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Article

Neural Network Optimization for Estimating Lower Limb Angular Velocity Based on Body Mass Index and Walking Speed

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Abstract: The angular velocity of lower limb joints is an important kinematic parameter that represents gait dynamics and is widely used as a reference in walking rehabilitation systems as well as assistive robot control. This study aims to optimize the neural network architecture to estimate the angular velocity of the hip, knee, and ankle joints by taking into account the Body Mass Index (BMI) and walking speed. The study was conducted using secondary gait data grouped based on BMI category, joint type, and gait phase. The estimation model was developed using a feedforward neural network with one hidden layer, where the number of neurons was varied from 5 to 30. The results showed that increasing the number of neurons in the hidden layer improved estimation accuracy until reaching an optimal condition in the range of 15–20 neurons, after which performance tended to saturate. The hip joint showed the most stable and accurate estimates, followed by the knee and ankle, while the late gait phase resulted in higher accuracy compared to the early gait phase. These findings emphasize the importance of optimizing neural network architecture to produce accurate and efficient gait parameter estimations for walking rehabilitation applications.

Keywords: Angular Velocity, BMI, Gait, Neural Network, Robot Rehabilitation, Walking Speed.

1. Introduction

Walking is a complex motor activity that involves the coordination of the neuromuscular system to maintain the dynamic stability of the body. Gait stability is achieved through the control of the center of mass (CoM) position relative to the base of support. Mechanically, gait stability is controlled through the modulation of foot placement, ankle moments, and regulation of the body's angular momentum [1]. The biomechanical parameters commonly used to evaluate gait include walking speed, cadence, step length, stance-swing time, joint angles, and joint angular velocity [2]. Walking speed is even referred to as the 'sixth vital sign' because it strongly correlates with the level of independence and quality of life [3]. Changes in these spatiotemporal and kinematic parameters are often associated with neurological disorders and an increased risk of falling [4].

Stroke is one of the leading causes of gait control disorders globally, resulting in hemiparesis, step asymmetry, reduced walking speed, and an increased double support phase [5]. The development of an IMU-based data acquisition system shows significant differences in kinematic parameters between post-stroke patients and healthy individuals [6], Meanwhile, the latest scoping review emphasizes the importance of a technological approach to enhance the objectivity of clinical gait assessment [7]. The disorder significantly increases the risk of falling in the first year post-stroke [5], so that gait rehabilitation becomes the main focus of therapeutic intervention.

Various rehabilitation approaches have been developed to improve walking function. Task-oriented training has been shown to improve gait parameters and balance [8]. The use of ankle-foot orthosis (AFO) is effective in improving foot drop and increasing walking stability [9], with different responses based on the Brunnstrom levels [9]. The development of robotics has introduced ankle-foot orthosis robots with auto dorsiflexion-plantarflexion control capable of producing constant angular velocity and gait phase detection [10], as well as robot-assisted gait training (RAGT) that supports intensive and repetitive training based on neuroplasticity [5]. The hip exoskeleton assist-as-needed system is also developed to provide assistance adaptively according to the patient's needs [11].

As technology develops, IMU-based wearable sensors have become objective and portable solution for gait monitoring. Systematic reviews show the widespread use of accelerometers and IMUs in measuring walking speed, cadence, and daily activities of stroke patients [3], as well as its integration with machine learning improves the prediction of walking function post-rehabilitation compared to traditional clinical models [12]. Global trends also show a significant increase in research on wearables and AI in stroke rehabilitation [13]. In the context of modeling, gait event detection using CNN on waist-worn IMU achieves high accuracy [4], Gait phase estimation using LSTM shows generalization capability towards variations in walking patterns [14], and the estimation of step length using a sequential neural network increases accuracy compared to conventional methods [15]. In addition, sensor-based augmented feedback has been proven to improve the effectiveness of gait rehabilitation [16], and the trend of modern rehabilitation is increasingly moving towards the integration of sensors and AI for adaptive systems [17]. However, most exoskeleton control systems are still based on fixed assistance profiles, making them less adaptive to individual variations [18].

Previous research has shown that joint angular velocity can be predicted using regression as well as a multilayer neural network based on BMI and walking speed, with higher performance in the neural network model [19]. However, the optimization of network architecture, hidden layer configuration, and the evaluation of the impact of estimation errors on control system stability have not been explored comprehensively. In closed-loop control systems, state estimation errors will affect actuation precision and can reduce the stability of the system's response to external disturbances. Therefore, this study proposes the optimization of a Neural Network for estimating lower limb angular velocity based on BMI and walking speed as a fundamental step in developing a stable, precise, and personalized adaptive gait control system for post-stroke rehabilitation.

2. Method

2.1 Research Methodology

This research is conducted to develop and optimize a neural network model in estimating lower extremity joint angular velocity based on Body Mass Index (BMI) and walking speed. The research methodology is systematically designed by utilizing secondary data from previous studies, so the main focus of this research lies in the development of the computational model and the evaluation of its performance, not on the direct process of gait data collection.

In general, this research methodology includes several main stages, namely the identification and utilization of secondary data, characterization and grouping of data, neural network modeling, the process of optimizing model architecture, and the evaluation of model performance based on statistical indicators. This methodological framework is designed to ensure that each stage of the research is logically interconnected.

2.2 Sources and Characteristics of Data

This study uses secondary data obtained from previous research regarding the estimation of lower extremity joint angular velocity based on Body Mass Index (BMI) and walking speed. The data used are the results of gait processing that have undergone acquisition, processing, and validation in the initial study, thus including BMI and walking speed as input variables, as well as Hip, Knee, and Ankle joint angular velocity as output variables in several gait phases.

To illustrate the structure of the dataset, the data is grouped based on BMI categories into underweight, normal, overweight, and obese. Additionally, the data is divided based on the type of joint and gait phase (phase 1 to phase 4), so the analysis is carried out specifically for each combination of joint and gait phase is presented in Figure 1.

Figure 1. Illustration of data collection

2.3 Data Distribution and Structure

The data used in this study were grouped to illustrate the distribution and structure of the dataset before neural network modeling was performed. The data distribution was analyzed based on Body Mass Index (BMI) categories. The grouping aimed to show the distribution of anthropometric characteristics in the dataset and to ensure the representativeness of the variations in the data used. The table of data distribution based on BMI categories is presented in Table 1.

Table 1. Distribution Table of Data used

BMI Category	**BMI Definition (kg/m²)**	**Total Data**
Underweight	BMI ≤ 18,5	1.568
Normal	18,6 – 23,9	1.847
Overweight	24,0 – 27,9	1.375
Obese	≥ 28,0	2.016
Total		**6.806**

2.4 Research Stages

The research stages are arranged systematically and illustrated in the form of a flowchart in Figure 2, which shows the neural network optimization flow starting from the utilization of secondary data to the determination of the optimal model configuration. The main focus of this study is on the analysis and modeling process, so the primary experimental stages are not included again.

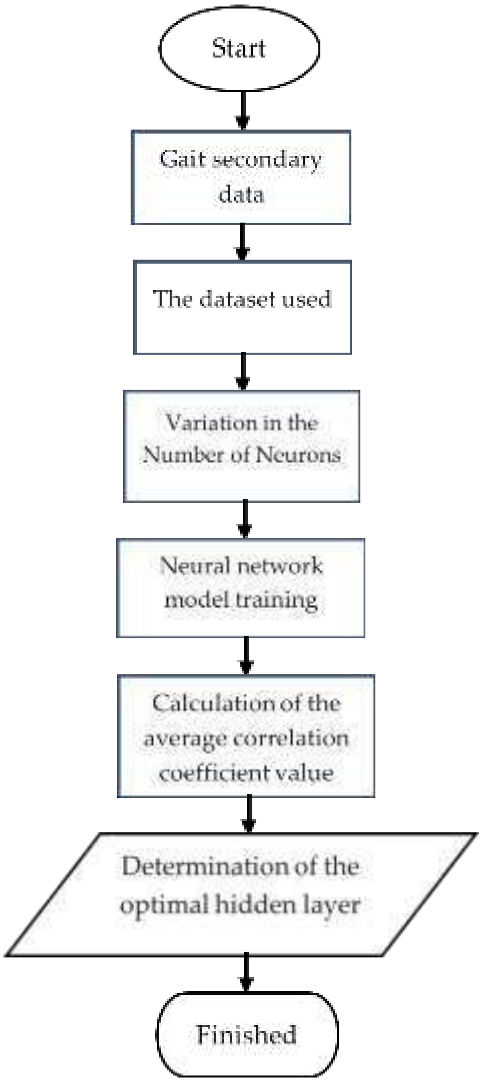


Figure 2. Flowchart Optimasi Neural Network.

2.5 Neural Network Modeling and Performance Evaluation

The estimation model was built using a feedforward neural network with one hidden layer. The number of neurons in the hidden layer was varied gradually, namely 5, 10, 15, 20, 25, and 30 neurons, to evaluate the effect of architecture complexity on estimation performance. The neural network training process was carried out using the Levenberg–Marquardt algorithm through the Neural Network Fitting facility in MATLAB software. This algorithm was chosen because of its ability to accelerate convergence and produce good estimation performance in nonlinear regression problems.

The performance of the model is evaluated using the correlation coefficient (R) between the neural network output and the reference angular velocity data. The R value is used as an indicator of the degree of agreement between the estimation results and the actual data. The optimal neural network architecture is determined based on the neuron configuration that produces the highest stable R value across various joints and gait phases, without showing indications of overfitting or performance saturation.

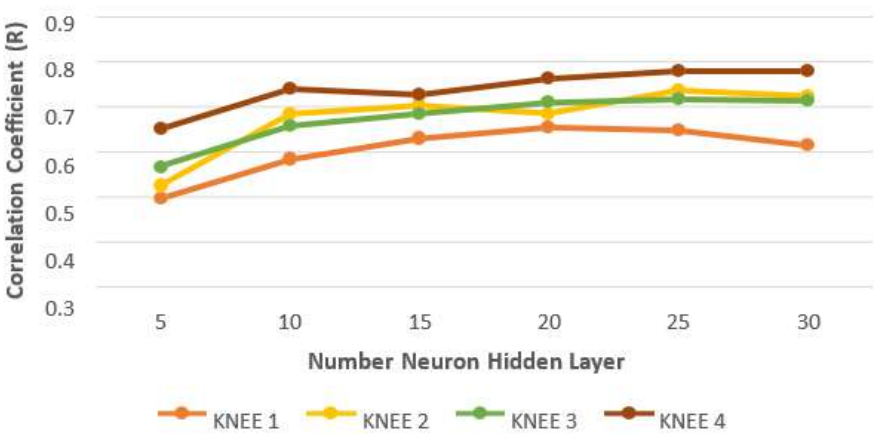
3. Result

The estimated lower limb angular velocity results were obtained from neural network modeling using MATLAB Neural Network Fitting with variations in the number of hidden layer neurons of 5, 10, 15, 20, 25, and 30 neurons. The model performance was evaluated using the correlation coefficient (R) between the neural network estimation results and the reference angular velocity data. The R values were analyzed for the three main joints, namely the hip, knee, and ankle, in the four gait phases.

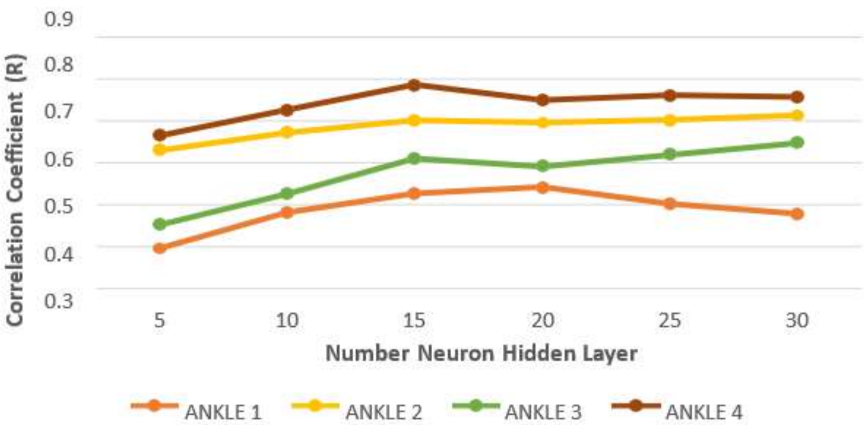
The correlation coefficient (R) values for each joint and gait phase are presented in Table 2, while the relationship between the number of hidden layer neurons and the R values is visualized through a graph. The table presentation aims to display the numerical values in detail, whereas the graph is used to show the trend of the model's performance against changes in neural network architecture complexity.

Tabel 2. The average value of the correlation coefficient (R) from neural network estimation results for variations in the number of hidden layer neurons for each joint and gait phase.

Hidden Neuron	Hip Fase 1	Hip Fase 2	Hip Fase 3	Hip Fase 4
5	0.671	0.850	0.678	0.759
10	0.728	0.880	0.737	0.797
15	0.762	0.888	0.727	0.822
20	**0.793**	**0.895**	**0.743**	**0.818**
25	0.770	0.893	0.763	0.816
30	0.749	0.899	0.759	0.798
Hidden Neuron	**Knee Fase 1**	**Knee Phase 2**	**Knee Phase 3**	**Knee Phase 4**
5	0.497	0.525	0.566	0.651
10	0.583	0.684	0.657	0.741
15	0.630	0.702	0.686	0.728
20	**0.654**	**0.686**	**0.710**	**0.762**
25	0.648	0.737	0.718	0.780
30	0.615	0.724	0.714	**0.780**
Hidden Neuron	**Ankle Phase 1**	**Ankle Phase 2**	**Ankle Phase 3**	**Ankle Phase 4**
5	0.392	0.627	0.448	0.662
10	0.477	0.668	0.522	0.724
15	0.523	0.698	0.607	0.783
20	**0.538**	**0.693**	**0.588**	**0.747**
25	0.498	0.699	0.616	0.758
30	0.474	0.715	0.645	**0.754**



(a)



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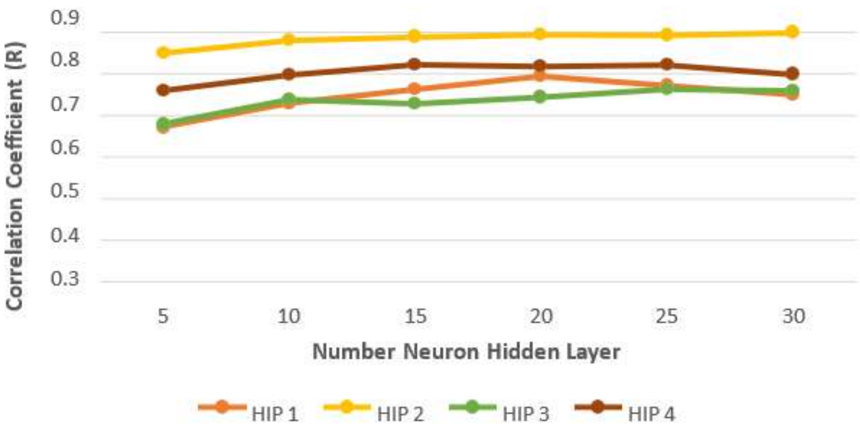

(c)

Figure 3. The effect of variations in the number of hidden layer neurons on the correlation coefficient (R) in joint angular velocity estimation.

The correlation coefficient (R) values from the estimation are presented in the form of a numerical table and visualized through a graph showing the relationship between the number of neurons in the hidden layer and the R value. The table presentation aims to show the quantitative values in detail, while the graph is used to observe the trend of changes in model performance as the complexity of the neural network architecture increases.

Based on the hip joint result table, it can be seen that all gait phases show a trend of increasing R values as the number of hidden layer neurons increases up to a certain point. In gait phase 1, the R value increases from 0.671 at 5 neurons to 0.793 at 20 neurons, then decreases at 25 and 30 neurons. A similar pattern is also observed in gait phase 3 and gait phase 4, where the R value increases up to a medium number of neurons before showing a tendency to stagnate or slightly decrease at a higher number of neurons. Gait phase 2 shows the highest R value among all phases and joints, with the value consistently increasing from 0.850 at 5 neurons to 0.899 at 30 neurons. The hip joint graph shows a relatively smooth and stable curve across all gait phases, indicating consistency in estimation performance against changes in the number of neurons.

At the knee joint, the R values shown in the table are at an intermediate level and indicate greater variation between gait phases compared to the hip joint. In gait phase 1, the R value increases from 0.497 at 5 neurons to 0.654 at 20 neurons, then decreases at higher neuron numbers. Gait phases 2 and 3 show a fairly significant increase in R values from small to medium neurons, with maximum values each ranging from 20 to 25 neurons. Gait phase 4 produces the highest R value at the knee joint, reaching around 0.780 at 25 neurons and remaining relatively stable up to 30 neurons. The knee joint graph shows a clear performance peak in the medium neuron range, followed by a flat or slightly decreasing trend at higher neuron numbers.

Meanwhile, the estimation results for the ankle joint show the lowest R values compared to the hip and knee joints in almost all gait phases. In gait phase 1, the R value increased from 0.392 with 5 neurons to 0.538 with 20 neurons, then decreased at 25 and 30 neurons. Gait phase 2 shows a relatively stable increase in R values up to 30 neurons, with a maximum value of around 0.709. In gait phase 3, the R value gradually increases from smaller to larger neurons, although at a slower rate compared to the other gait phases. Gait phase 4 produces the highest R value for the ankle joint, with a maximum value of around 0.783 at 15 neurons, before stagnating at a larger number of neurons. The ankle joint graph shows larger fluctuations compared to the hip and knee graphs, indicating sensitivity of estimation performance to changes in the number of neurons.

Overall, the results shown by the table and graph indicate that increasing the number of hidden layer neurons improves the correlation coefficient (R) values up to an optimal point, which is generally within the mid-range neuron count. Beyond this point, increasing the number of neurons does not necessarily lead to higher R values and, in some cases, even shows a decline in performance. The highest R values are consistently obtained at the hip joint, followed by the knee and ankle joints. Additionally, the late gait phase tends to produce higher R values compared to the early gait phase for all three joints.

4. Discussion

Research results indicate that variations in the number of neurons in the hidden layer have a significant impact on the performance of neural networks in estimating the angular velocity of lower limb joints. In general, increasing the number of hidden layer neurons boosts the correlation coefficient (R) between estimation results and reference data up to a certain point. This pattern suggests that adding neurons in the initial stages contributes to enhancing the model's capacity to learn the nonlinear relationships between Body Mass Index (BMI), walking speed, and joint angular velocity. In configurations with a relatively small number of neurons (5–10 neurons), the R value tends to be low, reflecting underfitting conditions, where the model's complexity is insufficient to represent the dynamic and varied characteristics of gait data across different joints and gait phases. Along with the increasing number of hidden layer neurons, particularly in the range of 15-20 neurons, the estimation performance shows the most significant improvement and is also consistent across almost all joint and gait phase combinations. In this range, the neural network is able to effectively capture nonlinear relationship patterns, reflected in the relatively more stable increase in R values. This configuration demonstrates a good balance between architectural complexity and model generalization capability. Conversely, with a higher number of neurons (25–30 neurons), performance improvement is no longer significant, and under some conditions, there is even a decrease in R values. This indicates performance saturation, where adding model complexity does not correspond to increased estimation accuracy, and may potentially reduce the model's efficiency and stability.

Analysis of results based on joint type shows differences in estimation performance characteristics. The hip joint consistently produces the highest and most stable correlation coefficient values across all gait phases. In contrast, the knee and ankle joints show lower and more fluctuating R values. The dynamics of knee and ankle movements are influenced by load adjustment functions, interaction with walking surfaces, and rapid changes during gait phase transitions, resulting in more complex patterns that are difficult to model consistently.

In addition to differences between joints, the influence of the gait phase is also clearly visible in the estimation results. The final gait phase tends to produce higher R values compared to the initial gait phase in all three joints. This indicates that the angular velocity pattern in the final gait phase is more stable and has a stronger relationship with the input parameters, namely BMI and walking speed. Based on the overall results, a neural network configuration with the number of hidden layer neurons in the range of 15–20 neurons was determined to be the most optimal configuration. This configuration is capable of producing high and consistent correlation coefficient values across various joints and gait phases, while avoiding excessive model complexity.

The difference in estimation performance between joints can be explained biomechanically. The hip joint has a more consistent movement pattern as the main driver during walking, making the relationship between input parameters and angular velocity easier for a neural network to learn. The knee and ankle joints have more complex movement dynamics due to their roles in load adjustment and interaction with the walking surface, resulting in lower and more fluctuating R values. The influence of the gait phase is also significant, with the late gait phase producing higher R values compared to the early gait phase. This indicates that the angular velocity pattern in the late walking phase is more stable and has a stronger relationship with input parameters. Thus, gait phase-based modeling proves to be relevant for improving estimation accuracy.

5. Conclusion

This study successfully demonstrated that optimizing neural network architecture, particularly in the number of hidden layer neurons, significantly affects the accuracy of lower limb joint angular velocity estimation based on Body Mass Index (BMI) and walking speed. The modeling results show that increasing the number of hidden layer neurons can improve the correlation coefficient (R) value until it reaches an optimal condition, before performance saturates at a higher number of neurons. A neural network configuration with the number of hidden layer neurons in the range of 15-20 neurons was determined to be the most optimal architecture because it can produce high estimation accuracy and also remain stable with an efficient model.

In addition, the research results show differences in estimation characteristics between joints and gait phases. The hip joint consistently produces the best and most stable estimation performance, followed by the knee and ankle joints, which show lower and more fluctuating correlation values. The final gait phase tends to provide higher estimation accuracy compared to the initial gait phase, indicating that the angular velocity patterns in the final walking phase are more stable and easier to model.

Overall, this study confirms that choosing the appropriate neural network configuration, taking into account joint characteristics and gait phases, is a key factor in the development of adaptive and applicable neural network-based gait estimation and control systems, particularly to support walking rehabilitation and robot-based assistive systems.

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