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MARV-X: Applying Maneuver Assessment for reliable Verification of Car-to-X Mobility Data

Jonas Firl, Hagen Stübing, Sorin A. Huss and Christoph Stiller

***Abstract*—Advanced Driver Assistance Systems (ADAS) employ single object information to provide safety, comfort, or infotainment features. While today's systems use common sensors like radar or camera to recognize and predict the future states of relevant traffic participants, next generation ADAS will also use data from additional sources like, e.g., Car-to-X (C2X) communication networks. We present a method, which uses information on other traffic participants and furthermore recognizes and considers their interactions in terms of traffic maneuvers. For this purpose, a probabilistic approach is presented, which identifies object interactions as well as different road characteristics. This method may find especially application in the C2X domain for evaluating the mobility of neighboring vehicles based on received messages.**

In this work we present MARV-X (Maneuver Assessment for Reliable Verification of Car-to-X mobility data), a tool embodying a two-stage process for reliable C2X mobility data verification. The first stage consists of a dedicated mobility estimator realized by a Kalman filter. In the second stage a plausibility check for highly dynamic traffic situations is applied using the advocated probabilistic traffic maneuver recognition. MARV-X is fully integrated into the vehicle's C2X architecture. Its effectiveness is demonstrated by means of extensive real world experiments.

***Index Terms*—Maneuver Assessment, Car-to-X Security, Mobility Data Verification.**

I. Introduction

PREDICTION of vehicle trajectories plays a decisive role in the development of Advanced Driver Assistance Systems (ADAS). This information is crucial for systems that assist the driver in terms of safety, comfort, and efficiency. To ensure utilizable prediction results, all available information related to the perception of the environment have to be taken into account, like, e.g., radar sensors, cameras, or information from Car-to-X (C2X) communication networks. While current systems already use information on individual objects (see, e.g., [1], [2]), the consideration of relations between different traffic participants is still a remaining challenge. For the purpose of improving prediction results in future systems, the interaction information has been identified as a crucial factor.

In order to recognize vehicle interactions in traffic scenarios in terms of driving maneuvers, various approaches have been developed in recent years. They mainly differ in the scenarios they may be applied to. In complex inner city scenarios like, e.g., intersections, approaches are limited to particular road geometries. Discriminative approaches are presented in [3]. In [4] trajectory clusters are learned and a metric for instantaneous recognition is defined to identify the closest cluster from the learned trajectory set. While promising results have been shown for specific intersections, a generalization towards arbitrary and a-priori unobserved road networks has not yet been achieved. This is basically due to a huge variety of possible road geometries as well as driving trajectories and the need for training. For recognition of the interactions of vehicles in more simplified scenarios like highways or rural roads, two different classes can be identified denoted as *logical* and *probabilistic approaches*.

Logical approaches apply different logical languages to model temporal and spatial scenario properties and rules, like, e.g., "vehicles may only turn right on a right turn lane". Representatives of such approaches employ modal logic [5] or description logic [6], [7]. While being capable of representing and reasoning in complex traffic scenes, such approaches have difficulties in handling uncertainties and ambiguities in the input data as well as in the recognition results. An extension of these approaches can be found in [8], where the use of logical languages and Markov networks are combined to recognize object relations in traffic scenes. Although Markov-Logic-Networks seem to be an interesting approach in this domain, their size grows exponentially with the number of objects modeled in the scene and hence, up to now, no implementation has been presented that is capable of handling temporal dependencies and continuous input data appropriately in real time.

A probabilistic model of graphical scene representations is offered by Bayesian Networks, which allow the modeling of complex situations. To consider spatial and temporal dependencies in traffic situations, Dynamic Bayesian Networks were introduced in [9]. While promising results have been reported in low-complexity tasks, such approaches tend to result in unfeasibly large networks as the complexity of the situation increases. An explicit probabilistic model describing the interdependence of a vehicle from its predecessor has recently been presented in [10], but it is still not clear how to generalize this model to arbitrary situations. Hidden Markov Models can be applied to keep model complexity low and to guarantee real time capability [11]. However, the input data of this approach, that may be considered by a HMM of a reasonable complexity, is not sufficient for recognizing complex situations in presence of multiple objects.

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The contributions of this work are manifold:

- A method for assessing maneuvers is presented based on probabilistic modeling. Compared to current works on situation assessment, which focus on interactions of two vehicles only, in this work the modeling of the vehicle surrounding is extended significantly. Hence, the entire traffic situation, including road characteristics, and other traffic participants is considered.
- The applicability and gained benefits of the maneuver assessment are demonstrated by means of a real ADAS application. As a promising technology for next generation ADAS, C2X plays a decisive role. C2X communication in terms of Car-to-Car (C2C) and Car-to-Infrastructure (C2I) communication aims to increase road safety and traffic efficiency by exchanging foresighted traffic information. C2X communication is based on the IEEE 802.11p [12] standard and enables time critical safety applications at very low data transmission delay. The advocated approach has been deployed for complementing existing C2X security modules, which are based on vehicle behavior analysis.
- In this work we show how this approach can be implemented and integrated into existing C2X architectures including relevant components and their interfaces. By means of this implementation, a comprehensive evaluation has been performed with real world data.

The paper is structured as follows: In Section II the theoretical framework for recognizing different traffic maneuvers is detailed. Its application in the field of the security of C2X communication networks is discussed in Section III. Evaluation results by means of real world experiments and implementation details are presented in Section IV. Conclusions and an outlook to future work are given in Section V.

II. Probabilistic Maneuver Recognition

In this section the general maneuver recognition approach is presented, which is build on preliminary work presented in [13]. First, the basic theory of the proposed probabilistic model is introduced briefly in Section II-A, namely *Hidden Markov Models* (HMMs). Then, the complete recognition stage is detailed in Section II-B.

A. Hidden Markov Models

HMMs have been applied in the last decades for pattern recognition issues, prominently in the field of speech recognition [14]. Other application areas may be found in, e.g., [15]. In this work we propose HMMs to recognize different traffic maneuvers by means of efficient evaluation algorithms.

A HMM $\lambda = (A, B, \pi)$ is a stochastical model, consisting of a process of hidden system states q_t and one process of observable system emissions o_t. It is defined by the following (see [14] for a more in-depth presentation):

- The set of hidden system states $X = (X_1, \ldots, X_n)$ and *state transition matrix* $A = \{a_{i,j}\}$ define a Markov chain, where $a_{i,j}$ is the probability for a transition from state i to state j, i.e., $P(X_j|X_i) = a_{i,j}$.

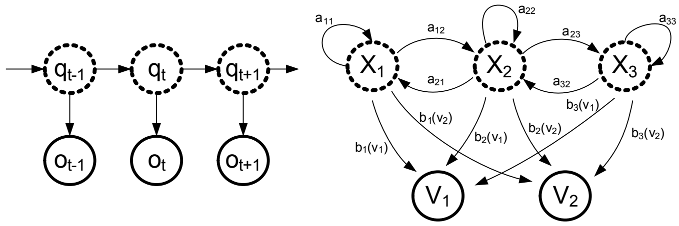


Fig. 1. Structure of a HMM. Left: Markov chain of hidden system states. Right: HMM with 3 system states and 2 (discrete) observation symbols V_1 and V_2.

- The *observation model* $B = \{b_i\}$ specifies the probabilities of observing V_k in state X_i, i.e., $P(V_k|X_i) = b_i(V_k)$.
- The *initial state distribution* $\pi = \{\pi_i\}$, i.e., $P(q_0 = X_i) = \pi_i$.

In Figure 1 a HMM example with 3 hidden states and 2 discrete observation symbols is illustrated. When using HMMs for instantaneous recognition tasks, two different tasks have to be addressed [14]. The first one is related to the training of the model parameters (A, B, π), which may be solved using the iterative *Baum-Welch Algorithm*.

The second task is concerned with inference algorithms in HMMs. More precisely, the probability $P(\vec{o}|\lambda_i)$ of an observation sequence $\vec{o}$ for a given model λ_i has to be computed. This allows to conduct a likelihood test that compares different models for a given observation sequence. Since the straight forward solution requires $O(N^T)$ operations, the recursive *Forward Algorithm* presented in [14] is applied, which reduces complexity to $O(N \cdot T)$.

B. HMM-based maneuver recognition

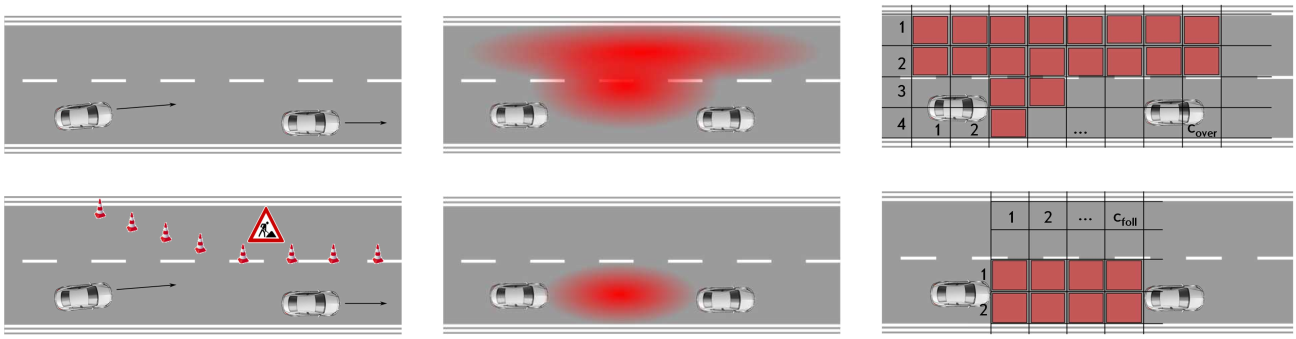
The basic concept for a traffic maneuver recognition based on HMMs has been presented in [11] and [16]. This work significantly extends this approach by improving the observation data.

1) Modeling: One HMM λ_i is trained for every traffic maneuver, namely *following*, *overtaking*, and *flanking* maneuvers. The system states of the model thereby correspond to the different stages of the modeled driving maneuver, as visualized in Figure 3. As the observation the relational data between the traffic participants at time t is considered, e.g.:

$$o_t := (d_x, d_y, v_{rel}, a_{rel}), \tag{1}$$

where d_x and d_y are the distances in longitudinal and lateral directions, v is the relative velocity, and a denotes the relative acceleration, respectively. For the selection of an appropriate coordinate system a lane-fixed system is considered [16]. An example of the observation distributions can be seen in Figure 3, where Mixtures of Gaussians (MoGs) were applied to model the continuous observation data, i.e., relative distances in longitudinal and lateral directions. The peaks of the distributions correspond to the different stages of the maneuver.

In order to recognize maneuvers, the Forward Algorithm is used to compute the probabilities $P(\vec{o}|\lambda_i)$ for all models. Due to the fact that these values are not of direct interest here (not the model λ_i, but the observation data $\vec{o}$ is given), the



(a) Motivation for free space consideration (example: overtaking recognition).

(b) Required free space for overtaking and following maneuvers.

(c) Definition of the occupancy grid for overtaking and following maneuvers.

Fig. 2. Usage of occupancy grids for free space consideration.

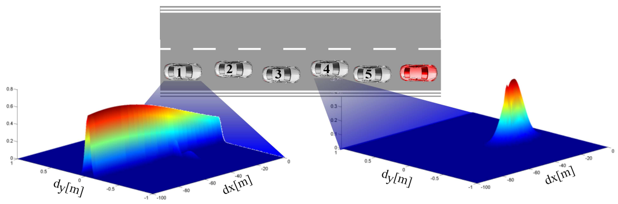


Fig. 3. System states of the HMM for following maneuvers and two schematic observation distributions MoG for two states and the observations d_x, d_y.

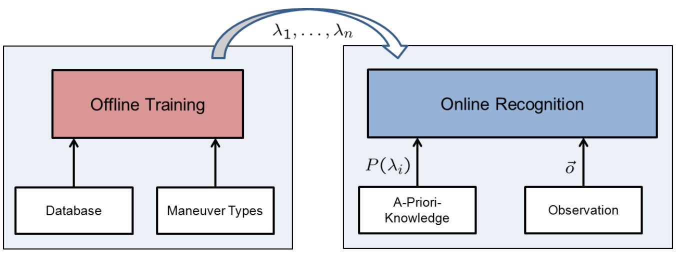


Fig. 4. Maneuver recognition system

relevant probabilities $P(\lambda_i|\vec{o})$ are calculated using the Bayes' theorem. The required a-priori probabilities $P(\lambda_i)$ provide the possibility to model the influence of different road types, see [16] for more detailed information. For example, overtaking maneuvers are more likely to occur on highways than on rural roads. The basic structure of the resulting recognition system is illustrated in Figure 4.

2) Free space consideration: The recognition system described in the last paragraph only considers the relative dynamic information between two vehicles. While, in theory, the observations may be extended to consider more than the interaction between two vehicles, such approaches would yield a prohibitive dimensionality of interdependent observations that prevents appropriate training in practice. A typical situation can be seen in Figure 2a, where two vehicles are driving on a highway with two different road occupancy conditions. Using the observation vector from definition (1), between the two vehicles on the right lane, both situations would lead to the same observations $\vec{o}$ and therefore to the same recognition results $P(\lambda_i|\vec{o})$. The consequence is that the obtained probability does not reflect the situation appropriately, i.e., the same probability for a lane change maneuver is predicted regardless of the occupancy status of the overtaking lane. In order to assess the situation correctly, the entire vehicle surroundings have to be taken into account, which includes:

- other traffic participants,
- static objects (e.g., construction sites, road boundaries),
- road characteristics (e.g., number of lanes).

These are explicitly considered in the following extended observation model. First, the required free space for the execution of every maneuver has to be defined, see Figure 2b. Note that the dimensions of the available free space may vary over time as vehicles move relative to each other. The next step is to define a mathematical description to consider this specific information in the current observation model. For this purpose, occupancy grids are introduced as depicted in Figure 2c. The link between this occupancy grid and the observation model is represented by a continuous observation variable $f \in [0, 1]$, with the following meaning of its boundary values:

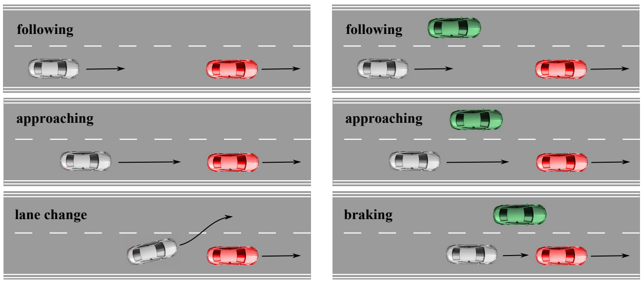
- 0: Maneuver execution is infeasible,
- 1: No restrictions for maneuver execution.

To extract the current value of f for a given maneuver from the occupancy grid, the occupancy values $f_{i,j}$ for every cell (i, j) have to be computed, denoting a blocked ($f_{i,j} = 0$) or unblocked ($f_{i,j} = 1$) cell. The overall value f for the complete grid is determined by:

$$f = \sum_{all\ cells(i,j)} \frac{1}{\#cells} f_{i,j} \tag{2}$$

While static influences (static objects and road characteristics) have binary values for $f_{i,j}$, other traffic participants are modeled by means of continuous distributions. The reason for this is that not the simple actual position of other vehicles is taken into account, but their path predictions. The higher the certainty of a maneuver blockage by another vehicle is, the lower the resulting value $f_{i,j}$ will be. For path predictions all available single object information (position, speed, heading) is taken into account.

With this recognition approach one of the major drawbacks of other methods is removed: not only two traffic participants may be considered, but in general any number of vehicles may be taken into account for the recognition of traffic maneuvers.



(a) Lane change maneuver (b) Braking maneuver

Fig. 5. Dynamic traffic maneuvers with similar pair-wise observations between the vehicles on the right lane: While an overtaking of the leading vehicle is likely in situation a) it is unlikely in situation b).

3) Maneuver prediction: The results of the maneuver recognition are exploited to improve the position information on single objects. The main motivation for this approach is that it is important to consider dynamic driving maneuvers as one of the most crucial difficulties for current path prediction algorithms. This is why an early prediction of these maneuvers can help to adjust the prediction algorithms in terms of accuracy.

a) Lane change prediction: Most dynamic lane changes (see Figure 5a), especially when conducted on non-urban roads, are performed during overtaking maneuvers. The critical dynamic situation can be seen at the bottom of Figure 5a, where suddenly a large lateral offset occurs due to the lane change. With the results of the maneuver recognition, this lane change can be predicted by comparing the recognition results $P(\lambda_i|\vec{o})$ of two different HMMS, i.e., following and overtaking maneuvers. The ratio

$$c_1 = \frac{P(\lambda_{over}|\vec{o})}{P(\lambda_{foll}|\vec{o})} \tag{3}$$

is an indicator for lane changes, where high values of c_1 correspond to high lane change probabilities. With this criterion, a lane change can be predicted before the lateral movement of the vehicle actually occurs. Related results were presented in [16].

b) Braking prediction: Sudden braking maneuvers, as illustrated in Figure 5b, require a slightly different approach to be predicted accurately. The reason for many braking maneuvers is the lack of free space on the left lane while the driver intends to overtake another vehicle. This divergence between the driver's intention and the actual maneuver feasibility requires an extension of the observation vector, Eq. (1). Therefore, two models with different observation vectors are introduced:

- *Driver's intention* is represented by a model λ_{over} with the observation vector in Eq. (1), which does not consider the required free space.
- *Maneuver feasibility* is represented by a model $\lambda_{over,f}$ with an extended observation vector according to Section II-B2 using the occupancy value f of Eq. (2), which now does also consider the required free space for a successful maneuver execution.

The corresponding ratio of the two models

$$c_2 = \frac{P(\lambda_{over}|\vec{o})}{P(\lambda_{over,f}|\vec{o})} \tag{4}$$

serves as an indicator for performing a sudden braking, where large values of c_2 are associated with large braking probabilities.

III. Application to Car-to-X Communication

The previously outlined maneuver recognition component finds application especially in the domain of vehicular safety, where a precise assessment and interpretation of the traffic situation is a necessary prerequisite. In the following section we focus in particular on upcoming Intelligent Transportation Systems (ITS) based on Car-to-X communication to demonstrate how the advocated maneuver recognition component can be deployed for verifying the trustworthiness of mobility data contained in frequently sent C2X messages. The developed framework has been fully integrated and evaluated for accuracy, as detailed in Section IV.

A. C2X Communication and Security

Since the initial earmarking of IEEE 802.11p frequencies [12] by the European Commission in 2008, vehicular communication networks have made great progress. Based on the message set as currently standardized by the ETSI, several field operational trials like DriveC2X [17] and sim$^{\text{TD}}$ [18] are conducted. Cooperative Awareness Messages (CAMs) contain a vehicle's mobility data in terms of position, speed, and heading and are sent within intervals from 1s to 100 ms [19]. In contrast, Decentralized Notification Messages (DENMs) are sent only upon detection of certain traffic events, like, e.g., black ice or traffic jams, and may be forwarded over longer distances [20].

The ETSI, furthermore, has identified security and privacy issues as a key-enabler for C2X and therefore has settled it as a cross-layer among all other ITS layers [21]. Consequently, the Car-to-Car Communication Consortium has developed a first proposal for a Public Key Infrastructure (PKI) [22], which provides digital certificates and signatures to authenticate the trustworthiness of C2X messages. This PKI deploys the standard IEEE 1609.2 [23] and is currently included into further standardization activities within ETSI WG 5.

However, securing inter-vehicular communication by means of cryptography represents a necessary, though not fully sufficient countermeasure against forging of messages. Any adversary, who has gained access to secret key material stored within the C2X module, will still be able to send authenticated messages. Such an attacker cannot be detected by means of cryptography only and, consequently, requires complementary security techniques based on behavior analysis. In the following, we present the underlying attacker model.

1) Attacker Model: In this work we assume a severe adversary, who has gained access to a vehicles internal network (GPS, CAN, etc.), and is therefore able to manipulate the information sent to the C2X module. Depending on the adversary's intentions, several attack scenarios are imaginable:

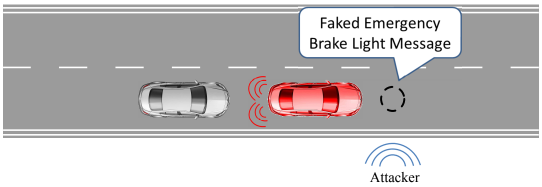


Fig. 6. Attack on Electronic Emergency Brake Light warning (EEBL) application.

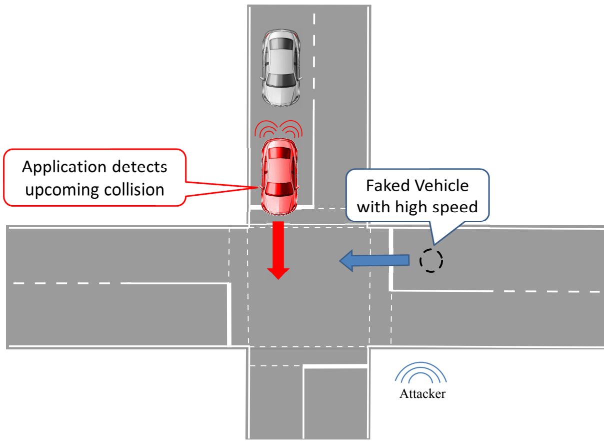


Fig. 7. Attack on Intersection Collision warning (ICW) application.

For instance, in Figure 6 an attack on the Electronic Emergency Brake Light (EEBL) use case is illustrated. We assume a roadside attacker, which is equipped with a common C2X module, including valid security credentials. By simulating a full brake to the C2X module, the respective warning message is created. If the adversary has also capabilities for manipulating the internal GPS interface, any reference position can be introduced. Since the final message will be signed using valid keys, those faked messages cannot be detected on the receiver side by means of cryptography. Hence, the driver will be alerted of a sudden full brake in front of him. As we expect drivers to instantly react upon warnings, such a situation may lead to unexpectedly performed collision mitigation maneuvers.

A similar scenario is depicted in Figure 7. The Intersection Collision Warning (ICW) represents a use case, where vehicles are monitoring cross traffic when entering an intersection in order to detect possible upcoming accidents. In the illustrated scenario a static roadside attacker sends a faked CAM, indicating a vehicle approaching the intersection with a very high speed. The application running on vehicle A's C2X module detects a potential hazard and notifies the driver accordingly. In principle, the previously described scenarios may also be caused by inaccurate readings from the GPS receiver or malfunctioning of the C2X sender hardware. We argue that for message evaluation on the receiver side no distinction between these two cases is made.

In this work a two-stage verification process for Car-to-X mobility data is proposed. The first stage consists of a Kalman filter as a means of applying the continuum of motion as the verification criterion. This Kalman filter based verification approach is currently being deployed within field operational trials like sim$^{\text{TD}}$ [24]. While being an effective and reliable estimator in most traffic scenarios, we identified considerable flaws in case of highly dynamic traffic scenarios like, e.g., sudden overtaking or hard braking maneuvers. In consequence, trustworthy messages may be evaluated as non-plausible, which will result in a decreased safety level of the overall C2X system. Since lowering the security threshold for message acceptance is not an option for the envisaged applications, we have investigated complementary techniques for increasing the reliability by means of maneuver recognition algorithms. Hence, we propose to include a second stage of C2X mobility verification and to calibrate our Kalman filter based model accordingly.

B. Mobility Data Verification

The proposed framework consists of a two-stage verification process (as pointed out in [25]). Accordingly, the first part of the evaluation is related to the comparison between received and predicted mobility data by means of a given mobility model as introduced in [24]. However, due to unavoidable inconsistencies of the deployed system model, the underlying Kalman prediction contains uncertainties. In order to achieve a higher reliability for the overall system, additional measures based on maneuver recognition via Hidden Markov Models as introduced in Section II-B are proposed.

1) Kalman filter for mobility data prediction: The Kalman filter (KF) method represents a well-known and effective approach to multi-target tracking. The KF is based on time-discrete models and may consider dynamic noise for its calculations. Because of these properties, this method is particularly well-suited to predict future states of adjacent vehicles based on C2X messages. Within in KF we denote the system state in terms of the vehicles' mobility data represented in Cartesian coordinates, i.e., the vehicles' position (p_x, p_y) and velocity (v_x, v_y). The accuracy of the system model is limited by the entropy of the data of received C2X messages. Since, in the present version of the CAM specification, only position, speed, and heading are transmitted, we build our system model under the assumption of constant velocity. Consequently, the previous system state will be transferred to the next state according to the motion assumptions by applying the state transition matrix.

For calculating the prediction error covariance matrix within the KF, we have to elaborate the error related to the system model. This tuning process is generally referred as system identification and is performed offline with the help of several reference traces. We observed slightly deviant behaviors for different road scenarios, i.e., motorways, rural or city roads. Although currently not yet implemented in our framework, we recommend a dynamic switching of the applied system noise matrix for an enhanced evaluation. In contrast, the measurement variances need not to be evaluated, because every mobility data transmitted via CAMs also includes additional values with respect to the specific accuracy.

2) Two-Stage Mobility Data Verification Flow: In Figure 8, the MARV-X system is illustrated based on a two-stage verification process. Similar to the fundamental scheme presented in [24], the mobility data is evaluated with respect to

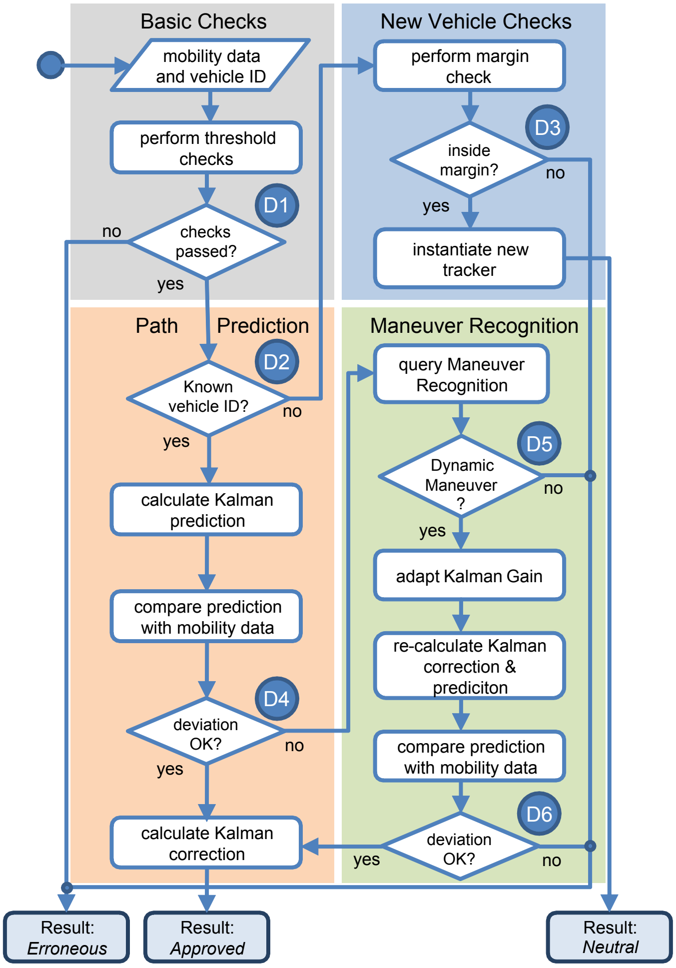


Fig. 8. MARV-X: Verification flow of mobility data in C2X communication using single step path prediction and probabilistic maneuver recognition.

physical and regulatory boundaries. These threshold checks are necessary in order to prevent inconsistent data to corrupt the ongoing evaluation. The list of the different checks applied can be found in [24] and includes, e.g., checks for maximum velocity, message freshness, and maximum message frequency. Since these checks are rather lightweighted and designed with appropriate tolerances, we require each of them to be passed successfully in order to continue the process (D1).

The first verification stage consists of a single state prediction and evaluation by means of the KF approach as presented in Section III-B1. Accordingly, for every adjacent vehicle within the communication range, the host car instantiates and maintains a tracker including a Kalman filter. The evaluation flow then proceeds as follows:

For new vehicles appearing within the communication range (D2), no sophisticated mobility verification can be applied. However, while driving along the road, new vehicles usually enter on the border of the host vehicle's communication range r_{max}. Considering a tolerance margin d_{margin}, we require a new vehicle to appear within the margin $r_{max} - d_{margin}$ and r_{max}. Note that these tolerance margins have to be adapted for different scenarios (e.g., in city scenarios, where starting vehicles may suddenly appear nearby the host vehicle). For higher reliability of the evaluation it is strongly recommended to apply complementary checks based on a vehicle's local sensors as proposed in [24].

For an already known vehicle ID (D2), the assigned vehicle tracker is selected and based on the given timestamp the Kalman prediction phase is triggered. The difference Δy_k between predicted state $\hat{x}_k$ and received mobility data $\tilde{y}_k$ is determined. Considering a maximum tolerable difference, the trustworthiness of the message is assessed.

The predefined *acceptance threshold* (AT) value has been selected based on expected GPS errors, which are typically in the range of $1-3$ meters for the deployed platform. In [24] evaluations have been carried out, which yielded acceptable performance margins for most traffic situations. However, due to inherent system inaccuracies, we observed much larger deviations in high dynamic scenarios. In order to avoid an incorrect assessment of messages in such situations, we apply further methods based on maneuver recognition in case that the deviation between predicted and received mobility data is too large (D4). The maneuver recognition component as described in Section II-A permanently assesses traffic situations of vehicles in the communication range and directly provides an estimate to the framework. The current implementation, as described in Section II-B, is capable of predicting two dynamic maneuvers, i.e., a suddenly overtaking or hard braking vehicle. In case the evaluated message has originated from a vehicle, which is currently performing such a maneuver, we know from experiments that the applied Kalman model reacts too slow on sudden changes of the vehicles trajectory and consequently has to be recalibrated. As already identified in Section III-B1, the Kalman gain represents the determining factor for weighting the predicted state against the measured data. Accordingly, in such highly dynamic maneuvers (D5), our evaluation framework adjusts the gain in a way that the internal system state is corrected towards the measurement. For doing so, the previous prediction and correction phase are reversed and recalculated. Considering an adapted Kalman model, the recalculation leads to an enhanced corrected state. Based on this state the next prediction is closer to the received mobility data. The deviation is calculated again and if it remains below the threshold now (D5), the message is marked as approved and the respective correction is performed. However, if the deviation still exceeds the predefined threshold, the message is finally evaluated as erroneous.

IV. Evaluation

The mobility data verification framework, as outlined in previous sections, has been fully implemented as Java/OSGI bundle and integrated as a central system component on the facility layer within the vehicle C2X architecture (see Figure 9), used for the sim^{TD} field operational trials [18]. As outlined in [18], sim^{TD} vehicles are equipped with two separate units. The CCU (Control Communication Unit) is based on a 400 MHz PowerPC with Linux running on top and communicates via Ethernet with the AU, which consists of a Dual Core 2.7 GHz processor with Windows Embedded as the operating system. Accordingly, incoming C2X messages

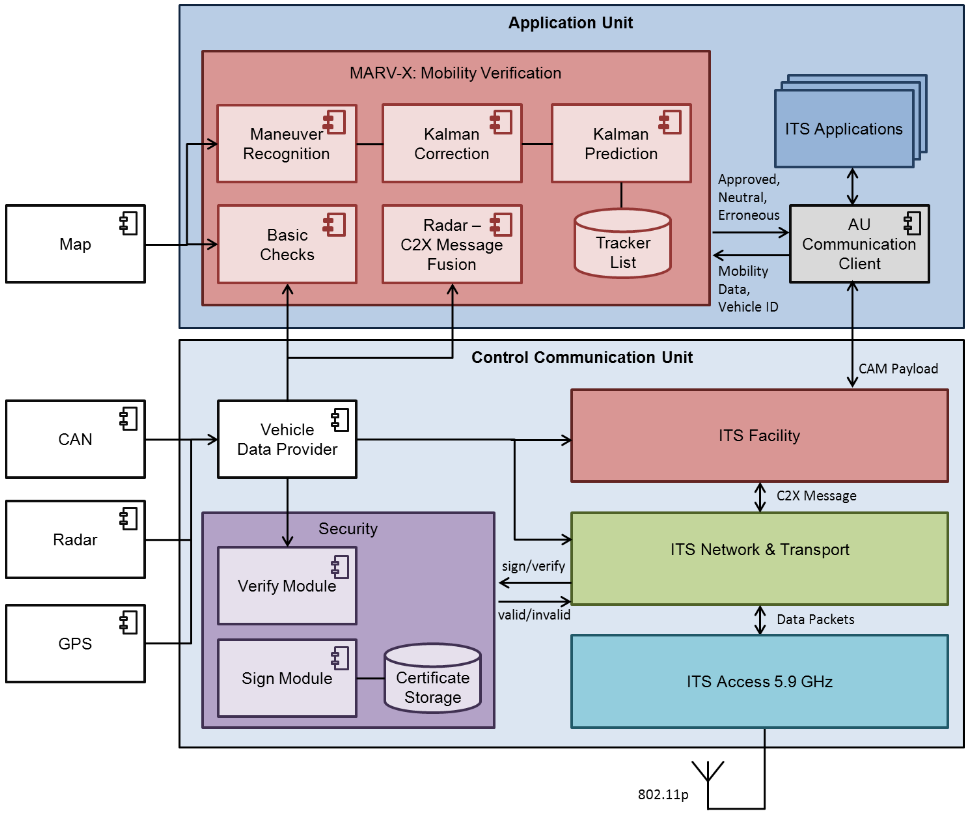


Fig. 9. Integration of mobility data verification framework into the C2X vehicle architecture

are parsed by lower communication layers and are handed over to the network layer for cryptographic verification. Within the sim^{TD} architecture, security is implemented as a service, meaning that the network layer explicitly has to call a function and to delegate the attached signature and certificate to the *Security Daemon* for verification. The returned result is binary, i.e., either the message is authenticated or not. In sim^{TD} invalid messages are not directly discarded, but are marked for further evaluation on higher layers.
The second security evaluation consists of the advocated mobility verification framework, located on the facility layer. Each verification stage (i.e., basic checks, Kalman filter, maneuver recognition, etc.) is realized as a separate Java package, which facilitates testing and allows a flexible switching between different configurations.

The sim^{TD} development environment offers various built-in test routines and debugging interfaces, which have been extensively used during the following evaluation. Especially the possibility for recording complete traces of received C2X messages together with own CAN data, using a *Trace Recorder*, was considered as very helpful for performing later offline evaluations.

Since the mobility verification is instantiated on the time critical path between network and application layer, any introduced latency has to be kept as low as possible due to safety reasons. For the presented implementation and target platform, an average latency of about 2.7 ms is measured for the Kalman stage. Thereby, about 1 ms can be attributed to threshold checks, as well as to administrative tasks like, e.g., function calls and search operations. The remaining 1.7 ms originate from the execution of the Kalman prediction and correction phase. In case of a triggered maneuver recognition, an additional delay of 1 to 4 ms is being added depending on the length of the processed observation sequence.

A. Common Traffic Scenarios

Regarding a validation of the effectiveness of the overall verification framework, two figures of merit are of general interest:

- *False Positive Rate-Path Prediction (FPR-P)*: The relative number of messages, which are evaluated as *Erroneous*, though they are correct. In other words, what percentage of trustworthy messages are discarded by the framework?
- *False Negative Rate-Path Prediction (FNR-P)*: The relative number of messages, which are evaluated as *Approved*, though they are *Erroneous*. This means, what percentage of faked messages pass the framework without being noticed?

In practice, the FNR-P can hardly be derived from experiments, since it heavily depends upon the underlying attacker model. For instance, a basic attacker, who is sending waypoints including discontinuities, will be filtered out by this approach. In contrast, a very sophisticated attacker, who applies a mobility model perfectly matching the C2X scenario, is not detectable at all. Obviously, the point from where on *False Negatives* will occur can be derived deterministically from the predefined acceptance threshold AT implemented by the

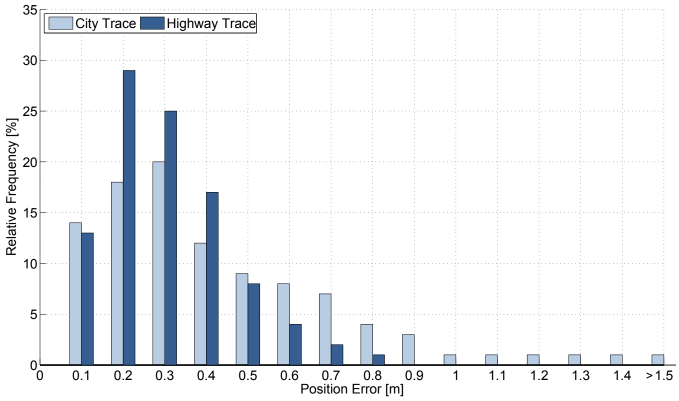


Fig. 10. Comparison of average deviation in city and highway scenarios [24]

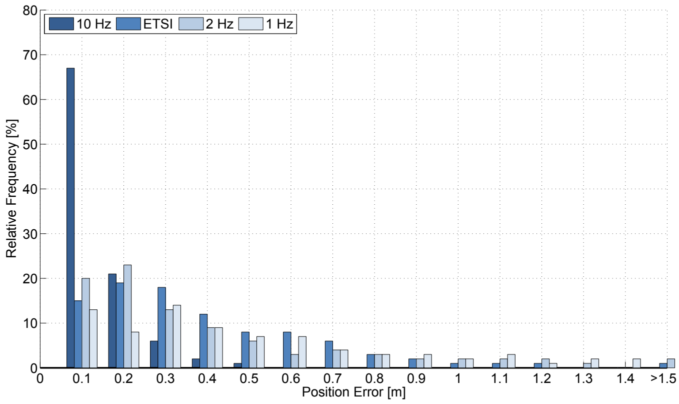


Fig. 11. Exemplary city-highway route for path prediction algorithm evaluation [24]

mobility verification framework. Hence, in the scope of this work, the focus is set on an evaluation of the FPR-P, i.e., the number of erroneously discarded messages. Especially in highly dynamic traffic maneuvers correct messages shall not be discarded by the verification framework due to safety.

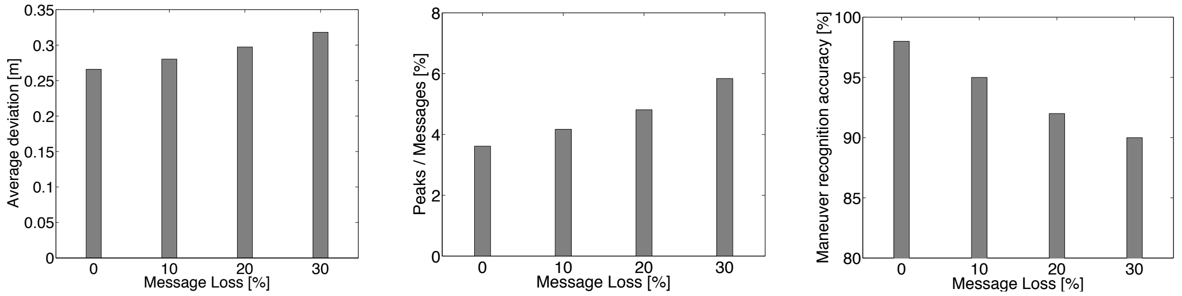
First experiments have been conducted in [24] and are related to a general evaluation of the path prediction verification stage in common traffic scenarios, i.e., scenarios without highly dynamic changes in the vehicles trajectory. Sim^{TD} equipped vehicles have been used to evaluate the prediction accuracy of the KF, which is considered as the determining factor for a correct assessment of received messages. Several test drives have been carried out for different road types and velocities varying from 30-50 km/h in city scenarios up to 100-140 km/h on highway scenarios. With respect to the different road types and scenarios, a deviating performance can be observed (see Figure 10). While for highway scenarios the prediction component proves an acceptable accuracy, city scenarios are more prone to errors. Besides the environmental differences in urban and highway scenario, also the message sending frequency has an impact on the prediction accuracy, as depicted in Figure 11. Obviously, the Kalman vehicle tracker performs best with shorter message intervals. Note that the verification framework shows a good performance, when being applied at the variable CAM frequency as specified by ETSI standards [19].

It can be concluded that the path prediction component features an acceptable performance in more than 95% of all cases. However, the remaining cases, for which the deviation considerablty exceeds the 1.5 meter margin, must not be neglected, because in these cases valid and potentially safety-relevant C2X messages may be discarded by the framework. A detailed analysis of the recorded traces yielded, that the higher deviations in urban environments basically originate from the decreased GPS quality available in street canyons. However, in highway scenarios, the deviations are mainly due to dynamic driving. Consequently, there is enough room for improving the FPR-P by means of the advocated maneuver recognition component.

B. Dynamic Traffic Scenarios

One way of reducing the FNR-P in highly dynamic scenarios represents the maneuver recognition component based on HMMs as described in Section II. In order to evaluate the effectiveness of this approach, overtaking and hard braking maneuvers have been reconstructed using 3 sim^{TD} equipped vehicles, considering a message sending interval as specified by ETSI [19]. Thereby, two vehicles are used to create the respective traffic situation on one lane, while the third vehicle is intended to model available free space on the second lane (see Figures 5a and 5b). In total, a sequence of more than 100 overtaking and 100 braking maneuvers have been recorded on real roads.
The first assessment is dedicated to a general performance evaluation of both components (i.e., path prediction and maneuver recognition), when being applied in such highly dynamic scenarios. Since the C2X message channel is considered to be lossy, the sensitivity of any C2X application towards message loss is of particular importance. In order to determine the accuracy with respect to message loss, the given traces are averaged. Additionally, for each trace and percentage of the message loss rate, about 1000 different variants were created. This high diversity of different traces becomes necessary in order to yield the true averaged behavior, since the accuracy of the path prediction component depends on the specific messages getting lost.
In Figure 12a the results for the average deviation between predicted and received mobility data are given depending on the message loss. The results of applying the component in dynamic maneuvers generally confirm the tendency already observed in common driving situations (see previous section IV-A), i.e., the accuracy of the path prediction declines with a reduced temporal and spatial resolution of the received messages. In the context of this work, those messages are of particular interest, for which the resulting deviation exceeds the predefined AT value. For these traces, such peaks will result into false positive hits, and as a consequence, will introduce safety flaws into the system. It can be observed that the relative occurrence of peaks, as depicted in Figure 12b, is increasing almost linearly with the number of lost messages.

For reasons of comparability the proposed maneuver recognition has been evaluated under the same system assumptions using exactly the same traces. The figures of merit of the maneuver recognition are defined as follows:



(a) Average Kalman deviation for different message loss rates

(b) Peaks per trace for different message loss rates

(c) Maneuver recognition for different message loss rates

Fig. 12. Performance evaluation of the message verification framework for different message losses.

- *False Positive Rate - Maneuver Recognition (FPR-M)*: The relative number of messages, which are associated to a dynamic maneuver, though the vehicle is actually in a steady mobility state.
- *False Negative Rate - Maneuver Recognition (FNR-M)*: The relative number of peaks, which occur during a dynamic maneuver, though no braking or lane change maneuver is detected.

Compared to the path prediction stage, the maneuver recognition is less sensitive towards possible message losses and features a high accuracy above 90% even when loosing up to 30% of all messages (see Figure 12c). This corresponds to a low *False Negative Rate (FNR-M)* and makes the maneuver recognition component particularly useful for compensating the shortcomings of the path prediction stage.

In the following sections the working principle for both dynamic maneuver types of the mobility verification framework is illustrated for the complete set of acquired data as well as for one sequence exemplarily.

1) Lane Change Maneuver Evaluation: The evaluation of the acquired set of lane change maneuvers is shown in Figure 13. In Figure 13a the results of the maneuver recognition are depicted for the complete set of lane change sequences. Due to different time durations, a normalization in time is required, which is done by linear time warping. For a greater significance of the results, all sequences are normalized in time with respect to the fixed point in time of the execution of the lane change (message 79 in Figure 13a).

The evaluation results for the first error type are represented in terms of a *ROC (Receiver Operating Characteristic)* curve depicted in Figure 13b. Thereby, the ratio c_1 as denoted in Equation (3) represents the determining parameter for weighting the FPR-M against the *True Positive Rate (TPR-M)*.

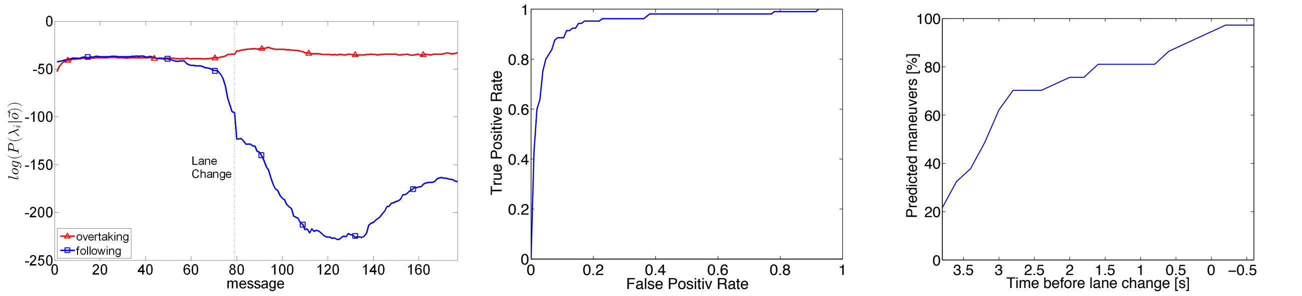
In Figure 13c the evaluation of the maneuver recognition is done for the TPR-M, where correct predicted maneuvers are plotted for different points in time. Thereby, the reference time is the execution of the maneuver, i.e., the time where the vehicle performs the lane change maneuver.

The graph at the top of Figure 14 shows the isolated behavior of the KF, when being applied at a sudden lane change maneuver. The x-axis (primary axis) denotes the CAM messages of the observed vehicle, as they are sequentially received by the host vehicle. On the y-axis (secondary axis) the deviation between predicted and received mobility data is plotted. The obtained results confirm the previously made hypothesis that the deviation Δy_k reaches its maximum during the last stage of the lane change maneuver (messages 37 - 52). For the given example, peaks with amplitudes up to 3 meters have been measured. In order to cover even higher peaks that may principally occur, the AT value initially had to be defined with a large tolerance between $3-5$ meters.

Based on the same data the maneuver recognition component evaluates the traffic situation in parallel. It can be concluded from the middle part of Figure 14 that the course of the evaluated probabilities reflects very well the actual state of the vehicle during the lane change maneuver. In fact, already when the first peak above 1 meter occurs (at message 37), the likelihood for a following maneuver drops significantly. At the same time the likelihood for overtaking stays at a constant level, which gives a clear indication of a pending lane change. At the bottom of Figure 14 the characteristics of the overall verification framework, as described in Section III-B, are visualized. For reasons of comparability, the evaluation has been carried out offline using the recorded real world traces. Taking into account the dynamic traffic situation of the observed vehicle, the occurred peaks become plausible to the observer vehicle. Therefore, the Kalman gain is adapted (at message 37) such that all subsequent peaks are decreased. In consequence, due to the enhanced reliability of the verification framework, the applied AT value can be refined to 1 meter. Note again that in general a reduction of this threshold comes along with an enhancement of the security level of the overall C2X system.

2) Braking Maneuver Evaluation: In Figure 15 the same evaluation as for the lane change maneuvers in the last section was performed. Thus, in Figure 15a the results for the maneuver recognition are depicted, normalized over all sequences with respect to the point in time of the sudden braking. The relation of FPR-M and TPR-M can be seen in Figure 15b in terms of the corresponding ROC curve. On the left hand side of Figure 15, the evaluation of the TPR-M can be seen for different points in time before and after the execution of the sudden braking maneuver.

The results of the hard braking sequence are depicted in Figure 16. The setup for this experiment is similar to the one before, apart from the fact that this time the overtaking



(a) Normalized results of maneuver recognition over all lane change sequences.
(b) ROC Curve for Lane Change Prediction
(c) Prediction accuracy for different points in times in reference to the maneuver execution.

Fig. 13. Evaluation of the Maneuver Recognition component for lane change maneuvers.

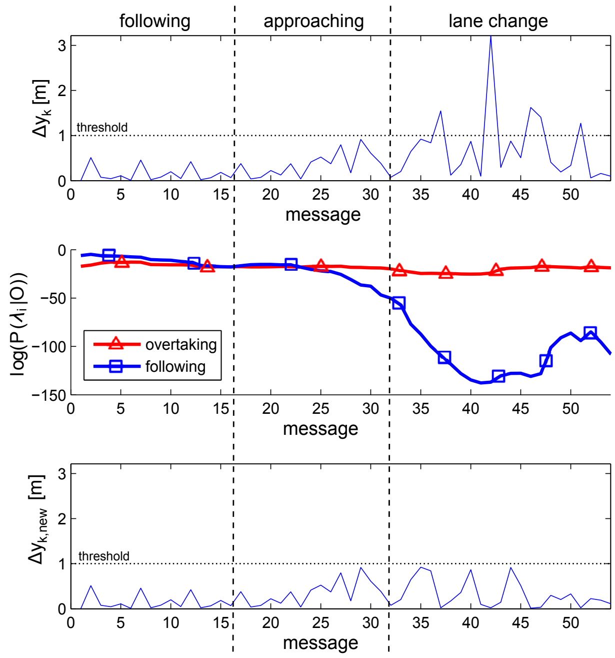


Fig. 14. Lane change maneuver - Top: conventional Kalman deviation Δy_k - Middle: log-likelihood of maneuver recognition - Bottom: maneuver-aware Kalman deviation $\Delta y_{k,new}$ with adapted Kalman gain for $c_1 = 1$ meter (see (3))

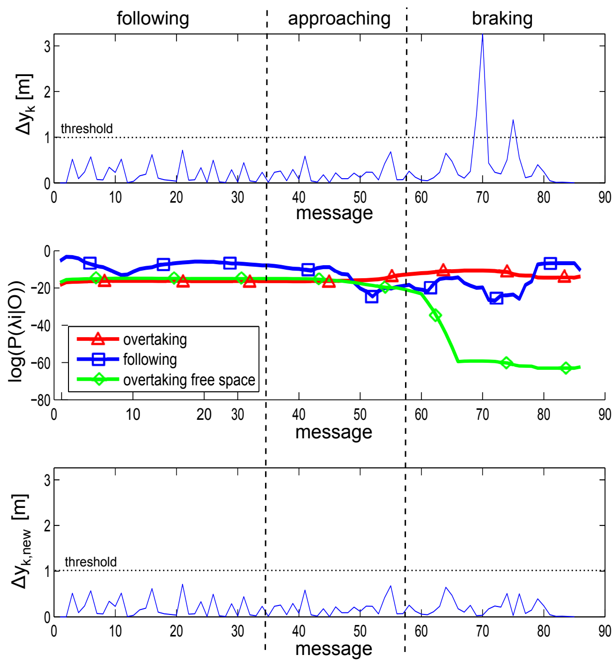


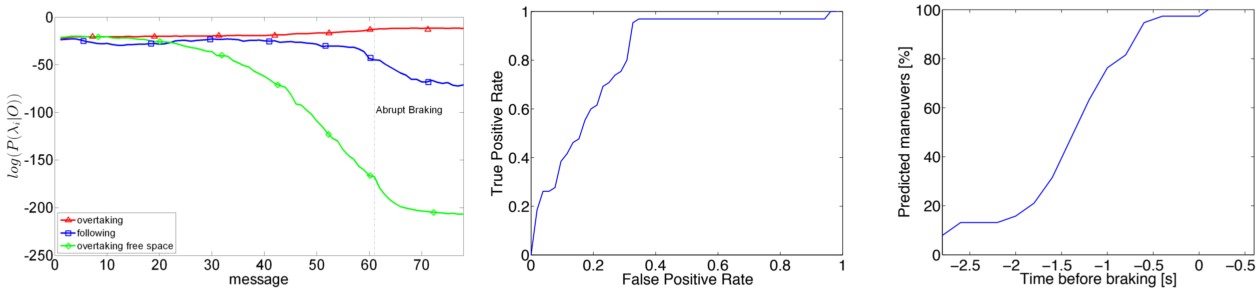
Fig. 16. Braking maneuver - Top: conventional Kalman deviation Δy_k - Middle: log-likelihood of maneuver recognition - Bottom: maneuver-aware Kalman deviation $\Delta y_{k,new}$ with adapted Kalman gain for $c_2 = 1$ meter (see (4))

maneuver cannot be conducted successfully, due to the third vehicle occupying free space on the left lane. In order to avoid a front-rear collision with the vehicle driving ahead, the observed vehicle performs a sudden full braking maneuver, leading to a peak in the graph of the deviation Δy_k (message 70, top of Figure 16).

The framework instantly queries the maneuver recognition component, which returns back the likelihoods for each traffic maneuver at the given instant of time. As illustrated in the middle of Figure 16, the driver's intention for overtaking (overtaking, no free space consideration) clearly diverges from the feasibility of actually conducting that maneuver (overtaking, free space consideration) due to insufficient free space. The dynamics of the traffic situation is correctly assessed by the proposed maneuver recognition and, thus, the path prediction model can be calibrated accurately. Adapting the Kalman gain, as outlined in Section III-B2, leads to a deviation $\Delta y_{k,new}$, which does not exceed the predefined AT value. In consequence, no messages are wrongly marked as erroneous anymore.

V. Conclusion and Future Work

For an assessment of complex traffic situations, one of the remaining challenges represents the recognition of interacting maneuvers between two or more traffic participants, like, e.g., overtaking, following and braking maneuvers. By exploiting this information a better prediction of future vehicle states is possible. In this work we presented a probabilistic framework based on Hidden Markov Models for modeling the spatial and temporal dependencies among vehicles. While current maneuver recognition approaches are using relative information between two traffic participants only, we presented



(a) Normalized results of maneuver recognition over all sudden braking sequences.

(b) ROC Curve for Braking Prediction

(c) Prediction accuracy for different points in times with reference to maneuver execution.

Fig. 15. Evaluation of the Maneuver Recognition component for sudden braking maneuvers.

a method using enhanced environment information. For this purpose adaptive, maneuver dependent occupancy grids were introduced modeling the availability of free space for executing a single maneuver. This way, the influence of static road characteristics such as road boundaries, blocked lanes, or construction sites as well as other traffic participants and their future trajectories, were included into the environment model.

It turned out that maneuver recognition is well-suited for the C2X domain, where it may compensate shortcomings of current mobility verification approaches that rely on path prediction based on Kalman filters. In this work we reviewed the actual sim^{TD} mobility verification framework and evaluated its effectiveness for dynamic overtaking and for hard braking maneuvers. Several trial runs with fully equipped sim^{TD} vehicles revealed a considerable mismatch between predicted and actual mobility data for highly dynamic scenarios. These inaccuracies, if not handled appropriately, may lead to an incorrect message evaluation. Consequently, the verification framework has to be extended by additional means. By evaluating the measured data obtained from the performed trial runs, we identified the Kalman gain as the determining factor for influencing the inertia of the applied prediction model. We introduced the proposed a probabilistic maneuver recognition based on Hidden Markov Models as the control medium for the Kalman gain. Experiments with varying message loss rates confirmed the general appropriateness of HMMs for C2X scenarios. Finally a comprehensive two-stage verification framework for mobility data was presented, which describes how the Kalman verification stage may be calibrated by means of a subsequent HMM stage. An implementation of the enhanced framework and a re-run of previous experiments yielded significantly improved accuracy values of the prediction model.

We conclude that our maneuver recognition based on HMMs provides reliable results on the basis of C2X data. Furthermore, maneuver recognition assessments can be used to calibrate mobility data verification approaches based on path prediction and to significantly increase their robustness. However, this probabilistic approach implies that there exists a certain risk of making incorrect assessments, which may lead to the discarding of valid messages for safety applications. In the scope of this work, these kinds of false positives are considered as acceptable for the sake of detecting malicious messages sent by an attacker.

For future work, the reliability of the framework has to be increased by including additional information using a vehicle's on board sensors like, e.g., radar and camera. Additionally, it is possible to extend the proposed framework by focusing on additional dynamic use cases like, e.g., intersection scenarios, where the host vehicle intends to turn into a street thus, crossing another vehicle's predicted path, or cases of abrupt accelerations.

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