Experimental Analysis of Pedestrians' Discomfort Zone for Personal Mobility Devices on the Footpath

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***Abstract*—In recent years, there is a sharp increase in the PMD (Personal Mobility Device) usage for first and last mile commute in developed nations such as Singapore. However, there is a lack of dedicated infrastructure for PMDs which forces them to share the path with pedestrians. This increases the safety risk for PMD riders as well as the pedestrians. This paper explains a practical experiment carried out to understand the reaction of the pedestrians to the PMDs. The effect of the factors such as speed of the PMD, passing distance, the gender of the pedestrians and the PMD model itself are considered in the pedestrian perception results. The results indicate that pedestrians are cautious to a newer PMD model and are more comfortable when they see a familiar PMD model. In addition to that, the effect of pedestrian gender on perception results is discussed. A sample prediction application is described which can alert the PMD riders if they are causing discomfort to the pedestrians in their path. The findings of our study validate the recent safety guidelines and speed limit regulations passed by Singapore's government for PMD users.**

***Index Terms*—personal mobility device (PMD), pedestrians, discomfort zone, footpath, perceptions**

I. Introduction

The first and last mile commute is an emerging transportation mode in the developed nations. PMDs facilitate faster and comfortable mode of transport for first and last mile commute without the hassles of maintaining an automobile. Singapore is one of the nations where commuters are accepting PMDs. However, the commuters using PMDs are a small group compared to the pedestrians. Hence, PMDs have to co-exist with the pedestrians and share the infrastructure with them. In recent years, the number of accidents caused by the use of PMDs has increased [1]. This calls for a thorough understanding of the interactions between pedestrians and PMDs. It will assist the lawmakers to pass legislation that can assure safety of everyone. Additionally, future infrastructure can be planned to safely incorporate PMDs as a part of transport system.

There are a wide variety of PMDs as described in [2]. This paper proposes an experimental procedure to study the psychological reaction of pedestrian towards a PMD. A typical footpath scenario of PMD approaching and passing a pedestrian is replicated in the experiment. The outcome of the experiment helps us in determining the discomfort zone of the pedestrian. From the earlier work [3], [4], it is found that speed and proximity of the PMD play a crucial role in determining the level of discomfort that pedestrians experience. This paper extends the existing work by finding the role of PMD type, noise, overtaking distance, age and gender of pedestrian in determining the comfort levels experienced by the pedestrian. A machine learning based application is developed as rider assistant system to predict and alert if his current motion state is causing discomfort to the approaching pedestrian.

The rest of the paper is organized as follows: In Section II, we review related works on the behavior of PMD riders around pedestrians and its corresponding distances. In Section III, we explain the design of the field experiment and observation on the pedestrian comfort perception. In Section IV, we cover the prediction application and visualization of the discomfort zone. Finally, we discuss the conclusion and future work in Section V.

II. Related Works

The maneuverability of PMDs such as accelerating, decelerating and sudden braking has been discussed in the context of overtaking/avoiding a pedestrian. Nishiuchi et al. [5] found that PMD riders' behaviors are like cyclists - both keep a similar L_t (Lateral Distance) to pedestrians. According to the Handbook of Traffic Engineering, the average L_t for cyclists to pass a confronting pedestrian is 1.2 m and 1.4 m in the event of overtaking. Based on the field data collected [5], L_t increased linearly when the relative speed between the PMD riders and the pedestrian became greater. In this regard, Miller et al. [6] found that PMD riders avoid the pedestrian at an average speed of 8.1 kmph with an average L_t of 0.91 m. Moreover, PMD riders change the direction to overtake the pedestrian from an average L_g (Longitudinal Distance) of 2.1 m [5], [6]. When PMD riders were asked to follow behind a walking pedestrian, they maintained a safe longitudinal distance ranged within 1.46-3.61m [3]. From the pedestrians' perspective, such longitudinal distance (L_g) can be their perceived safe distance to avoid collisions, which was found to be as high as 5.5 m, depending on the speed (5-20 kmph) of a confronting PMD riders [7] [8], or the size of the PMD [9].

Iryo et al. [3] investigated how PMD types (model: Segway, Robstep) affect riders' interaction with a pedestrian or a cyclist on the path. The average L_t and average L_g were found to be statistically significant between Segway and Robstep. Segway riders approached a standing pedestrian at 8.93 kmph (SD = 1.48), and changed their direction to avoid the pedestrian with a L_t of 0.81m (SD = 0.19). Robstep riders rode slower (6.59 kmph, SD = 1.4), and stayed farther to the pedestrian with a L_t of 1.00 m (SD = 0.16). However, the respective L_g for Segway users was 9.05 m (SD = 1.94) and 7.1 m (SD = 1.54) for Robstep users. In comparison with previous studies [5], [6], a shorter average L_g (2.1m) was reported while the PMD approaching speed was similar. These inconsistent results could be caused by the participant's riding experience. [5], [6] also established that experienced PMD users exhibit better agility in deceleration and rotational moves, and rode past a pedestrian faster by about 3.1 kmph on average than beginners do. In [8], authors considered such L_t and L_g as a personal space for individual PMD user and pedestrian. Dias et al. [10] integrated the reaction time into social force based simulation model to estimate pedestrians' safe avoid distance. To our best knowledge, all the studies found in the literature have studied the PMD's perception on a restricted demographic and the PMD model's impact is hardly investigated. This paper aims to bridge the gap by studying the impact of pedestrian gender along with the impact of latest PMD models on the perception of the pedestrians.

III. Field Experiments and Observations

A. Field Experiment Setup

For each session of the field experiment, a research assistant, a PMD rider and a pedestrian are required. The experimental setup is shown in Fig. 1. A 4 m wide and 100 m long area without any elevation is chosen to carry out the experiment. Yellow cones are used to mark 1.8 m area matching with the Singapore footpath width. An experienced PMD rider is hired to ride the PMD since the focus of our experiment is pedestrian's perception. Rider is instructed to dress identically for all the trials to minimize the visual impact and helmet is worn at all the time for safety. The eligible participant is instructed to act as a standing pedestrian on a designated spot. The PMD rider will approach in front of the participant and evades him/her. The distances L_g and L_t are highlighted with respect to the path of PMD and the position of the participant. L_g is the distance in front of the participant at which the PMD rider begins his evasive action. L_t is the distance between the participant and the PMD rider when the PMD rider has almost finished the evasive action and is in-line with the participant.

Initially, the participant is asked to close his/her eyes and stand facing towards the direction of the PMD approach. When the rider is approximately 8 m away from the participant, a bell is rung to indicate the participant to open their eyes. The rider passes the participant and halts. After each trial, participant will provide feedback to indicate his/her experienced comfort

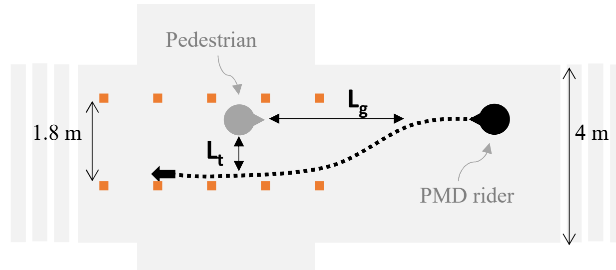

Fig. 1. Field experiment setup indicating PMD path and participant position

levels on a 7-point Likert scale. Two comfort levels, C_{lg} and C_{lt}, are recorded. C_{lg} is the comfort level experienced by the participant when the PMD rider begins the evasive action at a distance of L_g from the participant. C_{lt} is the comfort level experienced by the participant when the PMD rider completes the evasive action and passes by the participant at a distance of L_t. At any point of time during the trial, if the participant experiences a sense of danger, sufficient area is provided to step away from the designated spot. The field experiments were conducted over a period of four months from December 2018 to March 2019.

Before collecting the data, a sample demonstration is provided to familiarize the participant with the experimental procedure. To keep the scenario consistent, L_g is set to 3.0 m for all the trials. A total of 20 scenarios (4 PMDs x 5 Speed values) are carried out per participant to capture the effect of various parameters. To avoid learning effect, the sequence of scenarios is assigned randomly. Until the participant opens their eyes, they have no idea about the speed and type of the PMD that is approaching them.

The four types of PMDs along with their dimensions are shown in Fig. 2. PMD-A is an electric bicycle. It is selected because bicycle is commonly encountered by people in Singapore. The PMD-B and PMD-D are the electric scooters that are gaining popularity. PMD-C is a new model that is not available in the consumer market. The turning radius is lower, and the noise is higher when compared to other PMD types. No participant is familiar with this model. A diverse set of PMDs will help us to study the effect of the PMD type on the comfort level perception of participants.

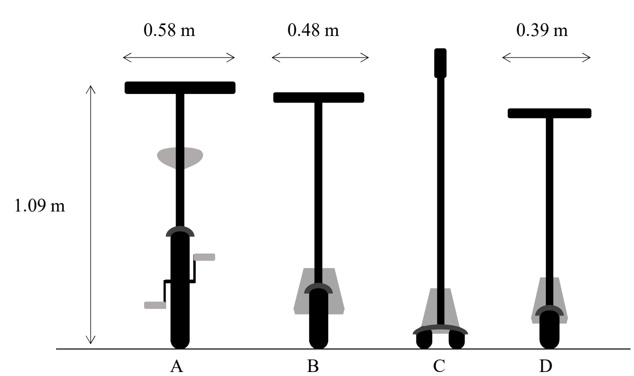

Fig. 2. Various PMD models used in the experiment

B. Pedestrian comfort perception

A total of 39 participants (18 Female, 21 Male), with an average age of 31.7 (SD = 9.6), have participated in the experiment. C_{lg} and C_{lt} ratings from the Likert Scale (1 to 7) are grouped into three categories namely Discomfort (0 to 3), Neutral (4) and Comfort (5 to 7).

Fig. 3 shows C_{lg} for various PMDs at different speed values. At PMD speed 0 to 10 kmph, more than 90% of participants experienced comfort for all PMDs except PMD-C, which is comfortable to 83% of participants. For speed 10 to 15 kmph, 82% of participants find PMD-A comfortable, about 70% of them find PMD-B and PMD-D comfortable and just 46% of the participants find PMD-C comfortable. For PMD speed more than 15 kmph, there is a drop in comfort levels with only about 40% of the participants feeling comfort towards all PMDs.

In addition to that, the impact of PMD type on the pedestrian perception C_{lg} can be inferred from the data. The participants are most familiar to PMD-A since they encounter bicycles regularly. Hence, they perceive least discomfort from PMD-A at lower speed. PMD-B and PMD-D receive almost same C_{lg} from the participants because they are visually identical to each other. However, at speed beyond 15 kmph, all PMDs create a sense of danger for the pedestrians irrespective of the PMD model. The Chi-Square test of independence is performed to check dependency of comfort level C_{lg} on the PMD type. At a confidence level of 95%, the test confirms that there is a significant dependency of C_{lg} on the type of PMD.

Fig. 4 shows the results of comfort level C_{lt} of participants to the lateral distance L_t. At PMD speed less than 10 kmph, about 90% of the participants felt comfort. When PMD speed increases to 10 – 15 kmph, the comfort levels for all PMDs drop down with PMD-C experiencing the least number of votes at 40%. Beyond PMD speed of 15 kmph, only 40% of the participants experience comfort levels towards all PMDs. The remaining participants expressed either neutral or discomfort levels.

Comfort level C_{lt} shows that the current footpaths in Singapore are comfortable to the pedestrians for speed upto 10 kmph. Beyond the speed of 10 kmph, pedestrians begin to experience discomfort. There were several instances during the field experiments wherein the participants moved onto the designated safety area when the PMD passed by them at a speed more than 10 kmph. Fig. 4 indicates that PMD-C has highest discomfort ratings for speed more than 10 kmph. Although statistical tests (at confidence level of 95%, p-val = 0.73) show that C_{lt} does not depend on PMD type, the lower turning radius of the PMD-C causes the rider to pass closely by the participants, maintaining smaller L_t than the other PMD models. Hence, this causes participants to feel comparatively higher sense of danger when PMD-C is passing by them.

To study the role of gender in comfort level perception, chi square test for independence is performed by categorizing speed into two levels (0 to 15 kmph and >15 kmph) as shown in Table I. At speed up to 15 kmph, the dependency of C_{lg} on gender is significant (at 95% confidence level). For speed more than 15 kmph, gender of the pedestrian does not play any role. On the other hand, C_{lt} is not dependent on the gender.

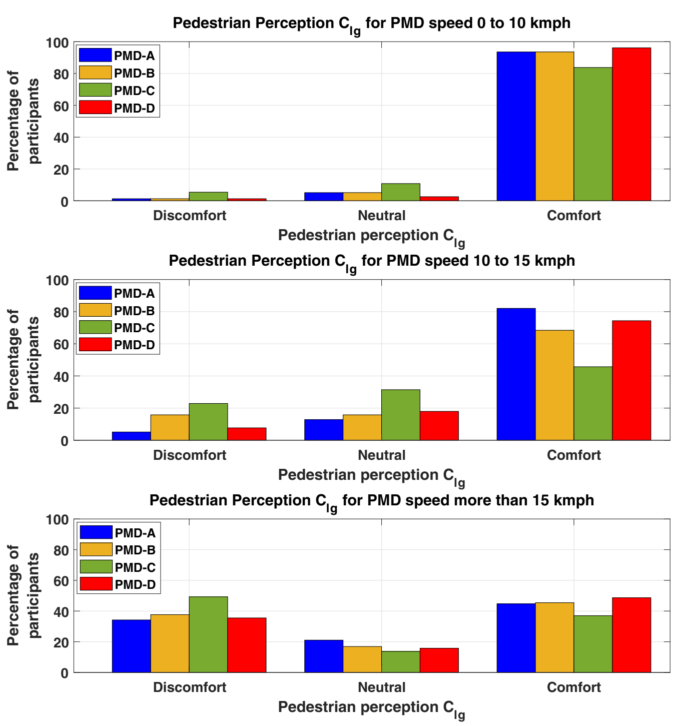

Fig. 3. C_{lg} experienced by participants for different speed ranges

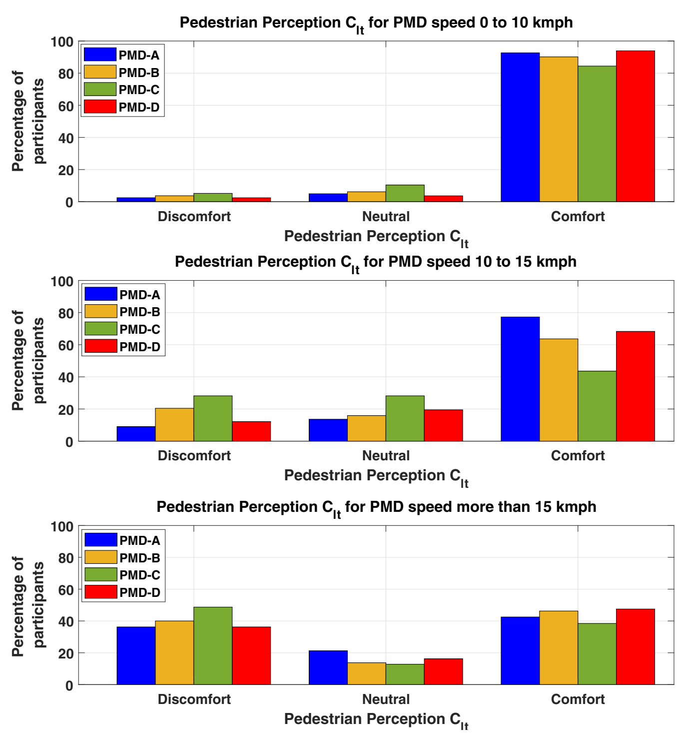

Fig. 4. C_{lt} experienced by participants for different speed ranges

TABLE I
CHI SQUARE TEST RESULTS FOR GENDER INDEPEDENCE

p-value for C_{lg}		p-value for C_{lt}	
speed <= 15 kmph	**speed > 15 kmph**	**speed <= 15 kmph**	**speed > 15 kmph**
0.03	0.56	0.18	0.21

To summarize the results from this section, the comfort levels of the pedestrians are dependent majorly on the speed of the PMDs. In addition to that, the comfort level C_{lg} is found to be dependent on the PMD type while Chi square test showed that C_{lt} does not depend on PMD type. Both C_{lg} and C_{lt} are found to be independent of gender except C_{lg} which has a weak association with gender at lower speed (<= 15 kmph).

C. Discomfort Zone Visualization

For visualization purpose, the heat maps of the discomfort zone are plotted as shown in fig. 5. The discussion will focus on passing distance, L_t, which is dependent on the width of the footpath. The pedestrian is set to stand at the origin while the discomfort zone is a contour graph surrounding the pedestrian. In the contour graph, the X-axis represents the distance L_t and the Y-axis represents the PMD speed (kmph). The PMD speed is discretized in 5 kmph steps. L_t is discretized in 10 cm steps. The regions are colored based on the comfort level percentage at a particular speed and distance. For instance, if 3 pedestrians felt comfort when PMD is approaching at 15 kmph and passing by at 60 cm, and 1 pedestrian felt uncomfortable, then the overall comfort level percentage will be 75% (0.75) for this instance. Likewise, the percentage is calculated for all distance-speed combinations and plotted as a contour graph.

To demonstrate the contour graph visualization and its usefulness in understanding the pedestrian perception, data for PMD-A and PMD-B is plotted in Fig. 5. It can be found that PMD-A makes the pedestrians feel comfortable only when it maintains a lateral clearance of 70 cm or above. However, PMD-B is required to provide a smaller clearance of 50 cm or above to avoid causing discomfort to the pedestrians. This is due to the type of the PMD. PMD-A shows wobbling behavior at lower speeds. This leads to causing discomfort to the pedestrians even at lower speeds. However, PMD-B is stable and more comfortable to ride at lower speeds when compared to PMD-A. From the graph, it can be said that PMD-B is more suitable for footpaths than PMD-A. It is important to note that the contour visualization data provides a clear view on the pedestrian zone when it is provided with a proper context with additional parameters such as PMD type, road length etc.

Additionally, pedestrians' discomfort zone is influenced by the size of the PMD. Due to different riding maneuvers for each PMD, the rider needs different clearances to traverse smoothly. For PMD-A, the electric bicycle has a wider handle-bar and the largest average passing distance (L_t), which is 67.3 cm (SD = 7.56). The typical double-handled scooter PMD-B has the average passing distance as 60.8 cm (SD = 8.76) and PMD-D has 52.1 cm (SD = 13.5). The one-hand controlled PMD-C reports the smallest passing distance (L_t) at 42.5 cm (SD = 9.77) due to its smaller turning radius compared to other PMD models.

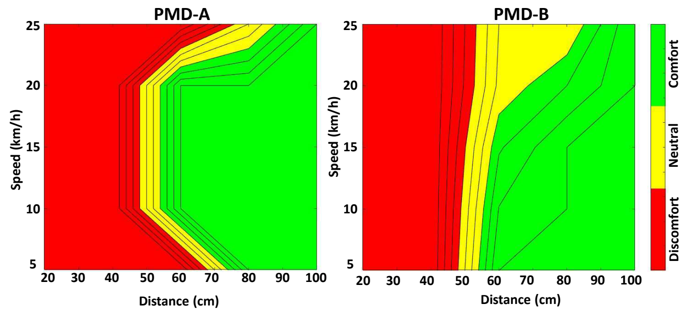

Fig. 5. Comfort and discomfort zones of pedestrian for PMD-A and PMD-B

IV. PREDICTION APPLICATION

In this section, a simple prediction algorithm is developed using Machine learning. This algorithm can be used as an advanced rider assistance system to provide safety alert to the PMD rider when there is an oncoming pedestrian. There are two steps, data preparation and Machine learning modelling.

A. Data preparation

The field experiment is recorded at 60fps using Kinovea, and trajectory of PMD is extracted using the videos. The coordinate system is xy-plane with the participant location as the origin and facing in the direction of y-axis. The PMD rider approaches the pedestrian in the negative y-axis direction. Since the PMD rider turns at L_g=3.0m, any coordinates beyond 3.5 m in Y-axis are excluded from the trajectory information. After the pedestrian is crossed, the trajectory data is not required. The outliers in the trajectory are caused due to parallax errors in the trajectory extraction. They are filtered out by removing the coordinates whose value deviates more than the three scaled median away from the median value. A moving average filter is used to further reduce the noise while retaining the same trajectory. After smoothing the data, the X and Y coordinates are used to calculate the instantaneous speed of the PMD and L_t. These values along with the PMD type (A, B, C and D), the gender and the age of the pedestrian will be input features for machine learning algorithms. The output label is pedestrian comfort perception C_{lt}.

The classifier model is built in MATLAB. Support Vector Machine (SVM) and Random Forest (RF) algorithms are applied for the data to predict the comfort level. The models are built as binary classifiers which are able to predict whether the pedestrian is comfortable or not. The 1-7 scale responses for comfort levels are converted to binary form by choosing the range 1-3 as "Discomfort", and the range 4-7 as "Comfort". Out of all input features, PMD type and the gender of the participant are categorical, and the remaining features are continuous. In addition, we grouped the speed of the PMD into five zones, viz., 0-5, 5-10, 10-15, 15-20, 20-25 kmph.

B. Discomfort prediction models

Based on different features combination, the prediction accuracy can change. It helps us to get an insight on which feature has more weights. Various combination of features are shown in Table II. Each column indicates one configuration with 1 indicating that the input feature is used and 0 indicating otherwise. Overall, the SVM model has better accuracy for predicting comfort level C_{lt} and takes less time for training compared with the RF model. Gender is an important feature that affects the accuracy of the model significantly. It can be seen that the SVM model's testing accuracy drops by 7% when gender is not provided as an input. The maximum validation accuracy that is obtained for SVM in predicting C_{lt} is 87.12%, while RF provided a relatively lower validation accuracy of 77.25% when all the input features are provided. Since the longitudinal distance L_g is constant, it is not used as an input in the prediction of comfort level.

The developed model can be built as a smartphone application. The smartphone can be mounted on the PMD and connected wirelessly to the PMD. Some of the recent models come with a dedicated control hub on the handlebar for the rider to interact with the PMD. They display the current speed, time and other important details. A camera is mounted on the PMD to get more information about the surroundings. The Machine learning model can be developed and integrated into this hub. The mounted camera will detect the age and gender of the oncoming pedestrian. The available footpath length is also estimated using the camera. The current speed of the PMD is already known. With this data, it is possible to detect the oncoming pedestrian's comfort levels. Further, it is possible to extend the application such that it provides a feasible passing clearance for the PMD rider to maintain so that the oncoming pedestrian does not feel discomfort. The camera application to detect the pedestrian and the footpath dimensions is already developed. The smartphone application development is in progress.

TABLE II
ACCURACY WITH DIFFERENT COMBINATIONS OF INPUT FEATURES

Input Parameters	Comfort C_{lt}					
	SVM			RF		
Speed	1	1	1	1	1	1
Distance L_t	1	1	1	1	1	1
PMD type	1	1	1	1	1	1
Gender	1	1	0	1	1	0
Age	1	0	1	1	0	1
Validation Accuracy(%)	87.12	85.69	86.04	77.25	77.32	78.88
Testing Accuracy(%)	74.03	75.32	67.53	70.13	74.03	68.83

V. Conclusion and Future Work

In this study, pedestrians' comfort perception is evaluated with respect to factors such as gender, PMD type and speed. The results showed that pedestrians tend to feel uncomfortable when PMD approaches them at more than 15 kmph on Singapore's footpath conditions. Further, the results showed that the pedestrian comfort level depends on their gender as well. Based on the obtained data, PMD assistant application is developed to assist the rider in maintaining sufficient clearance when approaching a pedestrian. Finally, visual representation and interpretation of the discomfort zone is provided for two PMD models. The paper has addressed some of the gaps in the literature regarding the pedestrian's perception to PMDs.

For the future work, several directions are available. Experiment setup can be improved to add more complexity in the scenario such as walking participants. Additionally, a diverse set of participants with different age groups and ethnicity will provide further insights that can be generalized irrespective of geographical location. Using the video data obtained from the field experiments, a PMD behavior model can be derived to carry out large scale simulations involving PMD and pedestrian interactions.

VI. Acknowledgement

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