An Automatic Recognition of Bicycle Riding State by Using a Smartphone

Jeong-Jin Yeo[1], Yoon-Ho Lim[1], Mun-Ho Ryu[2] and Yoon-Seok Yang[2]

[1] Department of Healthcare Engineering, Chonbuk National University, 567 Baekje-daero, deokjin-gu, Jeonju-si, Jeollabuk-do 561-756, Republic of Korea
[2] Division of Biomedical Engineering, Chonbuk National University, 567 Baekje-daero, deokjin-gu, Jeonju-si, Jeollabuk-do 561-756, Republic of Korea
yeojjin85@gmail.com, luhfriend1@nate.com, {mhryu, ysyang}@jbnu.ac.kr

Abstract. A bicycle is different from motor vehicles. It is driven by human power and a rider is fully exposed to the surrounding environment. Smartphone is very useful informatics device for bicycling with its small form factor, seamless access to mobile network, and mobile application contents. However, since a safe ring is most important, the rider should not be distracted from controlling the bicycle. A simple intelligence of bicycle which recognize how the riding is going on would help when we need an automatic alarm, signal light, or stoplight. This study aims to develop an automatic riding-state recognition technique by using a smartphone embedded with a 3-axis accelerometer. We applied the developed algorithm to 40 cycling data and obtained more than 95% of interval-recognition accuracy for 80.0% of the dataset. Further study will integrate a technology which can estimate the physical condition of the human rider for even more safe riding.

Keywords: riding-state recognition; accelerometer; smartphone, safe cycling

1 Introduction

Bicycle riding continues to draw attention in most countries by its eco-friendliness, energy saving, and promoting healthy lifestyle. Its population is so rapidly growing that 120 million bicycles are sold on the globe every year not only for commute but also for outdoor activity [1,2]. A bicycle is different from motor vehicles in that it is driven by human power and its rider is fully exposed to the surroundings. The smartphone is valuable informatics device for bicycling with its portability, seamless access to mobile network, and useful mobile application contents. So, there are increasing demands in young generation to install smartphone into their bicycle and to use mobile applications. The most important thing in cycling is safety, the rider should not be distracted from controlling the bicycle [3,4,5]. A simple intelligence of bicycle which recognize how the riding is going on would help when we need an automatic alarm, signal light, or stoplight. A precise measurement and analysis of bicycle motion will help us to develop such context-awareness technology. However, there has not been enough study on measurement of bicycle motion dynamics in various riding condition [4,6]. This study aims to develop an automatic riding-state recognition technique by using a smartphone embedded with a 3-axis accelerometer. We applied the developed algorithm to 40 cycling data and obtained more than 95% of interval-recognition accuracy for 80.0% of the dataset.

2 Experimental Section

A smart phone (SHW-M110S, Samsung Electronics, South Korea) was mounted close to the seat to obtain signals from major movement of the bicycle frame while excluding noisy motions like handle bar movement as shown in Fig. 1-(a) [3,4]. The phone has a tri-axis accelerometer (Bosch Sensortec BMA023; sensitivity 3.8 mg/LSB, range ±2 g) and runs on Google's Android 2.3.3 platform. An application was programmed to listen to sensor change events and transmit the sensor data and timestamp via Bluetooth to a PC, which saved the received data as a file.

Fig. 1. Acceleration measurement using smartphone mounted at the same position as the embedded wrist-watch. (a) Mounted on a seat post (left), (b) Accelerometer axes (center) and (c) Riding experiments on a slope with 10° inclination angle (right).

Fig. 1-(b) shows the smart phone with its accelerometer axes. The X and Y axes are in the plane of the phone, and the Z axis points outwards from the front face of the screen. The X and Y axes data were rearranged to be –Y and X for convenience in data processing. Since the sampling intervals are not guaranteed to be constant, they were converted to 10 ms constant sampling intervals with the timestamps. To collect acceleration dataset under various riding status, the bicycle installed with the smartphone was driven along the riding pathway shown in Fig. 1-(c). It allows bicycle to experience various patterns of acceleration occurring from down-hill and uphill riding with pedaling and braking forces. Total 5 male subjects (mean age: 27.1±1 years, mean height: 176±4.47 cm, mean weight: 72.2±4.86 kg) participated in the experiments. Prior to the experiments, we provided every participant with explanations about the objectives and procedures of the experiments and obtained signed permissions. All the participants had sufficient times for adjusting themselves to the experimental slope which has inclination angle of 10° before the measurement began. After 10 seconds of initial stand-by period, the bicycle ran down the hill, stopped, turned around, ran up the same hill, and then kept stopped for 10 seconds. This procedure was repeated 4 times with the bicycle installed with the smartphone for all the participants. Figure 2 shows typical plots of 3-directional acceleration patterns obtained from the experiments.

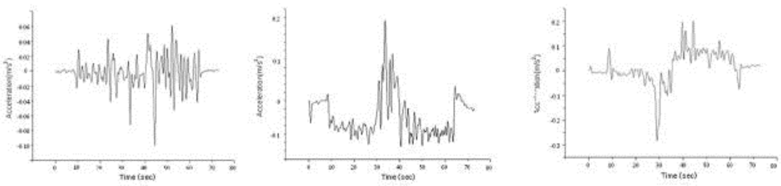

Fig. 2. Typical acceleration waveforms. (a) X-axis (left), (b) Y-axis (center) and (c) Z-axis (right).

Using the static gravity component which always reads in accelerometer's Z-axis as +1G upward, we can estimate the tilted angle of the coordinate axis of the accelerometer by combining its 3 components reading if it is in static position. However, when it is moving, since there also exist dynamic acceleration in addition to the static gravity component, it is hard to extract the postural information from the complicated accelerometer reading without using some additional inertial sensor like gyroscope [7]. But we figured out that there were some characteristic patterns in acceleration data which help to estimate its riding state, i.e., uphill or downhill riding, standing still, forced pedaling, and abrupt braking without use of any additional inertial sensors. Firstly, when a bicycle stands still, there is no force acting on it except gravity G (1G). Therefore the norm of the acceleration components must equal to G as shown in Eq. (1). If the bicycle stands still on level surface, that is, not inclined, Eq. (1) takes a special form of Eq. (2) and (3). In case of standing still, we can even estimate the tilted angle of the bicycle from combination of 3 directional components of the measured acceleration.

$$A_x^2 + A_y^2 + A_z^2 = G^2 \qquad (1)$$

A_x , A_y and A_z is the magnitude of acceleration on X, Y, and Z axis, respectively

$$A_x^2 + A_y^2 = G^2 \qquad (2)$$

$$A_z = 0 \qquad (3)$$

Secondly, when the bicycle is moving, there exist some external forces working on it other than gravity. This yields Eq. (4). Then, several specific relations hold for the different postural states which enable us to rationalize an algorithmic recognition of the states. The bicycle running on a level surface experiences the gravitational force projected onto its upward (X) or lateral (Y) directions only, which is shown in Eq. (5). Eq. (5) is similar to Eq. (2) but there is a non-zero forward acceleration onto the Z-axis as shown in Eq. (6), which is generated by rider's pedaling force. By combining Eq. (5) and (6), the riding on the level surface yields Eq. (7). When bicycle is running on either downhill or uphill, its 3-directional acceleration components are more interrelated. Still, a couple of analytic findings made it possible to identify each riding state, respectively. Figure 3 illustrates the directions of the gravitational and pedaling forces acting together on the bicycle during the downhill and uphill riding. As shown in the figure, the forward acceleration by pedaling, a, lies in the opposite direction to the backward acceleration by gravity G_z. As a consequence, the magnitude of net forward acceleration is calculated from their difference as shown in Eq. (8). From Eq. (4) and Eq. (8), we obtain Eq. (9) with the assumption that a is no larger than G_z in usual cases on the downhill riding. This can be assured by the Fig. 2-(c), where the first half of the signal shows lower mean value than the second half and the peak negative value corresponds to the braking for slowdown purpose. This results in Eq. (11) about the total magnitude of the acceleration acting on the bicycle.

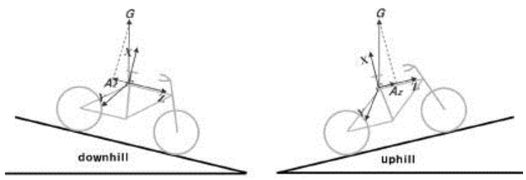

Fig. 3. Gravitational and pedaling acceleration acting on the bicycle at hill riding. (a) Downhill (left), (b) Uphill (right).

$$A_x^2 + A_y^2 + A_z^2 \neq G^2 \tag{4}$$

$$A_x^2 + A_y^2 = G^2 \tag{5}$$

$$A_z = a \tag{6}$$

a : forward acceleration generated by pedaling force

$$A_x^2 + A_y^2 + A_z^2 > G^2 \tag{7}$$

$$A_z = a - G_z \tag{8}$$

G_z : backward acceleration by gravity

$$A_x^2 + A_y^2 + A_z^2 < G^2 \tag{9}$$

$$A_z = a + G_z \tag{10}$$

$$A_x^2 + A_y^2 + A_z^2 > G^2 \tag{11}$$

Table 2 summarizes these characteristic patterns of acceleration components in various riding-state. It clearly shows that the several riding states of the bicycle can be differentiated based on the 3-axis acceleration measurement without using additional inertial sensors such as gyroscope even when it is running, that is, when there exists dynamic acceleration as well as the static gravity.

Table 2. The characteristic acceleration patterns experienced at different riding postural state.

	Flat ground	Uphill	Downhill
Standing	$A_x^2 + A_y^2 = G^2$	$A_x^2 + A_y^2 + A_z^2 = G^2$	$A_x^2 + A_y^2 + A_z^2 = G^2$
Riding	$A_x^2 + A_y^2 + A_z^2 > G^2$ $A_x^2 + A_y^2 = G^2$ $A_z = a$	$A_x^2 + A_y^2 + A_z^2 > G^2$ $A_x^2 + A_y^2 \neq G^2$ $A_z = a + G_z$	$A_x^2 + A_y^2 + A_z^2 < G^2$ $A_x^2 + A_y^2 \neq G^2$ $A_z = a - G_z$

3 Results and Discussion

Figure 4 presents some exampled results from the application of the developed algorithm. The annotations on the plots indicate the recognized riding-state and the results are superimposed on the Z-axis (forward) acceleration data for easy visualization. Figure 4-(a) and (b) are from two different participants.

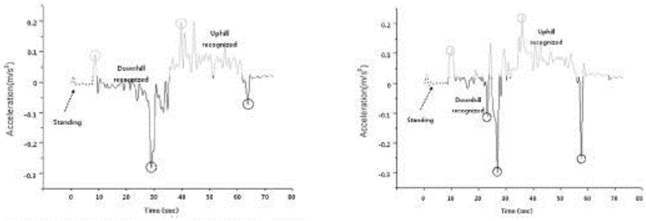

Fig. 4. (a) A recognition result from a participant (left) and **(b)** Another result from different participant (right).

The positive peaks marked with gray circle correspond to the pedaling acceleration, which are detectable simply by applying peak detection technique with some threshold. The negative peaks marked with black circle indicate a backward acceleration by forced braking, which can be spotted by using similar peak detection method. It should be noted that riding on road has lots of noise sources, including random vibration from road surface and bicycle body frame, and secondary oscillation from spring suspension. Such noisy signals are usually cause of errors in the recognition results. However, we found that some patterns in bicycle riding also disturb the correct classification of the riding-state. In the uphill riding, for example, when the pedaling acceleration was relatively small, the relation stated in Eq. (11) was not obviously satisfied, and consequently, a few of the uphill riding was not clearly recognized. It turned out that the Az larger than its usual value by Eq. (10) gave more accurate recognition results in practice. Some of downhill riding showed acceleration patterns which are not clearly differentiated from those acquired at standing on the flat surface. This is not only due to the noisy signals but also due to the fact that we usually don't apply strong pedaling force when downhill riding. As a consequence, the extra acceleration a is not much obvious. In such cases, the total variance of all acceleration components which is the measure of noisy fluctuation in the signal helped for more accurate recognition. Riding on road surface normally generates more vibrations than standing still. These supplementary criteria were added to the algorithm. The feasibility of the algorithm was verified using the smartphone. We calculated the interval-recognition accuracy on each riding data, which is defined as the ratio of correctly recognized portion to the whole riding period [7]. The 80.0% of the total riding dataset measured by smartphone showed interval-recognition accuracies greater than 95.0%.

4 Conclusion

We developed a prototype system for an automatic recognition of riding state of a bicycle by using a smartphone equipped with 3-axis accelerometer. The developed technique verified its feasibility by yielding the interval-recognition accuracies greater than 95.0% for 80.0% of the dataset. The system can acquire more detailed cycling information for longer period of time than any other conventional electronic bicycle accessories. For example, it has potential for more accurate calorimetric assessment of road-cycling by including slope-dependent exercise load than conventional speedometer-based approaches in which only moving distance and speed are took into account. Ongoing research is focusing on sharing the slope-related formation through the mobile network by using the smartphone. This will help other bicycle riders to have a priori information about cycling route for economic use of power. In further study, we will develop a technology which can estimate the physical condition of the human rider for much more safer riding.

Acknowledgments. This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Science and Technology (2012-008332).

References

1. Gatersleben, B., Appleton, K.M.: Contemplating cycling to work: Attitudes and perceptions in different stages of change. Transportation Research Part A. 41, 302--312 (2007)
2. Heinen, E., Maat, K., Wee, B.: The role of attitudes toward characteristics of bicycle commuting on the choice to cycle to work over various distances. Transportation Research Part D. 16, 102--109 (2011)
3. Landis, B.W., Vattikuti, V.R., Brannick, M.T.: Real-time human perceptions toward a bicycle level of Service. Transportation Research Record. 1578, 119--126 (1997)
4. Harkey, D.L., Reinfurt, D.W., Knuiman, M.: Development of the bicycle compatibility index. Transportation Research Record. 1636, 13--20 (1998)
5. Klobucar, M.S., Fricker, J.D.: Network evaluation tool to improve real and perceived bicycle safety. Transportation Research Record. 2031, 25--33 (2007)
6. Champoux, Y., Richard, S., Drouet, J.-M.: Bicycle structural dynamics. Sound and Vibration. 16--22 (2007)
7. Kavanagh, J.J., Menz, H.B.: Accelerometry: A technique for quantifying movement patterns during walking. Gait & Poature. 28, 1--15 (2008)