Lower Limb Joint Angle Estimation From Vertical Ground Reaction Forces Using Neural Networks

Parsa Yazdankhah
School of Mechanical Engineering
University of Tehran
Tehran, Iran
parsa.yazdankhah@ut.ac.ir

Mahdi Mehdikhani Sarvjahny
School of Mechanical Engineering
University of Tehran
Tehran, Iran
mahdi.mahdikhani@ut.ac.ir

Rezvan Nasiri
School of Electrical and Computer Engineering
University of Tehran
Tehran, Iran
rezvan.nasiri@ut.ac.ir

***Abstract*—In human biomechanics field, motion assessment by precise joint angle measurement is an important challenge due to its diverse applications, ranging from gait analysis and clinical rehabilitation to sports performance evaluation and assistive device design. Conventional approaches for lower limb joint angle measurement often rely on cumbersome wearable sensors, and subject-specific parameters, which are prone to error and very expensive. Addressing these limitations, we introduce a novel neural network-based framework capable of predicting lower limb joint angles from vertical ground reaction forces (vGRFs). Our method only requires the GRF sensor to measure the joint angle and accordingly, we reduce the experimental setup cost. Leveraging the potential of Recurrent Neural Networks (RNNs) to capture temporal dependencies in sequential data, we formulate an architecture to estimate ankle, knee, and hip joint angles. The model is trained on an available dataset of walking (including vertical GRF as input and joint angles as output). The generalization of the trained model is also tested using the walking trajectories of individuals with motor impairment; i.e., Parkinson's disability.**

***Index Terms*—Ground Reaction Forces, Gait Analysis, Neural Networks, Deep Learning, Joint Angle Estimation**

I. Introduction

IN the field of human motion analysis, accurately estimating lower limb joint angles plays a crucial role in various applications such as gait analysis, clinical rehabilitation, sports performance assessment, and assistive device design. Traditional methods for joint angle estimation often rely on wearable sensors placed on the body, which can be cumbersome and prone to errors. Also, these methods often rely on subject-specific anthropometric parameters, limiting their generalizability to larger populations. Accurate and real-time joint angle estimation from GRF measurements can provide valuable insights into movement patterns, muscle coordination, and the overall biomechanics of human locomotion.

The first study that issued the problem of the estimate of joint kinematics by using inertial sensors took place back in 1990 [1]. Over the following years, a number of methodological techniques have been proposed to estimate 2D and 3D joint kinematics utilizing wearable inertial sensors [2]. To address the challenge associated with the placement of wearable sensors, Wang et al. have introduced an innovative calibration procedure designed to easily and precisely position and align an inertial measurement unit (IMU) sensor with the clinical bone frame in a lower limb skeletal model [3]. This new method ensures accurate data collection for a more reliable and effective analysis.

In recent years, the emergence of neural networks has opened up new possibilities for improving the accuracy and efficiency of joint angle estimation [4]–[10]. Sivakumar et al. conducted a study in 2018 on the estimation of joint angle from ground reaction force using ANNs. They implemented a basic three-layer Feedforward Neural Network (FNN) and estimated ankle angles from measured vertical GRFs [8]. They also utilized a signal-based feature selection method using prior knowledge of the gait cycle based on five main gate events [11].

In 2001, Thomas Chau conducted a valuable study comparing two analytical techniques for gait data namely, neural networks and wavelet methods [5]. He concluded that although neural networks are found to be the most prevalent non-traditional methodology for gait analysis, wavelet methods, and gait waveforms are going to be identified as important data analysis topics for multiple gait signal interactions and quantitative comparisons.

Hence, Sivakumar et al. proposed a novel method based on wavelet neural networks to estimate ankle, knee, and hip joint angles using only the vertical GRF and the same feature extraction method they used in their last study [6].

In this study, we aim to overcome the limitations of traditional sensor-based methods by developing a neural network structure that takes vertical ground reaction forces (vGRFs) as input and accurately predicts the lower limb kinematics (joint angles).

The proposed architecture consists of a neural network that has both recurrent neural networks and feedforward neural networks stacked together to form the final architecture that facilitates the estimation of ankle, knee, and hip joint angles. Further, in the methodology section, a comprehensive explanation of this network structure will be presented.

Recurrent Neural Networks (RNNs) represent a class of neural networks specifically designed for sequential data processing, with a memory mechanism that enables them to retain information from previous inputs [12]. Widely applied in time-series analysis [13], RNNs have exhibited remarkable performance in tasks involving sequential data. In this article,

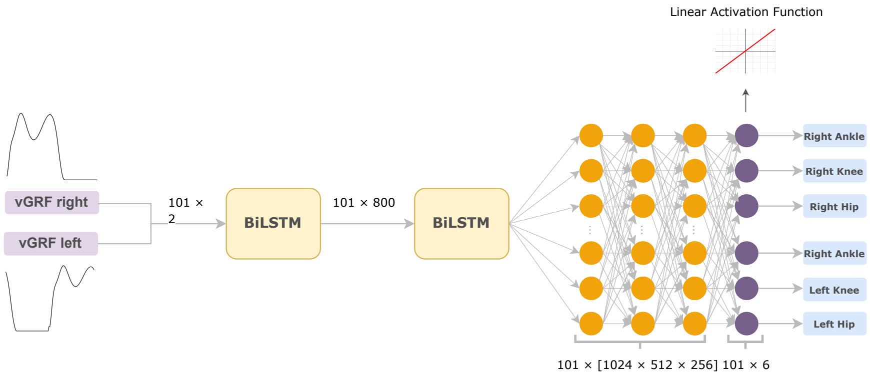

Fig. 1. Overview of the proposed joint angle estimation deep learning model

we explore an innovative application of RNNs to extract features from sequential vGRFs, leveraging their capacity to capture temporal dependencies in sequential data.

On the other hand, Feedforward Neural Networks (FNNs) serve as the fundamental architecture for deep learning and have demonstrated their adaptability in various domains [14]. These networks consist of layers of interconnected nodes where data flows unidirectionally, from input to output.

Despite the various approaches available in the literature for gait monitoring of individuals, there are several limitations in using sensor-based methods; Therefore, in this study, a novel method is proposed that provides accurate joint angle estimation from vertical ground reaction forces that could be recorded even from insole force sensors that would assure persistent condition monitoring for those with gait disorders alongside the healthy subjects.

In the next phase, it is planned to utilize the trained neural network to estimate the lower body kinematics of subjects with gait disorders (like Parkinsonian individuals), based on their movement data (GRF). If successful, this approach could be used for the general purpose of diagnosing gait abnormalities solely from the ground reaction force (GRF) data.

The remainder of this paper is organized as follows. Section 2 provides a comprehensive statement of the methodology and outlines the steps involved in the proposed approach. Section 3 presents results and performance evaluation, followed by a discussion in the very same section. Finally, Section 4 concludes the paper by summarizing the findings and discussing potential future directions of Artificial Neural Networks in advancing joint angle estimation from vGRFs.

II. METHODOLOGY

A. Dataset

In this study, the public dataset described in [15] is used to train and test the proposed method. This rich dataset consists of the walking kinematics and kinetics data of 42 healthy subjects, including both young and elderly adults. The dataset covers various walking trials conducted on both overground terrain and a treadmill, involving different walking speeds. In this dataset, lower extremity and pelvis kinematics were measured using a three-dimensional (3D) motion-capture system.

In [16], a comparison of sagittal plane gait characteristics between the overground and treadmill approach for gait analysis is conducted. It is noted that although the patterns of sagittal kinematic and kinetic data remain consistent across both approaches, noticeable differences in amplitude can be observed. Hence, employing each of these methods for gait analysis may result in different sagittal gait characteristics. For instance, [16] demonstrated that individuals exhibited slower walking speeds, shorter stride and stance times, as well as shorter and wider steps when using the treadmill approach, as compared to the overground approach.

As instrumented treadmills have become increasingly prevalent in gait analysis, in this study, treadmill data is only considered from the dataset. This choice helps ensure greater consistency in the gait characteristics extracted by the neural network.

In the next step, GRFs and joint angles are normalized based on the global minimum and maximum values across all subjects. This normalization is implemented to enhance the performance and stability of the neural network. For instance, Ankle angles are normalized based on the maximum and minimum values of all gathered data for the ankle. Indeed, this normalization approach ensures that the scale of features becomes consistent with one another. The processed data is finally truncated, labeled, and partitioned, with 15% of the data allocated for testing and an additional 15% designated

TABLE I
ANTHROPOMETRICAL INFORMATION OF THE DATASET OF HEALTHY SUBJECTS

Age Group	Gender	Count	Mean Age	Mean Mass	Mean Height
older	F	8	60.1	61.10	154.76
older	M	10	64.8	71.58	167.49
Young	F	10	25.9	58.92	162.91
Young	M	14	29.8	75.17	176.92

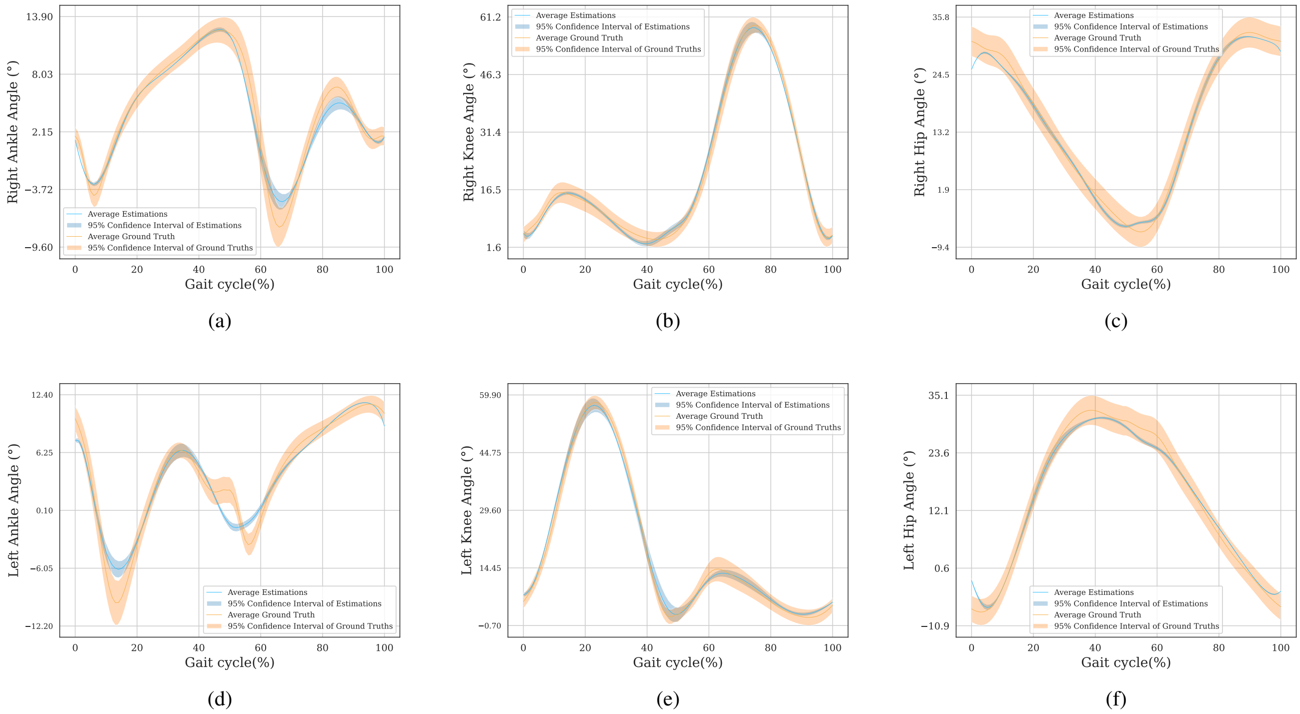

Fig. 2. Graphical comparison between average estimated angles of RNN (blue dashed line) and the ground truth (orange solid line) for healthy subjects. The blue shaded area represents 95% Confidence Interval of Estimations and the orange shaded area represents 95% Confidence Interval of ground truths.

for validation.

Finally, as discussed in the Introduction section, to validate the generalizability of the trained neural network, a dataset including kinematics and kinetics data of subjects with gait disorders is needed. Thus, a public data set of walking full-body kinematics and kinetics in individuals with Parkinson's disease [17] is taken into account. Afterward, all the pre-processing steps that were formerly discussed should be implemented on these data as well, for them to be prepared to be passed into the trained neural network, and investigate its performance. This dataset has two sections, each devoted to the kinematics and kinetics data of subjects when they are on and off medication. For the purpose explained, gait patterns with significant discrepancy in the overall trend is needed; Therefore, the off-medication portion of data is used, which sufficiently addresses the intended variation in gait patterns.

B. Neural Network Architecture

Recurrent Neural Networks have been shown to perform well for time-series applications in analyzing gait parameters. In [18] bidirectional LSTM was shown to outperform other methods for estimating joint angles. In this study, a deep learning model involving two stacked BiLSTM layers is used to capture temporal dependencies and contextual information from the input feature sequence. BiLSTM is a specialized variant of the LSTM neural network architecture. Using this architecture, it is possible to extract time-series features in both forward and backward directions. Indeed, BiLSTM includes an additional LSTM for the backward flow of data, thereby eliminating sequence dependence in a single direction.

In order to reduce over-fitting, dropout layers are used between the stacked BiLSTM layers, and the probability of dropout layers is set to 0.4. The Adam optimizer was implemented during training to minimize the loss function during gradient descent.

Following the two stacked BiLSTM layers, 4 layers of fully connected neural network (FNN) are used to estimate desired lower limb joint angles. Therefore, in the output layer of this neural network, a linear activation function is being applied, and six joint angles consisting of ankle, knee, and hip angles of the right and left foot are estimated using the extracted features. Moreover, dropout layers with the probability of 0.4, have also been used between these FNN layers to reduce over-fitting.

The overall structure of the deep learning model is shown in Fig. 1. The input of the model consists of two vectors of size 101 which are the GRFs for the left and right legs during the full gait cycle. The outputs are six vectors of size 101 which are the estimations of the lower body joint angles during the full gait cycle.

The model is trained on an available dataset of healthy subjects' walking (which is introduced in the Dataset section) including vertical GRF as input and joint angles as output. The generalization of the trained model is also tested using the walking trajectories of individuals with motor impairment; i.e., Parkinson's disability.

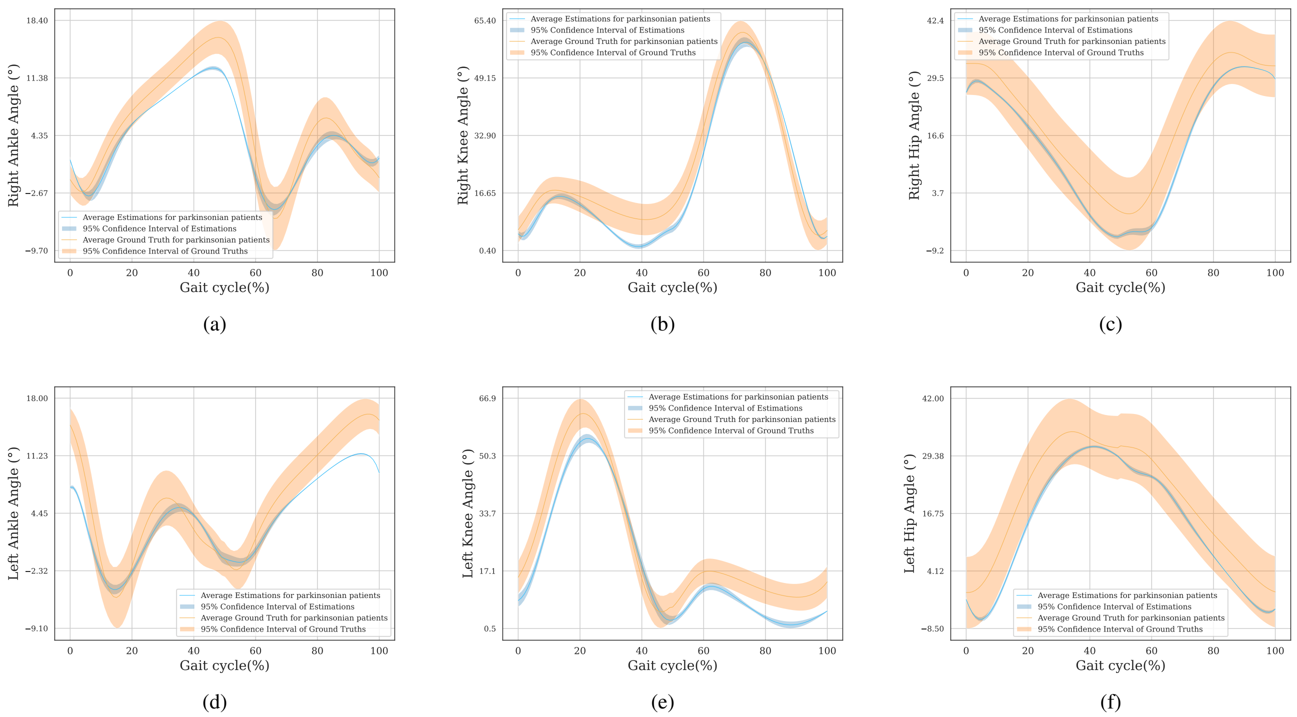

Fig. 3. Graphical comparison between average estimated angles of RNN (blue dashed line) and the ground truth (orange solid line) for patients with Parkinson's disorder. The blue shaded area represents 95% Confidence Interval of Estimations and the orange shaded area represents 95% Confidence Interval of ground truths.

III. Results

The considered neural network is trained based on the architecture of the network formerly explained. (Fig. 1) Table II demonstrates a brief summary of errors in the network which was trained using the proposed structure.

As it has been shown graphically in Fig. 2, the trained network has learned to predict lower limb joint angles with acceptable accuracy. This has been possible due to the policies applied to the network structure that prevented over-fitting. Thus, the trained network has got a generalizable approach and can now be tested on unhealthy subjects to test its performance on those individuals.

Now, to test the generalizablity of the trained model, the toolbox's performance is going to be examined over a walking dataset of subjects with Parkinson's disorder. It is worth mentioning that gait patterns of these subjects with motor impairment vary noticeably from those healthy individuals. As shown in Fig. 3 and Table III, despite the fact that the neural network was not trained using any of these patient's GRF and Angle data, because of the relatively robust architecture that has been proposed to eliminate over-fitting and to make the neural network more reliable to unforeseen data, even if it has different overall trend compared to data used for training, the network has been able to predict joint angles of these patients with relatively acceptable accuracy; Therefore, showcasing the capability of this neural network be a reliable source for monitoring motion analysis using only their vertical ground reaction forces. Also, errors from the prediction of joint angles of these patients are quite low which is again an approval of the generalizability of the proposed network.

Our results demonstrate a promising method that could be used to facilitate the growing need for constant monitorization of people with gait disorders. This way, only GRF sensor is required to measure the lower limb joint angles with relatively good accuracy, causing costly experimental setups to be dismantled.

TABLE II
Summary of Joint Angle Estimation Errors for Healthy Subjects for Each Angle

Angle Name	NRMSE (%)	MAPE (%)
Right Ankle	5.565	2.027
Right Knee	6.011	1.722
Right Hip	7.574	3.679
Left Ankle	5.693	1.889
Left Knee	4.015	2.281
Left Hip	8.495	3.574

IV. Conclusion

In this article, a novel algorithm is proposed for the estimation of the lower body joint angles based on only the measurements of vertical ground reaction forces. A deep learning model with 2 BiLSTM layers and 4 layers of FNN is used for the estimation of the joint angles based on the vertical GRFs.

TABLE III
SUMMARY OF JOINT ANGLE ESTIMATION ERRORS FOR SUBJECTS WITH PARKINSON'S DISORDER FOR EACH ANGLE

Angle Name	NRMSE (%)	MAPE (%)
Right Ankle	5.737	3.024
Right Knee	8.979	2.152
Right Hip	13.896	4.528
Left Ankle	6.592	1.949
Left Knee	8.296	3.592
Left Hip	12.093	4.241

Moreover, dropouts have also been implemented to address the over-fitting issue. It is shown that through using this method, it is possible to estimate the joint angles of the right ankle, right knee, right hip, left ankle, left knee, and left hip with NRMSE values of 5.56, 6.01, 7.57, 5.69, 4.01 and 8.49 respectively. In future studies, dynamical constraints could also be taken into account to further improve the generalizability of the trained neural network. This way, besides using MAE as the loss function, a dynamical loss is considered by calculating the difference between the prediction of GRF using an inverse dynamic model and the true values of the GRFs. However, developing an accurate inverse dynamic model is a must to calculate the GRFs properly, and to allow any improvements to be made. Nevertheless, the current deep learning model is able to predict the joint angles for individuals with Parkinson's disease with low errors, without even being considered in the training procedure.

REFERENCES

[1] A. T. M. Willemsen, J. A. van Alste, and H. Boom, "Real-time gait assessment utilizing a new way of accelerometry," *Journal of biomechanics*, vol. 23, no. 8, pp. 859–863, 1990.

[2] P. Picerno, "25 years of lower limb joint kinematics by using inertial and magnetic sensors: A review of methodological approaches," *Gait & Posture*, vol. 51, pp. 239–246, 2017. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0966636216306373

[3] S. WANG, Y. CAI, K. HASE, K. UCHIDA, D. KONDO, T. SAITOU, and S. OTA, "Estimation of knee joint angle during gait cycle using inertial measurement unit sensors: a method of sensor-to-clinical bone calibration on the lower limb skeletal model," *Journal of Biomechanical Science and Engineering*, vol. advpub, pp. 21–00 196, 2021.

[4] N. Sun, M. Cao, Y. Chen, Y. Chen, J. Wang, Q. Wang, X. Chen, and T. Liu, "Continuous estimation of human knee joint angles by fusing kinematic and myoelectric signals," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 30, pp. 2446–2455, 2022.

[5] T. D.-P. Chau, "A review of analytical techniques for gait data. part 2: neural network and wavelet methods." *Gait & posture*, vol. 13 2, pp. 102–20, 2001.

[6] V. Chhoeum, Y. Kim, and S. D. Min, "Estimation of knee joint angle using textile capacitive sensor and artificial neural network implementing with three shoe types at two gait speeds: A preliminary investigation," *Sensors (Basel, Switzerland)*, vol. 21, 2021.

[7] S. Davarzani, D. Saucier, P. Peranich, W. Carroll, A. Turner, E. Parker, C. Middleton, P. Nguyen, P. Robertson, B. Smith, J. Ball, R. Burch, H. Chander, A. Knight, R. Prabhu, and T. Luczak, "Closing the wearable gap—part vi: Human gait recognition using deep learning methodologies," *Electronics (Switzerland)*, vol. 9, pp. 1–17, 2020.

[8] S. Sivakumar, A. A. Gopalai, D. Gouwanda, and K. Lim, "Estimation of joint angle from ground reaction force in human gait," *2018 IEEE-EMBS Conference on Biomedical Engineering and Sciences (IECBES)*, pp. 623–628, 2018.

[9] S. Sivakumar, A. A. Gopalai, K. Lim, D. Gouwanda, and S. Chauhan, "Joint angle estimation with wavelet neural networks," *Scientific Reports*, vol. 11, 2021.

[10] H. Lim, B. Kim, and S. Park, "Prediction of lower limb kinetics and kinematics during walking by a single imu on the lower back using machine learning," *Sensors*, vol. 20, no. 1, 2020. [Online]. Available: https://www.mdpi.com/1424-8220/20/1/130

[11] M. Whittle, *Gait Analysis: An Introduction*. Elsevier - Health Sciences Division, 2007. [Online]. Available: https://books.google.com/books?id=HtNqAAAAMAAJ

[12] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 11 1997. [Online]. Available: https://doi.org/10.1162/neco.1997.9.8.1735

[13] Z. C. Lipton, J. Berkowitz, and C. Elkan, "A critical review of recurrent neural networks for sequence learning," 2015.

[14] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *nature*, vol. 521, no. 7553, p. 436–444, 2015.

[15] C. A. Fukuchi, R. K. Fukuchi, and M. Duarte, "A public dataset of overground and treadmill walking kinematics and kinetics in healthy individuals," *PeerJ*, vol. 6, 2018.

[16] R. Senden, R. Marcellis, K. Meijer, P. J. B. Willems, T. F. Lenssen, H. M. Staal, Y. Janssen, V. Groen, R. J. Vermeulen, and M. A. Witlox, "Comparison of sagittal plane gait characteristics between the overground and treadmill approach for gait analysis in typically developing children," *PeerJ*, vol. 10, 2022.

[17] T. K. F. Shida, T. M. Costa, C. E. N. de Oliveira, R. de Castro Treza, S. M. Hondo, E. Los Angeles, C. Bernardo, L. dos Santos de Oliveira, M. de Jesus Carvalho, and D. B. Coelho, "A public data set of walking full-body kinematics and kinetics in individuals with parkinson's disease," *Frontiers in Neuroscience*, vol. 17, 2023. [Online]. Available: https://www.frontiersin.org/articles/10.3389/fnins.2023.992585

[18] D. Hollinger, M. Schall, H. Chen, S. Bass, and M. Zabala, "The Influence of Gait Phase on Predicting Lower-limb Joint Angles," *IEEE Transactions on Medical Robotics and Bionics*, vol. 5, no. 2, pp. 343–352, 2023.