Behavior Classification Algorithms at Intersections and Validation using Naturalistic Data

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Abstract— **The ability to classify driver behavior lays the foundation for more advanced driver assistance systems. Improving safety at intersections has also been identified as high priority due to the large number of intersection related fatalities. This paper focuses on developing algorithms for estimating driver behavior at road intersections. It introduces two classes of algorithms that can classify drivers as compliant or violating. They are based on 1) Support Vector Machines (SVM) and 2) Hidden Markov Models (HMM), two very popular machine learning approaches that have been used extensively for classification in multiple disciplines. The algorithms are successfully validated using naturalistic intersection data collected in Christiansburg, VA, through the US Department of Transportation Cooperative Intersection Collision Avoidance System for Violations (CICAS-V) initiative.**

Fig. 1.   Red light violation at signalized intersection.

I. INTRODUCTION

The field of road safety and safe driving has witnessed rapid advances due to improvements in sensing and computation technologies. Active safety features like anti-lock braking systems and adaptive cruise control have been widely deployed in automobiles to reduce road accidents [1]. However, the US Department of Transportation (DOT) still classifies road safety as "a serious and national public health issue." In 2008, road accidents in the US caused 37,261 fatalities and about 2.35 million injuries. A particularly challenging driving task is negotiating a traffic intersection safely; an estimated 45 percent of injury crashes and 22 percent of roadway fatalities in the US are intersection-related [2]. A major factor in these accidents is the driver's inability to correctly assess and/or observe the danger involved in such situations [3]. This data suggests that driver assistance or warning systems may have an appropriate role in reducing the number of accidents, improving the safety and efficiency of human-driven ground transportation systems. Such systems typically augment the driver's situational awareness, and can also act as collision mitigation systems [4].

Research on intersection decision support systems has become quite active in both academia and the automotive industry. In the US, the federal DOT, in conjunction with the California, Minnesota, and Virginia DOTs and several US research universities, is sponsoring the Intersection Decision

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Support (IDS) project [3], [5]. In Europe, the InterSafe project was created by the European Commission to increase safety at intersections. The partners in the InterSafe project include European vehicle manufacturers and research institutes [6]. Both projects try to explore the requirements, tradeoffs, and technologies required to create an intersection collision avoidance system, and demonstrate its applicability on selected dangerous scenarios [3], [6].

This research is focused on developing algorithms that infer driver behaviors at road intersections, and validate them using naturalistic data. Inferring driver intentions has been the subject of extensive research. For example, Ref. [7] introduced a mind-tracking approach that extracts the similarity of the driver data to several virtual drivers created probabilistically using a cognitive model. Ref. [8] used graphical models and Hidden Markov Models to create and train models of different driver maneuvers using experimental driving data. More specifically, the modeling of behavior at intersections has been studied using different statistical models [9] and empirical models [10] . Red light running predictors have been developed to predict the time to arrival at intersections and the different stop and go maneuvers [11]. Other algorithms have used kinematic data to predict violations at signalized and non-signalized intersections [12].

This paper presents two novel classes of algorithms to classify driver behaviors at signalized intersections, and then successfully validates them on a large naturalistic dataset. First, it describes the driver behavior inference problem, and its different applications to driver assistance systems. Then, it introduces the two developed classes of algorithms, a discriminative approach based on Support Vector Machines (SVM), and a generative approach based on Hidden Markov Models (HMM), and highlights their strengths over exist-

	Classification: Compliant	Classification: Violating
Actual: Compliant	True Negative	False Positive
Actual: Violating	False Negative	True Positive

ing approaches. Finally, their performance is evaluated and analyzed on intersection data collected in Christiansburg, VA, as part of the DOT Cooperative Intersection Collision Avoidance System for Violations (CICAS-V) initiative [13].

II. PROBLEM STATEMENT

Consider an intersection controlled by a traffic signal as shown in Figure 1. As a vehicle approaches the intersection, the objective is to determine from a set of observations whether the driver will stop safely if the signal indicates to do so. Drivers who do not stop before the stop bar are considered to be violators, while those who do stop are considered to be compliant. Naturally, different drivers behave differently, and the variation in the resulting observations must be taken into account in the classification process.

The ability to classify drivers lays the foundation for more advanced driver assistance systems. In particular, these systems would be able to warn drivers of their own potential violations as well as detect other potential violators approaching the intersection. Integrating the classifier into a driver assistance system imposes performance constraints that balance violator detection accuracy with driver annoyance.

This requirement can be encoded in terms of signal detection theory (SDT), which provides a framework for evaluating decisions made in uncertain situations [14]. Table I shows the mapping between classifier output and the SDT categories. This implies the classifier must minimize the number of false positives (to minimize driver annoyance) while maintaining a high ratio of true positives (to correctly identify violators).

An underlying assumption for this classification is the availability of communication or sensing infrastructure to provide the observations needed to classify the driver's behavior. Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication systems are an active area of research and provide exactly this functionality [15], [16]. Alternatively, on-board sensors could be used to make these observations, especially when warning drivers of their own impending violations.

III. ALGORITHMS

Classifying human drivers is a very complex task because of the various nuances and peculiarities of human behaviors [17]. Researchers have shown that the state of a vehicle driver lies in some high dimensional feature space [18].

Discriminative approaches, such as support vector machines (SVM), are typically used in binary classification problems, which makes them appropriate for the classification of compliant vs. violating drivers. SVMs have several theoretical and practical advantages [19]. We highlight two of them: 1) training SVMs involves an optimization problem of a convex function, thus the optimal solution is a global one (*i.e.,* no local optima), 2) the upper bound on the generalization error does not depend on the dimensionality of the space.

Classification is often also performed using generative approaches, such as HMMs, to model the underlying patterns in a set of observations and explicitly compute the probability of a set of observations for a given model [20]. HMMs are well suited to the classification of dynamics systems, such as a vehicle approaching an intersection. The states of the HMM define different behavioral modes based on observations, and the transitions between these states capture the temporal relationship between observations.

A. SVM-BF

The first algorithm, denoted as SVM-BF, combines SVM and Bayesian filtering. It was introduced by the authors in [21], and is extended in this paper. The core of the algorithm is the SVM, a popular supervised machine learning technique based on the margin-maximization principle [19]. SVM has been successfully applied to several applications including text categorization, bioinformatics and database marketing [22]. It has also been used recently in the active safety research, including lane departure warning systems [17] and driver distraction detection algorithms [23]. The reader is encouraged to refer to reference [24] for a detailed description of SVM.

In brief, given a set of binary label training data $\{\boldsymbol{x}_i, y_i\}$, where $i = 1, \ldots, N, y_i \in \{-1, 1\}, \boldsymbol{x}_i \in \Re^d$, where N is the number of training vectors, and d is the size of the input vector, a new test vector $\boldsymbol{z}$ is classified into one class ($y = 1$) or the other ($y = -1$), by evaluating the following decision function

$$D(\boldsymbol{z}) = \text{sgn} \left[\sum_{i=1}^{N} \alpha_i y_i K(\boldsymbol{x}_i, \boldsymbol{z}) + b \right] \quad (1)$$

where the function $\phi(\boldsymbol{x}_i) \cdot \phi(\boldsymbol{x}_j) = K(\boldsymbol{x}_i, \boldsymbol{x}_j)$ is called the kernel function. It is the inner product between the mapped pairs of points in the feature space. $\boldsymbol{\alpha}$ is the *argmax* of the following optimization problem

$$\max W(\boldsymbol{\alpha}) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j y_i y_j K(\boldsymbol{x}_i, \boldsymbol{x}_j)$$

subject to the constraints

$$\sum_{i=1}^{N} \alpha_i y_i = 0 \quad \alpha_i \geq 0$$

Appropriate kernel selection and feature choice are essential to obtaining satisfactory results using SVM. Based on experimenting with different kernel functions and several combinations of features, the best results were obtained using the Gaussian radial basis function and combining the
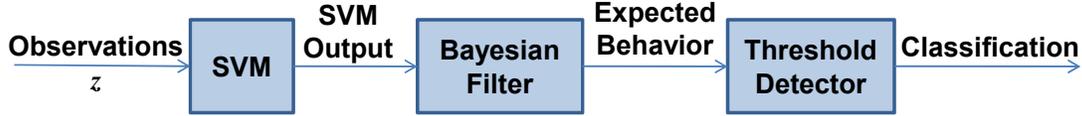
Fig. 2. The SVM-BF Architecture.

following three features: range to intersection, speed, and longitudinal acceleration.

The architecture of the SVM-BF algorithm is shown in Figure 2. At the beginning of each measurement cycle, the SVM module extracts the relevant features from the sensor observations. It then outputs a single classification (violator vs. compliant) to the Bayesian filter (BF) [25]. Using the current and previous SVM outputs, the BF estimates the probability of each classification of the next SVM output, which is equivalent to making an estimate of the behavior of the driver behavior. Using a threshold detector, the SVM-BF outputs a final classification, specifying whether the driver is estimated as violator or compliant at the current time step. To speedup the convergence of the BF, a discount function is added to the SVM-BF design to deemphasize earlier classifications, and therefore speedup convergence the closer the driver is to the intersection. For more details, please refer to the original SVM-BF algorithm [21].

This paper extends the original SVM-BF algorithm by using a sliding window over the features instead of point-based set of features, which proved to be essential in improving performance of the SVM-BF on the road traffic data. To elaborate, each feature consists of the means and variances of the previous K different measurements. When a new set of measurements arrives, it is added to the window along with the previous K-1 measurements, and so on. This change doubles the number of features at each cycle, but indirectly adds time dependency to the input, improving the SVM-BF model.

B. HMM-based

An alternative approach is based on the idea of learning generative models from a set of observations. Hidden Markov Models (HMM) have been used extensively to develop such models in many fields, including speech recognition [20], and part-of-speech tagging [26]. Of particular interest is isolated word detection where one HMM is generated for each word in the vocabulary and new words are tested against these models to identify the maximum likelihood model for each test word [20]. HMMs have also been used to recognize different driver behavior, such as turning and braking [8]. This motivates the use of HMMs to detect patterns that characterize compliant and violating behaviors.

Consider the case where two sets of observations are available: one known to be from compliant drivers and the other from violators. Each set of observations can be considered an emission sequence produced by an HMM modeling vehicle behavior. As described above, an unknown

vehicle must be classified when it crosses some predefined threshold. Rather than using the full history of observations for that vehicle, only the k most recent observations are considered. The value of k can be selected to capture the behavior of drivers reacting to the intersection and ignore normal driving behavior far from the intersection that may have little impact on whether they are compliant.

Rather than training one HMM to classify agents, two models, λ_c and λ_v, are learned from the compliant driver and violator training data, respectively. The compliant/violating labels originally attached to each sequence are absorbed into the set labels, leaving two sets of unlabeled data. This makes it a prime candidate for using the Expectation-Maximization (EM) algorithm to learn an underlying hidden model for each set [27].

Each HMM is characterized by an initial state distribution t, a matrix T of transition probabilities between states, and emission distributions $e(s)$ that are assumed to be Gaussian with unique mean and variance for every state s. These parameters are initialized randomly to avoid introducing bias in the learning process. Since the EM algorithm is only guaranteed to converge to a local maximum [27], several sets of initializations can be tested to reduce the effects of local maxima on the final model parameters.

Then, given a new sequence of observations, z, the forward algorithm [20] is used with λ_c and λ_v to find the the posterior probability of observing that sequence given each model, $P(z|\lambda_c)$ and $P(z|\lambda_v)$. The prior over the models is assumed to be uniform, $P(\lambda_c) = P(\lambda_v) = 0.5$, since nothing is known beforehand about whether the driver is compliant or violating. Then the likelihood ratio

$$\frac{P(z, \lambda_c)}{P(z, \lambda_v)} = \frac{P(z|\lambda_c)}{P(z|\lambda_v)} > \tau \qquad (2)$$

determines whether the driver is more likely to be compliant or violate the stop bar and assigns the corresponding classification. The threshold τ can be selected to adjust how conservative the classifier is. Figure 3 summarizes this architecture.

As with the choice of features in the SVM, the observations used for the HMM can have a dramatic impact on its performance. After experimenting with different observations, the following five observations yielded the best performance: range to intersection (Δx), speed (v), longitudinal acceleration (a), estimated time of arrival ($t_a = \Delta x/v$), and the required deceleration parameter ($RDP = \frac{v^2}{2\Delta x g}$, where g is the gravitational acceleration constant) described in Ref. [12]. In addition, the observations can be normalized
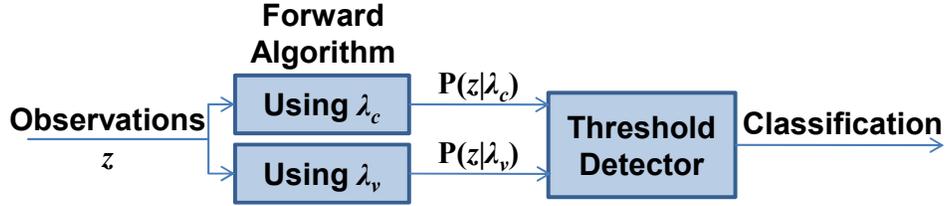
Fig. 3. The HMM-Based Classification Architecture.

Fig. 4. Satellite image of the Peppers Ferry intersection (US 460 and Peppers Ferry Rd, Christiansburg, Montgomery, Virginia 24073) taken from Google Earth. CICAS-V data from vehicles at Pepper's Ferry intersection were used to test the algorithms presented in this paper.

to remove any bias introduced by differences in the order of magnitude of the observations. This also facilitates the use of artificial weights on the observations to improve performance.

Since states have one emission distribution per observation, each state in the HMM represents a coupling between specific ranges of values for each observation. It is this coupling and the transitions between different coupled ranges that allows the HMM-based classifier to distinguish between compliant drivers and violators.

IV. DATA COLLECTION AND FILTERING

The roadside data used in this paper was collected as part of the Cooperative Intersection Collision Avoidance System for Violations (CICAS-V) project [13]. The CICAS-V project collected data on over $5,520,174$ approaches across three intersections. In this paper, the data from the Peppers Ferry intersection at U.S. 460 Business and Peppers Ferry Rd in Christiansburg, VA (See Figure 4) was used to evaluate the algorithms, providing a total of $3,018,456$ car approaches. The method of collection is detailed in Ref. [28]. A brief description is given below.

At the Pepper's Ferry intersection, a custom data acquisition system was installed to monitor real-time vehicle approaches. This system included four radar units which identified vehicles, measured vehicle speed, range, and lateral position at a rate of 20 Hz beginning approximately 150 m

away from the intersection, a GPS antenna to record the current time, four video cameras to record each of the four approaches, and a phase-sniffer to record the signal phase of the traffic light. These devices collected data on drivers who were unaware of the experiment as they moved through the intersection. The information from these units then underwent post-processing including smoothing and filtering to remove noise such as erroneous radar returns. In addition, the Geometric Intersection Description (GID), a detailed plot of the intersection accurate to within 30 cm, was used to derive new values such as acceleration, lane id, and a unique identifier for each vehicle. This information on each of the $3,018,456$ car approaches was then uploaded onto a SQL database [29], which we used to obtain the data analyzed in this paper.

Then, we further processed the data at the Aerospace Controls laboratory at MIT for the purposes of this research. Microsoft SQL Server 2008 Developer Edition was used to filter individual trajectories from the data collected in the CICAS-V project. From the $3,018,456$ car approaches, vehicle trajectories were classified as compliant or violating based on whether they committed a traffic light violation. Violating behaviors included drivers that committed a traffic violation at the intersection, defined as crossing over the stop bar after the presentation of the red light and continuing into the intersection for at least 3 m within 500 ms. Compliant behaviors included vehicles that stopped before the crossbar at the yellow or red light. The resulting dataset was further filtered to remove erroneous trajectories by ensuring that each trajectory was at least 10 m long and did not show discontinuities. Out of the filtered trajectories, $1,673$ violating and $13,724$ compliant trajectories were finally selected to be used in the classification algorithms.

Training and testing were performed on the selected vehicle trajectories using the m-fold cross-validation technique. This consists of dividing randomly the training set into m disjoints and equally sized parts. The classification algorithm is trained m times while leaving out, each time, a different set for validation. The mean over the m trials estimates the performance of the algorithm [30].

V. RESULTS

This section presents the results of the SVM-BF and HMM algorithms. Using the training trajectories collected as described in Section IV, the algorithms were tested in pseudo-real-time by running them over the testing trajectory
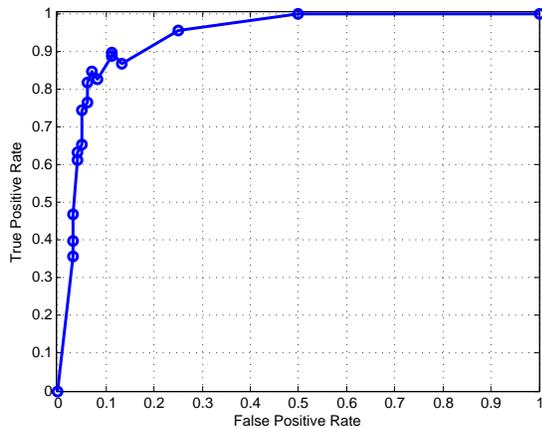
Fig. 5. ROC curve for the SVM-BF-based classifier.

TABLE II
SVM-BF CLASSIFICATION RESULTS

B Factor	Threshold τ	True Positive Rate	False Positive Rate
0.15	0.4	74.40%	5.10%
0.25	0.4	81.70%	6.10%
0.25	0.5	84.70%	7.10%
0.15	0.6	86.70%	13.30%
0.25	0.6	89.80%	11.20%

Fig. 6. ROC curve for the HMM-based classifier.

TABLE III
HMM CLASSIFICATION RESULTS

Threshold Constant	True Positive Rate	False Positive Rate
-30000	67.74%	8.99%
-25000	86.02%	10.11%
-20000	94.62%	11.24%
-10000	96.77%	15.73%
-5000	97.85%	16.85%

subsets of the database. A total of 400 trajectories were used for initial testing, with $m = 4$ for m-fold cross-validation. Current work at the Aerospace Controls Laboratory is considering approximately 10,000 trajectories extracted from the CICAS-V database. The observations from each trajectory are downsampled to 10 Hz to reduce the computational load without any significant loss of performance.

For each trajectory, the final output of the algorithms is taken when the estimated time to arrive to intersection reaches 1.6 seconds or when the distance to the intersection equals 10 meters, whichever condition happens first. The time and distance threshold values ensure that the driver has enough time to react to the warning [12]. To evaluate the results, the receiver operation characteristic (ROC) curve is used to display the true positive and false positive rate for each set of algorithm parameters, known as the Beta parameter in the SDT terminology [14].

A. SVM-BF

Figure 5 shows the ROC curve for the SVM-BF-based classifier. The Beta parameter here consists of the threshold constant introduced in Section III-A, and the B factor that appears in the Bayesian filter discount function [21] expressed as

$$\gamma(\Delta x) = A - B \exp(-C\Delta x) \qquad (3)$$

where the values of A and C have been fixed to 1 and 0.05 respectively, and Δx represents the distance of the vehicle to the intersection. The best size of the sliding window has been found to be 4. Table II highlights some of these results.
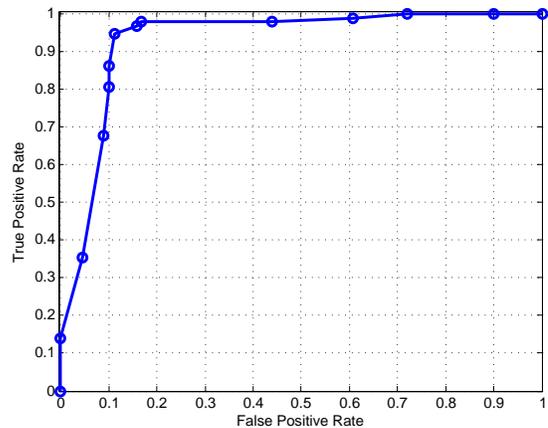
To obtain a false positive rate of 5% using a fixed threshold value τ, the B factor has to be decreased to around 0.15. This is equivalent to emphasizing more the earlier observations at the expense of being slower to react to late changes in the observation pattern, which can be seen in a lower true positive rate (row 2 vs. row 1 of Table II). Another natural trend seen in the results is that the true positive rate increases with an increasing threshold value. This can be explained by the decrease of the tolerance of the SVM-BF classifier towards risky drivers, leading also to more false positives.

B. HMM

Figure 6 shows the ROC curve for the HMM-based classifier. The Beta parameter here consists of the weights assigned to each observation type, the number of observations used k, and the threshold constant, which is defined as $\ln(\tau)$. However, to maintain a reasonable balance between true positives and false positives, it is sufficient to fix the weights and k and only vary the threshold constant. Table III highlights some of these results. The best weights for the speed and estimated time of arrival observations were found to be 2.5 and 1.25, respectively. All other observation weights were fixed at 1.0. A value of $k = 10$ was selected to use the observations from the one second just before the vehicle triggers the classification. A lower threshold constant biases the result toward negative classifications (*i.e.,* compliant), reducing the number of false positives at the expense of the true positive rate.

C. Discussion

As these results demonstrate, the best performing algorithms achieved high true positive rates while keeping false positive rates to some minimal levels. The SVM-BF is able to achieve lower rates of false positives on this dataset, perhaps making it a better option where driver annoyance is the primary concern. However, if detection accuracy is also a major concern, the HMM may be a better option as it returns a higher rate of true positives when the rate of false positives is allowed to increase past 10%. Testing on larger datasets will help improve performance for both algorithms as SVM and HMM are flexible approaches that adapt well to larger training data without an increase in model complexity.

VI. CONCLUSION AND FUTURE WORK

This paper introduced two new approaches for classifying driver behaviors at road intersections. The first one, denoted SVM-BF, combines a Support Vector Machines classifier with a Bayesian filter, to discriminate between compliant drivers and violators based on vehicle speed, acceleration and distance to intersection. The second one, HMM-based classifier, uses the EM algorithm to develop two distinct Hidden Markov Models for compliant and violating behaviors. The two algorithms were successfully validated on naturalistic intersection data collected in Christiansburg, VA, through the US Department of Transportation Cooperative Intersection Collision Avoidance System for Violations (CICAS-V) initiative. Future work will include training and validation on a larger dataset that consists of approximately 10,000 trajectories from the CICAS-V database, and optimizing parameter selection to minimize driver annoyance by keeping false positive rates below 5% while maximizing violation detections.

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