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Corridor Selection Under Semantic Uncertainty for Autonomous Road Vehicles

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Abstract— **Automated driving systems are likely to encounter situations in which their understanding of the road is uncertain. State-of-the-art systems only act on a single road hypothesis. If that hypothesis is incorrect, the likely consequence is an undesired behavior of the automated vehicle. This paper shows that the consideration of multiple road hypotheses in the selection of a driving corridor can improve the performance of an automated driving system and relax the requirements on its perception system. Two algorithms are presented that infer a corridor from a multi-hypothesis road representation with respect to different navigational goals.**

I. Introduction

The perception of the roadway based on onboard sensors is very challenging, especially under unfavorable road or environmental conditions [1], [2]. This results in uncertainty about the existence, the physical state, and the classification of entities [2]. For example, regarding the perception of roadway markings, this relates to uncertainty because of false-positive and false-negative detections, uncertainty about a marking's geometry, and uncertainty about its pattern.

Approaches to road understanding are still limited and frequently the inferred understanding of the roadway is incorrect [3]–[5]. It may be uncertain, for example, which of the perceived markings compose a lane. Since this kind of uncertainty relates to the contextual meaning of entities and their relations, it is called semantic uncertainty in the following. It may originate from the previously mentioned kinds of uncertainties, from shortcomings in the process of road understanding, or from an actually ambiguous road scene. The latter may be caused by missing or by outdated but still visible roadway markings, for example.

Due to the limited capabilities of today's onboard perception systems, most prototypical automated driving systems resort to highly-accurate digital maps [6], [7]. They provide the necessary understanding of the roadway and usually the exact lane geometry [8]. Their usage, however, depends on a highly accurate map-relative localization and on the map being up to date. Both conditions are unlikely to hold at all times, which may result in conflicting road hypotheses from a map and from the onboard perception.

Considering these aspects, automated driving systems are likely to encounter situations in which they cannot infer an unambiguous understanding of the road. This paper argues to represent and handle uncertainty in the process of action planning. First, this approach relaxes the requirements on the perception system if certain kinds of uncertainty can be handled in the process of action planning. Second, it can increase the performance of an automated driving system. For example, the system can continually consider multiple, similarly likely hypotheses and thus select its actions more consistently over time; or it can consider new hypotheses that did not accumulate much evidence yet and thus react faster to a changed situation. The latter point is addressed in the experimental evaluation.

The main contributions of this paper are 1) an experimental proof-of-concept that considering multiple road hypotheses is beneficial and 2) a framework for spatial and probabilistic reasoning about multiple and possibly contradicting road hypotheses. The relevant part of the experimental system's architecture is shown in Fig. 1. After a brief discussion of the state of the art in Section II, Section III introduces and extends the multi-hypothesis road representation published in [9]. It is the basis for the corridor selection algorithms discussed in Section IV. Section V provides a first experimental evaluation of the algorithms. They are evaluated on a typical problem that occurs with perception systems commonly used in development today.

II. State of the Art

Prototypical automated driving systems are commonly divided into the major subsystems of perception and behavior generation. The perception system creates an internal representation of the scene and the behavior generation system plans and controls the actions with respect to the system's function definition and its goals. Approaches to action planning generally expect the representation of the road to be unambiguous, correct, and for consistent plans, to be consistent over time [10]. Nagasaka and Harada [11] consider time-inconsistent estimates of physical states due to localization errors in the reference path generation with the intent to stabilize the driving behavior. Uncertainty about the understanding of the road is not considered in any known approach.

The perception and understanding of the roadway, on the other hand, is very challenging for automated driving systems. Töpfer *et al.* [5] create a probabilistic hierarchical model of roadway hypotheses and infer the most probable hypothesis by a graph search algorithm. The probabilistic model, however, is not well-suited for reasoning about multiple hypotheses during action planning. Nguyen *et al.* [12] additionally try to learn the situational reliability of the left and the right lane boundary, their geometric center, and the path of a vehicle in front as indicators for the course

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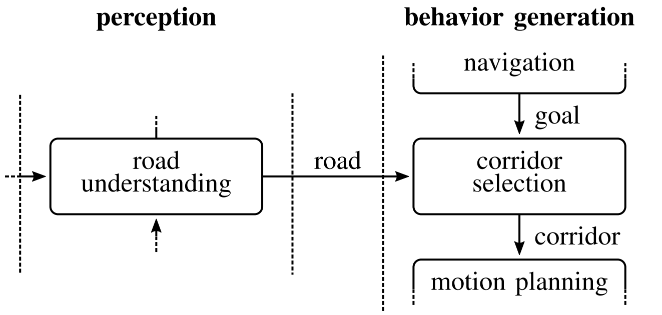


Fig. 1. Relevant section of the functional system architecture. The driving corridor is selected based on the multi-hypothesis road representation and the navigational goal.

of the ego lane. Abramov *et al.* [13] use a GraphSLAM approach to estimate a clothoid-based road model. Because of the strict model assumptions, the approach is limited to highways and cannot represent exit ramps and roadway junctions properly. Geiger *et al.* [4] jointly estimate the topology and geometry of roadway junctions, the locations of lanes and road vehicles, and their associations. Although the approaches are quite sophisticated, the inferred understanding of the roadway is frequently false. Yu *et al.* [14] infer a probabilistic semantic representation of the roadway. The semantic information, however, relies on an a-priori map and the represented uncertainty is actually about the map-relative localization. Recent studies, for example by Li *et al.* [15], indicate that the use of deep neural networks can improve the detection accuracy significantly. However, errors still occur and the obtained representation does not embody an understanding of the roadway.

Shalev-Shwartz *et al.* [16] define a "probably-approximately-correct sensing system" in an attempt to prove that a certain driving strategy never leads to accidents the automated driving system is to "blame" for. Their definition, however, solely includes misestimations of physical states and explicitly neglects all other kinds of perception errors.

III. Multi-hypothesis Road Representation

To represent semantic uncertainty about the road, a multi-hypothesis road model is employed. Compared with [9], it is extended by a probabilistic model and by a graph representing the spatial relations of boundary hypotheses.

The road model is exemplified in Fig. 2. The roadway's cross section is divided into strips. A strip is a roadway portion that has a certain meaning. It may represent a traffic lane, a shoulder, the area between a double line, or a full roadway without any markings. Geometrically it is defined by its two lateral boundaries. The strip-based model enforces a gapless (though not necessarily complete) representation of the roadway that enables the corridor selection to infer the meaning of each roadway portion. Laterally adjacent strips share a mutual boundary by definition. Boundaries may be longitudinal roadway markings, curbs, guardrails, et cetera, but also edges that mark changes in the ground surface.

In longitudinal direction, the roadway is divided into segments. A segment begins or ends whenever a boundary hypothesis begins or ends, two boundary hypotheses intersect, or a strip's meaning changes. This way, the lateral adjacency relations of strips are constant within a segment. Connectors (Fig. 2c, central elements) represent longitudinal adjacency relations of roadway and strip segments. To model junctions and changes in the cross section, segments can be connected to more than one adjacent segment on both levels. The lateral adjacency relations of boundary hypotheses are represented as a graph. In each segment, each boundary points to the adjacent boundaries on the left and on the right. (Fig. 2c, red and blue arrows). It allows to efficiently infer the intersection area of a set of strip hypotheses.

In order to express the semantic uncertainty, for each segment multiple hypotheses about the roadway can be represented. The result is a set of discrete road hypotheses

$$\mathcal{X}_{\text{road}} = \{x^1_{\text{road}}, x^2_{\text{road}}, \dots, x^N_{\text{road}}\}.$$

Each element is a hypothesis about the road network in the examined horizon. Hypotheses about a roadway segment, a strip segment, or a boundary are represented exactly once. If multiple roadway or strip hypotheses share a mutual strip or boundary hypothesis, they refer to the same unique element, as illustrated in Fig. 2c.

Hypotheses about roadway and strip segments are only connected in longitudinal direction if they are compatible. This decision is up to the perception system and is based on domain-specific knowledge. Road hypotheses are assumed to be *self-consistent*. In a consistent hypothesis, no part is in contradiction with another part of the same hypothesis. An example of an inconsistent hypothesis would be an exit lane that is separated over its full length by a continuous line from the other travel lanes. Either the marking must be broken in at least one segment or the portion of the roadway separated by the continuous line must have another meaning.

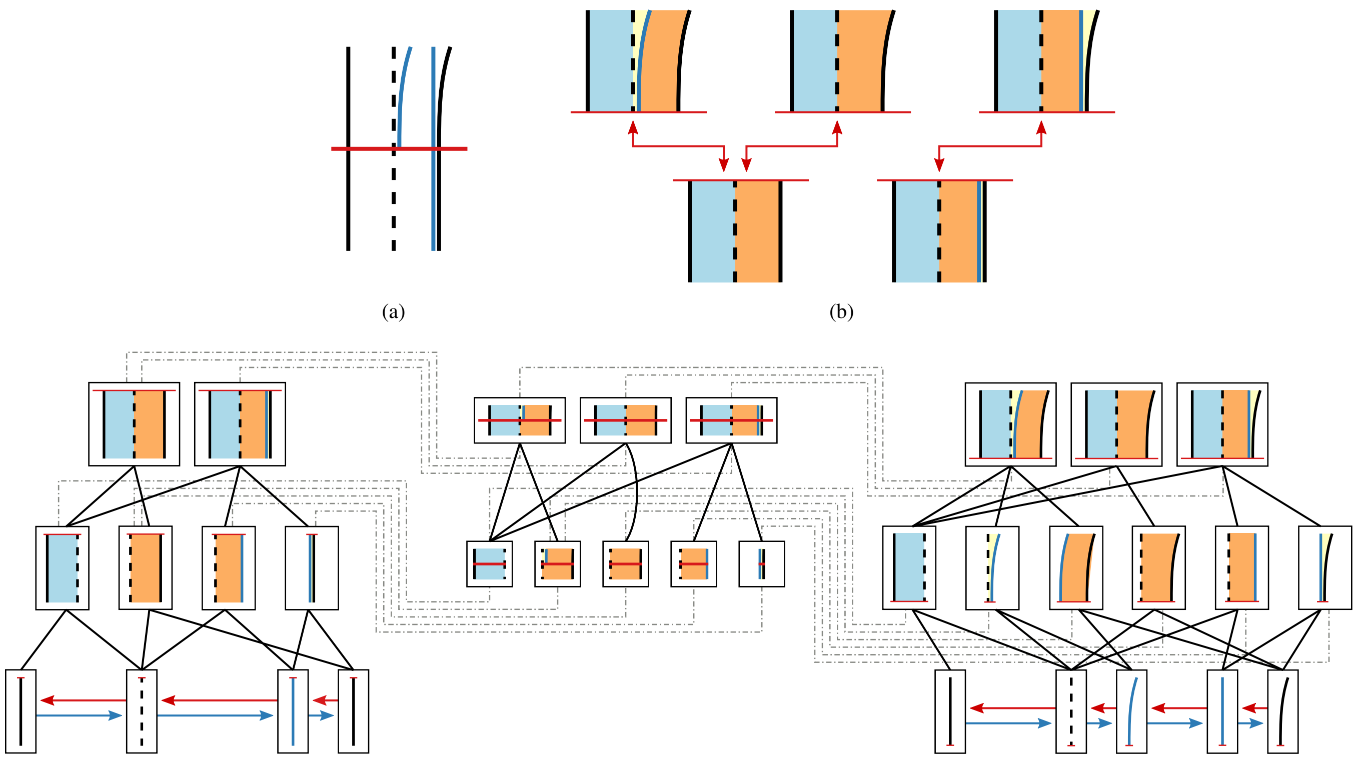
The following paragraphs discuss how to infer probabilities of hypotheses about roadway and strip segments that are part of multiple road hypotheses. Let $P(X_{\text{road}} = x|z_{0:t})$ denote the posterior probability distribution over all possible road configurations $x \in \Omega_{\text{road}}$ given all observations $z_{0:t}$ made by the perception system. The perception system is assumed to assign a probability value to each road hypothesis such that

$$P(x|z_{0:t}) \geq 0 \;\forall x \in \mathcal{X}_{\text{road}} \quad \text{and} \quad \sum_{x \in \mathcal{X}_{\text{road}}} P(x|z_{0:t}) \leq 1.$$

It is interpreted as the system's *degree of belief* that the corresponding hypothesis is true (with a certain tolerance regarding the geometric accuracy). In the following, the condition on the observations is omitted for readability. Road hypotheses are mutually exclusive. It follows that

$$P(\{x^i_{\text{road}}, x^j_{\text{road}}\}) = P(x^i_{\text{road}}) + P(x^j_{\text{road}}) \;\forall i \neq j.$$

This property in combination with the property of the data structure that all hypotheses are represented exactly once allows to efficiently infer the probability of hypotheses



(a)

(b)

(c)

Fig. 2. Extended model of the multi-hypothesis road representation [9]. (a) An example of a perceived roadway. Black boundaries are perceived with high evidence, blue boundaries with less evidence. (b) Roadway hypotheses as they could be generated by a perception system. The set of full-length hypotheses is modelled as a graph of segment hypotheses. (c) The hierarchical structure of hypotheses about boundaries, strips, and roadways within each segment and (in between) that of connectors of strip and roadway hypotheses. The red and blue arrows represent the graph of spatial relations between the boundaries.

about roadway segments and strip segments that are part of multiple road hypotheses. The operators defined in the following work on all kinds of operands in the same way. If the operand is a set, the result is the corresponding set with the operator applied to each element. Let operator seg return the requested roadway segment from a road hypothesis and let $X^s_{\text{rdw}} = \text{seg}(X_{\text{road}}, s)$ denote the true roadway in segment s. The probability $P(x^s_{\text{rdw}})$ that the roadway segment hypothesis x^s_{rdw} is true is the accumulated probability over all road hypotheses that contain x^s_{rdw}:

$$P(X^s_{\text{rdw}} = x^s_{\text{rdw}}) = P(\{x \in \mathcal{X}_{\text{road}} | \, \text{seg}(x, s) = x^s_{\text{rdw}}\}).$$

Accordingly, with $\mathcal{X}^s_{\text{rdw}} = \text{seg}(\mathcal{X}_{\text{road}}, s)$ and strips returning a roadway segment's set of strips, the probability $P(x^s_{\text{strip}})$ that the strip segment hypothesis x^s_{strip} is true is the accumulated probability of all hypotheses that contain x^s_{strip}:

$$P(x^s_{\text{strip}} \in \text{strips}(X^s_{\text{rdw}})) = P(\{x \in \mathcal{X}^s_{\text{rdw}} | x^s_{\text{strip}} \in \text{strips}(x)\}).$$

The joint probability $P(x^s_{\text{rdw}}, x^{s+1}_{\text{rdw}})$ of a pair of adjacent roadway segment hypotheses is the accumulated probability of all road hypotheses that contain both segment hypotheses:

$$P(X^s_{\text{rdw}} = x^s_{\text{rdw}}, X^{s+1}_{\text{rdw}} = x^{s+1}_{\text{rdw}}) = P(\{x \in \mathcal{X}_{\text{road}} | \\ \text{seg}(x, s) = x^s_{\text{rdw}} \wedge \text{seg}(x, s+1) = x^{s+1}_{\text{rdw}}\}).$$

The joint probability $P(x^s_{\text{strip}}, x^{s+1}_{\text{strip}})$ of a pair of longitudinally adjacent strip segment hypotheses is accordingly

$$P(x^s_{\text{strip}} \in \text{strips}(X^s_{\text{rdw}}), x^{s+1}_{\text{strip}} \in \text{strips}(X^{s+1}_{\text{rdw}})) = \\ P(\{(x^s_{\text{rdw}}, x^{s+1}_{\text{rdw}}) \in \mathcal{X}^s_{\text{rdw}} \times \mathcal{X}^{s+1}_{\text{rdw}} | \\ x^s_{\text{strip}} \in \text{strips}(x^s_{\text{rdw}}) \wedge x^{s+1}_{\text{strip}} \in \text{strips}(x^{s+1}_{\text{rdw}})\}).$$

A joint probability $P(x^s, x^{s+1}) > 0$ implies the existence of a corresponding roadway or strip connector in the data structure. The connector stores the joint probability, which makes it efficiently accessible.

IV. Corridor Selection

A. Performance Measure

The performance measure of the corridor selection is the intersection area of the selected corridor with the true target lane. Let x_{corr} denote the selected corridor. Operator target returns the target lane of the roadway and $X_{\text{target}} = \text{target}(X_{\text{road}})$ represents the true target lane. Operator A returns the set of points representing the area of a roadway portion. In the *optimal* case, the boundaries of the corridor are equal to the boundaries of the true lane ($\text{A}(x_{\text{corr}}) = \text{A}(X_{\text{target}})$). It is *acceptable* if one or both boundaries are inside of the true lane ($\text{A}(x_{\text{corr}}) \subseteq \text{A}(X_{\text{target}})$). It is *not acceptable* if one boundary is outside of the true lane ($\text{A}(x_{\text{corr}}) \not\subseteq \text{A}(X_{\text{target}})$).

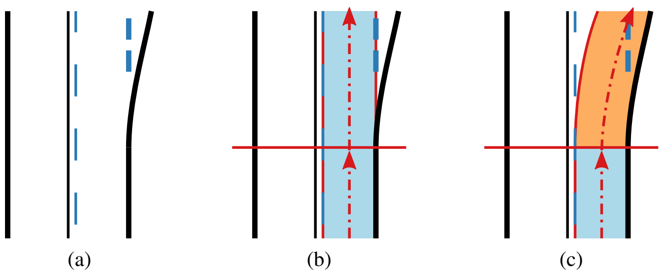


Fig. 3. Desired outcome of the corridor selection. The corridor is selected based on the perceived boundary hypotheses (black: high evidence; blue: low evidence). (a) Exemplary percept. (b) Most likely acceptable thru corridor. (c) Most likely acceptable exit corridor.

It is important to note that the performance of the overall system is in the first place determined by the performance of the perception system. The corridor selection can only improve the driving performance in a certain performance range of the perception system. At the upper end, in case of a perfect perception, the corridor selection returns the optimal corridor by definition. Below the lower end, if the stated preconditions are not fulfilled, the postconditions of the corridor selection are not guaranteed to hold either.

B. Scenario

The scope of this paper is the inference of corridors with certain properties from the multi-hypothesis road representation. To focus on this problem, a simplifying scenario is used. It allows to neglect aspects that affect the tactical lane selection and the navigation of the automated driving system and it allows a more descriptive formulation of the algorithms. The generalization or adaption to other scenarios is, to some extent, straightforward.

In the scenario, the automated vehicle drives on a roadway. Right-hand traffic is assumed. Exits are recurring along the road on the right, either in form of deceleration lanes or immediate exit ramps. Lanes are marked on the roadway. In some sections, however, some markings are not well perceivable by the perception system due to dirt or bad physical conditions of the markings. In other sections, there are old markings that are not removed properly. Lane widths may vary over the length of the road. It is assumed that there are no other road users. The automated vehicle is thus supposed to drive in the rightmost lane only. The task of the experimental system is to follow the road up to a certain point and then take the exit (e.g., triggered by a navigation system or by an operator). The subtask of the corridor selection is to infer an acceptable corridor from a set of road hypotheses. As illustrated in Fig. 3, depending on the navigational goal, either a *thru corridor* to stay on the current roadway or an *exit corridor* shall be selected.

C. Assumptions

Besides the simplifying scenario, for the same reason two assumptions about the constellations of road hypotheses are made, which are not required in general. They will be listed as preconditions of the corridor inference algorithms. Precondition (1) is that each roadway hypothesis contains a hypothesis about the rightmost thru lane. In general, the rightmost lane may be missing in incomplete hypotheses, especially if the vehicle is not driving in or next to the rightmost lane, for example, on multilane highways.

Precondition (2) states that all hypotheses about the rightmost thru lane have a mutual area of intersection in each segment. In general, a misunderstanding of an exit lane as a thru lane or vice versa may cause a violation of this assumption (cf. [14]). A possible solution is to infer two (or more) distinct corridors and select the one that complies best with the current goals. Making this decision involves weighing up the potential consequences of, for example, potentially leaving the desired route versus potentially driving in an undesirable lane. Such decisions are out of this paper's scope.

Conflicts between road hypotheses can make it impossible to infer a corridor that is acceptable with respect to all hypotheses. If the area of conflict is not far ahead and if the vehicle is in motion, it may be inevitable to select a corridor that is considered not acceptable for at least one hypothesis. Again, in such a situation it is essential to consider the potential consequences of a decision. One alternative might be to potentially cross a broken line whereas the other alternative might be to potentially cross a continuous line. Also decisions of this kind are beyond this paper's scope. To exemplify in the following how the multi-hypothesis representation can be used to reason about conflicts, it is assumed that each outcome of violating a hypothesis is equally undesirable.

D. Thru Corridor Inference

If the goal is to continue on the current roadway, the target lane is the rightmost thru lane. It is referred to as thru lane in the following. Operator thru returns the thru lane of a roadway. The operators left and right return the left and right boundary of a strip or of a corridor.

Since all consequences of selecting an unacceptable corridor are considered equally undesirable, a reasonable objective is to select the corridor $\hat{x}_{\text{corr}}$ with the highest probability of being acceptable:

$$\hat{x}_{\text{corr}} = \underset{x_{\text{corr}}}{\arg\max}\, P(\mathrm{A}(x_{\text{corr}}) \subseteq \mathrm{A}(\mathrm{thru}(X_{\text{road}}))).$$

The objective will be slightly relaxed later in this section in exchange for a significant decrease in the computational complexity of finding a drivable corridor. In the convenient case, all hypotheses about the thru lane are compatible, that is, their area of intersection constitutes a drivable corridor. Being compatible with all hypotheses implies the maximum likelihood of being acceptable.

The algorithm to infer the thru corridor is listed in Fig. 4. It iterates over all segments $S = (\mathrm{s}_1, \mathrm{s}_2, \ldots, \mathrm{s}_n)$ within the desired planning horizon, starting from the segment the vehicle is located in. For each segment s, the left and right boundaries of the thru lane hypotheses $\mathcal{X}^s_{\text{thru}} = \mathrm{thru}(\mathcal{X}^s_{\text{rdw}})$ are collected and sorted (lines 4 to 6 in Fig. 4). The

1: **function** INFER THRU CORRIDOR (
road hypotheses $\mathcal{X}_{\text{road}}$,
ordered segments S in desired horizon)
precondition (1) $(\forall s \forall x^s_{\text{rdw}})\ \text{thru}(x^s_{\text{rdw}}) \neq \emptyset$
precondition (2) $(\forall s \forall x^s_{\text{rdw}})\ \bigcap \text{A}(\text{thru}(x^s_{\text{rdw}})) \neq \emptyset$
precondition (3) $(\forall s)\ \text{left}(X^s_{\text{target}}) \in \text{left}(\mathcal{X}^s_{\text{target}})$
$\wedge\, \text{right}(X^s_{\text{target}}) \in \text{right}(\mathcal{X}^s_{\text{target}})$
precondition (4) $(\forall s \forall x^s_{\text{bnd}} \in \text{right}(\mathcal{X}^s_{\text{thru}}) \forall y^s_{\text{bnd}} \in \text{left}(\mathcal{X}^s_{\text{thru}}))$
$x^s_{\text{bnd}} = \text{right}(X^s_{\text{thru}}) \wedge \neg\, \text{drivable}(x^s_{\text{bnd}}, y^s_{\text{bnd}}) \Rightarrow$
$P(x^s_{\text{bnd}} \geq \text{right}(X^s_{\text{thru}})) > P(y^s_{\text{bnd}} \leq \text{left}(X^s_{\text{thru}}))$
$y^s_{\text{bnd}} = \text{left}(X^s_{\text{thru}}) \wedge \neg\, \text{drivable}(x^s_{\text{bnd}}, y^s_{\text{bnd}}) \Rightarrow$
$P(x^s_{\text{bnd}} \geq \text{right}(X^s_{\text{thru}})) < P(y^s_{\text{bnd}} \leq \text{left}(X^s_{\text{thru}}))$
2: $\hat{x}_{\text{corr}} \leftarrow ()$
3: **for each** segment s in S
4: $\mathcal{X}^s_{\text{thru}} \leftarrow \text{thru}(\text{seg}(\mathcal{X}_{\text{road}}, s))$
5: $B^s_{\text{left}} \leftarrow \text{sort}(\text{left}(\mathcal{X}^s_{\text{thru}}), \text{right to left})$
6: $B^s_{\text{right}} \leftarrow \text{sort}(\text{right}(\mathcal{X}^s_{\text{thru}}), \text{left to right})$
7: $\hat{x}^s_{\text{corr}} \leftarrow (\text{first}(B_{\text{left}}), \text{first}(B_{\text{right}}))$
8: **if** $\neg\, \text{drivable}(\hat{x}^s_{\text{corr}})$
9: $\hat{x}^s_{\text{corr}} \leftarrow \text{find}(\{x^s_{\text{corr}} \in B^s_{\text{left}} \times B^s_{\text{right}}\},$
$\text{drivable}(x^s_{\text{corr}}) \wedge \max_{x^s_{\text{corr}}} P(x^s_{\text{corr}}))$
10: **end if**
11: $\hat{x}_{\text{corr}} \leftarrow \text{append}\ \hat{x}^s_{\text{corr}}\ \text{to}\ \hat{x}_{\text{corr}}$
12: **end for**
13: **if** $\neg\, \text{drivable}(\hat{x}_{\text{corr}})$
14: **for each** adjacent pair $(s-1, s)$ in S
15: $W^{s-1} \leftarrow \{(l, r) \in B^{s-1}_{\text{left}} \times B^{s-1}_{\text{right}} |$
$l \leq \text{left}(\hat{x}^{s-1}_{\text{corr}}) \wedge r \geq \text{right}(\hat{x}^{s-1}_{\text{corr}})\}$
16: $W^s \leftarrow \{(l, r) \in B^s_{\text{left}} \times B^s_{\text{right}} |$
$l \leq \text{left}(\hat{x}^s_{\text{corr}}) \wedge r \geq \text{right}(\hat{x}^s_{\text{corr}})\}$
17: $\hat{x}^{s-1:s}_{\text{corr}} \leftarrow \text{find}(\{x^{s-1:s}_{\text{corr}} \in W^{s-1} \times W^s\},$
$\text{drivable}(x^{s-1:s}_{\text{corr}}) \wedge \max_{x^{s-1:s}_{\text{corr}}} P(x^{s-1:s}_{\text{corr}}))$
18: **end for**
19: **end if**
20: **return** $\hat{x}_{\text{corr}}$
postcondition $\text{drivable}(\hat{x}_{\text{corr}})$
postcondition $\hat{x}_{\text{corr}}$ is acceptable
21: **end function**

Fig. 4. Algorithm for the inference of an acceptable thru corridor. The formulation of the algorithm is intentionally verbose. Lines 4 to 7 correspond to the convenient case, lines 8 to 10 to the search for a drivable corridor in a single segment, and lines 13 to 19 to the search for an continuously drivable corridor. A compact formulation only combines the second for-loop with the segment ahead initialized to the most narrow pair of boundaries.

boundaries are sorted from the inside to the outside, as depicted in Fig. 5a. The intersection area and thus the first corridor candidate is obtained by taking the first elements of the ordered tuples of left and right boundaries B^s_{left} and B^s_{right} (line 7 in Fig. 4).

The occurrence of the true target lane's left and the right boundary in the sets of left and right boundaries implies that the intersection area is within or identical to the true lane. It is therefore listed as precondition (3) in Fig. 4. The inference of an acceptable corridor would otherwise rely on a false hypothesis.

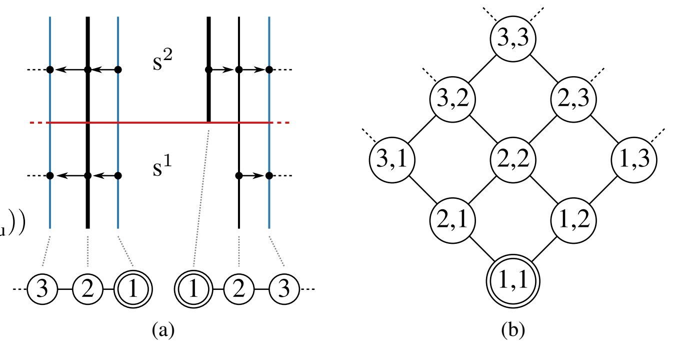


Fig. 5. Search space for the corridor inference. (a) Exemplary percept. Black boundary hypotheses have high, blue ones have low evidence. The boundaries are sorted in each segment from the inside to the outside. (b) Graph of possible boundary combinations in segment s^2. The search starts at the innermost boundary pair. Every traversal that increases the distance from the root node leads to a combination with lower probability of being acceptable.

If the intersection area does not constitute a drivable corridor, it is inevitable to select a corridor that is in conflict with at least one road hypothesis. In the following, it is first discussed how to find the drivable corridor with the highest probability in a segment. Afterwards, the approach is extended to find an over all segments continuously drivable corridor.

With $X^s_{\text{thru}} = \text{thru}(X^s_{\text{rdw}})$, the probability $P(x^s_{\text{corr}})$ that a thru corridor x^s_{corr} in segment s is acceptable is the accumulated probability of all compatible thru lane hypotheses:

$$P(\text{A}(x^s_{\text{corr}}) \subseteq \text{A}(X^s_{\text{thru}})) = P(\{x \in \mathcal{X}^s_{\text{thru}} | \, \text{A}(x^s_{\text{corr}}) \subseteq \text{A}(x)\}).$$

The drivable corridor with the highest probability is found by a graph search (line 9 in Fig. 4). The search space is the set of possible combinations of left and right boundaries, depicted in Fig. 5b. The root node is the pair of the innermost left and right boundary. Every traversal that increases the distance to the root node corresponds to ignoring a certain boundary and consequently leads to a combination with a lower probability of being acceptable. The optimum is found if a pair constitutes a drivable corridor and all nonvisited nodes are guaranteed to have a lower probability.

To ensure that an acceptable corridor is inferred, the probabilities of the road hypotheses must be distributed such that a boundary hypothesis that corresponds to a boundary of the true target lane is never ignored. Two boundary hypotheses that do not constitute a drivable corridor are said to be in conflict. The crucial point, at which it is determined whether an acceptable corridor is found or not, is a conflict between a true boundary hypothesis and another, obviously false, hypothesis.

In the following, the formulation of the precondition is derived for the right corridor boundary. To compare the relative location of boundaries, the relational operator $<$ returns whether the left-hand side boundary is left of the right-hand side boundary. The other relational operators are interpreted accordingly. The probability $P(x^s_{\text{bnd}})$ that the boundary x^s_{bnd} is the true right boundary of the thru lane in segment s is

$$P(\text{right}(X^s_{\text{thru}}) = x^s_{\text{bnd}}) = P(\{x \in \mathcal{X}^s_{\text{thru}} \,|\, \text{right}(x) = x^s_{\text{bnd}}\}).$$

A boundary hypothesis in conflict with a true boundary implies that the false hypothesis is located inside of the true lane. Vice versa, the true boundary is located inside of a false thru lane hypothesis. It is ensured that the true boundary hypothesis is not ignored if its probability of being located inside of the target lane is less than that of any conflicting boundary. It is equivalent to demand that the true boundary hypothesis must have a higher probability of being the boundary of the target lane or being located outside of it compared with any conflicting hypothesis. The probability that a hypothesis about the right boundary x^s_{bnd} is equal to or right of the true right boundary is its own probability accumulated with the probabilities of all hypotheses to its left:

$$P(x^s_{\text{bnd}} \geq \text{right}(X^s_{\text{thru}})) = P(\{x \in \text{right}(\mathcal{X}^s_{\text{thru}}) | x \leq x^s_{\text{bnd}}\}).$$

With respect to the right boundary, the precondition can then be formulated as

$$\begin{aligned}&(\forall x^s_{\text{bnd}} \in \text{right}(\mathcal{X}^s_{\text{thru}})\ \forall y^s_{\text{bnd}} \in \text{left}(\mathcal{X}^s_{\text{thru}}))\\ &\quad x^s_{\text{bnd}} = \text{right}(X^s_{\text{thru}}) \wedge \neg\, \text{drivable}(x^s_{\text{bnd}}, y^s_{\text{bnd}}) \Rightarrow\\ &\qquad P(x^s_{\text{bnd}} \geq \text{right}(X^s_{\text{thru}})) > P(y^s_{\text{bnd}} \leq \text{left}(X^s_{\text{thru}}))\end{aligned}$$

It is listed as precondition (4) in Fig. 4.

Since the corridor segments were inferred independently, they may be laterally misaligned such that the corridor as a whole is not drivable. For example, in Fig. 5a the most probable drivable corridor in segment s^1 is $(1, 2)$ whereas it is $(2, 1)$ in segment s^2. To find the drivable corridor in all segments S with the highest probability of being acceptable, it is necessary to globally maximize the joint probability $P(x^{\text{s}_1}_{\text{corr}}, x^{\text{s}_2}_{\text{corr}}, \ldots, x^{\text{s}_n}_{\text{corr}})$.

A more efficient solution is possible if the objective is relaxed to find any corridor that is guaranteed to be acceptable given that the preconditions hold. Obviously, the true target lane is drivable and with precondition (3) its boundaries are guaranteed to be part of at least one road hypothesis. This implies that for each pair of adjacent segments there is a combination of boundaries that is acceptable and drivable. Precondition (4) further ensures that this combination is more likely than any unacceptable combination. Therefore it is sufficient to adjust pairs of adjacent corridor segments by widening one or both of them such that the transition between them becomes drivable and their joint probability of being acceptable is maximized.

Because it is only allowed to widen corridor segments, a single iteration over the pairs of adjacent segments is sufficient. If narrowing a corridor segment was allowed, the transition between the previously visited pair of corridor segments could become undrivable again. Therefore, the search space is reduced to the boundaries of the current corridor and boundary hypotheses outside of it (lines 15 and 16 in Fig. 4). The joint probability $P(x^{s-1}_{\text{corr}}, x^s_{\text{corr}})$ that two adjacent corridor segments are acceptable is

$$\begin{aligned}&P(\text{A}\, x^{s-1}_{\text{corr}} \subseteq \text{A}(X^{s-1}_{\text{thru}}) \wedge \text{A}(x^s_{\text{corr}}) \subseteq \text{A}(X^s_{\text{thru}})) =\\ &\quad P(\{(x^{s-1}_{\text{strip}}, x^s_{\text{strip}}) \in \mathcal{X}^{s-1}_{\text{thru}} \times \mathcal{X}^s_{\text{thru}} |\\ &\qquad \text{A}(x^{s-1}_{\text{corr}}) \subseteq \text{A}(x^{s-1}_{\text{strip}}) \wedge \text{A}(x^s_{\text{corr}}) \subseteq \text{A}(x^s_{\text{strip}})\}).\end{aligned}$$

The optimization is otherwise analogous to searching for the drivable corridor with the highest probability in a single segment, except that the search space is four-dimensional now. Though it is still guaranteed that the found corridor is acceptable if the preconditions hold, it is not guaranteed anymore that it is the one with the highest probability of being acceptable.

Note that preconditions (3) and (4) cannot be verified online by the automated driving system since it would require knowledge of the ground truth. For this reason, these preconditions state the requirements on the perception system. Certainly, they are less strict than requiring an unambiguous and correct representation of the road.

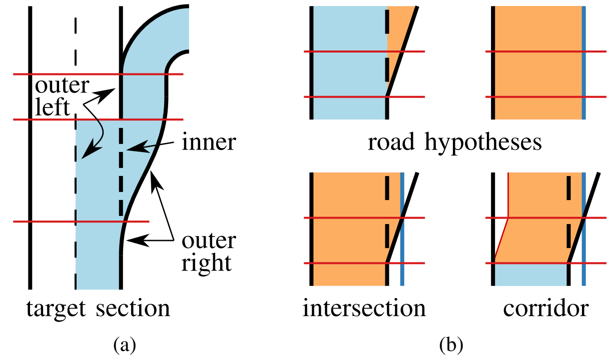


Fig. 6. Exit corridor inference. (a) Target section. It comprises the exit lane and the rightmost thru lane as long as it is legally allowed to change to the exit lane. After that point the exit lane is regarded as the new thru lane. (b) Intersection area and inferred corridor for the given road hypotheses.

E. Exit Corridor Inference

The inference of an exit corridor is structured similarly to the inference of a thru corridor. The important difference is that the target section spans both the thru and the exit lane if they exist in a segment. This is illustrated in Fig. 6a. For simplicity, precondition (4) is formulated stricter compared with the thru corridor inference. It is assumed that the intersection area of all hypotheses about the target section already constitutes a drivable corridor.

The algorithm is listed in Fig. 7. The first step is again to infer the intersection area in each segment. The self-consistency of road hypotheses (cf. Section III) implies that the area is legally traversable over its full width with respect to all road hypotheses. If there was a contradicting hypothesis, for example, as depicted in Fig. 6b, the respective boundary hypothesis would be picked as the right boundary of this road hypothesis' target section and the intersection area would be restricted by this boundary. Thus, it is impossible that the intersection area conflicts with any boundary

1: **function** INFER EXIT CORRIDOR (
road hypotheses $\mathcal{X}_{\text{road}}$,
ordered segments S in desired horizon)
precondition (1-3)
precondition (4b) drivable$(\bigcap \mathrm{A}(\text{target}(\mathcal{X}_{\text{road}})))$
precondition (5) $(\forall x \in \mathcal{X}_{\text{road}})$ x is consistent
2: $\hat{x}_{\text{corr}} \leftarrow ()$
3: **for each** segment s in S
4: $\mathcal{X}^s_{\text{target}} \leftarrow \text{target}(\text{seg}(\mathcal{X}_{\text{road}}, s))$
5: $B^s_{\text{left}} \leftarrow \text{sort}(\text{left}(\mathcal{X}^s_{\text{target}}), \text{right to left})$
6: $B^s_{\text{right}} \leftarrow \text{sort}(\text{right}(\mathcal{X}^s_{\text{target}}), \text{left to right})$
7: $\mathcal{B}^s_{\text{inner}} \leftarrow \text{inner}(\mathcal{X}^s_{\text{target}})$
8: **if** $\{x^s_{\text{bnd}} \in \mathcal{B}^s_{\text{inner}} | x^s_{\text{bnd}} < \text{first}(B^s_{\text{right}})\} \neq \emptyset$
9: $b^s_{\text{right}} \leftarrow \text{first}(B^s_{\text{right}})$
10: $\hat{x}^s_{\text{corr}} \leftarrow (\text{parallel}(b^s_{\text{right}}, -w), b^s_{\text{right}})$
11: **else**
12: $\hat{x}^s_{\text{corr}} \leftarrow (\text{first}(B^s_{\text{left}}), \text{first}(B^s_{\text{right}}))$
13: **end if**
14: $\hat{x}_{\text{corr}} \leftarrow$ append $\hat{x}^s_{\text{corr}}$ to $\hat{x}_{\text{corr}}$
15: **end for**
16: **return** $\hat{x}_{\text{corr}}$
postcondition drivable$(\hat{x}_{\text{corr}})$
postcondition $\hat{x}_{\text{corr}}$ is acceptable
postcondition $\hat{x}_{\text{corr}}$ is legally traversable
17: **end function**

Fig. 7. Corridor inference algorithm in case the goal is to take the next exit from the current roadway. To be more descriptive, the formulation is specialized on exits to the right. A generic version can handle exits on both sides. The computation of the corridor width w is omitted for simplicity.

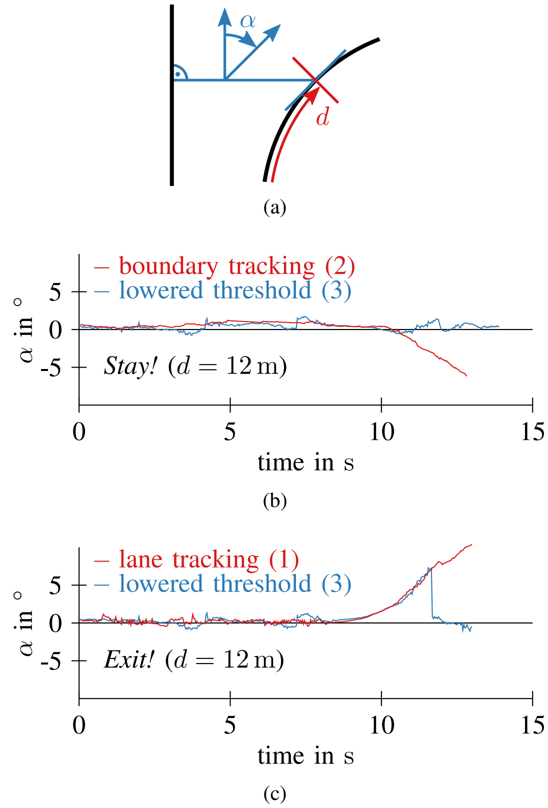


Fig. 8. Evaluation at a highway exit. (a) The orientation difference α between the planned path (right) and the desired path (left) is evaluated at run length d ahead of the vehicle's front axle and at the projection of that point onto the desired path. (b) Behavior when the goal is to stay on the roadway. With configuration (2), the system perceives a widening thru lane and the planned path diverges from the desired path. Eventually, the lane hypothesis is considered implausible because of its width and no path is planned anymore. With configuration (3), the lane marking is detected early enough and the planned path follows the desired path. (c) Behavior when the goal is to take the exit. With configuration (1), the system perceives no exit lane and the planned path follows the thru lane. With configuration (3), the exit lane is perceived eventually. From that point, the planned path is parallel to the desired path again.

that is not legally or safely traversable. The consistency of road hypotheses is therefore listed as precondition (5).

In case the intersection area contains parts of an exit lane hypothesis, the left boundary is set parallel to the right boundary (line 8 in Fig. 7). If the exit lane is in conflict with another road hypothesis, the inferred corridor only comprises a part of that exit lane (cf. Fig. 6b). The experimental system only selects the inferred exit corridor if it is fully compatible with at least one exit lane hypothesis. Otherwise, the thru corridor is selected. Note that in order to infer an exit corridor, not all road hypotheses need to contain an exit lane. For example, one hypothesis may consist of a widening thru lane and another of a thru and an exit lane in the same area.

V. EXPERIMENTAL EVALUATION

The focus of the experimental evaluation is on the benefit of being able to represent and consider multiple road hypotheses instead of only a single one. The corridor selection algorithms are evaluated at a highway exit. Although this is a quite ordinary scenario, in practice test vehicles may show an undesired behavior when no highly accurate map is available. Because of conventional systems' limited capability of reasoning about multiple road hypotheses, they instantiate new boundary hypotheses rather conservatively to avoid false-positive detections. Thus, in case an exit occurs, depending on whether a lane tracking [17] (a coupled tracking of parallel markings recognized as lanes) or an independent tracking of boundaries [18] is used, no hypothesis for the right boundary of the exit lane or for the inner boundary between thru and exit lane might be instantiated (at first). Consequently, only the thru lane (cf. [13]) or a widening lane might be perceived, respectively. As an experiment, the initialization threshold for new boundary hypotheses is lowered to increase the likelihood of detecting all relevant markings. Thereby the likelihood of false-positive detections increases, of course.

To measure the effect on the behavior of the automated vehicle, additionally to the performance measure discussed in Section IV-A, also the planned path of the vehicle is evaluated. The planned path is assumed to be the central path in the selected corridor (cf. Fig. 3). For the evaluation, a similar approach as in [12] is chosen. The planned path is compared with a desired path by the difference in their orientations α, as illustrated in Fig. 8a. The difference α is especially interesting at the point relevant for motion control because it directly affects the steering of the vehicle. For an assumed latency of the overall system of $0.5\,\mathrm{s}$ and a velocity of $85\,\mathrm{km/h}$, a rough estimate of this point is $12\,\mathrm{m}$ ahead of the front axle of the vehicle.

The experiments were carried out in open-loop mode with a camera-only perception system resembling the approaches described in [17] and [18]. The desired path was generated from a set of recorded paths driven by a human driver. The estimated accuracy of the absolute localization was better than $10\,\mathrm{cm}$ throughout the experiments. Three configurations were tested: (1) the original (conservative) parameter set in combination with lane tracking, (2) the original parameter set with independently tracked boundaries, and (3) a lowered initialization threshold for new boundaries with an independent boundary tracking again. For each configuration, the planned paths for staying on the roadway and for taking the exit were compared with the corresponding desired paths.

With configuration (1), only the thru lane is perceived and no exit corridor can be inferred. The planned path thus follows the thru lane, even if the goal is to take the exit, as can be seen in Fig. 8c. With configuration (2), a widening lane is perceived at first and the vehicle pulls to the right (Fig. 8b). This is, though unintentional, an acceptable behavior if the goal is to take the exit. The selected thru corridor is not acceptable, because it crosses the right boundary of the true thru lane. The resulting behavior is at least undesirable and may be unacceptable, depending on whether the boundary between thru and exit lane is detected and reacted to before the vehicle traverses it. Decreasing the initialization threshold in configuration (3) increases the number of false-positive boundary detections, but also leads to an earlier detection of the true boundary between thru and exit lane. During the experiments, at all times an acceptable corridor was selected, fulfilling the primary performance measure (Section IV-A). In contrast to configurations (1) and (2), configuration (3) enables the automated vehicle to follow the desired path for both navigational goals, even if the exit maneuver is initiated later compared with the human driver.

VI. Conclusion and Future Research

The experimental results show that considering semantic uncertainty in the process of action planning can improve the driving performance of an automated vehicle; here by reacting faster or at all to a changed situation. The performance of the overall system can only be improved in a certain performance range of the perception system though. The multi-hypothesis road representation allows to reason about contradicting road hypotheses. Probabilities of partial hypotheses and areas of conflict are inferred efficiently. The corridor inference is implemented by using basic graph-search algorithms. Though formulated with respect to a concrete scenario, the algorithms' core principles are generic and scalable. It was shown that the requirements on the perception system can be relaxed. They correspond to the stated preconditions of the corridor inference algorithms.

Selecting a corridor when road hypotheses are in conflict requires weighing potential consequences and their probability of occurrence. The focus of future research is thus to gain reliable confidence measures for road hypotheses and to integrate reasoning about consequences in the process of decision making.

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