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Accurate Positioning of Mountain Bikers using a Kalman filtered Combination of a Marker-Based Approach and Inertial Sensing

125 - Sportforschung in Österreich

Abstract

We present an approach based on augmented reality markers and inertial sensing to determine the position of mountain bikers without GPS. A helmet-mounted action camera is used as the input source for the marker detection, a bike computer measures the exact distance for the inertial sensing, and a smartphone both gives orientation data and serves as the central processing unit. Initial tests show that depending on the camera quality and resolution, an average accuracy between 0.17 m and 0.35 m can be achieved.

Keywords:

Positioning, marker-based positioning, mountain biking

1. Introduction

Particularly in downhill segments, competitive mountain bikers routinely experience the situation that in races or even in training rides some physiologically comparable athletes are faster than others. Clearly, the optimal racing line influences this gap – which can open quite quickly over a couple of turns – and is therefore also accessed in sports such as alpine skiing (Skaloud/Limpach 2003) and car racing (Vesel 2014). In addition, the style of braking (short and hard, or long but soft), the orientation of the bike in turns, and the drift of the wheels might also contribute. For all the mentioned characteristics, it is important to know the exact position on the track at a certain point in time to make an exact comparison between riders.

Since standard GPS-devices are not accurate enough for our purpose (Bauer 2013) and other systems (such as described by Arumugam 2013, Arumugam 2014, Kirkup et al. 2014) need additional special hardware, we present a positioning method for mountain bikers using a Kalman filtered combination of a marker-based approach and inertial sensing using commercial off-the-shelf components like mobile phones, action cameras, and bike computers. The presented approach can eventually be used to record and store a route taken on the optimal racing line (which would be performed by an expert rider). In addition, it can be compared with a route taken by a novice or intermediate mountain biker to give direct feedback in real-time, possibly by the use of augmented reality glasses

2. Positioning method

By using a helmet-mounted action camera and employing a computer vision algorithm, we obtain positions relative to markers, which are to be installed along the track. To make the positioning more robust against situations in which the obtained video quality does not meet our demands, we make use of the bike computer (which gives distance and speed) and a mobile phone's magnetometer.

Marker-based positioning is a method for calculating the position and orientation (pose) of a camera out of an image of the camera and some known natural or artificial markers (placed along the track) which are represented in the image. After testing a couple of marker detection libraries under realistic conditions outside, we chose the AprilTag framework (Olson 2011). One of the requirements was that the marker detection had to be robust against different and changing light conditions or partly occlusions. In this context, robust not only means trying to always get an identified marker even under the mentioned bad circumstances, but first of all not identifying markers with a false ID number. The false-positive rate should be as low as possible.

By using the four edge points of recognized artificial markers and a couple of camera specific parameters, it is possible to calculate the position of the camera in the marker coordinate system by solving the perspective n-point (PnP) problem (Nöll et al. 2011). Furthermore, we can use the ID of the marker to calculate the camera's position in a local track coordinate system where multiple markers are placed.

Due to diffuse frames, the calculated positions include an error and therefore form a point cloud which needs to be filtered. A local regression using robust weighted linear least squares and a second degree polynomial model was used for this.

To even get positions when no markers can be found, the results are then combined with other sensor values like distance, speed, and orientation. The combination of different sources for the calculation of the position with a Kalman filter (Kalman 1960) makes the results less error-prone and of course more accurate.

3. Evaluation and discussion

Based on Chin 1987 and Adusei 2002, we used the x Percentile (%x or x-th), circular error probable (CEP), root mean square error (RMSE), and average error to evaluate the developed positioning system.

For testing the proposed positioning method, we built a couple of 2D markers with side lengths ranging from 28 cm to 42 cm. The action camera which we used was the SJCAM SJ4000 WiFi (12 MP CMOS sensor, WIFI, max. video resolution 1920x1080 with 30 fps, 170° wide angle lens). During testing we found out that the best place to mount the camera is the helmet, as this reduces the vibrations to a minimum.

For the bike sensor measuring the exact distance, by counting the wheel revolutions via a magnet we used the Wahoo Blue SC speed and cadence sensor. This sensor is capable of counting the wheel and pedal revolutions and sending them to a smartphone via Bluetooth Low Energy. We mounted the sensor at the front wheel. In order to have a high resolution and accuracy, we mounted not only one magnet, but eight magnets instead. As a result, we got a distance event every 2.11 m / 8 = 0.26375 m. The Android-based phone, which is responsible for receiving the distance events from the bike sensor and measuring the orientation via its integrated compass, gyroscope, and accelerometer sensors were mounted on the top tube.

3.1. General accuracy test

The aim of the first test was to give an overview of the potential of the developed approach. Therefore, we set up a test track which includes a couple of turns (one marker for every turn) and also short straight sections. This test was also a basis for the other tests where different improvements and variations had been tested.

The positions of the markers and therefore the whole local coordinate system were measured with the use of a laser distance measuring device. The width of the test track was around ten m with a height of around 27 m. To evaluate the developed system, we marked a reference line along the track with a barrier tape, where the test rider had to ride during the test and measured 198 reference points along this path.

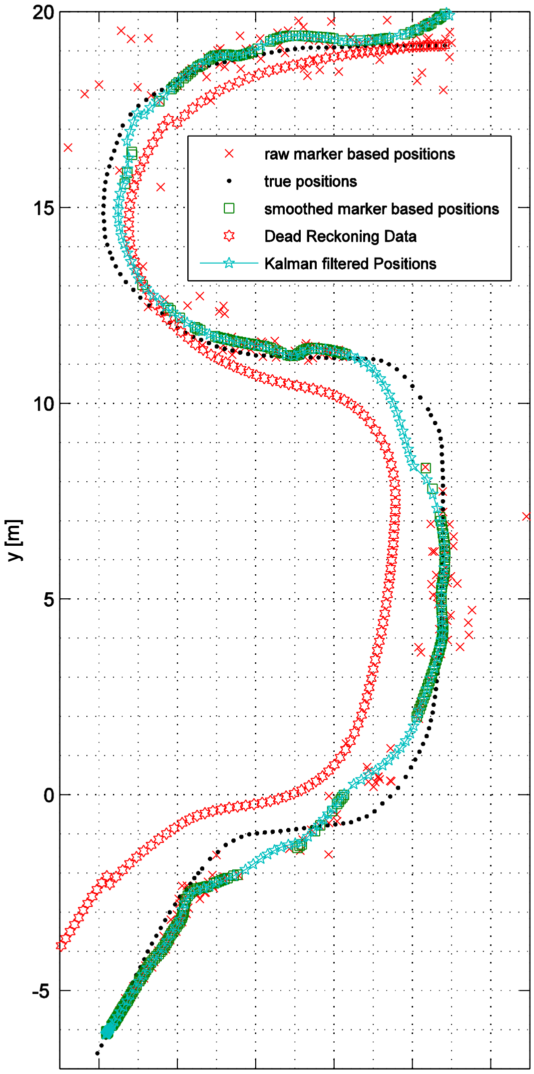

Figure 1: Results of the general accuracy test.

Figure 1 shows the positioning results of the general accuracy test. First of all, a simple concatenation of the inertial data sentences (dead reckoning) would not lead to satisfying results, as they would quickly drift away through the small error which is introduced by every measurement. Although the distance measurements are accurate due to the usage of the bike sensor, the orientation sensed by the smartphone internal sensors is not good enough for long term usage. But as we only use these measurements mainly as an extension to the marker based positioning approach in situations where no markers can be found, these inertial measurements are good enough for these shorter periods. Furthermore, in straight segments of the track they give us the opportunity to not place any

markers as most of the error is introduced in the turns. In situations where markers were found, they have a good distribution regarding the error so that their smoothing results in accurate positions.
Table 1 shows the performance measures for positions resulting from the marker based positioning only and for the final positions calculated by the Kalman filter.

	Marker-based	Kalman filtered
avg. accuracy [m]	0.35	0.29
RMSE [m]	0.43	0.37
CEP (50%) [m]	0.26	0.24
67% [m]	0.43	0.36
75% [m]	0.52	0.41
95% [m]	0.85	0.78
25% [m]	0.14	0.14
Median [m]	0.26	0.25

Table 1: Performance measures of the general accuracy test.

3.2. Going Test

Analyzing the single frames processed in the general test shows that the camera used for testing the developed approach is not good enough at sharp focusing while changing the camera orientation, as this is the case in turns. The consequences of this effect can be seen in the general tests at some of the turns where no positions can be extracted. With this test, we wanted to show how the metrics change when a better camera is used. Since we did not have access to a higher quality action camera, we walked through the test track to give the camera more time to focus better. The metrics listed in table 2 depict the improvement. For example, the average error drops from 0.35 m to 0.17 m.

	going test (marker-based)	general test (marker-based)
Avg. accuracy [m]	0.17	0.35
RMSE [m]	0.22	0.43
CEP (50%) [m]	0.14	0.26
67% [m]	0.19	0.43
75% [m]	0.24	0.52
95% [m]	0.47	0.85
25% [m]	0.06	0.14
Median [m]	0.14	0.26

Table 2: Performance measures of the going test.

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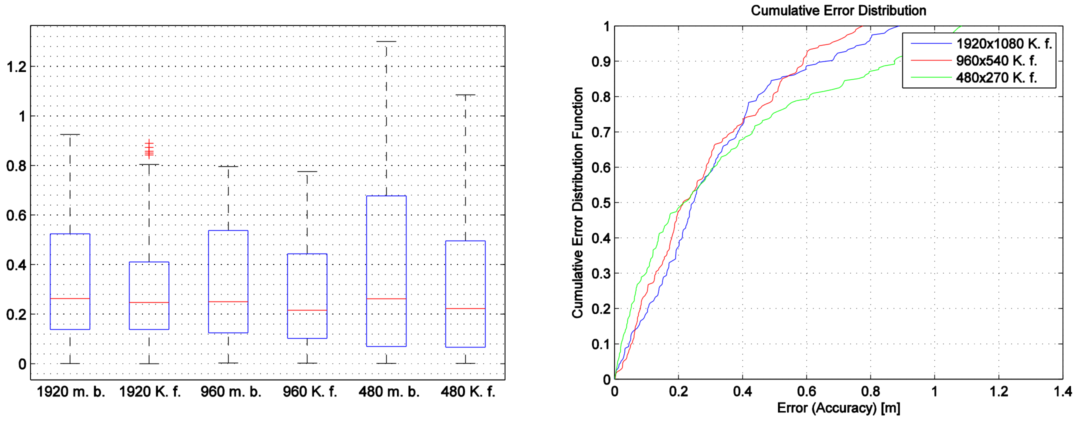
3.3. Reduced Resolution Test

With the current implementation, the position calculation on the mobile phone in real-time is not yet possible. At the moment, the frames per second rate for processing a video with the resolution of 1920x1080 is around 5 fps. There are two limiting factors. The first one is the time to extract the frames and access the raw bytes in order to process them in the CPU. The decoding of the frames is not the problem as this is running on the graphical processing unit, but the access at the CPU takes up to 100ms for a frame with the size 1920x1080. The second limiting factor is the processing time for the marker detection of the frame. Since this time is proportional to the used frame size, a reduction of the resolution implies a shorter processing time for a single frame. We therefore assessed the impact of a reduced resolution on the accuracy by reducing the resolutions to 960x540 and 480x270.

	1920x1080		960x540		480x270	
	m. b.	K. f.	m. b.	K. f.	m. b.	K. f.
avg. accuracy [m]	0.35	0.29	0.31	0.28	0.39	0.33
RMSE [m]	0.43	0.37	0.40	0.35	0.54	0.46
CEP (50%) [m]	0.26	0.25	0.24	0.21	0.26	0.22
67% [m]	0.43	0.36	0.38	0.33	0.49	0.39
75% [m]	0.52	0.41	0.53	0.44	0.67	0.49
95% [m]	0.85	0.78	0.78	0.68	1.07	0.98
25% [m]	0.14	0.14	0.11	0.10	0.07	0.06
median [m]	0.26	0.25	0.24	0.22	0.26	0.22

Table 3: Performance measures of the reduced resolution test.

Table 3 as well as the boxplot in figure 2 (m. b. – marker-based) show that for the marker-based positioning, the reduction of the frame size to 960x540 results in a comparable accuracy as the original resolution of 1920x1280. However, a further decrease in resolution to 480x270 leads to decreased accuracy. For the Kalman filtered approach with inertial sensing (figure 2, K. f.), we can observe that the larger the errors of the marker based positions are, the more they get reduced as the inertial sensing gets more influence.



(a) (b)

Figure 2: Boxplots of the errors with different resolutions with and without Kalman filtering (a). Comparison of the cumulative distribution functions for all three resolution tests using the Kalman filtered positions (b).

4. Conclusions and outlook

The evaluation of the implemented concept shows that depending on camera quality and resolution, an average accuracy between 0.17 m and 0.35 m can be achieved. One of the strengths of the proposed approach is that in situations where no position can be calculated by the markers, the inertial sensing component continues the positioning with acceptable results. A deficit of the current implementation is that real-time processing is not possible which should be addressed in further work, for example by performing the computation solely on the GPU. Provided the evaluation is extended and performed under more realistic conditions, such as difficult lighting and bumpy downhill sections, the presented approach could be the base for further studies to track and compare racing lines in mountain biking.

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