Predicting Hip Kinematics with CNN during Cycling Task

R. Ahmadi[1], A. Parsaei[2], A. Komeili[1,2]

[1] Department of Mechanical Engineering, University of Calgary, Calgary, AB, Canada
[2] Department of Biomedical Engineering, University of Calgary, Calgary, AB, Canada

Abstract—**The traditional method of analyzing hip joint kinematics during pedaling task involves motion capture system, which is a relatively expensive method with limited accessibility and lack of real-time applicability in clinical and training environments. To address this gap, this study leveraged a Convolutional Neural Networks (CNNs) model to predict the hip joint kinematics during pedaling task on a stationary cycling ergometer. The present study involved 10 participants (eight males and two females), without any injury in lower limbs to ensure the purity and relevance of the data. Using Vicon motion capture system, a comprehensive dataset of hip joint kinematics parameters were collected. A CNN model with five hidden layers was trained on this dataset.**

Our results showed a notable accuracy in predicting hip joint kinematics parameters with a Root Mean Square Error (RMSE) of 2.98±0.61° for hip flexion, 1.51±0.46° for hip adduction, and 1.73±0.49° for hip rotation. These values, within acceptable limits, demonstrate the model's robustness in hip measurements.

This study contributes significantly to the biomechanical study of hip joint, offering a potential integration of predictive models and real-time monitoring of hip joint kinematics during pedaling exercise with stationary ergometers.

Keywords— **Machine Learning, Motion Analysis, Cycling, Convolutional Neural Network.**

I. Introduction

Cycling, as a multifaceted physical activity, holds significant importance in different fields ranging from sports performance optimization to rehabilitation and ergonomics [1]. The accurate monitoring and prediction of hip joint kinematics during cycling tasks can be used to adjust training and enhance performance optimization. Enhancing our understanding of movement patterns and joint kinematics could lead to more effective injury prevention strategies. Moreover, it provides valuable insights into ergonomics for bike design and manufacturing [2], [3]. Traditional methods for analyzing human motion face several challenges. These methods include medical imaging techniques like fluoroscopy or magnetic resonance [4], [5], skin-based methods such as optoelectronic motion analysis cameras [6], [7], inertial sensors [8], [9], marker-based methods, and marker-less motion capture techniques [10]–[13]. These approaches require specialized equipment and laboratory spaces, creating a barrier due to resource intensity. High costs and limited access render lower limb analysis during cycling impractical for many clinical settings. Furthermore, the data collection and processing are labor-intensive, with the creation of dynamic musculoskeletal simulations often spanning several days, detracting from its practicality in everyday clinical practice [14].

In response to these limitations, advancements in machine learning (ML), particularly regression-based techniques, and human pose estimation algorithms showed promising solutions to replace manual work in kinematics analyses [15]–[18]. In these approaches, in-vivo posture data from several individuals are first collected via a skin-based motion capture system during various physical activities. A machine-learning, such as artificial neural networks (ANNs), is subsequently trained on these data. The ML based methods hold possibilities for predicting and understanding body kinematics without the need for costly sensors or cameras. However, they confront issues with generalization across various measures, tasks, and populations, alongside challenges in ensuring accuracy and robustness in motion analysis [15]–[19].

While numerous studies have explored various ML models in different activities [10], [15]–[22], a significant portion of studies [16], [17], [19], [20] used classic feedforward neural networks. It has been shown that CNN outperforms classic ANN models in predicting joint kinematics during gait [15], [21]–[23]. Nevertheless, the application of CNNs in analyzing and predicting the kinematics of cycling is yet to be conducted.

This study is aimed at developing a CNN model for predicting lower-body joint angles, particularly the hip joint, during a pedaling task on a stationary cycling ergometer, and validating the CNN by comparing its predictions with the motion capture measurements. The CNN was trained on a dataset of in vivo recordings, with the premise that embracing input complexity and the variability of data will bolster the model's resilience.

II. Materials and methods

A. Subjects and Task

The study involved ten healthy individuals, comprising eight males and two females. All participants were right-footed, aged at 24-39, BMI between 18 and 26 kg/m^2, and without a history of musculoskeletal disorders during the last three months. All in vivo experiments were carried out after institutional ethics committee approval and informed consent from subjects.

Each individual performed 50 cycles of pedaling at two cadences, with fast and normal self-selected pace. The test was repeated at 3 different saddle positions. To prevent fatigue development, subjects were free to take a rest between tasks or skip a task when it was too difficult to perform.

B. In vivo data collection

Lower-body kinematics data were recorded using a 10-camera Vicon motion capture system (Vicon Motion Systems Inc., Oxford, UK) (Vicon®, 2002) at a sampling rate of 100 Hz. Thirty-two passive reflective skin markers were placed on lower limbs (Figure 1). Pedal coordinates (X, Y, Z), time (percentage of task) duration of each cycle, saddle height, weight, and height of subjects were used as inputs into the CNN. The test was started by instructing the participant to stay upright for 3 seconds to allow static posture measurement for each experiment.

Lower-body link-segment models were reconstructed using the 3D coordinates of the 32 target markers (Figure 1) captured by the motion capture system. An OpenSim model [8] was scaled to build a personalized musculoskeletal model for each participant. The hip joint kinematics were computed using the OpenSim inverse kinematics (IK) tool (version 4.3).

Figure 1 Experimental setup and placement of markers

C. Development of CNN

CNNs are a specialized type of NN model that has shown remarkable performance in various tasks, including kinematics prediction and time-series data [15], [21]–[23]. This study used a CNN model with five hidden layers to estimate joint kinematics. First, the Standard Scaler function from the Sklearn library was used for scaling features and targets to ensure all variables are in the same range (between zero and one). Targets were scaled back to their original scale using the same scaler after predictions. Then, the model architecture was defined with an input layer size of 8. Then two convolutional layers were added, each followed by a max pooling layer. Both convolutional layers had 32 filters with a kernel size of three and a “ReLU” activation function. The max-pooling layers had a pool size of two. These layers helped reduce data dimensionality and identify the most prominent features. After the max-pooling layers, a flattening layer was used to convert the pooled feature maps into a 1D vector. Two dense layers with 32 and 16 units with a linear activation function were followed by a dropout layer to prevent overfitting. The output layer consisted of three units, with each unit predicting a specific hip joint angle: flexion, adduction, and rotation. The ’Adam’ solver (with a learning rate of 0.01), a stochastic gradient-based optimizer, was used for weight optimization, and the loss function was “Mean absolute error”. The Early Stopping function was used to monitor the validation loss and stop the training if the loss did not improve after five epochs. The batch size was set to 32, and the model was trained for a maximum of 100 epochs. In this model, the optimal activation function (among ’ReLU’, ’Sigmoid’, and ’Tanh’) in hidden layers, the optimizer (among ’Adam’, ’RMSprop’, and ’SGD’) and its learning rate (among 0.1, 0.01, and 0.001), and the number of neurons (between 16 till 256) in each convolutional layer were found through grid search.

D. Performance evaluation of the CNN

To investigate ML model performance for predicting the targets for the same participant, the intra-subject examination was performed. In the intra-subject examination, 70% of participants data were used to train the ML model and the other 30% was used to validate and test the model with a ratio of 50:50.

To compare the performance of the ML model with literature, the Root Mean Square Error (RMSE) and R^2 between the computed and predicted targets in test dataset were calculated for each cycle and each participant.

III. Results

The RMSE and R^2 results for joint kinematics are shown in Table 1. The ranges of motion for hip flexion, adduction, and rotation were 60, 20, and 15 degrees, respectively. As

Table 1 shows, the RMSE for hip flexion, adduction, and rotation reflects the model's varying precision during pedaling. Specifically, the RMSE was 2.98±0.61° for hip flexion, 1.51±0.46° for hip adduction, and 1.73±0.49° for hip rotation. The percentage of RMSE with respect to the range of motion for hip flexion, adduction, and rotation angle was 4.9%, 10%, and 11.5%, respectively, suggesting a more reliable prediction of hip flexion movement compared to others. This was reflected in a higher R^2 of 0.97 for hip flexion, compared to R^2 of 0.91 and 0.89 for hip adduction and rotation, respectively. Even though there is a lower RMSE in adduction and rotation compared to the flexion angle of the hip joint, their range of motion was smaller, which means the model is less accurate in the prediction of hip adduction and rotation angles.

Table 1: RMSE values across hip joint angles predicted by the ML model and compared with those calculated from the OpenSim through inverse kinematics (ground truth).

	RMSE	R^2
Hip flexion	2.98±0.61	0.97±0.06
Hip adduction	1.51±0.46	0.91±0.11
Hip rotation	1.73±0.49	0.89±0.15

Examples of the predictions by CNN (dashed line) compared against those measured by OpenSim during a full cycle for participants are displayed in Figure 2. As can be seen, the CNN model provided the best predictions by following OpenSim inverse kinematics output (solid line) for hip flexion and better than hip adduction and rotation.

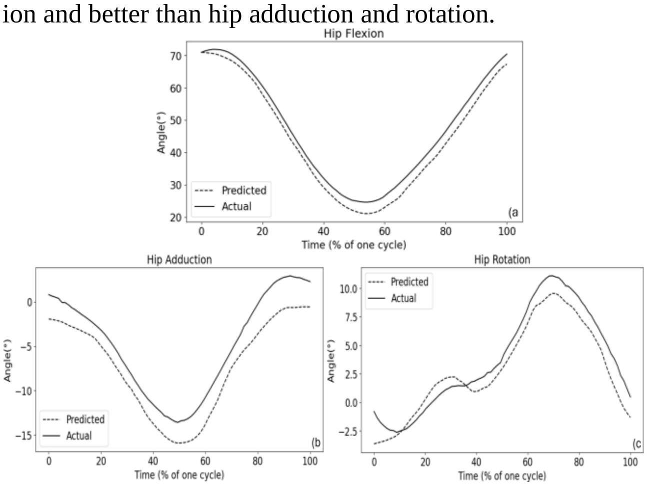

Figure 2 Joint angles predictions by CNN model (dashed line) compared to joint angles derived from OpenSim IK tool (solid line) across one cycle for hip flexion (a), hip adduction (b), and hip rotation (c) angles.

IV. Discussion

The present study effectively showcased the utilization of an innovative approach, the CNN model, for predicting hip joint kinematics. The CNN model exhibited satisfactory performance, with the RMSE values for hip flexion, hip adduction, and hip rotation within acceptable limits, signifying the model's robustness in capturing the complex dynamics of joint movements compared to other models [10], [15], [17], [18], [24]. These studies have reported RMSEs for hip flexion, hip adduction, and hip rotation between from 3.4° to 7.2°, 2.6° to 4.2°, and 2.0° to 3.22°, respectively.

The inclusion of CNN model in our predictions is a step forward in biomechanical modeling, offering a more realistic and practical representation of model confidence, which is especially critical in clinical applications. The ability of the CNN to closely predict the actual movement patterns, as evidenced by the time-series analysis, supports its potential for deployment in the development of personalized rehabilitation plans and orthotic designs, where motion capture study may not be feasible. Despite the lower correlation observed in some joint kinematics (hip adduction, and rotation), the model still provides valuable insights into the movement patterns, which can be further refined with additional data or more sophisticated modeling techniques.

The study's findings suggest the potential integration of predictive models and real-time monitoring of kinematics of the hip joint during cycling exercise with stationary ergometers. This CNN-based method has the potential to have a meaningful impact on the clinics by introducing a method that eliminates the need of motion capture systems. The next steps involve the prediction of other joint angles of lower limbs, and increasing the number of participants. The study will continue by recruiting patients with hip osteoarthritis to investigate the effectiveness of ML model in prediction of joint angle improvement through rehabilitation programs.

V. Conclusions

In this study, it was demonstrated that ML techniques could be accurate enough to be considered as an approach to address the limitations inherent in traditional biomechanical analysis methods. It was further highlighted that the high performance and capability of CNN models make them especially suitable for predicting the joint kinematics of the lower limb, thereby reinforcing the applicability of ML in biomechanical studies. Successful implementation of this CNN model enables us to monitor changes in patient body movement outside the clinic, where a motion capture system may not be available.

Conflict of Interest

The authors state that there is no conflict of interest to report.

Acknowledgment

Authors acknowledge the support of participants in data collection and financial support of Alberta Innovate (AICE-Concept 222300358).

References

[1] J. N. Sommar *et al.*, "Overall health impacts of a potential increase in cycle commuting in Stockholm, Sweden," *Scand J Public Health*, vol. 50, no. 5, pp. 552–564, 2022.

[2] G. Atkinson, "Science and cycling: current knowledge and future...," 2003.

[3] A. A. Gatti, P. J. Keir, M. D. Noseworthy, M. K. Beauchamp, and M. R. Maly, "Hip and ankle kinematics are the most important predictors of knee joint loading during bicycling," *J Sci Med Sport*, vol. 24, no. 1, pp. 98–104, 2021, doi: https://doi.org/10.1016/j.jsams.2020.07.001.

[4] F. Vogl, P. Schütz, B. Postolka, R. List, and W. Taylor, "Personalised pose estimation from single-plane moving fluoroscope images using deep convolutional neural networks," *PLoS One*, vol. 17, no. 6, p. e0270596, 2022.

[5] B. Postolka, W. R. Taylor, R. List, S. F. Fucentese, P. P. Koch, and P. Schütz, "Tibio-femoral kinematics of natural versus replaced knees-A comparison using dynamic video fluoroscopy," in *XXVIII Congress of the International Society of Biomechanics (ISB). Program & Abstracts*, ISB 2021, 2021, pp. A42–A42.

[6] P. Dehghan and N. Arjmand, "The National Institute for Occupational Safety and Health (NIOSH) Recommended Weight Generates Different Spine Loads in Load-Handling Activity Performed Using Stoop, Semi-squat and Full-Squat Techniques; a Full-Body Musculoskeletal Model Study," *Hum Factors*, p. 00187208221141652, Nov. 2022, doi: 10.1177/00187208221141652.

[7] M. Ghasemi and N. Arjmand, "Spinal segment ranges of motion, movement coordination, and three-dimensional kinematics during occupational activities in normal-weight and obese individuals," *J Biomech*, vol. 123, p. 110539, 2021.

[8] S. Apte, H. Karami, C. Vallat, V. Gremeaux, and K. Aminian, "In-field assessment of change-of-direction ability with a single wearable sensor," *Sci Rep*, vol. 13, no. 1, p. 4518, 2023.

[9] A. M. Nasrabadi, A. R. Eslaminia, P. R. Bakhshayesh, M. Ejtehadi, L. Alibiglou, and S. Behzadipour, "A new scheme for the development of IMU-based activity recognition systems for telerehabilitation," *Med Eng Phys*, vol. 108, p. 103876, 2022.

[10] S. D. Uhlrich *et al.*, "OpenCap: Human movement dynamics from smartphone videos," *PLoS Comput Biol*, vol. 19, no. 10, pp. e1011462-, Oct. 2023, [Online]. Available: https://doi.org/10.1371/journal.pcbi.1011462

[11] E. Knippenberg, J. Verbrugghe, I. Lamers, S. Palmaers, A. Timmermans, and A. Spooren, "Markerless motion capture systems as training device in neurological rehabilitation: a systematic review of their use, application, target population and efficacy," *J Neuroeng Rehabil*, vol. 14, pp. 1–11, 2017.

[12] G. Serrancolí *et al.*, "Marker-Less Monitoring Protocol to Analyze Biomechanical Joint Metrics During Pedaling," *IEEE Access*, vol. 8, pp. 122782–122790, 2020, doi: 10.1109/ACCESS.2020.3006423.

[13] T. Nath, A. Mathis, A. C. Chen, A. Patel, M. Bethge, and M. W. Mathis, "Using DeepLabCut for 3D markerless pose estimation across species and behaviors," *Nat Protoc*, vol. 14, no. 7, pp. 2152–2176, 2019.

[14] A. Seth *et al.*, "OpenSim: Simulating musculoskeletal dynamics and neuromuscular control to study human and animal movement," *PLoS Comput Biol*, vol. 14, no. 7, pp. e1006223-, Jul. 2018, [Online]. Available: https://doi.org/10.1371/journal.pcbi.1006223

[15] S. M. Moghadam, T. Yeung, and J. Choisne, "A comparison of machine learning models' accuracy in predicting lower-limb joints' kinematics, kinetics, and muscle forces from wearable sensors," *Sci Rep*, vol. 13, no. 1, p. 5046, 2023.

[16] M. Mohseni, F. Aghazadeh, and N. Arjmand, "Improved artificial neural networks for 3D body posture and lumbosacral moment predictions during manual material handling activities," *J Biomech*, vol. 131, p. 110921, 2022.

[17] R. R. Bini, V. B. Nascimento, and A. Nibali, "Validity of neural networks in determining lower limb kinematics in stationary cycling," *Sport Sci Health*, 2023, doi: 10.1007/s11332-023-01075-7.

[18] T. Yeung, A. Cantamessa, A. W. Kempa-Liehr, T. Besier, and J. Choisne, "Personalized Machine Learning Approach to Estimating Knee Kinematics Using Only Shank-Mounted IMU," *IEEE Sens J*, vol. 23, no. 11, pp. 12380–12387, 2023, doi: 10.1109/JSEN.2023.3267398.

[19] I. Boukhennoufa, Z. Altai, X. Zhai, V. Utti, K. D. McDonald-Maier, and B. X. W. Liew, "Predicting the internal knee abduction impulse during walking using deep learning," *Front Bioeng Biotechnol*, vol. 10, p. 877347, 2022.

[20] M. Błażkiewicz and A. Wit, "Artificial neural network simulation of lower limb joint angles in normal and impaired human gait," *Acta Bioeng Biomech*, vol. 20, no. 3, pp. 43–49, 2018.

[21] M. Mundt, W. R. Johnson, W. Potthast, B. Markert, A. Mian, and J. Alderson, "A comparison of three neural network approaches for estimating joint angles and moments from inertial measurement units," *Sensors*, vol. 21, no. 13, p. 4535, 2021.

[22] M. Sharifi Renani, C. A. Myers, R. Zandie, M. H. Mahoor, B. S. Davidson, and C. W. Clary, "Deep learning in gait parameter prediction for oa and tka patients wearing imu sensors," *Sensors*, vol. 20, no. 19, p. 5553, 2020.

[23] S. M. Moghadam, T. Yeung, and J. Choisne, "The Effect Of IMU Sensor Location, Number Of Features, And Window Size On A Random Forest Model's Accuracy In Predicting Joint Kinematics And Kinetics During Gait," *IEEE Sens J*, 2023.

[24] Y. Yun, H.-C. Kim, S. Y. Shin, J. Lee, A. D. Deshpande, and C. Kim, "Statistical method for prediction of gait kinematics with Gaussian process regression," *J Biomech*, vol. 47, no. 1, pp. 186–192, 2014.