BikeGesture: User Elicitation and Performance of Micro Hand Gesture as Input for Cycling

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Abstract
The use of hand gestures has a potential as an promising input metaphor. Wearables like smart textile and data gloves can provide hand gesture recognition to potentially replace, augment or improve existing input methods. Although recent bikes provide advanced functions with electro mechanical components, the input metaphor still relies on mechanical switches or levers. In this paper, we investigate the acceptance and performance of using hand gesture during cycling. Through an observational study with 16 users, we devised a taxonomy of hand gestures. Users prefer subtle micro hand gestures to ensure safe cycling while maintaining a flexible controllability. We also implemented a wearable prototype that recognizes these gestures. In our evaluation, the prototype shows an average of 92 % accuracy while showing similar response time to existing mechanical inputs.

Author Keywords
Gesture; Bike; Input Device; Wearables

ACM Classification Keywords
H.5.2 [Information interfaces and presentation (e.g., HCI)]: User Interfaces

INTRODUCTION

Recent developments in electro-mechanical components (e.g. electronic shifting and suspension locking) and use of peripherals (e.g. headlights and bike computers) during cycling have increased input requirements for the bike. However, previous study [4] showed that adding physical input controls would affect negatively on cycling safety. Moreover, limited physical volume of bike's handlebar makes it hard to implement all control components in accordance with increased bike functions.

Currently, users control a bike using mechanical inputs installed/mounted on the handlebar such as shift levers, twist levers and buttons. These inputs often lead users to move a hand from one place to the other or require visual attention during manipulation. To this extent, bike manufacturers have started to employ wearable input devices for bikes [21], but they still relied on simple triggers like fingertip pressing. While glove-based hand gesture inputs have been explored widely for design, robotics, medicine and computer applications space [14], relatively few research has focused on cycling. Furthermore, gloves are commonly equipped during cycling for hand protection and warmth, which reduces the doubts about users' willingness to wear additional equipment.

In this paper, we aim to explore acceptable hand gestures for input controls during cycling. Based on devised gestures, we further investigate performance in terms of reaction time. This verifies the performance of using explored gestures. Throughout exploratory study with users, we devised 10 hand gestures based on finger contact, bending, and hand tilting. We found that users preferred microgestures [23], instead of whole hand gestures. In addition, some whole hand gestures were found to have safety concerns. We implemented a wearable prototype for evaluating and demonstrating bike functions and peripheral devices controls during cycling.

RELATED STUDY

Recognition of hand gestures have been implemented using electromyography (EMG) [12], capacitance sensing around the wrist [15], and strain sensing on the skin [11]. Beside, previous works employ smart textile [25], magnetic sensing [3], and vision system [9] to provide finger-level controls. However, these works focus on enabling interactions rather than exploring a set of acceptable gestures from end-users. To this extent, other works have done gesture elicitation studies for domains like mobile interaction [16], TV control [19], and surface computing [22], but few studies have focused on the hand gestures interaction with bike components during cycling. Recently, microgestures have been highlighted with mobile and discrete nature of interactions [2, 23]. Throughout our work, we bring out a taxonomy of microgestures for cycling which reflects safety concerns and controllability with handlebars.

Previous works demonstrate interactive system for cycling including navigation through vibration [18], visual feedback using smart eyeglass [17], and head-up display [4]. Recent research and commercial works also incorporated hand gestures control during cycling [1, 4, 8, 10, 20]. However, there is little or no research on studying input metaphors for cycling. Yoon et el's work [25] illustrated that the performance of current input metaphors can be improved by adopting wearable inputs with multimodal sensing capabilities. We implemented a prototype as a glove integrated with multi-modal sensing capabilities (finger bending, pressing, and hand tilting). With the proposed prototype, we recognized 10 microgestures discovered from an exploratory study. Thus, we suggest using hand-based microgestures as a new input metaphor during cycling. The study results

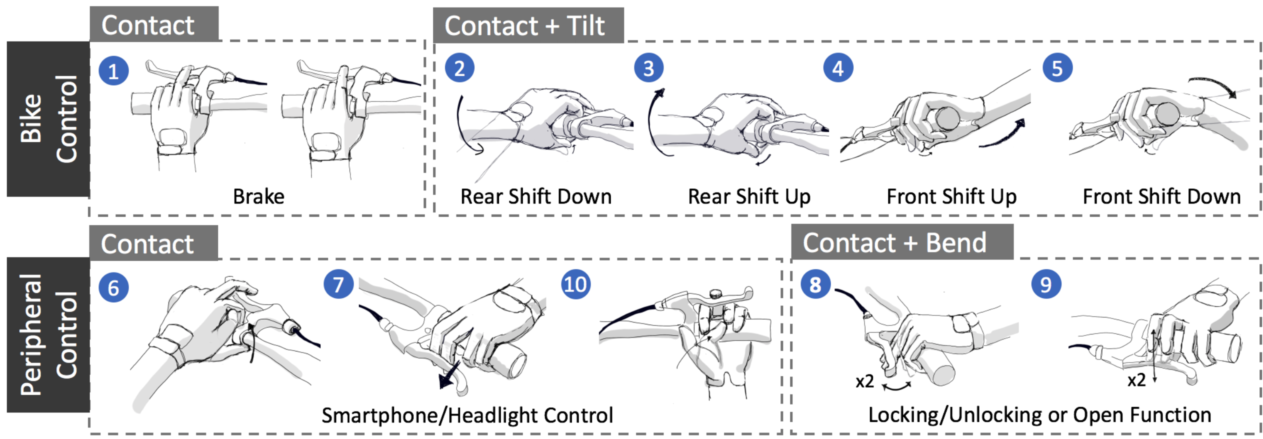

Figure 1: Hand gestures elicited from exploratory study. A total of 10 microgestures from users' inputs are illustrated with *Gesture ID*.

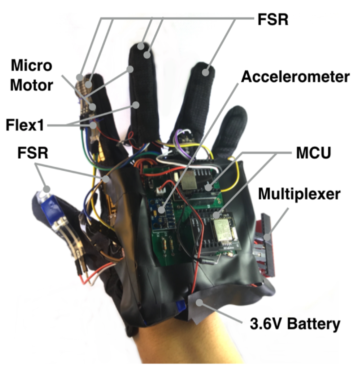

Figure 2: Our prototype: microgesture-based glove

verify that microgestures show competitive performance comparing to existing mechanical inputs.

EXPLORATORY STUDY: DESIGNING GESTURES

We conducted interview and observation study with users to gain a better understanding of feasible gestures for cycling. We carried out multiple sessions like previous work [24] to finalize gestures. We recruited 16 participants (3 female, ages 23∼43, average = 26, SD = 5.32) with different backgrounds including daily bike users, pro-cyclist, bike engineers, and local bike dealers. All participants had experiences with existing bike's input methods such as controlling gear shifting and interacting with bike computer. To reduce *legacy bias* from previous experiences, we forced participants to produce multiple interaction proposals for each function [13]. We then observed user's gesture demonstration with a bike handlebar while they were seated and pedaling on the bike. We asked users to complete following questions and tasks:

1. *What are primary input mechanisms used during cycling?* Participants explain and demonstrate main input mechanisms used based on their experiences.
2. *Do you encounter any problems with current input mechanisms during cycling?* Participants list factors that affect current controls during cycling.
3. *How might hand gestures be used during cycling?* Participants illustrate hand gestures for different bike functions and demonstrate with a bike handle bar.

We collected gestures from user's responses which include 1) legacy-inspired gestures such as hand tilting while pressing an index finger with a thumb (*Gesture ID* 2) and 2) newly suggested hand gestures like pressing side of the finger (*Gesture ID* 6). After collecting gestures from all participants, we had an evaluation session with same group to rate all collected gestures based on *Feasibility*, *Attention*, and *Interference* [24]. Based on these ratings, we formed

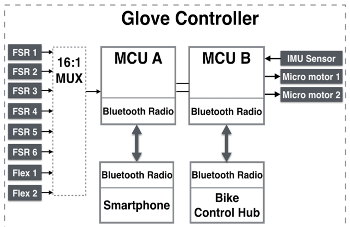

Figure 3: The schematic workflow of the prototype

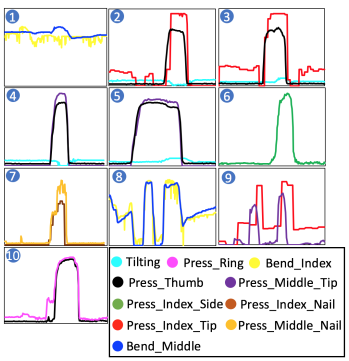

Figure 4: Graphs of sensor signals for all microgestures. The horizontal and vertical axes represent time and amplitude respectively. Each color represents different sensors used in our prototype and numbers indicate *Gesture ID* in Figure 1.

a taxonomy of 10 hand gestures for cycling which will be further evaluated.

Safety concern and microgestures for cycling

All users report that existing mechanical input methods often cause safety issues. First, users need to move a whole hand from one place to another for interacting with peripheral devices such as headlight, mobile device, or electric component of bikes. Participants also mentioned that current eyes-on interactions with mechanical buttons easily lead to interference with cycling. To overcome these issues, participants suggest microgestures for interactions during cycling rather than whole hand gestures. Participants also emphasize advantages of using microgestures: 1) less motions for executing inputs and 2) less visual attentions for executing inputs.

Exploratory study with users helped us formulating a taxonomy of microgestures for cycling. We categorize gestures according to sensing requirements and functions.

Contact: Participants preferred various types of finger contacts. Main categories include 1) inter-finger contact, 2) tab on the side of a finger, and 3) contact top/bottom side of a finger with surrounded structure.

Bending: Participants selected finger bending as a potential gesture element since it represents user's natural hand posture like open/close grips. Participants showed strong interests in utilizing only few magnitude levels since they cannot guarantee fine-grained controls of finger bending.

Tilting: All participants mentioned using hand tilting as an essential gesture element. They inherited *Tilting* from current bike input metaphors where most bikes adopt twisting-lever for changing gears.

Multimodal Physical Sensing: Within the devised taxonomy, more than half of gestures merge multiple sensing properties (e.g. tilting while contact). Primary reason for multimodal physical sensing was to avoid unintentional triggers.

Function Mapping: Participants showed strong adherence in mapping legacy-inspired gestures to *Bike Controls*. Several participants mentioned that it was hard for them to apply random hand gestures like inter-finger contact to bike-related controls like shifting gears.

PROTOTYPE

To fulfill requirements from devised microgestures, we focus on embedding sensors to recognize inter-finger contact, finger bending, and hand tilting (Figure 2). For contact sensing, we attach a total of 6 force-sensitive resistors (FSR) to : 1) fingertips of index, middle, and ring finger, 2) fingernails of index and middle fingers, and 3) inner side of the index finger. We selected Flexiforce A201 (0.38" diameter) FSR for fingertips and inner side of index finger, and Interlink 400 FSR (0.5" diameter) for fingernails. Two flex sensors (4.5" length) are embedded on top of index and middle fingers to capture finger bending. We captured hand tilting by attaching accelerometer to the back of hand. Two microcontrollers integrated with a Bluetooth 4.0 Low Energy (Nordic nRF51822, clock speed 16 MHz, 2.4 GHz band) process analog readings from all sensors and transmit computed *Gesture ID* to either smartphone or bike control hub. These two microcontrollers communicate with each other via serial communication.

To recognize different gestures, we employ a multi-class thresholding. Along with various threshold ranges, we utilize different set of sensors to recognize different gestures. As shown in Figure 4, we observe significant changes in sensor readings within devised microgestures. This supports that proposed microgestures are distinguishable only

Presented \ Selected (class)	1	2	3	4	5	6	7	8	9	10
1	48	0	0	0	0	0	0	0	0	0
2	0	48	1	0	0	0	2	0	1	0
3	0	2	49	0	2	5	4	1	0	0
4	1	0	1	46	0	0	0	0	3	1
5	0	0	0	0	53	0	0	0	0	0
6	0	0	0	6	1	47	0	0	1	0
7	0	2	2	0	0	0	47	0	0	0
8	0	2	1	0	0	0	0	50	0	0
9	5	0	0	2	1	2	0	0	49	0
10	0	0	0	0	0	0	0	0	0	53

Figure 5: Confusion matrix of different input types. Rows indicate presented inputs and columns refer to selected inputs. Class is same as *Gesture ID* used in Figure 1.

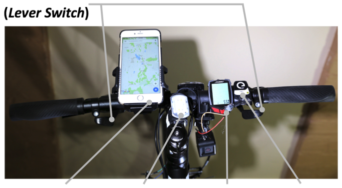

Figure 6: The study setup with existing mechanical inputs

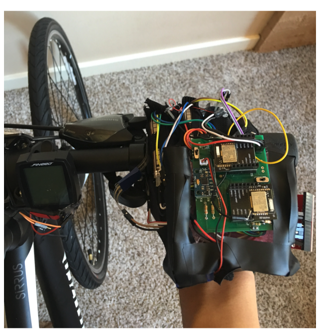

Figure 7: The study setup with our prototype

with raw signals. For example, *Gesture ID 3* We implement smooth filters on each pressure sensor and bend sensor. Moreover, no user-dependent calibrations are used during our evaluations or demonstrations.

PRELIMINARY EVALUATION

To explore the performance of microgestures with real users, we carried out two preliminary evaluations: 1) accuracy test on gesture classification and 2) reaction time measurements for existing mechanical inputs and microgesture-based glove. Both evaluations took place in a lab environment where we asked users to sit on the bike and pedal during the session. The results show that users attain an average accuracy of 91 % with uncalibrated raw sensor readings to differentiate 10 microgestures. The reaction time comparison results show that suggested microgestures perform as good as existing bike inputs.

Accuracy Test

For accuracy test, we intentionally design our algorithm with multi-class thresholding based on raw sensor signals. Although machine learning technique [6] can further enhance classification performance, we are more interested in verifying the reliability and the stability of raw signals from microgestures. We recruited 11 participants (three females) with a mean age of 27 (SD = 3.27, all right-handed). We asked participants to execute every gesture designed in our prototype (10 classes) for 5 times with randomized orders. No user dependent calibration was done.

Figure 5 illustrates the confusion matrix of different microgestures. All gestures show similar accuracy which shows equal performances across microgestures. Overall accuracy comes out to be 91 %. We also count number of unintentional triggers. In a total of 550 trials (11 users $\times$ 50 trials), there are 15 unintentional triggers (2.73 % of total data) which bring overall accuracy down to 88 %. The main source of unintentional triggers is the fitting of the glove. Participants who show good fits with our glove (4 participants) commit 50 % less unintentional triggers.

Reaction Time

The purpose of comparison study is in two folds: 1) explore reaction time performance comparing to existing input metaphor with various gesture sets containing different number of gestures and 2) investigate performance of individual microgestures. We recruited 8 participants (two females) with mean age of 24 (SD = 2.23, all right handed). Figure 6 illustrates our study setup for mechanical inputs and microgesture-based glove with a real bike. During the study, we restricted users from looking at the handlebar region to simulate cycling environment. After the study, we took a short survey to retrieve NASA-TLX ratings [7].

In this study, we had 4 sets containing different number of gestures (2, 4, 6, and 8 gestures). Within each set, users performed tasks using both input devices: handlebar with common mechanical inputs and our glove prototype with microgestures. We called random functions mapped to specific gestures. Participants triggered called functions using the given input devices. In order to capture time durations, we used video data for mechanical inputs and outputs from microcontroller for microgestures. We adopted within-subject design for this study since individual performance varies in controlling different input devices. In order to minimize a learning effect, we randomized the order of gesture sets and provided sufficient practice time before each set (10 minutes). We collected a total of 1536 data points (8 users$\times$4 sets$\times$2 methods$\times$24 trials).

Figure 8 represents reaction time using mechanical inputs and devised microgestures with our prototype. On the aver-

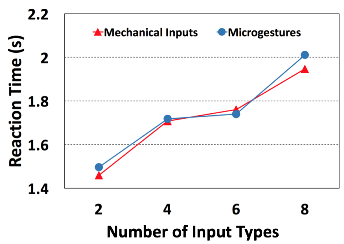

Figure 8: Reaction time for input execution using mechanical inputs and a set of devised microgestures with different number of input types in each set (2,4,6 and 8 gestures)

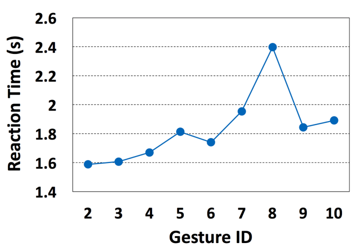

Figure 9: Reaction times for different *Gesture ID*

age, it required 0.03s (1.3%) more reaction time to use microgestures comparing to mechanical inputs. A two-sample t-test shows that reaction time results are from the same distributions with p=0.21. This indicates that the response time performance of existing inputs and microgestures are similar. Furthermore, both input types show increase in overall reaction times for large number of input types.

Within the microgesture performance, we looked at individual gesture performance. As shown in Figure 9, we notice that legacy-inspired microgestures (*Gesture ID* 2∼5) showed 20% faster reaction time than newly suggested gestures (*Gesture ID* 6∼10). This indicates that users perform better with microgestures that adopt motions from handling existing inputs . *Gesture ID* 7 & 8 exhibited highest reaction times. These two gestures utilize top part of fingers which are often not involved in input controls.

DISCUSSION & FUTURE WORK

During our user study, we observed that mechanical inputs like buttons required user's whole visual attention during execution. Users had to find and locate the buttons before execution. In contrast, no subsequent visual attentions were required for controlling with microgestures. This implies that employing microgestures has a potential to reduce workloads for active exercise like cycling. Our post NASA-TLX survey supports where users rate *Physical* and *Temporal* demand lower (27.7 % and 23.5 %) for using microgestures over existing mechanical inputs.

Participants' reaction time was high when they performed *Gesture ID* 7 & 8. This indicates that participants did not feel comfortable about directly using top side of fingers. This is aligned with previous study on human's natural hand motion with tools [5] that humans utilize only inner and side of fingers to manipulate tools. Also, higher reaction time in newly suggested microgestures (*Gesture ID* 6∼10) show users' high inclination towards legacy-inspired gestures for cycling. Thus, UI designers/researchers who work on microgestures for cycling should consider mapping legacy-inspired gestures for main bike controls since their functions are more crucial than those of peripheral devices.

Based on this preliminary test results, we are interested in pursuing the study in real environment settings to understand in-depth performance of micro hand gestures during cycling. We plan to incorporate machine learning technique to provide reliable gesture recognition. Currently, we are working on reducing the size of the hardware to provide lightweight and solid prototype.

CONCLUSION

In this study, we conducted exploratory studies to form a taxonomy of feasible gestures for cycling. We devised 10 microgestures that has a potential to work as bike inputs based on users' feedback and ratings. We implemented a glove prototype that captures microgestures. The accuracy test shows that microgestures can be easily recognized utilizing only raw sensor signals. The preliminary comparison study shows that microgestures perform similar to existing mechanical inputs in terms of response time. The evaluation results show the feasibility of adopting microgestures as potential inputs for cycling. With suggested future works, we believe that micro hand gesture can become an alternative inputs for cycling.

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