BikeSafe: Bicycle Behavior Monitoring via Smartphones

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UbiComp/ISWC'17 Adjunct, September 11–15, 2017, Maui, HI, USA

ACM ISBN 978-1-4503-5190-4/17/09...$15.00
https://doi.org/10.1145/3123024.3123158

Abstract
Monitoring the bicycle safety is of great importance. The current methods either require specific hardware supports or are expensive to implement. In this paper, we propose BikeSafe, a smartphone-based system to track bicyclist movements and alarm their dangerous riding behaviors in real time. Preliminary experiments over 12 participants show that the overall detection accuracy of BikeSafe on riding behavior achieves 86.8%, and that of the illegal way riding reaches around 90%, satisfying the practical operation in daily usage.

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g.,HCI)]: Miscellaneous

Introduction
Bicycle is a worldwide and principal transportation tool due to its convenience, environment-friendliness and low cost. However, bicycle safety issue is easily overlooked by many cyclists. According to a recent report in 2014 [5], there were 726 killed and an additional 50,000 injured in US due to traffic accidents that involves cyclists. Dangerous riding behaviors is one of the main causes of such tragedies. Specifically, frequent lane weaving or stand riding sometimes provokes balancing difficulties and high risk of falling for the bike rider, and riding a bike against the direction of legal traffic usually causes head-on collision or traffic congestion.

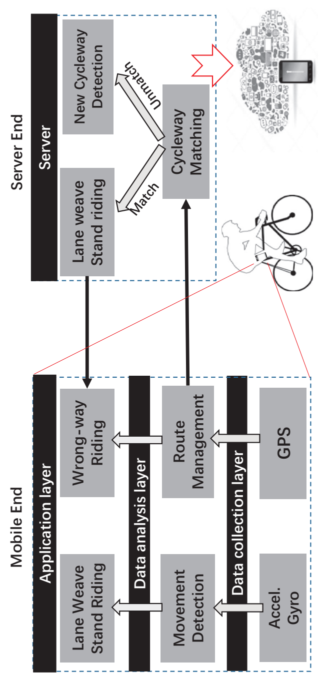

Figure 1: The system architecture

Therefore, a real-time, ubiquitous and efficient system to improve the bicycle safety is urgently needed.

A broad-range of research works has been conducted on this point. Cyber-Physical bicycle [6] performs automated rear-approaching vehicle detection via video and audio sensors. LightLane [1] highlights a bike path around a bicycle on the roadway by projecting an image, reminding the motorists to keep a safe passing distance. However, these works require professional hardware supports and are often with high cost. BikeNet [2] constructs a mobile sensing platform on a bicycle to gather the riding data and the environmental variables. BikeSafe envisions to move one step further of this work, providing a pervasive and efficient system to monitor the bicyclist riding behaviors with smartphones. Like many mobile sensing works [4, 3], it evokes the embedded accelerometers and gyrometers of smartphones to monitor the cyclists' movements and employs the GPS to track their riding directions, with which it infers two common and dangerous riding actions (*i.e.*, the frequent lane weaving and standing riding) and detects the wrong-way riding. Compared with previous works, BikeSafe avoids the professional hardware equipment, and provides an real-time alarm when the cyclists run in an illegal bike way.

The key challenges are two folds. 1) How to identify discriminative behaviors of the riders from noisy environmental measurement. 2) How to determine the legal riding directions of cycleways without prior knowledges. To cope with this issue, we design a specific feature-extraction mechanism for each kind of data, and construct a crowdsourcing platform to learn the legal riding direction of cycleways. BikeSafe has been evaluated on 12 users over 2 weeks. The experimental results show that the overall detection accuracy of riding behaviors is around 86.8%, and that of the wrong-way riding reaches about 90%, which are promising for the practical operation in daily life.

System Overview

Fig. 1 shows the architecture of BikeSafe. It consists of a client end and a server end. The client end employs smartphone sensors to track movements of cyclists and to record their GPS information at the **data collection layer**. These data are then processed by the **data analysis layer** to detect dangerous events including lane weaving, stand-riding and wrong-way riding. Once a dangerous event is detected, the **application layer** reminds the cyclist via pre-defined alarm mechanisms. We elaborate on the details of each layer as follows.

System Design

Data Collection Layer. We assume a BikeSafe user carries a smartphone while riding a bike. The data collection layer evokes the built-in accelerometer to record 3D-acceleration and angular acceleration data to infer the movements of the cyclist. It also turns on the phone GPS to track the routes of the user to determine the riding directions.

Data Analysis Layer. The data analysis layer consists of a riding movement detection module and a riding route management module. The former detects frequent lane weaving and stand-riding. The latter is responsible to detect wrong-way riding.

In the *riding movement detection module*, BikeSafe distinguishes *(i)* frequent lane weaving: weaving or swaying across the lane more than twice per minute; *(ii)* stand-riding: standing on the pedal to ride and *(iii)* normal riding. Frequent lane weaving and stand-riding are two dangerous riding behaviours because they easily lead the riders to lose balance. The riding movement detection module infers these two behaviors by analyzing the 3D-acceleration and angular traces. Specifically, lane weaving alternatively increases the forces of the left and the right sides, thus resulting in large angular acceleration values. For stand-riding, the legs of the rider tend to move in a wider range

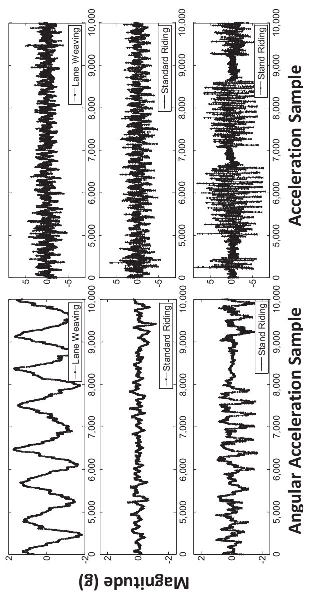

Figure 2: The angular acceleration and acceleration samples.

than for normal riding, which leads to larger acceleration readings. Fig. 2 shows the distinctive acceleration patterns of the three riding movements. The amplitude of the angular acceleration for lane weaving and the acceleration for stand-riding are notably larger than normal riding. Therefore, BikeSafe differs these three riding movements using the following acceleration features. (1) Average Magnitude: $\sum_{j=1}^{N} a_j$; (2) Standard Deviation: $\sqrt{\frac{1}{N}\sum_{j=1}^{N}(a_j-\mu)^2}$; (3) Average Absolute Difference: $\frac{1}{N}\sum_{j=1}^{N}|a_j-\mu|$; (4) Binned Distribution: $\sum_{i=1}^{K}\sum_{j=1}^{N} sign\left[a_j - a_{min} + \frac{(i-1)}{K}(a_{max}-a_{min})\right]\left[a_{min} + \frac{i}{K}(a_{max}-a_{min}) - a_j\right]$. a_j, μ, a_{min} and a_{max} are the jth sample, the average value, the minimal and maximal samples of the sliding window with N samples. K is a preset range of bins divided by $a_{max}-a_{min}$, which is empirically set as 10 according to the experiment results. To characterize the temporal patterns of the acceleration traces, we apply the constrained Hidden Markov Model (CHMM) for classification.

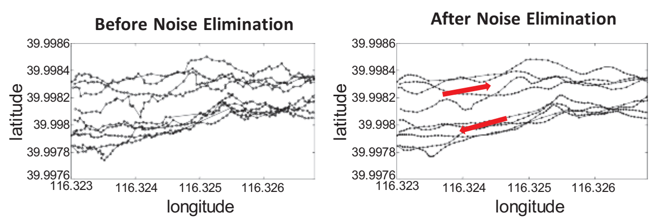

Figure 4: The GPS traces before and after noise elimination.

In the *riding route management module*, BikeSafe detects whether the user rides against the legal directions of the route, *i.e.*, wrong-way riding. Fig. 3 illustrates the work flow of the wrong-way riding detection. BikeSafe first eliminates noises in the raw GPS traces by removing the GPS samples whose error radius are larger than 20 meters, and adopts the Weighted Moving Average (WMA) to smooth the trace. Fig. 4 shows the GPS traces before and after noise removal. The GPS traces naturally cluster into two groups, indicating two cycleways. Afterwards, BikeSafe uploads the GPS traces to the server and match them with the GPS trajectories in the server via Dynamic Time Warping (DTW). If matched, BikeSafe determines the rider's current position and then compares his/her riding direction with the legal direction of the cycleway. BikeSafe computes a rider's riding direction by partitioning his/her GPS trajectory into disjointed segments. Assuming a GPS segment with a start coordinate (X_1, Y_1) and an end coordinate (X_2, Y_2), the riding direction τ is computed as $\tau = arctan(\frac{Y_2-Y_1}{X_2-X_1})$. The two red arrows in Fig. 4 show the legal directions calculated by the method above. If unmatched, BikeSafe regards this GPS trace as a new route candidate. A new route is generated after more than 3 route candidates with a Hausdorff distance smaller than a preset threshold τ. In this work, the threshold is empirically set as 5m. A cycleway is calculated as the centerline of these candidates. Its legal direction is also consistent with the three candidate routes, which is calculated as above.

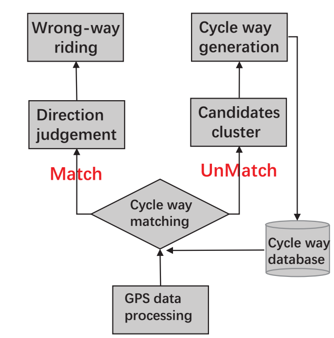

Figure 3: The workflow of the wrong-way riding detection.

Application Layer. The application layer reminds riders of their dangerous riding behaviours detected by the data analysis layer. Once a dangerous riding event is detected, BikeSafe delivers vibration and sound to remind the rider.

Preliminary Evaluation

We evaluate the performance of BikeSafe in terms of the accuracy of dangerous riding event detection and the energy consumption. A total of 12 volunteers participate in the experiments. Each volunteer puts a smartphone in his/her trouser pocket and rides a bike during the experiments. The ground-truth is manually labelled. Fig. 5 illustrates the experiment scenarios.

Performance of Dangerous Riding Event Detection. Table 1 shows the confusion matrix of the riding movement detection module in distinguishing normal riding, stand-riding and lane weaving. As shown, the inference accuracy of each riding movement is higher than 80%, and the overall accuracy is 86.8%.

Table 1: The confusion matrix of riding movement

Ground Truth	Inference		
	Normal	Stand	Lane Weaving
Normal	84.1%	7.9%	6.9%
Stand	5.6%	87.8%	4.7%
Lane Weaving	10.3%	4.3%	88.4%

Performance of Wrong-way Riding Detection. We first use the Hausdorff distances to compare the GPS traces generated by BikeSafe with the true GPS traces of cycleways. More than 91% pairwise distances are within 5m, and 98% computed riding direction are consistent to the legal riding directions. We then evaluate the accuracy of wrong-way riding direction detection (see Table 2). We compare the rider's riding direction with the legal cycling direction of the trajectories stored in the database. As shown, the true positive rate is higher than 90%, indicating that BikeSafe can detect most wrong-way riding events. The 13.3% false positive rate shows that the normal riding is rarely misclassified as the wrong-way riding.

Figure 5: The experiments.

Condition	Test	
	Positive	Negative
True	93.2%	6.8%
False	13.3%	86.7%

Table 2: The performance of wrong-way riding direction detection.

Energy Consumption. As a smartphone application that runs continuously during bike riding, it is important to evaluate the energy consumption of BikeSafe. Fig. 6 shows the results recorded by a power tracker. BikeSafe consumes around 3% energy per 10 minutes, which is acceptable for daily use.

Conclusion

Preventive bicyclist protection is crucial to redcue the unexpected bike accident rate. In this paper, we propose BikeSafe, a wearable and efficient mobile system to monitor the riding behaviors. It utilizes the embedded sensors of smartphone to monitor the dangerous riding actions and check whether the cyclist goes on a wrong-side. Experimental results of 12 participants demonstrate our system is practical in daily life.

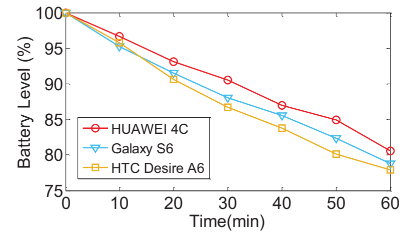

Figure 6: Power consumption.

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