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Relating Subjective Ride Quality Ratings to Objective Measures

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Abstract

Agencies have long used subjective roughness ratings from panels of users to inform policy development on road maintenance strategies. The commoditization of electronics motivated the development of more objective, automated, and cost-effective measurement technologies. Consequently, there has been an explosion of ensemble measurements using smartphones or connected vehicles. Nevertheless, agencies have no means of relating those sensor-based measurements to their customary linguistic scale of human perceived roughness levels. This research relates subjective ratings of roughness from regular passengers of public bus transit to simultaneous smartphone-based objective measures of roughness. The findings are that regular bus riders consistently distinguished between the extreme values of measured roughness but not the intermediate values. Ratings are also less distinguishable for smoother rides than for rougher rides. The experiments also reveal a phenomenon of *roughness acclimation* that leads to biased ratings from regular users of a road segment.

Keywords: bus ride quality; connected vehicles; panel ratings; road profilers; road roughness

Declaration of Interest: None

1 Introduction

Transportation agencies use ride quality ratings to inform policy development on road network maintenance from resurfacing to replacement. Prior to the introduction of objective measures such as the international roughness index (IRI), agencies used panel ratings of ride quality based on the subjective opinions of users deemed to be experts (Gillespie, Sayers, & Queiroz, 1986). For instance, agencies used a present serviceability index (PSI) to represent a present serviceability rating (PSR) based on the ride comfort experienced across pavements of varying condition. However, with the introduction of technologies to measure pavement roughness, agencies began to transition away from expert panels to reduce expenses and inconsistencies. Manufacturers progressively introduced new equipment to improve the consistency of IRI data but even so, the reporting methods were inconsistent among agencies (Múčka, 2017). Consequently, agencies began to develop mathematical relationships to predict their familiar linguistic categories of perceived roughness from the IRI measurements. Even so, the considerable extent of the road network and high traffic volumes hindered practical IRI assessments. Also, agencies could not afford to more frequently monitor pavement roughness because of the relatively prohibitive cost of specialized vehicles such as inertial profilers.

To find more affordable solutions, researchers recently began to investigate the viability of combining measurements from smartphones or connected vehicles (Bridgelall, et al., 2020). However, such approaches can produce large measurement variations because of differences in device sensitivity, orientation, and placement (Medina, Salim, Underwood, & Kaloush, 2020). Future connected vehicles offer the potential to reduce such measurement variations by adopting standards and methods of calibration. In anticipation of achieving standardized objective roughness measures from future connected vehicles, agencies will still need to know how those measures relate to roughness levels perceived by human riders.

The **goal** of this research, therefore, is to relate a recently proposed objective measurement of ride quality using smartphones to subjective ratings from the traveling public. The experiments used five different bus route segments to evaluate the extent that the traveling public could perceive objective differences in the ride quality. The experiments associated the roughness measured for each trip with responses from a corresponding ride quality survey. Bus riders rated their perceived ride quality within one of five linguistic categories ranging from "very smooth" to "very rough." Hence, the **contributions** of this research are:

1) A direct comparison of how subjective ride quality ratings from public transit users correspond to the objective values of ride roughness measured.
2) Show how trends in the association of measured and perceived roughness levels uncovered the phenomenon of roughness acclimation.

The organization of the remainder of this paper is as follows: Section 2 reviews the literature on ride quality assessments and evolution. Section 3 discusses the method used to objectively measure ride quality using a smartphone, the data collection setup, and the ride quality survey. Section 4 displays the results through a series of statistical charts and tests. Section 5 discusses the implications of the results and the main findings. Section 6 concludes the study, offers considerations for replicating the work, and hints at future work.

2 Literature Review

Early methods of ride quality assessment surveyed panels of experts to report roughness levels on a subjective rating scale (Faris, BenLahcene, & Hasbullah, 2012). However, an early investigation of ride quality rating scales found that there was widespread disagreement on comfort criteria based on g-forces and vibration frequency (Dempsey, Coates, & Leatherwood, 1977).

To improve the consistency of rating ride quality, Nick and Janoff (1983) were among the first to develop models to predict subjective ratings from objective measurements of profile roughness (Nick & Janoff, 1983). They found that with careful instructions, the mean subjective ratings were directly proportional to the mean measurements of roughness using a Mays ride meter. The R^2 of their regression models were greater than 0.91. Their finding also highlighted that, to achieve high accuracy and consistency, the development of useful regression models requires the use of expert raters. With this understanding, Janoff (1986) later introduced a “ride number,” which related objective measurements of a physical profile roughness to a subjective rating scale of repair needs. However, the method limited assessments to pavement profile frequencies between 0.125 and 0.630 cycles per feet (Janoff, 1986). As new methods of physical profile measurements evolved, transportation agencies began to update their regression models. For example, in 1986, the Texas Department of Transportation (DOT) regressed panel ratings on measures of the root-mean-square of vertical acceleration (RMSVA) to update its present serviceability index for pavements (Nair & Hudson, 1986). In addition to roughness measurements, some condition indices also incorporate measurements of structural factors and transversal unevenness (Ruotoistenmäki & Seppälä, 2007).

The need for a global standard of ride quality assessment emerged, which resulted in the International Roughness Index (IRI). The IRI emerged as the most widespread measure of ride roughness; it measures the accumulation of absolute vertical profile displacement (Gillespie, Sayers, & Queiroz, 1986). Even so, agencies around the world specify the IRI differently (Múčka, 2017). In fact, Liu et al. (1999) found that subjective ratings based on the ride number did not correlate well with the IRI based on a regression R^2 of only 0.62 (Liu, Gazis, & Kennedy, 1999). Their explanation was that humans are more sensitive to “jerk” motions due to changes in vertical accelerations rather than accumulated vertical displacements. In agreement, Yu et al. (2006) later found that jerk, which is speed sensitive, can be a better predictor of subjective roughness ratings (Yu, Chou, & Yau, 2006). With the development of many different scales of perceived ride comfort, Loprencipe et al. (2017) found that they could lead to different ride quality assessments for the same pavement (Loprencipe & Zoccali, 2017).

Although it is not the focus of this research to study the various sources of ride roughness and how they relate to pavement condition, it is helpful for readers to understand that variations in vehicle speed, suspension system design, route geometry, and driving behavior such as abrupt accelerations, braking, and sharp turning can produce varying degrees of ride roughness even when traversing the same pavement segment (Loprencipe, Zoccali, & Cantisani, 2019). For example, Wåhlberg (2006) found that driver training to operate buses for greater fuel efficiency also resulted in more comfortable passenger rides (Wåhlberg, 2006). Maternini & Cadei (2014) found that the increased accelerations from traversing roundabouts also reduced the levels of ride comfort (Maternini & Cadei, 2014). In related works, Zhao et al. (2016) applied the ISO 2631 standard to measure bus ride comfort using smartphones, but the results were not consistent without signal filtering and spatial transformation (Zhao, Guo, & Zeng, 2016). Barabino et al. (2019) developed a new scale to evaluate bus driving style by using the ISO 2631 standard (Barabino, Coni, Olivo, Pungillo, & Rassu, 2019).

More recently, new methods to objectively measure ride quality with smartphones and crowdsourcing has emerged (Medina, Salim, Underwood, & Kaloush, 2020). Loprencipe et al. (2021) found that inertial measurements correlated well with typical pavement roughness indices

(Loprencipe, de Almeida Filho, de Oliveira, & Bruno, 2021). Such methods extend beyond road pavements to include railways (Rodríguez, Sañudo, Miranda, Gómez, & Benavente, 2021). Recently, Bridgelall (2022) introduced a composite roughness index (CRI) to characterize roughness from multidimensional movements along any path, including linear and rotational motions (Bridgelall, 2022). This work accessed and used the data from the Bridgelall (2022) experiments.

Despite the proliferation of studies that use smartphones to collect roughness data, there are some important limitations. For example, different smartphone brands and models produce different results because of variations in the sensitivity of their embedded sensors. Hence, Yang et al. (2020) discussed methods to calibrate smartphones for more consistent measures of roughness (Yang, Hu, Ahmed, Bridgelall, & Huang, 2020). Crowdsourcing will also produce large variations in measurements because of the wide variety of smartphone brands and models used, differences in their accelerometer sample rate, and the uncontrollability of their placement and orientation in vehicles.

3 Methodology

The methodology was a two-step process. It involved using the same smartphone to collect objective roughness data while surveying individual bus riders to rate the roughness of each bus ride. The next three subsections describe the roughness index used, the data collection, and the linguistic categories used to characterize the level of roughness experienced.

3.1 Roughness Index

The measurements used the CRI introduced by Bridgelall (2022) because it is the only index that accounts for roughness produced by the three linear and three angular dimensions of motion (Bridgelall, 2022). Accelerations along the linear dimensions produce roughness in the lateral, longitudinal, and vertical directions whereas accelerations in the angular dimensions can produce discomfort such as head tossing, swaying, or other rotational motions.

The measure uses a RIF-transform to compress g-force units per meter of travel distance for each of the six roughness components. The formula is

$$R_g^L = \sqrt{\frac{1}{L}\sum_{n=0}^{N-1}|g_n v_n|^2 \Delta t_n} \quad (1)$$

where g_n is the g-force sampled by the embedded smartphone inertial sensor. v_n is the vehicle speed sampled by the embedded smartphone speed sensor. Δt_n is the time interval between recording samples of those sensor signals. L is the traversal distance window size for compressing the measured signals with a RIF Transform to produce an average g-force experienced (in one of the six roughness dimensions) per unit of travel distance L. N is the number of signal samples taken within each distance window and n is the sample index. Per the Bridgelall reference, the interpretation of RIF-index R_g^L is the average g-force experienced in one of the six roughness dimensions specified after traveling a distance L along the traversal path. As described by Bridgelall (2022), the composite measure is the resultant roughness R_T^L experienced as

$$R_T^L = \sqrt{(R_x^L)^2 + \left(R_y^L\right)^2 + (R_z^L)^2 + \left((R_w^L)^2 + \left(R_p^L\right)^2 + (R_r^L)^2\right)^2} \quad (2)$$

where R_x^L, R_y^L and R_z^L are the RIF-indices of roughness in the lateral, longitudinal and vertical directions, respectively. Similarly, R_w^L, R_p^L, and R_r^L are the RIF-indices of roughness due to changes in yaw, pitch, and roll, respectively.

3.2 Roughness Data Collection

Bridgelall (2022) simultaneously collected CRI measurement data and ride quality survey responses from bus passengers. For consistency, the same smartphone (iPhone® 6S) collected the data to produce the CRI values for all bus rides. The smartphone used a free app called PAVVET that provided data files with samples of the variables g_n, v_n, and Δt_n for computation of the RIF indices offline (Yang, Hu, Ahmed, Bridgelall, & Huang, 2020). The setup was identical on each bus; sticky tape secured the smartphone flat onto the center seat. That is, an identical setup that used both the same smartphone and app assured data consistency. There were at least 30 data collection sessions per route segment, which amounted to a total of 164 data collection sessions across all route segments. A total of 18 different buses traversed the five different route segments. The setting was Fargo, North Dakota in the United States. The labels for the routes were EM (from Essentia Hospital to the Mall), SG (from Sanford Hospital to the Ground Transportation Center), UG (from University Drive to the Ground Transportation Center), MW (from the Mall to Walmart), and WM (from Walmart to the Mall). Bridgelall (2022) provides further details of the data collection, setup, and route map in his paper describing the nature of the CRI (Bridgelall, 2022), so this paper does not repeat those.

3.3 Roughness Surveys

At the end of each trip, research personnel handed out a simple survey that asked respondents to rate the roughness of the bus ride into one of five linguistic categories: 1: “very smooth,” 2: “smooth,” 3: “neutral,” 4: “rough,” and 5: “very rough” without providing any further instructions. Hence, the survey reflected the subjective opinions of regular bus riders rather than those of ride quality experts. Road unevenness, bus operator controls, and variations in the suspension system performance were the main sources of roughness variations within and across route segments. Therefore, every bus ride produced a different level of roughness that the riders rated subjectively, and the device simultaneously measured objectively.

4 Results and Discussions

There were 334 survey respondents across all route segments. Figure 1 is a box plot that summarizes statistics of the CRI measurement from each of the five route segments. The box plot shows several statistics simultaneously—the mean (blue vertical line with gray vertical line extended to the horizontal axis), median (yellow vertical line), standard deviation (blue horizontal solid line), mid-quartiles (blue box from the 25th percentile to the 75th percentile), and data extent from the minimum to the maximum values (blue horizontal dotted line), as labeled. It is evident that the distributions of the measured CRIs for each route segment overlapped. For example, there were large overlaps in the standard deviations of the CRI distributions from route segments UG and WM, and SG and EM. However, a statistical test revealed that the mean roughness across each route segment was different. With an analysis of variance (ANOVA) F-statistic of 6.703 and a p-value of 0.004, the statistical test rejected the null hypothesis that the distribution means were the same. That is, the mean CRI for each route was significantly different in a statistical sense, which meant that the objective ride quality was also different.

Figure 2a shows the rating category distribution of the survey responses for each route segment. Figure 2b shows the corresponding proportion of all respondents for the rating categories in each route segment.

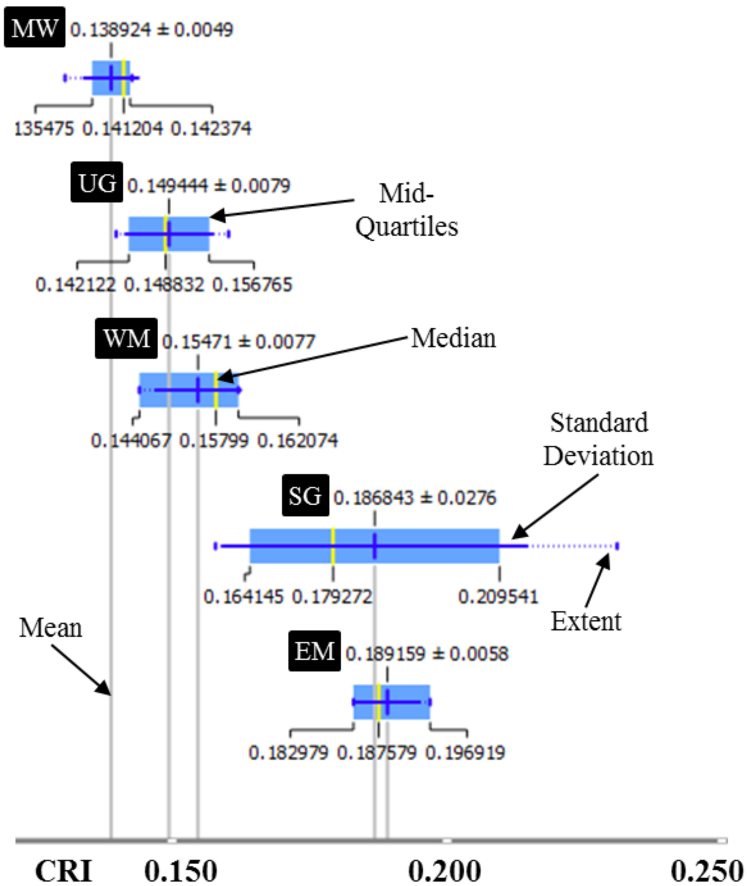

Figure 1: Box plot of CRI measurements for each route.

There was a mix of roughness levels perceived for each route, but their distributions were different. Most respondents rated their ride as "smooth" across all route segments. The proportion of respondents rating the ride as "rough" increased in correspondence with the mean CRI value for each segment. Conversely, the proportion of respondents rating their ride as "very smooth" decreased with increasing mean CRI value for each segment. No one rated a ride as "very rough" for any of the segments.

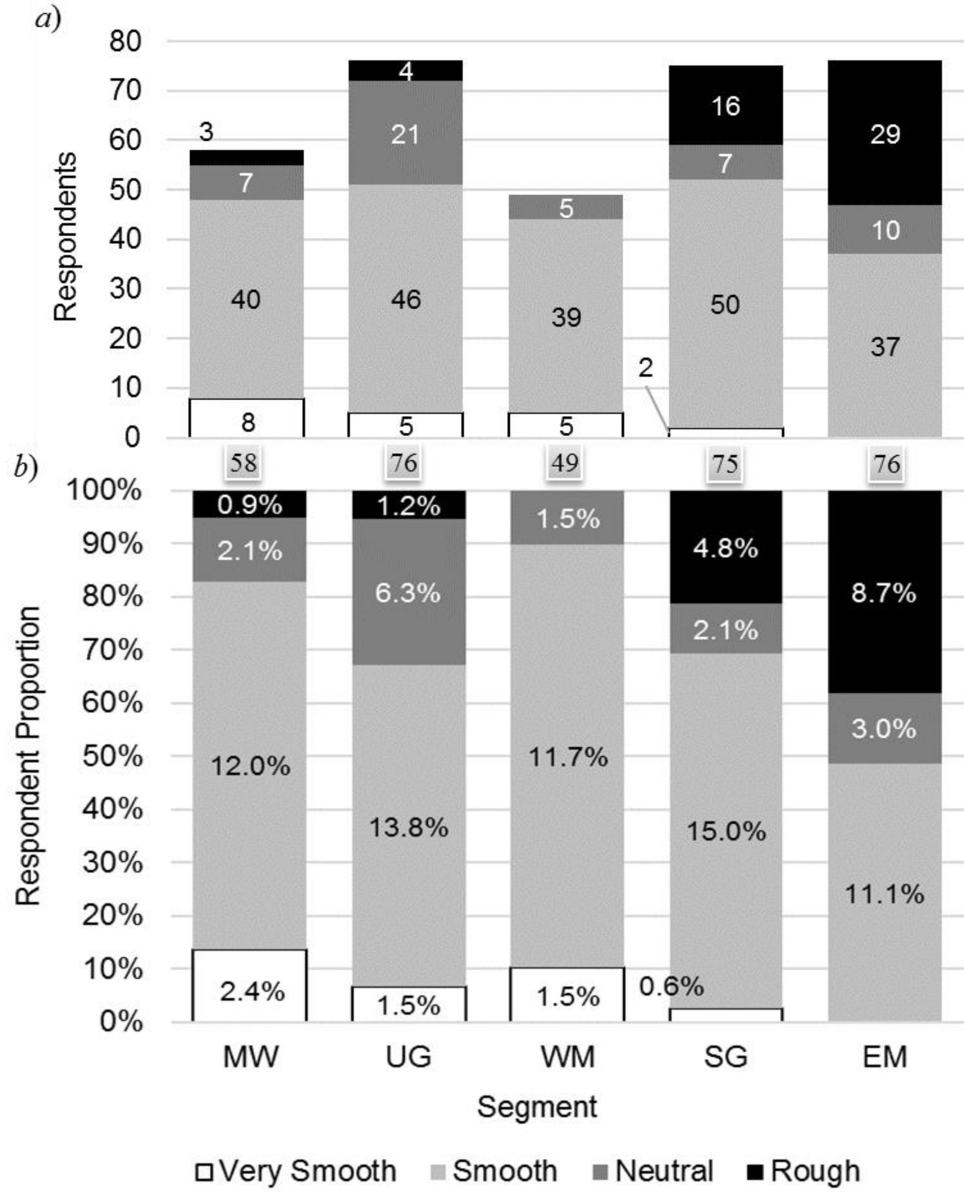

Figure 2: a) Number and b) proportion of respondents by segment and rating category.

Figure 3 is a box plot of the CRI measurements associated with each of the rating categories across all segments. Table 1 summarizes the results of the associated ANOVA or t-tests, which rejected the hypothesis that the CRI means are indistinguishable, except for the case between “smooth” and “neutral” ratings where the p-value is much greater than 0.05.

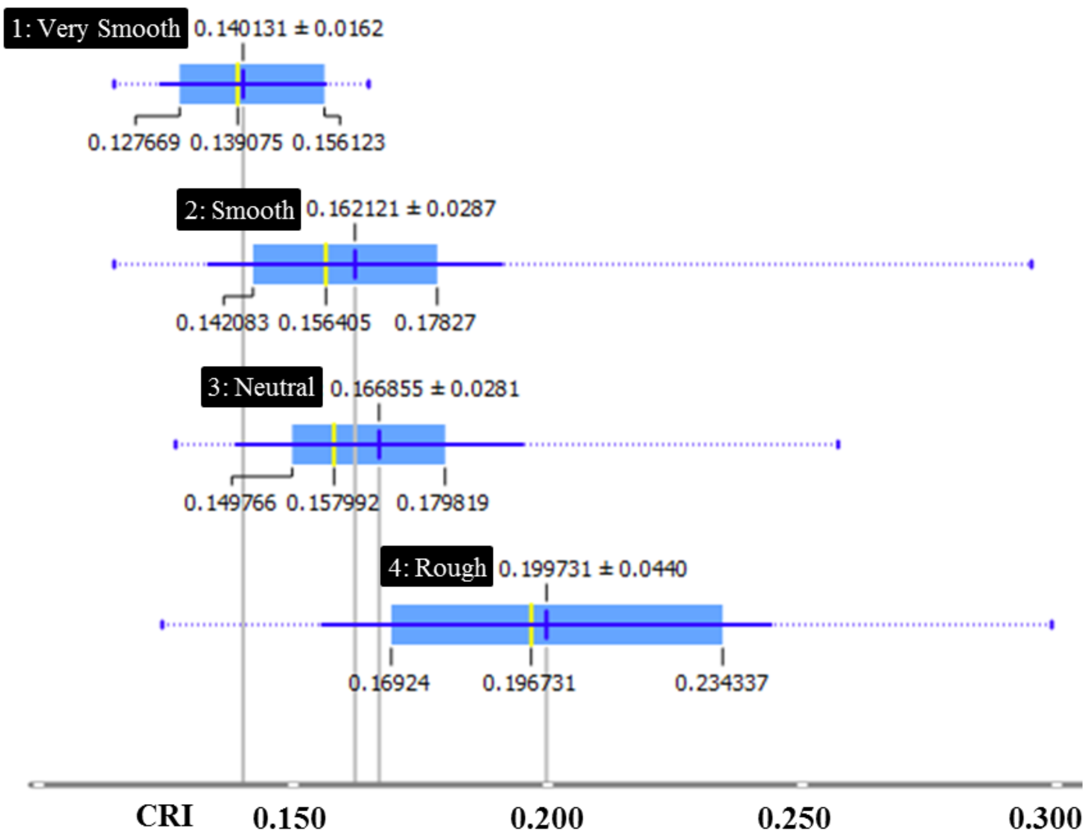

Figure 3: Box plot of CRI measurements associated with each category of roughness rating.

Table 1. Statistical Tests for Distinguishability of Distribution Means

ANOVA or T-Test	F-Statistic	p-value	H0: Series means are indistinguishable
Distributions 1, 2, 3, 4	25.776	0.000	Reject
Distributions 2, 3	1.067	0.289	Cannot reject
Distributions 1, 2, 4	37.532	0.000	Reject
Distributions 1, 3, 4	24.198	0.000	Reject

This result suggested that in general, riders associated both “smooth” and “neutral” ratings with nearly the same range of measured CRI values. There is a distinct separation of CRI distributions between the “very smooth” and “rough” ratings. The mean CRI value for the combined “smooth” and “neutral” distributions of 0.165 is a suitable threshold that clearly distinguishes between “very smooth” and “rough” ratings. Hence, agencies can conduct similar experiments with their own unique sensor setup and vehicle to produce similar statistics that reveal a distinguishing CRI threshold above which their particular application of ride quality assessment may warrant further scrutiny.

Figure 4a plots the average CRI measured for each route segment and Figure 4b plots the average CRI associated with each rating category of ride quality. For the two roughness routes of EM and SG, the trend is monotonically increasing mean CRI values with categories of increasing roughness perception. The trend is not as consistent for the smoother routes of MW, UG, and WM. For the MW and WM segments, there was no significant difference in the average CRI values associated with the “smooth” and “neutral” categories. The trends were nearly the same for the smoother UG and WM segments. This suggests that the perception of roughness differences for the lower CRI values measured might be less discernable.

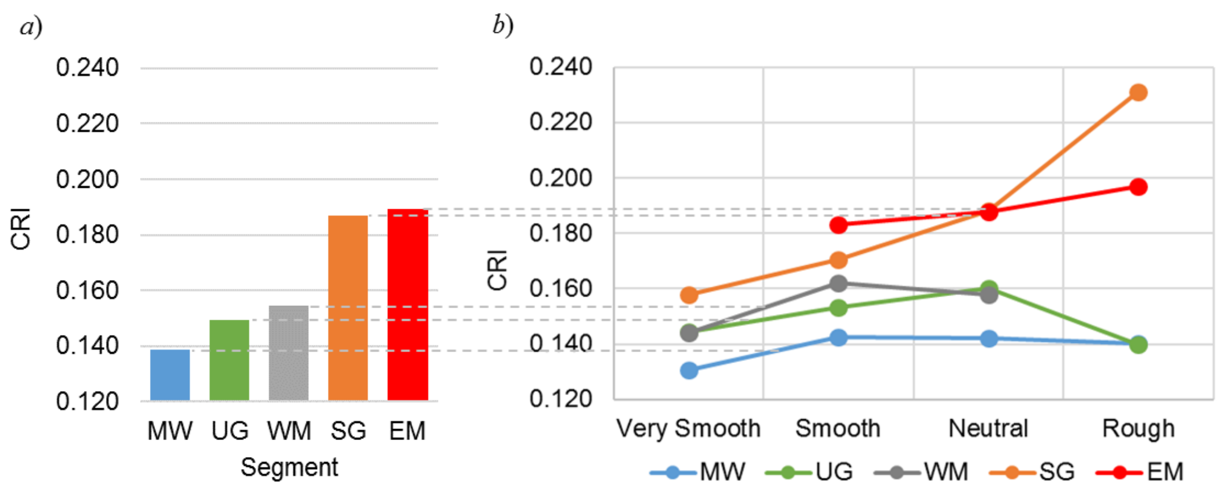

Figure 4: Average CRI a) by route segment and b) average CRI associated with each rating of ride quality.

There was an anomaly for the MW and UG segments where the average CRI associated with the “rough” rating was lower than those of all the other rating categories. However, this result was likely due to an extreme rating by a small minority because only seven riders (Figure 2a) rated those two segments in the “rough” category. There were no ratings for “very smooth” on the EM segment, which was the roughest segment based on the objective CRI measurements.

There were also no ratings for “rough” on the WM segment, which was approximately 23% less rough than the roughest route segment based on the average CRI value measured.

Across all route segments, riders clearly distinguished between the extreme values of measured roughness with ratings of “very smooth” and “rough” rides. However, riders associated the intermediate values of measured roughness as either “smooth” or “neutral” without a statistically clear distinction between their mean values. These results suggest that the traveling public can more consistently perceive differences in ride quality when the overall ride is rougher than when it is smoother. This result parallels the physics of signal detection. That is, it becomes more difficult for a receiver to distinguish between the amplitudes of a weak signal that is also noisy than it does for a stronger signal that has the same amount of noise as the weaker signal.

An interesting finding was that the average CRI within each roughness rating category consistently increased in accordance with increasing overall route roughness. For example, the average CRI measured for the “rough” category increased by 64% from 0.140 for the smoother MW and UG segments to 0.230 for the rougher SG segment. That is, for the smoother routes, ratings of “rough” corresponded to much lower CRI values measured than for those of the roughest route. The pattern repeated for all the other rating categories, albeit the proportional increase was less. This result suggested that there was “roughness acclamation” such that the threshold of roughness perception increased as the route segments became rougher. The roughness acclimation phenomenon suggests that using the traveling public to obtain subjective assessments of ride quality could lead to non-uniform ratings and significant biases across different road segments.

5 Conclusions

The measurement of ride quality for the entire road network is an important but expensive endeavor for transportation agencies in any nation. Over the years, methods to assess ride quality evolved from the subjective ratings of expert panels to their association with objective values derived from new measurement technologies. Both the subjective rating scales and the objective means of ride quality measurements varied and evolved over time. The emergence of connected vehicle technology presents a new opportunity to enact policies and standards for measuring the ride quality of all road networks, automatically and continuously. Hence, it is important to examine the relationship between such objective measures of ride quality and the levels of roughness perceived by the traveling public.

To emulate measurements from connected vehicles, this research used a smartphone on board buses to measure roughness from multidimensional motions and surveyed the riders to rate their ride quality into linguistic categories of roughness. The main policy considerations are that while the objective measurements of ride quality were distinguishable among different road segments, the corresponding subjective measurements were only distinguishable in the extremes of perceived roughness levels. That is, the traveling public was able to consistently distinguish between "very smooth" and "rough" rides but not rides with intermediate levels of roughness. In general, the ability of riders to distinguish among roughness categories becomes easier as the road segments become rougher.

Another important policy consideration is that roughness acclimation exists in ride quality ratings. That is, regular riders of a rough route appear to become acclimated to the ride quality and have an elevated threshold of roughness perception relative to riders of a smoother route. Hence, potential policies to replace expert panels with regular riders, perhaps by using app-based surveys, should consider this phenomenon because it can lead to non-uniform, inconsistent, and biased results. Policymakers need to be aware that using smartphones can result in large variations in roughness measurements. Furthermore, measurements of roughness that utilize onboard inertial sensors account for perturbations due to driver behavior as well as road geometry and surface irregularities. Therefore, a limitation is that when the application is to isolate roughness due only to roadway anomalies, the analyst must separate the signals from each accelerometer direction, process them separately, and interpret them accordingly. Policies to enable connected vehicle measurements of ride quality should consider the standardization of sensor location, orientation, calibration, and sample rate to provide consistent ride quality evaluations. Future work will use the same method to compare the CRI of railroads with hi-rail personnel ratings to improve maintenance planning and decision making.

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