How to Accurately Determine the Position on a Known Course in Road Cycling

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Abstract. With modern cycling computers it is possible to provide cyclists with complex feedback during rides. If the feedback is course-dependent, it is necessary to know the riders current position on the course. Different approaches to estimate the position on the course from common GPS and speed sensors were compared: the direct distance measure derived from the number of rotations of the wheel, GPS coordinates projected onto the course trajectory, and a Kalman filter incorporating speed as well as GPS measurements. To quantify the accuracy of the different methods, an experiment was conducted on a race track where a fixed point on the course was tagged during the ride. The Kalman filter approach was able to overcome certain shortcomings of the other two approaches and achieved a mean error of $-0.13\,\mathrm{m}$ and a root mean square error of $0.97\,\mathrm{m}$.

Keywords: Cycling, GPS, Kalman filter, Road cycling, Feedback

1 Introduction

With the increasing popularity of advanced cycling computers, new possibilities for feedback become available for the majority of road cyclists. This allows to guide cyclists during training and competition, for example to provide the rider in real-time with a strategy on how to ride. Garmin Ltd., one of the leading manufacturers of cycling computers, introduced a rudimentary real-time feedback feature with their 'Virtual Rider'. It shows information about how far off the rider currently is, compared to a previous ride in terms of time and distance. A critical point in providing this kind of track specific feedback is to know the precise location of the cyclist on the track. Moreover, Garmin Ltd. recently provided an API ('Connect IQ') allowing to develop custom apps for their cycling computers that may provide real-time position dependent feedback for athletes.

Using commercially available sensors and devices is subject to various problems. Distances derived by an odometer (as included in commercially available speed sensors) can lead to errors if the rider chooses a slightly different route than in the reference recording, e.g., by cutting curves. An additional source of error when using an odometer is, that the exact circumference of the wheel must be known. A small error in this parameter leads to a continuously increasing error in the calculated distance during the ride. Another option that can provide information about the position of the rider is the Global Positioning System (GPS), or similar but less common systems like GLONASS and Galileo. The accuracy of the GPS position strongly relies on satellite coverage and landscape settings and can be expected to range from 5 m to 10 m in a stationary setting [1],[2]. Studies indicate, that this range is also feasible for dynamic applications like cycling: In an experiment where cyclists were riding on cycling lanes in a city, 55 % of the recorded data points were located in a range of less then 2.5 m outside of the actual lane and 86 % in a range of less then 10 m outside of the actual lane [3]. From the experience of recreational road cyclists, the best self-reported accuracies of satellite based positioning on commercially available cycling computers are about 3 m.

In professional road cycling, the difference between the top athletes' performances has become very small and therefore the term 'aggregation of marginal gains' has become popular. It describes the concept that small performance improvements in different areas will add up and make a significant difference. One of these areas is the right choice of strategy during races. For individual time trials optimal strategies can be derived mathematically, based on modeling the cycling dynamics and the riders fatigue. First experiments in the laboratory indicate potential of this method to improve performance in real races [4]. In order to transfer the laboratory results to the field it is crucial to precisely determine the current position on the course, to provide the proper feedback. In this paper we experimentally investigated the accuracy of different methods to determine the riders current position on a course in order to get a clear view about what accuracy can be expected.

2 Methods

The position on the course is defined as the traveled distance during a reference ride along the course trajectory. Such a trajectory can be defined by georeferenced road data, or by one's own measurement. In this paper, we define the reference course trajectory by measuring the lateral and longitudinal GPS coordinates during a ride. These measurements are approximated by a cubic smoothing spline with the MATLAB function 'csaps' [5]. The arc length of the spline ideally corresponds to the recorded distance provided by the odometer. This approach defines a mapping between a two-dimensional GPS coordinate and a one-dimensional distance along the course. Therefore, the feedback can be defined corresponding to that distance, e.g., at an arbitrary position given by a distance of s [m], the athlete should ride applying a computed pedal power of $P(s)$ [W]. Thereby, the methods used for the mapping are not crucial. For this study, we chose the described approach since the spline approximation both smooths the recorded data and interpolates between two recorded data points in a suitable manner.

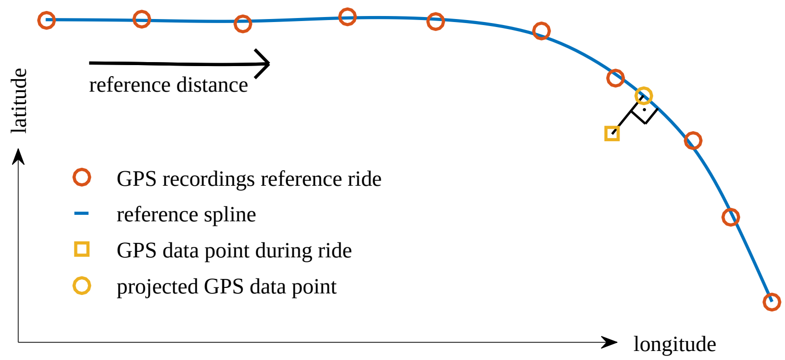

Fig. 1. Schematic representation of the reference trajectory. In a first step, the reference trajectory is calculated based on measured GPS coordinates and corresponding distance values. The red dots represent the recorded latitude and longitude GPS coordinates. Through those points a smoothing spline is placed, the arc length is provided by the recorded distance (blue). With this reference trajectory, in future measurements, GPS coordinates are projected onto the reference spline to get the arc length of the projected point on the spline (yellow), which corresponds to the reference distance of the recorded GPS point.

We consider three methods of deriving the reference distance during a subsequent ride:

1. Associate the reference distance with the distance provided by the odometer of the external speed sensor.
2. Projection of GPS coordinates onto the reference trajectory. The arc length of the reference trajectory at the projected point provides the reference distance. See Figure 2.
3. Kalman filter [6] based on the discrete dynamic system

$$\begin{aligned} x_{t+1} &= x_t + \Delta t v_t \\ v_{t+1} &= v_t \end{aligned}$$

   with speed v, reference distance x and sampling interval $\Delta t = 1$ s. The measurements used in the Kalman filter are the speed values provided by the external speed sensor and the reference distance as derived in method 2. The covariance matrix of the observation noise R was estimated by previous experiments and resulted in the following values:

$$R = \begin{bmatrix} 1.042\,\mathrm{m} & 0 \\ 0 & 0.001\,76\,\mathrm{m\,s^{-1}} \end{bmatrix}$$

Method 1 is based solely on measurements of the speed sensor, while method 2 incorporates only GPS measurements. To increase the accuracy and compensate shortcomings of these two methods, the data of both sensors is combined in method 3 using a Kalman filter.

Fig. 2. Experimental setup: The left picture shows a screenshot of the application. The number in the top shows the current speed and the gray box is the button that was pressed each time the marker was passed. The picture in the middle shows the physical realization of the marker: A rounded bar, taped on the 50m line of the track. The Garmin hub speed sensor is presented in the right picture, mounted on the hub of the front wheel of the test bike.

All data was collected with an Android application on a Sony Xperia Z1 Compact smartphone. The application was generated with the Pegasos [7] framework. GPS was recorded by the phone's internal GPS sensor while speed and distance were measured by an external Garmin hub speed sensor (Fig. 2, right). Additionally, a button was integrated to the Pegasos front end to allow the rider to tag specific positions on the road during the ride, which are used for the evaluation of the method. Figure 2 (left) shows a screenshot of the application. The smartphone was mounted on the handlebar in reach of the right hand, to allow to press the button with the thumb while still being able to hold the handlebar firmly. Speed data was recorded with a sampling frequency of 3.79 ± 0.71 Hz and GPS with a sampling frequency of 1.00 ± 0.02 Hz. For further use, all data was resampled uniformly at 1 Hz by applying a low pass filter in form of a Gaussian filter with $\sigma = 1$ s.

Two rides were conducted on the 4th lane of a 400 m oval running track. Both rides were performed on the same bike, by the same rider who was instructed to stay in the middle of the lane. Each ride started at the beginning of the 100 m track and a marker was placed at the 50 m line. At the marker position the rider pressed the button on the smart phone to tag the position. To improve the accuracy of the button press, the marker was a 2 cm high, rounded plastic bar as shown in Figure 2 (center). With this construction, the rider did not only have a visual feedback of the position of the marker but also a haptic one. In the first ride, the reference trajectory was recorded. One lap on the course was performed, the first pass of the marker tagged the beginning of the lap and the second passing tagged the end of the lap. This lap was replicated to form a virtual reference ride of 35 laps. In the second ride, all 35 laps were completed in

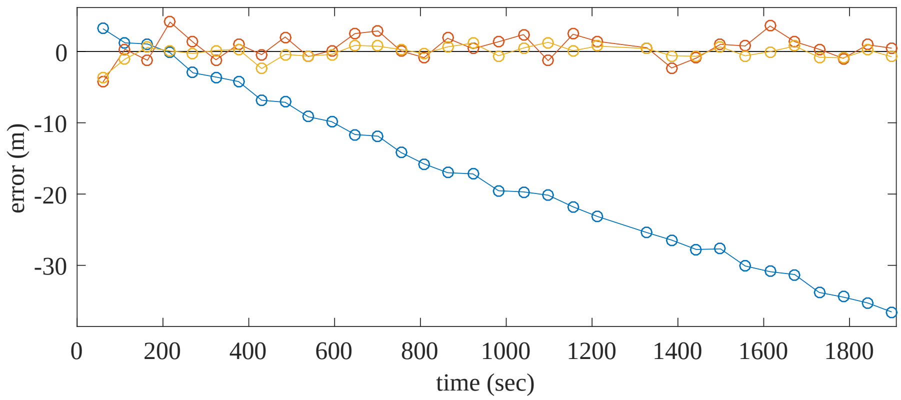

Fig. 3. Position error at the marker points relative to the marker tags in the reference ride. The blue curve shows the recorded distance of the speed sensor, the red curve the distance determined by projecting the GPS coordinate onto the reference trajectory and the yellow curve shows the result of the Kalman filtering.

Table 1. Mean error and accuracy (root mean square error) of the position derived by the different methods at the marker positions in meter.

Method	Mean error	Accuracy
Speed sensor	-17.27	20.93
GPS projection	0.58	1.80
Kalman filter	-0.13	0.97

a row on the track. The button was not pressed correctly in lap 1 and 24, hence the number of valid marker tags totals to 33.

3 Results

At each marker position, the positioning error was determined as the difference of the distance in the reference ride and the corresponding distance derived by the different methods. Figure 2 shows these errors of the different distance estimation methods at the marker positions. In the distance returned by the speed sensor, a clear drift over time can be detected while the errors of the methods considering GPS measurements stay in the same range throughout the whole test. Table 1 shows the resulting mean error and the root mean square error of the derived position at the markers. The root mean square error is provided as a measure of accuracy of the different methods. Projecting the GPS coordinates onto the reference trajectory led to a mean error of 0.58 m and a root mean square error of 1.80 m. The extension using the Kalman filter improved these results with a mean error of -0.13 m and a root mean square error of 0.97 m. Additionally, the GPS sensor provided information about the accuracy of the measured horizontal coordinates for each measured point. The mean self-proclaimed accuracy at marker positions was 3.07 m.

4 Discussion

In order to determine a precise, absolute position on a course, using only the odometer is obviously not applicable, because the error increases over time. Three potential problems occur if using the odometer only: (1) A consistently different choice of line in the test ride compared to the reference ride introduces a drift as can be seen in Figure 2. Since we chose a course with a high portion of uniform curvature this phenomenon most likely was amplified. (2) The total distance is calculated over the number of rotations of the wheel. So, if the wheel diameter is estimated wrongly, an error sums up with each rotation. (3) The distance at the starting point has to be estimated correctly, since the error that is done there is passed on to all consecutive measurements. Altogether, the distance provided directly by the odometer is not suitable to precisely estimate the riders position on a given course.

Due to the shortcomings described in the previous paragraph, GPS measurements have to be taken into account. They provide a global measure, independent of previous measurements, which avoids that the error constantly increases during the ride. For the pure GPS measurements, a self-proclaimed accuracy of about 3.07 m in the two-dimensional horizontal plane was provided by the sensor. Since the proposed application is to estimate the position on a given course, the two-dimensional GPS coordinates are projected into one dimension: the distance along the course. This projection already improved the accuracy of the determined position. One serious issue with using GPS only is that under certain circumstances the GPS signal can vanish, for example in a dense forest or in a tunnel. In this case, no or only very poor information about the current position is available. Therefore, a Kalman filter was employed, incorporating GPS and speed measurements. It can handle the loss of sensor information by using model predictions and by including both, speed and GPS sensors. The accuracy of the determined position is further improved by this method. The achieved accuracy of 0.97 m is about twice as good as with the method projecting the GPS coordinates onto the spline and about three times better than the self-proclaimed accuracy of the original GPS measurements.

5 Conclusion

To provide cyclists with feedback during training sessions or races, the precise position on the course may have to be be known. The naive approach, taking the distance provided by the bike computer is unstable and cannot be recommended. A Kalman filter incorporating the GPS position along the course as well as speed measurements provides stable and accurate distance values. The achieved accuracy of 0.97 m should be sufficiently good for most practical applications and is better than using only GPS coordinates. To validate the accuracy of the experimental approach, it is planned to include measurements of the accelerometer of the smart phone. With this additional data, it should be possible to detect the marker position more precisely than with the virtual button operated by the rider. Future work will apply the proposed Kalman filter method to provide real-time feedback to finish a course in the shortest possible time. A strategy for the whole course is precalculated and during the ride, the proposed speed for the current position is presented to the rider.

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