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Review: Pedestrian Behavior Analysis and Trajectory Prediction with Deep Learning

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Abstract: It is becoming increasingly necessary for artificially intelligent systems to be able to monitor, evaluate, and anticipate the actions of humans as more of these systems are deployed in human-populated places. For an autonomous vehicle to make intelligent navigation decisions, a comprehensive analysis of the movement patterns of surrounding traffic agents and precise projections of their future trajectories are required. In this paper, we investigate how to assess the behavior of pedestrians and predict their trajectories using a unified deep learning model. Specifically, we look at how to do both of these things. Investigate the methods that were utilized to collect data and evaluate performance, as well as any surprises, challenges, insights, and recommendations that occurred as a result of the investigation's findings.

Keywords: Trajectory Prediction, Pedestrian Behavior Analysis, deep learning

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1. Introduction

Pedestrians account for 22% of the worldwide 1.24 million deaths caused by traffic accidents every year [1]. Most of such deaths occur when pedestrians are crossing a street at sunset and may be caused by poor visibility and drivers' fatigue. Many researchers have focused on the development of algorithms that estimate pedestrians' intentions of crossing streets. However, the problem is still challenging, since pedestrians can move in any direction and suddenly change motion. Such a prediction is a prerequisite for the safe operation of automated vehicles In recent years, rapid advances in location-acquisition technologies have led to large amounts of time stamped location data. Positioning technologies like Global Positioning System (GPS)-based, communication Network-based (e.g. 4G or Wi-Fi), and proximity-based (e.g. Radio Frequency Identification) systems enable the tracking of various moving objects, such as a vehicle, people, and natural phenomena. A trajectory is represented by a series of chronologically ordered sampling points. Each sampling point contains spatial information, which is characterised by a multidimensional coordinate in a geographical space, and temporal information, which is represented by a timestamp.

Trajectory prediction (TP) is of great importance for a wide range of location-based applications in intelligent transport systems such as location-based advertising, route planning, traffic management, and early warning systems.

To increase the safety of autonomous driving, the prediction of surrounding vehicles and pedestrians is one of the most important issues. In planning and control, detection, tracking, and collision avoidance of the obstacles are critical. Usually, in behaviour modeling of pedestrians on the walkway, their interaction with other traffic participants can provide clues to increase the accuracy of prediction systems. Most recently, deep learning-based approaches have become popular due to their superior performance in more complex environments compared to conventional techniques. i.e. Vehicle monitoring, behaviour, and safety analysis at intersections and Vehicle behaviour analysis with a focus on trajectory clustering and topic modeling methods and Anomaly detection techniques using visual surveillance and likewise Vehicle behavior prediction and risk assessment in the context of autonomous vehicles.

Contribution of the paper is to review the Pedestrian Behaviour Analysis and Trajectory Prediction using a unified deep learning approach which discusses the research challenges, findings and suggestions.

The remaining paper is organized as section 2: describes Pedestrian Behavior Analysis, Section 3 describes the Unified Deep Learning Approach, section 4 describes the Challenges, Section 5 describes the Datasets used, Section 6 explains the Factors Influence pedestrian behavior and section 7 and 8 illustrates findings and suggestions, Section 9 concludes the paper.

2. Pedestrian Behavior Analysis

Several studies have focused on the construction of systems that increase the safety of pedestrians on the streets. Pedestrian behavior modeling is gaining increasing attention and can be used for various applications including behavior prediction [2–3], pedestrian detection and tracking [4–5], crowd motion analysis [6–7], and abnormal detection [8–9]. A pedestrian detection system is a crucial component of advanced driver assistance systems since it contributes to road flow safety. The safety of traffic participants could be significantly improved. If these systems could also predict and recognize pedestrian's actions.

Modeling pedestrian behaviors is challenging. Pedestrian decision making is complex and can be influenced by various factors. The decision-making process of individuals [10], the interactions among moving and stationary pedestrians [11], and historical motion statistics of a scene provide information for predicting future behaviors of pedestrians. While existing works focused some of these aspects with simplified rules or energy functions.

2.1 Classical methods for trajectory prediction:

The problem of trajectory prediction or path prediction has been extensively studied. There are many classical approaches, including Bayesian networks [12][13], Monte Carlo Simulation[14], Hidden Markov Models (HMM) [15], linear and non-linear Gaussian Process regression models [16], etc. These methods focus on analyzing the inherent regularities of objects themselves based on their previous movements. They can be used in simple traffic scenarios in which there are few interactions among cars, but these methods may not work well when different kinds of vehicles and pedestrians appear at the same time.

Trajectory prediction of pedestrians in dense crowds using LSTM and GANs has been studied extensively [17, 18]. On the contrary, trajectory prediction of road-agents has been explored in lesser detail, as the inter-agent dynamics that govern the motion of pedestrians in a crowd are much different from the dynamics between vehicles in traffic. Despite this challenge, Deo et al. [19] combined LSTMs with Convolutional Neural Networks (CNNs) to predict the trajectories of vehicles on sparse U.S. highways. Chandra et al. [20, 21] proposed algorithms to predict trajectories in urban traffic with high density and heterogeneity. For traffic scenarios with moderate density and heterogeneity, Ma et al. [22] proposed a method based on reciprocal velocity obstacles. Some additional deep learning-based trajectory prediction methods include [23]. However, these methods only capture road-agent interactions inside a local grid. In contrast, graph-based approaches such as [24] for trajectory prediction of road-agents and [25] for traffic density prediction consider all interactions independent of local neighbourhood restrictions. However, these deep learning methods do not predict the behavior of road-agents, nor do they resolve long-term prediction error.

2.2 Pedestrian Trajectory Prediction Models

Existing models for pedestrian trajectory prediction can be broadly categorized into three types – physics-based, planning-based, and trajectory-based models.

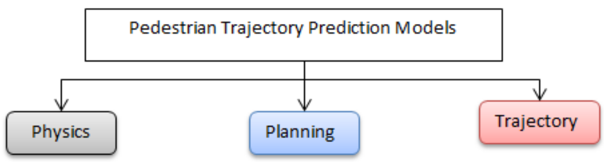

Figure 1. Pedestrian Trajectory Prediction Models

Physics-based models express pedestrian motion either as individual kinematic models (constant velocity, acceleration or turn) or using an Interacting Multiple Model (IMM) framework combining the above unique kinematics. These models cannot reliably predict over 1s in crossing scenarios as they are unable to predict motion changes such as turning at crosswalks. Recently, studies have modeled crossing decisions to improve trajectory prediction. For example, Kooij et al. [26] modeled a pedestrian crossing laterally as a switched linear dynamical system. They used contextual cues such as vehicle-pedestrian distance, and head-orientation to identify if an approaching pedestrian will stop at the curb or continue to cross the road. However, these studies [27], [28] considered only laterally approaching pedestrians but did not think the behavior of pedestrians already waiting at the crosswalk and still had short prediction horizons (2 s).

Planning-based models represent pedestrian behavior as a Markov Decision Process, use pedestrian goal locations, and formulate the motion prediction as an optimal planning problem [29], [30]. These models, by attributing goal-seeking behavior to pedestrians, were able to make long-term predictions.

Trajectory-based models are used to predict future pedestrian trajectories based on their past trajectories. These methods do not assume any pedestrian dynamics, but instead, learn the dynamics from the observed data. A common approach is to cluster the trajectories from the empirical data using Gaussian process [31] or vector fields and learn the motion patterns. More recently, deep learning models [32] have been developed to predict pedestrian trajectories using observed trajectories. However, the planning-based and trajectory-based models are limited in their application to crosswalk scenarios, as they do not explicitly incorporate pedestrians' waiting behaviour.

2.3 Emotion Classification from Pedestrian Motion

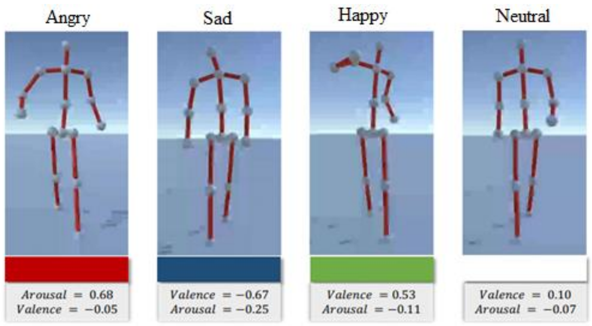

Figure 2. Emotion Classification from Pedestrian Motion.

From the above figure 2. it shows that emotion classification from the pedestrian motion as angry, sad, happy and Neutral with valence and Arousal parameters.

3. Unified Deep Learning Approach

When using deep neural networks to model pedestrian behaviors, the main difficulty is how to make good use of pedestrian walking information as the input of systems. A straightforward way was to use dense optical flow maps to describe motions of a whole frame.

Deep CNNs[33] have shown impressive performance on various vision tasks [34], such as image classification [35], object detection [36], object tracking [31], and image segmentation [32,33]. However, no deep model has been specially designed for pedestrian behavior modeling. The main difficulty arises from how to design the network input and output, which properly encode pedestrian behavior information and are also suitable for CNN.

The motion patterns of a whole frame were represented by dense optical flow maps for tasks such as motion segmentation [34], action recognition [35], and crowd scene understanding [36]. Trajectories were most widely used for pedestrian behavior understanding in non-deep-learning approaches. However, it is not clear how to make them suitable as the input and output of CNN[37], as they are of variable lengths and observed in different periods.

4. Challenges

Research challenges in trajectory prediction and pedestrian behavior analysis.

1. TP approaches are limited to short-term predictions and cannot handle a large volume of trajectory data for long-term projections.
2. How to handle heterogeneous data models or multimodality in mixed traffic conditions
3. Feature extraction from trajectories in real-time
4. Trajectory to driver behavior mapping to improve real-time navigation.
5. developing an integrated driving behavior model in mixed traffic conditions
6. Predicting the future positions of dynamic agents and planning
7. Jointly reason and predict the future trajectories of all the agents in a scene conditioned on the observed trajectories.
8. Understanding human motion analysis towards significant behavior predictions
9. Emotion Classification from Pedestrian Motion in Dense Traffic Conditions

5. Datasets Used

Table 1. Pedestrians Dataset

Dataset	Agents	Scenarios	Sensors
UCY	People	Zara / students	Camera
ETH	People	Urban	Camera
VIRAT	People / vehicles	Urban	Camera
KITTI	Vehicles / cyclists/ people	Highway / rural areas	Camera / LiDAR
ATC	People	Shopping center	Range sensor
Daimler	People	From moving vehicle	Camera
Central Station	People	Inside station	Camera
Town Center	People	Urban street	Camera
Edinburgh	People	Urban	Camera
Cityscapes	Vehicles/ people	Urban	Camera
Argoverse	Vehicles / people	Urban	Camera / LiDAR
Stanford Drone	Vehicles / cyclists/ people	Urban	Camera
TrajNet	People	Urban	Camera
PIE	People	Urban	Camera

ForkingPaths	People	Urban / Simulation	Camera

6.Factors Influence Pedestrian Behavior

Factors that influence pedestrian behavior into two groups, the ones that directly relate to pedestrians (e.g. demographics) and environmental ones (e.g. traffic conditions).

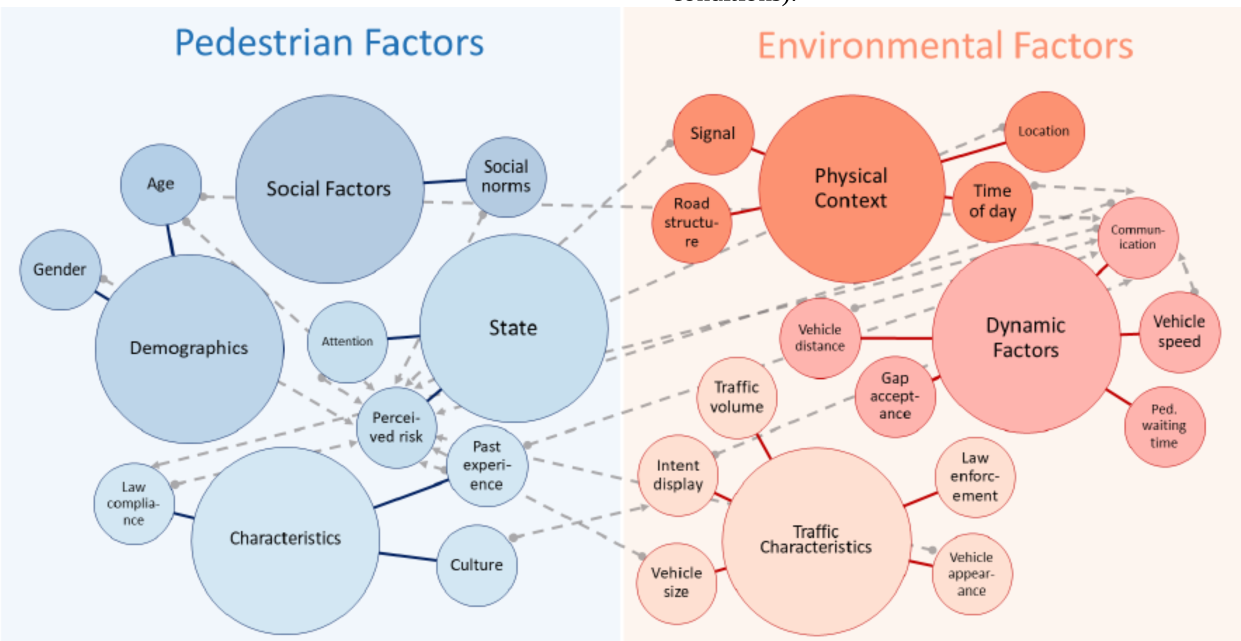

Figure 3. Factors Influence pedestrian behavior

From the above figures 3. It has analyzed that Factors Influence pedestrian behavior in two ways, such as demographic factors and characteristics and his/her social status. Similarly, it also correlates to the environmental factors such as Physical Context and dynamic elements and its traffic charatectirestics.

6.1 Motion Prediction System: Standard Approach

a. Initial trajectory state (Collect the data from stimuli)
b. Preliminary trajectory estimation process: Apply ML-based classification model based on historical data (Apply prediction method)
c. Vehicle trajectory prediction process. (Visualize)

Due to the stochastic nature of human decision making and behavior, the exact prediction of trajectories is rarely possible, and we require measures to quantify the similarity between predicted and actual motion.

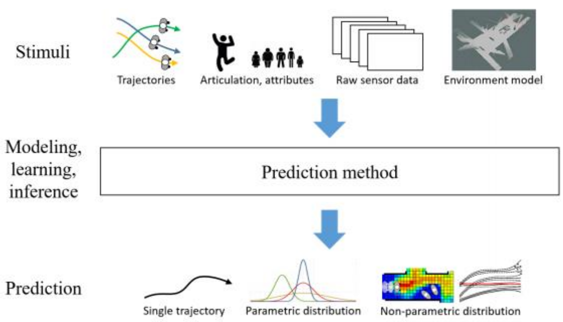

Figure 4: Typical elements of a motion prediction system

7. Findings

a. With growing numbers of intelligent autonomous systems in human environments, the ability of such systems to perceive, understand and anticipate human behavior becomes increasingly important. Specifically, predicting future positions of dynamic agents and planning considering such predictions are key tasks for self-driving vehicles, service robots and advanced surveillance systems.
b. A pedestrian detection system is a crucial component of advanced driver assistance systems since it contributes to road flow safety. The safety of traffic participants could be significantly improved. If these systems could also predict and recognize pedestrian's actions.

8. Suggestions

- To develop a unified deep learning framework for handling Short-term and long-term trajectory prediction based on a scalable clustering algorithm.
- Future work would focus on incorporating interactions between pedestrians and vehicles into the framework.
- Context understanding concerning features of the static environment and its semantics for better trajectory prediction is still a relatively unexplored area.
- Prediction of Human Motion & Traffic Agents in Dense Environments.
- Make use a deep learning-based methodology that provides both point estimates of future actor positions and their uncertainty, allowing for a deeper understanding of traffic state.
- Design data-driven based Recurrent Neural Network (RNN) for forecasting human trajectories and Emotion Classification.

9. Concussions

In this study, we take a look at the top priorities for predicting the paths of pedestrians and analyzing their behavior. Here, we take a look back at some of the more traditional approaches to trajectory prediction, including pedestrian trajectory prediction models. Research obstacles in trajectory prediction and pedestrian behavior analysis are also discussed, as is how a unified deep learning technique combines with the notion and its significance. Provides context for the data by detailing its creation and identifying its key drivers. Conclusions and recommendations are provided at the end.

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