Article

TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Transportation Research Record
1–8

DOI: 10.1177/0361198118790328
journals.sagepub.com/home/trr
SAGE

Bicycling Simulator Calibration: Proposed Framework

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Abstract

Bicycling simulation allows for the low-risk experimental study of human factors within transportation environments. A cyclist pedals on a stationary bike trainer, which is instrumented to detect the speed of the wheel and the steering angle of the bicycle. This paper proposes a speed calibration procedure to increase the validity of the simulator results, by using an independent bicycle computer for comparing the simulator speed. The speed ratio, defined as the simulator speed divided by the bike computer speed, approaches one when the simulator is properly calibrated. The effect of tire pressure was analyzed by examining the speed ratio for various tire pressures. The optimal tire pressure was selected as the one that provided a speed ratio closest to one when all other factors were held constant. In the final calibration, a gain factor was used to modify the simulator speed calculation that was embedded in the simulator's bicycle dynamics model. Following calibration, the final simulation speed was within 99.5% of the bicycle computer speed, indicating that the physical speed of the wheel was accurately modeled in the simulation environment. The calibration procedure uses general equations and techniques that can be applied to other bicycling simulators to calibrate speed measurements and improve the consistency of experimental data worldwide.

Bicycling simulation allows for the careful examination of bicyclist behaviors and interactions with various elements in the built environment in a controlled experimental setting. Novel or existing infrastructure can be analyzed to determine the effectiveness of traffic control devices. Interactions between conflicting modes of travel can be evaluated with surrogate safety measures to understand crash risk. The controlled and repeatable nature of human-in-the-loop simulator experimentation provides a means to develop explanatory mechanisms for transportation user behavior, which is difficult to extract from naturalistic experiments (*1*). The virtual reality environment significantly reduces the risk for participants, who can be exposed to risky scenarios while avoiding potential harm (*2*).

The ability to extrapolate conclusions from simulation studies to real-world practice requires that the simulation and real-world performances be matched. Thus, calibration, measurement accuracy, and validation must be given careful attention. Simulated environments may not yet be able to emulate every nuance of real-world experiences, but they are sufficient to create environments in which user responses are similar to those they give in the real world (*1*). Thus, these simulations include relative validity—meaning that users respond in the same direction as in the real world—but do not include absolute validity—meaning that the simulation response is not yet identical to the real-world response in both magnitude and direction (*2*). In fact, reducing some of the variability that is experienced in the real world contributes to the power of simulation in controlled experiments, as almost all environmental factors are administered. However, because of the limited number of bicycle simulators worldwide, results from such simulators have been considered less rigorous than similar results from the comparatively more mature field of driving simulation (*3*).

The Oregon State University Bicycle Simulator is the focus of this calibration effort, although the procedure could be applied to other bicycling simulators (Figure 1). The simulator uses SimCreator (Realtime Technologies Inc.) as the simulation software package, which manages the vehicle dynamics and visual field. For the bicycle simulation, the vehicle dynamics are modified to create a vehicle that has the characteristics of a bicycle. The user's vehicle has a narrower, shorter wheelbase and reduced

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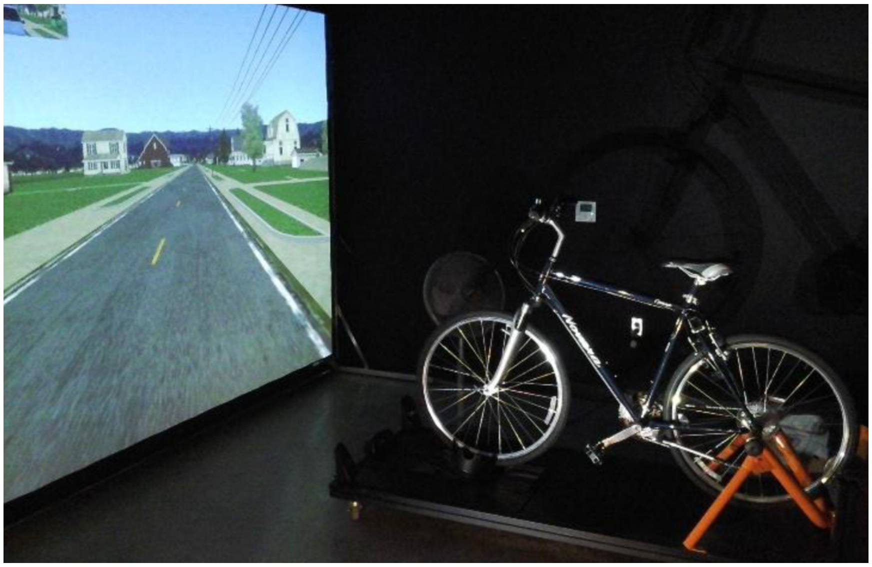

Figure 1. Calibrated Oregon State bicycle simulator.

speed to emulate the performance of a bicycle. The simulator has two input devices: a cradle for the front wheel to capture the steering angle, and an instrumented stationary bike trainer to capture the speed of the bicycle (Figure 2). The visual field is projected on a screen in front of the cyclist, and a surround sound system provides audio. The platform is adjustable for various bicycle sizes, including a children's bike.

Methodology

Calibrating the wheel speed input between real-world and virtual bicycling will increase the validity of the bicycling simulator. Wheel speed was calibrated through an independent bike computer (Figure 2), which calculated the physical speed of the wheel based on the wheel size and a spinning magnet attached to a spoke (Figure 3). The physical speed of the wheel was transferred through the bike trainer onto a rotational sensor, which the bicycle simulator used to calculate the simulation speed.

Speed data from the bike computer were exported and compared with the speed data recorded by the simulation computer (Figure 4). Two factors, gain and tire pressure, were investigated to understand the operational interface between the bicycle and the simulator. The gain factor, embedded in the vehicle dynamics package in the simulation software, was used to calculate the wheel speed based on the angular speed from the rotation sensor input. The gain factor can be defined by the operator and used to calibrate the simulated speed measurement.

Figure 2. Bicycle computer used to collect the physical speed of the wheel.

The interface between the tire and the bike trainer effected the transfer of motion from the wheel and the input device to the computer. The tire pressure and tightness of the bike trainer on the tire are related to the amount of friction or rolling resistance. If the rolling resistance is too low, the tire will slip past the trainer, especially if the cyclist is exerting high torque. Previous research on bicycle tire pressure has found an

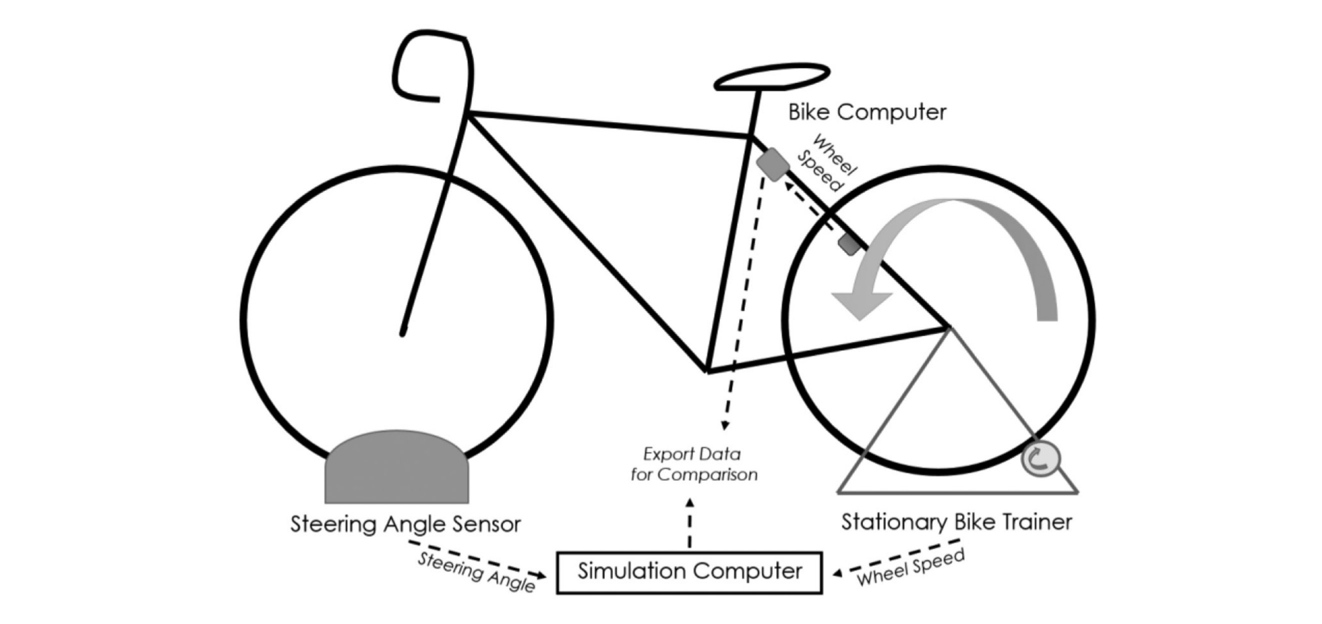

Figure 3. Wheel speed calibration diagram.

inconsistent relationship between tire pressure and rolling resistance, with tire diameter being a better indicator of rolling resistance (*4*).

Various tire pressures between 40 and 60 pounds per square inch (psi) were tested with one cyclist using consistent gearing to determine the effect of tire pressure on speed measurements. The manufacturer's recommended tire pressure for the bicycle was 50–60 psi. Higher pressure was expected to reduce slip, decreasing the variance of the simulation measurement. Equation 1 shows how the tire pressure factor and gain factor influence the simulated speed measurement.

$$\text{Speed}_{\text{Sim}} = \text{Speed}_{\text{Wheel}} * \text{Tire Pressure Factor} * \text{Gain Factor} \tag{1}$$

where

$\text{Speed}_{\text{Sim}}$ is the observed wheel speed calculated from the simulation;

$\text{Speed}_{\text{Wheel}}$ is the actual speed of the physical wheel;

Tire Pressure Factor accounts for losses caused by the tire/bike trainer interface; and

Gain Factor is a variable in the simulation for speed calibration.

Equation 2 shows the relationship between the bike computer and the wheel speed, where $\text{Speed}_{\text{Bike Computer}}$ is the speed recorded by the bike computer.

$$\text{Speed}_{\text{Bike Computer}} \approx \text{Speed}_{\text{Wheel}} \tag{2}$$

The goal was to minimize the difference between speed observations. Speed measurements of the bike computer and the simulator were converted to common units (mph), and the delta speed was calculated as the difference between the simulation speed and the bike computer measured speed, as

$$\Delta\text{Speed} = \text{Speed}_{\text{Sim}} - \text{Speed}_{\text{Bike Computer}} \tag{3}$$

To account for variations in the magnitudes of speed measurements, a ratio of the two speed measurements was used (Equation 4). The bike computer speed, which directly represents the wheel speed, was used as the denominator. Ratio values greater than one indicate overestimates of bike speed, whereas values less than one indicate underestimates. Calibration occurs as the speed ratio approaches one.

$$\text{Speed Ratio} = \frac{\text{Speed}_{\text{Sim}}}{\text{Speed}_{\text{Bike Computer}}} \tag{4}$$

The simulation computer collects data during the whole simulation, but the bike computer only collects data while the rear bicycle wheel is moving. At the startup and termination of the simulation, several seconds of data are collected that do not have corresponding bike computer data. The time series for the simulation was trimmed to make it equal to the time series of the bike computer (Equation 5). A similar process was used to trim the end of simulation data by removing all zero-speed data recorded during simulation shut down.

$$\begin{aligned}\text{Sim Time}_{\text{Modified}} &= \text{Sim Time}_{\text{Original}} \\ &- \text{Time Step of First Non Zero Speed}\end{aligned} \tag{5}$$

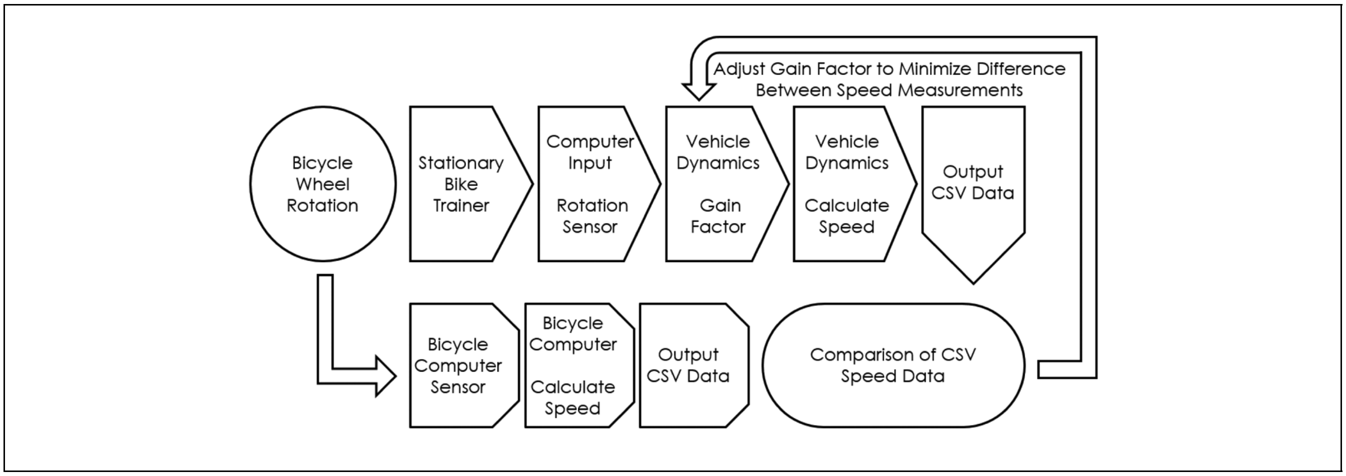

Figure 4. Flowchart of the comparison of two speed measurements.

The time intervals must be set to the same frequency. Instead of aggregating the higher-frequency simulation data, the bike computer data were disaggregated to match the higher frequency of the simulation computer. Each of the time intervals was rounded to the tenths place, and then the corresponding bike computer speed was matched to each time step. Under this framework, each bike computer speed corresponded to around 850 simulation speed measurements. This disparity in data resolution resulted in error, especially following large changes in speed. For example, when a participant stopped for a traffic signal in the simulation, the bike computer data were slow to respond to the change in speed, and then again slow to respond to the acceleration on the green indication. A potential improvement would be to use a geometric estimate of the higher resolution speeds based on the current and next bicycle computer speed measurements, as shown by

$$\begin{aligned}\text{Speed}_{\text{Est}} &= m(x - x_0) + y_0 \\ &= \frac{\text{Speed}_{n+1} - \text{Speed}_n}{\text{Time}_{n+1} - \text{Time}_n} * (\text{Time}_{\text{Est}} - \text{Time}_n) + \text{Speed}_n\end{aligned} \tag{6}$$

where

$\text{Speed}_{\text{Est}}$ is the estimated speed in the high-resolution interval;

Speed_n is the previous speed measurement (from the bike computer);

Speed_{n+1} is the next speed measurement;

Time_{Est} is the high-resolution interval;

Time_n is the previously measured interval (from the bike computer); and

Time_{n+1} is the next measured interval.

Inversely, the simulation data could be aggregated by using a moving average or a Kalman filter, to remove much of the noise and decrease the computational effort. These methods create a local average based on nearby data points, reducing data variability caused by short-term fluctuations, while maintaining the general trend of the data. A moving average formula is shown by

$$\begin{aligned}\overline{\text{Speed}_{\text{MA}}} &= \overline{\text{Speed}}_{\text{Previous MA}} \\ &+ \frac{\text{Speed}_{\text{Current Interval}}}{n} - \frac{\text{Speed}_{\text{Previous Interval}}}{n}\end{aligned} \tag{7}$$

where

$\overline{\text{Speed}_{\text{MA}}}$ is the simple moving average speed estimate;

$\text{Speed}_{\text{Current Interval}}$ is the simulation speed measurement at current time; and

n is the number of intervals included in the average.

Results

A graphical comparison of the two speed measurements was used to check the initial alignment of the data, as shown in Figure 5. Large variance between speeds followed large changes of speed because of the large difference in sampling rate, as evident around the 16,000th step when the participant stopped the bicycle. The much higher data resolution for the simulation contributed to some of the noise in the simulator speed. However, in general, the speeds followed the same trends. In Figure 5, the noise in the simulation speeds indicates that the system does occasionally over- or underestimate the speed for short durations. These events are typically very short, as the simulator records data at 85 Hz.

Tire Pressure

One participant rode the bicycle simulator while data on tire pressure were collected. In general, the ride was at least 5 min long using the same gearing for each run.

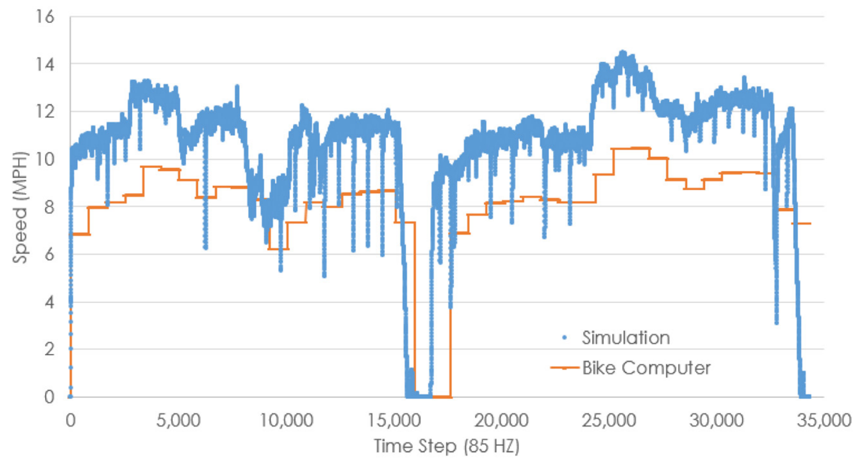

Figure 5. Comparison of speed data from typical participant.

Figure 6. Digital tire pressure gauge during tire pressure analysis.

The tire pressure of the rear tire was set at 40 psi and increased by 5 psi increments up to 60 psi. A digital tire pressure gauge was used to ensure accurate pressure measurements, as shown in Figure 6.

Figure 7 shows the distribution of speed ratios for each tire pressure. A speed ratio of one indicates that the bike computer speed and the simulator speed were perfectly calibrated. The high variance for the 40 and 55 psi data was caused by the low bike computer speeds during the startup and termination portions of the run. During these 10-s intervals, the bike computer speed was much lower than the simulation speed, resulting in large speed ratios. Although the speed ratio means were similar, an analysis of variance (ANOVA) test indicated that they were statistically different (F value 1165.75, $P < 0.000$). A Tukey honest significant difference (HSD) test was used for multiple comparisons of the tire pressure, with all pairs except 45 and 50 psi ($P = 0.711$) being statistically different. This result indicates that tire pressure had a statistically significant influence on the speed ratio.

Descriptive statistics for the various tire pressure speed ratios are shown in Table 1. The speed ratios indicate the relative difference in measured speeds. For example, with a tire pressure of 40 psi and a bike computer speed of 10 mph, the simulator speed mean would be 13.49 mph. The lowest speed ratio corresponded to 40 psi, indicating that the simulator and bike computer were most calibrated at this tire pressure.

Gain Factor

Various gain factor settings were tested to analyze the effect of the gain factor on simulator speed. A single participant rode for 300 s at each setting, using the same gearing and tire pressure for all runs. The participant pedaled the bike to a steady-state speed before the simulation began to minimize variance during the startup period. The steady-state speed was maintained through the end of the simulation to reduce variance further.

Tire pressure was set to 60 psi during the gain factor analysis. This tire pressure is not the optimal tire pressure determined in the tire pressure experiment. Both data sets were collected before the data were analyzed, and it was incorrectly assumed that the higher tire pressure would reduce the slip the most. The factors were tested independently, however, and it is not expected that a significant interaction between the factors exists, as one is a physical relationship and the other is a software setting. The final

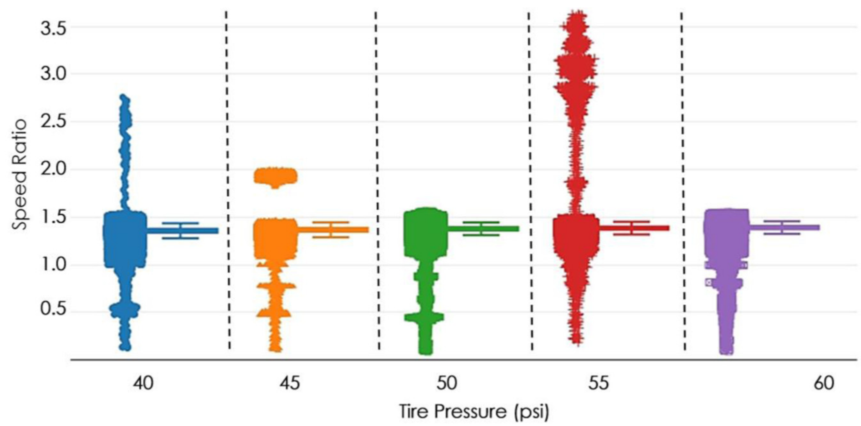

Figure 7. Distribution of speed ratios for each tire pressure.

Table 1. Descriptive Statistics for Various Tire Pressure Speed Ratios

Tire pressure	*N*	Speed ratio mean	SD	SE	95% CI Lower	95% CI Upper	Min	Max
40	35,375	1.349	0.0869	0.000462	1.349	1.350	0.1233	2.757
45	47,882	1.368	0.0990	0.000452	1.367	1.369	0.0975	1.998
50	39,332	1.369	0.0772	0.000389	1.368	1.370	0.0841	1.567
55	32,220	1.420	0.2854	0.001590	1.417	1.424	0.1846	3.626
60	34,964	1.380	0.0831	0.000444	1.379	1.381	0.0914	1.549
Total	189,773	1.376	0.1439	0.000330	1.375	1.376	0.0841	3.626

Note: SD = standard deviation; SE = standard error; CI = confidence interval; Min = minimum; Max = Maximum.

Table 2. Gain Factor Settings and Speed Ratio Descriptive Statistics for Each Simulation Run

Gain factor	*N*	Speed ratio mean	SD	SE	95% CI Lower	95% CI Upper	Min	Max
0	23,487	−3.1E-7	3.44E-5	2.25E-7	−7.5E-7	1.29E-7	−0.003	0.002
0.1	22,556	0.995	0.140	0.00093	0.993	0.996	−6.88E-7	1.275
0.1	22,837	0.975	0.126	0.00084	0.973	0.976	−2.43E-8	1.252
Default*	22,147	1.585	0.194	0.00130	1.582	1.587	−8.12E-9	1.894
0.2	21,651	2.070	0.244	0.00166	2.066	2.073	−2.26E-8	2.391
1	23,487	8.190	3.191	0.02082	8.149	8.230	−9.454	11.792
Total	136,165	2.328	3.056	0.00828	2.311	2.344	−9.454	11.792

Note: SD = standard deviation; SE = standard error; CI = confidence interval; Min = minimum; Max = Maximum.
*Default gain factor is 0.15707963267949.

calibration using 40 psi should be even more accurate than described here.

Table 2 shows the various gain factor levels and descriptive statistics for each of the runs. An ANOVA analysis indicated that the differences between gain factors were statistically significant (F value $= 115845$, $P <$ 0.000). A Tukey HSD test indicated that each of the factors was significantly different except for the two 0.1 runs. The slightly different speed ratios with the same gain factor of 0.1 were evidence of random system variability. Setting the gain factor to zero reduced the simulation speed of the bicycle to zero, and setting the gain

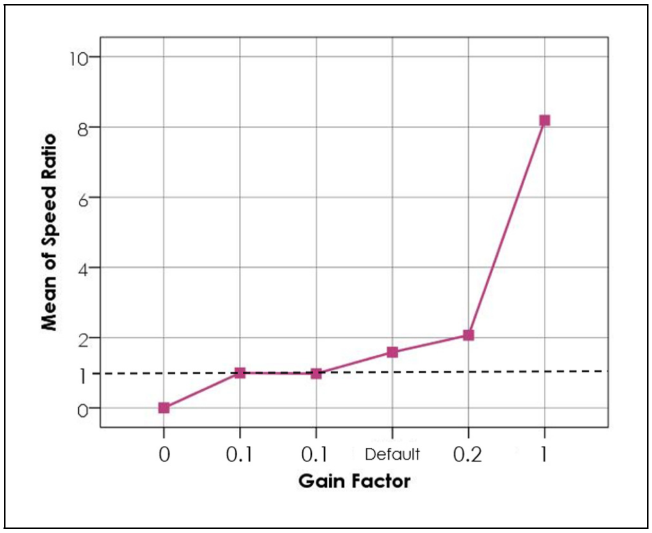

Figure 8. Speed ratios for each gain factor (speed ratio of one corresponds to proper calibration).

factor to one dramatically increased the simulation speed of the bike (8.19 times faster than the real speed of the wheel). With a gain factor of one, the simulated bike would reach speeds of 65 mph, and then become unstable and crash with any steering input. Setting the gain factor to 0.1 produced the most calibrated results, with the simulated speed within 97.5% to 99.5% of the bike computer speed.

Figure 8 graphically shows how the gain factor relates to the speed ratio from the data in Table 2. The *X*-axis shows the values that were tested during the sensitivity experiment, which should be interpreted as categorical variables. Theoretically, any speed ratio could be achieved by adjusting the gain factor; therefore, a solid line was used between the data points. The target value was a speed ratio of one, as this was the indicator of good calibration. During the experiment, the gain factor was adjusted following the principles of Newton's Method, adjusting the value in an iterative fashion to approach the goal of a speed ratio of one. Additional steps could have been performed (0.095 or 0.15), but 99.5% was determined to be acceptable for demonstration purposes.

Conclusions

Bicycle simulator studies provide an experimental framework to evaluate novel and existing infrastructure and human factors while controlling for environmental factors and reducing risk to participants. Calibrating the inputs of the bicycle simulator improves the authenticity of the user experience. The calculated speed of the rear wheel was compared with an independent speed observation from a bike computer to minimize the difference between measurements. Calibrating the observed simulator speed and the actual speed of the bicycle wheel should make the simulation more representative of real cycling, thereby improving the user's experience and the applicability of the results.

The speed ratio, or the simulated speed divided by the bike computer speed, was used to evaluate the influences of tire pressure and gain factor. Various tire pressures were tested based on the manufacturer's recommended tire pressure range, with 40 psi having the most accurate and statistically significant speed ratio measurement. A gain factor of 0.1 brought the simulation to within 99.5% of the bike computer speed, indicating good calibration. The calibration could be further improved by additional refinement after testing tire pressures outside of the manufacturer's recommendations and additional gain factor settings.

The general procedure describe here can be applied to other bicycling simulators around the world. The use of a commercially available bike computer allows for the comparison of simulator speeds against an independent speed measurement. The calibration of speed measurements could increase the repeatability of experimental data across different simulators. The speed ratio framework enables discussion of the difference between the real speed of the bike and the simulated speed, which is especially important when validating simulator results to real-world experiences.

Future Research

The experiment as described only explored the steady-state speed, to minimize speed variance. Evaluating acceleration or deceleration would be difficult using the current bike computer because of data resolution, as the system only records data every 10 seconds. Acceleration events are likely to be much shorter than this interval. Deceleration events are a potential performance measure during experimentation, as they reflect braking as a response to simulated conflicts. These events could be used as a measure of reaction time, specifically involving stopping situations. The calibration effort only focused on speed, but speed is a fundamental property of any human-in-the-loop simulator.

This research creates a standard procedure for bicycle simulator speed calibration. Applying this methodology to other bicycle simulations will help to improve fidelity of bicycling simulation in general, as speed measurements will have a common calibration procedure. The future of this research thread includes applying this procedure to other bicycle simulators, developing a procedure to analyze the calibration of steering input through observation of visual latency, and validation studies to match simulator performance to field experiments.

Future research for validation of the simulator will help to answer questions about the human perception of the simulation. The focus of this research was to calibrate the calculated speed of the simulator to a physical measurement of the speed of the wheel, rather than to calibrate the human perception of speed. The implication is that a calibrated simulator will better emulate the real-world experience. However, because of the relative validity of simulation research, the participant's perception of the simulation speed is arguably at least as important, if not more so. Because of the limits of what sensor information can be presented in a simulator environment, the simulator may seem much faster or slower to participants than the real-world experience. Therefore, a study of user perceptions of bicycling simulation should be performed with the research question, "Does the bicycle simulator match user expectations from riding a real bicycle?" This feedback mechanism should be used to validate the simulator to match user expectations.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Horne, Hurwitz; data collection: Horne; analysis and interpretation of results: Horne, Ghodrat Abadi; draft manuscript preparation: Horne, Ghodrat Abadi, Hurwitz. All authors reviewed the results and approved the final version of the manuscript.

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The Users Performance Section (AND00) peer-reviewed this paper (18-02150).