Driver's Decision Analysis in Terms of Pedestrian Attributes —A Case Study in Passing by a Pedestrian—

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***Abstract*—In this paper, we report a case study on driver's decision in terms of pedestrian attributes. Among various traffic situations, the situation that a vehicle passes by a pedestrian is one of the major situations. To build a safety driving system that supports a non-experienced driver in such a situation, we analyzed how experienced drivers decide to handle the vehicle in such a situation. Since pedestrian's behavior can be considered as a key factor for the decision, and also the behavior is different depending on their "attributes," such as walking or stopping, noticing the vehicle or not, using a smartphone, etc., we analyzed what pedestrian's attributes affect the driver's decisions. For the analysis, we first built a large-scale dataset of driving data. Using the dataset, we clarified what attributes are dominant for the driver's decision.**

I. Introduction

Technologies for Intelligent Transportation Systems (ITS) have been developed actively in recent years to reduce traffic accidents. Especially, since many pedestrians are involved in traffic accidents, their safety is one of the most important issues to be secured. To avoid traffic accidents involving pedestrians, the driver of a vehicle needs to find pedestrians and control the vehicle to avoid them.

Among various traffic situations, the situation that a vehicle passes by a pedestrian is one of the major situations drivers often feel danger. Experienced drivers would decide how to control the vehicle by considering the surrounding environments when passing by a pedestrian. In general, the driver slows down when it requires attention to the pedestrian and speeds up when it becomes safe. Therefore, the decisions are mainly classified into the following three types:

- Drive normally (ignoring the pedestrian because he/she is in the distance).
- Reduce the vehicle speed while paying attention to the pedestrian.
- Increase the vehicle speed under the judgement that passing by the pedestrian is safe.

If we can know how experienced drivers decide in such situations, we can make a system for supporting non-experienced drivers in similar situations. Therefore, focusing on a situation that a vehicle passes by a pedestrian, our goal is to build a system which predicts a decision that a driver should follow in a given situation.

Recently, there are some works which predict a desirable decision based on the analysis of a driver's activities. Yoshihara *et al.* [10] have analyzed a driver's activities in blind corners. They analyzed braking operations of five experienced drivers and 24 elder drivers in blind corners and built a computational model for safety driving. Pongsathorn *et al.* [11] proposed a path prediction method for avoiding a parking vehicle based on a risk potential map. Meanwhile, the work proposed in this paper focuses on the situation when a vehicle passes by a pedestrian.

In the situation that a vehicle passes by a pedestrian, a driver of the vehicle considers various factors in the surrounding environment. The main factor can be the behavior of the pedestrian. If the pedestrian seems to come onto the road, the driver will step on the brake. Therefore, pedestrian behavior analysis is an important technology, and actually, it is one of the hot topics in the computer vision field. Alahi *et al.* [5] have proposed a method named Social LSTM for pedestrian path prediction by jointly predicting the paths of all the pedestrians in a scene. Some methods for a pedestrian's path prediction and destination prediction have also been proposed [6], [7], [12].

Pedestrian's behavior varies depending on individual pedestrians, and essentially it is difficult to predict it. In the driving situation, experienced drivers focus on various statuses of a pedestrian:

- Which orientation is the pedestrian facing?
- Is the pedestrian walking or stopping?
- Is the pedestrian aware of the own vehicle or not?

We call these statuses as "attributes" of the pedestrian. We consider that these attributes are key factors for predicting the pedestrian's behavior, while the pedestrian's behavior is the key factor for predicting the driver's decisions. Therefore, we assume that these attributes affect the driver's decision, and directly analyze what attributes are dominant in forming

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the driver's decisions. Since it is unclear what attributes are important to predict the driver's decision, the purpose of our work is to clarify the important attributes based on a large number of driving data.

There are various methods for recognizing pedestrian's attributes from an image of a pedestrian. Ge *et al.* [13] proposed an age estimation method from a full-body image. Since the orientation of a pedestrian is considered as an important factor, there are many researches on orientation recognition of a pedestrian [1], [2]. Tao and Klette [3] have proposed a method focusing on body parts of a pedestrian, which uses Random Forest as a classifier. Flohr *et al.* [4] have proposed a method that improves the recognition accuracy of the orientation by utilizing the correlation between the body and the head orientations. Kawanishi *et al.* [14] have proposed a classifier training method for orientation estimation of a pedestrian. Recently, mobile devices such as smartphones are widely spreading and many pedestrians use the devices while they walk. It is an issue gaining global attention. We *et al.* [15] have proposed a recognition method whether a pedestrian is using such a device or not, namely, Texting-while-Walking. In this work, we assume these attribute recognition methods work perfectly, and use the manually-annotated data instead of the outputs of the attributes recognition methods.

Our contributions are summarized as follows:

- We constructed a driving dataset from 84 scenes of passing by a pedestrian.
- We analyzed the effects of pedestrian's attributes on driver's decisions.
- We clarified the important attributes for the driver's decisions.

II. Analysis of the Driver's Decision Affected by Pedestrian's Attributes

The aim of this work is to analyze the driver's decision when passing by a pedestrian, and what kinds of pedestrian attributes contribute to the decision. Since the groundtruth of a driver's attention cannot be obtained, we analyze the decision based on the timing of the acceleration and the braking by the driver. From a careful observation during driving, we confirmed that a driver makes three types of decisions for safety driving. For example, if a pedestrian is distant and exists on the sidewalk, the driver may decide that it is not necessary to reduce the vehicle speed. However, if a pedestrian is just about to cross the road, the driver will step on the brake. In addition, if a pedestrian is looking at a smartphone while walking, the driver will carefully keep an eye on the pedestrian. From these points of view, we can assume that the driver's decision is strongly affected by the pedestrian's attribute. From the opposite side of view, if a pedestrian's attribute can be recognized by computer vision technique, the AI of the vehicle can understand the driver's decision and it can be used for the improvement of safety and drivability of the vehicle. Therefore, we focus on the analysis on the effects of pedestrian's attributes on the driver's decisions.

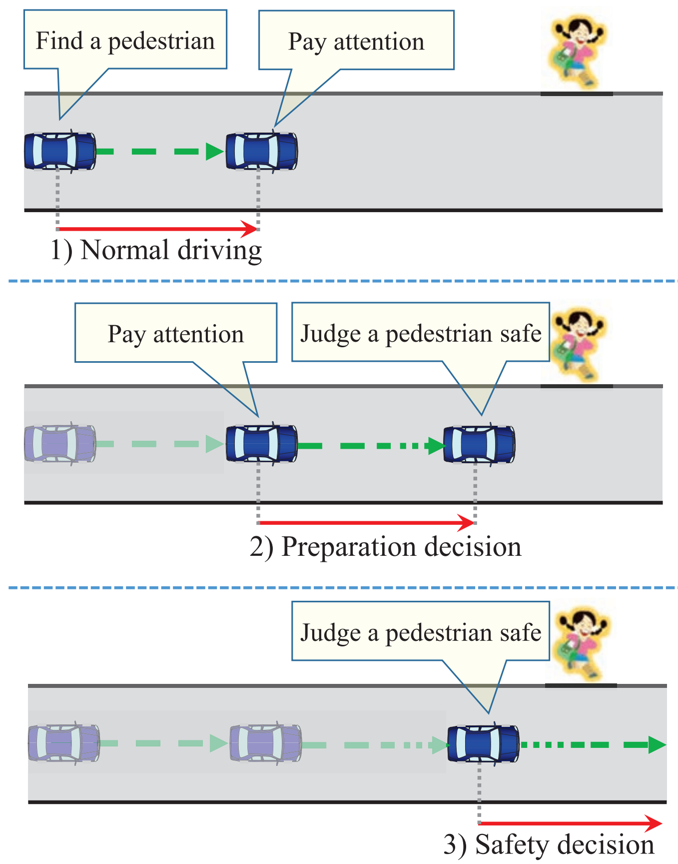


Fig. 1. Overview of driver's decisions when passing by a pedestrian.

In the situation of passing by a pedestrian, the following decision transition can be observed for avoiding collisions with pedestrians. Before becoming aware of a pedestrian, the driver drives as usual. Once the driver notices the existence of the pedestrian, the driver may take some actions according to the found pedestrian. If the vehicle approaches the pedestrian (closer than a certain distance), the driver begins to reduce the vehicle speed and keeps his/her attention to the pedestrian. Since this can be considered as a preparation action for collision avoidance, we call this as "Preparation decision". If the vehicle further approaches and the driver judges that no collision will occur, the driver will increase the vehicle speed. We call this as "Safety decision".

Based on the above observations, we consider three types of driver's decisions as follows.

1) Normal driving: Driving as usual.
2) Preparation decision: Intend to reduce the vehicle speed while paying attention to the pedestrian.
3) Safety decision: Intend to increase the vehicle speed under the judgement that passing by the pedestrian is safe.

Figure 1 shows an overview of the above three decisions.

The next section describes the details of the dataset construction step for analyzing the effects of pedestrian's attributes on driver's decisions.

Fig. 2. Example of defining each driver's decision.

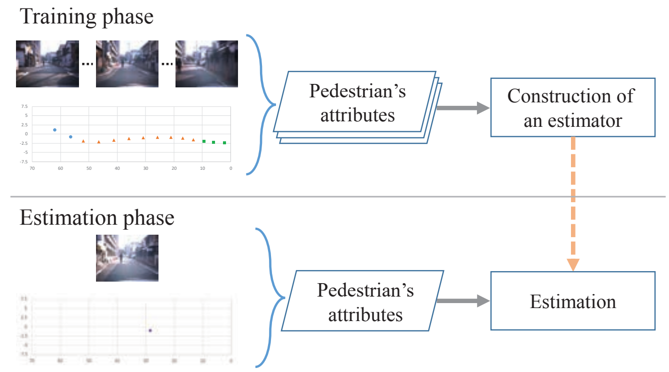


Fig. 3. Flowchart of the analysis.

A. Dataset construction

Since driver's decisions vary widely due to its driving situation, it is very important to obtain various data for analysis of passing by pedestrians. To do this, a special vehicle equipped with various sensors (3D LIDAR, wide/narrow angle view cameras, GPS, and CAN signals) was developed. Experienced drivers (instructor of a driving school) drove this special vehicle along a pre-planned path including an urban area, and various data were collected. Here, the collected data includes in-vehicle camera videos, 3D point clouds obtained from a 3D LIDAR, the amount of accelerations and braking pressures obtained by CAN signals.

After collecting the data, we extracted scenes of passing by a pedestrian, and then performed frame-by-frame manual annotation by choosing one of the three driver's decisions mentioned above. "Normal driving" and "Preparation decision" were divided by the timing of the release action of the acceleration pedal or the action of stepping on the brake. Here, these actions can be recognized by the accelerator position and brake pressure signals. "Preparation decision" and "Safety decision" were divided by the timing of re-acceleration. Figure 2 shows examples of different driver's decisions when passing by a pedestrian. As can be seen in the figure, the driver sometimes keeps his/her foot on the accelerator pedal until the vehicle completely passes by a pedestrian. On the other hand, the driver sometimes does not release the accelerator pedal until the end. From these observations, safety decision may occur from when finding a pedestrian.

Next, the pedestrian's attributes were annotated by referring to the in-vehicle camera images and the 3D point cloud data. Finally, a dataset consisting of pairs of the driver's decision and pedestrian's attributes was constructed.

B. Driver's decision analysis based on pedestrian's attributes

To confirm the effects of pedestrian's attributes on driver's decision, the proposed method employs factor analysis for finding out what kinds of pedestrian attributes contribute to the driver's decision. To do this, recognition based factor analysis was employed in this paper. The flowchart of this analysis is shown in Fig. 3.

First of all, the pedestrian's attributes are concatenated as an attribute feature vector frame-by-frame. Then, the driver's decision estimator is constructed using the feature vector. Since this paper considers three driver's decisions when passing by a pedestrian, a multi-class SVM is used as the estimator. Finally, by taking a greedy evaluation approach, the rank of important pedestrian's attributes for driver's decision is calculated. Here, multiple estimators are constructed by increasing the number of features (pedestrian's attributes) based on its contribution to the estimation accuracy, and its order is used as the rank of the importance of pedestrian's attributes.

III. Experiments

This section describes details of experiments to confirm the effects of pedestrian's attributes on driver's decisions.

A. Specification of the dataset

The following four attributes were manually annotated.

- Body orientation (4 directions)
- Action (walking, running, stopping, riding a bicycle)
- Awareness of the vehicle
- Texting-while-Walking

In addition to the above, the dataset also included the following environmental factors.

- Pedestrian's location (relative position from the vehicle)
- Existence of sidewalk

We determined these attributes based on the in-vehicle camera images and the 3D point cloud data. In regard to awareness of the vehicle, we determined that a pedestrian was aware of the vehicle when he/she looked at it.

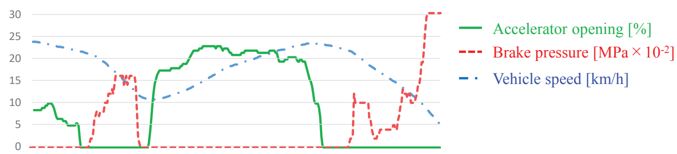
In addition, transition of the accelerator position and the brake pressure level were captured through CAN signals. According to the criteria described in section II, annotations of the driver's decision were determined every 0.5 seconds. An example from this dataset is shown in Fig. 4.

This dataset consisted of 84 situations passing by a pedestrian, and in total, 1,048 pairs of driver's decision and pedestrian's attributes were manually annotated.

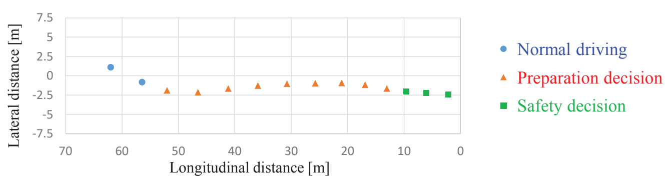
B. Results of factor analysis

According to the method described in section II-B, the correlation between pedestrian attributes and driver's decisions were evaluated. This evaluation was repeated ten times, and the average classification accuracy was calculated in a 10-fold cross validation manner.

(a) In-vehicle camera video.



(b) Driver's behavior data.



(c) Pedestrian's relative positions from the own vehicle.

Fig. 4. Example from the dataset.

Table I shows the obtained results through the validations. The results show that the accuracy of the estimator tends to improve as the number of used pedestrian's attributes increased. From these results, it can be confirmed that the combination of multiple pedestrian's attributes contributes to the decision of the driver.

C. Analysis of the effective pedestrian's attributes

Next, we tried to find out what kinds of pedestrian's attributes contribute to the driver's decision. This is done by taking a greedy approach explained in section II-B. Table II shows the results of selected pedestrian's attributes.

As seen in the table, the most important attribute for the driver's decision was the location of the pedestrian. The second important factor was the body orientation of the pedestrian, and the third one was the action of the pedestrian.

Figures 5–9 are visualization of pedestrian's location with driver's decision. In these figures, blue circles indicate "Normal driving", orange triangles indicate "Preparation decision", and green squares indicate "Safety decision". Each figure corresponds to each body orientation of pedestrians. As seen in these figures, it can be clearly confirmed that the driver's decision is different by body orientations of pedestrians. From these results, body orientations of pedestrians is one of the most important factor that affects the decision of the driver.

As seen in Table II, less effective pedestrian's attribute was the awareness against the vehicle. This can be because the driver mainly uses body orientation of the pedestrian for determining the awareness at the vehicle. Accordingly, the awareness at the vehicle was strongly correlated with a specific body orientation, and thus the overall contribution of the feature became small.

TABLE I
DRIVER'S DECISION CLASSIFICATION RESULTS USING PEDESTRIAN'S ATTRIBUTES.

Input attributes	Accuracy
Location	55.6 %
Location + Body orientation	58.9 %
Location + Body orientation + Action + Sidewalk + Awareness	67.5 %
All attributes	66.7 %

TABLE II
RESULTS OF SELECTED PEDESTRIAN'S ATTRIBUTES.

	Added attributes	Accuracy
1st	Location	55.6 %
2nd	Body orientation	58.9 %
3rd	Action	63.5 %
4th	Sidewalk	66.0 %
5th	Awareness	67.5 %

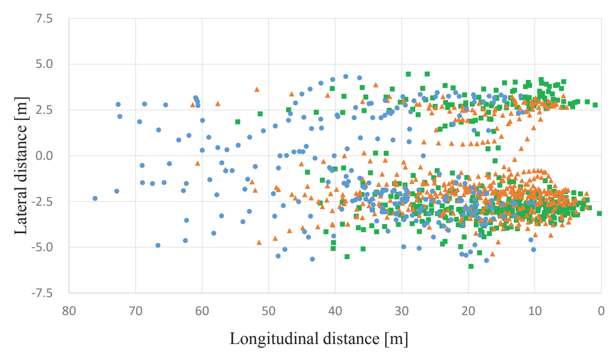


Fig. 5. Data plotted on the location (Body orientation: all).

Although recognition of Texting-while-Walking is very important for safety driving, its contribution was not so high. We consider that this is because the amount of data including Texting-while-Walking was quite small in the dataset. Therefore, due to insufficient training data, its contribution could not be evaluated correctly. In our future work, we intend to increase the number of Texting-while-Walking data, and will perform further analysis.

IV. CONCLUSION

This paper presented an analysis on the effects of the observed pedestrian's attributes on driver's decisions. By focusing on the scene that a vehicle passes by a pedestrian, the proposed method found out the kinds of pedestrian's attributes that contributed to the driver's decisions. Through experiments, we confirmed that multiple pedestrian's attributes, especially the body orientation and the action of a pedestrian affect the decision of the driver.

Future works will include the analysis of more pedestrian's attributes, and the extension of the dataset. Since there are various pedestrian's attributes that should be considered, further analysis will be necessary. We also plan to develop

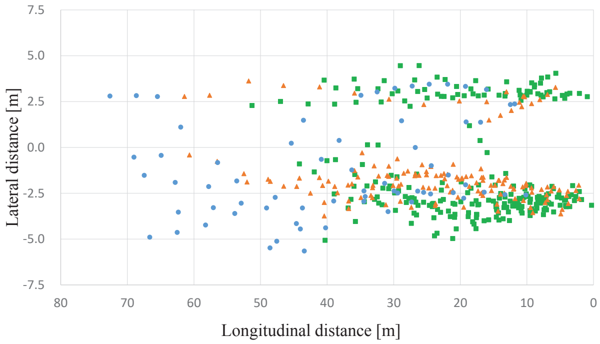


Fig. 6. Data plotted on the location (Body orientation: front).

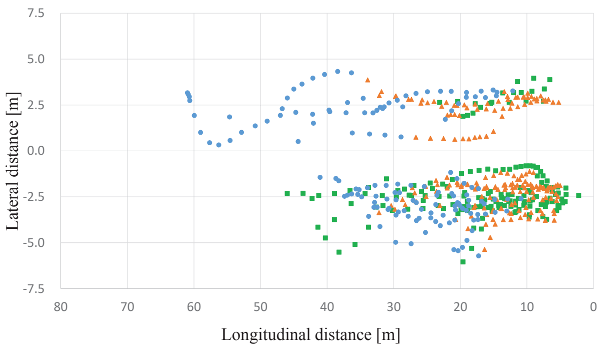


Fig. 7. Data plotted on the location (Body orientation: backward).

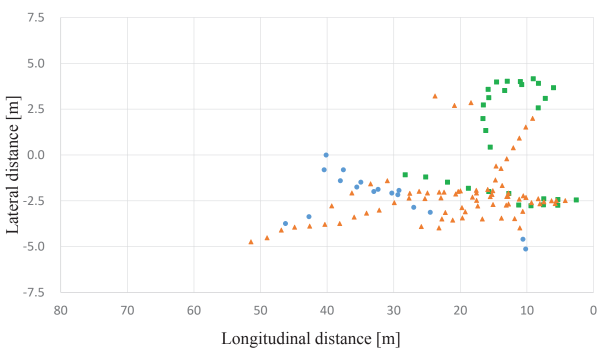


Fig. 8. Data plotted on the location (Body orientation: inside of the road).

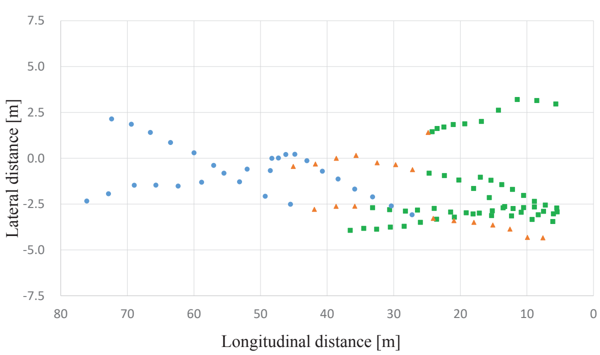


Fig. 9. Data plotted on the location (Body orientation: outside of the road).

a recognition method of driver's decision from pedestrian's attributes. For this, it is very important to develop an automatic estimation method of the driver's decision by recognizing the pedestrian's attributes from in-vehicle camera images and other sensors.

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REFERENCES

[1] D. Baltieri, R. Vezzani and R. Cucchiara, People Orientation Recognition by Mixtures of Wrapped Distributions on Random Trees, In Proceedings of the 12th European Conference on Computer Vision, 2012, pp. 270–283.
[2] K. Goto, K. Kidono, Y. Kimura and T. Naito, Pedestrian Detection and Direction Estimation by Cascade Detector with Multi-classifiers Utilizing Feature Interaction Descriptor, In Proceedings of 2011 IEEE Intelligent Vehicles Symposium, 2011, pp. 224–229.
[3] J. Tao and R. Klette, Part-based RDF for Direction Classification of Pedestrians, and a Benchmark, In Proceedings of Workshop on Intelligent Vehicles with Vision Technology in the 12th Asian Conference on Computer Vision, 2014, w11-p2.
[4] F. Flohr, M. Dumitru-Guzu, J.F.P. Kooij, and D.M. Gavrila, Joint Probabilistic Pedestrian Head and Body Orientation Estimation, In Proceedings of 2014 IEEE Intelligent Vehicles Symposium, 2014, pp. 617–622.
[5] A. Alahi, K. Goel, V. Ramanathan, A. Robicquet, L. Fei-Fei and S. Savarese, Social LSTM: Human Trajectory Prediction in Crowded Spaces, In Proceedings of 2016 IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 961–971.
[6] C.G. Keller and D.M. Gavrila, Will the Pedestrian Cross? A Study on Pedestrian Path Prediction, IEEE Transactions on Intelligent Transportation Systems, vol. 15, no. 2, 2014, pp. 494–506.
[7] E. Rehder and H. Kloeden, Goal-Directed Pedestrian Prediction, In Proceedings of 2015 IEEE International Conference on Computer Vision Workshop, 2015, pp. 139–147.
[8] S.-H. Chen, J.-S. Pan and K. Lu, Driving Behavior Analysis Based on Vehicle OBD Information and AdaBoost Algorithms, In Proceedings of the International Multi-Conference of Engineers and Computer Scientists 2015, vol. 1, 2015, pp. 102–106.
[9] A. Sonawane, S. Dhabe, U. Nadgouda, V. Jadhav and G.V. Mane, A Systematic Approach for Real-Time Clustering and Analysis of Drivers' Driving Behavior using OBD-II, International Journal of Engineering Science, vol. 6, no. 5, 2016, pp. 5047–5052.
[10] Y. Yoshihara, E. Takeuchi and Y. Ninomiya, Accurate Analysis of Expert and Elderly Driving at Blind Corners for Proactive Advanced Driving Assistance Systems, Transportation Research Board 95th Annual Meeting, no. 16-1992, 2016.
[11] P. Raksincharoensak, T. Hasegawa and M. Nagai, Motion Planning and Control of Autonomous Driving Intelligence System Based on Risk Potential Optimization Framework, International Journal of Automotive Engineering, vol. 7, no. AVEC14, 2016, pp. 53–60.
[12] M. Kitani, B.D. Ziebart, J.A. Bagnell and M. Hebert, Activity Forecasting, In Proceedings of the 12th European Conference on Computer Vision, 2012, pp. 201–214.
[13] Y. Ge, J. Lu, X. Feng and D. Yang, Body-based Human Age Estimation at a Distance, In Proceedings of 2013 IEEE International Conference on Multimedia and Expo Workshops, 2013, pp. 1–4.
[14] Y. Kawanishi, D. Deguchi, I. Ide, H. Murase and H. Fujiyoshi, Misclassification Tolerable Learning for Robust Pedestrian Orientation Classification, In Proceedings of the 23rd International Conference on Pattern Recognition, 2016, pp. 481–486.
[15] F. Shinmura, Y. Kawanishi, D. Deguchi, I. Ide, H. Murase and H. Fujiyoshi, Recognition of Texting-While-Walking by Joint Features Based on Arm and Head Poses, Computer Vision — ACCV 2016 Workshops, 2016, pp. 452–462.