Detection of Lane Changing Vehicles with Wavelet Transform and K-Nearest Neighbor Algorithm

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Abstract— **Traffic management is getting more complicated due to the increasing urbanization rate day by day. Therefore, many models have been developed using smart transportation systems to overcome this problem. Lane changing, which is one of the important issues of smart transportation, is one of the basic driving behaviors that has a major impact on traffic efficiency, safety, and flow. Many various approaches have been presented in the literature for lane changing detection. In this study, a novel method for lane changing detection with a wavelet transform approach is presented. In the study, the pNEUMA dataset was used to evaluate the performance of the proposed method. In detecting lane changing, the azimuth angles of the vehicles were calculated using the WGS-84 coordinates in the dataset. Multi-level discrete wavelet transform, and lateral deviation were applied to the azimuth series of vehicles on a sample street in the dataset, and the data obtained were then classified with K-Nearest Neighbor Algorithm to determine whether there was a lane changing. In addition, the direction and time of the lane changing were determined by using the maximum amplitude obtained with wavelet transform methods. The proposed approach in the study achieved an average accuracy rate of 98%. Compared to other approaches, the proposed method has less computation complexity and therefore can find results more quickly.**

Keywords— intelligent transportation systems, classification, lane changing, traffic

I. INTRODUCTION

Lane changing (LC) is one of the most important driving tasks observed in the traffic flow. Compared to other daily routine driving behaviors, the LC maneuver is more complex and requires drivers to be aware of surrounding traffic conditions (for example, the speed and distance of the vehicle ahead and gaps in the current driving lane). LC has attracted great interest especially in highway systems. Due to the lack of data covering urban roads, lane changing maneuver has not been studied sufficiently on urban roads. For this reason, in this study, lane changing detection was carried out using a dataset with data on urban roads.

LC detection has been performed by many researchers using machine learning methods such as Hidden Markov Model (HMM), support vector machine (SVM), and artificial neural network (ANN). The spectral time-frequency analysis partitioning approach has been used by Zheng and Hansen [1] to generalize potential LC and Lane Keeping (LK) candidates. The classification was performed with dynamic time warping (DTW) and HMM approaches, and these approaches were compared with each other. Dou et. al. [2] developed a model about the prediction of drivers' LC maneuver on highways. Vehicle and road surface condition information were used for the detection of LC. The ANN and SVM models were combined and then was compared with other classifiers in the literature. A neural network is one of the popular approaches used in LC estimation because of its ability to generalize, learn and resolve uncertainties. Ding et. al. [4] applied a backpropagation artificial neural network model and performed LC detection on past vehicle data. Then, the training time and accuracy results of the applied model were compared with the results obtained using the Elman network model. According to the study performed by using a driving simulator and NGSIM data, the applied model has reached high accuracy in traffic flow on urban roads.

Recently, deep learning methods have been used frequently to detect LC maneuvers. The convolutional neural network (CNN) is one of these methods. Back and He [3] used the information of extracted edge from the region of interest in the original image. They employed SVM based framework to detect the LC behavior. Before that, the principal component analysis (PCA) has been applied to reduce the dimension of the images. The authors stated that the accuracy reached 68.5% when tested on actual driving data. Besides, they have implemented a CNN-based LC classifier using extracted edge information as input and reached 79.7%. LC was predicted using the group-based CNN model and three different types of physiological signals of the driver's. Gao et. al. [5] performed raw data labeling using SVM with density-based clustering. They tested the proposed model on highD dataset, which created using camera-equipped drones. Wei et. al. [6] developed a deep learning-based computer vision system using deep CNN to predict LC. This approach was considered the inadequacy of GPS data in lane-level decision-making and the cost of using LIDAR in order to achieve high accuracy. The authors stated that detection performed in 0.028 seconds per image with 86.95% accuracy.

As a result of inadequate traffic penetration rates, privacy issues, GPS errors, etc. various problems may arise. Therefore, it can be difficult to take account of traffic situations in arteries and busy city centers. In order to solve such problems, data has been collected from the traffic flow in the areas where traffic congestion was faced by using the swarm of drones [7]. Barmpounakis et. al. [8] detected the LC using the vehicle coordinate information contained in these data. The azimuth angle of the instantaneous latitude and longitude of the vehicles has been determined comparing with the true north. They used the peak detection tool to determine the peaks that mean LC in the azimuth graphic. The authors stated that LC maneuvers of the vehicles were detected with 96% accuracy.

In this study, the data of the vehicles in the region determined as the study area was extracted from the pNEUMA dataset [9]. The azimuth angle of the vehicle was calculated using the latitude and longitude information in these data. These angle series were filtered using the Finite Impulse Response (FIR) filter. The lateral deviation was calculated by using filtered series, level and maximum amplitude properties were obtained by applying multi-level discrete wavelet transform. LC in urban roads was detected with the K-Nearest Neighbor (K-NN) classifier applied to the lateral deviation and maximum amplitude features.

II. METHODOLOGY

A. *Dataset*

The current trajectory data can be insufficient in terms of spatial and temporal coverage. More comprehensive trajectory data is required for complete vehicle tracking and processing the traffic flow dynamics of the relevant vehicle accurately. The pNEUMA dataset was employed in this study. This dataset is provided by The Laboratory of Urban Transport Systems (LUTS) of the Ecole Polytechnique Federale de Lausanne(EPFL) deploying a swarm of drones over the city of Athens, Greece, in October 2018. It contains 10 different zones recorded in the morning peak hours for weekdays. The recording area is 1.3^2 km that covers roads of different densities and different numbers of lanes. The dataset includes the speed, acceleration, traveled distance, and vehicle type (car, taxi, bus, motorcycle, medium vehicle, and heavy vehicle), as well as allowing for a large number of new features that can be generated using location information.

B. *Lane Changing*

LC maneuver is defined as a vehicle crossing the lane line between two adjacent lanes. LC process usually takes a few seconds. It basically begins with the emergence of motivations that cause LC and is completed when the vehicle is laterally stable in the target lane. In the study, LC detection was performed using azimuth, lateral deviation, and wavelet transform. As indicated in Fig. 1 where LC steps are shown, the WGS-84 coordinates of a vehicle were for the azimuth, that is, the angle series was obtained by taking 2 points in the study.

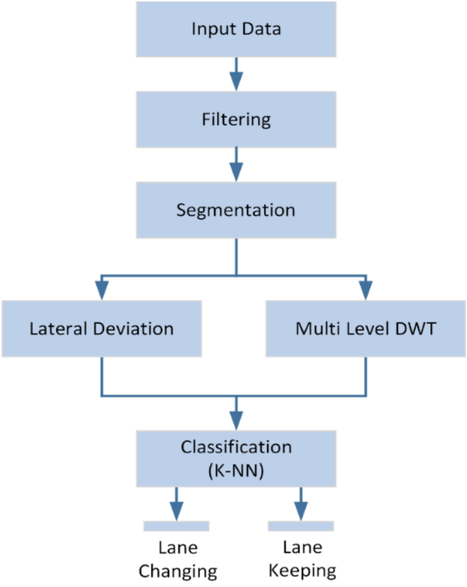

Fig. 1. Flowchart of developed LC detection model

Due to a high level of noise in the dataset, the moments when the vehicle in the angle series stopped were removed, and then the noise was removed with the FIR filter. Lateral deviation and multilayer wavelet transform are applied to the noiseless series. Compared with freeways, many more lane changes occur in urban roads. In Fig. 2, the lane changes in urban roads are shown the thin lines between the dense lines.

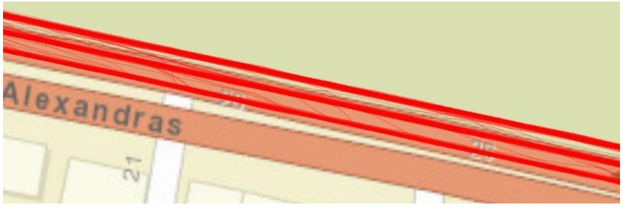

Fig. 2. Thin lines between dense lines represent LC of vehicles

1) *Azimuth*: The term of azimuth describes the angle formed by two lines; one that connects the current position to the North Pole, the other is the current position and the next position. In this study, the azimuth that is the angle between the direction of movement of the vehicles with the North Pole was calculated using the WGS-84 coordinate of the vehicles in the pNEUMA dataset.

When the azimuth of the road and the azimuth of the vehicle are compared, it has been observed that the two angles show similarities in a straight road. When the vehicle starts to change lane, the azimuth of the vehicle starts to increase or decrease depending on the vehicle's movement way. After the azimuth reaches the local maximum or minimum, that is, when the vehicle completes the lane changing, because the azimuth of the road remains constant on straight roads, it will gradually return to its original value.

To calculate the azimuth of the vehicle with the specified equation given in (1) was used.

$$az_x = \alpha tan2[(\sin\Delta\lambda * \cos\varphi 2), (\cos\varphi 1 * \sin\varphi 2 - \sin\varphi 1 * \cos\varphi 2 * \cos\Delta\lambda\,)] \tag{1}$$

where $\varphi 1$ and $\varphi 2$ are the initial and final latitude of the vehicle, $\lambda 1$, and $\lambda 2$ are the initial and final longitude of the vehicle, respectively. The difference between two longitudes is called $\Delta\lambda$.

To smooth noisy azimuth series, a window-based finite FIR was utilized. Multi-level DWT was applied to the smoothed trajectories data with the objectives of optimizing the lane-changing algorithm and identifying the peak.

2) *Lateral Deviation:* Using the latitude and longitude data in the form of WGS-84 coordinates, the distance traveled by the vehicle between two consecutive coordinates is calculated using (2). The lateral deviation is calculated as in (3) with the azimuth of the road, the instantaneous azimuth of the vehicle, and the calculated distance information in (2).

$$dist = 6371 * 2 * \arcsin\,((sin^2\Delta\varphi/2 + cos\varphi_1 * cos\varphi_2 * sin^2\Delta\lambda/2)^{\frac{1}{2}})] \tag{2}$$

$$dy = dy + \sin(az_x - az_{road}) * dist \tag{3}$$

In the classification to determine whether vehicles have changed lanes or not, the cumulative sum of lateral deviation over the distance traveled by a particular vehicle is used as a second feature. Due to the use of the distance traveled by the vehicle, noisy data are not visible in the cumulative sum of lateral deviation when the vehicle stopped because of traffic signals or congestion.

3) Wavelet Transform: Multi-level decomposition of the signal can be performed with multi-level DWT. Approximation and detail coefficients are obtained by applying multi-level DWT. Multi-level DWT was applied to the denoised azimuth series obtained by calculating the azimuths of each vehicle. Approximation or scaling coefficients represent the signal as low pass. The detail coefficients are wavelet coefficients. At each subsequent level, the approximation coefficients are divided into a rough low pass and high pass coefficients, which are approximation and detail coefficients respectively. The scale and shift variables of LC vehicles were determined using Haar, Daubechies, and Symlet wavelets. The maximum amplitude levels of each vehicle are determined according to the detail coefficients separately. The coefficients of detail obtained by applying Haar, Symlet, and Daubechies wavelets to azimuth-time series of different lengths as 12 levels were investigated. The level of maximum amplitude was determined as the level at which the LC takes place. Fig. 5 shows the detail coefficients for a vehicle selected randomly from the dataset. As seen in the figure, the maximum amplitude of the vehicle that changes lanes is in the 8th level. The scale and shift variables were determined according to the detail coefficients of the level where the LC occurred. While the scale variable corresponds to the level at which the LC occurs, the shift variable corresponds to the order of the coefficient at the level where the maximum amplitude is reached. Child wavelets are generated from the mother wavelet $\psi(t)$ using (4)

$$\psi_{j,k}(t) = \sqrt{1/2^j} * \psi((t - k * 2^j)/2^j) \qquad (4)$$

where j is the scale parameter and k is the shift parameter both which are nonnegative integers.

III. EXPRERIMENTAL RESULTS

Leoforos Alexandras avenue in the dataset was chosen for the evaluation of the LC model. The avenue is a 400 m three-lane artery. The test dataset includes 388 vehicles in the study area shown in Fig. 3 between 10:00 - 10:30 on October 24, 2018. These vehicles do not include motorcycles and turning vehicles that need a different approach in which detection of LC maneuver.

As shown in Fig. 5, level 8 has the maximum amplitude that is proper wavelet length for lane-changing detection of a selected vehicle. The time of lane changing was determined in seconds using the scale and shift variables. The sampling period is $Ts = 0.4$ seconds, depending on the data used. After the child wavelets are generated using (4), their lengths and start and endpoints are determined. The starting point of this wavelet was specified as t_0 and its end point as t_e. The time when the vehicle changes lane whose detail coefficients are shown in Fig. 5, was calculated as 179.2 in seconds type using the expression $(t_0 + t_e) / 2 * Ts$. This calculated value corresponds to the time after the first data of the vehicle is recorded. In other words, the vehicle changed lane 179.2 seconds after the first recording time. Besides, the lane where the vehicle passes to was determined by the sign of the maximum amplitude. If its sign is positive, the vehicle passes to the right lane and the negative to the left lane. It is understood that the vehicle given as an example in Fig. 5 passes from its current lane to the lane on its right because of a positive sign.

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Fig. 3. Study area to evaluate the performance of the model

The classification of LC and LK was successfully performed with K-NN on Haar, Daubechies, and Symlet wavelets. The performance results of the proposed model are shown in Table I. The best result was achieved using the Haar wavelet with 98% accuracy. Although not as good as Haar, the classification was carried out with remarkable accuracy on Daubechies and Symlet wavelets, too. 60% of the dataset was used as training, and the rest is used as a test. Only a few vehicles are incorrectly classified for each class. In Fig. 4, it is seen how many incorrect classifications have been made in which classes for each mother wavelet.

TABLE I. PERFORMANCE RESULTS OF THE PROPOSED MODEL

Type of Wavelet	Precision	Recall	F1-Score	Accuracy
Haar	0.97	0.98	0.97	0.98
Daubechies	0.95	0.95	0.95	0.96
Symlet	0.94	0.92	0.93	0.94

Fig. 4. The confusion matrices of Haar, Daubechies, Symlet wavelets

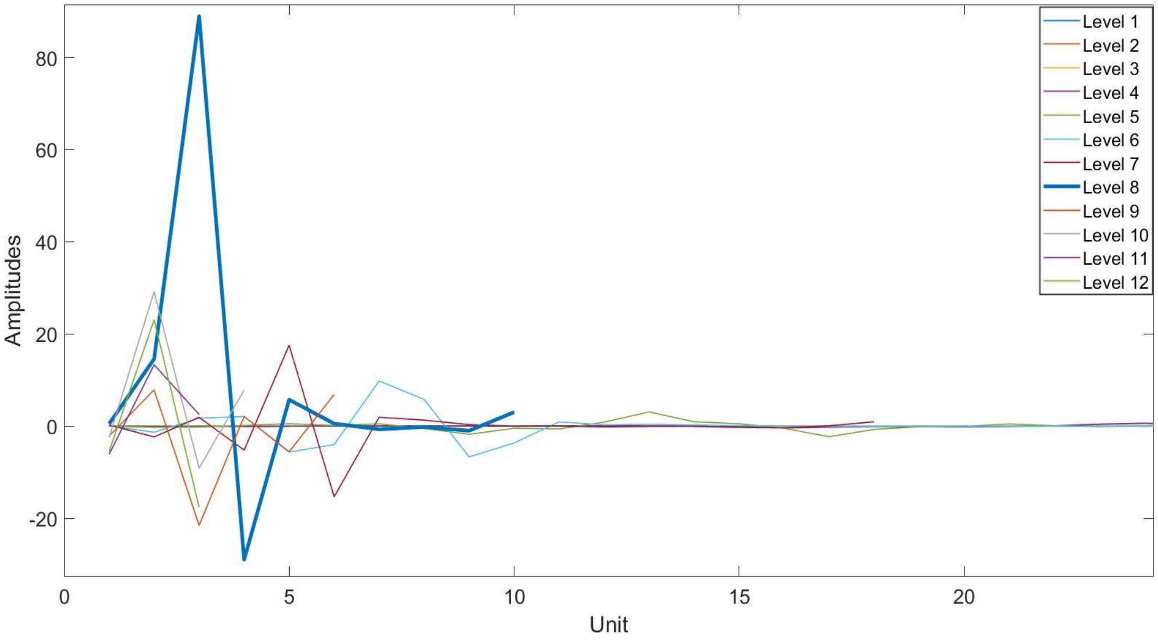

Fig. 5. Detail coefficients of the LC vehicle

IV. CONCLUSION

LC maneuver is the basic type of vehicle movement modeled by signal processing and machine learning methods earlier, and mostly deep learning techniques recently. In this study, multi-level DWT used to predict the LC maneuver with only the position data that has WGS-84 format of vehicles. The Leoforos Alexandras in the pNEUMA dataset consisting of 388 vehicles was used to train and test the proposed model. Three mother wavelets, which are Haar, Daubechies, and Symlet, were used in multi-level DWT. Amplitudes and lateral deviation features for each mother wavelets were obtained and then used in a K-NN classifier. We confirmed that the proposed method has been successful in detecting the LC maneuver. Experimental results show that the proposed method is successful in detecting the LC maneuver. In future studies, the success of the proposed method can be increased by applying different filtering methods due to very noisy vehicle data.

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