Journal of Science & Cycling
Breakthroughs in Cycling & Triathlon Sciences

OPEN ACCESS

Conference Abstract

Machine Learning Models to Predict Kinetic Variables in Cycling

Andres Torres [1,3,*], François Nougarou [2,3], and Frédéric Domingue [1,3]

[1] Laboratoire de technologies & d'innovation pour la performance sportive (L-Tips), Université du Québec à Trois-Rivières, QC, Canada
[2] Laboratoire de signaux et systèmes intégrés (LSSI), Université du Québec à Trois-Rivières, QC, Canada
[3] Département de génie électrique et génie informatique, Université du Québec à Trois-Rivières, Trois-Rivières, QC, Canada

* Correspondence: (AT) andres.torres2@uqtr.ca

Received: 1 March 2024 **Accepted:** 19 March 2024 **Published:** 10 August 2024

Abstract: This study aimed to predict the index of effectiveness based on lower limb joint kinematics in the sagittal plane and four additional metrics (individual's mass, power output, pedalling cadence, and horizontal knee position). Seventeen cyclists performed nine submaximal tests of 1 min. Joint kinematics were recorded using a three-dimensional motion capture system and pedalling kinetics were assessed via instrumented pedals. After min-max normalization, several predictor selection methods were applied. The performance of all models was evaluated by 10-cross validation. An artificial neural network model was developed with high accuracy (Adjusted R^2 = 0.95). Seven multiple linear regression models were developed highlighting a model of 11 predictors (Adjusted R^2 = 0.86). With this model, the most important predictors that influence the index of effectiveness are known. These models can be integrated into 2D or 3D motion capture systems, which could be useful for bike fitting professionals and trainers to evaluate cyclist's pedalling technique.

Keywords: Machine Learning; Cycling Biomechanics; Modelling; Movement Analysis; Index of Effectiveness; Pedalling Forces

1. Introduction

To perform a comprehensive analysis of a movement, biomechanics requires kinematic and kinetic data. In cycling, the kinematic data are obtained using motion capture systems focusing mainly on the joint angles of the upper and lower limb. In practice, information about the joint angular velocity and joint angular acceleration of lower limbs is not often studied in bike fitting analysis. As for the kinetics, it is necessary to use instrumented pedals to know the forces applied by the lower limb to the pedals. With the information obtained from the pedals, it is possible to evaluate the pedalling technique through metrics such as the index of effectiveness (IE). The IE is defined as the ratio of the tangential force to the total force applied on the pedals (Millour, Velásquez, & Domingue, 2023). Despite the importance of this metric, there are some gaps due to the cost of the technology and the few suppliers, which limit their implementation in bike fitting. Moreover, these factors have limited the understanding of the biomechanical factors that influence pedalling technique. In the bike fitting process, it is not clear whether the transmission of forces to the pedals is efficient (Bini, Hume, & Croft, 2011; Menard, Domalain, Decatoire, & Lacouture, 2016). In sports, machine learning has become a methodology to solve complex problems, such as variable prediction, signal forecasting and data classification. Cycling has not been an exception to these applications, such as the estimation of saddle height (Gatti, Keir, Noseworthy, Beauchamp, & Maly, 2022) and the assessment of body position (Rodrigo Rico Bini et al., 2023). Machine learning models have a wide variety of techniques that can be implemented to create predictive models. Applications vary from multiple linear regression (MLR) to the more complex such as artificial neural networks (ANN). Other regression methods that can be used are the Least Absolute Shrinkage and Selection Operator (LASSO), ridge regression, principal component regression (PCR), and partial least square regression (PLSR), among many others.

Our approach is to develop machine learning models to predict the index of effectiveness (IE). The lower limb joint kinematics variables in conjunction with the power output, individual's mass, pedalling cadence and Knee Over Pedal Spindle (KOPS) are proposed as predictors of the dependent variable IE.

2. Materials and Methods

Seventeen healthy cyclists volunteered to participate (2 women and 15 men, 36 ± 12 years old, 1.74 ± 0.06 m, 72.4 ± 8.6 kg). All participants were recreational road cyclists and voluntarily participated in the tests. For motion capture, the STT-SDMA motion capture system was used, composed of eight optoelectronic cameras with a capture frequency of 50 Hz. Eight active markers were installed on the left side of the cyclist to obtain the lower limb kinematic data. To determine the pedalling forces, the Forped system was used with a capture frequency of 450 Hz. The bicycle was installed on a training base. The capture time was 1min through nine power and cadence conditions. All kinematic variables were computed relative to the crank angle, from 0° to 360°. Subsequently, only the values every 45° were used, i.e., 72 kinematic data points per participant (8 points × 3 joints (hip, knee, ankle) × 3 kinematic values (joint angle, joint angular velocities, joint angular accelerations)). Moreover, additional variables, i.e., power output, cyclist's mass, pedalling cadence and KOPS were included, resulting in 76 predictor candidates. The methodology used is shown in Figure 1.

3. Results

Seven regression models and one ANN model were developed to predict IE. Table 1 shows the characteristics of all models.

Several methods for the selection of predictors were used to develop the models. In MLR models, the four assumptions were verified.

To develop the models, the ratio 80 % training and 20 % testing was used. The Adjusted R^2 and the residual standard error (RSE) were used to evaluate the models. The performance of all models was evaluated by 10-cross validation. The ANN composed of 21 predictors and one hidden layer consisting of 35 neurons, is the model that offers greater precision and low error. In addition, the regression models show acceptable accuracy. The MLR models have an advantage concerning ANN, because the contribution of each predictor is known through the regression coefficients. In particular, MLR with 11 predictors is a model that requires fewer variables. The predictors of this model highlight the cyclist's mass, power output, and femur, knee and ankle joint angular velocities at 270°. In addition, femur kinematics in the first quadrant, i.e., TDC-90°, is also an essential predictor. The PLSR model also provides good performance.

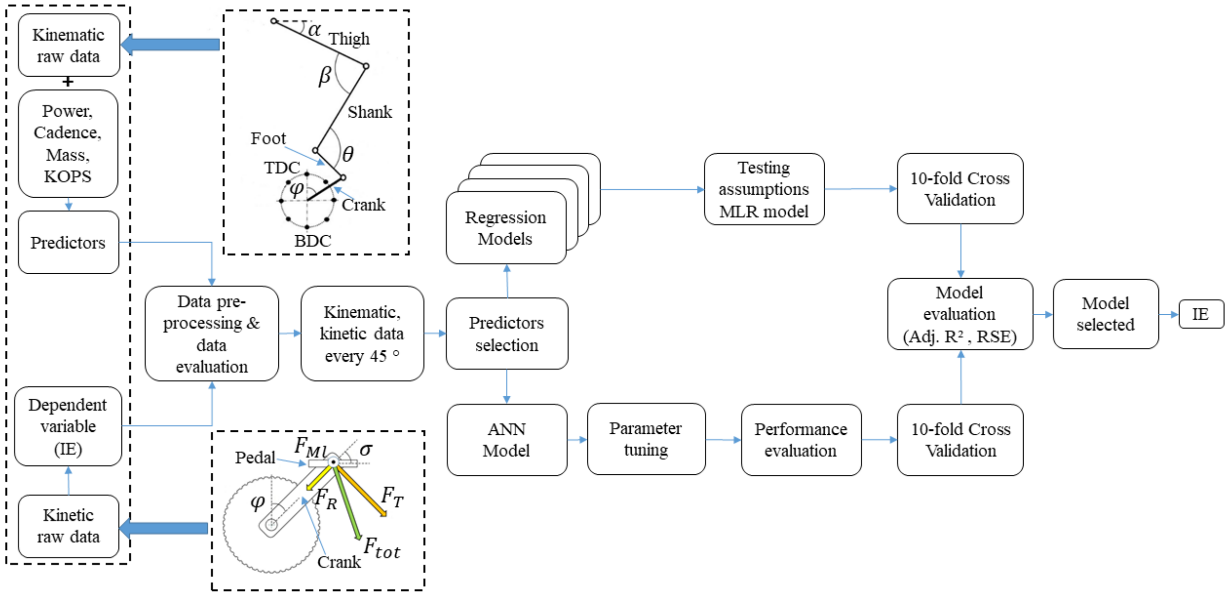

Figure 1. Diagram of the methodology

Table 1. Characteristics of machine learning models.

Model	Predictors selection method	# Predictors selected	Adj. R^2	RSE
MLR	Stepwise forward	23	0.88	2.63
MLR	Stepwise backward	21	0.89	2.51
MLR	Best subset	11	0.86	2.81
LASSO	L1 Regularization	45	0.84	3.04
Ridge	L2 Regularization	73	0.74	3.87
PCR	Orthogonal linear combinations	50	0.85	2.89
PLSR	Orthogonal linear combinations	17	0.89	2.76
ANN	Recursive feature elimination	21	0.95	0.14

4. Conclusions

Machine learning models offer several possibilities for predicting variables in cycling. The kinematic factors that influence the IE are identified. It is possible to accurately predict the IE using an ANN model based on 21 predictors (Adjusted R^2 = 0.95). The model that allows us to know the influence of each variable on the IE is the MLR model with 11 predictors (Adjusted R^2 = 0.86). This model predicts the IE with the minimum number of predictors.

5. Practical Applications

The machine learning models can be integrated into motion capture systems to estimate variables related to pedalling kinetics. These models allow the evaluation of pedaling kinetics without the use of instrumented pedals. Other metrics could be estimated to evaluate pedaling technique, such as positive impulse proportion (PIP). This allows for a more complete analysis of the bike fitting process.

Funding: This work was supported by Canada Foundation for Innovation.

Acknowledgments: The authors thank all the participants who volunteered to participate in the study.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Bini, R. R., Hume, P. A., & Crofta, J. L. (2011). Effects of saddle height on pedal force effectiveness. Procedia Engineering, 13, 51-55. doi: 10.1016/j.proeng.2011.05.050

2. Bini, R. R., Serrancoli, G., Santiago, P. R. P., Pinto, A., & Moura, F. (2023). Validity of Neural Networks to Determine Body Position on the Bicycle. Research Quarterly for Exercise and Sport, 94(4), 905-912. doi: 10.1080/02701367.2022.2070103
3. Gatti, A. A., Keir, P. J., Noseworthy, M. D., Beauchamp, M. K., & Maly, M. R. (2022). Equations to prescribe bicycle saddle height based on desired joint kinematics and bicycle geometry. European journal of sport science, 22(3), 344-353. doi: 10.1080/17461391.2021.1902570
4. Menard, M., Domalain, M., Decatoire, A., & Lacouture, P. (2016). Influence of saddle setback on pedalling technique effectiveness in cycling. Sports Biomechanics, 15(4), 462-472. doi : 10.1080/14763141.2016.1176244
5. Millour, G., Velásquez, A. T., & Domingue, F. (2023). A literature overview of modern biomechanical-based technologies for bike-fitting professionals and coaches. International Journal of Sports Science & Coaching, 18(1), 292-303. doi: 10.1177/17479541221123960