Journal of Science & Cycling
Breakthroughs in Cycling & Triathlon Sciences

OPEN ACCESS

Estimation of the drag force: a neuronal approach

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Received: date; Accepted: date; Published: date

Context

Aerodynamics is a key factor in improving cycling performance and the measurement of the drag force is therefore of the utmost importance. Among all the existing methods, the wind tunnel remains the reference thanks to its reliability. However this approach is not an option for most cyclists due to its cost and lack of availability. Such technique is also extremely time consuming and its integration into an iterative bike adjustment process is hard to implement in practice.

In this context, previous works have shown that 3D scan coupled with computational fluid dynamics (CFD) can successfully approximate the wind tunnel measurements at a lower cost [1,2]. Following this idea, we have developed a new computer vision-based method to estimate the aerodynamic drag of cyclists [3]. First a 3D model of the cyclist is built by a system that captures the motion and the morphology of a parametric body model using 4 RGB-D cameras; subsequently, a CFD solver processes this model to estimate the aerodynamic resistive forces. In another work we also showed a good experimental agreement between our 3D+CFD technique and wind tunnel [4]. Our system can therefore be an affordable alternative to wind tunnel measurements. This promising solution makes it possible to quickly build a synthetic 3D+t model of a cyclist with a relatively light device but the CFD computing remains nevertheless quite time consuming.

Data recording *3D point cloud and parametric model*

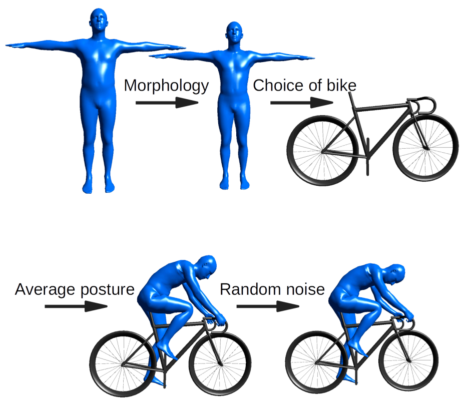
In this study, following the idea developed in [5], we propose to design a learning-based system that approximates CFD simulations for the specific case of a cyclist on his bike. In our approach, the 3D shape for which the drag force is calculated is entirely defined by the morphology and the posture of the rider plus the dimensions of the bike. This set of parameters and the wind speed should therefore be sufficient to predict the drag force.

Method

We trained a neural network with parametric models identical to those produced by our 3D scanning device. The drag force computed by the CFD software was used as ground truth. Several thousands of data are required to train the neural network and, as we did not have enough real data, we built a synthetic data set from randomly chosen parameters.

Dataset

For each sample, a gender and the morphological parameters are first randomly drawn. The bike frame is chosen according to the resulting body size. The saddle height, handle bar height and the stem are randomly altered around the nominal values. The body model is placed on the bike for a random hand pose and crank angle. Finally, the head flexion, spine flexion, elbow flexion and shoulder torsion are randomly modified. Then, the input/output training pair is created by computing the drag force for a randomly chosen wind speed and direction.



Steps to create a cyclist model

More than 100,000 simulations were collected from 11000 different morphologies and postures coupled with several wind directions and speeds ranging from 20 to 60 km/h. Note that about 1/3 of the data corresponds to a headwind because this specific case is the main use case.

Dimension reduction

The full body model is described by 75 posture and 10 morphology parameters. 50 additional parameters are required for the bike. To avoid over fitting, we need to drastically reduce input space of the neural network. To do this while minimizing the loss of information as much as possible, we have kept only the following parameters: gender, the 4 most statistically significant morphological parameters, saddle height, crank angle, handle bar height, horizontal distance between bottom bracket and handle bar, hand pose (top, brake, or down), average left and right shoulder torsion, average left and right elbow flexion, head and back flexion. By adding wind speed and direction, only 16 input parameters are thus retained in total.

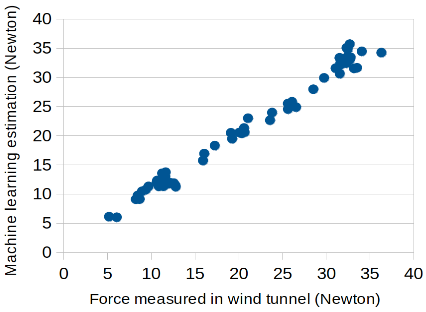
Learning

4 different multilayer perceptrons (MLP) with 1, 2, 5 and 8 hidden layers were tested. The architecture with 5 hidden layers provided the best results, with 25, 10, 10, 6 and 5 neurons in the successive hidden layers. The LeakyReLU activation function was used between all hidden layers, and a linear activation function is applied in the output layer. LeakyReLU has the advantage of solving the problem of vanishing gradient which becomes particularly useful in deeper neural networks.

Results

25% of the data has not been used for learning and kept for validation. On this dataset, the root mean square difference (RMSE) between the estimated drag force and the CFD is 0,95 Newton. This first evaluation is encouraging but cannot be the considered as an indicator of the expected error on real data, because the synthetic data does not include all the small variations seen in the real world.

To assess the approach more realistically, we compared the drag force estimated from the complete chain 3D scan/machine learning against the drag force measured in a wind tunnel. The graph below shows all data pair for multiple cyclists, postures and wind speeds; the RMSE is about 1,2 Newton.



ML estimation against wind tunnel measurement

Conclusion

In this work we presented a machine learning-based technique to quickly approximate the results of a time-consuming CFD simulation of a cyclist riding on his bike. The key idea is to use a parametric description of the cyclist shape as input to a neural network.

The results are very encouraging (RMSE of 1,2 Newton against wind tunnel measurements) but for now only variations having an impact on the input parameters can be observed. This excludes the shape of the helmet or the diameter of the frame tubes for example. However, this technique could advantageously replace the CFD part of our drag force measurement system.

Reférences

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