



Situation assessment and decision making for lane change assistance using ensemble learning methods



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ABSTRACT

Lane change maneuvers contribute to a significant number of road traffic accidents. Advanced driver assistance systems (ADAS) that can assess a traffic situation and warn drivers of unsafe lane changes can offer additional safety and convenience. In addition, ADAS can be extended for use in automatic lane changing in driverless vehicles. This paper investigated two ensemble learning methods, random forest, and AdaBoost, for developing a lane change assistance system. The focus on increasing the accuracy of safety critical lane change events has a significant impact on lowering the occurrence of crashes. This is the first study to explore ensemble learning methods for modeling lane changes using a comprehensive set of variables. Detailed vehicle trajectory data from the Next Generation Simulation (NGSIM) dataset in the US were used for model development and testing. The results showed that both ensemble learning methods produced higher classification accuracy and lower false positive rates than the Bayes/Decision tree classifier used in the literature. The impact of misclassification of lane changing events was also studied. A sensitivity analysis performed by varying the accuracy of lane changing showed that the lane keeping accuracy can be increased to as high as 99.1% for the AdaBoost system and 98.7% for the random forest system. The corresponding true positive rates were 96.3% and 94.6%. High accuracy of lane keeping and high true positive rates are desirable due to their safety implications.

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1. Introduction

1.1. Problem and motivation

Lane change maneuvers are essential during automobile trips. Drivers change lanes to follow a preferred route to reach their destination, or to improve their driving experience or level of service. In order to change a lane, a driver has to take into consideration several factors that affect safety. These factors include, speed and position of the subject vehicle and vehicles in the target lane, geometric characteristics of the road, vehicle characteristics, and others. The decision to change a lane is made after determining that a safe gap is available in the target lane. An inaccurate assessment of this gap by a driver may result in a crash, thus making it one of the higher risk driving maneuvers. Some previous studies indicate that lane changing and lane merge maneuvers account for approximately 5% of all crashes and as high as 7% of all crash fatalities (Chovan, Tijerina, Alexander, & Hendricks, 1994; Habenicht,

Winner, Bone, Sasse, & Korzenietz, 2011; Rodemerck, Habenicht, Weitzel, Winner, & Schmitt, 2012). Due to the importance of the lane changing decision, recent literature focus on various aspects of lane changing such as discretionary lane-change characteristics (Wang et al., 2014) multiple-vehicle collisions (Nagatani & Yonekura, 2014), predicting driver lane changing behavior (Zheng, Nagoya, & Suzuki, 2014), modeling highway lane changing (Wang et al., 2014), detecting lane change cut-ins using video images (Lee, Kim, Lee, Lee, & Kim, 2013), lane changing on curved roads (Guo, Ge, Yue, & Zhao, 2014), lane changing and heavy vehicles (Yang, Wang, & Wang, 2014), lane changing rules for microscopic modeling (Hable & Schreckenberg, 2014), and lane changing trajectory tracking (Ren, Zhang, & Wang, 2014).

Decreasing the number of lane change crashes is a priority for both transportation agencies and automobile companies. Transportation agencies are looking for countermeasures that can improve driving behavior by encouraging safer driving practices. For example, defensive driving education encourages safe driving practices including safe lane changing. Some agencies in the US have used dynamic message signs to alert drivers to 'stay in lane' in high traffic or high-risk locations. Likewise, automobile companies are leveraging technology to provide drivers with lane change assistance to make those movements safer. With the increase in the deployment of sensor technology in automobiles, advanced

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driver assistance systems (ADAS), such as adaptive cruise control, collision avoidance, and lane-departure warning, have become a reality in recent years. ADAS offers additional safety and convenience by providing drivers with timely warnings of unsafe conditions and, in some situations, take actions on behalf of the driver.

1.2. Literature review

Recent applications of lane change assistance systems focus on providing warnings for risky situations. The ISO standard 17387 (2008) Lane Change Decision Aid System (LCDAS) specifies three different types of warning systems: Blind Spot Warning, Closing Vehicle Warning, and Lane Change Warning. Blind Spot Warning systems alert drivers if any objects are occupying their blind spots or areas that cannot be observed in the rear-view and side-view mirrors. Closing Vehicle Warning system detects a fast approaching vehicle from behind in adjacent lanes. Lane Changing Warning system incorporates the function of both Blind Spot Warning and Closing Vehicle Warning. These systems initiate a warning depending on a set of rules based on the distance between the subject vehicle and the target vehicle in the adjacent lane. Schubert, Schulze, and Wanielik (2010) proposed a situation assessment strategy for automatic lane-change maneuvers. Vehicle trajectories were first predicted by one of the motion models: constant turn rate and acceleration (CTRA) model. Then, lane changing maneuver decisions were made based on Bayesian networks. Habenicht et al. (2011) described the system architecture as well as human machine interface of a maneuver-based lane change assistance system, but did not discuss the algorithmic background of situation assessment and decision making.

Studies of driver lane change behavior (Hidas, 2005; Hou, Edara, & Sun, 2012; Toledo, Koutsopoulos, & Ben-Akiva, 2007) indicate that additional factors such as subject vehicle speed and speed difference between subject vehicle and target vehicle (s) also affect a driver's decision to change lanes. Therefore, current warning systems may be susceptible to a higher false warning rate, for example during congested conditions where the spacing between vehicles is short. False warnings could hurt the credibility of a system and may create confusion and distraction to drivers. To this end, Hou, Edara, and Sun (2014) proposed a lane change model for situation assessment and decision making using Bayes classifier and decision trees. The lane changing model can perceive its environment and make decisions on lane change maneuver like an experienced human expert. Real-world microscopic traffic data that describe driver lane change behavior was used to train the Bayes classifier and decision trees. A simple majority voting principle was used to combine the two classifiers to obtain the best results. The prediction accuracy was 94.3% for nonmerge events and 79.3% for merge events.

1.3. Contribution

The main objective of this paper is to apply ensemble learning methods to improve the accuracy of existing lane change assistance systems. Two ensemble learning methods, random forest and AdaBoost, were applied to achieve a higher classification accuracy for situation assessment and decision making for lane change assistance. The methodological advantages of combining individual classifiers using ensemble learning methods for making lane change decisions were investigated. Situation assessment and decision making is essentially a binary classification problem. The output is a class label of "lane changing" (make a lane change maneuver) or "lane keeping" (keep driving in the current lane). Accuracy is the most critical component in the system, due to its safety implications. There are several reasons for investigating ensemble learning methods for this research. Pattern classification research (Breiman, 2001; Freund & Schapire, 1996) showed that

ensemble learning methods such as bagging and boosting improves classification accuracy over individual classifiers. These ensemble learning methods produce a combined classifier whose variance is significantly lower than the base classifier and also reduce the bias of the learning algorithm. These advantages of ensemble learning resulted in a wealth of applications in different areas such as software defect prediction (Laradji, Alshayeb, & Ghouti, 2015), financial trading (Booth, Gerding, & McGroarty, 2014), remote sensing (Zhang et al., 2014), inadequate information (Du, Wang, Leng, & Fu, 2014), indoor localization (Calderoni, Ferrara, Franco, & Maio, 2015), detection of web images (Sun, Sudo, & Taniguchi, 2014), landslide displacement prediction (Lian, Zeng, Yao, & Tang, 2014), and structured prediction rules (Cortes, Kuznetsov, & Mohri, 2014).

Thus, the contribution of this paper lies in the development of an accurate lane change assistance system using ensemble learning methods. The system is tested using real-world data obtained from a publicly available dataset and thus can be compared with other methods in the future. The focus on increasing the accuracy of safety critical lane change events can have a significant impact on lowering the occurrence of crashes. This is the first study to explore ensemble learning methods for modeling lane changes using a comprehensive set of variables.

The remainder of the paper is organized as follows. In Section 2, the methodology is introduced. The algorithmic backgrounds of both random forest and AdaBoost are described. Section 3 provides a detailed description of data collection, data reduction, and input variables used for developing the model. Section 4 presents the performance of the proposed ensemble learning methods and compares them with results of previous research. Conclusions are drawn in the final section.

2. Methodology

2.1. Random forest

Bagging or bootstrap aggregating is an approach to reduce variance of an estimated prediction function. Bagging performs especially well for high-variance and low-bias procedures. The essential idea in bagging is to average many noisy but approximately unbiased models. Decision trees are ideal candidates for bagging, since they are noisy and have relatively low bias. Random forest (Breiman, 2001) is an ensemble method based on the idea of bagging that builds a large group of un-pruned trees. A random forest reduces the variance of bagging by reducing the correlation between the trees. This is achieved through random selection of the input variables in the tree growing process. The random forest algorithm for classification applications is described as (Hastie, Tibshirani, & Friedman, 2009),

1. For $k = 1$ to K :
 - a. Draw a bootstrap sample from original training dataset.
 - b. Grow a tree T_k with the bootstrapped dataset by recursively repeating the following steps for each node until the minimum node size is reached.
 - i. Randomly select m predictors from all the predictors.
 - ii. Use the predictor variable among m predictors that makes the best split to split the node into two descendant nodes.
2. Output a collection of trees $\{T_k\}_1^K$.

To predict a test data case, the data is pushed down all the trees. Each tree will produce an output class label. The end result is the majority voting of all trees. Breiman (2001) recommends

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