

SMARTcycling: Assessing cyclists' driving experience

Pedro Vieira¹ and João P. Costeira² and Susana Brandão³ and Manuel Marques⁴

Abstract—Due to economic and environmental issues, bicycles have been regaining their significance as a transportation vehicle in urban scenarios. To further drive this desirable trend, policy makers must have the tools to access current bicycle infrastructures and road safety concerns. Fundamental for this assessment is a deeper understanding of how cyclists use current infrastructures, if the cycling experience results in stressful events, and the conditions of the current infrastructure. We here introduce a new platform, SMARTcycling, that, by taking advantage of the mobile power available to a smartphone, captures and stores data from several sensors, namely an action camera, a cardio signal acquisition belt, and smartphone's Global Positioning System (GPS) coordinates. The data is further processed and, through visual cues, we access the cyclist driving events and road condition cues. SMARTcycling also detects the cyclist stress using the electrocardiograms (ECG) from the belt. We further contribute by making available a dataset containing the sensors data from 10 paths over two cities in Portugal. On this dataset, we show our initial promising results on event detection, road condition identification and stress assessment.

I. INTRODUCTION

Current trends in Europe and North America show that bicycles are regaining their significance as transportation[1]. This trend is socially desirable, as it has positive impact in health, environment and traffic [1], [2], [3]. There are several studies available that focus on factors that condition bicycle use [4] but there are few tools to access the cyclists' real commuting experience and how it impacts adoption rates.

Namely, there is currently no tool for the automatic identification of driving events that may condition this experience, e.g., the presence of obstacles or distance to other commuters, and current assessments are based on a-posteriori reporting[4]. The assessment of driving events, their mapping and analysis is very important for guiding city planning to positive cycling experiences which may well encourage more people to travel by bicycle.

In this work we introduce a new tool, SMARTcycling, that enables the assessment of cyclists driving experience. SMARTcycling captures and processes data from three sensors: an action camera, a smartphone mounted on a bicycle

and a cardio acquisition belt, mounted on the cyclist, for Electrocardiography (ECG). It returns a collection of sensors data, including GPS coordinates, and the identification of several maneuvers, stressful situations and road conditions.

In this context, the availability of smartphones is fundamental for collecting information over time and space as they allow recording and storing of data from different sensors such as video from cameras, and directly associating it to a single position in the map through GPS.

Several applications were previously developed for accessing drivers' driving experience, identifying maneuvers and road condition using the fusion of data collected by a smartphone mounted on some vehicle with suspension[5], [6], [7]. However, such tools focused on inertial sensors, such as accelerometers, and thus cannot be directly transposed to bicycles, as their natural vibration considerably corrupts signal cues. Initial results show that, by using action cameras, which are prepared for handling movement, and simple sequence filtering, SMARTcycling can detect and identify different types of driving events and road condition. Examples are turning left movements, the presence of holes and the existence of a safe run-away path to the right of the cyclist in case of a stressful event.

Furthermore, as far as the authors are aware, SMARTcycling is the first tool that identifies stressful situations for the cyclist using an ECG belt. The ECG allows a direct risk and stress assessment, sparing a-posteriori reporting.

Besides its processing capabilities, SMARTcycling also provides a smartphone application, Bike Monitor, that allows to collect data from the camera and smartphone. More information about the application can be found at: <http://users.isr.ist.utl.pt/~manuel/smartbike/>.

Finally, we also make available the data collected for this study. The dataset covers a total of 10 paths, 8 in Lisbon and 2 in Ponta Delgada and contains the synchronized data of all the sensors.

The overall structure of SMARTcycling is presented in Fig. 1, highlighting its two different functionalities: data acquisition and data processing. Thus, the main contributions of this work are

- an Android application, described in Section III;
- a new dataset of driving events, described in Section IV;
- a new approach, detailed in Section V, to identify cyclist's maneuvers based on image processing;
- a new approach, described in Section VI, for road condition classification;
- preliminary results, described in Section VIII, of all the data processing approaches.

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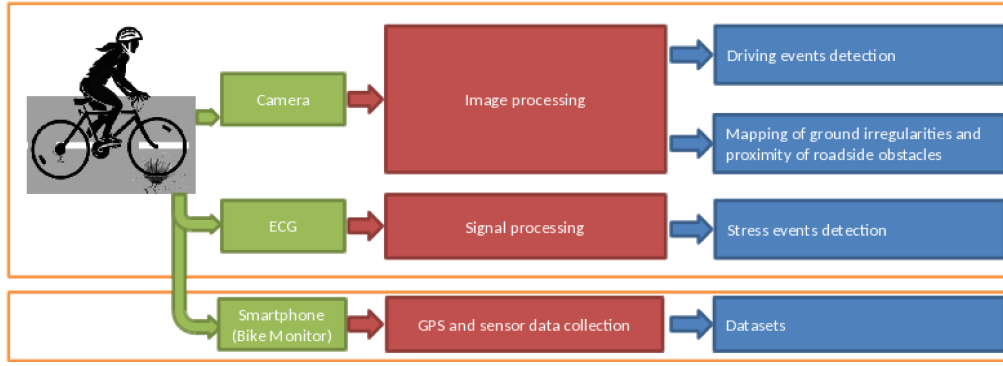


Fig. 1. SMARTcycling lay-out

II. RELATED WORK

While in recent years research has been carried out to evaluate existing urban infrastructures, [4], [8], as far as the authors are aware, SMARTcycling is the first tool focused on assessing cyclists' experience in real time through smartphones. Also, the assessment of driving experience and identification of events has been thoroughly studied in motorized vehicles [5], [6], [7], [9], [10], [11], [12], [13], [14], and we here focus on bicycles, that are less stable and thus the adequired data is more noisy.

As bicycles are often seen as a dangerous transport, there are many studies assessing what impacts cyclists' safety, e.g., [4], [8] relate the risk of accidents with the number of cyclists going through a given lane or intersection. Namely, [4] accesses the probability of impact by other cyclists and [8] accesses the probability of impact by motorists. Furthermore, the approach used in [4] also collects cyclist path data using the smartphones' GPS as a replacement for direct counting of users at a given point. In this work, we introduce a new tool that can be used for the cyclists' risk assessment, namely i) by collecting and synchronizing data from different sensors, not just GPS, over the cyclist path; ii) by identifying riders maneuvers which can be used to identify typical responses to stressful situations, e.g., caused by large numbers of cyclists or cars; and iii) by identifying the road condition both in terms of the quality of the floor and the presence of escape routes to the right, out of the traffics' way.

There is extensive work done on detection and identification of driving events in cars using either smartphone sensors or the Controller-Area Network bus [5], [6], [7]. However, algorithms mostly depend on the use of inertia sensors, such as accelerometers and gyroscopes for the detection of maneuvers. In this work we contribute to the identification of driving maneuvers by introducing a new approach based mainly on image processing and optical flow. The impact of the natural shake resulting by cyclist's movement is filtered at the computation of optical flow.

From the several tools for the identification of road anomalies that have been presented previously [9], [10], [11], [12], [13], [14] all are use either expensive and dedicated devices or smartphones in cars or motorbikes with good suspension systems. However, all have privacy issues and depend on user

engagement, constraining their actual use. SMARTcycling opens the possibility of large scale assesement, as municipalities often provide public bicycle sharing programs, where it can be easily deployed.

III. BIKE MONITOR

SMARTcycling is a study tool built with a smartphone data acquisition interface - the Bike Monitor. To further complement the data provided by phone sensors, SMARTcycling collects data from an action camera, as these are designed for use under heavy vibration environments and have designed mounts for that purpose, resulting in cleaner and nicer videos. It also collects data from an ECG belt.

The overall structure was mounted as showed in Fig. 2. We note that the action camera is mounted on the bicycle frame to avoid displacement of the viewangle caused by the frequent changes in the steering wheel.

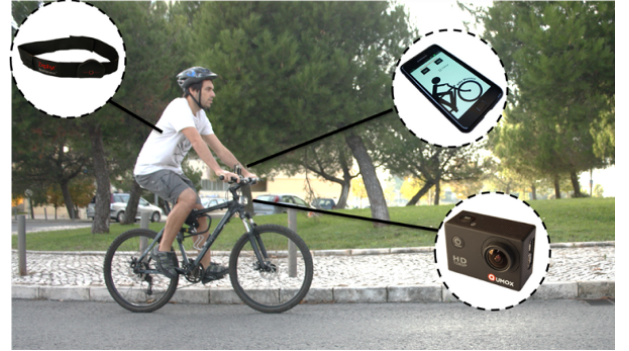


Fig. 2. Data acquisition setup. The ECG belt is placed in the cyclist chest, the action camera is fixed on the bicycle frame facing forwards and the smartphone is fixed to the handle.

Bike Monitor runs on Android operative system and has a very simple interface, illustrated in Fig. 2, that allows starting and stopping of data recording. The data is stored locally, i.e., GPS and action camera data are stored in the smartphone, and belt data is stored within the belt.

IV. DATASET

Using Bike Monitor, a user cycled over ten paths in two cities: two in Ponta Delgada, and eight in Lisbon. Each path

has an average of 6 km, but distances ranged from 5 to 7 km. On each path, different set of events occurred, but here we focus on six categories:

For each path, we collected data from 5 different events of each categories, except for the turning right and left. As turnings are less common events, we collected on average three examples of each per path. For each event, we collected data corresponding to a video snippet of 3 frames. We separated the dataset in two parts, 5 paths were used as examples of different events and the other 5 were used for testing the capacity to detect and recognize those events.

To identify driving events, SMARTcycling uses video sequences from the action camera to compute a descriptor based on optical flow, namely the Lucas-Kanade algorithm [15]. Optical flow provides indirect information about the 3D scene structure by looking into the movement pattern between two images caused by changes in the viewers position.



Fig. 3. Example of the optical flow associated with the car mirror over a set of three frames.

By comparing the optical flow in different image parts for a known set of events, we compose a labeled dataset of descriptors. When analyzing new image sequences, SMART-cycling compares their optical flow with those in the dataset and uses a k-Nearest Neighbor classifier.

Optical flow

Angle Histograms

Descriptor

Fig. 4. Estimating a descriptor from the optical flow. SMARTcycling considers only the image bottom part, which it splits in six parts, and for each computes an optical flow histogram. Each entry in the histogram aggregates all the flow in a given direction.

6 evenly spaced rectangles as shown in Fig. 4. For each rectangle, SMARTcycling computes a histogram of flow vector directions, considering 8 evenly divided bins from 0 to 2π rad. The descriptor is then a vector $x \in \mathbb{R}^{48}$ corresponding to the concatenation of all histograms, ordered as showed at the bottom part of Fig. 4.

B. Classification

Classification is performed in two steps. First SMARTcycling checks whether the bicycle is stopped and, if not, it identifies the maneuver on a second step. When the bicycle is Stopped, we expect the optical flow to be minimal on all rectangles. Thus, to identify Stopped events, we compute the mean of the absolute value of all optical flow over the six rectangles. If the mean value is low, then the bicycle must be stopped.

We classify the other five events using a k-Nearest Neighbor algorithm, where the training subset histograms are compared with the histograms of the testing images. The nearest 10 histograms determine the category of the image to be classified using the category with the largest number of neighbors.

Our preliminary results, presented in Section VIII, show that our simple approach for classification performs achieves very promising results.

VI. ROAD CONDITION IDENTIFICATION

The road condition depends both on the presence of obstacles, either in the cyclist lane or on its right side, and depends also on the quality of road surfaces. We can detect both events using the image processing based on optical flow descriptors described above.

We built a roadside obstacle proximity detector by analyzing the average size of the vectors from the top-rightmost rectangle in relation to the average size of the vectors from the entire image. If the average size of the vectors from the rectangle C is bigger than the average size of the vectors from the entire image, then those points must be closer to the cyclist, resulting in an obstruction or obstacle in the roadside.

To measure the obstruction proximity, SMARTcycling uses the ratio between the average sizes of the vectors from the rectangle C, highlighted in Fig. 5, over the average size of all image vectors. We refer to this ratio as the Right Proximity Ratio, (RPR). The output of this analyse, as showed in Section VIII-B, is a map where regions where there was some obstruction are highlighted.

The detection of ground irregularities follows the same approach as the event detection, as in the presence of holes in the street there is an upward flow that is not present in any other event.

VII. MEASURING STRESS

Studies show that there is a relation between the variation of heart Inter-beat Intervals (RR) and the level of stress of a person[16], referred to as Heart Rate Variability (HRV).

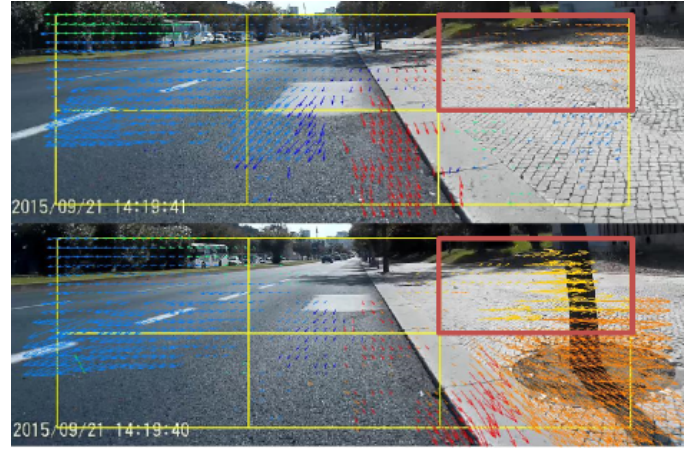


Fig. 5. Analysis window with marked rectangle used on the roadside obstacle proximity detector.

SMARTcycling calculates the HRV using frequency domain method as it requires a smaller time sample to perform the analysis, in contrast to time domain methods[17]. In this method the power spectral density of the RR intervals is calculated, S_{RR} . From the resulting PSD we know that: a) low frequencies (LF) - 0,04 Hz a 0,15 Hz correspond to the sympathetic stimulation (Stress) [18]; b) high frequencies (HF) - 0,15 Hz a 0,4 Hz correspond to the parasympathetic stimulation (Relaxed) [18].

Stressful events lead to an increase in the low frequencies components when compared to the higher frequencies. There are no guidelines regarding the normal values for the LF/HF ratio as it changes from person to person based on their age, weight, height, and cardiac health [18], [19]. For this reason, SMARTcycling evaluates the cyclist stress condition by analyzing the increase in the total weight of low frequencies when compared to the total weight of high frequencies. This is done by computing LF/HF ratio from the power spectral density S_{RR} using eq. 1,

$$\frac{LF}{HF} = \frac{\int_{0.05}^{0.15} S_{RR}(f)df}{\int_{0.15}^{0.4} S_{RR}(f)df}. \quad (1)$$

The higher the LF/HF ratio, the more stressful the event.

One limitation of this method is that in exercise sessions there is an increase on the sympathetic stimulation, resulting in an increase in the LF/HF ratio. However after the stabilization of Oxygen consumption (VO_2), this stimulation decreases, returning to normal values [17]. We take into account this aspect when analyzing the LF/HF ratio values by revisiting the video a-posteriori.

VIII. EXPERIMENTAL EVALUATION

To evaluated the capacity of SMARTcycling to identify driving events, road condition and Stressful events we took two approaches. First we assess the accuracy of our image processing tools when classifying different driving events and also the presence of ground irregularities. Then we analyzed in detail one of the paths in the testing dataset, both in terms of cyclist stress and in terms of road condition evaluation.

A. Accuracy of image processing

SMARTcycling shows a good preliminary accuracy on the classification of driving events.

For each event on the testing dataset, we used the video snippet with three consecutive frames to compute the descriptor. The results from the proposed classification approach are represented in Fig. 6 in the form of a confusion matrix. Using a color scheme to represent the distribution of classifications for events of each category, the matrix shows that SMARTcycling achieved precisions ranging from 0.8 for event **Turn Right** and 0.6 for event **Turn left**.

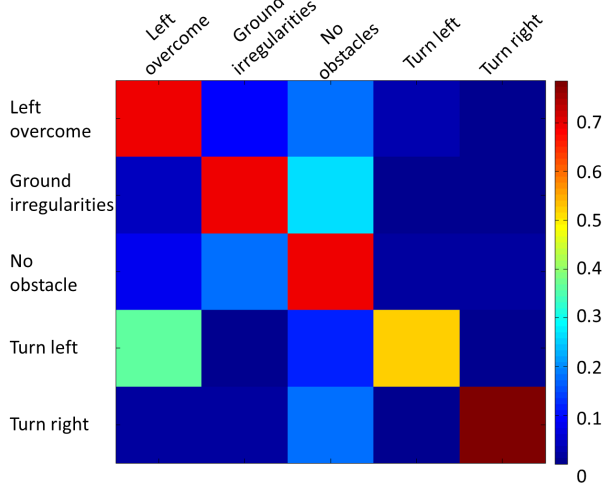


Fig. 6. Confusion matrix, representing the distribution of classifications for each class of events. Colors represent fraction and dark red is closer to 1, while blue is closer to 0.

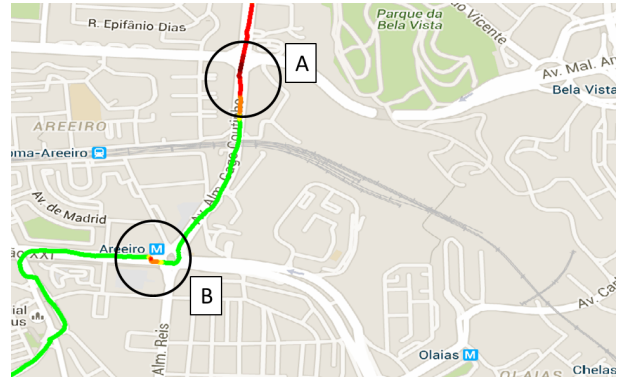
The event **Turn left** was sometimes mistaken by **Left overtaken**, as both events present similar optical flow patterns on the left-hand side rectangles. However, considering the large noise conditions under which this data was retrieved, it is noticeable that the results were very similar to those obtained in cars' data [6].

B. Stress and road condition evaluation

We analyze a path in Lisbon that crosses one of its main avenues and a very busy round-about. In that path we look into evidences of cyclist stress' using the LF/HF ratio. We also access the path road condition, using both the Right Proximity Ratio (RPR) and hole detection.

We represent the amplitude of the LF/HF ratio in Fig. 7(a). The figure represents a subset of the complete path, namely the final of the avenue, marked A, and the previously mentioned round-about, marked B. The A part is up-hill, and the high ratio value is the result of the extra effort the cyclist has. On the other hand, the point in B is the result of having a car passing too close to the cyclist, as showed in Fig. 7(b). This map illustrates that, while multiple factors can lead to high LF/HF ratios, stressful moments are more focused in space and can be easily detected.

We represent RPR in Fig. 8, and illustrate the regions of high and low ratios in the call-out images linked to the map.



(a) LF/HF ratio Map



(b) Stress Event from region B

Fig. 7. Assessing stress

We note that regions where the ratio is high, top call-out, are associated with parked cars, which effectively limit the cyclist options in situations as those illustrated in Fig. 7(b).

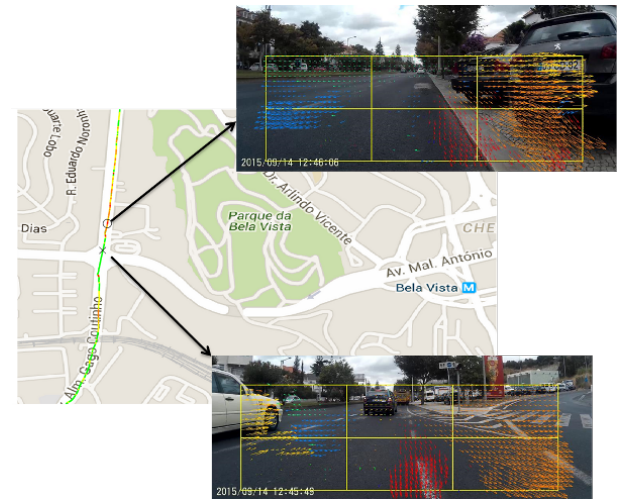


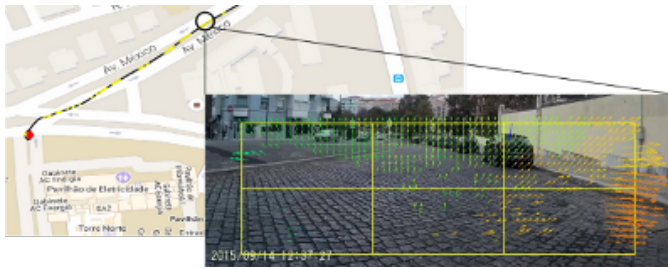
Fig. 8. Right Proximity Ratio Map (RPR)

Finally, we show the result of hole detection in Fig. 9(a). As expected from the confusion matrix in Fig. 6, not all the detections actually correspond to true holes and in Fig. 9(b) we show two examples of a detection, the topmost shows a true detection, while the bottom one shows a false detection.

The main difference is that the road on the former exhibits a paved floor, while the road on the second exhibits cobbles, a disappearing feature still present in some roads in Lisbon. As mentioned, the holes detection depends on the identification of regions with vertical optical flow and these features dominate on the cobble's irregular surfaces. We could further separated the two events if we used longer time sequences, where holes would appear in smaller time intervals.



(a) True positives



(b) False positives: cobbles produce the same upward pattern as holes.

Fig. 9. Hole detection

IX. CONCLUSIONS

We have introduced the SMARTcycling tool for the assessment of cyclists commuting experience. The tool is composed of two very different functionalities. The first is the ability to record and synchronize the multiple sensor data and the GPS position through an easy to use Smartphone app. The second is the ability to identify events and road anomalies that may be linked with risky or stressful situations.

We have showed a good accuracy on events classification, even though bicycles intrinsically present frequent shake due to lack of suspension and to rider's movement. For the accuracy contributed the efficient use of image based descriptors, which are often dismissed when inertial sensors are available for modeling driving events. In this work we overcame the noise that would be present in the image, by using an action camera and filtering obvious outliers in the computation of the optical flow by using multiple frames.

We also showed that SMARTcycling has a very high potential to help city planning as it allows to identify regions of potential stress to cyclists and identify ground irregularities.

In future work we expect to further access the difference between high LF/HF ratio due to physical effort and stress.

Furthermore, we consider also exploring different ways to disambiguate between events using longer frame sequences, or other smartphone sensors, e.g., gyroscopes. Another aspect worth exploring is the use of accelerometers to estimate the camera orientation with respect to the road and thus predict changes in the optical flow resulting from different camera positions.

Finally, we envision SMARTcycling as a tool fully centered on the smartphone, as camera's quality further improves in these devices. To achieve that we will build on top of the current stress detector and use it to learn both stress related environments and riders' reaction from the multiple smartphones sensor's output.

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