Predict Knee Kinematics During Stationary Cycling via Machine Learning Regression Models

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Abstract— Enhancing athletes' performance and preventing injuries increasingly require an understanding of lower limb kinematics, particularly in the rehabilitation of lower extremities using a cycling ergometer. There are several methods for capturing and simulating kinematics and kinetics of body motion. Motion capture systems are a common tool for motion studies, that involve placing reflective markers on the lower limbs (at about 36 locations), as well as the use of cameras to track the trajectory of markers. However, marker-based systems require complex and expensive equipment and are limited to the laboratory environment. Moreover, the system might face some difficulties in finding trajectories of markers when they are occluded by body parts or equipment in the study. Although there are some techniques to predict the location of the missing markers in the recorded data, they are typically time-consuming and require expert users to perform. Thus, the purpose of this study is to integrate machine learning (ML) methods to develop a model that can predict markers' location during a cycling task on a stationary bicycle. The model inputs were individual's anthropometric information, including weight, age, gender, and height, as well as the cycling device dimensions. A NN model was trained by providing ground truth labels from the motion capture system. The coefficient of correlation between the predicted and actual knee joint angle was 0.99, indicating an excellent overall performance of the model. However, for certain angles, the error between the predicted and actual knee joint angle was 20%.

Keywords— **knee kinematics, injury prevention, lower limb, machine learning, cycling ergometer, Neural Network, regression model.**

I. Introduction

Studying kinetics and kinematics of lower limb motion enhances understanding of the biomechanics of movement and provides a tool to reduce the risk of injury, improve body performance, and advance therapeutic medical devices [1], [2], [3]. Training devices, such as cycling ergometers, are commonly used for personal training and rehabilitation purposes. Numerous studies have been conducted on cycling devices to reduce the risk of injury and improve performance [1], [2]. The impact of these devices on health and human body performance is assessed through the study of motion kinetics and kinematics, muscle activation, physiological reactions, and biological responses. A de facto standard for studying the kinematics of motion is marker-based motion capture systems. However, these systems involve marker placements on multiple anatomical locations that is associated with human error and reduced repeatability [6]. The effect of human experience on the results of marker-based motion studies is magnified when smaller body parts are being studied, because of the limited range of motion and increased possibility of markers occlusion. For example, tracking human ankle joint angle or foot motion is significantly affected when a marker is misplaced by a few millimeters, while studying knee joint angle is less affected by variation in marker placements. Recently, a variety of markerless studies, such as vision-based methods, have been developed in the fields of biomechanics [6]. However, these methods are currently limited to specific motions in laboratory conditions and are not generalized. For instance, walking, jogging, or jumping were studied with markerless methods, while activities that involve complex movements performed by multiple individuals at high speeds presented challenges when using markerless methods. Some complicating factors include the occlusion of markers by body parts or objects and the blending of trajectory markers within the camera's focal line. Moreover, the sensitivity of cameras to reflective surfaces is another challenge, which will make the postprocessing time-consuming [4].

We aim to reduce the limitations of the marker-based motion methods for analyzing the kinematics of pedaling task on a cycling ergometer by training a Neural Network (NN) regression model that can predict marker's location on lower limb using subject's height, weight and the cycling ergometer dimensions.

II. Proposed methods

A. Participants

To train the ML model, we recruited 10 healthy participants (Female: 5, Male: 5) with no recently reported injuries in the lower limbs, height 150-185 cm, and weight 55-90 kg. Ethics approval was obtained from the University of Calgary Ethics Board (Ethics application #2452).

B. Test protocol

After measuring participant's weight and height, they were outfitted with 36 reflective markers on anatomical landmarks as described in Fig. 1 and Table. 1. Subjects performed 3 static and 1 dynamic trials for camera calibration [8], [9] followed by the main test. The main test involved 24 trials of pedaling, each lasted 15 seconds, using a cycling ergometer. Participants pedaled at self-selected and maximum cadences, with four different saddle positions in both horizontal and vertical directions with a step size of 13.50 mm. A motion capture system with 10 cameras (Vicon Motion Systems Inc., Oxford, UK) (Vicon®, 2002) at a sampling rate of 100 Hz, captured the trajectory of markers during the test. This set of data was used to measure kinematics parameters which then were considered as ground truth for training the NN model. The test began with the left pedal at 3 o'clock position for each trial [7]. Later, all the collected data were labeled and processed in Nexus software (Nexux2.15).

a

b

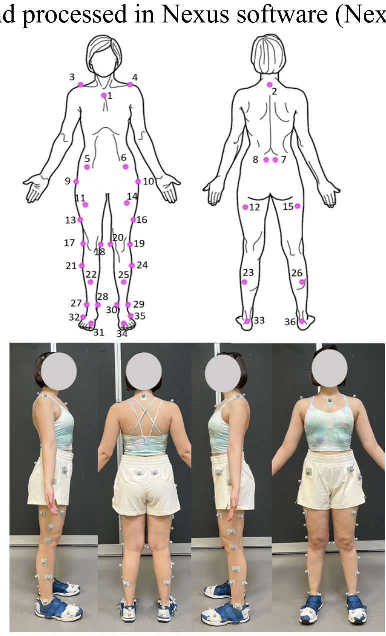

Figure 1- (a) Schematics and (b) actual locations of 36 markers placed on the subject to track the body segments motion.

Table 1 Description of marker's location

Marker	Location	Marker	Location
1	Sternum	19	L.LFE
2	C7	20	L.MFE
3	R.shoulder	21	R.DLS
4	L.shoulder	22	R.PALS
5	R.ASIS	23	R.PPLS
6	L.ASIS	24	L.DLS
7	R.PSIS	25	L.PALS
8	L.PSIS	26	L.PPLS
9	R.HJC	27	R.Lateral Malleolus
10	L.HJC	28	R.Medial Malleolus
11	R.DLT	29	L.Lateral Malleolus
12	R.PAT	30	L.Medial Malleolus
13	R.PPLT	31	R.2nd Metatarsal Head
14	L.DLT	32	R.5th MTP
15	L.PAT	33	R.Calcaneus
16	L.PPLT	34	L.2nd Metatarsal Head
17	R.LFE	35	L.5th MTP
18	R.MFE	36	L.Calcaneus

Finally, a musculoskeletal model was created by importing Vicon's data for each marker into OpenSim-inverse kinematics (IK) tool (version 4.3). Our hypothesis was that a trained NN model can predict the knee joint angle by providing the participants anthropometric data and cycling device dimensions in each crank position for every time frame.

C. Machine Learning Model-Neural Network (NN)

The NN was used because of its flexibility and ability to adapt to database where there are a variety of input parameters influencing the outcome. To train the NN model for the estimation of knee joint, a dataset consisted of nine inputs was used, including weight, height, the saddle position, the pedal coordination in each x, y, and z axes, cadence, duration of each cycle and time. First, the data was split into training, validation, and test sets with the ratio of 70%, 15%, and 15%, respectively. The validation set was used to detect early signs of overfitting and the test set was considered to ensure an unbiased estimation of the model's performance on unseen data. Then to prepare the input data for the NN, the dataset was scaled using Min-Max scaling function (between 0 and 1). TensorFlow library was used for training, validation, and testing with a batch size of 64 and a maximum of 100 epochs. Three hidden layers were created with 128, 64, and 32 neurons in each layer with a ReLu activation function, which followed by a 0.5 dropout to prevent the over-fitting. An output layer consists of one unit with a linear activation function was created. For the optimization of the model, the 'Adam' optimizer (with a learning rate of 0.001) and the loss function with the 'patience" of 20 were used. This means that for every 20 data samples, the learning rate decreases and stops the training when there is not any improvement in the output after checking 20 data samples. Moreover, the callback class and early stopping were implemented to help improve training efficiency and prevent over-fitting.

III. Results

In the designed regression model, Root Mean Squared Error (RMSE) and R^2 were calculated as the metrics to evaluate the performance of the loss function and model prediction. The R^2 for the knee joint angle was 0.99±0.12 and the RMSE was 2.12±0.71.

The comparison between the predicted knee joint angle by the NN model (red dashed line) and the OpenSim (blue solid line) is provided in Fig. 2. The good overlap between the two methods is an indication that the NN model predicted the knee joint angle very well compared to the one calculated using the human body model in OpenSim.

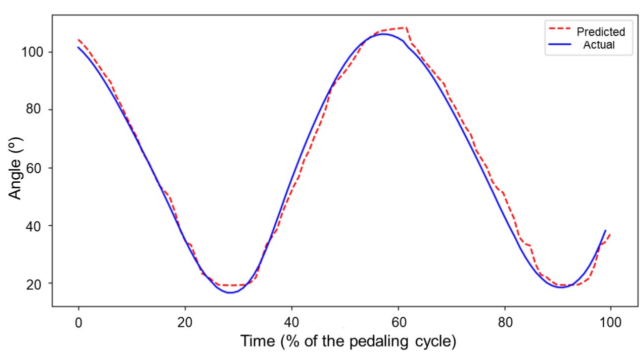

Figure 2- Comparison between knee joint angle in degrees (°) calculated in OpenSim (blue solid line) and predicted from NN model (red dashed line)

IV. Discussion

This study presents a successful development of a NN model for the prediction of the knee joint kinematics during cycling tasks. Based on the model's performance metrics, we can see that it captures the complex relationship between various cycling parameters and knee angle. The employed NN model showed promising results in predicting the knee joint angle, and it can be generalized and applied to predict the kinematics of other joints in individuals with different fitness levels and age ranges. Nevertheless, it is important to recognize that the predictive performance may vary based on the cycling modality, such as indoor versus outdoor cycling, and different cycling power levels. As a result, further studies could incorporate larger and more diverse participant cohorts and investigate additional features to enhance predictive accuracy. Furthermore, for more accurate results, the NN architecture, optimizer, and training parameters, such as hyperparameters, could be further adjusted to improve the model performance. The developed NN model and markerless approach could have substantial implications for clinical practice, especially in sports medicine and rehabilitation clinics. Here, analyzing patients' movements provides critical information that aids in making informed decisions for devising more effective treatments. The developed NN model can also be used to develop personalized training programs, optimize cycling technique, and reduce risk of injuries by predicting anormal large knee joint angles during the exercise. Improving this model and expanding it into other body joints can also be considered in future studies.

V. Conclusions

This study demonstrated that the ML integration, particularly NN models, in the study of human body motion during pedaling, can predict joint kinematics with a high accuracy Moreover, it has the potential to overcome the constraints associated with the conventional use of motion capture systems, especially for pedaling task, where some markers may be occluded by bicycle frame and not captured by cameras in specific positions. The result of this study can be extended to clinics, or in research labs without access to the motion capture system. The proposed method offers multiple benefits, such as the potential for extension to the study of additional body parts and the advantage of saving time and costs compared to using motion capture systems. Improving and optimizing the proposed method will pave the road for developing efficient and cost-effective methods for conducting kinematics analyses.

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Conflict of Interest

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

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