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Lane Change Intent Prediction for Driver Assistance: On-Road Design and Evaluation

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Abstract— **Automobiles are quickly becoming more complex as new sensors and support systems are being added to improve safety and comfort. The next generation of intelligent driver assistance systems will need to utilize this wide array of sensors to fully understand the driving context and situation. Effective interaction requires these systems to examine the intentions, desires, and needs of the driver for preemptive actions which can help prepare for or avoid dangerous situations. This manuscript develops a real-time on-road prediction system able to detect a driver's intention to change lanes seconds before it occurs. In-depth analysis highlights the challenges when moving intent prediction from the laboratory to the road and provides detailed characterization of on-road performance.**

I. Introduction

Of the 40,000 fatalities on U.S. roads in 2009, 18% involved lane control (merging/changing lanes 2.0%, negotiating a curve 14.2%, and passing other vehicle 2.0%) [1] which highlights the need lane change assistance systems with time- and safety-critical capabilities. The next generation of advanced driver assistance systems (ADAS) will need to make use of a holistic awareness of the surround, vehicle, and driver in order to predict and mitigate dangerous or uncomfortable circumstances.

These predictive systems provide the early notification necessary for an ADAS system to engage in assistive actions. Since drivers only use their blinkers half the time before a lane change [2], they could be engaged automatically to notify surrounding vehicles of the impending maneuver. Blind spot systems might be better accepted if warnings were only presented when needed (driver is not aware of blind spot vehicle). ACC assisted overtakes could be made more natural by accelerating into the lane change rather than waiting to clear a lead vehicle. Or, in risky situations, the vehicle could warn the driver of impending danger or could even take over control of the vehicle to completely avoid collision.

However the false alarm rate on such systems must be extremely low in order for the system to be effective. A high error rate could cause the driver to get distracted or annoyed and consequently disregard or disable the offending ADAS system. This paper presents a real-time lane change intent detection implementation (Fig. 1) in order to understand how previously reported offline classifiers [3]–[7] perform in on-road situations; especially with respect to the false positive rate. New analytical methods are proposed to more realistically characterize and improve the intent prediction performance in "real" situations. Utilizing a new holistic driving dataset, rather than a small set of exemplars, it is shown that on-road prediction must be improved in order to be useful for production.

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II. Related Research

Automotive researchers have long been interested in understanding drivers since they play a central role in driving [8]. Through recognition and understanding of a driving behavior, it is possible to characterize the driving situation. Tijerina et al. [9] found that there were between 65-92% probabilities of glancing at a mirror prior to a left or right lane change, and a recent NHTSA study [2] determined that these visual searches last on average 1.1 seconds. Early recognition of the driving situation would be extremely beneficial for ADAS by improving system performance or early priming of corrective behaviors, *e.g.* suppress lane departure warnings and engage a lane change assistant when a driver wants to make a lane change.

Unfortunately, it is not possible to exactly know what a driver wants, rather it must be inferred at small time scales based on vehicular measurements. Oliver and Pentland [10] were able to distinguish between 7 distinct driving maneuvers, each decomposed into a sequence of actions using (coupled) HMMs. Recently, Berndt *et al.* [11] used HMMs for continuous prediction of lane changes and turns. The first 3 HMM action states were used for early detection. Other researchers have focused on a single maneuver, such as lane change, and adopted traditional machine learning and pattern recognition techniques. An HMM utilizing vehicle dynamics measurements was able to distinguish between lane keeping and lane changes [12]. Salvucci *et al.* [13] incorporated vehicle dynamics, lane, and ACC radar information into a driver cognitive model of lane change. Researchers in San Diego have used the relevance vector machine to predict driver intentions to change lanes [3], [7], brake [5], and turn [4]. These studies developed a holistic understanding of the driving situation by utilizing a number of sensors. They relied heavily on the patterns of visual search (eye and head motion) that precede maneuvers for predictability.

While it has been shown that a driver's lane change intent can be predicted, such a system has not been implemented and deployed in a moving vehicle. It is currently unknown how the performance of the above intent prediction schemes will translate from the laboratory into a real vehicle and whether intent prediction is ready for the next generation ADAS.

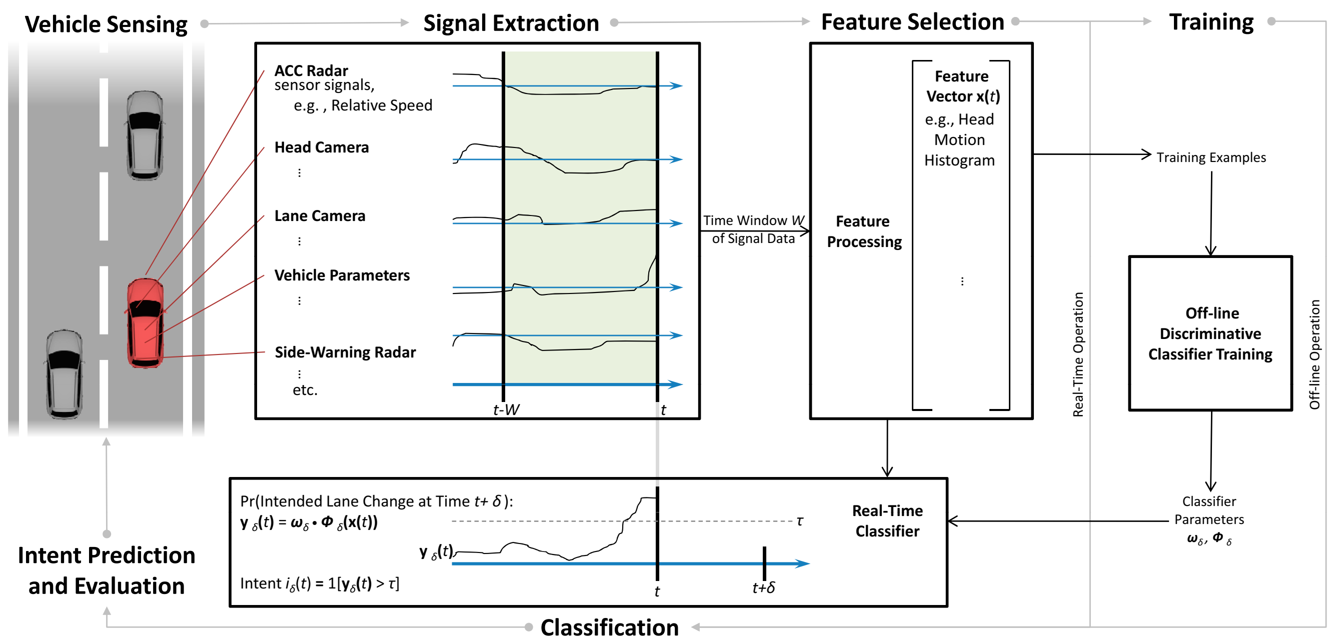


Fig. 1: Overview of Real-time Intent Detection System.

III. Holistic Intent Detection Framework

The real-time holistic intent detection framework is depicted in Fig. 1. While driving, a block of data is collected from all the signals from each of the sensor systems, processed, and concatenated to produce a feature vector. A supervised offline process utilizes the feature vector to train a discriminative lane change classifier whose weights are used to produce an output time series of lane change intent probability score every 33 msec during "real" driving.

A. LISA-X Automotive Testbed

A new automotive testbed was designed to observe and capture the full driving context using production-grade sensors to determine what can be accomplished with current technology and minimal additional costs. The testbed vehicle, dubbed Laboratory for Intelligent and Safe Automobiles X (LISA-X), is a 2008 Volkswagen Passat Variant 3.6L, modified to include the following sensors for holistic data capture [6]:

1) Adaptive Cruise Control (ACC) Radar
2) Side Warning Assist (SWA) Radars
3) Lane Departure Warning (LDW) Camera
4) Head (HEAD) Tracking Camera

The ACC and SWA radar systems are used to get surrounding obstacle information from the front and rear respectively. The LDW camera system tracks the road markings to determine position within a lane. The only research level system, the monocular head camera system, monitors the driver's head position and orientation. These sensor subsystems were tightly integrated into the vehicle body to ensure minimal distraction during driving.

LISA-X can capture, record, and process all of the additional sensor sub-system data along with the other more traditional vehicle dynamic signals delivered along the CAN-bus. During operation, over 200 sensory signals are captured, timestamped, and synchronized at 30 Hz to provide a rich description of the driving experience by observing the vehicle, environment, and driver state.

B. Holistic Maneuver Descriptor

A descriptor of the full driving context is constructed by concatenating the signals from the sensor subsystems into a large feature vector

$$x(t) \quad = \quad \begin{bmatrix} \bar{\nu} \\ \bar{\alpha} \\ \bar{\varsigma} \\ \bar{\lambda} \\ \bar{\eta} \end{bmatrix} \quad = \quad \begin{bmatrix} \text{Vehicle} \\ \text{ACC} \\ \text{SWA} \\ \text{LDW} \\ \text{HEAD} \end{bmatrix} . \tag{1}$$

The vector $x(t)$ represents all signals and measurements taken from a short time window of the past $W = 2$ seconds. The descriptor incorporates temporal patterns in $N_w = W *$ 30fps $= 60$ frames of historical time series values, *e.g.* head rotation

$$\bar{\eta}_{j...j+N_w-1}(t) = [Yaw(t - N_w - 1), \ldots, Yaw(t)], \tag{2}$$

as well as higher-level window measurements, *e.g.* the amount of time spent glancing to the side

$$\bar{\eta}_{j+N_w}(t) = \sum_{k=t-N_w-1}^{t} \mathcal{I}[Yaw(k) > 30] \tag{3}$$

where $\mathcal{I}[.]$ is the indicator function. The higher-level measurements are features designed provide highly discriminative dimensions to the features space by incorporating "expert" knowledge drawn from human experience and provide maneuver indicators. This helps limit the size of $x(t)$ and condition noisy or sparse sensor signals for improved machine learning robustness to limited data.

C. Subsystem Signals and Features

After processing all the signals, the feature vector $x(t)$, of approximately 500 dimensions, is constructed from the window of sensor data. A summary of the relevant features from each of the sensor subsystems is presented below.

1) Vehicle Signals $\bar{\nu}$: The CAN-bus provides measurements of the vehicle's dynamic state and controls. This supplies several time series features which include the steering wheel angle, yaw rate, and blinker state signals, as well as indicators of blinker direction and length of time it is active.

2) ACC Signals $\bar{\alpha}$: The ACC system is able to track a lead vehicle using a narrow cone RADAR. The 4 ACC features relate to a lead vehicle and account for the distance to the ACC vehicle, the relative speed of the ACC vehicle, the measured time gap with the ACC vehicle in seconds, and the difference between the current vehicle speed and the desired speed (ACC set speed).

3) SWA Signals $\bar{\varsigma}$: The SWA system is able to track a number surround vehicles in the rear and sides using a paired RADAR system and delivers the position $(s_x^i(t), s_y^i(t))$ and relative velocity $(s_u^i(t), s_v^i(t))$ of each obstacle i. The large rear area is quantized into three smaller critical zones which correspond to the blind spots in the rear of the vehicle as shown in Fig. 2. Each zone is defined to be between $-15 < y < -5$ meters behind and defined by the size of adjacent lanes

$$Z_1 = \{x | -5 < x < -1.65\} \quad (4)$$

$$Z_2 = \{x | -1.65 < x < 1.65\} \quad (5)$$

$$Z_3 = \{x | 1.65 < x < 5\}. \quad (6)$$

The SWA blind spot features indicate the occupancy and speed state within a critical zone z as

$$\varsigma_z = \max_i \frac{1}{N_w} \sum_{k=0}^{N_w-1} s_v^i(t-k) \quad (7)$$

where the i indicate all tracked vehicle at the current time t. The features ς_z and are intended represent deterring factors since the presence of a vehicle in the adjacent lane would impede a maneuver.

4) LDW Signals $\bar{\lambda}$: The LDW system provides measurements of the vehicle position with respect to the road and the road geometry. The LDW features correspond to the recent time series of vehicle lateral deviation (position within the lane), lane curvature, and vehicle yaw angle with respect to the lane.

5) HEAD Signals $\bar{\eta}$: Unlike the other sensor subsystems, the HEAD system does not monitor the driving environment, instead it focuses on the driver. Since preparatory glances are a major indicator of a lane change maneuver [2] there are a large number of features generated for the HEAD systems to better infer driver actions. The features include the time series of head yaw position, yaw motion (derivative of yaw position), a histogram of head yaw values, a histogram of yaw motion values, a histogram of head pitch position, and an indicator signal of significant yaw rotation (3).

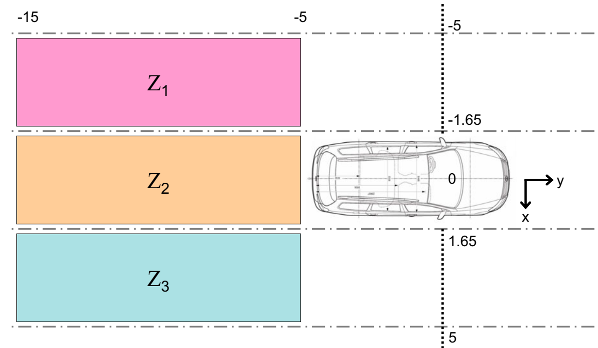


Fig. 2: Three SWA regions of interest: driver-side lane in pink, ego-lane in orange, and passenger-side lane in blue. The SWA features consist of the average longitudinal speed in each of these regions and indicate motivators and deterrents to a lane change.

D. Sparse Classifier for On-Road Intent Prediction

The lane change inference algorithm utilized in this work is based on the work of McCall *et al*. [3] which has been shown to be effective at early detection of intent in other studies [4]–[7]. A Bayesian extension to the popular SVM, called a relevance vector machine (RVM) [14], discriminates between lane change and lane keeping. The basic form of the RVM classifier is given as follows:

$$y_\delta(t) = \omega_\delta \cdot \phi_\delta(\mathbf{x}(t)) \quad (8)$$

where $\mathbf{x}(t)$ is the input feature vector at time t and ω a learned weight vector. The output y then represents the probability that $\mathbf{x}$ belongs to a particular class. In this case, we determine whether $\mathbf{x}$ represents an intended lane change at a particular time δ in the future.

The RVM is particularly useful because its use of a parameterized prior helps prune large feature vectors and facilitate a sparse representation (in ω_δ). This allows selection of a few of the most useful features without specific multi-modal modeling assumptions and enables fast computation for real-time classification. In this way, all the sensor sub-systems can be treated equally and the most distinct and relevant signals for lane changes are automatically determined during training.

IV. On-road Performance Characterization

The on-road pattern recognition is significantly different than in the laboratory setting. In the laboratory, independent examples are presented to the classifier while in the real-world case, evaluations must be made continually as new data arrives. This continuous operation has direct impact on performance characterization because of a large imbalance between positive and negative examples, consecutive evaluations will perform similarly, and decisions must be made in real-time.

A. Driving Data Collection

In order to train and test the lane change intent classifier, a new sensor rich database of naturalistic driving was collected

TABLE I: Lane Change Prediction Datasets

Label		Data Set	N_{people}	N_{runs}	Hours	Description
D		Long runs for Training	15	24	14.5	782189 frames
	D_{train}	Training Examples				266+/2606- examples
	D_{test}	Cross Validation Test Examples				101+/879- examples
T		Long runs for Testing	4	18	7.9	427497 frames

using the instrumented LISA-X vehicle. The data collection was performed in San Diego and Palo Alto by the VW Electronic Research Laboratory (ERL). The 15 (12 male, 3 female) participants were of varying nationalities, with ages ranging from their 20s to 50s, and had various amounts of driving experience and familiarity with ACC functionality.

1) Training Database: For each driver, a data collection run consisted of two phases of approximately 30 minutes each. In one phase, a driver was instructed to stay in the "slow lane" and engage the ACC when it was safe and comfortable to do so, passing when necessary. In the second collection phase, the driver was free to drive normally without the ACC function engaged in order to obtain completely natural driving behaviors. Drivers (especially those not familiar with ACC operation) had a tendency to behave differently when the ACC was active than in their normal day-to-day driving behavior.

The complete training dataset, D, contained 24 driving runs for 14.5 total hours of driving data (CAN messages and raw videos) in a variety of driving conditions. Almost 500 instances of lane changes were automatically detected based on lane deviation information (some were manually marked when lane tracking was unreliable). A positive example was constructed from a $W = 2$ second chunk of data δ seconds prior to the lane. For a lane change at time t_{lc} this resulted in measurements between times $[t_{lc} - \delta - W, t_{lc} - \delta]$.

Several validation criteria were used to ensure training samples were taken from highway driving with valid sensor reading, resulting in 367 instances of "good" lane changes. These training examples were split into two separate subsets for cross-validation training. The set D_{train}, with 266 positive examples, was for training the classifier while D_{test}, with 101 examples, was for assessing the performance during training. Negative examples were randomly selected between lane change occurrences at a 10:1 ratio.

2) Testing Database: The independent testing dataset T, consisted of 7.9 hours of completely uncontrolled driving during 18 separate data runs by a 4 person subset of the drivers involved in set D. Drivers were free to use ACC as desired and were not prompted with any directions. Dataset T contained over 400,000 evaluation windows but only 229 lane changes. Table I summarizes the lane change prediction datasets.

B. From Laboratory to Roads

In the laboratory setting, pre-specified examples are fed to the classifier to determine performance but in real-world settings, the classifier must continually evaluate data as it arrives. Practically, this results in much lower false positive rates because of the significantly larger number of evaluations (although this does not necessarily translate to "better" performance). This necessitates the development of new analytical methods for more realistic characterization and improvement of intent prediction in "real" situations.

1) Traditional Evaluation: During the intent classifier training, performance is evaluated with a small cross-validation test set D_{test}. The blue ROC curve generated using this set of labeled positive and negative examples (Fig. 3a) provides the traditional performance evaluation in the laboratory setting, and is similar to those seen in prior work [3].

In addition, even with the wide variety of driver's behavior prior to a lane change, the RVM intent classifier has quite consistent performance and could be expected to perform just as well on a larger population. Using an analysis of variance, treating the subjects as random factors, there was a significant separation between the lane change and lane keeping classes ($F(1, 14) = 674, p < 0.001$).

2) On-Road Evaluation: Dataset T was used to analyze the on-road performance of the predictor response during continuous operation. In this experiment, a first-in first-out measurement buffer is maintained as data is continuously streamed to output the probability of lane change every 33 msec. The two ROC curves, in blue and green, are shown in Fig. 3a for detection time of $\delta = 2.5$ [seconds] using all the sensor subsystems. The ROC from the on-road set T is better than for D_{test} because of the greater rate of negative examples, causing a very low false positive rate.

While the traditional ROC curve analysis makes the classifier seem quite strong, viewing the results on a scale more meaningful for in-vehicle usage a different story unfolds. Fig. 3b presents the same ROC but using false positives per second [FP/sec] rather than the traditional (and academic) false positive rate. The seemingly "good" laboratory classifier with 50% TPR and only 1% FPR translates into a false detection every 3 seconds. In order to have acceptable on-road performance the prediction FPR must be greatly improved.

C. Lowering Classifier FPR

The intent classifier performance analysis using real units [FP/sec] shows that false detections are the main source of error. These false positives are mainly the result of two phenomena. First, on-road evaluation presents data sequentially and continually (in overlapping time windows), which results in temporal consistency. Second, a classifier is designed to detect a lane change δ seconds before its occurrence, but the classifier is not always precise in its prediction time.

1) Time Series Dependency and Multi-suppression: In classical pattern classification setups, data is selected, either

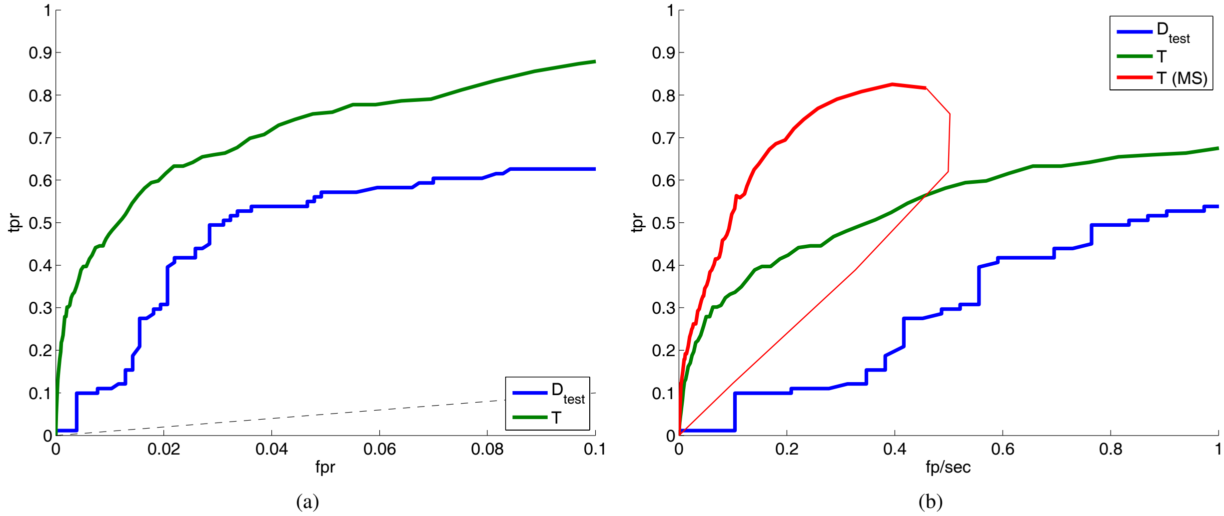


Fig. 3: Plots comparing the $\delta = 2.5$ intent ROC curves with all sensor subsystems for the different test sets. (a) The traditional TPR vs FPR ROC curve used to asses classifier performance with results on T higher due to the much larger number of negative examples in the set. (b) ROC curve utilizing real units demonstrates the laboratory evaluation does not translate well on-road. The on-road performance can be greatly improved by lowering the number of false positives using a multi-suppression technique (MS) as shown in red.

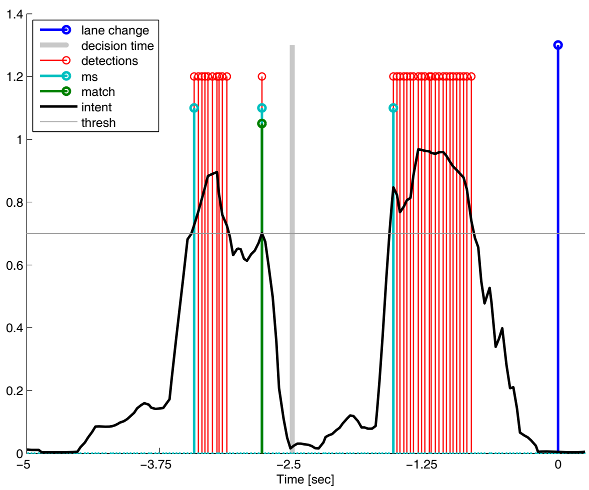


Fig. 4: The evolution of lane change probability (black) 5 seconds prior to a lane change (blue). The red denotes all frames with probability above the detection threshold. No detection occurs at $\delta = 2.5$ seconds because of inherent behavioral variability. Using multi-suppression (cyan), only the first detection in a sequence is counted and the best matching detection (green) within a small match window can be determined.

positives or negatives examples, and fed to a classifier to test its response. The implicit assumption is that individual examples are independent. In the on-road case, a sliding window is used on time series data which results in non-independent samples. Two consecutive windows will contain almost identical data and therefore will have similar responses. The plot in Fig. 4 shows the evolution of intent probability of the $\delta = 2.5$ classifier in black for a number of seconds before a lane change.

Ideally, a single large value would spike at 2.5 seconds prior to the lane change, but in this case there are actually two major responses at 3.5 and 1.25 seconds prior. As the lane change approaches, the probability of lane change increases and a number of time instances are above the detection threshold. Each of the red deltas indicate a detection but there is only one lane change which means most of them are considered false positives. With the assumption that consecutive detections arise from the same intent, a single detection can be extracted on the rising edge of the intent signal. This multiple detection suppression technique logically handles the time series effect but may change the detection time away from δ. After this "multi-suppression" only 3 detections remain in this segment. The detection that matches (Section IV-C.2) the lane change is the closest to δ as shown in green while the remaining 2 detections are false detections, which is dramatically less than the red.

The on-road performance after multi-suppression (MS) is shown in red in Fig. 3b. The MS scheme results in performance gain over traditional evaluation but introduces an interesting looping behavior in the ROC curve. This does not cause any problems because it occurs only at very low thresholds and in practice only larger thresholds would be used to ensure high confidence.

2) Imprecise Prediction Timing and Match Windows: Even though an intent classifier was trained to infer the lane change δ seconds before its occurrence, the cues that signify an oncoming lane change may not always happen at the exact same time, due to the variability in human behaviors. As demonstrated in Fig. 4, although a detector is designed for a specific time δ, the detections are not localized and can occur before or after this time. Therefore, during performance evaluation, there must be some flexibility to allow examples within a small time window around δ to

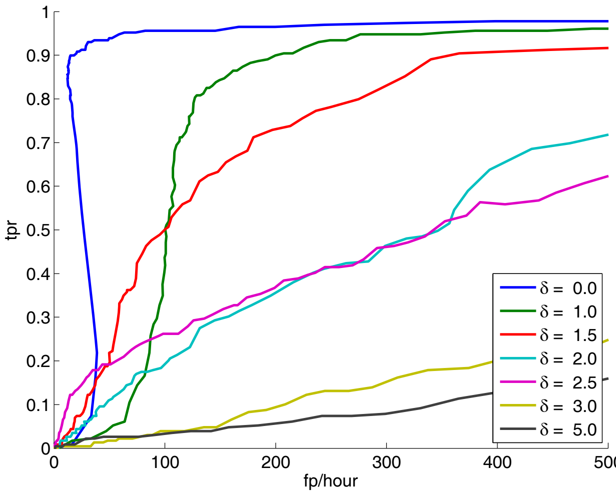


Fig. 5: Real units ROC curve for the lane change intent classifier at different detection timings. The closer to the lane change the better the performance and prediction horizons beyond 3.0 seconds are completely unreliable.

be considered a positive as well.

In order to determine if the classifier was able to correctly infer the lane change δ seconds early, a small match window (± 1 sec) is used to soften the δ constraint to consider a close detection as a match (green in Fig. 4) while any other detections not matched are considered false positives.

D. On-Road Results

In Fig. 5 the predictor performance is given in false positives per hour for various detection times δ. Predictions made earlier than 3 seconds before a lane change are unreliable indicating there are few distinctive behaviors in the $[-7, -3]$ seconds time range as expected. Fig. 6 depicts the head yaw and lane deviation variation from the positive training set. Lane deviation is very useful within $[-2, 0]$ seconds but is uninformative earlier. In contrast, head motion during scans is significant between $[-3, 1.5]$ seconds before a lane change, much closer to the lane change time than was previously reported [2]. The choice of $W = 2$ [seconds] ensures the scan behavior in contained in a data window, although predictions made closer to the lane change have generally better performance.

During on-road use, data is collected in a sliding window and the holistic classification engine is able to predict oncoming lane changes in real-time as demonstrated in Fig. 7a (although not localized at $-\delta$ seconds before the maneuver). The ROC analysis demonstrated it is possible to achieve detection rate in the 80% but false positives were a concern. Since the majority of highway driving is in a lane-keeping mode, it is particularly important to eliminate false positives to reassure the driver of system performance.

The multi-suppression technique helped reduce false positive evaluation frames and the match window relaxed detection timing during continuous evaluation for a more indicative performance curve. However, there are still a variety of other reasons for a false positive which limit the prediction engine's effectiveness, among them:

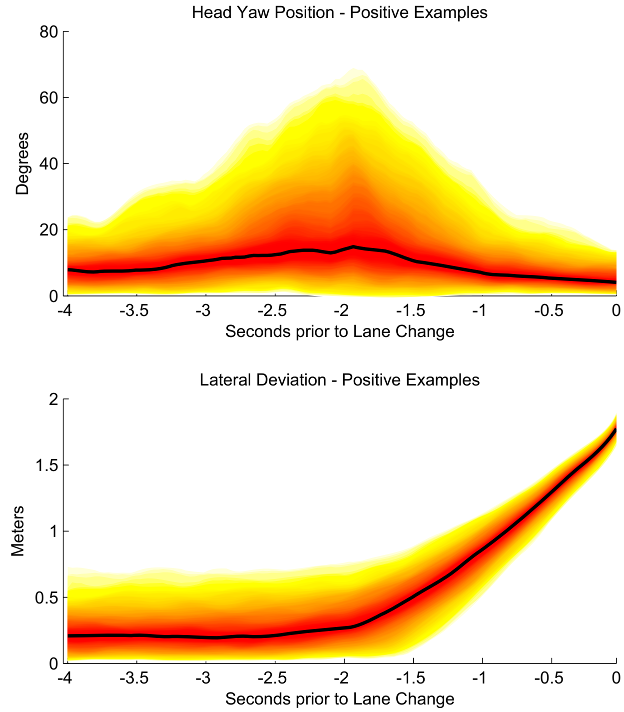


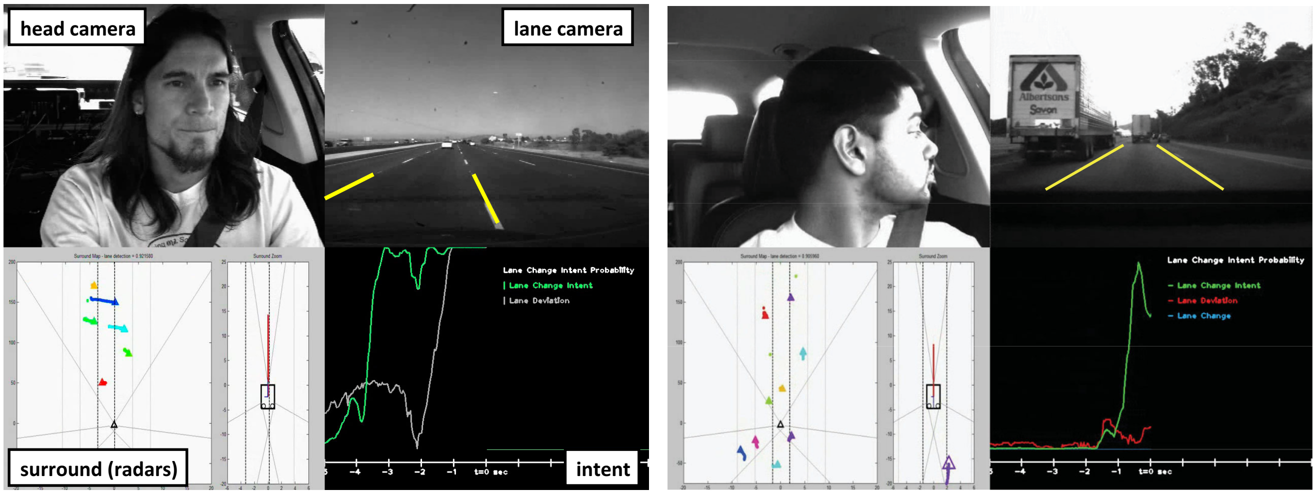
Fig. 6: Distribution of head yaw and lane deviation signals during lane changes. Before -2 seconds, it is very difficult to predict an oncoming lane change using just lateral deviation. In contrast, a driver's yaw when scanning tends to occur between $[-3.0, 1.5]$ seconds before a lane change.

- events that look similar to lane changes (merges, exits),
- lane changes close to times of poor sensor readings,
- an intent without a corresponding maneuver, i.e. an aborted lane change,
- predictions which occur outside of the match window.

Fig. 7b highlights a difficulty when dealing with intentions and the holistic approach. Here a driver looks over his shoulder and appears as if he will make a lane change but does not actually change lanes. The intention to maneuver existed but it is difficult to quantify without the existence of the lane change. Hence, this is arguably a "true" false positive because an assistance system could be engaged based on the driver desires. The evaluation criteria is strict in these cases (counting as a false positive) because an ADAS must have guarantees about the oncoming maneuver in order to assist properly. This is also why merely detecting the lane change in advance is not sufficient; it must be detected δ seconds in advance.

V. Concluding Remarks and Future Directions

Real-time driver intention understanding is a key for the successful development of next generation driver assistance systems. Automotive systems operate under safety and time-critical constraints, where every millisecond helps to save lives. These these precious moments can be gained by deeper understanding of a driver's intentions and early predictions of maneuvers. But, the traditional laboratory methods for training and evaluation of prediction schemes do not provide



(a) (b)

Fig. 7: Examples of on-road intent detection which display the head and lane viewing cameras, the surround map, and the lane change intent output probability. (a) An example of lane change intent successfully detected 2-3 seconds prior to the lane change. (b) An example of an aborted intent, in which the pink vehicle in the blind spot most likely caused the driver to abstain from the lane change.

effective indicators of continuous on-road performance. In order to more realistically characterize operation, this work introduced a multi-supression technique, for a single localized detection, and match window, to relax the prediction timing constraint, to dramatically lowered the false positive rate from successive evaluations. The resulting classifier was able to reliably predict lane changes up to 3 seconds before the actual maneuver thanks in large part to a head viewing camera which directly observed the driver. Still, in order to be road ready, early prediction schemes will need to explicitly account for the correlated nature of vehicular measurement (time series) data and use contextual information as a prior for output probability calculation.

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