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Probabilistic Approach for Automated Reasoning for Lane Identification in Intelligent Vehicles

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Abstract— **This paper proposes a probabilistic model for automated reasoning for identifying the lane on which the vehicle is driving on. The solution is based on the visual information from an on-board stereo-vision camera and *a priori* information from an extended digital map. The visual perception system provides information about on-the-spot detected lateral landmarks, as well as about other important traffic elements such as other vehicles. The proposed extended digital map provides lane level detail information about the road infrastructure. An Object-Oriented Bayesian Network is modeled to reason about the lane on which the ego-vehicle is driving on using the information from these two input systems. The probabilistic approach is suitable because of the uncertain and inaccurate nature of the sensorial information. Due to the need of lateral painted landmarks, the method is dedicated to the segment of roads linked to an intersection.**

Keywords-component; Intelligent vehicles, information modeling, Object-Oriented Bayesian Network, automated reasoning, lane identification

I. INTRODUCTION

In the field of intelligent vehicles, the in-vehicle Advance Driving Assistance Systems (ADAS) are based on the perception and interpretation of the vehicle's surrounding. In order to make the road a safer and friendlier environment, the next generation of ADAS must be able to evaluate the situation in which the ego-vehicle is in, based on the sensorial perceived information and suggest (or even apply) the best course of action.

The sensorial perception of the environment is characterized by uncertainties and inaccuracies; state of the art literature suggests the use of probabilistic approaches for handling the uncertain and inaccurate sensorial information, in the direction of solving problems such as: identifying driving situations, situation assessment, detecting and estimating the driver maneuvers. Alternatives of probabilistic models are: evidence theory, Dempster-Shafer theory, Bayesian networks etc.

In this paper the problem of identifying the lane on which the vehicle is driving on is addressed. A solution is proposed based on a Bayesian network [1] model that uses sensorial information from a stereo-vision system [2], together with information from a proposed extended digital map [3].

The remaining of this paper is structured in the following way: Section II presents the hierarchical description of the proposed solution; Section III presents the modeling of the solution in the form of a Bayesian network (BN). In Section IV the experimental results of the proposed approach are illustrated and in Section V the conclusions are being drawn.

II. HIERARCHICAL DESCRIPTION OF THE PROPOSED SOLUTION

The problem of lane identification is modeled in several levels illustrated in Figure 1. In the first level, the information about the lateral landmarks (type of lane delimiters and type of painted arrows) from both the digital map and the corresponding visually detected lateral landmarks is modeled (Visual Information I). In this level, the ego-lane is identified based on the matching of the type of lane delimiters from the two input systems. The second level of the architecture provides additional information about other visually detected traffic elements, such as: other vehicles. If such traffic elements are detected, they also help to reason about the ego-lane. In the third level, the ego-lane is identified based on the information in the first two levels.

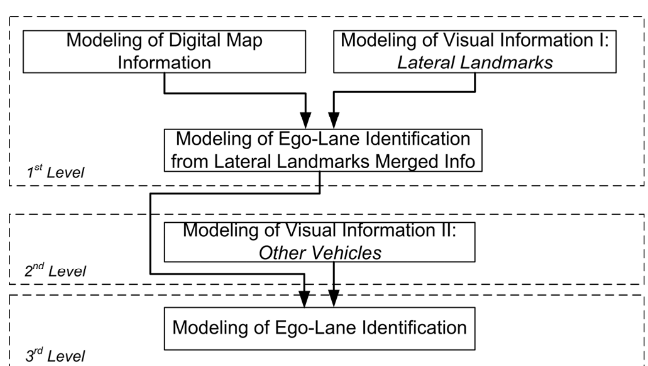

Figure 1. Hierarchical description of the proposed solution

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III. MODELING OF THE LAYERS IN THE HIERARCHICAL STRUCTURE

Based on this hierarchical structure, the Bayesian network in Figure 2 is proposed as a probabilistic model for automated reasoning for identifying the lane on which the ego-vehicle is driving on. The proposed BN follows the three previously described layers.

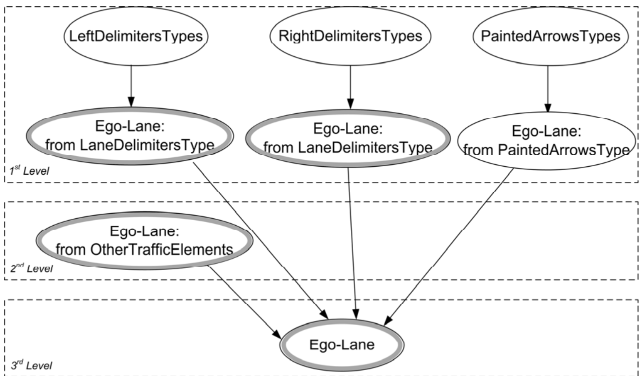


Figure 2. The structure of the proposed Bayesian network

A. *Modeling of the Digital Map Information*

Digital maps have developed considerably over the last years, and have gained an increasing importance in the driving function: aiding the navigation and assisting the driver. For this, the digital maps have to increase their level of detail, providing more information about the road infrastructure, not only the road centerline, but also information such as: speed limits, road curvature, number of lanes/ way, the lanes' widths etc. In [3] such an extended digital map is proposed based on the free source *OpenStreetMap* (www.openstreetmap.org).

In this approach, the necessary information from the map is about the road geometry (number of lanes of a way per each driving direction, the widths of the lanes), and about the lateral landmarks (the type of lateral lane delimiters and the type of painted arrows, for each lane).

In the proposed BN, the nodes that encode the map information are: *LeftDelimitersType, RightDelimitersType* and *PaintedArrowsType*s. For the first two nodes, the set of states is defined by the type of lateral lane delimiters for all the lanes of the way in question, in the driving direction. Similarly, for the third node, the type of road painted arrows defines the set of states. This information is extracted from the digital map for the road segment on which the vehicle is travelling on. These three nodes are parent nodes to the nodes: *Ego-Lane:fromLeftDelimitersType, Ego-Lane:from RightDelimitersType* and *Ego-Lane:fromPaintedArrows Type;* the states of these nodes are: $L_1, L_2, \ldots, L_n$, the identifiers of the lanes of the way in the driving direction; (n is the number of lanes in the driving direction, the numbering starts from the leftmost lane in the driving direction, to the rightmost one).

The parameters of the nodes in this layer are estimated using Maximum Likelihood Estimation (MLE); for this, the digital map information is used as the training set of data. For the child node, parameter estimation means constructing their conditional probability tables (CPTs), i.e. finding the probability for each state, for each configuration of its parent's states:

$$\theta_{ijk} = P\left(X_i = j \mid pa\left(X_i\right) = k\right) \qquad (1)$$

i = the node, j = the state, k = configuration of parents. Using MLE, each parameter is estimated using the formula:

$$\theta^*_{ijk} = \frac{m_{ijk}}{\sum_j m_{ijk}} \qquad (2)$$

where m_{ijk} = number of cases where $X_i = j$ and $pa(X_i) = k$.

B. *Modelling of the Visual Information I*

The sensorial perception system considered in this paper is a stereo-camera system [2] (field of view 70º and a medium range of 20 meters), mounted on-board of the experimental vehicle. This system provides information about the perceived environment, and constitutes the primary source of information for the proposed solution.

The first type of information used from this system is the perceived type of lateral lane delimiters: type of lane markings [4] and curb information [5]. This information is matched with the map information in order to get a first idea about the lane on which the ego-vehicle is travelling. While the digital map information about the lateral landmarks of the road segment is used as a priori information in the constructed BN, the visual information about the same landmarks provides the evidence for the nodes in the BN that model the map information. It can be observed that both *left* and *right* lane delimiters information is used. This is where the Object Oriented Bayesian Network (OOBN) [6], [7] approach is useful. One of the most challenging tasks in using a BN approach is the modeling of the problem domain and the construction of the CPTs, especially if the scale of the problem is considerably large. The advantage of using an OOBN approach is that it introduces reusability: instances of the same class are being used for the parts of network that appear more than once. In this model, two instance of the same class *Ego-Lane:fromLaneDelimiters Type*, for *left* and *right* lane delimiters are being used (Figure 3).

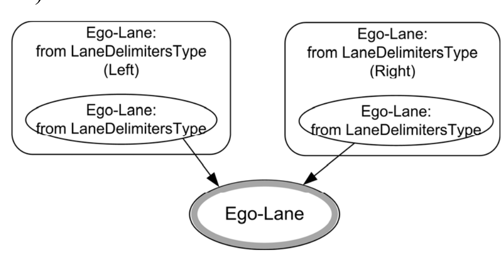


Figure 3. The two instances of the same class in the proposed OOBN

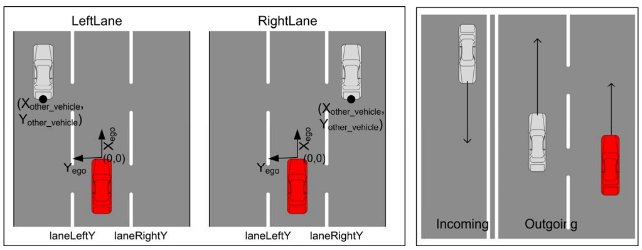
In a very similar way, the information about the painted arrows is modeled.

C. Modeling of the Visual Information II

In the second level of the architecture, the information about other visually detected traffic elements, such as other vehicles is used. The *other vehicles* are classified by the following criteria:

-the relative lateral position: vehicles that are travelling on the *left/right lane* with respect to the ego-lane (Figure 4 (a))

-the relative behavior: vehicles that are *incoming* or *outgoing*, i.e. travelling in the opposite or same direction as the ego-vehicle (Figure 4 (b)). This classification is done based on the relative speed of the detected vehicle with respect to the ego-vehicle's speed, obtained from visual processing, and therefore subject to inaccuracies.



(a) (b)

Figure 4. Other vehicles classification by (a) the relative lateral position (b) the relative behavior (ego-vehicle – red, detected vehicle – white)

Hence, the other vehicles are classified as follows: *LeftIncomming*, *LeftOutgoing* and *Right Outgoing*. For each category a node is modeled in the BN. The states of the nodes are the lane identifiers L_1, L_2,...,L_n.; the prior probabilities are equality distributed over the set of states. These nodes are all instances of the class *Ego-Lane: fromOtherTrafficElements* (Figure 5).

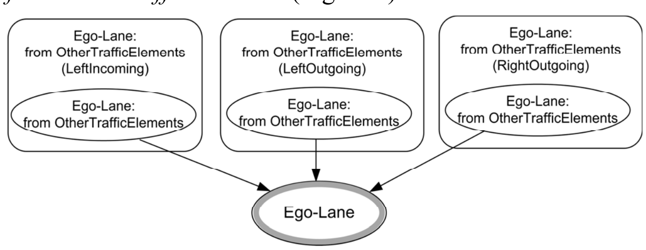


Figure 5. Instances of the class *Ego-Lane:fromOtherTrafficElements*

The computation of the likelihood (soft-evidence) for these nodes is done using the visual information (the relative lateral position, the ego-lane width) and the map information (the number and widths of the lanes, in both directions). Figure 6 illustrates how the discrete probability distribution is computed for a segment of road with three lanes per driving direction, for the scenario in which a vehicle is detected as identified as *LeftOutgoing.* According to the relative distance to the ego-vehicle two situations appear: Situation 1 the relative distance is approximately equal to the ego-lane's width, then the likelihood of this node is P(L_1 ,L_2 ,L_3)= {0, 0.5, 0.5} (top graphic) and Situation 2, the relative distance is about twice the ego-lane's width, then the likelihood is P(L_1, L_2, L_3)= {0, 0, 1} (bottom graphic).

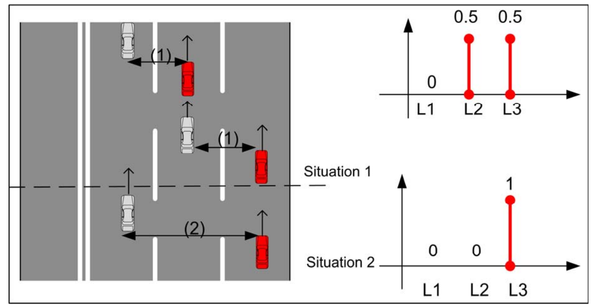


Figure 6. A vehicle is detected and classified as *LeftOutgoing;* two situations appear according to the relative lateral distance to the ego-vehicle; the associated likelihoods for the two situations are illustrated to the right.

In a very similar way, the likelihood for a *LeftIncoming* node is computed; for that case the information about the number of lanes in the opposite direction is also required.

D. Modeling of the Ego-Lane Identification

The goal of a BN is to infer the states of the immeasurable variables, given the evidence of the measurable (observable) variables; in this case the goal is to infer the state of the *Ego-Lane* node in the network based on the evidence of the nodes in the first two layers. The states of the *Ego-Lane* node are L_1, L_2,...,L_n (n is the number of lanes per driving direction), and have an equal weight discrete probability distribution. The reasoning is done in a BN through the *inference* mechanism, which propagates the evidence of the observable nodes in the entire network and updates the beliefs (posterior probabilities) of the other nodes. There are several inference algorithms that perform well in complex BNs; the one used in this approach is Pearl's or Polytree algorithm [8]. Using this algorithm the belief of the *Ego-Lane* node is computed based on the evidence of the parent nodes. The final decision is given by:

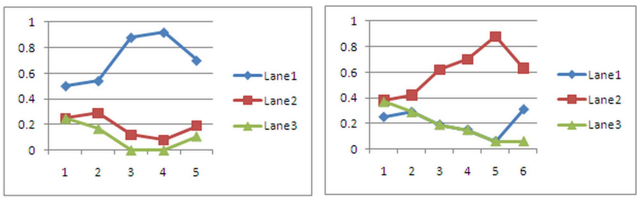
$$\text{Ego}-\text{Lane}^* = \underset{\lambda \in \text{Ego}-\text{Lane}}{\arg\max}\ P(\lambda) \qquad (3)$$

Thus, the state of the Ego-Lane node with the highest probability gives the answer to the lane identification problem.

IV. EXPERIMENTAL RESULTS

In order to test the proposed solution several study case road segments, from Cluj-Napoca, Romania have been modeled, i.e. lane level detail information about the road segments have been manually added into the proposed extended digital map. The Bayesian network is constructed using the SMILE lib [9], the implementation is C++. The BN is constructed automatically for each new road segment using the digital map information; reasoning is done using the visual information as evidence.

Figure 7 illustrates how the probability distribution for the states of the *Ego-Lane* node evolves according to the visual evidence. The two cases correspond to two road segments in the center of Cluj-Napoca, each segment has three lanes per driving direction. The cases illustrated in the graphics correspond to different situations of visual evidence; it can be observed that as evidence sustaining a certain lane hypothesis accumulate, the probability for that lane increases, while the probability for the other lanes decreases. Figure 7 (b) case (6) illustrates the case in which there exist contradictory visual evidence (for example the detected painted arrow sustains a different hypothesis (L_1) than the other visual information (that sustain L_2)); in this case the P(L_1) increases, while P(L_2) decrease from 88% to 63%, but still the lane with the highest probability is L_2, and hence identified as driving lane. Similar cases of contradictory sensorial evidence do appear due to the uncertain and noisy nature of the sensorial perception. The advantage of the probabilistic approach is its ability to handle successfully these uncertainties.

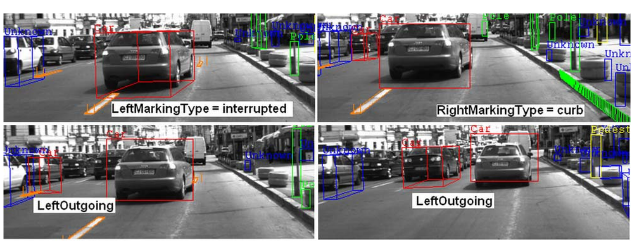


(a) (b)

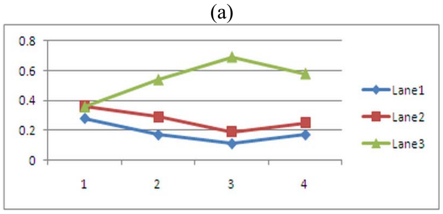
Figure 7. (a) Case of 3 lanes per driving direction L_1, L_2, L_3 and the visual evidence is the following: (1) VisualLeftDelim=MapLeftDelim(L_1), (2) VisualRightDelim=MapRightDelim(L_1)=MapRightDelim(L_2), (3) Visual PaintedArrow=MapPaintedArror(L_1), (4) VisualRightOutgoing=L_1, (5) (1)-(4) without (3);

(b) Case of 3 lanes per driving direction L_1, L_2, L_3 and the visual evidence is the following: (1) VisualLeftDelim=MapLeftDelim(L_2)= MapLeftDelim(L_3), (2) VisualRightDelim=MapRightDelim(L_1)=MapRight Delim(L_2), (3) VisualLeftOutgoing=L_2, (4) VisualRightOutgoing=L_2, (5) VisualPaintedArrow=MapPaintedArror(L_2), (6) VisualPaintedArrow=Map PaintedArror(L_1)

Figure 8 shows examples of how the lane identification algorithm performs on a sequence of video recordings of the test-vehicle on a certain road segment. Figure 8 (a) illustrates examples of visual information used as evidence and Figure 8 (b) shows the results of the reasoning in the BN (i.e. the beliefs of the node *Ego-Lane*) for these cases.



(a)



(b)

Figure 8. (a) Visual information used as evidence in the proposed BN (b) The beliefs of the node *Ego-Lane* for the 4 cases: (1) for top-left image evidence *LeftDelimitersType*= interrupted, the belief is P(L_1, L_2, L_3)= {0.28, 0.36, 0.36}; (2) for the top-right image, adding the evidence *RightDelimitersType*= curb, the belief is P(L_1, L_2, L_3) = {0.17, 0.29, 0.54}; (3) for the bottom-left image, adding hard evidence for node *LeftOutgoing*= L_3, the belief is P(L_1, L_2, L_3) = {0.11, 0.19, 0.70}; (4) for the bottom-right image; adding soft evidence P(L_1, L_2, L_3) = {0, 0.5, 0.5} for node *LeftOutgoing*, the belief is P(L_1, L_2, L_3) = {0.17, 0.25, 0.58}.

V. Conclusions

The contributions of this paper are: the proposed solution of modeling the problem of lane identification in intelligent vehicles through a probabilistic approach, in the form of a Bayesian network; the modeling of the digital map information in construction of the BN; the analysis, interpretation and modeling of the visual information such that it can be used as evidence in the constructed BN. The proposed framework performs automated reasoning for lane identification, based on the a priori information from the extended digital map and on the spot information from the visual perception system.

The results of the experiments show how the uncertain and inaccurate sensorial information is used with success in order to obtain a better knowledge about the ego-vehicles lateral position and a better overall scene understanding.

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The Bayesian Network described in this paper was created using the GeNIe modelling environment developed by the Decision Systems Laboratory of the University of Pittsburgh (http://dsl.sis.pitt.edu/).

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