# Locating Intersections for Autonomous Vehicles: A Bayesian Network Approach

Kyoung-Ho Choi, Sungkwan Joo, Seong Ik Cho, and Jong-Hyun Park

*ABSTRACT—A novel idea is presented to locate intersections in a video sequence captured from a moving vehicle. More specifically, we propose a Bayesian network approach to combine evidence extracted from a video sequence and evidence from a database, maximizing evidence from various sensors in a systematic manner and locating intersections robustly.*

*Keywords—Telematics, ITS, Bayesian network, navigation.*

## I. Introduction

Recently, automatic vehicle driving has become a key research area in intelligent transportation systems (ITS). For automatic vehicle driving, locating intersections in a video sequence captured from a moving vehicle is an essential step [1]-[3]. A model-based approach was proposed by CMU researchers for intersection recognition [4]. They proposed an intersection model with masks and compared the masks with a segmented road. This approach was suitable for Y-shaped intersections. Another approach was proposed by J. Miura and others [5]. A curved mirror is used at intersections and properties of the object are used, such as hue and saturation of the pole. The properties are modeled as a Gaussian distribution and the probability of the object to locate intersections is calculated. One disadvantage is that an additional object must be installed at intersections. We propose locating intersections using a Bayesian network (BN) approach.

This letter can be summarized as follows. First, we analyze the causal relationship between events happening at intersections. Second, we construct a BN based on the analyzed causal relationship to successfully combine feature evidence extracted from a video sequence and evidence from a database to locate intersections robustly.

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## II. Analyzing the Causal Relationship

To model the relationship, video sequences captured from a moving vehicle are carefully analyzed. Based on the analysis, it is difficult for a computer vision engine to distinguish intersections from 1) building entrances, 2) parking lot entrances, 3) cars parked on the road, 4) wastebaskets, and 5) other unidentified objects on the road. Furthermore, cars parked on the road, wastebaskets, and so on can be grouped as unidentified objects that could possibly lead a computer vision engine to a misunderstanding. The relationships among events happening at intersections are summarized in Table 1.

For instance, it is highly likely that an intersection exists if a computer vision engine locates an intersection based on features of the road from images (marked as ⓐ in Table 1) and a DB also indicates there is an intersection on the road (marked as ⓑ in Table 1). In other words, information from a database (DB), such as a map indicating the location of intersections, also adds evidence of the existence of an intersection, giving more credit to the result from the computer vision engine. The top three rows in Table 1 show the relationship between data from a DB and intersection/non-intersection. The bottom two rows indicate the relationship between data from a computer vision engine and intersection/non-intersection. Based on the relationship summarized in Table 1, we propose a BN as shown in Fig. 1.

Table 1. Relationships among events at intersections.

| Evidence | Intersection | Non-intersection | | |
|---|---|---|---|---|
| | | Building entrance | Parking lot entrance | Road with unidentified objects |
| Intersection in DB[b] | Yes | No | No | No |
| Building entrance in DB | No | Yes | No | No |
| Parking lot entrance in DB | No | No | Yes | No |
| Cars turning right/ left | Yes | Yes | Yes | No |
| Big variation in road boundary length [a] | Yes | Yes | Yes | Yes |

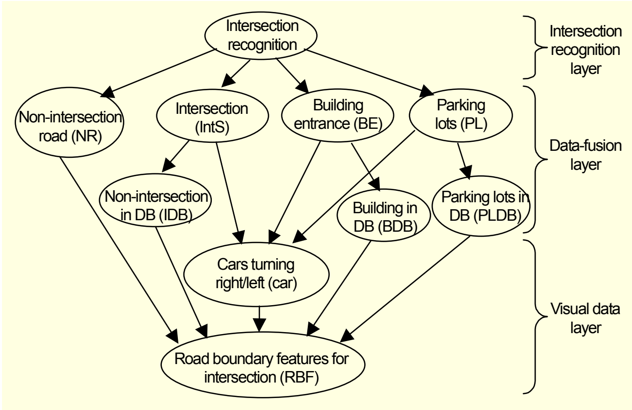



Fig. 1. Architecture of the proposed Bayesian network.

## III. Constructing the Bayesian Network

The proposed BN consists of three layers. The first layer is the intersection recognition layer. It decides if an intersection located by a computer vision engine is a true intersection or a false positive, such as the entrance of a parking lot or a building. The second layer is the data-fusion layer. It combines data from the DB, such as the existence of an intersection, building entrance, and parking lots, and so on, with a decision from the computer vision engine. If the computer vision engine detects an intersection based on road-boundary features, it sets RBF=1 (see Fig. 1 for the parameters) and checks data from the DB. If the data from the DB indicates that there is an intersection along the road, IDB is set to 1 (IDB=1). Then, as indicated in (3), the probability of IntS=1 (the existence of an intersection) is calculated. The last layer is the visual data layer, which extracts features of the road boundary and tracks cars to check if they turn right or left in a video sequence. As indicated in Table 1, all nodes are discrete-valued in the proposed BN. The joint probability can be calculated as (1) and simplified by using a conditional independence relationship as

$$\begin{aligned} \mathrm{P(IntS, IDB, Car, RBF)} &= \mathrm{P(IntS)} \times \mathrm{P(IDB \mid IntS)} \\ &\times \mathrm{P(Car \mid IntS, IDB)} \\ &\times \mathrm{P(RBF \mid IntS, IDB, Car)}, \end{aligned} \tag{1}$$

$$\begin{aligned} \mathrm{P(IntS, IDB, Car, RBF)} &= \mathrm{P(IntS)} \times \mathrm{P(IDB \mid IntS)} \\ &\times \mathrm{P(Car \mid IntS)} \times \mathrm{P(RBF \mid IDB, Car)}, \end{aligned} \tag{2}$$

where Car is set to 1 in the event of a car ahead turning right or left.

The probability of the existence of an intersection can be decided using probabilistic inference as follows. True is denoted by 1 and false is denoted by 0. If a computer vision engine locates an intersection (RBF=1), and the evidence of an intersection from the DB is true (IDB=1), then the probability of the existence of an intersection is

$$\begin{aligned} &\mathrm{P(IntS = 1 \mid RBF = 1, IDB = 1)} \\ &= \frac{\mathrm{P(IntS = 1, IDB = 1, RBF = 1)}}{\mathrm{P(RBF = 1, IDB = 1)}} \\ &= \frac{\sum_{\mathrm{car}} \mathrm{P(IntS = 1, IDB = 1, RBF = 1, Car = car)}}{\sum_{\mathrm{inst,\,car}} \mathrm{P(IntS = ints, IDB = 1, RBF = 1, Car = car)}}. \end{aligned} \tag{3}$$

The complexity of an algorithm for a BN approach depends on the complexity of the networks deployed. In the proposed approach, the structure of the BN is simple.

## IV. Experimental Results

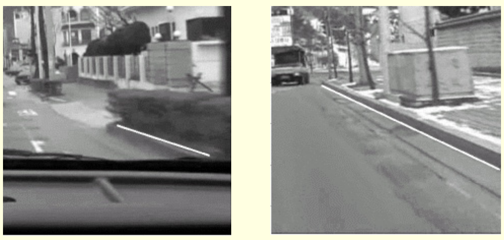
For the experiments, video sequences were collected for 1.5 hours from a moving vehicle (driven around 45 - 60 km/h) in downtown Daejeon, South Korea. We selected 33 video clips including several intersections from the video sequences. More than 1000 frames were included in each video sequence and a Pentium IV 2 GHz CPU was used for testing.

We first implemented a computer vision engine to extract road boundaries from the video sequences, locating intersections based on the dynamics of the length of the road boundary in our previous research [6]. Due to variations including shadows and cars parked on the road as shown in Fig. 2, the engine is likely to fail to locate intersections. The proposed BN approach overcomes this difficulty. In our implementation, as indicated in Table 1, all nodes were discrete-valued and the probability of each node was decided by counting the number of corresponding events in the captured video sequences manually. In our simulations, the Matlab toolbox was used to calculate the probability of the proposed BN [7].

The computer vision engine provided an initial decision for the location of intersections and the proposed BN approach made the final decision, producing more reliable results. Figure 3 shows an example of recognition results. Based on the length of the road boundary, the computer vision engine made an initial decision for an intersection. Then, by combining the proposed BN approach, we calculated the probability of an intersection. For Fig. 3(a), the probability of the existence of an intersection was calculated by setting IDB=0 (the DB indicates that there is no intersection along the road) and BE=1 (the DB indicates that there is building entrance along the road), producing low probability for the existence of an intersection (Prob. is 0.067), which means it is a false positive due to noise, such as a building entrance located ahead. For Fig. 3(b), the probability of the existence of an intersection was calculated by setting IDB=1 (the DB indicates that there is an intersection along the road), Car=1 (a car is turning right), giving high probability for the existence of an intersection (Prob. is 0.98).

(a) (b)

Fig. 2. Various captured environments: (a) road with shadows and (b) a car parked on the road, blocking the road boundary and making it hard to locate an intersection.



(a) (b)

Fig. 3. Example of locating an intersection: (a) recognized as a false positive (Prob. is 0.067 with BN approach) and (b) recognized as a true intersection (Prob. is 0.98 with BN approach).

Table 2 shows the performance analysis of two methods. Out of 57 initial decisions made by the computer vision engine based on road-boundary features, 29 intersections were located correctly, showing 50.8% correct. The proposed BN approach shows a recognition rate of 84.2%, reducing false positives significantly.

Table 2. Performance analysis for the BN approach.

| | Vision-based approach | Proposed BN approach |
|---|---|---|
| Recognition rate | 50.8% (= 29/57) | 84.2% (= 48/57) |
| Replace | 5.88 | 5.77 |
| Delete | 7.94 | 9.34 |

$$\text{Recognition rate} = \frac{\text{number of correctly located intersections}}{\text{total number of intersections in test video sequences}}$$

## V. Conclusion

We proposed a novel BN approach to locating intersections in a video sequence recorded from a moving vehicle. To maximize evidence from various sensors, we analyzed the causal relationship of events happening at intersections and constructed a BN, combining the evidence from a database, such as the location of intersections and features from a computer vision engine. The proposed BN approach can be applied to building a location-aware engine for applications such as robotics, mobile mapping systems [8], and so on.

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