Identification of Anomalies in Lane Change Behavior Using One-Class SVM

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***Abstract*—Advanced driver assistance systems are required to detect latent hazards posed by surrounding vehicles and generate an appropriate response to enhance safety. Lane changes constitute potentially risky maneuvers, as drivers involved encounter latent hazards due to surrounding vehicles. A careful study of lane change behavior is therefore essential in identifying potential abnormalities that may lead to various hazards, during the process of a lane change. In this study, an anomaly detection technique is used to compare snapshots of normal and dangerous lane change maneuvers, to identify the abnormal instances. A one-class support vector machine is used and tested for novelty identification of naturalistic driving study data. The results show that the technique is able to detect dangerous lane changes with high accuracy. In addition, results suggest that dangerous behavior could occur before, after or during a lane change maneuver.**

I. Introduction

According to US Department of Transportation (DOT) traffic accidents are the cause for around 37,000 fatalities and 230.6 billion dollars in economic loss every year in the US [1]. Most of these accidents are due to reckless driving (speeding, distractions, etc.). These statistics magnify the need for an advanced driver assistance system (ADAS) that is able to take over partial or full control of the vehicle when necessary in order to avoid possible hazards.

One of the tasks of driver assistance system is to generate a situational awareness of the surroundings by predicting other drivers' actions and making decisions to avoid a possible crash. In addition to predicting the exact action, detection of abnormal or dangerous behaviors in high-speed and interactive situations such as lane changes will increase the level of caution exercised by the ADAS.

In general, any action during driving that may result in harm to the vehicle or its occupants, other road users (pedestrians and other drivers) as well as various installations on the road may be considered dangerous behavior. Dangerous driving may be caused by a driver who is aggressive, inexperienced or distracted. It may also result from a reaction to a sudden change in the road environment during driving.

Lane changes constitute one of the most dangerous maneuvers compared to others because acceleration of vehicles involved is required. In addition, driver must scan various sections of the roadway simultaneously before, during and after the lane change. An example of normal and dangerous lane changes is shown in Fig. 1. In the top picture, the red vehicle performs a lane change while there is enough of safety gap between the surrounding vehicles on the desired lane. In the bottom picture, the red vehicle plans to change its lane without considering the safety space. It may increase the speed to fit in the small gap in the desired lane, which increases the risk of accident for all the surrounding vehicles.

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In this study, Support Vector Machine (SVM) classification is used to analyze lane change maneuvers in a naturalistic driving dataset and identify abnormal instances in different stages of a lane change.

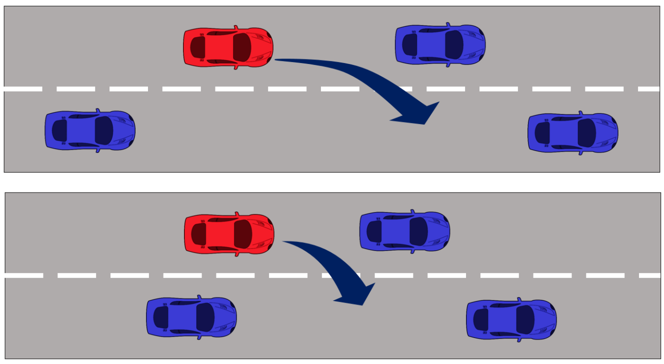


Fig. 1: Examples of (a) normal and (b) dangerous lane change

II. Literature Review

Nowadays vehicles are equipped with a variety of sensors and other devices to collect and store information during the drives. These devices improve safety while driving and the data collected in the process can be used to study driver behavior. Since driving can be seen as a very complicated sequence of activities, modeling driver behavior could be accomplished using two broad categories of approaches. In one category, several behaviors are modeled with low accuracy representing a wider scope. In the other category, approaches have narrow scope of behaviors but result in high accuracy [2]. They are more practical because they allow the practitioner to focus on more complicated and potentially dangerous scenarios. Most of techniques technique reviewed in this paper are from this category.

Various probabilistic methods have been used for driver behavior modeling. For instance, a Bayesian model was developed for prediction of the driving task [3]. Some approaches have specifically focused on modeling a driver behavior at intersections using rule based estimation and Hidden Markov Model (HMM) in [4] and [5] respectively. In [6], a model based on multi-class Support Vector Machines (SVM) and statistical feature extraction is proposed for estimation of driver behavior. In [7] and [8], a fuzzy logic based technique is introduced for driver action estimation at intersections, which considers the order of data in time unlike most of the driver models in literature.

As mentioned before, lane change is one of the important scenarios in the intelligent transportation field and it has been widely used for classification and modeling purposes. Bonnin et al [2] proposed a computational architecture based on a Scenario Model Tree (SMT) that combines several behavior classifiers hence giving it the ability to anticipate behavior of the surrounding vehicles in different scenarios.

Prediction of the driver behavior is beneficial for driver and ADAS decision making, but it depends on sensors and devices for vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communications. Moreover, most of the techniques presented earlier require time-series data from the surrounding vehicles to result in an accurate prediction. When all the essential devices or data are not available, detection of abnormal or dangerous maneuvers generates a basic situational awareness which has a large impact in maintaining safety.

In [9], a safety model for lane change is developed based on lane departure warning that can be used for decision making about the safety of the maneuver and may help prevent crashes occurring during lane changes on highways. However, this model is not general and only considers one specific scenario in which the driver is distracted and there are several cars on the road.

In [10], an assistance system is developed with the aim of reducing drivers' uncertainty during lane change in an attempt to increase traffic safety. In this study, participants performed lane changes under various conditions in a driving simulator experiment. However, the results are based on a simulator experiment, which renders the study not universal for the design of an assistance system. The authors in [11] and [12] have developed a two stage reasoning based framework that uses driving event recognition to determine various levels of danger for different scenarios. Instead of using labeled data, the danger level is derived from a Fuzzy Inference System (FIS) with a hierarchical decision strategy. Then, Hidden Markov Models are trained for seven scenarios including lane changes. However, since the danger level is inferred from unlabeled data and the FIS was designed based on the authors' opinion, it is subjective and not likely to be a reliable indication. In addition, a HMM based classifier is proposed in [13] which is able to detect dangerous cut-in behaviors on highways. This paper also uses decisive features of the lane change behavior to improve the classification performance. However, this technique requires time-series, and will not perform as well in case it receives insufficient data.

The main challenge in identification of dangerous driving behavior in lane change is developing a framework which includes almost all the dangerous scenarios. However, such a framework is impossible to define since each dangerous maneuver is unique and situation-dependent. Therefore, one-class SVM, which is a novelty detection classifier is used to distinguish between normal and dangerous lane changes. The classification method presented in this study is based on the work in [14] for analysis of flight data. This study utilizes several parameters that are measured by the car sensors during the drive. The goal is to analyze the data at various sections during a lane change. If a change in normality is detected between two sections, a more detailed analysis can be performed between those points.

The rest of this paper is organized as follows. In section III the proposed classifier system is explained. Section IV describes the naturalistic datasets utilized as well as the simulation setup, results and discussion. Finally, the conclusion and future work are given in section V.

III. Proposed Method

In this section, the classifier used for distinguishing abnormal from normal lane changes is introduced.

A. One-Class Classifier

One-class classification is used in machine learning to differentiate objects of one class from the remaining objects, after being trained by objects of that specific class. This type of classification is more challenging than traditional classification because the classifier cannot learn from objects of all other classes. This technique has several applications in literature including outlier detection, anomaly detection and novelty detection [14]. One-class classification is chosen in this study because it is able to detect anomalies. As described earlier, one-class classifier can handle cases where one class has well sampled data, while the other class has data of very diverse samples. In this case, it is difficult to determine a specific class for the poorly sampled data.

B. Support Vector Machine Novelty Detection

Support Vector Machines (SVM) is a supervised machine learning technique which was first introduced by Boser, Guyen and Vapnic in 1992. In SVM the margin between class boundary and training patterns is maximized. This serves as an alternative to other training methods such as least square error [15].

A support vector machine develops a hyperplane in higher dimensional space which transforms a nonlinear classification into a linear one. Therefore, the separation can be performed more easily. A "Kernel Function" $k(x, y)$ is used to map the variables into the higher dimensional space.

In this problem let $x_1, x_2, \ldots, x_l \in \mathbb{R}^n$ be the "normal driving" training data, and $\phi : \mathbb{R} \rightarrow F$ be the mapping that transforms the training data into a higher feature space F. The kernel $k(x, y) = (\phi(x), \phi(y))$ is a positive definite function and utilizes the mapping ϕ. In order to avoid wide distances in larger feature spaces, a Gaussian kernel function $k(x, y) = exp(-\|x - y\|^2/2\sigma^2)$ is chosen here to restrain the effect of distance, as since its value decreases with distance but ranges only from 0 to 1. Then, the objective function is defined by maximizing the number of training points within the margin (minimizing the training error) by solving the following quadratic programming problem using Lagrange multipliers:

$$\begin{aligned} \min_{\omega\in F,\xi\in\mathbb{R}^l,\rho\in\mathbb{R}} \quad & \frac{1}{2}\|\omega\|^2 + \frac{1}{\nu l}\sum_{i=1}^{l}\xi_i - \rho \\ subject\ to \quad & (\omega.\phi(x_i)) \geq \rho - \xi_i \quad \xi \geq 0 \end{aligned} \tag{1}$$

Where ρ is the margin variable, ξ_i the individual error term, ω a weight factor in F, and ν is the fraction of the training set to be regarded as outliers [14]. Finally, the decision functions is given by:

$$f(x) = sgn\left(\sum_{i=1}^{N_s}\alpha_i k(s_i, x) - \rho_0\right) \tag{2}$$

Where α_i are the Lagrange multipliers which are weighted in the decision function. N_s is the number of support vectors, s_i represents a support vector, and ρ_0 is obtained from the optimization problem.

The appropriate kernel and its associated parameters must be chosen by the user for each problem. Also, ν which is the fraction of the training data to be categorized as outliers is chosen instead of an error penalty. In this paper, the toolbox {e1071} for R is used for programming the SVM classifier [16].

C. Normal and Abnormal Lane Change Detection

The purpose of this method is to differentiate abnormal driving from normal driving, specifically for lane change scenarios.

In the proposed approach, a lane change maneuver is divided into multiple discrete segments, and for each segment one classifier is trained using the normal driving data. Later, both normal and dangerous testing sets are used on the models to evaluate the performance of the classifier. Therefore, the sections where abnormality often occurs can be identified and used for more detailed analysis.

1) Naturalistic Driving Data: The dataset used for training and testing the one-class SVM consists of two naturalistic driving study (NDS) datasets. The normal driving data is manually extracted from the 2nd Strategic Highway Research Program (SHRP 2) data samples, and the dangerous driving data is obtained from the 100-Car naturalistic driving study instances as it was suggested in [17].

SHRP 2 NDS was conducted with 3,000 volunteer drivers aged 16-98 over 3 years in several sites across the United States. Vehicles used had unprecedented scale of sensors installed on them. The sensors collected data on driver and vehicle performance as the volunteers go about their ordinary driving routines. For data extraction, the SHRP2 videos were watched and lane changes that with no visible risk (e.g. abrupt or near crash events) were marked as normal lane changes.

The 100-Car Naturalistic Driving Study database contains many extreme cases of driving behavior and performance, including severe fatigue, impairment, judgment error, risk taking, aggressive driving, and traffic violations [18]. The dangerous dataset was extracted by studying the event description of 100-car set and marking the near crash lane change events that the subject vehicle is at fault

IV. SIMULATION AND RESULTS

In this section, performance of the proposed method is evaluated using the "normal" and "dangerous" driving datasets. Therefore, the evaluation metrics, model training, and discussion of the results are presented here.

A. Performance Metrics

A confusion matrix is used to evaluate the classification performance in this study. There are four parameters in this matrix; true positive (TP) is the number of correctly identified positive instances, true negative (TN) is the number of correctly identified negative instances, false positive (FP) is the number of incorrectly identified positive instances, and false negative (FN) is the number of incorrectly identified negative instances.

Accuracy (3) is one of the measures used to evaluate the performance of a classifier. However, in case the two classes of data are not balanced in size, its value will be biased toward the larger set which is misleading. Thus, additional measures are used to thoroughly describe the performance. The measures include Recall, Specificity, and Geometric mean (G-mean) [19], [20].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

Recall, which is also known as Sensitivity measures the number of positive instances correctly classified.

$$Recall = Sensitivity = \frac{TP}{TP + FN} \tag{4}$$

Specificity is used to evaluate the ability of a classifier in recognizing negative samples.

$$Specificity = \frac{TN}{TN + FP} \tag{5}$$

Geometric mean is used to assess the balanced classification performance between positive and negative classes.

$$Gmean = \sqrt{Recall \times Specificity} \tag{6}$$

The error metric used in this study is the balanced error (BE). It is able to check the accuracy of positive and negative predictions simultaneously.

$$BE = \frac{1}{2} \times \left(\frac{FP}{FP + TN} + \frac{FN}{FN + TP} \right) \quad (7)$$

The BE serves as a useful error metric in this study due to the inconsistency between the positive and negative datasets.

B. Model Training and Simulation

In this paper, normal and abnormal characteristics of "left to right" lane changes are analyzed due to the possibility of blind-spots in such maneuvers which makes them more challenging than right to left lane changes. A total of 65 lane change maneuvers are collected for the "normal" and "dangerous" classes combined. 25 events belong to the normal set while the remaining 40 are from the dangerous set. The training to testing set ratio is 4:1 (that is 80% of data used for training and 20% for testing), so normal lane change has 20 events for training and 5 sets for testing. All the train and test samples have lengths of 10 seconds and are split into 10 segments as mentioned in section IV. The number of segments varies depending on length of available data and the trade off between accuracy and computation speed. Here, each segment corresponds to one second during the lane change. Therefore, each section is represented by a training set and testing set that contains data taken at that segment. The parameter values in the normal set were scaled to [0,1], in order to prevent the features with relatively larger values from saturating the SVM model. On the other hand, it is necessary that the abnormal values in the dangerous set are not lost during normalization. Therefore they are scaled according to the scaling values obtained from the train set.

The variables used for classification of lane change are velocity, yaw-rate, and both longitudinal and lateral acceleration. Here, the mean values of velocity and yaw-rate of normal and dangerous datasets are plotted through ten samples. It can be seen in Fig. 2 that the average velocity of normal lane change is kept almost constant during the maneuver, while the average velocity of dangerous lane changes keeps increasing which is an indication of risky behavior. It should be noted that the change in the speed values is due to the differences in roadways on which the data was recorded. It does not necessarily imply that normal lane changes are faster than the dangerous ones. Furthermore, the average yaw-rates plotted in Fig. 3 demonstrate that yaw-rate changes are more drastic in dangerous lane changes.

In order to demonstrate the effectiveness of one-class SVM, its performance is compared with a conventional SVM classifier. Since conventional SVM has two classes, it must be trained with both normal and dangerous datasets. The dataset for the "normal" class is the same as for the one-class support vector machine (OC-SVM), with 20 sets as training and 5 sets as testing data. On the other hand, the "dangerous" maneuver class dataset consists of 30 sets for training data and the remaining 10 sets as testing sets.

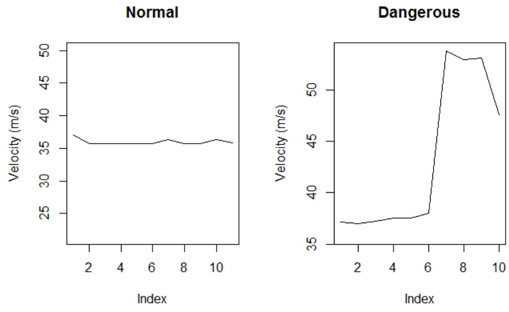


Fig. 2: Comparison of the average velocity in normal and dangerous (left to right) lane change maneuvers.

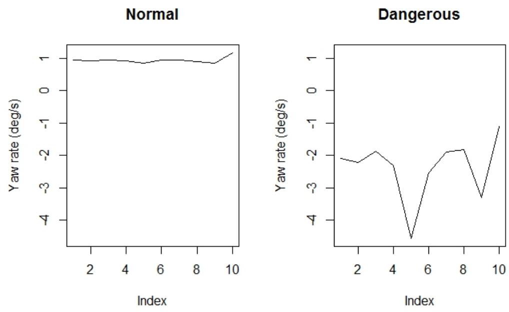


Fig. 3: Comparison of average yaw-rate in normal and dangerous (left to right) lane change maneuvers.

C. Results and Discussion

Once the SVM models are trained for different points of the lane change maneuver, the test data that consists of 5 normal driving instances and 40 dangerous instances are used to evaluate the performance of the classifier. The classification results are presented in Table I.

The third row of the table shows accuracy of segment SVM models throughout the ten seconds. As all the values are higher that 80%, and most of them are higher than 91% it can be concluded that the model has a satisfactory classification performance. However, as there are unequal numbers of instances in the normal and dangerous testing sets, accuracy is not able to quantify the classification performance by itself.

Recall, which was defined in (4) shows the percentage of true (normal) instances correctly classified. Its high values show that the model is well trained, as it can correctly classify almost all the normal driving data at all snapshots. The significance of this measure is to give an indication of a well trained SVM model. Since the model is trained with only one class of data, even if it is poorly trained it may still detect dangerous data as anomalies, but such detection is not useful.

Since the objective of this study is to identify dangerous lane changes, the ability of the classifier to distinguish between normal and abnormal behavior is especially important. Specificity, which is defined in (5), assesses the percentage of correctly identified negative (dangerous) instances. Table I

TABLE I: One-class SVM performance measures for Left to Right Lane change

	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7	Sample 8	Sample 9	Sample 10
Normal Data Prediction	5/5	5/5	5/5	4/5	5/5	5/5	5/5	5/5	5/5	5/5
Dangerous Data Prediction	37/40	36/40	36/40	36/40	37/40	38/40	39/40	39/40	39/40	39/40
Accuracy	0.93	0.91	0.91	0.88	0.93	0.966	0.977	0.977	0.977	0.977
Recall	1	1	1	0.8	1	1	1	1	1	1
Specificity	0.925	0.9	0.9	0.875	0.925	0.95	0.975	0.975	0.975	0.975
G-mean	0.9617	0.948	0.848	0.935	0.961	0.8717	0.987	0.987	0.987	0.987
Balanced Error	0.03	0.05	0.05	0.15	0.03	0.025	0.01	0.01	0.01	0.01

TABLE II: Binary SVM performance measures for Left to Right Lane change

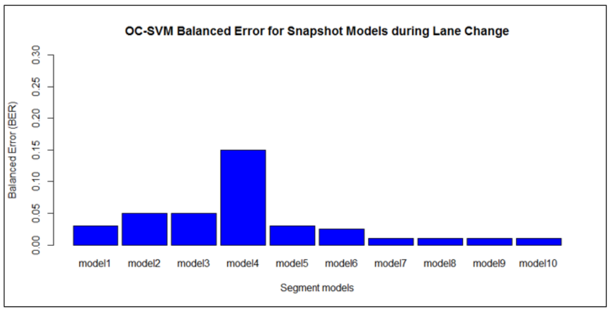
	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7	Sample 8	Sample 9	Sample 10
Normal Data Prediction	5/5	5/5	4/5	5/5	5/5	5/5	5/5	5/5	5/5	5/5
Dangerous Data Prediction	7/10	6/10	6/10	7/10	7/10	8/10	6/10	6/10	7/10	8/10
Accuracy	0.8	0.733	0.66	0.8	0.8	0.966	0.733	0.733	0.8	0.866
Recall	1	1	0.8	1	1	1	1	1	1	1
Specificity	0.7	0.6	0.6	0.7	0.7	0.8	0.6	0.6	0.7	0.8
G-mean	0.8366	0.774	0.692	0.836	0.836	0.894	0.774	0.774	0.836	0.894
Balanced Error	0.15	0.2	0.3	0.15	0.15	0.1	0.2	0.2	0.15	0.1

demonstrates that other than two segment models, the rest of the models have specificity of 90% or higher.

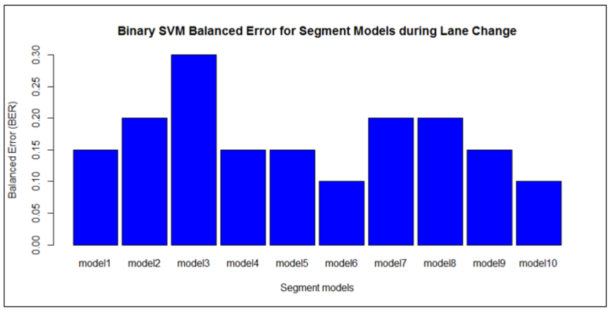
The G-mean (6) and BE (7) are the performance measures which explain the overall classification of the model regarding both classes. G-mean has very high values for almost all the models and BE which is an error metric has very small values. These measures confirm that the SVM models have a good classification performance, which is consistent with observations based on accuracy, sensitivity, and specificity measures.

Most of the models that detected slightly less numbers of dangerous lane changes are at 2, 3, and 4 snapshots which are located around the beginning and middle of the maneuver. It can be concluded from the Table I that dangerous lane changes are more similar to normal lane changes around the start of the maneuver, and therefore they are hard to classify at the beginning stages. As it gets closer to the middle part of the maneuver, the danger signs get more obvious and it is easier to identify a dangerous lane change. As it can be seen in the table, around samples 6, 7, and 8 almost more than 90% of the events are correctly identified. Finally, the surprising outcome of this study is that according to the BE results, even the finishing part of the maneuver still has some abnormal features and can easily be classified as dangerous. This is contrary to the assumption that once the driver has successfully changed the lane, he/she will resume driving normally.

It has to be noted that even normal lane changes usually include acceleration and fast reaction to some extent. Therefore, what differentiates normal from abnormal lane change is not necessarily the main action of changing lanes, but it could be due to the actions that happened before or after that. It is interesting that the anomalies in the common misclassified events between segment models 3 and 4, the dangerous behaviors were identified during and after the main maneuver (speeding during the lane change, or sudden change of lane to avoid hitting another vehicle). The bar plot of the balanced error (Fig. 4(a)) shows the distribution of classification errors during the lane change maneuver. It can be seen that the error is higher around the first half of the maneuver, which is because of similarities between normal and dangerous behavior, during changing lanes.



(a)



(b)

Fig. 4: Balanced error for segment models of OC-SVM (a) and binary SVM (b) during lane change

The classification results of conventional SVM are shown in Table II and Fig. 4(b). As it can be seen from the performance measures, nearly in all the segments the accuracy, specificity and G-mean are lower and the balanced error is higher than its corresponding value from the one-class SVM. It can be inferred that conventional SVM is not as capable of one-class SVM in finding abnormal instances, as it tries to group a data point to its most similar group, and does not consider the existence of an outlier. On the other hand, one-class SVM detects any point that does not fit its pre-trained model.

For the application of anomaly detection in the driving data, conventional SVM will not be helpful for two main reasons. First, a comprehensive abnormal driving dataset may not be available for all maneuvers. Also, it is nearly impossible to determine a specific model for dangerous driving, because many factors can cause a driving maneuver to become dangerous and each scenario is unique in its own way.

V. CONCLUSIONS

The goal of this paper is to distinguish between normal and abnormal lane change instances. Since it is not practical to define a specific model for abnormal lane change, the classification method utilized here is a one-class support vector machine which is ideal for detecting abnormality in a set of well sampled training data. In this study, instead of training the classifier with the entire observations time series, data was discretely sampled at ten segments during the maneuver and then a SVM model was developed for each of the ten sections. The advantage of this discrete sampling is that an abnormality profile can be developed for the maneuver. Such profile provides insight on different stages of the lane change and an analyst can study the occurrence of abnormality with greater detail. Moreover, since the classfier requires only data points for each segment of the maneuver, it is suitable in a situation that the complete time-series is not available.

The simulation results showed that all the one-class SVM models in different instances are able to classify normal driving events correctly and detect dangerous driving events as well. On the other hand, conventional SVM could classify most of normal lane changes correctly, but it was not able to accurately classify the dangerous instances. According to the SVM model outputs, dangerous behaviors usually happen any time during a maneuver, not necessarily when the vehicle is on the lane marks while changing lane. In fact, the results show that the most dangerous behaviors happen at the beginning and final stages of a lane change. The abnormality can be further investigated by performing additional analysis on the results. The outputs of this step can help the analysts to identify the most normal and the most dangerous lane change scenarios.

Future work will involve the comparison of the performance of OC-SVM to that of other classification techniques. A controller will then be designed for the ADAS not only to detect a possibly dangerous maneuver at the early stages but also to execute an action to avoid an accident with minimum loss.

VI. ACKNOWLEDGMENT

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