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Cooperative Validation of CAM Position Information Using C-V2X

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***Abstract*—Cellular-Vehicle-to-Everything (C-V2X) communication is an essential component of future automated traffic systems as well as a promising technology for mobile robot applications. In those scenarios, the vehicles typically exchange location data obtained by on-board positioning modules such as satellite receivers or sensor-based SLAM (Simultaneous Localization and Mapping). As such information is vital for cooperative applications, its validation is an important safety feature. In this paper, we propose a method to repurpose available information from C-V2X to estimate the distance between sender and receiver. By analyzing the timing of Cooperative Awareness Messages (CAMs) within the C-V2X resource grid it is possible to derive fairly accurate distance information, which can be used to validate the location data contained within the payload. Such validation is helpful in case of technical failures of positioning modules or intentional transmission of fraudulent location data. Our analysis based on MATLAB simulation shows a positioning error of 30 m for typical traffic and robot scenarios. One key learning is that existing C-V2X signal information can be used to achieve this performance even in the presence of multipath fading. Although the positioning is not yet precise enough for stand-alone use, it is useful for overall safety and reliability measures in cooperative vehicular and robotic applications.**

I. Introduction

The exchange of positioning information is a foundational function of many cooperative intelligent systems. Applications ranging from automated traffic systems utilizing Global Navigation Satellite System (GNSS) data to robotic systems utilizing Simultaneous Location and Mapping (SLAM) require agents to be aware of agents outside of their own sensor range (Fig. 1). Failures in a positioning module can therefore disrupt not only a single agent's ability to function but also impair distributed functionality such as early collision warning systems or predictive path planning. While simple on-board checks such as outlier detection can allow single agents to diagnose problems autonomously, systematic malfunctions might remain undetected. The deployment of fully redundant positioning modules is a common approach to discover further error cases. Some systematic errors can, however, not be detected on-board, e.g. due to limitations in the utilized technology. In this case, an external reference is required to classify errors. Existing approaches cooperatively validate or improve positioning using a combination of high precision environmental models for error prediction and distributed algorithms that require communication of significant amounts of sensor data between the agents. In this paper, we propose an alternative scheme that utilizes existing timing information, which is already measured within the communication system, to validate broadcast positions with low complexity and overhead. Our approach is tailored to cellular vehicle-to-everything (C-V2X) communications, specifically to cooperative awareness messages (CAM). In a CAM-scenario, agents are synchronized to a reference clock and periodically broadcast their position. When a receiver detects such a message, we use its detected offset to the reference clock as a measure of the distance to the sender. Comparing the position contained in the payload with the estimated distance, each receiver is able to evaluate the plausibility of the received data. Building on this local estimation at each receiver, we investigate how multiple receivers can combine their information through voting or trilateration to yield a cooperative validation scheme with higher accuracy. The classification performance of our approach depends on the number of receivers and the desired position tolerance which we characterize in the discussion of our experimental results. In the remainder of this paper, we explain the underlying validation approaches in Section II and the design of our simulation in Section III. Section IV contains our validation

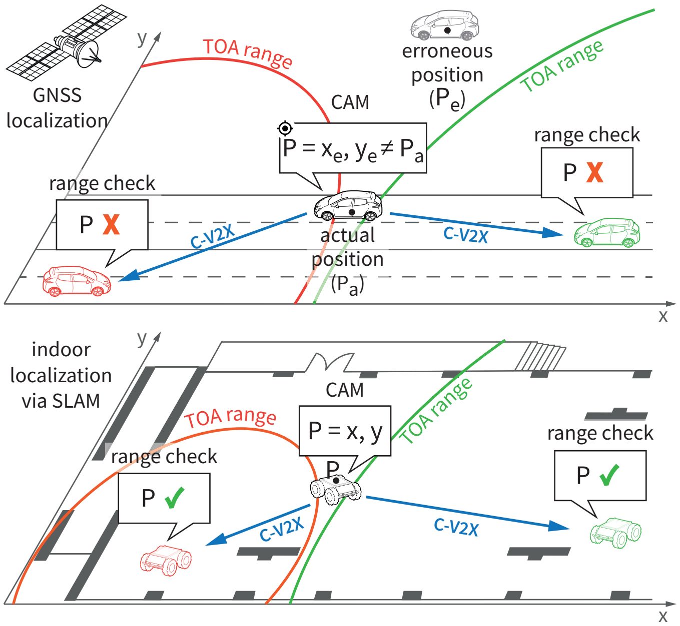

Fig. 1. Validation of CAM positions for vehicles on a highway and rescue robots inside an exhibition hall/shopping mall. On the reception of messages the time of arrival (TOA) is used to estimate the range to the transmitter.

results. We finally conclude the paper in Section V.

A. Related Work

The research in the field of the enhancement of GNSS positioning is manifold, as GNSS localization errors might have severe impacts on the system safety. An algorithm for local interference compensation of GNSS systems is introduced in [1]. While a possible accuracy gain of more than 45% is achievable, high precision 3D models of the environment are necessary for this ray-tracing approach. The enhancement of vehicles GNSS position by cooperative information exchange is presented in [2]. V2X communication is used to exchange GNSS pseudoranges to compute reliable confidence domains. Localization using LTE signaling has also been studied in the past. In [3] the achievable localization accuracy of LTE positioning reference signals is investigated. While sub-centimeter level precision is achieved within this analysis, these results are not realistic as propagation effects are not included. The maximum positioning accuracy for Vehicle-to-Infrastructure (V2I) communication over LTE is investigated in [4]. For the maximum LTE bandwidth of 100 MHz sub-meter level position accuracies are achievable. An LTE-based vehicular position tracking in the field is studied in [5]. The ESPRIT and Kalman Filter for Time-of-Arrival Tracking (EKAT) algorithm is used to obtain position accuracies around 20-30 m based on LTE downlink signals. Vehicle-to-Vehicle (V2V) based cooperative localization is presented in [6]. GNSS measurements are exchanged to mitigate multipath effects and improve the positioning accuracy to fulfill the safety requirements for autonomous driving. An 802.11p-based approach using V2V and V2I communication to improve vehicles GNSS accuracy is proposed in [7]. Instead of timing information, the received signal strength of periodic beacon messages is used to achieve a estimation accuracy of approximately 1 m. However, this precision is based on aggregation of multiple measurements over time, not for a single measurement.

Of course it is also always possible to add a secondary localization system to improve the position accuracy i.e. add Ultra-Wideband (UWB) systems with centimeter precision [8] for robotic indoor scenarios or as in [9], where UWB ranges are exchanged over V2V communication to achieve a localization accuracy at sub-meter level.

In this work we aim for a low complexity approach to validate position information without the need for additional hardware such as UWB and by utilizing timing information already present within C-V2X modems, rather than requiring additional computational effort for channel estimation schemes such as ESPRIT.

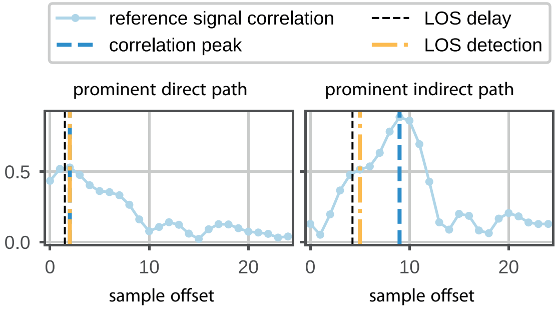

Fig. 2. Examples of the cross correlation of expected and received reference signals. Due to multipath fading the prominent path does not always correspond to the LOS, which is vital for position estimation.

II. RANGE ESTIMATION AND VALIDATION USING C-V2X

The C-V2X specification is a part of the fourth and fifth generation of mobile communication systems (4G and 5G) standardized by 3GPP. It has been specifically designed to allow ad-hoc broadcasting of periodic status messages. This communication pattern enables cooperative awareness which is especially useful in intelligent transportation systems (ITS) for road safety and autonomous driving as well as in cooperative robotic applications such as exploration or search and rescue missions. The automotive sector has standardized cooperative awareness messages (CAM) to enable next generation vehicles, to exchange GNSS positions and further status information such as speed or heading. On lower layers, periodic ad-hoc communication in C-V2X is enabled by a number of design attributes that set it apart from infrastructure-based mobile communication. The physical sidelink is a direct communication link between C-V2X agents, that is independent from cellular network coverage, using a distributed channel access scheme. Furthermore, the number of reference signals utilized for signal detection and channel estimation is increased, addressing high relative speeds of agents and decentralized time synchronization. Timing of transmissions is organized in a fixed grid of subframes of 1 ms. Assuming sufficient synchronization among the UEs, the time elapsed between the local start of a subframe and the start of a received signal, the sample offset, can be used as an estimate for the signal propagation time and thus the distance to the sender. The accuracy of this estimate depends on the synchronization error and the signal detection method. At the receiver, pre-computed, expected demodulation reference signals (DMRS) are usually cross-correlated with received signals to detect the start of a specific transmission. The maximum of this correlation indicates the instance of the reference signal that arrived with the highest power, increasing the chance of successful decoding. It is important to note that in a multipath environment, the strongest path might not always be the direct line-of-sight (LOS), making a correlation peak less than ideal for range estimation, see Fig. 2. Furthermore, the precision of the range estimate depends on the sampling time of the receiver. In C-V2X, it is derived from the utilized channel bandwidth. For a sidelink channel bandwidth of 10 MHz the sampling time is approximately 65 ns (15.36 MHz rate) which translates to a range estimation granularity of 19.53 m. With these considerations on precision and accuracy of timing offset based range estimation in mind, the remainder of this section, details our proposed approach to evaluate and combine measurements.

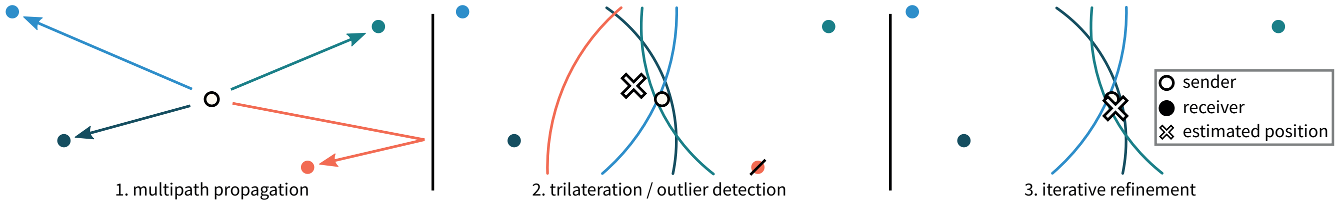

Fig. 3. Iterative trilateration scheme that increases robustness against outliers caused by multipath propagation. The scheme is most effective against small outlier ratios, thus we first attempt to recover LOS information as illustrated in Fig. 2.

A. *Secondary correlation metrics for path detection*

We expect prominent paths in the propagation channel to result in path length and power dependent peaks in the reference signal correlation data. As a low complexity method of detecting prominent paths, we extract local maxima and saddle points from the correlation function by additionally analyzing its central finite difference. Since multipath fading in combination with Doppler shift, can cause minor additional peaks in the correlation function, we apply a threshold of half of the global peak used for frame decoding to identify strong paths and use the first sample matching these criteria as an estimate of the LOS delay. A comparison of the basic peak correlation and the extended LOS detection is shown by Fig. 2.

Applying the method described above yields a number of sample offsets that are estimated to represent a path the physical signal could have taken through the environment. We utilize this information to validate received position data using two different methods.

B. *Matching range and prominent path occurrence*

We can expect that distances to accurate positions coincide with detected prominent path lengths more often than distances to erroneous positions do. Based on this statistical correlation, each receiver can classify a received message autonomously: After decoding a message, the receiver uses the received position data to determine its hypothetical distance to the sender. The validity of the position data is classified by evaluating whether the corresponding sample offset coincides with a prominent path candidate. To enhance the confidence of the estimation, the votes of multiple receivers can be combined in a majority decision.

While this approach is simple and requires no computational effort other than the LOS detection, it does not exploit information contained in the geometrical relation of multiple measurements. In order to incorporate this information, which is readily available through the CAM message exchange, we propose an additional approach that starts by estimating the position of the sender through timing information.

C. *Trilateration via LOS path*

When a message has been successfully decoded, the correlation function is analyzed to find a LOS delay as described above. The estimated LOS timings of multiple receivers are aggregated to trilaterate the sender's position. The difference between this position and the CAM position is the trilateration error, that will be used as performance indicator within this work. This estimation requires knowledge of other receiver's positions and estimated ranges. Since positions are already exchanged through CAM, a straightforward approach could be to insert a list of past measured ranges into a CAM broadcast. The trilateration approach analyzed in this paper starts with an initial linear approximation [10], followed by a Gauss-Newton optimization. Robustness against timing errors caused by multipath propagation and sampling granularity is increased by an iterative outlier removal scheme as presented in [11]. Range measurements disagreeing with the current estimate are iteratively removed until all residuals lie within a one sample range, as illustrated in Fig. 3. The performance of both approaches depends on the number of receivers whose estimates are combined. Hence we evaluate three vehicular highway scenarios with different traffic densities: free, stable and congested (7, 20, 40 vehicles/km/lane) based on [12].

III. SIMULATION DESIGN

The performance of our proposed validation schemes is evaluated through numerical simulations based on standardized C-V2X channel models and performance data. A GNSS based time synchronization of all agents, as defined in the C-V2X standard, is assumed. For the simulation of the C-V2X physical layer, the MATLAB LTE Toolbox is used. The receiver sensitivity is set to match the Block Error Rate (BLER) to receive power relationship of the field experiments published in [13]. To obtain a computationally efficient way of running large scale simulations, we first abstract block and timing error models based on 1,000,000 simulated physical layer transmissions. The receive power, BLER distribution and the fitted BLER model based on a logistic function is shown in Fig. 4.

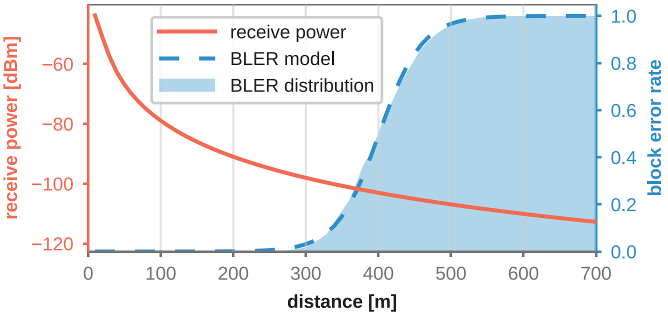

Fig. 4. BLER distribution based on receive power measurements from [13] and the resulting model abstraction used in the simulation.

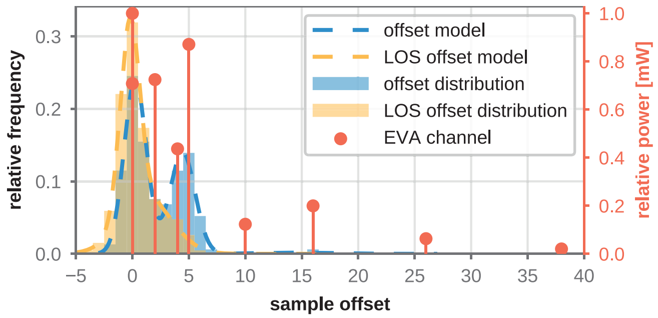

Fig. 5. EVA channel and offset distribution for correlation peak and LOS detection with fitted Gaussian Mixture Models.

The propagation channel is modeled with the Extended Vehicular A model (EVA) as proposed by 3GPP for fading [14] and an ITU P.1411-6 vehicular communication model for path loss [15]. Histograms showing the timing detection accuracy of peak and LOS detection schemes are shown in Fig. 5. Note that the peak detection scheme detects strong indirect paths in a large number of cases. The resulting timing offsets coincide with strong delay taps in the EVA channel model. Our proposed LOS detection scheme is able to reduce these false detections, although not completely eliminate it. To ease the computational load of subsequent simulations, the timing detection errors are fitted through Gaussian Mixture Models that are overlaid in Fig. 5. A summary of the relevant simulation parameters used in this paper is depicted by TABLE I.

IV. Validation Results

With models for successful decoding and timing detection in place, we can efficiently evaluate the range matching and trilateration approaches for position validation. Each validation scenario places a number of vehicles randomly on a stretch of road as specified in TABLE I. One vehicle then sends a position that is affected by a random error of up to 500 meters, which is the maximum transmission range (Fig. 4). Since the validation task is a classification problem, sensitivity and specificity are used as the primary statistical performance measures. Sensitivity, also known as the true positive rate describes the proportion of erroneous positions that are correctly identified. The specificity (true negative rate) defines the proportion of valid positions, that are classified as such. These metrics are related to the position tolerance i.e. the difference between a CAM position and an estimated position above which the CAM position is classified as invalid.

TABLE I
Simulation Parameters

General parameters	
lane-width	3.7 m
number of lanes	10
lane-length	1500 m
traffic densities	7, 20, 40 vehicles/km/lane
C-V2X parameters	
sidelink frequency	5.9 GHz
sidelink channel bandwidth	10 MHz
resource blocks per subchannel	10
modulation and coding scheme	5
sampling rate	15.36 MHz
transmit power	23 dBm
fading channel model	EVA [14]
pathloss channel model	ITU P.1411-6 [15]

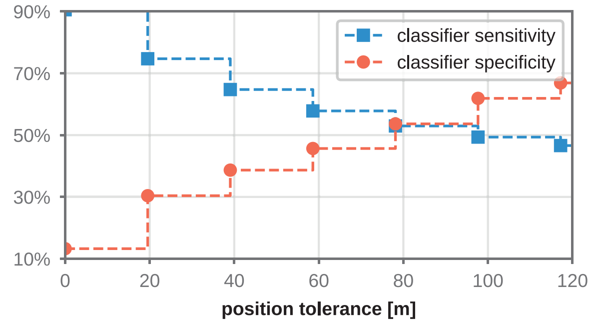

Fig. 6. Validation performance for a single receiver using the range matching approach. The discrete steps are due to the C-V2X sampling rate.

A. Range matching based classification

For the range matching based approach each receiver evaluates the cross correlation of the received and the expected reference signal at the sample that corresponds to the hypothetical distance to the sender. Therefore it is possible for each receiver to individually decide whether the senders position is accurate. In Fig. 6 the sensitivity and the specificity of an individual offset evaluation is presented. For this method a sweet spot at 80 m position tolerance exists, as this is the only tolerance where both, the sensitivity and the specificity are above 50 %. The combination of multiple classification results for different traffic densities is shown in Fig. 7. Using majority voting, we can boost the ensemble confidence to around 60 % in low traffic densities and 80 % in high traffic densities. But again, this can only be achieved at the sweet spot.

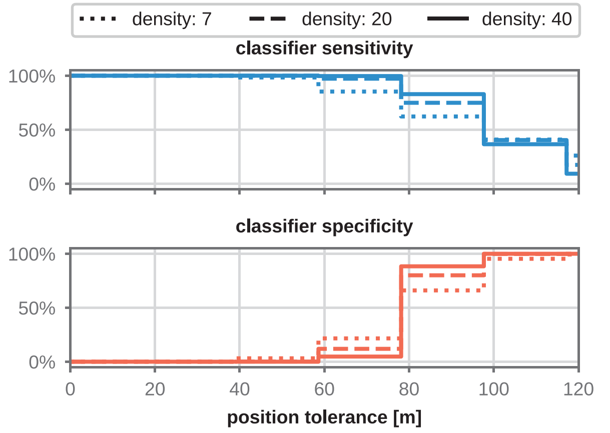

Fig. 7. Sensitivity and specificity of the offset evaluation combined from multiple receivers for different traffic densities (in [vehicles/km/lane]). The discrete steps are caused by the C-V2X sampling rate.

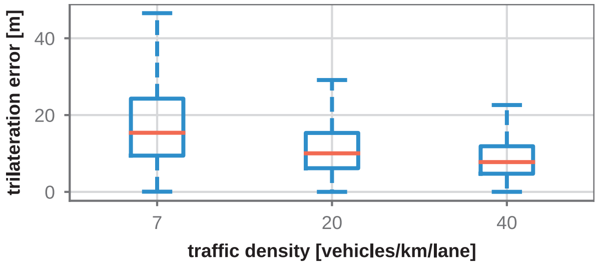

Fig. 8. Trilateration error for different traffic densities.

B. *Trilateration based classification*

Fig. 8 depicts the trilateration error for different traffic densities. As expected a higher traffic density decreases the maximum trilateration error from 50 m to 22 m. For a stable traffic density (20 vehicles/km/lane) a maximum trilateration error of 30 m and a median error of 10 m can be achieved. The sensitivity and specificity of the triangulation based validation approach is shown by Fig. 9. Invalid positions can be classified with approximately 99% confidence across all evaluated tolerances. The sensitivity slightly decreases when tolerance increases. This can be explained by an increase of the valid area and together with its circumference, making it likelier for simulated positions to lie close to this decision boundary. These positions are harder to classify and slightly more of them are falsely classified as valid. The specificity of the classification highly correlates to the distribution of the trilateration error. The saturation of the specificity is reached if the position tolerance matches the maximum of the trilateration error (shown in Fig. 8). Starting from this point, all correct positions can be classified as such and the classification is almost perfect. For a traffic density of 7 vehicles/km/lane a a position tolerance of 50 m is necessary to reach a sensitivity of 99 % and a specificity of $\approx$100 %. For a density of 40 vehicles/km/lane even better results are achieved for half the position tolerance.

V. CONCLUSION

In this paper, we presented how existing measurements from the C-V2X physical layer can be used with little computation and communication effort to validate positioning data. Using a trilateration algorithm, and an position tolerance of 22-50 m, we classify errors with a confidence of 99% even in low traffic densities while at the same time being robust against false positives. When decentrally validating ranges for a minimum complexity approach, there is a sweet spot in which each receiver acts as a weak classifier for both positive and negative cases. Using majority voting, we can boost the ensemble confidence to around 60 % in low traffic densities and 80 % in high traffic densities. In future work we will evaluate whether neural networks can effectively validate ranges based on the receiver correlation values without overfitting to specific channel models. Furthermore, we consider gathering real world data with C-V2X capable hardware to validate the concept introduced in this work.

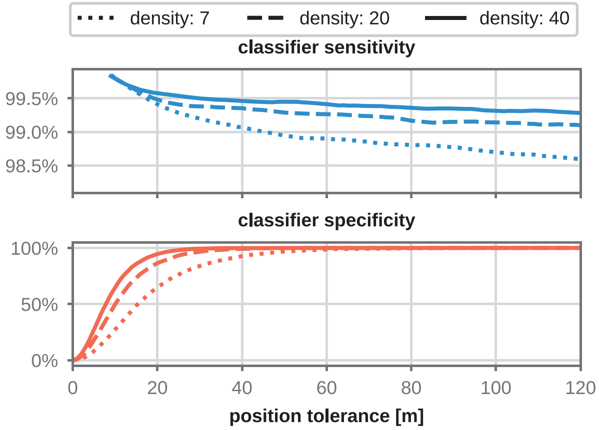

Fig. 9. Classification performance using trilateration on offsets obtained by LOS detection for different traffic densities (in [vehicles/km/lane]).

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