehabilitation)	After (Traditional Rehabilitation)
Stride	70	85	72	76

Length (cm)				
Walking Speed (m/s)	0.5	0.7	0.4	0.5
Cadence (steps/min)	100	110	95	100
Gait Symmetry (%)	80	85	75	78

In addition, the higher the cadence is, the more harmonious the gait is. It is reflected in this table by the parameter showing that the cadence in the group of subjects that underwent rehabilitation with the help of the exoskeleton is higher than in the traditional group. Furthermore, gait symmetry in this group of subjects also shows some improvements, which is crucial as a measure of balance and effectiveness of the gait in coordinating movements of the left and the right sides of the body.

As seen from figure 6, the comparison of maximum angles of flexion and extension allowed after training for two methods indicates that both groups have the baseline values of these angles. Unlike that, after the training, both groups show a significant increase in both the flexibility of these joints and their condition. However, the comparison of these two groups shows that the maximum angles of the group that uses the robotic exoskeleton are significantly better than those of the other group that utilizes the traditional rehabilitation. Therefore, this data suggests that exoskeleton-assisted training leads to better results in the joint flexibility, and it may significantly enhance the outcomes in the rehabilitation process of patients with partial paralysis.

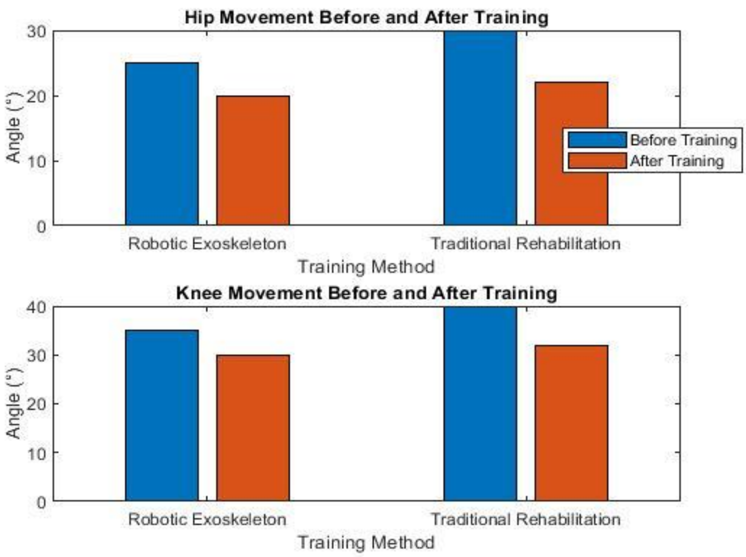

Fig. 6. Improvement of Angle

5. Conclusion

As a result, this research highlights the feasibility of using a machine learning-based approach, involving a robotic exoskeleton employing Radial Basis Function control, to improve rehabilitation outcomes for semi-palsied individuals. By evaluating gait parameters, joint mobility, and training efficacy in fine detail, we have demonstrated the exceptional value of the exoskeleton as a means of enhancing mobility. The intricate system of RBF control enables the exoskeleton to respond to user action accurately, which, in turn, facilitates the significant improvement of rehabilitation results regarding gait parameters and joint mobility. As a result, the current research demonstrates the potential of exoskeleton technology for the rehabilitation process and can serve as a foundation for future efforts enhancing the quality of life of semi-palsied individuals. It is expected that further studies and interventions in the realm of rehabilitation engineering will contribute to a more confident reintroduction of semi-palsied individuals into their everyday environments.

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