Extended Existence Probability Using Digital Maps for Object Verification

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Abstract—A main task for automated vehicles is a complete and robust environment perception. Especially, an error-free detection and modeling of other traffic participants is of great importance to drive safely in any situation. Therefore, multi-object tracking approaches, based on object detections from raw sensor measurements, are commonly used. However, false object hypotheses can occur due to complex, arbitrary scenarios with a high density of different traffic participants. For that reason, the presented approach introduces a probabilistic model to verify the existence of a track. Therefore, an object verification module is introduced, where the influences of multiple digital map elements on a track’s existence are evaluated. Finally, a probabilistic model fuses the various influences and estimates an extended existence probability for every track. In addition, a Bayes Net is implemented as directed graphical model to highlight this work’s expandability. The presented approach, reduces the number of false positives, while retaining true positives. Real world data is used to evaluate and highlight benefits of the presented approach, especially in urban scenarios.

I. INTRODUCTION

For automated vehicles, a complete and accurate perception of the local environment is required. In particular, the detection and modeling of all traffic participants is necessary to enable automated driving. For environment perception, the vehicle is equipped with a large variety of different sensors to receive a full and precise depiction of the surrounding. To make use of this huge amount of data and to be able to model other traffic participants, multiple subsequent algorithmic steps are necessary. Commonly, the first step creates object hypotheses of every detected traffic participant from the raw sensor data, like [1–3] show. Afterwards, these hypotheses are used as measurements by multi-object tracking filters, here the Labeled Multi-Bernoulli Filter (LMB) [4]. The LMB filter estimates a multi-object state based on noisy measurements, while considering clutter and missed detections over subsequent time steps. Besides, the spatial state distribution and a label, an existence probability for each track is calculated [4]. Any track exceeding a minimum required existence probability is considered in subsequent modules.

Although these algorithms are well known and have great success, there are many arbitrary scenarios with high densities of different traffic participants where the object detection and consequently the multi-object tracking can fail. As a result, false objects hypotheses are detected and existing objects are absent. Finally, these false positives or missing objects can lead to wrong assumptions and to an unknown behavior during the later processing steps, e.g. a trajectory generation of automated vehicles.

In this work, an extended existence probability is developed with the objective to represent the presence of an object regarding contextual information from digital maps. Due to the additional information, a reduction of falsely detected objects is achieved, while correctly detected objects are retained. In the literature, several ways to integrate map information and to improve an object perception system exist. Hosseinyalamdary et al. [5], proposed an approach, where the point cloud of a LiDAR scan is directly filtered regarding OpenStreetMap (OSM) [6]. Consequently, the preprocessing of raw sensor data is sped up and erroneous detections are reduced. However, this concept loses information within the first processing steps that cannot be retrieved later on. Hence, map elements that are not depicted in the digital map can result in missing objects. Another approach is presented by Danzer [7], where road information influences the prediction step of a multi-object tracking. The results show, that the estimation accuracy benefits from using contextual information. Since, [7] focuses on a vehicle tracking system, this paper proposes an approach to integrate digital map information which is independent regarding the object class. The main idea of this work derives from the authors’ previous publication [8], where a high-level fusion module subsequent to the multi-object tracking is introduced. In addition to digital maps, object hypotheses from a dynamic occupancy grid map are considered to increase the perception performance. Results show that, due to redundant information the fused object states achieve better accuracy.

This paper focuses on an object verification solely based on contextual information from digital maps, which is integrated into the environment model as a functional module. A major reason for the presented system layout is the modularity and scalability, which is developed under the consideration of different approaches introduced by [9–11] for automated vehicles. Integrating digital map information can be challenging in edge cases, hence this work implements probabilistic models to consider uncertainties in the digital map and tracks’ state. Therefore, digital map elements from highly precise mapped roads by Atlatec GmbH [12] and building outlines from OSM [6] are incorporated. These contextual information
This paper is structured as follows: In Section II, an overview of the functional system architecture is given. Here, necessary components and, especially, the digital map elements are described and motivated. Section III describes the probabilistically modeled influences and introduces their fusion concept to estimate the extended existence probability. An evaluation of the algorithm based on real world data is then discussed in Section IV. Finally in Section V, the work is summarized and an outlook is given.

II. FUNCTIONAL SYSTEM OVERVIEW

Since this work presents a component in the latter stages of a perception system, a short insight of necessary preprocessing functional modules will be given in the following section. Note that, the presented system architecture depicts only a subset of all components for an automated vehicle, e.g. other sensors, free space modeling or behavior planning are missing.

The introduced object verification module is a part of the perception layer, see Fig. 1. This system architecture separates the sensor and the perception layers. Subsequently, an application layer would follow with modules like behavior planning or trajectory generation, what is not part of this work and thus not further considered. In the sensor layer, multiple sensor types are decoded and transmitted to the perception layer, with a corresponding timestamp. Main characteristics and properties of the perception layer modules are given in the following.

A. Ego Motion & Localization

First of all, the dynamic states of the automated ego vehicle are essential. Since digital map information is used, the localization of the ego vehicle in a global reference coordinate system is required. Therefore, an Inertial Measurement Unit (IMU) and a Differential Global Positioning System (DGPS) generate measurements, which are filtered with an Extended Kalman Filter (EKF) to estimate the global ego motion state given by

\[
\hat{s}_{\text{ego}} = [x, y, v, a, \varphi, \omega]^T,
\]

where \(x\) is the UTM east coordinate, \(y\) the UTM north coordinate, \(v\) the absolute velocity and \(a\) the absolute acceleration. Further, \(\varphi\) is the UTM orientation and \(\omega\) the yaw rate. In addition, the EKF estimates a covariance matrix \(\hat{P}_{\text{ego}}\) for the full state. Inaccuracies of the position and orientation have a direct impact on the coordinate transformation from the vehicle coordinate system to the global coordinate system and vice versa. Due to this, the uncertainty of the localization needs to be considered in a fusion system using map information. Since the ego state \(\hat{s}_{\text{ego}}\) is essential for multi-object tracking and digital map processing, it is directly transmitted.

B. Digital Map Processing

During the digital map processing, a local map section around the ego vehicle is created. Loading and processing the whole map would result in increased latencies and computational costs. In the presented approach, the local map consists of two different map sources. As the first source, highly accurate set of lanes \(L\) mapped by Atlatec GmbH [12] are available in the lanelet2 format [13]. The second source of digital map data is OpenStreetMap (OSM) [6]. OSM data is publicly available and provides a high density of map information, but with unknown inaccuracies and inconsistencies. In the presented approach, the digital map processing module extracts building outlines \(B\) that are used to verify the tracked object state. Because these building outlines can overlap in the OSM data, an additional processing step merges overlapping outlines. Finally, the local building outlines are represented as polygons in UTM coordinates. The complete digital map information is shown in Fig. 2, where the roads \(L\) (black) and buildings \(B\) (grey) are visualized at an intersection in the city center of Ulm, Germany.

C. Object Detector & Multi-Object Tracking

The multi-object tracking module is supposed to estimate the state of any other road user. Because of temporal filtering, clutter is suppressed and the estimated state is highly accurate. In this work, a point object tracking using an object detector during in the preprocessing, which generates hypotheses from raw sensor measurements. In the literature, there are a high variety of different object detectors for any sensor type. Hence,
this work focuses on one implementation of an object detector to highlight the post processing steps of the object verification module. Here, the fast object detector for LiDAR point clouds of Herzog [1] is implemented. These detections are used as point object hypotheses.

In the perception layer, there is no restriction, which multi-object tracking algorithm is used. Here, an LMB filter of Reuter et al. [4] is implemented, which tracks the generated detections using a Constant Turn Rate and Acceleration (CTRA) motion model. The filter holds a set $\mathbf{S}_m = \{s_1, \ldots, s_m\}$ of tracked objects, where

$$\hat{s}_\tau = [x, y, v, a, \varphi, \omega]^T$$

is a single target state vector. Here, the state represents a two dimensional position with $[x, y]^T$ at the geometric center, including an orientation $\varphi$ in the ego vehicle coordinate system. Moreover, the absolute velocity $v$, acceleration $a$ and yaw rate $\omega$ are estimated. The covariance matrix $P_{\tau}$ contains the corresponding variances and covariances of every state. Besides their dynamic states, every tracked object has a unique label $\ell$, a classification probability $P_{\tau}(c)$ and an estimated existence probability $r$. For detailed information on how this existence probability is calculated, see [4]. In this work, the extraction of tracks using a minimum threshold $\theta_r$ serves as baseline during evaluation. Finally, every estimated track is transmitted to the object verification module.

D. Environment Model

The object verification module is part of the environment model. Here, multiple information sources are combined to generate a complete and accurate list of objects in the local environment. For the benefit of modular expandability, the algorithm is not integrated into the multi-object tracking. The presented object verification receives data from the ego motion and localization, the digital map processing and the multi-object tracking. As output, the set $\mathbf{S}_n = \{s_1, \ldots, s_m\}$ containing every validated track is computed. Here, the estimated state vectors are unchanged and equally to the tracks’ states from the multi-object tracking. However, the number of validated tracks $m$ can be smaller than the number of tracks $n$. In order to decide if an object is valid, an extended existence probability $\eta$ is calculated using different influences from the digital map elements. In the end, a final threshold $\theta_\eta$ is applied to publish all valid tracks. The subsequent Section III gives a detailed insight on how the extended existence probability is determined.

III. EXTENDED EXISTENCE PROBABILITY FOR OBJECT VERIFICATION

The object verification module estimates an extended existence probability for every received track. Therefore, negative and positive influences are modeled probabilistically using the track states and digital map elements. In this section, firstly the influences and their calculation are introduced. Secondly, the inference of estimate the extended existence probability from all influences is presented.

A. Influence Models

In the presented approach, a major design decision is the modeling of multiple influences on the track’s existence and evaluating them independently. In this work, only the most effective one is highlighted. For example, negative influences modeling the occlusion by buildings or class depending limited dynamics do not achieve significant improvements and are challenging to parameterize correctly. However, influences based on information from the digital map elements $B$ and $L$ have a high impact. In order to combine a track’s state with digital map data, the track’s pose $\tau$ is transformed into the UTM coordinate system using the global ego state $\mathbf{1}$. The spatial uncertainty of the track

$$\hat{P}_\tau' = \begin{pmatrix} \sigma_{\tau,xx}^2 & \sigma_{\tau,xy}^2 \\ \sigma_{\tau,yx}^2 & \sigma_{\tau,yy}^2 \end{pmatrix},$$

transforms to global coordinates

$$\hat{\Sigma}_\tau = R \cdot \hat{P}_\tau' \cdot R^T + \hat{P}_\text{ego},$$

using the rotation matrix

$$R = \begin{pmatrix} \cos(\varphi) & -\sin(\varphi) \\ \sin(\varphi) & \cos(\varphi) \end{pmatrix}.$$

Here, $\varphi$ is the UTM orientation from $\mathbf{1}$ and $\hat{P}_\text{ego}$ is the ego motion’s spatial localization uncertainty matrix. In the following, various influences are described, which consider this global spatial covariance matrix. In addition, these influences are calculated for every track $\tau$, however for better readability, this corresponding subscript is omitted in the equations.

1) OSM Building Influence: A major challenge for camera or LiDAR based sensors are reflections from glass facades of buildings, which results in false positive tracks within a building. For that reason, the first influence considers building outlines $B$ to detect a containment and, consequently, negatively influence the extended existence probability. Here, an uncertainty of the OSM mapping process has to be considered. Therefore, similar to Nuss et al. [9], the convolution of the polygons with a multivariate normal distribution $N(\mu_B, \Sigma_B)$ models the two-dimensional uncertainty of the building outlines. The covariance $\Sigma_B = \mathbb{I} \cdot \sigma_\eta$ incorporates a design parameter $\sigma_\eta$, which defines a transition from the building
The track's pose relative to the lane. Since traffic participants increase the extended existence probability integrated with the goal to define a positive influence and probability has a decreasing impact on the track's extended existence building outline position.

Information is the lanelet map with lanes \( L \) probability of the track's position being inside a building. With the goal to define a positive influence and probability has a decreasing impact on the track's extended existence building outline position.

The second source of digital map covariance has to be considered. Therefore, a perpendicular line within the lane boundary and, consequently, the normal distribution along this line. The mean is set to \( x'_b = -3\sigma_b \). For clarification, an example of the probability functions is shown in Fig. 3, where the two-dimensional covariance matrix of the track is reduced to the perpendicular line. The dimension reduction along the perpendicular line results in an approximation error, and due to that, an overestimation of the probability at the building’s edges can occur. For simplification, this approximation error is neglected. Finally, the building containment probability

is the integral over the building’s PDF and the cumulative distribution function

of the track’s PDF. The containment probability defines the probability of the track’s position \( x'_b \) being smaller than the building outline position \( x'_b \). In the presented approach, has a decreasing impact on the tracks extended existence probability \( \eta \) and, therefore, defines a negative influence.

2) Lanelet Influence: The second source of digital map information is the lanelet map with lanes \( L \). These lanes are integrated with the goal to define a positive influence and increase the extended existence probability \( \eta \) depending on the track’s pose relative to the lane. Since traffic participants around a street are in most cases relevant objects for trajectory planning, this lanelet influence should confirm true tracks. Integrating the lanes \( L \) is split into four sublevels. Therefore, tracks are evaluated if they are on the road or near the road and if they are correctly positioned or aligned relative to the lane. Here, a road refers to the entity of all parallel lanes. Evaluating the lanelet influence is similar to the building influence calculation. First, a perpendicular line between the nearest lane border and the track is calculated and, subsequently, the track’s spatial covariance is reduced along this dimension to define the PDF \( f_T(x) = \mathcal{N}(x; \hat{x}_T, \sigma_T^2) \).

Starting with the evaluation if a track is on the road, the width \( w_r \) is extracted from the lanelet map. Using the cumulative distribution function \( F_T(x) \), the probability

indicates whether a track is on the road.

Secondly, tracks near the road, e.g. pedestrians on the sidewalk, should be validated and positively weighted. Therefore, a design parameter \( \sigma_r \) defines a transition width of the road boundary and, consequently, the normal distribution \( f_R(x) = \mathcal{N}(x; x'_r, \sigma_r^2) \) models the road boundary similar to the building PDF. The probability

uses the cumulative distribution function \( F_R(x) \) and defines, if a track is near the road and should be validated.

The third sub level is designed to positively influence vehicles that are located within the boundaries of their associated lane. Therefore, a perpendicular line within the lane boundary is defined and a normal distribution \( f_L(x) = \mathcal{N}(x; x'_l, \sigma_{l,x}^2) \) across the lane is assumed. Here, the mean \( x'_l = -\frac{w_l}{2} \) is set to the lane center point and the variance \( \sigma_{l,x}^2 = \left(\frac{w_l}{6}\right)^2 \).
is defined such that $3\sigma_{l,x}$ lies on the boundary. This results in the probability

$$P_{LP}(x) = \int_{-\infty}^{\infty} f_T(x) \cdot f_L(x) \, dx,$$  \hfill (12)

which models the tracks’ positioning related to the associated lane center point.

The last probability based on the lanelet map, score the quality of the track’s orientation related to the course of its associated lane. In consequence, tracks following the lane course are positively influenced. Here, the normal distribution $f_L(\Delta \varphi) = \mathcal{N}(\Delta \varphi; 0, \sigma_{\varphi}^2)$ models the distribution over the orientation difference $\Delta \varphi = \varphi'_r - \varphi'_i$, where $\varphi'_r$ is the lane’s course and $\varphi'_i$ the track’s orientation. The mean is set to zero and the variance is $\sigma_{\varphi}^2 = (\frac{\pi}{2})^2$. As a result, the orientation difference evaluates between $-\frac{\pi}{2}$ and $\frac{\pi}{2}$. Furthermore, with the tracks orientation distribution \(f_T(\Delta \varphi) = \mathcal{N}(\Delta \varphi; \Delta \varphi', \sigma^2_{\varphi,\varphi'})\), the lane alignment probability

$$P_{LA}(\Delta \varphi) = \int_{-\infty}^{\infty} f_T(\Delta \varphi) \cdot f_L(\Delta \varphi) \, d\Delta \varphi,$$  \hfill (13)

models a similarity between the track’s orientation and the associated lane’s course. Obviously, overtaking or backwards moving tracks have an orientation difference greater than $\frac{\pi}{2}$ and, subsequently, their probability is zero. Since, the probability (13) only models positive influences these tracks will not be removed and this behavior can be neglected.

Since a track can be associated to multiple lanes, the probabilities of (12) and (13) are evaluated for every possible lane. In the end, the lane with the highest sum of both probabilities is taken for further processing.

### B. Inference of the Extended Existence Probability

In the previous subsections, five probability models regarding the OSM building $B$ and the lanelet map information $L$ have been introduced. For further processing, the described probabilities are separated into positive $i^+$ and negative $i^-$ influences. Tracks within a building’s outline could be false positives, hence the building probability is defined as negative influence \(P(i^-) := P_C(x)\). In contrast, the lanelet influences are developed to confirm tracks and, as a result, their probabilities have a positive influence on the track, so that \(P(i^+) := P_{OR}(x)\), \(P(i^+_N) := P_{NR}(x)\), \(P(i^+_L) := P_{LP}(x)\) and \(P(i^+_A) := P_{LA}(\Delta \varphi)\). These positive and negative influences are fused to estimate the extended existence probability $\eta$. Therefore, two different approaches are developed, which infer and fuse the probabilities.

First, an independent influence model (IIM) is introduced. The main idea of the IIM is an estimation of $\eta$ without a consideration of any correlations between influences. With the IIM, all negative influences are combined using the conditional distribution

$$P(i^-) := P(i^-|P(i^+), ..., P(i^+_m)) = \prod_{k=1}^{m} 1 - P(i^-_k),$$  \hfill (14)

Since only the building probability proved to be suitable as negative influence, this distribution reduces to

$$P(i^-) := P(i^-|P(i^+_1)) := 1 - P_C(x).$$  \hfill (15)

On the other hand, the positive influences are modeled as an equally weighted accumulated average

$$P(i^+) := P(i^+|P(i^+_1), ..., P(i^+_m)) = \frac{1}{n} \sum_{k=1}^{m} P(i^+_k).$$  \hfill (16)

Using the IIM, the extended existence probability

$$\eta = \frac{P(i^-) + P(i^+)}{2},$$  \hfill (17)

calculates an average of negative and positive influences. With this calculation, $\eta$ is equal 0.5 if the track is not impacted by any influence. In addition, heuristic weights could parameterize the impact of any influence, but for reduction of design parameters, this is not considered.

The second approach proposed to estimate the extended existence probability from all influences, is a Bayes Net (BN) \[14]. The main idea of the BN is a generalization of the IIM, considering weights and dependencies between the influences. Therefore, a directed graphical model is created by choosing the nodes with structural knowledge. The defined graphical model is visualized in Fig. 6. This figure shows a base graph (red nodes), with all introduced components. The graphical model merges multiple influences into superordinate nodes by combining influences from the lane and map. Additionally, Fig. 6 depicts a minor graph extension (grey node) using a classification probability $P_{\tau}(e)$ of the track as neutral influence. This extension is intended to illustrate how simple more components can be added to the BN and how this approach can be scaled. Finally, after defining all conditional probability tables of the BN, the extended existence probability $\eta$ can be inferred.

In the end, after inference of the IIM, the base BN or the BN with classification extension (BNe), every track $\tau$ has an
IV. EVALUATION

In this section, an evaluation of the proposed algorithm is given. Therefore, the different approaches IIM, BN and BNe are compared to each other and to a baseline. As baseline, the conventional approach using a threshold $\theta_r$ for the existence probability $r$ of the LMB filter is used.

A. System Setup & Dataset

To record real world data, the experimental vehicle of Ulm University [15] was used. The ego motion estimation and localization use a highly precise Automotive Dynamic Motion Analyzer (ADMA) and a DGPS. For environment perception, the LiDAR sensor Velodyne VLP-32 is mounted on the vehicle’s roof at the front. Object detections generated from the sensor’s measurements are tracked with an LMB filter as described in Section II-C. Since the KITTI dataset, which is used to train the detector, only provides labels in the front of the vehicle, traffic participants on the sides and back of the vehicle cannot be detected reliably. In consequence, even after LMB filtering, false or missed objects can occur. However, this behavior is not relevant and a compensation of the dataset’s characteristics during evaluation has no meaningful impact on the effectiveness of the presented approach. The algorithm is implemented within the robot operating system (ROS) framework using C++.

For evaluation, two datasets have been recorded and the estimated tracks are manually labeled as true positive or false positive. The first dataset scenario takes place in the urban area of Ulm and consists of 13,065 samples with 8,302 true positives and 4,763 false positives. Each sample represents a track at a single time step of the whole record. A major challenge in the urban area are false measurements occurring at glass facades. In consequence, the detector and LMB filter fail and produce multiple false positives. The second scenario is recorded at a rural suburban area near Ulm and consists of 5,634 samples with 2,936 true positives and 2,698 false positives. Compared to the urban sequence, higher velocities, more vegetation and less buildings are present.

In the presented work, two design parameters are defined in Section III. For the following evaluation, $\sigma_b = \frac{1}{3}$ m and $\sigma_r = 1.0$ m led to the best results.

B. Evaluation on Real World Data

The main goal of the algorithm is the reduction of false positives while retaining all true positives. Depending on the selected threshold, true positives can falsely be removed and, in consequence, false negatives emerge. On the other hand, when false positives are removed, true negatives emerge, leading to better results with a lower false positive rate. In consequence, a trade-off between falsely removed tracks and correctly removed tracks is required. This behavior is shown and discussed in the following.

As evaluation metrics, the true positive rate and the false positive rate are calculated and a receiver operating character-
istics (ROC) is generated. For further details on this common evaluation metric, see Fawcett’s work [16]. The ROC is created by a step-wise increment of 0.01 for the thresholds \( \theta_y \in [0, 1] \) for IIM, BN and BNe and \( \theta_r \in [0, 1] \) for the baseline. Starting from 0, the conditions \( \eta \geq \theta_y \) and \( r \geq \theta_r \) are always true and in consequence, no tracks are removed. On the other hand, when the thresholds are set to 1, the conditions are always false and every track will be removed. The resulting ROC for the urban and the rural dataset are shown in Fig. 7.

The ROC show, that the presented approaches using the IIM, BN or BNe achieve better results than the baseline regarding the false positive rate. Especially in the urban scenario, a lot of false tracks within buildings can be removed. Since, in the rural area these buildings are less present the impact is lower there. Besides the buildings, the lanelet influence enables a confirmation of true tracks near and on a road. In the rural scenario, a steep increase of the IIM, BN and BNe can be seen, which occurs at an decreasing threshold where the lanelet influence has more impact and tracks near the road are confirmed.

To highlight the differences between the presented approaches, the precision, recall and accuracy are evaluated at certain operation point for the thresholds \( \theta_y = 0.35 \) and \( \theta_r = 0.05 \). These thresholds are chosen to maximize the true positive rate, while minimizing the number of false negatives, what corresponds to the top right corners in the ROC. The resulting set of tracks \( \hat{S}_r \) is transmitted to the behavior and trajectory planning and false negatives can lead to arbitrary behavior and possibly fatal consequences. That is why, choosing the threshold \( \theta_y \) should focus on minimizing the number of false negatives. Overall, the three approaches IIM, BN and BNe do differ only slightly by less than 1%. Compared to the baseline, especially, the recall is approximately 10% higher in both sequences. In consequence of multiple false positives in the urban area occurring within buildings, the precision is 6% higher and the accuracy 10%. Whereas in the rural area, the precision and accuracy differentiate only around 2%. Finally, the BN can easily be extended with more influences like shown with the BNe. As a consequence, this approach is recommended.

V. CONCLUSION

In summary, the presented approach introduces an algorithm to incorporate digital map information into an extended existence probability of tracked traffic participants. Therefore, multiple probabilistic models define influences of map elements. Furthermore, an independent probabilistic model and a Bayes Net infer the introduced influences to estimate an extended existence probability. Based on this probability, false tracks can be removed and, consequently, the false positive rate is reduced. Finally, an evaluation on real world data in an urban and rural area show the significance and performance of the presented approach.

For future work, the algorithm can be extended with more map elements, e.g. crosswalks or bicycle lanes to consider vulnerable road users. Here, the Bayes Net should be applied and the optimal graphical model can be trained.

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