A Comfort Measuring System for Public Transportation Systems Using Participatory Phone Sensing *

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ABSTRACT

Participatory phone sensing is a new sensing paradigm that asks volunteers to contribute their phones' sensing capabilities and gather, analyze, and share local knowledge about their surroundings. While most existing participatory phone sensing systems are standalone structures without cross-system integration, in this study, we propose a novel Comfort Measuring System (CMS) for public transportation systems. CMS exploits the GPS and 3-axis accelerometer functions of modern smart phones to measure the comfort level of vehicle rides. Then, it mashes up the sensed data with the authorized data of the public transportation system, and provides a detailed comfort statistics as a value added service. Using real data collected from a CMS deployed in Taipei City, we show that the system can achieve a high hit rate in trajectory matching of phone sensed data and the authorized bus data. Moreover, based on the statistics, we demonstrate that the system is capable of ranking the comfort levels of the bus services provided by different agencies, and monitoring the comfort levels of the transportation system overall. The system is also highly scalable without the cost of deploying a sensing infrastructure. We believe that it has the potential to provide a durable and large-scale comfort measuring service for public transportation systems.

1. INTRODUCTION

The *comfort* of rides has been identified as one of the top criteria that affect customers' satisfaction with public transportation systems, and it has been shown that *comfort* is an important consideration for passengers that use public transportation [16, 20, 21]. However, conventional comfort measuring approaches rely on either personal interviews [22] or literature surveys [19], which are generally labor-intensive and time-consuming, and are thus limited in terms of scalability and timeliness.

With recent advances in sensing technologies and mobile handheld devices, *participatory phone sensing* has emerged as a new sensing paradigm that exploits the sensing capabilities of modern smart phones to gather, analyze, and share local knowledge about the mobile phone owners' surroundings [18]. Unlike conventional sensing systems, participatory phone sensing does not rely on dedicated sensing infrastructures and the top-down model of data collection. Actually, it is more penetrative, because it supports *grassroots* sensing (i.e., the bottom-up model), and it encourages participation at personal, social, and urban levels [18].

The concept of participatory phone sensing has been implemented in a variety of real-world applications. For instance, *CenseMe* [28] uses the microphone and accelerometer of smart phones to infers users' activities and social context. Meanwhile, *SoundSense* [27] employs machine learning techniques to classify both general sounds (e.g., music and voices) and discover novel sound events specific to individual users in their daily lives. In [17], Azizyan and Choudhury propose using ambient information (e.g., microphone, camera, accelerometer, and Wi-Fi) to classify the location of a mobile phone. *Nericell* [29] employs mobile smartphones for rich monitoring of road and traffic conditions via an array of sensors (GPS, accelerometer, microphone) and communication radios. Finally, trajectory sensing applications (e.g., *Mobile Google Maps* [8], *Waze* [6], *GeoLife* [7], and *CarWeb* [2]) use the GPS of smart phones to collect users' daily life trajectories and provide different location-based services as an incentive, such as real-time traffic reporting [6, 8] and trajectory recommendation [2, 7]. However, one weakness of these applications is that they are all standalone systems without cross-domain knowledge and cross-system integration. As a consequence, they are limited in their ability to provide value-added services, and they cannot profile large-scale transportation systems as a whole.

In this study, we propose a novel Comfort Measuring System, called CMS, for measuring the comfort levels of rides on public transportation systems. The CMS system is comprised of three parts: 1) data obtained through participatory phone sensing by volunteers who sense and score their daily transportation experiences; 2) the authorized data of public transportation systems, which provides the reliable, accurate, and detailed information about vehicles in the system; and 3) a matching algorithm that mashes up the results of (1) and (2) for further analysis and statistical purposes. Using the VProbe tool [15] and the authorized bus data provided by the Taipei e-bus system [14], we deployed the CMS system in Taipei City. During a 70-day experiment, we collected 425 trajectories, labeled with vehicle identifiers, from 15 volunteers. Based on the results, we make the following observations.

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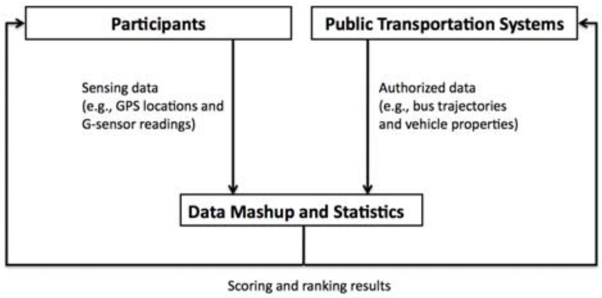


Figure 1: The architecture of the CMS system

1. The proposed trajectory matching algorithm can achieve a high hit rate of 93.7%, as long as the contributed sensing data is correct (i.e., without GPS errors) and the trajectory of the vehicle measured is included in the authorized data.
2. In Taipei City's public bus system, 4% of the bus rides are considered comfortable, 17% are uncomfortable, and the rest are in between the two extremes.
3. There is no significant difference in the comfort levels of bus services provided by different bus agencies in Taipei City; and the comfort levels vary a lot among bus services operated by the same agency.
4. Light buses are more uncomfortable than low-floor and the standard (single-decker) buses.

The remainder of this paper is organized as follows. In Section 2, we present the CMS system and a trajectory matching algorithm. In Section 3, we provide a preliminary set of experiment results for the CMS system deployed in Taipei City, and we investigate the factors that affect the comfort levels of public transportation systems in detail. We then summarize our conclusions in Section 4.

2. THE COMFORT MEASURING SYSTEM

In this section, we present the proposed Comfort Measuring System (CMS) for evaluating public transportation systems. CMS is comprised of three components: data collected through *participatory sensing by volunteers*, *authorized data of public transportation systems*, and *data mashup and statistics*, as shown in Figure 1. We discuss each component in the following subsections.

2.1 Data Collected through Participatory Sensing by Volunteers

The CMS system exploits the capabilities of modern smart phones to sense commuters' transportation experiences in a distributed and participatory manner. CMS does not rely on any particular applications, and it supports many existing smart phone applications that provide raw sensed data about *trajectories* and *vibration measures*, e.g., Dynolicious Log Box [5], MobileLogger [11], SensorLogger [13], Sensor Monitor [12], and VProbe [15].

Specifically, a trajectory is the path of a moving object (i.e., a vehicle) through space. It is usually represented by a set of discrete sample points on the path with a fixed time interval between every two contiguous data points. Each data point contains a timestamp of the sample, and its geographical location information (i.e., the latitude and the longitude).

In addition, the vibration measures contain a sequence of 3-axis accelerations collected by the G-sensor, which is a 3-axis accelerometer now available in most off-the-shelf smart phones. We let $\widetilde{a}_t^x$, $\widetilde{a}_t^y$, and $\widetilde{a}_t^z$ denote, respectively, the accelerations sensed at time t on the X, Y, and Z axes of the smart phone; then we apply the calibration algorithm proposed in [26] to calculate a_t^x, a_t^y, and a_t^z, i.e., the real accelerations at time t on the X, Y, and Z axes fixed to the center of the earth.

We let a_t denote the acceleration of the moving object estimated at time t; and following the ISO 2631 standard [24], we obtain the value of a_t by

$$a_t = \sqrt{(1.4a_t^x)^2 + (1.4a_t^y)^2 + {a_t^z}^2}, \tag{1}$$

and calculate the *acceleration level* at time t, i.e., L_t, by

$$L_t = 20 \log \frac{a_t}{a_{ref}}, \tag{2}$$

where a_{ref} is a normalization factor with a constant value equal to $10^{-5} m/sec^2$ [25]. Then, following [4], we obtain the *comfort index* at time t, i.e., C_t, by

$$C_t = \begin{cases} 1 & \text{, if } L_t \leq 83dB \\ 2 & \text{, if } 83dB < L_t \leq 88dB \\ 3 & \text{, if } 88dB < L_t \leq 93dB \\ 4 & \text{, if } 93dB < L_t \leq 98dB \\ 5 & \text{, if } 98dB < L_t \leq 103dB \\ 6 & \text{, if } 103dB < L_t \end{cases} \tag{3}$$

Finally, we calculate the comfort level of a trajectory by averaging all the C_t scores that belong to that trajectory. Intuitively, the smaller the average comfort level, the more comfortable will be the transportation experience.

2.2 Authorized Data of Public Transportation Systems

The CMS system requires the authorized data of public transportation systems, including the vehicle identifiers (i.e., license plate numbers), the vehicles' trajectories, and other miscellaneous information, such as the agency names, the types of the vehicles, and the route numbers. By using the identifier and trajectory information, the CMS associates commuters' sensed data with the authorized data (which we consider in the next subsection), and thereby enables the scoring and ranking of each vehicle in the public transportation system by outsourcing the measurement task to the crowd (i.e., exploiting participatory sensing by volunteers). Moreover, by considering other information about vehicle attributes, CMS can provide more insights into the public transportation system; for example, *Which type of vehicle is most comfortable? Which bus route is most comfortable? Which bus agency provides the most comfortable rides in the city?* In the past, gaining such insights would not have been possible without the deployment of a large-scale infrastructure.

With recent advances in GPS and wireless broadband technologies, an increasing number of major cities world-wide have implemented real-time tracking systems for their public transportation systems, e.g., Boston (MA, USA) [10], Cambridge (UK) [1], Chicago (IL, USA) [3], Seattle (WA, USA) [9], and Taipei (Taiwan) [14]; thus, they provide perfect testing grounds for the CMS system. In this study, we acquired the authorized data of the *Taipei e-bus system* and evaluated the CMS system in Taipei City. However, the CMS system can be applied in any city anywhere, as long as there are people willing to contribute sensing data and the authorized data of the city's public transportation system is available.

The *Taipei e-bus system* was deployed by the Taipei City Government in 2004. In the system, each participating bus has an on-board unit (OBU), which is a thin-client with a GPS receiver and a GPRS interface. The OBU transmits the bus's information (the bus identifier, GPS location, and status codes) to the network control center (NCC) via the GPRS connection periodically (every 15 $\sim$ 25 seconds). In 2010, the e-bus deployment involved 4,028 buses (including low-floor buses, public light buses, and standard single-decker buses) covering 287 routes and 15 operating agencies. The system covers nearly the entire greater Taipei area (i.e., Taipei city, Taipei county, and Keelung City). There are more than 180 million passenger-trips every day. Through our collaboration with the Taipei City government, we were allowed to download real-time bus data every minute. On average, there are 3,865 trajectories and 3,235,460 data points each day.

2.3 Data Mashup and Statistics

In this subsection, we present the trajectory matching algorithm, which finds the most similar trajectory in the authorized data for a given trajectory contributed by a participant. We let TP^k denote the k-th data point of the trajectory logged by the participant's smart phone ($k = 1, 2, \cdots, M$), and let TG_i^j denote the j-th data point of the i-th trajectory in the authorized data ($i = 1, 2, \cdots, G$ and $j = 1, 2, \cdots, N$). Moreover, we define $[TP^k]_i^*$ as the interpolated data point of TP^k on the i-th trajectory in the authorized data (using linear interpolation and based on the timestamp of TP^k).

Then, we define Δ_i as the *trajectory distance* between the user-input trajectory and the i-th trajectory of the authorized data. The value of Δ_i is calculated by Equations 4, where $dist(*, *)$ is a distance function that reports the Euclidian distance between the two input GPS locations. Finally, the matching algorithm finds the trajectory $\widetilde{i}$ that has the minimum Δ_i value for $i = 1, \cdots, G$, and regards the $\widetilde{i}$-th trajectory of the authorized data and the user-input trajectory record as the movement of the same vehicle. Thus, the CMS system mashes up the comfort level measurement of the user-input trajectory with the vehicle of the $\widetilde{i}$-th trajectory in the authorized data and manipulates the statistics accordingly.

$$\Delta_i = \sum_{k=1}^{M} dist(TP^k, [TP^k]_i^*) \tag{4}$$

$$\widetilde{i} = \arg\min_i \Delta_i \tag{5}$$

3. PRELIMINARY RESULTS

We now present the preliminary results of the CMS system that we deployed in Taipei City in March 2010. Figure 2 shows a snapshot of the deployed system, called TPE-CMS[1]. Using VProbe [15] as the sensing tool[2], we recruited 15 volunteers to collect bus trajectories in the city. We also asked the volunteers to label each trajectory with the vehicle identifier (i.e., the license plate number), and then used the proposed trajectory matching algorithm to compare the volunteers' labels with the matching results.

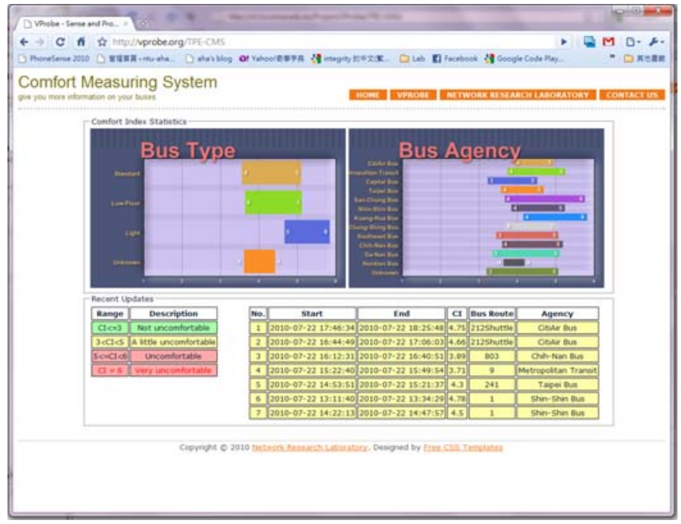


Figure 2: The screen snapshot of the TPE-CMS system

Table 1: The hit rate of the proposed trajectory matching algorithm

Results	# of trajectories	Percentage
Correct	357	84%
No bus data	41	9.64%
GPS errors	3	0.71%
Miss-matched	24	5.64%

Between March 15 and July 22, 2010, the volunteers contributed a total of 425 trajectories with labels. From the results shown in Table 1, we observe that the proposed matching algorithm can achieve a hit rate of 84% (357/425) in finding the vehicle identifier of the user-input trajectory. Moreover, when analyzing the missed cases, we found that 41 trajectories were missmatched because, according to the authorized data, the vehicles of the labeled trajectories were not in service (i.e., the OBUs were not turned on or they encountered some technical problems). In addition, 3 trajectories were missmatched because there are obvious GPS errors in the user-input trajectories. Thus, after discarding the two cases, our trajectory matching algorithm achieved a hit rate of 93.7% (357/381), which is highly accurate and favorable for the CMS system.

From the results shown in Figure 3, we observe that, among the collected trajectories, only 4% of them were described as comfortable (i.e., $C_t \leq 3.0$), 17% of them were uncomfortable (i.e., $C_t \geq 5.0$), and the rest were in between the two extremes [24]. Moreover, the results in Figure 4 show that the trajectories of bus agency 7 are relatively more uncomfortable than those of the other agencies, while

[1]TPE-CMS: measuring comfort levels of Taipei buses; http://vprobe.org/TPE-CMS/

[2]The sample rates of VProbe are 1 Hz for the GPS and 40 Hz for the G-sensor.

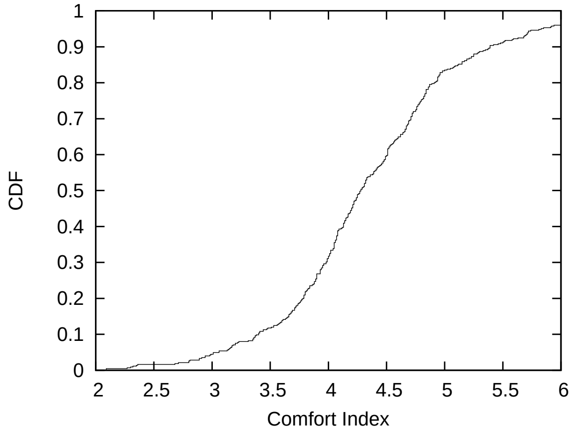
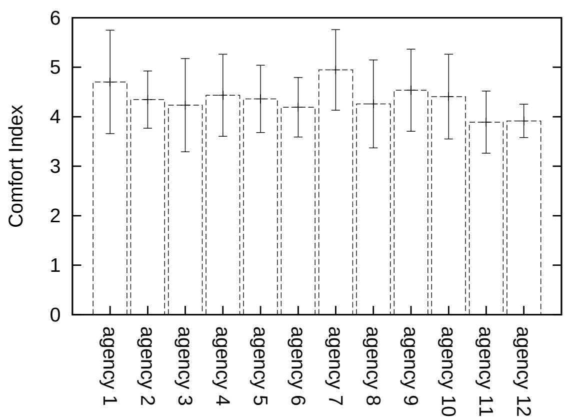
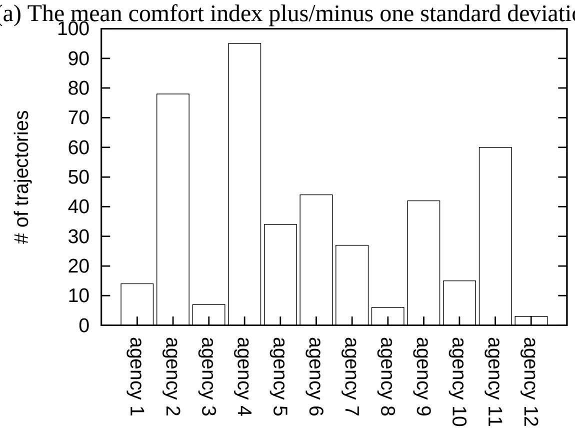


Figure 3: The CDF distribution of the comfort index among the collected trajectories



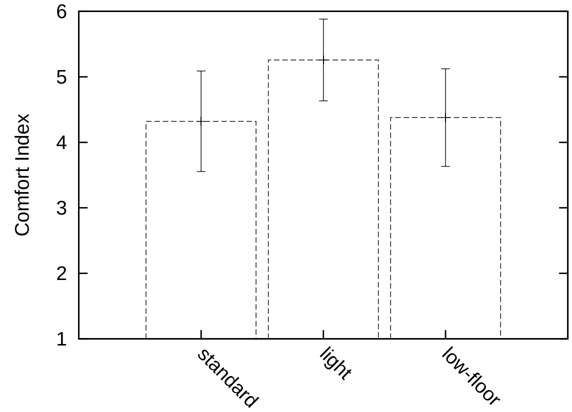
(a) The mean comfort index plus/minus one standard deviation



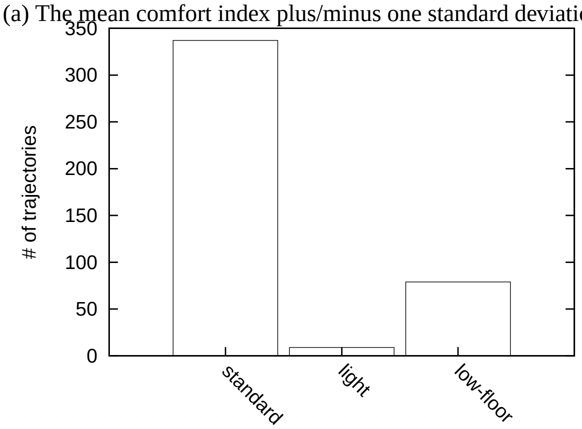
(b) The number of trajectories

Figure 4: The statistics of the collected trajectories based on the bus agencies

the trajectories of bus agencies 11 and 12 are more comfortable. We also observe that the standard deviation of the comfort index is quite large for most bus agencies. The result indicates that the comfort index of trajectories is widely spread, and that 'trajectory diversity' (i.e., the difference in the comfort index across trajectories) does exist within most bus agencies.



(a) The mean comfort index plus/minus one standard deviation



(b) The number of trajectories

Figure 5: The statistics of the collected trajectories based on the bus types

We also investigated the impact of bus types on the comfort indexes of the trajectories. The results in Figure 5 show that the trips on light buses are more uncomfortable than those on low-floor buses and standard buses. This is because the light buses serve suburbs where the routes are usually winding and the roads may not be in prime condition. Interestingly, the trajectories of low-floor buses and standard buses have similar comfort index values, which is counterintuitive to recent reports [23]. The reason is that the low-floor buses serve urban areas; thus, it is inevitable that they will stop more frequently to allow passengers to board/disembark. As a result, there are no significant differences in the comfort indexes of the trajectories of low-floor and standard buses.

4. CONCLUSION

In this paper, we propose a Comfort Measuring System (CMS) for public transportation systems. CMS exploits data collected through participatory phone sensing to measure the comfort level of each vehicle ride. It then mashes up the sensed data with the authorized data of the public transportation system to provide detailed insights into the comfort levels of vehicle rides. Using real data collected from the CMS system deployed in Taipei City, we validate the proposed trajectory matching algorithm, and show that it can achieve a hit rate of 93.7%. Moreover, based on the statistics, we show that only 17% of bus rides in Taipei are considered uncomfortable, and there are no significant differences between different bus agencies.

We also find that the comfort level varies a lot among the bus services provided by the same agency, and smaller buses are the least comfortable vehicles. Work on analyzing other factors that affect comfort levels is ongoing (e.g., road conditions, drivers' behavior, and traffic congestion). We hope to report the results in the near future.

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