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Lane Identification and Ego-Vehicle Accurate Global Positioning in Intersections

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***Abstract*–This paper proposes a method for achieving accurate ego-vehicle global localization with respect to an approaching intersection; the method is based on the data alignment of the information from two input systems: a Sensorial Perception system, on-board of the ego-vehicle, and an *a priori* digital map. For this purpose an Extended Digital Map is proposed that contains the detailed information about the intersection infrastructure: detailed landmarks accurately measured and positioned on the map. The data alignment mechanism is thus based on superimposing the sensorial detected landmarks with the corresponding, correctly positioned map landmarks stored in the new Extended Digital Map. The data Alignment Algorithm requires as input, beside the information from the two input systems, the ego-vehicle driving lane. This information is inferred by using a probabilistic approach in the form of a Bayesian Network; the uncertain and noisy character of the sensorial data require such a probabilistic approach in the quest of the ego-lane.**

I. INTRODUCTION

The problem of navigation is an intensely research topic in the context of driving assistance systems and of autonomous driving. Ego-vehicle global localization is one of the important matters regarding navigation, in all the driving contexts: urban environments (roads, U-turns, intersections), highways etc.. Research has been conducted in the direction of combining information from various input systems: (1) GPS and vehicle sensors (VS), (2) on-board perception systems (3) digital maps (standard digital map, RNDF [1]), (4) infrastructure monitoring systems and cooperative systems (vehicle-to-infrastructure and vehicle-to-vehicle communication [2-3]) for achieving accurate global localization.

In [4] a Kalman filter is used to integrate vehicle sensors information (in state prediction) with DGPS information (in update stage) and for localization. The employed dynamic model is a bicycle model. The authors also recognize the usefulness of a digital map with high precision for accurate localization, in some specific cases (U-turn overlapped with GPS outages), but also underlined the shortage of such a map for commercial use.

In [5], the authors propose to combine data from: GPS, vehicle sensors (steering angle sensors, odometers), vision sensors and a very precise digital map, in an iterative process (a Particle Filter) for estimating the localization parameters. The vision information provides the position and the orientation of the vehicle, with respect to a lane side; then digital map is then used to transform this information into a global reference. In this approach, a high definition NavTech map is available.

The problem of accurate vehicle localization is resolved in [6] also by using a Particle Filtering based on feature extraction from a predicted image. The image is created from the map feature data. The approach combines the image landmarks, information from vehicle odometry and information from a low-cost Global Navigation Satellite System (GNSS) receiver.

The solution proposed in [7], for vehicle localization in urban environments has as a centerpiece a detailed digital map of the environment, containing features useful for localization: lane markings, tire marks, pavement etc. For the building of the map state-of-the-art equipment is used (INS, SICK laser range finders, GPS). The built map is then used to correlate the on the spot LIDAR measurements with the ones on the map. Table I summarizes the accuracy of some of the proposed localization methods.

The special case of intersection has received a great attention; European projects such as SAFESPOT [8] and INTERSAFE [9] have dedicated their efforts towards improving traffic safety in intersections. In [9] the concept of Local Dynamic Map (LDM) [3] is introduced, as a form of world modeling. The LDM is a hierarchical structure, containing both the static information about the road structure (from digital maps), as well as the temporary and dynamic information about the environment traffic (from on-board perception system and from the infrastructure).

The idea introduced in [10] is to model the environment in the form of a network, a graph of the road. The road is structured in the form of a graph, where an edge represents a lane and the nodes joints of edges. The advantage of the proposal is that the smallest unit in the environment representation is now the lane, and not the road, hence environment representation becomes much more detailed.

The same idea of combining the information from various resources (on-board sensors, digital map, cooperative systems, and route planner) is found in [11]. What the approach brings new is the Object Oriented architecture of the world model, which has several advantages: extensibility, reusability (due to the API), interoperability, real-time performance.

In [12] a Bayesian Network (BN) [13-14] approach is used in order to localize a possible intersection; for this the information from an on-board detection system is fused with the information from a data base that stores minimal *a priori* road information. The idea is continued in [15], where a similar mechanism is used, this time for Lane Detection.

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An accessible solution for Lane Identification is presented [16], using only standard GPS receivers and inter-vehicle communication. Using that the absolute positioning errors are common errors for GPS receiver relatively close to each other (the same principle is used by DGPS), the solution uses the relative distances between GPS rovers' measurements (in a Markov localization process) to estimate the lane positions, of the different vehicles that communicate.

TABLE I COMPARISON OF POSITION ACCURACY IN THE LITERATURE

Ref	Sensors	Lateral Position Error	Longitudinal Position Error
[5]	GPS + VS + Map +Vision	0.08 m	0.48 m
[6]	GPS + odometry + Map +Vision	0.35 m	0.77 m
[7]	GPS + IMU + odometry + LIDAR + built map	<0.1m	<0.3m

This article continues the idea of fusing the information of an on-board visual perception system with the data from an *a priori* digital map, in order to improve the ego-vehicle global positioning. The visual perception system (which will also be referred to as sensorial, in this paper) detects and classifies objects in the environment (road landmarks, other vehicles, pedestrians, poles). The idea of the proposed method is to align the road lateral and longitudinal landmarks obtained through visual analysis (lateral lane delimiters and stop-line), with the corresponding map landmarks, accurately measured. For this purpose, an Extended Digital Map (EDM) that contains the precise measurements of the road landmarks, required for the data fusion with the visual information, is proposed. This solution is especially dedicated to the special case of intersections, in the effort of improving safety in this accident-prone segment of road. There exist several applications that require the accurate localization prior to an intersection: (1) an enhanced environment representation -obtained by combining the information from the visual perception system with the information from the EDM; (2) an intersection traversal module - that uses the information from the enhanced environment representation in order to establish the possible trajectories of the ego-vehicle through the intersection; (3) a collision avoidance system for intersections - that establishes the possible collision points. This approach uses the specific road landmarks detected by the visual perception system (stop-line, lateral lane delimiters, painted arrows) for localization, therefore this solution is limited to those segments of roads containing the upper mentioned landmarks.

II. The Proposed Solution

Fig. 1 illustrates the logic scheme of the proposed approach. The initial position of the ego-vehicle is given by a standard GPS receiver, whose precision is of order of meters. This value is used in the map-matching algorithm, in order to detect the road-way, joint to the intersection, on which the ego-vehicle is travelling, while approaching the intersection. The map information corresponding to this identified way is the one that is used in the data alignment process. The localization method consists of two steps:

The first step (Lane Identification) is to identify the lane of the road-way, on which the ego-vehicle is travelling on. This information is necessary for the lateral alignment of sensorial (visual) data, with map data. The proposed approach for Lane Identification is in the form of a Bayesian Network, which performs reasoning based on the sensorial information and on the additional new map information, from the EDM.

The second step (Data Alignment), consists of superimposing the information about the same landmarks: stop-line and lateral lane delimiters, from the two data input sources, in different Coordinate Systems (CS): Vehicle Coordinates (VC) and World Coordinates (WC)). For the longitudinal alignment the relative position of the visually detected stop-line is required, while for the lateral alignment, the ego-lane is necessary.

Even if the sensorial information is used in both steps, this is not redundant since different data are being used: for Lane Identification – lateral landmarks (lateral delimiters type, painted arrows type and information deduce from reasoning on other visually detected objects) and for Data Alignment – longitudinal landmarks (the stop-line in VC) (see Fig. 1).

III. The Sensorial Perception System and The Extended Digital Map

A. *The Sensorial Data Preprocessing & Reasoning*

The primary source of information about the surrounding environment is an on-board stereo-camera system [17] (sensorial perception system). This system is beyond the scope of this paper, and only the data provided by it is used as input data to the proposed solution. It provides the following structured representation of the environment: the parallelepiped form of the detected objects, as well as their classification (cars, pedestrians, poles, painted road markings: lateral lane delimiters, painted arrows, stop-lines). Also the information about the ego-lane and lateral curbs is provided. For cars, their relative speed with respect to the ego-vehicle speed is also provided.

In the Sensorial Data Preprocessing & Reasoning module, the sensorial data is processed such as to provide to the Lane Identification module the information in the required format, and that is:

- the type of the *Left* and *Right Delimiters* (*Double, Single, Curb*) of the ego-lane,
- the type of *Lane Painted Arrow* (*forward, left, right, left-forward, right-forward*) detected on the ego-lane,

the type of the ego-lane (*leftmost (LM), rightmost (RM), middle (M)*) inferred from the information from the *other vehicles*, from the lateral *distance to lateral lane markings* and from the lateral *distance to curb*. For this, some basic reasoning is done using simple decision trees, with information from both the sensorial perception as well as from the digital map.

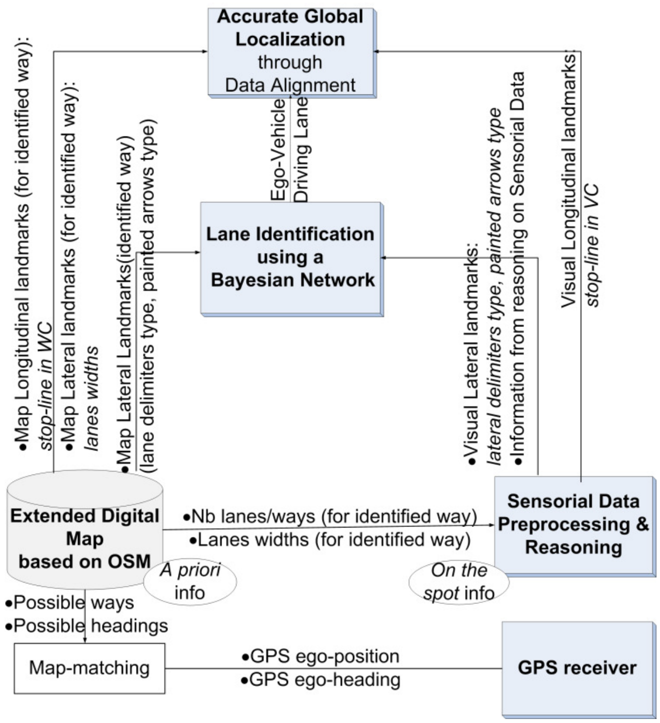


Fig. 1 Logic schema for accurate global localization using the identified lane, in intersection

It is important to mention that, in this approach, the general case when there are three lanes per driving direction are taken into consideration. For more lanes per way further research is required.

B. *The Extended Digital Map*

In order to perform the data alignment of the sensorial information, with the *a priori* information about the road infrastructure, in the demarche of achieving accurate global positioning, a system is required to store this accurate and precisely measured information about the road. The necessity of a detailed digital map, for driving assistance systems has been widely recognized and researches exist in this direction of building such maps ([18], TeleAtlas, NavTech), even if they still are not commercially available. Therefore, for the purposes of this approach, a model of such a required high precision map has been designed and built, using as a starting point the open source digital map *Open Street Map* (OSM) [19]. This map provides only the basic information about the streets and intersections. The proposal is to extend this information with additional information about the detailed road geometry, near the intersections.

The information required by the data alignment is called the *necessary information.* Examples of such information are: the number of lanes per way, the width of each lane, the lane lateral delimiters types, the lane painted arrows, the global coordinates of the center of each lane and of the stop-line.

Additional *useful information* for improving the ego-vehicle's knowledge about the navigation environment (such as: the possible directions of navigation through the intersection or in-out lane pairs, risk level attributes etc.), for a potential driving assistance system, can be added.

The implementation idea of the EDM is the following: use the existing database structure and build on top of it, such that the existing information will not be modified. Similar tables with the existing ones are created to store the additional information proposed and to make the joint with the existing tables. An additional primitive is introduced: the *lane* data primitive; this is the smallest unit in the road geometry. This way information about each lane (*laneWidth, leftDelimiter, rightDelimiter, paintedArrow* etc.*)* is added in the database in the form of key-value pairs (e.g. (key = *laneWidth,* value = *3.2*), (key = *leftDelimiter,* value = *double*), (key = *paintedArrow,* value = *forward*). Adjoint lanes do not share the lane marking information. The information about the painted arrows is limited for now to their type: *forward, left, right, leftForward, rightForward* etc. The additional information has a similar structure with the existing one. Also, the XML formatted structure of the .osm file is kept; the new information is structured in a compatible way: the attributes are in the form of tags with (key, value) pairs.

IV. Lane Identification using a Bayesian Network

A. *Introduction to Bayesian Networks*

BNs are part of the family of probabilistic graphical models, combining principles from mathematical and engineering domains: probability theory, statistics, and graph theory. They are used to model cause – effect relations. A BN is a representation of a joint probability distribution (JPD) over a finite set of discrete random variable. It has two components:

(1) $G(V,A)$ the DAG whose nodes $\{X_1, .., X_n\} = V$ correspond to the random variables, and whose set of arcs A define the direction of influence between nodes. The graph G encodes the conditional independence assumption: each variable is independent of its non-descendents given its parents in G.

(2) Θ the set of parameters of the network, i.e. the set of all the conditional probabilities of all the variables given its parents:

$$\Theta = \{P(X_i \mid \pi_{X_i}) : X_i \in V\} \qquad (1)$$

where π_{Xi} stands for the set of parents of X_i. If X_i is a root node, then π_{Xi} is empty and the expression $P(X_i|\pi_{Xi})$ simply stands for the prior probability of X_i. Together, the probabilities collectively quantify the probability distribution associated with the variables in the graph. Due to the graph's conditional independence property and by applying the chain rule of probabilities, the JPD can be decomposed:

$$P(X_1, X_2, ... X_n) = \prod_{i=1}^{n} P(X_i \mid \pi_{X_i}) \qquad (2)$$

The advantage of having the JPD in a factored form is that it is possible to evaluate all inference queries by marginalization, by summing out over irrelevant variables.

One of the most important aspects in the BN is the *inference mechanism* [15]. In any BN there are two types of nodes (evidence/observed nodes & query nodes). The inference mechanism computes the posterior probabilities (or beliefs) for the variables that are queried, given the evidence of the observed variables. There are more algorithms that perform inference in BN: polytree (Pearl's algorithm [20]), variable elimination algorithm, variation message passing, relevance tree and others.

B. The Modeled BN for Lane Identification

The uncertain and noisy nature of the sensorial information requires a probabilistic mechanism that performs well even under such conditions, therefore the Bayesian Network for Lane Identification was a suitable approach. Based on the theory, the BN in Fig. 2 was modeled to suit the current problem.

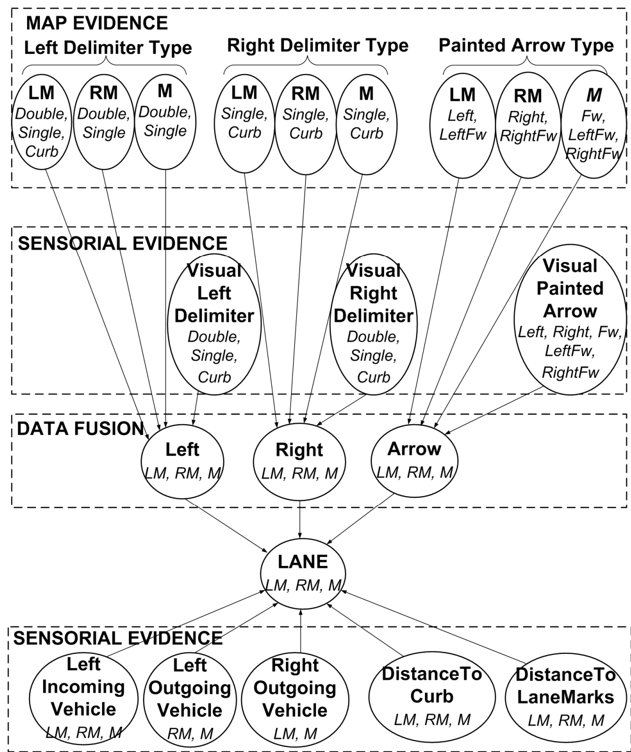


Fig. 2 The modeled Bayesian Network for Lane Identification; the nodes with their corresponding states (*LM = Leftmost lane, RM = Rightmost lane, M = Middle lane, Fw = Forward*).

Each node has several states (see Fig. 2) with corresponding probabilities. The root nodes are defined through *a priori* probabilities; while the child nodes are define through CPTs. In the proposed BN:

(1) *the evidence nodes* contain either Map or Sensorial (Visual) information. All of them are root nodes, so *a priori* probabilities are initially set for them. These probabilities change when evidence is being brought to the BN, from the EDM or from the sensorial data.

(2) *the query nodes* (*Left, Right, Arrow* and *Lane*), are child nodes and their probabilities are initially set based on modeled CPTs. Their beliefs change according to the evidence brought by the Map and the Sensorial System, i.e. they change according to the evidence nodes, through an inference algorithm. They answer to questions such as: "*what ego-lane type is inferred from the left side lane delimiter information?";* or, the main question, "*what ego-lane type is inferred from all the map and sensorial information?"*. As it can be seen in Fig. 2, the *Left, Right* and *Arrow* nodes perform the data fusion of information from the two input system. The *Lane* node is the final node; all the other nodes serve as evidence for this node. Its CPT table contains 3^6*2^2 rows (6 parent nodes with 3 states and 2 parent nodes with 2 states).

C. Example of BN Inference

The algorithm used is in this approach for BN inference is *Pearl's (Polytree) algorithm*; the belief of a node in a polytree is computed by the formula:

$$Bel(X) = P(x \mid e) = \alpha\pi(x)\lambda(x) \qquad (3)$$

This inference method is also known as message passing; the information necessary for belief computation reaches the node through messages. There are two types of messages:

(1) from parents to children $\pi(x)=P(x|e^+)$ – transmits the a priori evidence of the parent to the node

(2) from children to parents $\lambda(x) =P(e^-|x)$ – transmits the likelihood evidence, i.e. the belief of the child node based on the evidence of the parent node.

In the proposed approach the interest is in the causal-parameters, hence we are interested in the $\pi(x)$ messages. For the case of multiple parents $U_1,\dots U_p$ of child X, the causal parameter is compound:

$$\pi(x) = \sum_{u_1,\dots u_p} P(x \mid u_1,\dots u_p)\prod_{j=1}^{p} \pi_X^{U_j}(u_j) \qquad (4)$$

Consider the case in which the ego-vehicle is approaching the intersection on a segment of road which has the following configuration illustrated in Fig. 3(a). This observation sets the evidence for the nodes in the Map Evidence layer; therefore their *a priori* probabilities are: *P(MapLMLeftDelim=Double)=1; P(MapRMLeftDelim= Single)=1; P(MapMLeftDelim=Single)=1; P(MapLMRightDelim=Single)=1; P(MapRMRightDelim= Curb)=1; P(MapMRightDelim=Single)=1; P(MapLMPaintedArrow =Left)=1; P(MapRMPaintedArrow =Right)=1; P(MapM PaintedArrow=Fw)=1;*
and all the other map probabilities are 0. In order exemplifying how the inference mechanism works, let us consider the node *Left*, and imagine the case when the visual systems detects as *LeftDelimiter* a *Double* line. The belief of node *Left* is computed according to equation (4), hence

$$\pi(LM) = \dots + P(LM \mid D,S,S,D)\pi(D)\pi(S)\pi(S)\pi(D) + \dots$$

where *D* is *Double*, *S* is *Single* and *LM* is *Leftmost*, i.e,.

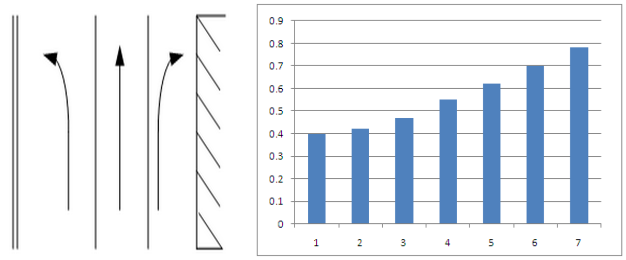
$$\pi(LM) = 0 + \dots + 0.9*1*1*1*1 + \dots 0 = 0.9,$$

where the value of $P(LM|D,S,S,D) = 0.9$ is from the *Left* node's CPT. Using equation (3) and the fact that $\lambda(LM)=1$ from the initial conditions of the Polytree algorithm:

$$P(LM) = \alpha\pi(LM)\lambda(LM) = \alpha * 0.9 * 1 = 0.9,$$

where α is normalization constant equal to 1, in this case. Similarly, $P(RM) = P(M) = 0.05$.

This demonstrates how the inference mechanism works in the BN. In a similar way, the belief of node *Lane* changes according to different observations brought by the visual perception systems to the Sensorial Evidence nodes. For the same map evidence as previously, Fig. 3 (b) illustrate how the belief of the node Lane increases when sensorial information sustains the *Lane=LM*.



(a) (b)

Fig. 3 (a) Map Evidence from the EDM (b)Lane node's belief when the following sensorial information is being added to the BN: (1)*P(Left=LM)=0.9* (2)*P(Right=LM)=0.48* (3)*P(Arrow=LM)=0.9* (4)*P(VisualLeftIncoming=LM)=1* (5)*P(VisualRightOutgoing)=1* (6)*P(VisualDistToCurb)=1* (7)*P(VisualDistToLaneMarks)=1*

V. Ego-Vehicle Global Localization through Data Alignment

Finally, after obtaining the ego-vehicle driving lane, the Alignment Algorithm (AA) can be used to attain the accurate global position. The AA is dedicated to the intersection scenario. The sensorial landmarks are in VC, and represent their relative position with respect to the ego-vehicle. The same landmarks exist in the EDM, in WC. By superimposing the same landmarks, from the two input system, through a series of geometric transformations, and by applying the same transformations to the ego-vehicle coordinates, the improved ego-vehicle global position is achieved. The steps of the AA:

(1) A *preprocessing* step: in which the data is brought into the same CS: East North UP (ENU) [21].

(2) 1^{st} step: *rotate* the sensorial stop-line around the ego-vehicle coordinates such as to superimpose it to the map stop-line.

(3) 2^{nd} step: *longitudinally translate* the ego-vehicle's coordinates and the previously rotated sensorial stop-line until the latter it superimposes the map stop-line.

(4) 3^{rd} step: *lateral translation* - uses the identified ego-lane; the ego-vehicle's coordinates and the previously translated sensorial stop-line are again translated, until the latter superimposes the map stop-line segment identified to correspond to the ego-lane. The new obtained ego-vehicle coordinates gives the improved ego-vehicle global localization.

VI. Experimental Results

A. The Bayesian Network Evaluation

The BN approach for Lane Identification is considerable better than any deterministic if-clause based mechanism, since it probabilistically takes into account all the pieces of information and fuses it, in order to infer the most probable output. It is a suitable method since it works well even under conditions of uncertainty, specific to the visual perception systems. Experimental results show that as the system provides more evidence about the position of the vehicle on one lane, the probability of that particular lane increases. If the evidence is noisy, uncertain or contradictory, the network still performs well according to our experiments. For contradictory map and sensorial information the probabilities of the lanes will be more distributed, but still the lane with the largest accumulated evidence (even if the difference in small) will be the winning one. In Fig. 4 it is illustrated how the states of the Lane node fluctuate for different situations.

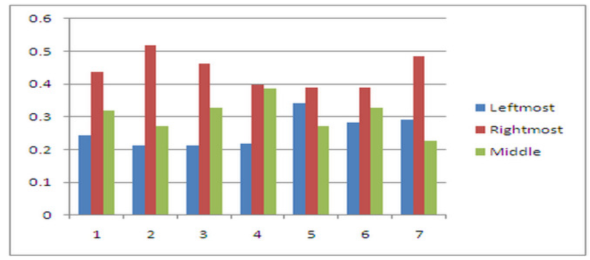


Fig. 4 Example of adding contradictory information to the BN (1) same evidence from the sensorial and map data for RM lane, then *P(RM) = 0.437*; (2) if add VisualPaintedArrow as in Map, *P(RM) increases to 0.52*; (3-5) else, if add VisualPainedArrow different from Map, *P(RM) decreased* (7) if no VisualPaintedArrow, but VisualDistToCurb = RM and LeftIncoming = LM, *P(RM) increases to 0.482.*

The method was tested for more than 120 situations in which, only different input sensorial data was taken into consideration, the results are encouraging (Table II).

TABLE II BN EXPERIMENTAL RESULTS

Correct	Correct (1%-3% diff.)	Incorrect (1%-3% diff.)	Incorrect	Equal probability
0.75%	0.09	0.01	0.125	0.025

B. The Alignment Algorithm Evaluation

The AA method for global localization was successfully implemented and experimented in some specific intersection scenarios. For this purpose, the infrastructure of the intersections in question was modeled in detail using satellite images and on the spot high precision measurements, done using GNSS equipment (Leica 1200 Series System). The tests consisted of the ego-vehicle approaching the intersection from one of the measured roads. The initial GPS ego-vehicle position was obtained with a standard GPS receiver (precision ≈ 5 m, update ≈ 1 Hz). The GPS obtained ego-vehicle position was corrected using the AA. Fig. 5 illustrates an example of the GPS global localization and of the AA corrected positions; for longitudinal positioning the visually detected stop-line is used, while for lateral positioning, the lane number (Middle) obtained from the BN. GPS_Pos1-2 are the 1^{st} and 2^{nd} GPS readings when the stop-line is first detected, at distances 20m, 15m respectively; AA_Pos1 and AA_Pos2 are the corrected positions. Similar, GPS_Pos3-8 are the GPS readings when the stop-line is visually detected at distances 14m, 13m, 12m, 10m, 9m, 8m; AA_Pos3-8 are the corresponding corrected positions. Finally, GPS_Pos9-10 are the GPS readings when the detected stop-line is at distances

3m, 4m respectively, and AA_Pos9-10 are the corrected values - the red triangle illustrates the ego-vehicle's origin and the detected stop-line.

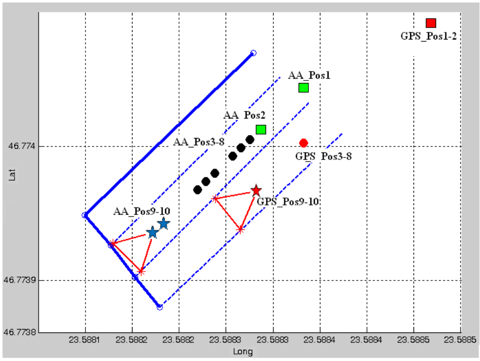


Fig. 5 Example of the GPS readings vs. AA corrected positions against a road segment prior to an intersection, in LL coordinates.

The proposed solution considerably improves the standard GPS localization, reducing the error from orders of meters to orders of centimeters (Table III - the reference point selected for comparing the GPS and AA results is the middle of the identified ego-lane, at the detected distance to the stop-line).

TABLE III AA EXPERIMENTAL RESULTS

Method	Mean Absolute Position Error	Mean Lateral Position Error	Mean Longitudinal Position Error
GPS	10.6 m	6.5 m	7.7 m
AA	0.18 m	0.12 m	0.10 m

VII. CONCLUSION AND FUTURE RESEARCH

This method uses an on-board visual perception system together with a detailed digital map (based on OSM) in the process of accurate global localization prior to an intersection. Through this method, the ego-vehicle global improves considerably the positioning given by the standard GPS. The precision of the AA is given by the accuracy of the sensorial perception (the stop-line detection accuracy, is in the range of 0.5%.. 3% with better accuracy in the near range, up to 10 m the errors are below 2%). Hence, the method's performance is given by the visual perception system's performance.

Future research include: introducing a Dynamic BN for temporal inference of the ego-lane, studying the case with more than three lanes per way.

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