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Conference Abstract

Artificial Intelligence in Cycling – Live Positional Tracking Using On-Bike Aerodynamic Sensors

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Abstract: An investigation looking into the application of Artificial Intelligence for live positional tracking using on-bike aerodynamic sensors. In this study data from the wind tunnel and outdoor conditions were collected using a system from Body Rocket Ltd. By applying a Gradient Boosted Machine to the force and moment data the discrete positons of a rider on a bike were successfully identified for a rider in the wind tunnel within the dataset it was trained on to 100% accuracy. When applied to blind data collected from the wind tunnel the models accuracy was limited with a performance of 45%, however, with a new model built around data collected outdoors the accuracy of this model was found to be 100%. Overall this study finds that with machine learning techniques it is possible to identify positions of a rider on a bike just from the raw force data and with further research there is potential to determine a continuous range of positions outside of the discrete positons investigated in this study.

Keywords: Positions, Bike Fit, Aerodynamics, Body Rocket, Machine Learning

1. Introduction

Finding the optimal rider position on a bicycle is important for both comfort and aerodynamics. It has been shown that a rider is responsible for up to 80% of the drag a bike, rider system experiences (Kyle & Burke, 1984) therefore ensuring that a rider is maintaining an optimal position can be vital for performance (Crouch et al., 2017). Thus, minimising their coefficient of aerodynamic drag area (CdA) throughout a race (e.g. a time trial) would increase their chances of victory (Lukes et al., 2005; Fintelman et al., 2015; Jongerius et al., 2022), especially if this information were provided to allow real-time adjustments (Peeters et al., 2020). Previous research has shown the potential for inertial measurement units to provide feedback to riders during time trial cycling that could help them maintain their position on the bike (Winter et al., 2023). However, the study used a static cycling trainer in a laboratory environment and did not investigate the relationship between changes in body position and the relationship to drag profiles. Therefore, it is unknown if such inertial measurement units could provide feedback that would allow optimisation of cycling aerodynamic position in the field.

Recently, an on-bike sensor system (Body Rocket Ltd, Sussex, UK) has been developed to measure the aerodynamic drag of a rider in isolation. The system utilises 4 force sensors; one on the handlebar, one on the saddle and one on each pedal. The locations of the sensors are shown in **¡Error! No se encuentra el origen de la referencia.**. As each of these sensors are at the contact points of the bike, the drag of the rider can be determined through measuring the horizontal force at the sensor. The system also measures moments on the saddle and handlebar.

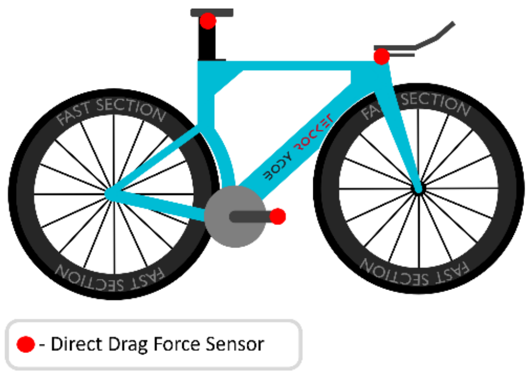

Figure 1. Diagram of where the four sensors of the Body Rocket system are located.

Equipped with this force and moment data, the aim of this pilot study was to use machine learning techniques to determine the different positions a rider might assume whilst riding. The investigation consists of three parts; 1. to verify whether with artificial intelligence and machine learning techniques it is possible to identity rider positions from a wind tunnel dataset, 2. to determine whether the same model is accurate with a blind data-set from the wind tunnel, 3. to test whether the model could be applied to open road cycling.

2. Materials and Methods

Four data-sets were provided by Body Rocket Ltd, two from the University of Southampton wind tunnel (Hampshire, UK), Wind Tunnel 1 (WT1) and two from Flanders' Bike Valley (Beringen, Belgium), Wind Tunnel 2 (WT2). These data-sets included one rider assuming the same 4 positions (see Figure 2) over the 4 datasets (head down, baseline, head up and hands on the aero-pads). To ensure the rider was maintaining the position, video footage was taken in the wind tunnel allowing each run and each position to be compared seen in **¡Error! No se encuentra el origen de la referencia.**.

Figure 2. Images from WT1 of a rider adopting four distinct cycling positions. With position number indicated by the circled numbers.

In WT1 three wind speeds tested were tested; $15.2ms^{-1}$, $13.2ms^{-1}$ and $11.2ms^{-1}$. In WT2, two speeds were tested at; $16.2ms^{-1}$ and $12.8ms^{-1}$.

Initially, to the force and moment data (which can also be referred to as features), a Principal Component Analysis (PCA) was performed to reduce the dimensionality of the data (Shlens, 2014). A multiclass Gradient Boosted Machine (GBM) decision tree model was then trained on the PCA score data to classify the 4 different cycling positions. To train and test the model, the datasets were split with 80% used to train the model and the 20% held back for subsequent blind testing of the model on this first dataset.

Subsequently, two male riders were recruited and asked to ride on an outdoor (OD) velodrome (Brighton, Sussex, UK) maintaining the same 4 positions as shown in Figure 2. Both riders completed 4 laps in each position using a bike equipped with the Body Rocket Ltd (Sussex, UK) system, set-up to their personal anatomy and preferences. To reduce sources of error and accidental movement of the rider on the bike, riders were observed as they rode around the track and at the start finish line an image of the rider was taken. This image was then compared for each run in each position to establish their position.

In the wind tunnel images were taken of the riders to identify the changes in position. As the changes at the outdoor velodrome were smaller computer vison software (Openpose; Cao et al., 2019, 2017; Wei et al., 2016) was used to determine rider position. From the processed images the joint location information was compared from each run to quantify changes in position (see **¡Error! No se encuentra el origen de la referencia.**).

Figure 3. Openpose processed images of one rider during outdoor velodrome testing. Blue lines represent rider limbs with dots representing axes of movement (Cao et al., 2017, 2019; Wei et al., 2016) overlay.

The force and moment data collected from the Body Rocket Ltd system underwent the same pre-processing as performed to the wind tunnel data.

2.1 Statistical analysis

Three metrics were used to measure accuracy of the machine learning model; the log loss, mean-squared-error, and classification success. The log loss establishes the accuracy of the model for each tree built in the case for a decision tree-based model, which is then compared between the training and testing datasets. Mathematically this can be described by Equation (1), where; y_i is the true prediction, $\widehat{y_i}$ is the model prediction and N is the number of samples (Seto et al., 2022). As the units from the log loss are unitless, in this paper they will be referred as positional log loss units (PLLU).

$$Logloss\ [PLLU] = \frac{1}{N}\sum_{i=1}^{N}\left(y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i)\right)$$

Equation 1

The smaller the log loss the greater the accuracy of the model. However, if the training loss is less than the testing loss then it is likely the model is overfitted and will have poor performance.

The mean squared error (MSE) takes the sum of the differences between the true values and the predicted values then divided by the sample size. The smaller this value the more accurate the model. As can be seen in Equation (2) where N is the number of samples, y_i is the true prediction and $\widehat{y_i}$ is the prediction (Hodson et al., 2021). As the same with the log loss, the MSE will be referred to as Positional Mean Squared Error (PMSE).

$$MSE\ [PSME] = \frac{1}{N}\sum_{i=1}^{N}(y_i - \widehat{y_i})$$

Equation 2

The percentage of classification success of the GBM was modelled as the percentage of correctly classified predictions. As can be seen in Equation (3) where; CS if the classification success F_p is the number of false positives, F_n is the number of false negative and N is the number of samples.

$$CS = \left(1 - \frac{F_p + F_n}{N}\right) \times 100\%$$

Equation 3

Included in the pre-processing, the data was normalized between 0 and 1 and outliers outside of 3 times the standard deviation were removed. When the models were tested using the blind data, normalization was performed relative to the training dataset. Post processing, a 6 second modal moving average was applied in order to remove noise within the raw prediction data.

To visually represent the accuracy of the models, data were plotted as time vs. position to categorize the 4 positions used the WT or OD.

As the GBM is a tree-based model, the number of leaves is also important to consider. If there is a very high number of leaves the model is likely to be over fit and conversely is there is a low number of leaves it is likely to be underfit. Whilst building the model stopping rounds were used. This allows for the model to be built beyond the specified number of trees in the building process. If the models log loss continues to decrease the number of trees (and therefore leaves) will increase and if the log loss increases the number of trees will be that with the lowest log loss.

3. Results

The following results are presented in graphs alongside an overview of all the results.

3.1 Wind Tunnel data

For WT1, a GBM was built with 75 trees and stopping rounds of 15. The log loss of the model was 0.00035PLLU and the mean squared error was 0.00129PMSE, leading to a model with a small error. With a modal average filter applied to the positional data over time the classification accuracy was found to be 100% as can be seen in Figure 1 as the modal moving average (the red trace) is exactly the same as the true position (the green trace).

The WT2 dataset produced a 85 leaf GBM with a log loss of 0.00080ALLU and mean-squared error of 0.00022PMSE, leading to a 100% classification accuracy when filtered by time (see Figure 2**)**. In WT2, the rider moved from position 1 to position 4 twice but over a longer period of time than WT1 (2000 vs 600 seconds for WT2 vs WT1, respectively).

3.2 Blind data

From both WT1 and WT2 a blind dataset was produced. With the data collected from WT1 the model performed with a log loss of 4.29312PLLU on the blind dataset, a respective MSE of 0.53055PMSE and a classification accuracy of 45 %.

With the WT2 dataset the model performed with a log-loss of 6.08763 PLLU, a MSE of 0.68907 PMSE and classification accuracy of 29%.

3.3 Outdoor data

For Rider 1 a 100 leaf model was produced and performed with a log loss of 0.01498PLLU, MSE of 0.00377PMSE and classification success of 99.63%. Visually the performance of the model can be seen in Figure 6. A number of mis-classifications can be seen in Figure 6, however, with the modal moving average applied an accuracy of 100% is achieved.

For Rider 2 a 100 leaf model was produced and performed with a log-loss of 0.02163PLLU with a respective MSE of 0.00606PMSE and classification success of 99.33% (see Table 1). Visually the performance of the model can be seen in Figure . Similar to the results obtained from Rider 1, the results here show a 100% accuracy after the modal moving average is applied.

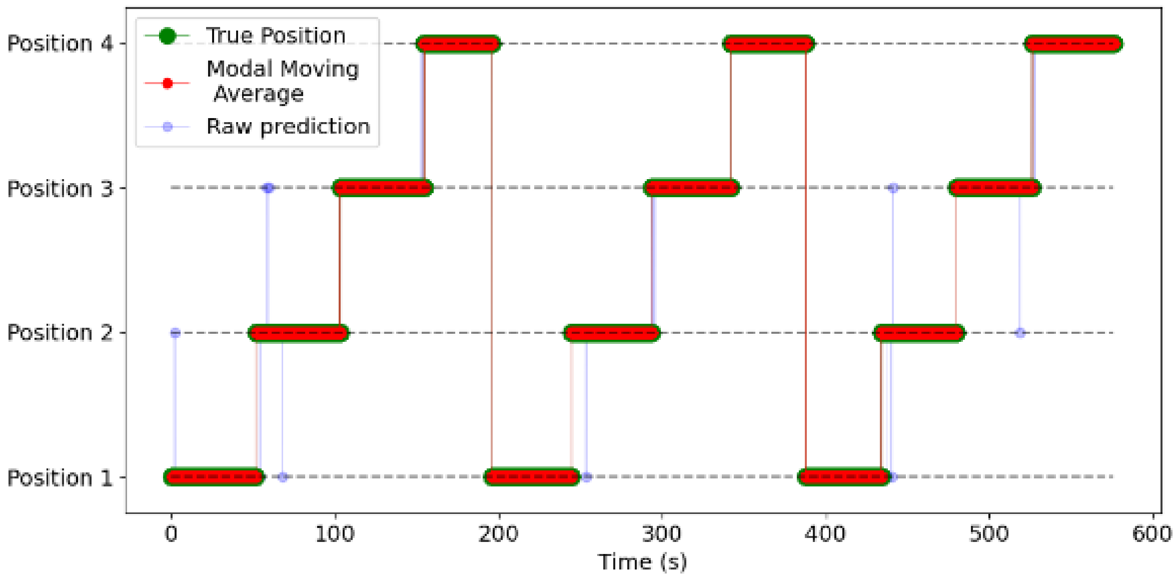

Figure 1. Output position of a rider in WT 1 moving between position 1 to 4 three times throughout the test, green; True position, blue; raw output position from a trained Gradient Boosted Machine (GBM) and red; a moving modal average applied to the GBM output data.

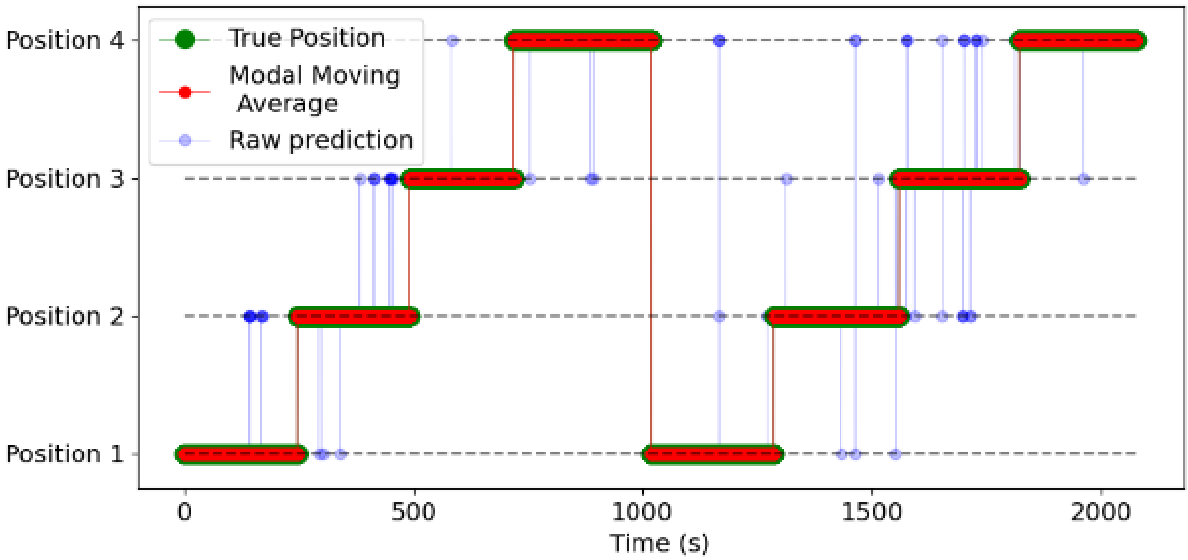

Figure 2. Output position of a rider WT2 moving between position 1 to 4 on two occasions, green; True position, blue; raw output position from a trained Gradient Boosted Machine (GBM) and red; a moving modal average applied to the GBM output data.

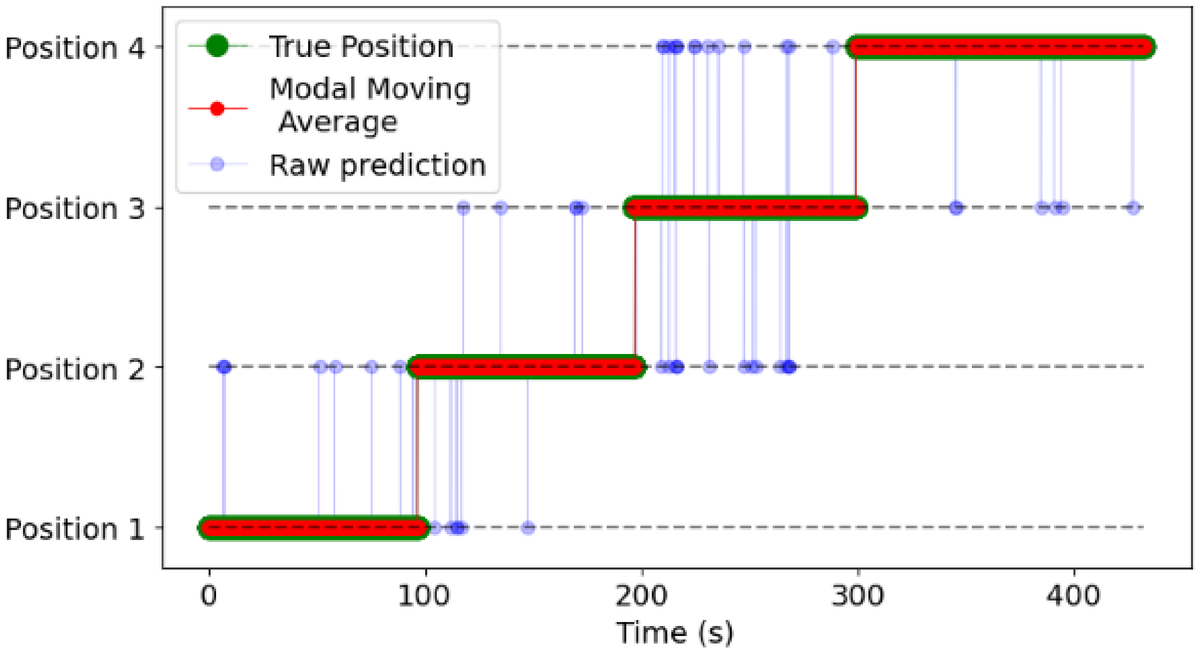

Figure 6. Prediction data from Gradient Boosted Machine built on data collected from Rider 1 moving between position 1 and position 4 over a period of 400-500 seconds during OD riding. Green; True position, blue; raw output position from a trained Gradient Boosted Machine (GBM) and red; a moving modal average applied to the GBM output data.

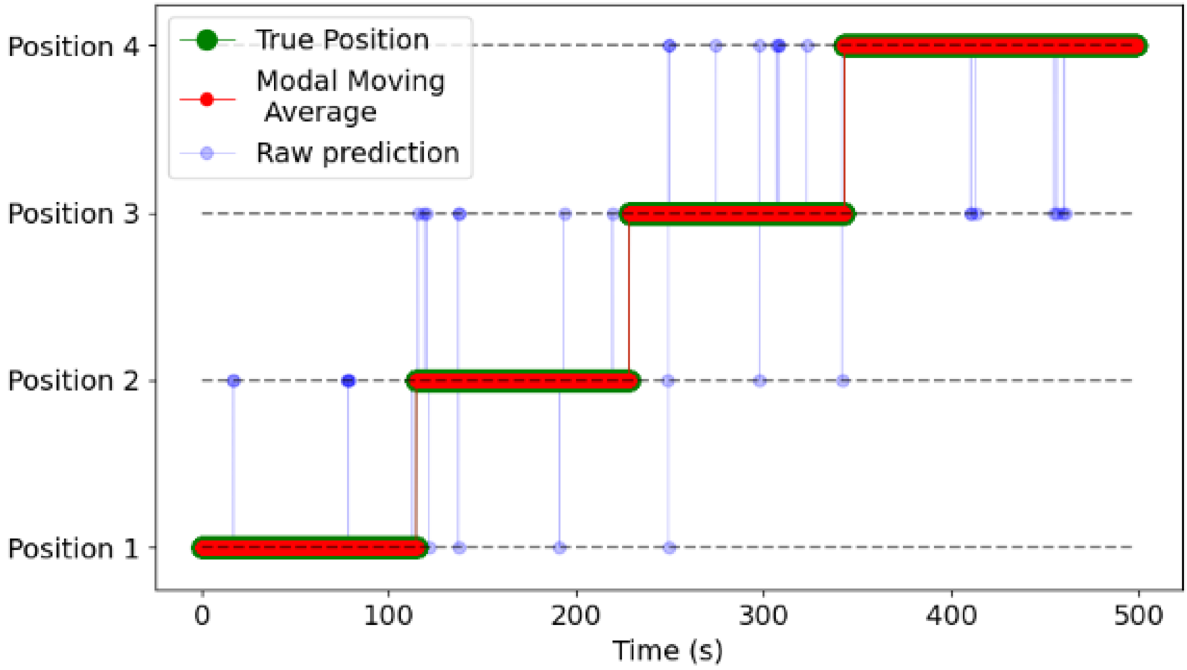

Figure 7. Prediction data from Gradient Boosted Machine built on data collected from Rider 2 moving between position 1 and position 4 over a period of 400-500 seconds during OD riding. green; True position, blue; raw output position from a trained Gradient Boosted Machine (GBM) and red; a moving modal average applied to the GBM output data.

Table 1. Table of performance metrics from the models produced in WT1 and WT2 and from the OD velodrome data

Model and dataset	Log-loss (PLLU)	MSE (PMSE)	CS (%)	Number of trees
WT1 (Train & Test)	0.00035	0.00129	99.96	75
WT1 (Blind)	4.29312	0.53055	45.03	75
WT2 (Train & Test)	0.00080	0.00022	99.97	85
WT2 (Blind)	6.08763	0.68907	28.48	85
OD– Rider 1	0.01498	0.00377	99.63	100
OD – Rider 2	0.02163	0.00606	99.33	100

4. Discussion

From the results obtained from WT1 and WT2 the Body Rocket system has the ability to differentiate the discrete positions a rider might typically assume on a bike, from large changes such as hands on the aero pads (leading to upright body position) to small changes such as head angle.

When comparing the two models produced from wind tunnel data, similar accuracies are observed between WT1 (providing a 99.957% classification success) and WT2 datasets (producing a 99.969% classification success). When a modal moving average is applied to the data the predictions are improved further as can be seen in Figure 1 and Figure 2 where the output prediction has a 100% classification success in predicting the position of the rider. Both models are of similar complexity in being built with 75 trees and 85 trees for WT1 and WT2 respectively.

In this pilot investigation intra-dataset variability is high. When comparing the results from WT1 and WT2, it is clear that the model created from WT1 performs better overall (see Table 1). The difference in these reported results may be due to the wind tunnel's design, specifically, WT1 had a rigidly fixed platform whereas WT2 allowed for some movement whilst pedalling. In addition, as the dataset collected from WT2 occurred before WT1 Body Rocket system developments may have played a role in the variability between results.

Regardless of which WT dataset is used it is likely that the models are overfit. To overcome this, more data is needed, alongside the possibility of further pre-processing, involving additional feature selection, prior to training on model, specifically selecting highly correlated force and moment data alongside omitting data that is not. If features that appear highly correlated to the output are combined to create a set of new features this could further increase the performance of the model produced.

In this pilot investigation the outdoor data is compelling with reliability between the two riders in classifying position providing 100% accuracy after a modal moving average is applied. Before the application of the modal moving average the model appears to be nosier than that produced from the WT, likely due to the effect of environmental conditions associated with outdoor riding. From Figure 6 and Figure , data from Rider 1 demonstrates greater stability with less mis-classifications of position compared to rider 2. This can be seen from the raw outputs (blue traces) on the plots, additionally this can be further seen in Table 1 as rider 1 has a classification success of 99.63% compared to rider 2's 99.32%.

5. Practical Applications

Overall, it can be concluded that machine learning methods can be used to classify discrete positions of a rider on a bike. This finding provides athletes with the ability to optimise aerodynamic position on a bicycle using a sensor system, such as the Body Rocket system, and bespoke machine learning models. The impact of these findings offers the possibility for riders to train to these positions without the need for wind tunnel testing. Moreover, if live on-bike feedback is provided, riders can identify for themselves when they are maintaining the most aerodynamic position during time trial situations, likely leading to improved performance.

While in this study we have focused on 4 discrete positions, future work might explore the determination of a continuous range of positions which may characterise, for example, head, torso, and hip angle.

6. Conclusions

The results of this study demonstrate that machine learning can be used to classify rider position from force and moment data collected by the Body Rocket System. In a wind tunnel setting less complicated models are needed to produce an output of 100% classification accuracy with a modal moving average. However, applied to a blind dataset the models are less accurate. The results from the outdoor testing demonstrate 100% classification accuracy after applying a modal moving average. However, these models are more complex, likely due to the inherent variability in outdoor conditions.

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Conflicts of Interest: The analysis described in this paper was performed independently by the University of Kent.

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