Contents lists available at ScienceDirect

## Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

### 



TRANSPORTATION RESEARCH



<sup>a</sup> Graduate School of Information Science and Technology, The University of Tokyo, Hongo, Bunkyo-ku, Tokyo 113-8654, Japan <sup>b</sup> Institute of Industrial Science, The University of Tokyo, Komaba, Meguro-ku, Tokyo 153-8505, Japan

#### ARTICLE INFO

Article history: Received 30 May 2015 Received in revised form 9 July 2016 Accepted 25 July 2016

Keywords: Pedestrian behavior Signalized intersection Active safety system Connected vehicle Dynamic Bayesian Network

#### ABSTRACT

Active safety systems which assess highly dynamic traffic situations including pedestrians are required with growing demands in autonomous driving and Connected Vehicles. In this paper, we focus on one of the most hazardous traffic situations: the possible collision between a pedestrian and a turning vehicle at signalized intersections. This paper presents a probabilistic model of pedestrian behavior to signalized crosswalks. In order to model the behavior of pedestrian, we take not only pedestrian physical states but also contextual information into account. We propose a model based on the Dynamic Bayesian Network which integrates relationships among the intersection context information and the pedestrian behavior in the same way as a human. The particle filter is used to estimate the pedestrian states, including position, crossing decision and motion type. Experimental evaluation using real traffic data shows that this model is able to recognize the pedestrian crossing decision in a few seconds from the traffic signal and pedestrian position information. This information is assumed to be obtained with the development of Connected Vehicle.

#### 1. Introduction

Autonomous driving and connected vehicles are expected to significantly improve traffic safety and convenience by alleviating the burden of a driver. Currently, they are implemented as a form of an advanced driver assistance system (ADAS) to partially aid drivers. It is also expected that fully autonomous and connected vehicles will emerge as the key component of intelligent transportation systems, replacing human drivers in the near future.

Accidents involving pedestrians are one of the leading causes of death and injury around the world. On the other hand, there is no doubt that the reduction of these accidents should be considered in the development of autonomous driving and connected vehicle. Pedestrian detection has been an active research area and significant progress has been reported over the last two decades (Enzweiler and Gavrila, 2009; Dollar et al., 2012; Dalal and Triggs, 2005; Felzenszwalb et al., 2010; Llorca et al., 2012; Alahi et al., 2014). In addition, the classification of the type of road users was proposed by Zangenehpour et al. (2015). However, the detection and classification are not sufficient to direct the operation of vehicle in driving, especially in crowded urban areas. The reason is that many pedestrians appear around a vehicle, and the frequent detection of pedestrians makes the vehicle brake or be at a stop. In order to reduce traffic accidents as well as smooth the driving task, more advanced

<sup>\*</sup> This article belongs to the Virtual Special Issue on "CA Vehicles".

<sup>\*</sup> Corresponding author.

*E-mail addresses*: hashimoto@kmj.iis.u-tokyo.ac.jp (Y. Hashimoto), guyanlei@kmj.iis.u-tokyo.ac.jp (Y. Gu), qmohsu@kmj.iis.u-tokyo.ac.jp (L-T. Hsu), m-iryo@iis.u-tokyo.ac.jp (M. Iryo-Asano), kamijo@iis.u-tokyo.ac.jp (S. Kamijo).

collision avoidance systems are required not only to detect pedestrians around vehicles, but also to understand and predict the behavior of pedestrians. For this purpose, many researchers have worked on pedestrian path prediction and motion classification in the last few years.

A popular choice for target state estimation is the Kalman filter (KF). Pedestrian position, velocity, acceleration can be estimated with appropriate dynamical models and measurement models. Generally, the KF is based on the assumption that pedestrian dynamics approximates a linear dynamical system (LDS), which represents that a pedestrian walks at a constant-velocity and it is formulated as a linear operation. The KF can further be used for prediction by propagating the current state with the dynamical model. The KF was proposed to track pedestrian in image space (Binelli et al., 2005), ground plane (Bertozzi et al., 2004) and 3D space (Alonso et al., 2007). Moreover, various derivative versions of KF, such as extended KF (EKF) and unscented KF (UKF) have been applied for pedestrian tracking as well (Meuter et al., 2008; Junli and Reinhard, 2012). Trajectory provides significant information for state prediction, such as position and velocity. However, pedestrians can instantly change their walking direction, abruptly or start/stop walking. It is not sufficient to assume a single dynamical system for the pedestrian movement. Schneider and Gavrila (2013) proposed a more flexible system, which is composed of multiple linear dynamical models. The multiple models were used to distinguish the different motions of pedestrian, such as walking, stopping, bending in and starting.

Since the pedestrian behavior has highly dynamic property, motion changes indicate the crucial information from the view of traffic safety. The motion changes appear on the posture of pedestrian, which can be observed by considering the visual feature in image space. Koehler et al. (2013) proposed to detect pedestrian's initiation of gait using Motion History Image. Keller and Gavrila (2014) applied dense optical flow to two different models to judge whether the pedestrian approaching the curb will cross in front of the ego-vehicle or stop at the curbside. One model is a Gaussian Process Dynamical Models (GPDM) (Wang et al., 2008) trained with walking and stopping motion separately. The other model adopts probabilistic hierarchical trajectory matching, which matches the trajectory of the feature vector with database classified by motion types. While they employed 2-dimensional features which are vulnerable to ego-motion or change of the observing direction, Quintero et al. (2014a,b) used 3D body language to predict path and classify motions. They applied GPDM systems trained with accurate motion capture data to the pose estimated from noisy disparity images.

Besides the pedestrians own intention, the surrounding environment also affects the behavior of pedestrians. Researchers started to consider the contextual information for pedestrian behavior analysis. Kooij et al. (2014a) focused on the surrounding situations and enriched the impact factors, which cause physical motions of pedestrians. They assumed that the pedestrian decision whether to cross a road way or stop before crossing is influenced by three factors: existences of approaching vehicles, the pedestrian awareness of them and the spatial layout of the environment. In addition, the authors employed the Dynamical Bayesian Network (DBN) to model the relations among the behavior and those factors. Kooij et al. (2014b) also proposed a method based on spatio-temporal context, which switches LDSs according to the pedestrian position from a vehicle perspective. In contrast to the above-mentioned approaches, which aimed at short-time path prediction (~1 s), the method proposed by Bonnin et al. (2014) realized an accurate/early detection for pedestrians' crossing intention at a specific location: zebra-crossings, to percept the intention of pedestrians. It is valid to take account of contextual information in pedestrian behavior analysis, since pedestrians do not move randomly. Usually, they assess the traffic situations and have intention or planning at the same time. From the view of whole intelligent transportation systems, the contextual information.

Besides the context-based model proposed by Kooij et al. (2014a), there are many approaches making use of Bayesian Network (BN) or its application to time-series data: DBN. They are applied to models of semantic traffic situations or human behavior. Gindele et al. (2010) used a DBN to model the vehicle behavior. Integrating drivers' intentions and interactions to achieve the intentions, the proposed DBN estimates their behaviors and predicts their trajectories. Platho and Eggert (2012) proposed to model the traffic situation of intersection using BNs. The complicated intersection scenarios were decomposed into several sets of simple configurations. Each configuration contains an affecting and an affected entity such as a red traffic signal and a stopping vehicle, respectively. Moreover, Patterson et al. (2003) proposed to use DBN model to recognize the traveler's transportation mode: {*foot, car, bus*} from noisy GPS data stream and additional knowledge, such as existences of parking plots and bus stops.

Our work is highly inspired by Kooij et al. (2014a). We focus on a specific yet crucial scenario: the signalized intersections. The pedestrian behavior at the intersections is highly related to the state of traffic signal, instead of distance between pedestrians and vehicles. In this paper, we propose to use DBN to model the pedestrian behavior at signalized intersections. The proposed DBN probabilistically integrates relations among contexts, pedestrian intention, motion type and physical movement in the way pedestrians actually behave. The model estimates the whole state of a pedestrian in the Bayesian filtering framework. In addition, in the development of the model, we incorporated the traffic engineering knowledge (Iryo-Asano et al., 2015). Moreover, we are aiming to estimate the pedestrian intention, because the intention controls pedestrian behavior in a long period, which is the essential source of driving safety.

The remainder of the paper is organized as follows. In Section 2, we discuss pedestrian behavior at intersections as the motivation and problem statement for this study. In Section 3, we present the details for the DBN-based pedestrian behavior model including the filtering method. Experimental evaluation of the proposed system, including training data collection, is described in Section 4. Finally, we conclude this paper and discuss future work in Section 5.

Download English Version:

# https://daneshyari.com/en/article/526229

Download Persian Version:

https://daneshyari.com/article/526229

Daneshyari.com