慣性計測ユニットを使用した危険な自転車運転の検出

Detecting Dangerous Cycling Behaviors with Inertial Measurement Unit

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1 Introduction

Single-handed riding behavior is omnipresent, usually transient, but always jeopardizing. It threatens every road user with surged risk of bicyclist-involved crushes. For instance, engaging in distracted secondary tasks during cycling is shockingly prevalent and contributes to driver error, sometimes resulting in tragedies. On the other hand, modern smartphones have versatile functions, such as environmental sensors, data processors, and instant feedback. These rich functions allow human activity recognition technologies to be deployed to smartphones without any additional devices.

In this study, we propose DoubleCheck: a single-handed cycling detection method. Our proposed method estimates `double-handed` and `single-handed` cycling conditions using smartphone-embedded motion sensors using an vector autoregressive (VAR) machine-learning model and a wavelet scattering network. Our demonstrably effective approach (§3) collects time-frequency-domain features via lightweight computing from input motion data. We evaluated the performance of the proposed method using motion data from 22 participants during bicycle riding on two road surfaces. The resultant F1-score of 0.98 for the accuracy of determining cycling hand(s) and 0.69 for distraction recognition validate DoubleCheck's practical safety-checking capability (§4). The contributions of this work are summarized as follows:

- A method for single-handed cycling monitoring using a smartphone
- A feature extraction scheme using the wavelet scattering network and vector autoregression model
- A model performance evaluation

2 Motivation & Feasibility Study

The scope of single-handed events in this study includes two types of cycling behaviors: two-handed cycling and single-handed cycling. Research have suggested that impulsive distracted behavior of cyclists is not likely to be reduced from legislation alone, and effective strategies include constraining proximate characteristics such as phone inaccessibility [1]. If we could collect single-handed cycling event data, the information could be used to provide just-in-time suggestions for preventing dangerous cycling behaviors. Therefore, the objective of this research is to propose a single-handed cycling detection method that satisfies the following requirements:

- **Hand Detection:** The exact cycling hand(s) must be automatically detected on different road profiles.

- **Practicability:** The capability is restricted to the built-in IMU sensor of an off-the-shelf smartphone for real-time detection and classification of single-handed cycling.

3 Approach

Figure 1 presents DoubleCheck' s basic design, including the three steps used to estimate whether the rider is single-hand cycling. In the first step, DoubleCheck collects motion data from an off-the-shelf smartphone. In the second step, the raw data collected from the motion sensor are smoothed, sliced, and streamed into the vector autoregression (VAR) model and the wavelet scattering network for the *data processing* step. Then, during the *detection* step, a support vector machine (SVM) classifier is trained to identify single-handed cycling, and another LSTM network for recognizing distraction behaviors. We realized our method by MATLAB.

3.1 Data Collection

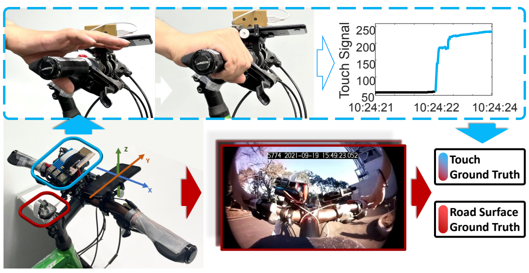

Figure 3: Data collection platform.

To build a classification model using supervised machine learning for single-handed cycling, we prepared labeled motion data for single- and double-handed cycling. To compile the dataset, we assembled a test bike mounted with an off-the-shelf smartphone (Google Pixel-3a equipped with Android 11 OS), a capacitive touch sensor (SKU-6515) and a cycling log camera (VR-220). The test bike is presented in Fig. 3.

The ground-truth acquisition procedure is illustrated in Fig. 3. The touch status was recognized by capacitance readings from the Raspberry Pi-controlled tactile sensor and validated by watching cycling log videos. During cycling, the touch data and motion readings were continuously collected by the Raspberry Pi (RPi), transmitted to the smartphone via a mobile hotspot, and stored in CSV-format files. The sample rate of all sensors was 80 Hz. Additionally, the RPi recorded 60-fps cycling log videos with millisecond timestamps for post hoc analysis.

4 Evaluation

In this section we respond to the following questions with evaluation of hand detection and distraction recognition.

How efficient is DoubleCheck in detecting single-handed cycling behavior?

4.1 Experiment Protocol

Comprehensive experiments last more than 2 months to construct the dataset. Our cycling experiment is permitted by our Institutional Review Board (IRB). We invited 22 participants to join our experiment, there are 13 males and 9 females. Overall, each of the participants performs several cycling behaviors on our test bike: *Left-hand cycling on road (Left-R), left-hand cycling on pavement (Left-P), normal cycling on road (Both-R), normal cycling on pavement*

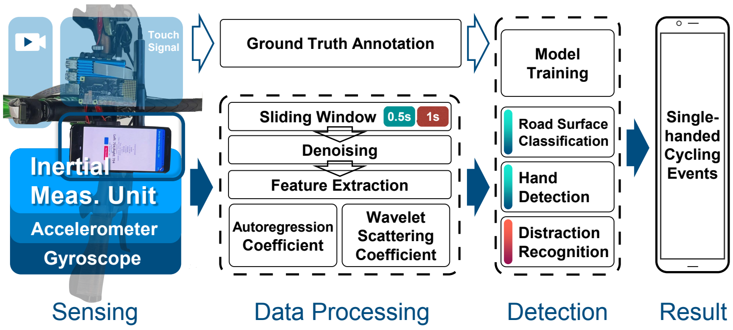

Figure 1: DoubleCheck workflow.

Figure 2: Experiment Road Surfaces.

(Both-P), right-hand cycling on road (Right-R), right-hand cycling on pavement (Right-P),Taking from Pocket (Take-from-Pocket), Smartphone Tap (Phone-Tap). Noted that during *Left/Right-R/P*, the rider is asked to drop the spare arm naturally besides his or her body

A whole process takes one person about an hour with three to four minutes cycling for each cycling behavior. Intervals for rest takes two to five minutes or more time if the cyclist is tired. In total, we have sorted and labeled cycling data for about 6.5 hours long. The ratio of asphalt road and pavement sections are roughly equal.

4.2 Overall Accuracy

The assessment of our model in the following part is through 10-fold cross-validation (10-Fold) and leave-one-member-out cross-validation (LOMO). We first explore the accuracy of our method's core objective binary classification.

We leverage 10-Fold to evaluate the SVM in comparison with other recurring methods in human activity recognition researches The result in Fig. 6 displays that the SVM outperforms the else approaches with higher F1-score. In addition, methods like Perceptron also reach high accuracy, further proving our extracted features are effective. For LOMO, the F1-score of DoubleCheck also exceeds 0.97. Fig. 4 displays the detailed performance. The worst case happens with the 21st participant whose F1-score is 0.92, proving our system to be an effective check against single-handed cycling across individual variety with user-friendly adoption that personalized pre-training is not needed. Fig. 4 shows the capability comparison of DoubleCheck on asphalt and pavement. For all participants except one, the method yields better results on pavement. The outcome shows that rugged road surfaces tend to amplify single-handed-cycling-brought differences in movement features. However, the classifier still attains high accuracy on asphalt road with an average F1-score of 0.96. The curve displays the robustness of our method.

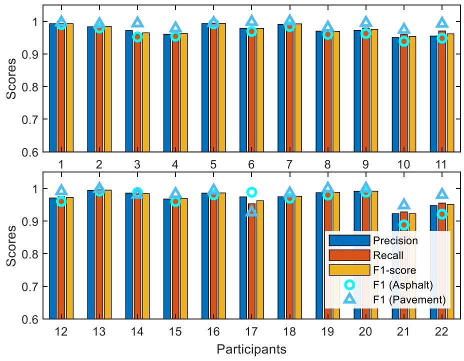

Figure 4: Performance of Hand Detection.

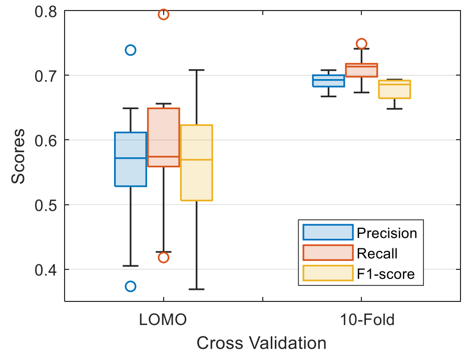

Figure 5: Performance of Distraction Recognition.

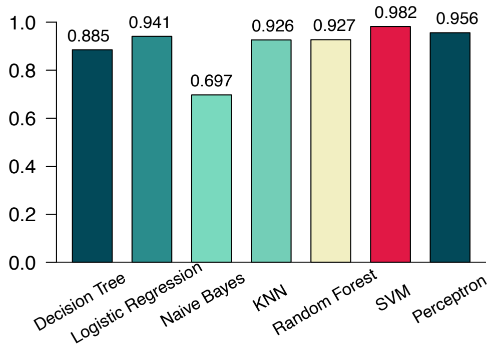

Figure 6: Cross Validations of Hand Detection

Given the high accuracy in the hand detection, we evaluate the distraction recognition in the single-handed cycling scenario. For the training dataset, a proper portion of samples from classes *Left&Right-R* composes the class *Hand-Drop*. Recognition performance are presented in Fig.5 The average F1-score in 10-Fold is 0.69. The numbers drop to 0.57 in LOMO. The results imply that the distraction behaviors within our scope can somehow affect motion patterns, yet the differences may be very blurred and unstable regarding our current recognition scheme.

5 Conclusion

We proposed DoubleCheck: a smartphone-based cycling-aid for single-handed riding detection and distraction recognition. We leveraged an embedded tri-axial accelerometer and gyroscope to acquire motion readings and introduced an VAR model with a wavelet scattering network, which yielded representative cycling activity. Experiments with 22 subjects demonstrated the performance of our system with an F1-score of 0.98 for the accurate detection of cycling hand(s) and with a score of 0.69 for accurately identifying distracted cycling behaviors. We envision that our work will facilitate safer bicycle commuting with no more than a software update on a smartphone, and it will shed light on future schemes for mobile riding interactions.

References

[1] R. K. Brandt, S. Haustein, and M. Møller, "Cyclists' phone use in relation to proximate environmental characteristics - a qualitative study," *Journal of Transport & Health*, vol. 23, p. 101283, 2021. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2214140521003133