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STUDY OF SENSOR, PROCESSING TECHNIQUES AND DEEP LEARNING-BASED APPROACHES TO THE PROBLEM OF FORECASTING PEDESTRIAN TRAJECTORY

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ABSTRACT

One of the primary issues of computer vision problems in the automobile industry, particularly in advanced driver assistance systems, is the prediction of pedestrian trajectories. For many applications, including autonomous cars, mobile robotics, and state-of-the-art surveillance systems, the capacity to predict people's future actions on the street is a crucial but difficult-to-implement job. Improvements in sensors and related signal processing technologies now aid the performance of state-of-the-art pedestrian trajectory prediction algorithms. At last, this work reveals the gaps in the literature and suggests future avenues for study.

***Keywords**: trajectory prediction; pedestrian behaviour; autonomous vehicles; sensor technologies; deep learning*

I. INTRODUCTION

Twenty-three percent of the 1.35 million people killed annually in automobile accidents [1] are pedestrians. Most of these terrible accidents occur near pedestrian crossings when heavy traffic and visibility are low. Pedestrians have almost little safety in the case of a collision. Therefore, it is crucial for safety reasons to lessen (eliminate) these effects. “To aid the driver in such a situation, new technologies must be developed to reduce the number of accidents (by up to 93.5%, according to [2]), such as predicting the pedestrian's trajectory and behavior and mitigating the driver's consequential errors (e.g., fatigue, inadvertent cognitive distraction).” The safety of the driver and other road users, including pedestrians, may be increased by minimizing the effects of human mistakes. More than half (55%) of these incidents reportedly occur on rural roadways, whereas just 37% occur in metropolitan areas.

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[3]. There are twice as many pedestrian accidents at night as during the day. Low visibility is the primary cause of these mishaps [4].

According to [5], autonomous vehicles should fulfill the needs of "vulnerable road users" in terms of safety. Bicyclists and pedestrians are especially defenseless since they have no physical barriers to protect them. Pedestrian trajectory prediction (PTP) applications have expanded in scope and significance in recent years. Predictions of pedestrian trajectories are used in many areas of research and development, including social robot platforms and autonomous driving. A person's social contact with other pedestrians on their way to their destination is included in this forecast. Pedestrians stay together by following the tracks made by the flows around them. They can avoid most accidents by choosing the safest path. Individual pedestrians' gaits, accelerations, and speeds define their unique mobility patterns. In order to learn and grasp certain movement qualities unique to an individual, it is essential to create a system that can utilize the first observations connected to that person. It is necessary to keep track of the location of any pedestrians at the site for a certain amount of time (in seconds). Each person's future coordinate must be estimated based on their current position and specific time. The pedestrian coordinates (in meters) pinpoint a person's precise position relative to a fixed point that is different in every scenario and is picked randomly.

Due to the unpredictable nature of human movement—in response to obstacles, automobiles, other people, etc.—predicting a pedestrian's trajectory is difficult. There is the potential for a shift in human behavior due to (sudden) occurrences within the scene [6]. People who were planning on taking a particular bus, for instance, are more likely to increase their pace (and even start running if they were strolling) in order to make it there in time. PTP becomes increasingly challenging to do when the scenario has more moving parts. The ideal case situation is when the pedestrian's final destination also serves as the last point of the trajectory pattern. It is not always possible to predict a pedestrian's final location in the actual world. The trajectory sequence from the past may be used to deduce the pattern. The advanced driver assistance system is the vehicle part most directly responsible for the dramatic decrease in traffic deaths and the overall improvement in road safety (ADAS). It is possible that the ADAS system will not always be able to correctly identify the pedestrian's final destination without the use of deep learning techniques.

II. LITERATURE REVIEW

Using direct row data in a 3D Cartesian coordinate system from sensors, the authors of [7] created a complete roadside LiDAR data processing system to forecast the future paths of people in real-time. Information such as XYZ coordinates, the number of data points, the distance between the LiDAR and the pedestrian, the pedestrian's speed, the tracking ID, the time stamp, the frame number, and the label was included in the derived future trajectory. An internal motor moved the X, Y, and Z axes in a Velodyne Lidar VLP-16 LiDAR sensor from

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San Jose, California. “The Nave Bayes method [8] was implemented at the input of the model for various ranges for probability calculation and an ideal combination of features to classify the sequence data from the sensor, such as trajectories of feature-based classifications.”

Using just a single camera and some 2D LiDAR data, Bu et al. [9] suggested a technique for estimating the location of pedestrians in 3D. This strategy utilizes three distinct networks (orientation network, regional proposal network, and PredictorNet) to provide more precise bounding box predictions. The orientation network resizes and crops the input data to calculate the orientation angles. The region proposal network uses the inputs from the orientation network to construct pedestrian bounding boxes that are not orientated. PredictorNet employs the pedestrian feature map learned from earlier networks to generate a conclusive prediction and classification.

Völz et al. offered a variety of architectures [10] that may be compared and contrasted to determine whether or not a pedestrian intends to cross the street at a certain crosswalk. “The cross-validation accuracy was 96.21% after they used a dense neural network architecture to identify pedestrian intents based on information from several time steps.” Using recurrent neural networks, which enabled feeding data back into the dense neural networks for a more precise analysis of the time-series characteristics, they were able to achieve a cross-validation accuracy of 95.77%. Picture features are retrieved using convolutional neural networks by proposing convolving learned filters along the LiDAR image. These features are then utilized to categorize the data. These writers employed the Theano [11] and Lasagne [12] DNN implementation frameworks in Python to realize their architectural visions.

Mohammadbagher et al. [13] introduced a novel method for a real-time estimate of pedestrian location, velocity, and acceleration. They employed an object-detection-based deep neural network architecture to determine who the pedestrians were in the LiDAR picture (YOLOv3 Pytorch). The odometry data gathered by the GPS and IMU sensors were utilized to pinpoint the exact location of the ego vehicle and, by extension, the pedestrian of interest in the picture. The model was put through its paces in two separate trials using a variety of visual conditions, where the scientists found success.

On-board LiDAR sensors need additional sensors like radar or cameras to assist the systems in autonomous driving, while roadside LiDAR sensors may function without them. Although roadside LiDAR sensors may offer trajectory-level and real-time data collecting, they are not widely used due to their expensive cost and restricted uses. The authors of [14] presented a subsystem to manage people at crosswalks using deep learning techniques directly on data from a fusion of camera and LiDAR sensors. The scientists employed convolutional neural networks (CNNs) and camera data to identify pedestrians, and then used LiDAR point cloud information to pinpoint their locations in still photos.

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However, broad deployment of LiDAR sensors may soon be viable because of recent breakthroughs in LiDAR technology and publicly available public data (e.g., scenes prediction challenge and Lyft Motion Prediction for Autonomous Vehicles). Since roadside LiDAR cannot directly apply the techniques used for onboard LiDAR data processing, it is vital to investigate the foundations of this technology, including installation plans and effective and efficient online and offline data processing methodologies.

III. Sensor Technologies for Pedestrian Trajectory Prediction

A. Automotive Sensing

A self-driving vehicle (SDV) has been modified with sensors and technologies to allow it to navigate roadways without human involvement. SDVs use a variety of sensors (including LiDAR, radars, and cameras) to identify objects in their proximity, anticipate their future trajectory, and estimate the motion uncertainty of those items [15]. Sensors and the systems that interpret their data also provide a hand, alerting drivers to potential dangers and helping them avoid them or automating driving shifts in tandem to cut down on human error [16]. Providing warning and safety applications relating to the external environment is not always possible based only on readings about internal sensors (termed "proprioceptive").

SDVs get data about their surroundings using exteroceptive sensors. As the data is processed, it might lead to the identification of additional contextual elements and surrounding objects. Due to advancements in camera technology and image processing, SDV external sensing has become more relevant in recent years [17]. Autonomous driving assistance relies heavily on camera and image processing systems, as noted in [18]. LiDAR sensors are the most essential for cars. It has omnidirectional sensing and is not light-dependent, making it superior to cameras. Ultrasonic and radar sensors account for 25% of the market, while other exteroceptive sensors (such as microphones) account for 18%. (see Figure 1).

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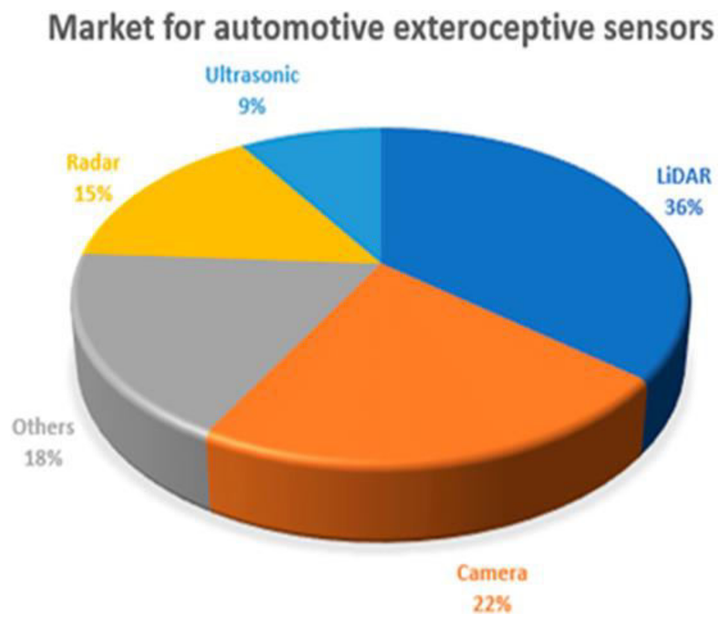

Figure 1. Exteroceptive sensors are expected to develop faster in the automotive sensors market (compound annual growth rate (CAGR), 2017-2022).

B. Radar

The significant functions of automotive radar systems are to detect and assess the size, motion, distance, relative velocity, and direction of interest (such as pedestrians, other vehicles, or bicycles) [19]. Radar can monitor the whole scene because it uses reflected electromagnetic waves, which are received and sent at the same time. Due to their inconvenient nature, radar data have been employed for predicting pedestrian trajectories only in a few instances up to this point.

Pulses of radio waves are sent by radar systems and may reflect off of anything in the driver's path. There was an issue with conflicting data from delayed reflected pulses reaching the sensor.

Doppler shift, a change in frequency caused by the motion of an item, may be used to calculate an object's relative velocity (e.g., pedestrians). Recent versions of automotive radar systems operate at 24, 79, and 77 GHz, and their beam widths may span 9 degrees to 150 degrees [20]. [21] Radar has three distance ranges that it may use, depending on the weather conditions: long range (10-250 m), medium range (1-100 m), and short range (10 m) (0.15–30 m). As it relates to distance, distance estimate plays a crucial function. The distance between a source and a target is measured regarding the round-trip time delay of the electromagnetic waves involved.

An individual's characteristic micromotion produces what is known as a micro-Doppler effect, which may be thought of as a relatively significant but subtle Doppler shift [22]. The

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micro-Doppler signature, which is the time-dependent periodic velocity pattern resulting from the periodic movement of limbs, is another crucial idea. Multiple methods, including extraction and matching, may be used to zero in on the motion of pedestrians. Using a Kalman filter and a Gaussian distribution to identify pedestrian motion, the authors of [23] created a system that uses radars from cars and Doppler radars to detect motion. A human motion may be tracked in real-time by examining the Fourier spectrogram of Doppler frequency. They gathered four sets of data from various settings to evaluate the methodology. In [24], another method for anticipating the actions of pedestrians is presented. They digitally recorded the motion of each body component by using radar readings and motion capture sensors that worked in tandem. The scientists employed a CFAR algorithm to estimate each range doppler cell based on a detection threshold. However, only data from a single pedestrian is supplied, limiting our understanding of the outcomes and defining movement behavior characteristics.

Pedestrians' motion and appearance modalities were combined into the tracker using a Bayesian framework given by Dubey et al. [25]. A latent feature vector was used in conjunction with a distance measure to distinguish between classes and learning characteristics for each. Using a hybrid tracking and classification system, we were able to extrapolate pedestrian trajectories from a series of waypoints traveled at constant speeds. The authors utilized the MATLAB Driving Scenario Designer to develop their various situations. To estimate the direction of pedestrian movements in complicated circumstances, the authors of [26] proposed a technique based on the micro-Doppler signature acquired from a vehicle MIMO radar. This technique takes one vantage point of pedestrians and uses regression techniques to deduce the mobility direction from the micro-Doppler signal. The authors simulated car-based scenarios in which a pedestrian is seen by numerous input/output radar sensors in order to verify their suggested technique.

The market for autonomous driving assistance technology is expanding, and with it comes the opportunity for automotive radar to become a more potent answer to the challenge of predicting the paths of pedestrians. The principle, modulation, and signal processing of automobile radar are all part of this evolution.

C. LiDAR

Laser-reflecting sensors called LiDAR (light detection and ranging) can identify things in a vehicle's immediate vicinity. It is good knowledge that LiDAR sensors release regular bursts of light, say, once every 30 ns. The sensor's emitted beam of light has a typical wavelength of 905 nm and is coaxial with the reflected light element [26]. “In addition to its high precision, LiDAR's circular and vertical mode of operation makes it possible to acquire 3D models, which are spatial representations of coordinates obtained by recording the distance and direction of the returning light pulses as data points, which are then organized into point clouds.” In the event of changing traffic circumstances, LiDAR sensors allow for the novel

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gathering of data at the trajectory level. These sensors can detect and report on objects up to 42 degrees in the vertical field of view and 360 degrees in the horizontal field around the vehicle using 3D point clouds [27] that are unaffected by ambient lighting conditions (see Figure 3). LiDAR technology's limited sensitivity to ambient light and weather is a significant drawback. There is a common belief that LiDAR sensors are too slow for applications that must react in real-time. Low-cost LiDAR sensors (USD $100 and less) typically feature a single laser beam and low power requirements (starting from 8 W). Meanwhile, the latest LiDAR sensor models use laser arrays to improve the resolution of the point cloud (up to 128).

Among the many sensors available for an autonomous car, LiDAR sensors stand out due to their ability to provide more explicit images regardless of lighting. “Even if the data's accuracy is diminished in poor weather, including rain or fog, the LiDAR sensor may be utilized correctly in high-frequency applications in mild weather (e.g., creating a perception layer in case of an autonomous vehicle).” The high-quality LiDAR functioned in any light level, creating detailed regional maps for a personal car. These maps may benefit behavior predictions concerning the immediate surroundings and moving vehicles. Predictive route planning for an autonomous vehicle relies heavily on predictions of environmental behavior, such as the likelihood that a car in front of it will make a turn.

Figure 3.” A 3D-LiDAR sensor could be employed for short, medium, telescopic, or combinations (dual short range, dual medium) range. Here, a Velodyne HDL-64E sensor and its generated points cloud. (Images source: www.velodynelidar.com; accessed on 29 October 2021).”

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There are presently three primary applications for LiDAR sensors in autonomous cars [28-31]: obstacle identification, vehicle detection, and lane marker detection. While LiDAR sensors placed along highways only offer scattered data points, onboard LiDAR sensors may comprehensively describe things by using dense point clouds. An example of pedestrian recognition in raw LiDAR point clouds is shown in Figure 4. Data quality depends on how far a LiDAR device is from the pedestrian.

IV. DEEP LEARNING PARADIGMS FOR PEDESTRIAN TRAJECTORY PREDICTION

Several deep learning-based approaches have been offered in recent years as potential solutions to the PTP issue. In this part, we will go through the most popular approaches in this field and classify them by the DNN architectural style they use. The discovered deep learning-based algorithms employed three main types of architecture for predicting pedestrian trajectories.

A. Trajectory Prediction Based on RNNs

Vanilla RNN is a recurrent neural network that builds on a two-layer, fully connected network by adding a feedback loop to the hidden layer. By making just a straightforward adjustment, sequential data models may be optimized. Data from previous phases is also used by the Vanilla RNN and is kept in the anterior hidden neurons, making it possible for the network to perform better.

Using a long short-term memory (LSTM) structure, we could satisfactorily handle the problem of dealing with long-term information preservation [32]. By modeling latent data characteristics, the LSTM has shown promising early results in the NLP field; it is now being used in predicting pedestrian trajectories. “For instance, Sun et al. [33] employed the LSTM model to learn the target environment's environment and people's activity patterns through long-term observations (i.e., several days to several weeks).”

Fragkiadaki et al. [34] demonstrated using recurrent neural networks with encoder-recurrent-decoder (ERD) architecture to predict human body posture in a motion capture system and movies. “When applied to the LSTM model, ERD design adds nonlinear encoder and decoder networks before and after recurrent layers to improve accuracy and generalization.” Input data is represented by the encoder, while the output of the recurrent layers is translated into the required visual form by the decoder. Therefore, the suggested design can anticipate where people would be going based on the current and past positions of their whole bodies.

The social LSTM model was suggested by Alahi et al. [35] to predict joint trajectories in continuous areas. Because of the impact of others around them, LSTMs use a social pooling approach to disseminate the knowledge contained in the concealed state to surrounding pedestrians. Their model performs better than state-of-the-art approaches on several different

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data sets. As a result of using a separate LSTM model for each trajectory, they coined the term "social LSTM" to describe the methodology they used. ETH [36] and UCY [37] were used to validate this model.

Using LSTM, S. Dai et al. [38] suggested a model for predicting trajectories in space and time. They claim that LSTM networks are incapable of characterizing the spatial interactions between several vehicles simultaneously. Furthermore, they highlighted the gradient vanishing issue in LSTM models. They connected the inputs and outputs of two sequential layers to tackle the problem of trajectory prediction under heavy congestion and deal with gradient vanishment. Interstate 80 and U.S. Route 101 datasets were used to evaluate the suggested model. Their model was claimed to improve the accuracy of trajectory prediction seen in previous state-of-the-art models.

To train a single model for the whole human body without needing a spatial encoding layer, Martinez et al. [39] devised a technique that employs RNN with gated recurrent unit (GRU) architecture. Instead of dealing with exact angles, they modeled velocities. They put out a new model for first-order motion derivatives that they called "residual architecture." Indications were made that the prognosis was more precise and operations went more smoothly.

In order to forecast the paths of many pedestrian models simultaneously, Hug et al. [40] recommended using a long short-term memory (LSTM) model with a mixture density layer (MDL) model combined with a particle filter approach. Their TensorFlow implementation made advantage of vectorized computations. Their theory was tested on a number of "T"-shaped crossroads. When conducting their tests, the scientists relied on images from the Stanford Drone Dataset. In these tests, we simulated situations when maximum likelihood predictors would be useless because of their inability to supply many hypotheses simultaneously. One example is the use of roundabouts at junctions.

In [41], a long-term prediction model was suggested that uses RNNs. Together, the encoder and decoder framework can foresee people's movements and ego trajectories. The authors said their approach could be used to foretell people's futures at any time interval. The Cityscape dataset [42] was used in both training and evaluation.

B. Trajectory Prediction Based on Convolutional Neural Networks

One kind of DNN, the convolutional neural network (CNN), excels at tasks like object categorization and recognition (including handwritten digits, characters, and faces). “Figure 10 depicts the standard architecture of a convolutional neural network (CNN), which consists of several layers of convolutional, non-linearity, pooling, dropout, batch normalization, and fully connected components.” Training and tuning the network allows CNNs to pick up on object characteristics. These properties comprise the essential discriminative information

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needed for the strong identification of the targeted objects thanks to the careful selection of network design and parameters.

Using a recurrent mixed-density network, Rehder et al. [43] developed a way to predict where pedestrians will go next based on their current location and a series of photographs. “A forward-backward network and an MDP (Markov decision process) network are two designs used to construct a trajectory prediction, such as in goal-oriented motion planning.” Pedestrians' visuals and locations are used as design parameters. A convolutional neural network (CNN) is used to process the picture. The input for an LSTM network is the joined position vector and CNN output. The network then generates a probability distribution map as an output, representing the most likely paths pedestrians will take in the future. The authors trained and evaluated their proposed network in the wild by collecting stereo recordings from repeated drives through urban and residential regions, each annotated by hand to identify pedestrians.

Using a convolutional neural network (CNN) for long-term motion and a Bayesian assessment of the present dynamic environment as input, S. Hoermann et al. developed a technique [44]. In addition to the network that carries out the segmentation of the static and dynamic sections, a single neural network is used to analyze the scenes. The authors developed a loss function that considers the balancing of unbalanced pixels across categories and relies on the use of uncommon dynamic cells. They demonstrated the network's ability to make accurate predictions for up to three seconds in very complicated situations involving many people using the road simultaneously. To top it all off, the network can recognize several kinds of maneuvers, such as left and right turns and interactions between drivers.

An encoder-decoder architectured multi-agent tensor fusion (MATF) network was suggested by Zhao et al. [45]. To maintain spatial links between features and capture interactions between the agents, the spatial-centric method employs a flexible network that can be trained in contextual pictures of the environment with sequential trajectories of the actors. When learning stochastic predictions, their model stores the past trajectories of several agents separately and decodes recurrently to a single agent's future trajectories via adversarial loss. “The ETH-UCY dataset, the Stanford Drone Dataset, and the NGSIM Dataset were used during training [46].”

V. CONCLUSION

As the most vulnerable road users, pedestrians have the greatest need for safety measures. These tragic statistics underline the critical need for improved pedestrian safety measures. “Different types of sensors need to be developed, features need to be extracted from the processed sensor information, features need to be analyzed and classified, and finally, pedestrians and their behavior need to be detected and tracked; this requires analysis of not only the pedestrians, but also the drivers, interfaces, and

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human factors." Radar, light detection and ranging (LiDAR), and video cameras, or a combination of these, are the most common types of sensors used in PTP applications. All sensors have their advantages and disadvantages in terms of the data they can collect. These sensors are installed in moving cars to collect data on traffic patterns or at fixed positions along streets to gather intelligence. Information on the location and movement of people is crucial.

Present-day systems are more effective at resolving the PTP issue since they use deep learning techniques. These techniques take as input a set of historical pedestrian locations and provide a set of predicted future places. We conducted an in-depth analysis of the literature and found that RNNs, CNNs, and GANs are the three most promising DNN architectures for pedestrian trajectory prediction. These methods are not mutually exclusive and are often used in tandem with one another.

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