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Detection of Driver Styles in Lane Changes using Wavelet Transform

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Abstract: Lane change detection is crucial for intelligent transportation systems, as it affects traffic flow on both macroscopic and microscopic levels. Lane change models are widely used in traffic and transportation studies, making it important to understand the factors that affect drivers' lane changing behavior. In this context, we proposed a novel model for detecting lane changes by applying wavelet transform to high-resolution data from unmanned aerial vehicles. The model was trained and tested using empirical lane changing data from pNEUMA. Firstly, the azimuth angle was calculated on WGS-84 coordinates of each vehicle found in the specified road segment. Next, a multi-level wavelet transform was applied to the azimuth series using mother wavelets such as Haar, Daubechies, and Symlet for each vehicle. Machine learning method was applied to extracted features to detect lane changing. Additionally, the lane changing style of drivers was classified as sudden or normal using the same model. The results indicate that the proposed data-driven model is able to accurately detect lane changes and the type of lane change.

Keywords: intelligent transportation systems, traffic flow, lane change style, wavelet transform
Categories: I.2.0, I.2.1, I.2.6
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1 Introduction

Lane changing is one of the most fundamental driving behaviors. It can cause several impacts on traffic stream such as, oscillation [Ahn and Cassidy 2007], safety [Zheng et al. 2010] and efficiency [Zheng et al. 2011], [Keyvan-Ekbatani et al. 2016]. These impacts show that the importance this driving behavior which is an important part of intelligent transportation systems (ITS) for the management of road traffic.

Lane changes are significant information in transportation systems because they can cause accidents or blockages if they occur too frequently. When a lane is closed due to an accident, vehicles in that lane may have to change lanes, leading to an abnormal number of lane changes. This abnormal number of lane changes can be used to detect traffic accidents automatically. Additionally, lane change data can also be used to determine the type of lane change performed by a driver, such as whether the driver made the change aggressively or safely.

Until now, lane change data has mainly been collected using roadside sensors or traffic cameras. However, with the advancement of technology, lane change data is also being collected using unmanned aerial vehicles (UAVs). The traditional methods of collecting lane change data have some limitations, such as high cost and limited coverage associated with the frequent placement of sensors on the roadside. UAVs can overcome these limitations by providing high-resolution data at a lower cost and with wider coverage.

In our previous study [Avcı et al. 2021], we proposed a new method for lane change detection and determining how drivers perform a lane change. In the method, the azimuth angles were calculated from the vehicle positions. Lane changes of different types of vehicles according to azimuth angles were determined by three main wavelet methods which are Haar, Daubechies, and Symlet of wavelet transform. The fact that the data used was collected by using UAVs enabled the study to be carried out successfully by providing high resolution of the data. To address the aforementioned issues, we developed a signal processing-based model for the entire lane changing process of a vehicle.

In addition to lane change detection, this paper aims to detect lane change style using an urban road dataset created using UAVs. We developed a model for style of lane change detection using multilevel wavelet transform, using the coordinate information of different types of vehicles in the dataset. We tested the model using three different mother wavelets, and measured the success of the model for the detection of lane change style using machine learning classifier. The contributions of our model are as follows:

- Due to the high amount of variation in the Azimuth angles of the vehicle, it is necessary to normalize the angle values. An FIR filter has been applied for this purpose.
- Lane change style detection was performed only with the wavelet transform. The distinct features and advantages of wavelet transforms (multi-resolution analysis, localization, data compression and noise reduction) are especially beneficial when detecting short-lived events like lane changes.
- Unlike other methods in the literature, the proposed method has less processing costs and a high success rate with the use of the Wavelet transform.

The remainder of this paper is organized as follows; In section 2, we briefly discussed the study carried out for lane change. Section 3 describes the proposed lane change detection and detection method for drivers' lane change styles. The performance of the detection models were discussed in section 4. Finally, the paper is concluded in Section 5.

2 Literature Review

Due to the scarcity of data on lane changes, there are not many studies in the literature focusing on urban roads. Despite this, the lane change maneuver has been modeled in various ways and has gained significant attention, particularly in road transport networks. Compared to other routine daily driving behaviors, lane change maneuvers are more complex and require drivers (or decision-makers) to be aware of the surrounding traffic conditions (e.g. the speed of the vehicle ahead, distance, and gaps in the current driving lane) when changing lanes. As a result of increased uncertainty and decision errors during lane change maneuvers, a successful lane change decision increases the mental workload and stress of the driver and makes driving more difficult. Studies on lane change can be grouped under different categories and examined. In general, studies are divided into trajectory-based, vision-based, and pattern-based.

In a study [Leakkaw and Panichpapiboon 2018] using steering wheel rotation data from mobile sensors mounted on the steering wheel, lane changes were detected with a 95% success rate for precision and recall metrics across all speed ranges. However, according to the authors, the study fell short of detecting multiple simultaneous lane changes and lane changes on winding roads. Lane changes, which are an important part of driving support and autonomous driving systems, can also be detected with vision-based solutions using image processing techniques. In a vision-based study [Wei et al. 2019], the authors reported that by applying a computer vision-based deep learning approach to images acquired via a vehicle-mounted front camera, the study achieved an 87% accuracy rate for real-time lane change detection. However, the work only covered highways, and additional research is required for detecting lane changes on urban streets. Lane change was detected by a support vector machine using edge information extracted from the original image's region of interest in a [Baek and He 2018]. In the approach tested on real driving data, dimension reduction was performed using principal component analysis and provided an accuracy rate of 68.5%. Similarly, in another study [Wang et al. 2018] using edge information, lane change was detected with an accuracy of 79.7% with a convolutional neural network-based approach. A stacked sparse autoencoder model was developed in another study, which extracted useful information from images to classify lane changes, resulting in an accuracy of around 96% [Li and Sun 2017]. Preprocessing methods such as graying, filtering, and binarization are also specified as crucial in increasing the success of these methods by authors. The phenomena in traffic arteries and dense city centers are challenging to solve and analyze. This situation may occur as a result of the stages of analysis and processing of data sets collected by various methods. Therefore, in addition to existing methods, new significant traffic-related phenomena can be developed. In a study [Barmpounakis et al. 2020] where drone data were processed, the authors firstly performed lane detection. Afterwards, azimuth was used for lane change detection. The authors stated that the study, which included manual annotations, achieved a success rate of 95%.

According to the World Health Organization(WHO), traffic accidents are a major problem in terms of mortality. Factors contributing to traffic accidents, which affect more than 1.3 million people and rank ninth on the list of causes of death, include: driving ability, substance use, health issues, education level, and driver awareness. These factors are used to describe different types of drivers, such as disabled, sleepy, young, aggressive, and distracted drivers. These factors also affect drivers' lane change style. For example, as can be seen in Fig. 1, drivers can make lane changes normally or suddenly.

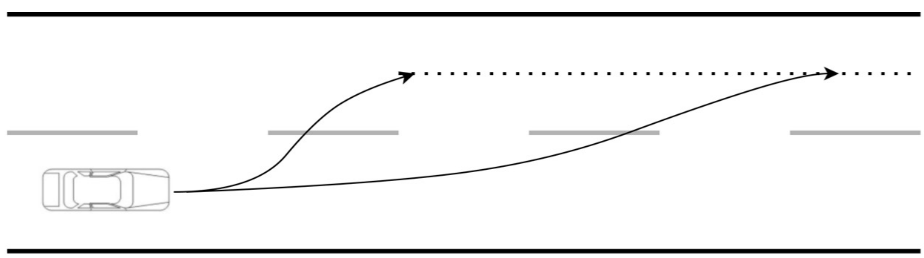

Figure 1: Lane changing styles

Determining the driving type of a driver can aid in the development of intelligent transportation systems and the implementation of necessary precautions. In a study by Quintero et al. [López et al. 2012], driving styles were classified as aggressive and moderate using a specific approach. The method developed in the study involved analyzing lateral and longitudinal data using features such as brake, throttle, and steering.

Moreover, research conducted by Aljaafreh et al. [Aljaafreh et al. 2012] used deceleration and acceleration features in the lateral and longitudinal directions to classify driving styles as below normal, normal, aggressive, and very aggressive using a method they proposed to predict driving style based on an acceleration model. According to the study, only the movements of the vehicle that resulted in lane changes were considered in determining the driving styles, without taking into account the relationship with neighboring vehicles.

Previous studies reviewed have focused on the relationship between lane changes and driving styles, but these methods have deficiencies in detecting lane changes when considering driving styles. A new method was proposed by [Woo et al. 2019] to detect lane changes by analyzing the driver's unique driving patterns, such as speed, acceleration, and steering behavior in a developed study. The method used machine learning algorithms to learn the individual driving styles of drivers and to detect lane changes more accurately. A new feature was extracted to define driving styles based on the risk-taking behavior of drivers while following a preceding vehicle. Lane change estimation based on driving style at each time step was conducted using a detection method model based on vehicle movements and a determined gap acceptance model. The study used simulation data for experiments.

The research by [Ali et al. 2020] delved into the dynamics of failed lane-changing attempts in both traditional and connected driving environments, highlighting gaps in the current lane-changing decision models. Utilizing a wavelet transform technique, the study identified these failed attempts with significant precision when tested on various datasets, notably the NGSIM and driving simulator data. The study, while insightful, primarily relies on the wavelet transform method without an extensive comparison to other techniques and focuses on a single type of failed lane-changing attempt. Additionally, the model's exclusion of human factors and dependence on NGSIM data, which lacks socio-demographic information, may limit its real-world applicability and depth of understanding.

3 Methodology

3.1 Dataset

In recent years, UAVs equipped with state-of-the-art devices and high-quality cameras have become an important tool for traffic data collection. The use of UAVs allows for obtaining higher quality information about traffic and making more accurate estimates. The pNEUMA dataset [Barmpounakis and Geroliminis 2020], created using a drone swarm, provides large-scale and high-resolution information about roads in urban centers. Compared to the well-known Next Generation Simulation (NGSIM) trajectory dataset [Kovvali et al. 2007], pNEUMA has a larger scale and higher spatial coverage, making it useful in various traffic-related fields.

The focus of this paper is to detect lane changes in the pNEUMA dataset, and to identify the lane changing profile using trajectory data. This paper utilizes a portion of Leoforos Alexandras road, which contains signalized intersections, links, and bus stops, as seen in Fig. 2 to verify the effectiveness of the proposed algorithm.

Figure 2: Study area

However, since the pNEUMA dataset does not allow for direct data filtering, data must first be extracted for the specific area of the road on which the study is being conducted. After extracting the necessary data, 2-wheeled vehicles that move 90 degrees or differ in driving behavior are ignored in the study. The elimination of turning vehicles in the area where the study was conducted has been carried out using the bearing equation which is given at equation 1 and an optimal threshold angle determined through experimental studies.

3.2 Azimuth

The term azimuth refers to the angle between the line connecting the current location to the North Pole and the line between the current location and the next location. In this study, the azimuth angle was calculated using the WGS-84 coordinates of the vehicles in the pNEUMA dataset. By comparing the azimuth of the road with the azimuth of the vehicle, it can be observed that the two angles are similar on a straight road. However, the azimuth of the vehicle begins to increase or decrease as the vehicle starts to change lanes. Once the azimuth reaches a local maximum or minimum, indicating the completion of the lane change, it gradually returns to its original value as the azimuth of the road remains constant on straight roads.

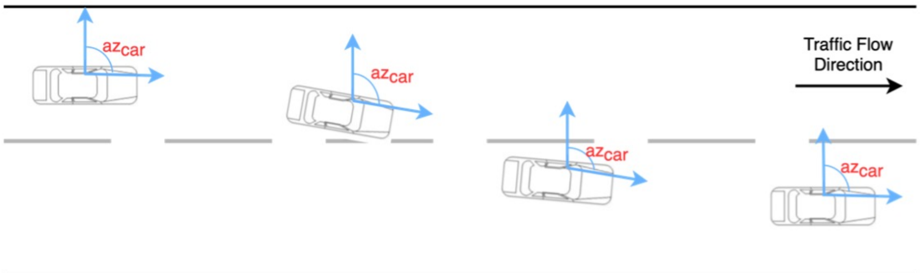

Figure 3: Azimuth of a lane changing vehicle

In accordance with the position data extracted from the data set, azimuth was obtained using bearing equation 1 [Barmpounakis et al. 2020].

$$az_x = atan2(sin\Delta\lambda \times cos(\phi_2), cos(\phi_1) \times sin(\phi_2) - sin(\phi_1) \times cos(\phi_2)) \tag{1}$$

ϕ_1 in the equation represents the latitude of the starting point, ϕ_2 the latitude of the consecutive point. $\Delta\lambda = \lambda_1 - \lambda_2$ where λ_1 is the longitude of the starting point, and λ_2 the longitude of the consecutive point.

Due to the movement of UAVs during the creation of the dataset, the obtained azimuths contain high levels of noise. As a result, a window-based finite impulse response (FIR) filter was utilized to remove the noise from the azimuth data. The FIR filter was designed using the Hamming window with empirically determined values. The required values for cutoff or filter order was determined to be 80, and for frequency constraint, it was 0.07. These values were used to perform the smoothing operation by convolving the azimuth series with the coefficients obtained from the FIR filter.

3.3 Lateral Deviation

Lateral deviation refers to the amount of horizontal displacement of a vehicle from its intended path or lane while it is moving. In the context of lane changing detection, lateral deviation is an important factor because it helps determine whether a vehicle is staying within its lane or if it is beginning to change lanes. By monitoring the lateral deviation of a vehicle, an intelligent system can detect when a vehicle starts to move out of its lane and into another lane. This information can be used to warn the driver or other vehicles on the road of the potential lane change and prevent accidents.

In this context, lateral deviation models are widely used to create a better classifier for lane changing maneuver [Barmpounakis et al. 2020, Von Leeuwen 2010]. Classifiers that can predict whether a vehicle will change lanes in the short term can be used to improve driving assistance systems. If such a system detects an interfering neighboring vehicle, it can react accordingly to prevent sudden braking and provide a smoother and safer ride.

$$dist = 6371 \times arcsin((\frac{(sin\Delta\phi)^2}{2} + cos(\phi_1) \times cos(\phi_2) \times (sin\Delta\phi)^2)^{(}\frac{1}{2}) \tag{2}$$

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

Lateral deviation of any vehicle can calculate using equation 2 and equation 3 where ax_x defines the vehicle of x's azimuth and the az_{road} defines the azimuth of the road that be selected for the experiments. These equations are also known as haversine formula in the literature.

Lane changing detection of vehicles was determined by using d_y in equation 3, which is the cumulative sum of lateral deviation over the distance traveled by a particular vehicle, as a second attribute in the classification step of this study. Since the distance traveled by the vehicle is used, when the vehicle stops due to traffic signals or congestion, the lateral deviation at these moments will be zero, so noisy data does not appear in the cumulative sum.

3.4 Wavelet Transform

The wavelet transform serves as a powerful tool for decomposing time–frequency data, excelling in deriving local details from non-stationary time series datasets. In contrast to the Fourier transform, the WT offers a dual representation of time and frequency, termed scale in the context of wavelets [Ali et al. 2020].The wavelet transform has the unique capability of providing simultaneous time and frequency information. This becomes particularly advantageous when detecting events like lane changes in vehicles, as such event may manifest as transient changes in specific frequency components. The wavelet transform is adapted at detecting such rapid alternations.

Localization is events like changes often result in sharp, short-duration changes in the signal. Wavelets are known for their capability to capture spikes, discontinuities, and other singular features in signals, making them apt for this analysis. The other essential offer of wavelet transform is data compression. Wavelets can efficiently compress signals by filtering out unnecessary data, leading to faster and more efficient analysis. Additionally, the wavelet transform is effective in noise reduction while preserving the fundamental components of a signal. For vehicle detection, effectively minimizing background noise aids in more accurate detection.

The basic idea of wavelet analysis is to decompose and reconstruct signals and overcome the limitations of the short-time Fourier transform. It is used to extract time-frequency information on non-stationary signals. Wavelet transform can focus on details by automatically adapting to time-frequency signal analysis requirements. Thus, wavelet transform, which is not constrained by a stationary hypothesis, is a major breakthrough since the Fourier transform. There are two types of wavelet transform: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). In this study, DWT was used to decompose and reconstruct data due to the discrete structure of the azimuth series for lane change.

When using the wavelet transform, an original time series is decomposed into low frequency series and multiple high frequency series using scaling, $\phi(t)$, and mother basis wavelet function $\psi(t)$. The approximate coefficient, the detail coefficient of the discrete wavelet transform was formulated as follows,

$$\alpha_0(k) = \frac{1}{\sqrt{N}} \sum_{n=1}^{N} y(n)\phi_{0,k}(n) \tag{4}$$

$$d_m(k) = \frac{1}{\sqrt{N}} \sum_{n=1}^{N} y(n)\psi_{m,k}(n) \tag{5}$$

where $y(n)$ is the azimuth series, m and k are the expansion and contraction of the sub-signals in the frequency domain and the translation in the time domain [Wang et al. 2021].

Wavelet transform has been employed many times in traffic oriented tasks. [Adeli and Samant 2000] detected the freeway accident while [Boto-Giralda et al. 2010] forecasted the traffic flow and traffic dynamics near work zones was investigated by [Adeli and Gosh-Dastidar 2004]. Its versatility is further showcased in studies related to detecting traffic bottlenecks and oscillations [Zheng et al. 2011].

The wavelet transform method, which is the main stage of the study for the lane change problem, is used together with the different mother wavelets. Haar, daubechies(dbN) and symlet(symN) wavelets are important wavelets used in discrete time series. The Haar wavelet is the first of the wavelets and is the simplest type of wavelet. The technical disadvantage of Haar wavelets is their discontinuity, which makes them non-differentiable. However, this feature can be an advantage for the analysis of discrete signals. The db2 and sym2 are more complex than the Haar wavelet and can provide a more detailed representation of the frequency components of a time series. The db2 wavelet has a shorter support than the Haar wavelet and can capture more complex features in the time series. The sym2 wavelet is similar to the db2 wavelet, but with more vanishing moments. Overall, orthogonality, symmetry, vanishing moment, regularity and compact support are the general characteristics of wavelet basis.

3.5 Multi-level Discrete Wavelet Transform

Multilevel discrete wavelet transform (Multi-level DWT) is a wavelet-based signal analysis method [Mallat 1989]. This is a technique that applies wavelet decomposition recursively to the approximation coefficients obtained at each level of decomposition which is illustrated in Figure 4. Multilevel time-frequency features can be obtained from time series using different type of wavelet transform. The features are extracted by decomposing the time series into sub-series in the form of high and low frequency level by level [Wang et al. 2018]. The output of multi-level DWT is a set of coefficients that can be used to analyze the signal at different scales or resolutions. The number of levels of decomposition determines the degree of signal analysis and the number of sub-bands that are produced.

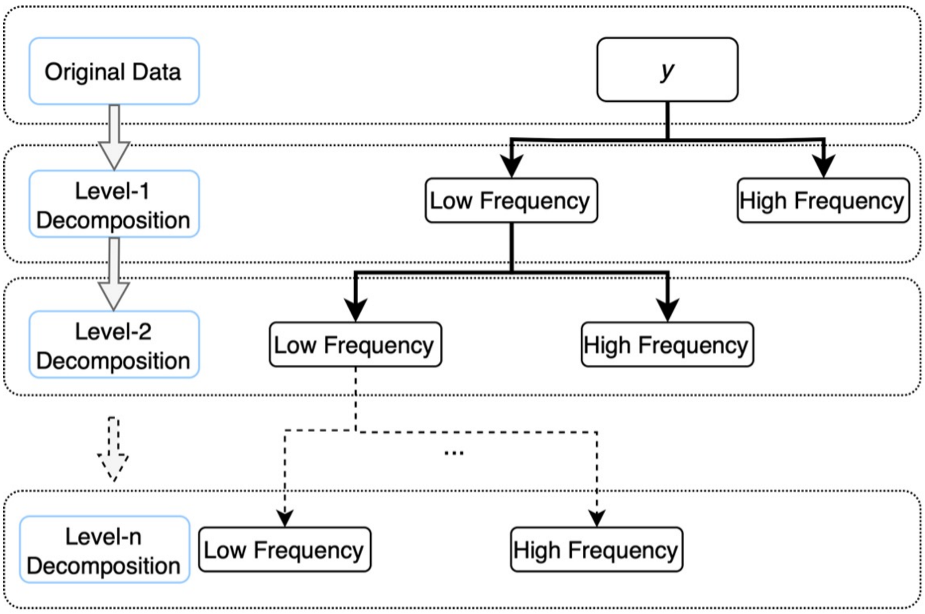

Figure 4: Schematic diagram of n level wavelet decomposition

3.6 Lane Changing Detection

A lane change maneuver can be defined as a vehicle crossing the lane line between two adjacent lanes. The lane change process usually takes a few seconds and begins with the emergence of motivations for the lane change and is completed when the vehicle is laterally stable in the target lane.

The WGS-84 coordinates of each vehicle were used to obtain the azimuth, which is a crucial step in the lane change and lane change style classification. The azimuth series of vehicles in the selected study area were obtained by taking two consecutive positions of a vehicle. Moments when the vehicles stopped and turned were removed from the dataset, and noise in the azimuth series was removed using a FIR filter due to the high noise level of the dataset. Then, lateral deviation and multilevel wavelet transform were applied to the series. Finally, by using the scale and lateral deviation features obtained from the multilevel DWT, it was determined whether the vehicles made normal or sudden lane changes.

3.7 Lane Changing Style Detection

In this study, the determination of the style of lane change, which has important effects on traffic models, was carried out. Lane changes can occur normally or suddenly in two different ways. Sudden lane changes can cause significant changes in the traffic flow and even lead to serious accidents. Therefore, determining the style of lane change is crucial for traffic models in ITS.

Figure 5: Lane changing style samples from Alexandras, first one is sudden change, the other is normal change

The style of lane change was investigated by analyzing the vehicle's lane changing maneuvers, and the lane change was classified as normal or sudden which are illustrated in Fig. 5. The wavelet length, which expresses the scale factor of the DWT, was determined by applying the steps in which the lane change was detected. A higher scale factor value detects normal lane changes, while a smaller scale factor creates a wavelet that detects sudden lane changes. This way, sudden or normal lane changes in the series can be detected according to the scale factor. Scale coefficient features were extracted for each main wavelet type used in this study. In addition to the extracted features, lane changing was labeled as normal or sudden using manual annotation method. By using the scale features obtained from wavelets and labeled class information, classification was performed with machine learning, and lane changing styles were classified successfully as normal or sudden change.

4 Experimental Results

Leoforos Alexandras avenue in the pNEUMA dataset was selected for the evaluation of the proposed model. That avenue is a 400m three lane artery which includes bus stops and many intersections which leads to lane changing. Vehicles that have two wheels or involving 90-degree movements in their route, which require a different model to detect their movements excluded from this study. Additionally, because of direction of study area northbound or southbound vehicles were eliminated. Table 1 and Table 2 shows how many vehicles change between which lanes.

	To Lane 1	**To Lane 2**	**To Lane 3**
From Lane 1	-	33	-
From Lane 2	24	-	80
From Lane 3	-	10	-

Table 1: Number of vehicles changing lanes on October 29,2018

	To Lane 1	**To Lane 2**	**To Lane 3**
From Lane 1	-	29	-
From Lane 2	17	-	28
From Lane 3	-	36	-

Table 2: Number of vehicles changing lanes on October 30,2018

	Accuracy	**Sensitivity**	**F1-Score**	**ROC**
Haar	0.98	0.97	0.95	0.98
Daubechies(db2)	0.95	0.95	0.93	0.94
Symlet(sym2)	0.95	0.94	0.93	0.94

Table 3: The performance metrics results for lane change with different mother wavelet basis on October 29, 2018

Lane changes occur more frequently on urban roads than on highways. The intersections, bus stops, and mandatory turns at the end of Leoforos Alexandras avenue frequently force drivers to change lanes.In the selected study area for lane change detection, out of a total of 388 vehicles remaining after the pre-processing step, 110 vehicles were identified to have changed lanes on October 30, 2018 while 147 out of 431 vehicles changed lanes on the same road on October 29, 2018. In the study, lane change and lane change style

	Accuracy	**Sensitivity**	**F1-Score**	**ROC**
Haar	0.99	0.98	0.97	0.99
Daubechies(db2)	0.97	0.95	0.96	0.97
Symlet(sym2)	0.95	0.94	0.94	0.95

Table 4: The performance metrics results for lane change with different mother wavelet basis on October 30, 2018

		Accuracy	**Sensitivity**	**F1-Score**	**ROC**
Haar/db2/sym2	**October 29, 2018**	0.92	0.93	0.91	0.91
Haar/db2/sym2	**October 30, 2018**	0.94	0.94	0.92	0.93

Table 5: The performance metrics results for lane change style based on all mother wavelets

were detected and analyzed separately by using K-NN, one of the machine learning methods. In the lane change detection process performed using the K-NN classifier, the dataset was separated as 70% training and 30% as testing, and a 2-feature classification was performed using the detail coefficient level feature and the lateral deviation feature. K value of the classifier was selected as 3 for the K-NN. As can be seen in Table 3, classification was achieved with notable accuracy using Haar, db2 and sym2 wavelets, reaching 99%, 97%, and 95% on October 29, 2018. In the test carried out on the October 29, 2018, the accuracy reached to 98% for Haar, 95% for db2 and, 95% for sym2.

On the other hand, level features obtained from multilevel-DWT based on db2, sym2, and Haar wavelets were used to detect lane change styles. Depending on the wavelet length, it was categorized whether the vehicle changed lanes in a normal manner or suddenly. In data from October 29, 2018, 28 out of 147 vehicles were identified to have made a sudden lane change while it was found that on October 30, 2018, 10 out of the 110 vehicles that changed lanes did so in a sudden fashion, while the rest changed lanes normally. Moreover, by utilizing the scale coefficient features extracted from applying Haar, db2, and sym2 wavelets in combined version, the classification of lane changing style was achieved using a K-NN algorithm with an accuracy of 94% for October 29 and 92% for October 30.

5 Conclusions and Future Work

In this paper, we introduced a new approach to detect lane change and its style. In particular, we used azimuth and wavelet transform methods to obtain required features for detection. In the first step, vehicles that have two wheels or involving 90-degree movements in their route were excluded from the study which needs a different modeling approach. In the following step, FIR filter was applied to the dataset containing noise because of UAVs. After this important step that contributed to increasing the accuracy rate, wavelet transform was applied and the lateral deviations of the vehicles were calculated. Finally, lane change and lane change style were detected successfully by applying K-NN machine learning method. The experimental results demonstrate that our model detects the lane changes with the average accuracies of 98% for Haar, 95% for db2 and sym2 on October 29 while 99% for Haar, 97% for db2 and 95% for sym2 on October 30. Subsequently, the model detects lane changing styles with accuracy of 92% and 94% for each day, respectively.

It is possible to create a more successful model by applying different filtering methods to the very noisy vehicle location data for future works. Instead of calculating the azimuth angle, which is one of the lane change detection steps, a model can be designed by calculating the vector angle using 3 consecutive position information. In addition, models for accident analysis can be created with the detection of lane change style.

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