2018 21st International Conference on Intelligent Transportation Systems (ITSC)
Maui, Hawaii, USA, November 4-7, 2018

Estimation of Driver's Insight for Safe Passing based on Pedestrian Attributes

Fumito Shinmura[1], Yasutomo Kawanishi[2], Daisuke Deguchi[3], Takatsugu Hirayama[1], Ichiro Ide[2], Hiroshi Murase[2] and Hironobu Fujiyoshi[4]

Abstract— **In order to reduce traffic accidents between a vehicle and a pedestrian, recognition of a pedestrian who has a possibility of collision with a vehicle should be helpful. However, since a pedestrian may suddenly change his/her direction and cross the road, it is difficult to predict his/her behavior directly. Here, we focus on the fact that experienced drivers usually pass by a pedestrian while preparing to step on the brake at any moment when they feel danger. If driver assistant systems can estimate such experienced driver's decisions, they could early detect the pedestrian in danger of collision. Therefore, we classify the driver's decisions into three types by referring to the accelerator operation of drivers, and propose a method to estimate the type of the driver's decision. The drivers are considered to decide their actions focusing on various behaviors and states of a pedestrian, namely pedestrian's attributes. Since the driver's decisions change along the timeline, the use of a temporal context is considered to be effective. Thus, in this paper, we propose an estimation method using a recurrent neural network architecture with the pedestrian's attributes as input. We constructed a dataset collected by experienced drivers in control of the vehicle and evaluated the performance, and then confirmed the effectiveness of the use of pedestrian's attributes.**

I. Introduction

Pedestrian's safety on the road is one of the most important issues since traffic accidents injure many pedestrians every year. To prevent traffic accidents with pedestrians, it is important to find pedestrians in danger of collision with a vehicle. Research has been widely conducted on pedestrian detection [1] by in-vehicle camera [2] and 3D LiDAR (Light Detection and Ranging) [3]. On the other hand, there are still few studies to predict the behavior of a pedestrian.

For safety in a driving situation, drivers decide their actions focusing on various behaviors and states of a pedestrian. These behaviors and states are important for the prediction of the behavior of a pedestrian. Thus, in this paper, we consider the behaviors and states of a pedestrian as his/her attribute. Actually, many researchers have worked on pedestrian attribute recognition [4], [5]. Some of them focused on the recognition of a pedestrian's body orientation to predict his/her moving direction [6], [7]. Meanwhile, some of them focused on the recognition of risky behaviors by a pedestrian [10] to estimate the risk of accidents. Some other researchers focused on the early detection of a pedestrian crossing the road [11]. They attempted to predict the road crossing by detecting the beginning of crossing as early as possible.

Including these works, pedestrians crossing the road are usually recognized as dangerous and the others are recognized as not dangerous. However, a pedestrian may suddenly change his/her direction and cross the road. Thus, pedestrians walking on the road side are also not always safe, and it is difficult for the existing works to accurately predict the risk of a pedestrian stepping into the road.

One method to improve driving technique is to imitate the driving of an experienced driver. Likewise, if a system can estimate the driving of an experienced driver, it would be helpful for the assistance of safety driving. When an experienced driver encounters a pedestrian, he/she can take appropriate actions by predicting the pedestrian's behaviors. If passing by a pedestrian cannot be judged as safe, the driver will approach the pedestrian while preparing to step on the brake at any moment. Meanwhile, once passing by the pedestrian is judged as safe, he/she will pass by increasing the speed.

Since an experienced driver decides appropriate driving operations by predicting pedestrian's behaviors, the estimation of the driver's decisions would be helpful for the prediction of pedestrian's behaviors. More specifically, if a system can estimate the driver's decision of stepping on the accelerator pedal or not, it could predict the risk of collision with the pedestrian. Therefore, it is important to estimate such experienced driver's decisions. On the other hand, the estimation of the vehicle speed would not be helpful for the prediction since the vehicle speed does not always represent the driver's decisions. For example, in the case of keeping the vehicle speed, there are two kinds of driver actions; a case that the driver keeps the speed by softly stepping on the accelerator pedal, and a case that he/she keeps the speed by releasing the accelerator pedal while preparing to step on the brake pedal. There is a difference between the two cases regarding the driver's decision.

In this paper, we propose a method to estimate a driver's decision in the case of passing by a pedestrian based on the pedestrian's attributes. We approach this problem by referring to the information on the accelerator operation of experienced drivers, namely,

- Stepping on the accelerator pedal.
- Releasing the accelerator pedal (and preparing to step

[1]Fumito Shinmura and Takatsugu Hirayama are with the Institutes of Innovation for Future Society, Nagoya University, Nagoya, Aichi, Japan shinmuraf@murase.is.i.nagoya-u.ac.jp

[2]Yasutomo Kawanishi, Ichiro Ide and Hiroshi Murase are with the Graduate School of Informatics, Nagoya University, Nagoya, Aichi, Japan

[3]Daisuke Deguchi is with the Information Strategy Office, Nagoya University, Nagoya, Aichi, Japan

[4]Hironobu Fujiyoshi is with the Department of Robotics Science and Technology, Chubu University, Kasugai, Aichi, Japan

TABLE II
ESTIMATION ACCURACY.

Input	Accuracy
Basic method: Vehicle speed and pedestrian's position	56.8 %
Proposed method: Vehicle speed, pedestrian's position and body orientation	65.5 %

C. Results

The estimation accuracy is shown in Table II. The method using the vehicle speed, the pedestrian's position, and the body orientation showed better performance. We consider that our approach based on the pedestrian's attributes is effective for the estimation of the driver's insight. In order to improve the estimation accuracy, the use of pedestrian's attributes related to the driver's insight is very important.

An example of experimental results is shown in Fig. 6. Color bars indicate the types of the driver's insight; the blue, orange, and green bars indicate *Usual*, *Brake preparation*, and *Safety judgment*, respectively. The upper bar (Correct) indicates the correct type of the driver's insight. The middle bar (Baseline) indicates the estimation results by using the vehicle speed and the pedestrian's position, and the bottom bar (Proposed) indicates the result by using the vehicle speed, the pedestrian's position and the body orientation.

Here, the proposed method using three attributes showed a better performance. Focusing on the part of brake preparation, the method estimated the transition of the type of the driver's insight approximately five frames (= 0.25 seconds) earlier than the correct timing. On the other hand, the baseline estimation method without the pedestrian's body orientation showed a worse and unstable performance.

Another example of the experimental results is shown in Fig. 7. Here, both methods could not estimate well. The proposed method estimated the driver's insight to be *Safety judgment* in the early period since the pedestrian was facing the vehicle side. However, the type of the driver's insight actually changed to *Brake preparation* slightly before passing by the pedestrian. Therefore, the driver's insight may have been affected by a factor other than the body orientation of the pedestrian; The driver may have decided to release the accelerator pedal since the vehicle speed became too fast. We need to consider other attributes to improve the estimation accuracy in our future work.

In other cases of the misclassification, the driver's insight was affected by the pedestrian's age. There was little difference between the case of an adult and an elderly pedestrian, but, there was a difference between the case of a child and others. It seemed that the driver decided to decrease the speed more largely since he/she paid more attention to the child. Meanwhile, the driver's insight was also affected by a factor other than pedestrian's attributes. The road structure affected pedestrian's behaviors and the driver's insight. For example, a pedestrian might cross the road near an intersection. The driver releases the accelerator pedal regardless of the pedestrian's body orientation when passing by such a pedestrian since he/she pays more attention to the crossing.

VI. CONCLUSION

In this paper, we defined three types of driver's insight, and proposed a method to estimate them using a neural network based on LSTM learned from actual driving data of experienced drivers. Since the driver's insights are strongly affected by pedestrian's attributes, we proposed an estimation method based on them.

The performance of the proposed method is currently not sufficiently good, so we need to improve it. We will need to consider other attributes than those considered in this paper. In addition, the amount of driving data is not sufficient for the training of our network model. There are only a few scenes in the dataset for a certain body orientation, and then the estimation cannot be performed well. We plan to collect a large amount of driving data, and analyze key factors for estimating the driver's insight. Future work also includes estimation in the case of passing by multiple pedestrians. In such a case, we need to first estimate a pedestrian whom a driver is paying attention to.

ACKNOWLEDGMENT

This research was supported by the Center of Innovation Program (Nagoya-COI) from Japan Science and Technology Agency, JST, and Grant-in-Aid for Scientific Research from the Ministry of Education, Culture, Sports, Science and Technology.

REFERENCES

[1] P. Dollar, C. Wojek, B. Schiele and P. Perona, Pedestrian detection: An evaluation of the state of the art, IEEE Trans. Pattern Anal. Mach. Intell., vol. 34, no. 4, 2011, pp. 743–761.
[2] J. Li, X. Liang, S. Shen, T. Xu, J. Feng, and S. Yan, Scale-aware Fast R-CNN for pedestrian detection, IEEE Trans. Multimed., vol. 20, no. 4, 2018, pp. 958–996.
[3] Y. Tatebe, D. Deguchi, Y. Kawanishi, I. Ide, H. Murase, and U. Sakai, Pedestrian detection from sparse point-cloud using 3DCNN, In Proc. 2018 Int. Workshop on Advanced Image Tech. (IWAIT), 2018, C4-4.
[4] H. Fukui, T. Yamashita, Y. Yamauchi, H. Fujiyoshi, and H. Murase, Robust pedestrian attribute recognition for an unbalanced dataset using mini-batch training with rarity rate, In Proc. 2016 IEEE Intell. Veh. Symp. (IV), 2016, pp. 322–327.
[5] D. Li, X. Chen, and K. Huang, Multi-attribute learning for pedestrian attribute recognition in surveillance scenarios, In Proc. 3rd IAPR Asian Conf. on Pattern Recogn. (ACPR), 2015, pp. 111–115.
[6] J. Tao and R. Klette, Part-based RDF for direction classification of pedestrians, and a benchmark, Computer Vision —ACCV 2014 Workshops, Lecture Notes in Computer Science, vol. 9009, 2014, pp. 418–432.
[7] Y. Kawanishi, D. Deguchi, I. Ide, H. Murase, and H. Fujiyoshi, Misclassification tolerable learning for robust pedestrian orientation classification, In Proc. 23rd IAPR Int. Conf. on Pattern Recogn. (ICPR), 2016, pp. 481–486.
[8] D. Baltieri, R. Vezzani, and R. Cucchiara, People orientation recognition by mixtures of wrapped distributions on random trees, Computer Vision —ECCV 2012, Lecture Notes in Computer Science, vol. 7576, 2012, pp. 207–283.
[9] F. Flohr, M. Dumitru-Guzu, J.F.P. Kooij, and D.M. Gavrila, Joint probabilistic pedestrian head and body orientation estimation, In Proc. 2014 IEEE Intell. Veh. Symp. (IV), 2014, pp. 617–622.

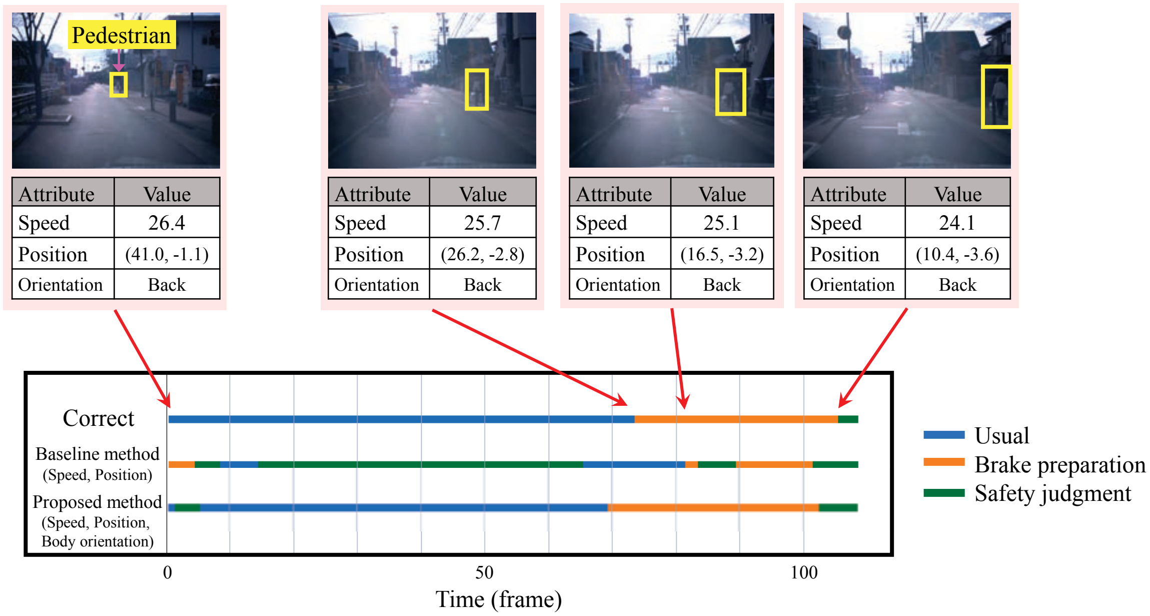

Fig. 6. Example of the experimental results (1).

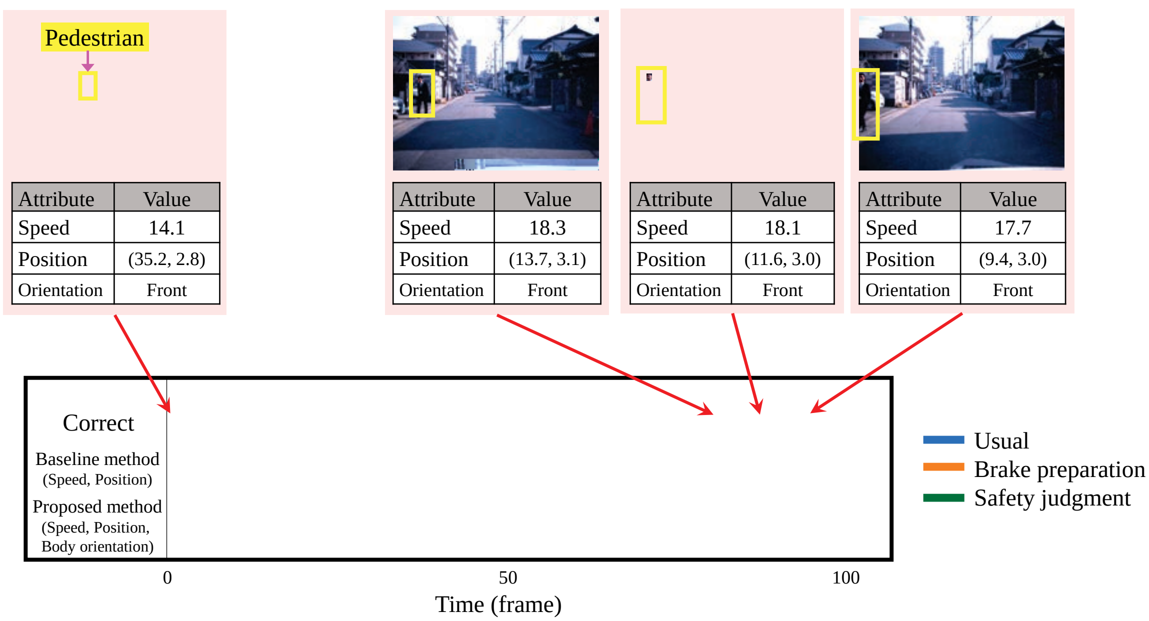

Fig. 7. Example of the experimental results (2).

[10] 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, Lecture Notes in Computer Science, vol. 10116, 2016, pp. 452–462.

[11] S. Köhler, M. Goldhammer, S. Bauer, K. Doll, U. Brunsmann, and K. Dietmayer, Early detection of the pedestrian's intention to cross the street, In Proc. 15th IEEE Intell. Transp. Syst. Conf. (ITSC), 2012, pp. 1759–1764.

[12] C.G. Keller and D.M. Gavrila, Will the pedestrian cross? A study on pedestrian path prediction, IEEE Trans. Intell. Transp. Syst., vol. 15, no. 2, 2014, pp. 494–506.

[13] F.-H. Chan, Y.-T. Chen, Y. Xiang and M. Sun, Anticipating accidents in dashcam videos, Computer Vision —ACCV 2016, Lecture Notes in Computer Science, vol. 10114, 2016, pp. 136–153.

[14] K. Xu, J, Ba, R. Kiros, A. Courville, R. Salakhutdinov, R. Zemel, and Y. Bengio, Show, attend and tell: neural image caption generation with visual attention, J. Mach. Learn. Res., vol. 37, 2015, pp. 2048–2057.

[15] M. Shimosaka, K. Nishi, J. Sato, and H. Kataoka, Predicting driving behavior using inverse reinforcement learning with multiple reward functions toward environmental diversity, In Proc. 2015 IEEE Intell. Veh. Symp. (IV), 2015, pp. 567–572.

[16] A.L. Maas, A.Y. Hannun, and A.Y. Ng, Rectifier nonlinearities improve neural network acoustic models, 30th Int. Conf. on Mach. Learn. (ICML) Workshop on Deep Learning for Audio, Speech, and Language Processing, 2013.

[17] F. Shinmura, Y. Kawanishi, D. Deguchi, I. Ide, H. Murase, and H. Fujiyoshi, Driver's decision analysis in terms of pedestrian attributes —A case study in passing by a pedestrian—, In Proc. Workshop on Human Factors in Intelligent Vehicles in the 20th IEEE Int. Conf. on Intell. Transp. Syst. (ITSC), 2017, pp. 32–36.