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Prediction of Surrounding Vehicles Lane Change Intention Using Machine Learning

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***Abstract* — To widen the range of deployment of autonomous vehicles, we need to develop more secure and intelligent systems exhibiting higher degrees of autonomy and able to sense, plan, and operate in unstructured environments. For that, the vehicle must be able to predict the intention of other traffic participants to interact coherently with its world. This paper addresses the prediction of lane change maneuver prediction of surrounding vehicles on highways. Two lane change prediction approaches based on machine learning are presented, the first is based on Support Vector Machine and the second on Artificial Neural Network, NGSIM dataset is used for training and testing. Used features are extracted from this dataset. The proposed approaches achieve a good performance, the results show improvement over the state of art in terms of prediction time and accuracy.**

Keywords* — *machine learning; support vector machines; artificial neural networks; lane change; intention prediction, autonomous vehicles; NGSIM

I. Introduction

Autonomous driving is one of the biggest challenges in automotive industry today. Navigation of an autonomous vehicle with considering the dynamics of all obstacles, road structure and user's safety is a very complex task. It needs to make a precise decision within few seconds. The autonomous vehicle uses information provided by sensors like Inertial Measurement Unit (IMU), Radar, Lidar and camera to track its current states and to understand surrounding environment. Sensing the current states of traffic participants is not sufficient to plan a collision-free trajectory, it is important to have future information about vehicles states. During an autonomous driving, the vehicle perceives its surroundings through its sensors, the fusion of data from multiple sensors permits the perception subsystem to construct descriptions of the environment. Based on these descriptions, the vehicle tries to predict in advance other drivers' intentions.

[1] presents different methods of intention prediction, traffic motion prediction approaches can be classified into three categories physics-based, maneuver-based and interaction-aware models. The first category uses the laws of physics to describe motion models. Maneuver-based and interaction-aware models are generally more abstract and give relatively long-term predictions. Maneuver-based prediction take each traffic participant independently, and consider that the motion is a set of discrete maneuvers (Fig .1) (lane change left, lane change right, lane keeping... etc.).

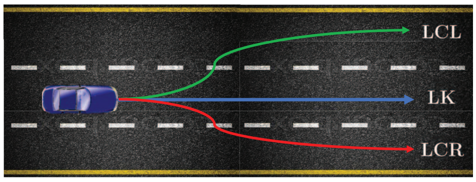
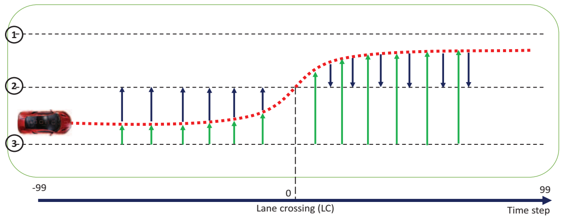
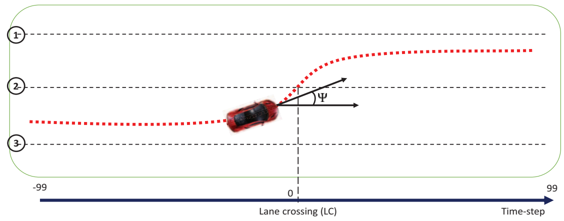


Figure 1: Lane change and Lane keeping scenarios

Lane change is a succession of critical actions that's need constant attention and correct assessment, which makes it one of the most common causes of accidents on highway [2]. An automated system must predict the intention of this maneuver as soon as possible to make the best decision. Sensors onboard a vehicle monitor different features like position and relative speed of each vehicle enters the detection field, using these features, the system tries to detect the lane change intention. Lane change prediction problems are mainly treated as classification problems, in [3] and [4] a Support Vector Machine (SVM) is used for lane change intention prediction. In [3] An evaluation study was performed using various combinations of window size, feature sets and non-overlapping vs overlapping representations. For the test, real-world data set of four driver subjects is used. The performance of the system is presented by 87% of all true positives within the first 0.3 seconds from the start of the maneuver. In [4] four features are selected: lateral position with respect to (w.r.t) a lane, steering angle w.r.t the road and the first derivative of these tow features. To obtain a probabilistic output from SVM, a generalized Bradley-Terry model is used. Bayesian filter was introduced to reduce the rate of false alarms and missed detections. The results showed



(a)



(b)

Figure 2: Features Calculation: (a) Yaw angle (b) Distance to left and right marking

that the used approach can predict the lane changes before 1.3 seconds with a significant precision of classification (100% of recall).

This paper is organized as follows. Section 2 introduces the used dataset and the proposed lane change representation is detailed. The results are carried out in section 3. Section 4 concludes and outlines future works.

II. Maneuver Representation and Features Selection

A. Extraction of Lane Change and Lane Keeping Maneuvers

In this work, the public dataset NGSIM is used for training and testing [5]. It contains detailed vehicle trajectory information. Moreover, NGSIM is widely used for the research, development, and validation of behavioral algorithms [6]–[8]. Our work consists to predict three types of maneuvers: Lane Change Right, Lane Change Left and Lane Keeping (Fig .1). For detecting the lane crossing, we use the lane ID feature to track the position of the vehicle on the road, when the lane ID changes between 1 and 5 (lane 1 is farthest left lane; lane 5 is farthest right lane), lane crossing event happens. Therefore, we can extract lane changes automatically and we can also classify the direction of changes (right, left). For each event we take 100 time-steps (10s) before and 100 time-steps (10s) after lane crossing, so if the instant of intersection between trajectory and lane making considered as a reference time t0, the trajectory in the interval [t0-10s , t0+10s] is the lane change trajectory segment.

B. Features Extraction

As mentioned in the previous description, NGSIM dataset offer many features related to vehicle trajectory, so we extract the features that are most relevant to lane-changing: Local Position, Velocity and Acceleration. Based on the extracted features and using road structure, we determine other features to satisfies the constraints of the lane changing model:

- Distance to lane marking: The distance to lane marking in our case represent the distance between the front center of the vehicle and the lane marking.(Fig .2.a)
- Yaw angle w.r.t the road: Yaw is the vehicle orientation heading angle related to the road. Changes in yaw can be a very important sign to detect a lane change.(Fig .2.b)
- Yaw rate: Yaw rate is the first derivative of the Yaw, this feature used to flow the rate of changes in vehicle orientation w.r.t the road.
- Lateral velocity and acceleration: Lateral dynamic is very significative feature that gives a lot of information before the lane change event happens. Therefore, we have used local coordinates related to the road to calculate lateral acceleration and velocity.

Based on the chosen criteria, it was possible to extract from NGSIM: 180 Lane Changes to the Right, 400 Lane Changes to the Left, and 1000 Lane Keeping maneuvers. In order to create our an homogeneous dataset, we take the same number of trajectories for each class, so we take 180 trajectories of each maneuver, with using 8 features(longitudinal velocity, lateral velocity, longitudinal acceleration, lateral acceleration, distance to left marking, distance to right marking, yaw angle and yaw rate related to road).

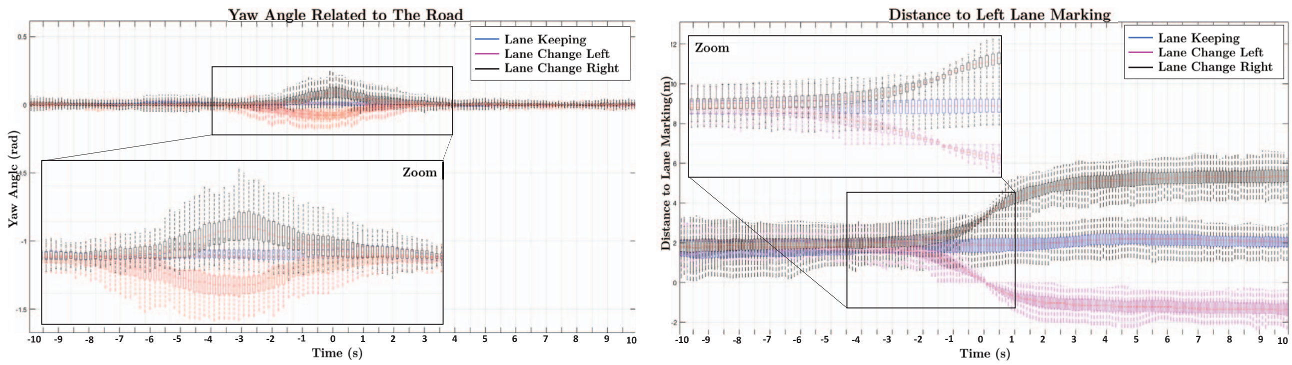
C. Lane Change Representation

In NGSIM, lane changes are realized by human drivers, that's make the representation of this maneuver very complicated. Therefore, we assume that the movement of vehicles to be of Markov process, it means that the state at the next step is independent from the past states. From the resulting dataset we take 180 trajectories for each event (Lane Change Left (LCL), Lane Change Right (LCR) and lane Keeping (LK)).

In order to follow the evolution of each maneuver over time, we present graphically the features in the form of boxplots. Each boxplot describes 180 values of one feature in one time-step. Fig .3 illustrates two features (Distance to lane marking and Yaw angle) boxplot representations for:

- Three types of maneuver (LCL, LCR, LK).
- 180 subjects for each maneuver.
- 200 time-steps (20s) starting form the 100th time-step before lane crossing and finishing at the 100th time step after lane crossing.

After representing all features during lane changing and lane keeping, we can notice that important changes starts on average 3s before lane crossing. Using boxplots, we



(a) (b)

Figure 3: Boxplot representation of (a) Distance to lane (b) Yaw angle for the three maneuvers

choose the most relevant features that represent an important difference between the three classes. The selected features are: longitudinal and lateral velocity, longitudinal and lateral acceleration, distance to left and right marking, yaw angle and yaw rate related to road.

III. Results and Analysis

The final dataset is constituted of 180 trajectories for each one of the three classes, each trajectory is composed of 21 samples. Therefore, 11340 features vectors were obtained. The prediction performance was evaluated: 8000 remaining samples were used to train the classifier and 3340 samples were used as the test samples. The goal was to develop and train a system that predicts the vehicle maneuver.

The input of our system is a vector composed of the eight selected features over 2s of trajectory. In real time applications the vector is updated each time step. The output is one of the three classes of maneuvers.

SVM implementation was done using libSVM [9], different kernel functions can be chosen during the classification, corresponding to the different transformed feature spaces. Four types of kernel are tested: Linear, Polynomial(Poly), Radial basis function (RBF) and sigmoid. Comparing the recall of each one (Tab .I), we find that the best classification performance is achieved using polynomial kernel of the third order. For ANN, the used network comports one hidden layer, the rectified linear unit function is used as an activation function, with Limited-memory Broyden-Fletcher-Goldfarb-Shanno (BFGS) solver. To take into account interrelations among the processing elements, full connection architecture is used.

Table I: Evaluation results of SVM with different kernels

Kernel	Linear	Sigmoid	RBF	Poly 1	Poly 2	Poly 3
Recall	0.949	0.873	0.932	0.944	0.953	0.957

A. Evaluation Metrics

To simplify the interpretation of our results, we propose the following terminologies and metrics:

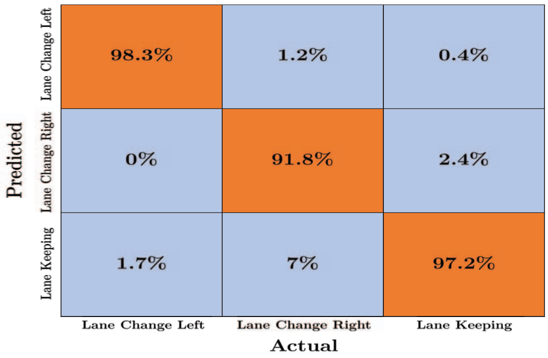
- Lane Crossing: The moment when the vehicle trajectory and the lane marking intersect.
- Prediction Time: The time interval between lane change detection instant and lane crossing.
- Recognition Rate: corresponds to the number of elements correctly identified by the system on the total number of elements
- Classes: Class 1: Lane Change Left (LCL) Class 2: Lane Change Right(LCR) Class 3: Lane Keeping(LK)
- Accuracy: is the fraction of correctly classified samples by all maneuvers
- Precision: is defined as the number of true classifications of an event over the number of true plus the number of false classifications of the same event.
- Sensitivity (recall): represent the true positive rate, or the ability to correctly classify a sample.
- F1-Score: is a weighted average of the true positive rate (recall) and precision

B. Evaluation Study

We have evaluated the proposed Lane-change prediction and classification systems using the dataset presented previously. Lane change and lane keeping cases in NGSIM are used for training and evaluation of the algorithms. In order to show the classification performance of each proposed method, the confusion matrix is calculated, as well as all evaluation metrics. An illustrative examples of vehicles lane change will be presented using the results of the proposed approaches. We report results in term of evaluation metrics of predicted classes with respect to true maneuvers.

C. Classification Results

The confusion matrix representation is used to evaluate the obtained results, The confusion matrix is a tool for measuring the quality of a classification system. Each column of the matrix represents an actual (or reference) class, while each row represents the predicted class. One of the interests of the confusion matrix is that it quickly



(a)

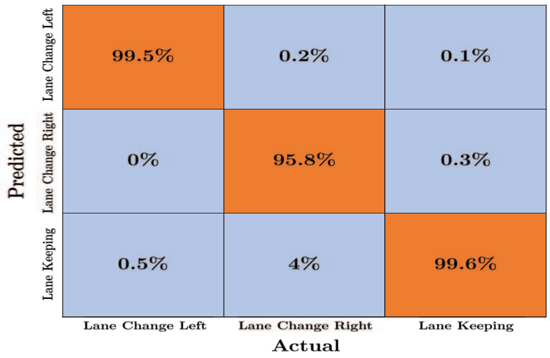


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Figure 4: Confusion Matrix of used approaches : (a) SVM (b) ANN

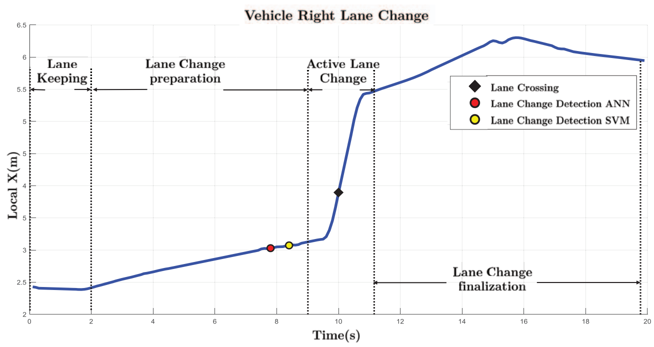
Table II: Evaluation results of SVM and ANN using Selected Features

Approache	Recall	Accuracy	Precision	F1 -score	Avg Prediction Time(sec)
SVM	0.957	0.971	0.958	0.957	1.95
ANN	0.983	0.988	0.983	0.983	2.33

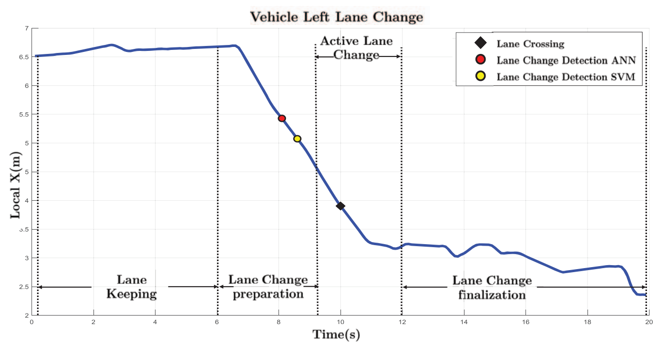
shows whether a classification system is able to classify correctly.

(Fig .4) represents the confusion matrices and (Tab .II) and (Tab .III) show the performance of Support Vector Machine and Artificial Neural Network classifier respectively. Concerning SVM, The prediction accuracy of this approach is 97.1%. The sensitivity, the precision and F1-score are almost the same 95.7%. For Artificial Neural Network approach, it is apparent that ANN is very accurate with 98.8%. Regarding other metrics, the classification has an important sensitivity precision and F1-score 98.3%. Prediction time depend to driving mode, a conservative driver starts the lane change very early and take more time to cross the lane marking, what's make the prediction time larger. Contrariwise, an aggressive driver takes less time to change the lane, therefore the time between lane change detection and lane crossing is very short. In this work, we notice that ANN detects lane change earlier than SVM (Tab .III), the average prediction time for Left Lane Change is 2.4 seconds with ANN and 2 seconds with SVM, regarding Right Lane Change the average prediction time is 2.2 seconds for ANN and 1.9 seconds with SVM. While the predictions results of ANN are better compared with those of SVM, the difference is not very important in term of evaluation metrics and prediction time. One can clearly see from results, that the selected features are very effective because they use observations of vehicle dynamic and road structure.

To further illustrate the performance of proposed methods, we plot vehicle Lateral (X) coordinate of the front center of the vehicle with respect to the left-most edge of the section of highway in the direction of travel during the evolution of lane change (Fig 5 (a and b)). In each figure, lane crossing , SVM lane change detection and ANN lane change detection instants are presented. Each figure represents an example of the studied lane change events (LCL and LCR). Focusing on lane change detection instants, we note that ANN is able to predict the maneuver earlier than SVM, but both approaches show significant prediction time.



(a)



(b)

Figure 5: Vehicle lateral trajectory (a) during a Right Lane Changing (b) during a Left Lane Changing

IV. Conclusion and Future Works

In this work we have tested two lane change prediction approaches, Support Vector Machine and Artificial Neural Network. The lane change event is composed of three sub-events, the preparation part during which the driver takes the decision and starts to adjust vehicle parameters to make the maneuver, the second part is lane crossing, and the last part is keeping the new lane. We exploit the changes during the preparation phase to predict lane change. Based on vehicles features extracted from the NGSIM dataset, we have elaborated a lane change model that use dynamic parameters and road features to classify three events: left lane changing, right lane changing and lane keeping. When trained and tested with the final dataset, the two algorithms are able to predict lane change and lane keeping accurately on an average 1.95 for SVM and 2.33 for ANN. Future works will include vehicles interaction by adding other features related to vehicle neighborhood and develop others approaches to enhance accuracy and prediction time.

References

[1] S. Lefèvre, D. Vasquez, and C. Laugier, "A survey on motion prediction and risk assessment for intelligent vehicles," *ROBOMECH journal*, vol. 1, no. 1, p. 1, 2014.

[2] G. Fitch, S. Lee, S. Klauer, J. Hankey, J. Sudweeks, and T. Dingus, "Analysis of lane-change crashes and near-crashes," *US Department of Transportation, National Highway Traffic Safety Administration*, 2009.

[3] H. M. Mandalia and M. D. D. Salvucci, "Using support vector machines for lane-change detection," in *Proceedings of the human factors and ergonomics society annual meeting*, vol. 49, no. 22. SAGE Publications Sage CA: Los Angeles, CA, 2005, pp. 1965–1969.

[4] P. Kumar, M. Perrollaz, S. Lefevre, and C. Laugier, "Learning-based approach for online lane change intention prediction," in *2013 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2013, pp. 797–802.

[5] J. Halkias and J. Colyar, "Next generation simulation fact sheet," *US Department of Transportation: Federal Highway Administration*, 2006.

[6] N. Deo and M. M. Trivedi, "Multi-modal trajectory prediction of surrounding vehicles with maneuver based lstms," in *2018 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2018, pp. 1179–1184.

[7] Y. Hu, W. Zhan, and M. Tomizuka, "Probabilistic prediction of vehicle semantic intention and motion," in *2018 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2018, pp. 307–313.

[8] C. Dong, Y. Zhang, and J. M. Dolan, "Lane-change social behavior generator for autonomous driving car by non-parametric regression in reproducing kernel hilbert space," in *2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2017, pp. 4489–4494.

[9] C.-C. Chang and C.-J. Lin, "Libsvm: A library for support vector machines," *ACM transactions on intelligent systems and technology (TIST)*, vol. 2, no. 3, p. 27, 2011.