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Road Sign-Aided Estimation of Visibility Conditions

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Abstract

Reduced visibility on roadways caused by localized fog can impact the traffic flow in many ways: traffic speed, travel time delay, reduced capacity and accident risks. This paper presents a novel approach to estimate visibility conditions using an onboard camera and a digital map. Based on a traffic sign detector's characteristics in the fog, and registering detection by vision and information encoded in the map, we are able to accurately determine the current visual range in hazy conditions. Quantitative results are provided on a large experimental data set of driving environment with various level of fogginess.

1 Importance of visual range estimation

Reduced visibility on the highway caused by fog, dust, or smoke impacts the traffic flow: traffic speed, speed variance, travel time delay, reduced capacity and accident risk. The extreme unpredictability of such natural phenomena, especially in term of density and spatial extent, often makes it impossible to respond in a timely fashion to sudden local change in visibility conditions.

According to a study based on NHTSA data [1] over 10 years (2002-2012), in the US only three percent (3%) of weather-related crashes happened in the presence of fog. Even though accidents caused by this type of visibility impairment represent a small percentage of total accidents on highways, they are generally catastrophic and deadly: 9% of weather-related fatalities.

One of the many challenges faced by vehicle vision applications is the impact of adverse conditions through sensors impairment, especially cameras. Optimizing ADAS performance by mitigating the effects of weather on the roadways requires accurate, timely, and reliable information on current weather and visibility conditions. Fog detection and monitoring is however often prone to the unpredictable nature of fog with sudden changes and local variations.

This paper presents a method to detect hazy situations and estimate the visibility distance by detecting traffic sign and using *a priori* information on their implantation on the infrastructure. A forward facing in-vehicle camera grabs images of the road environment in conjunction with a road sign detector. Detected region of interest (ROI) are associated to the true road sign location extracted from a digital map encoding an accurate and up-to-date inventory of traffic signs. Registration of these two sources of information enables an estimation of the visibility distance under hazy conditions.

Section 2 gives an overview of onboard sensors-based methods for visual range estimation. Section 3 presents the traffic sign detector and the effects of reduced visibility on its operating range. The method to infer visibility distance from traffic sign detection and map informations is described in Section 4. Experimental results are presented in Section 5.

2 Previous works in visibility characterization

By convention, the meteorological visibility distance is usually defined as the maximal distance an object can be seen with a contrast of five percent. Following the Koschmieder law modeling the fading effect of fog on the albedo of objects, visibility distance d_{vis} is defined as a measure inversely proportional to the extinction coefficient of the fog β [2]: $d_{vis} = \frac{ln(20)}{\beta}$.

Authors seldom tackled the issue of fog density estimation (β or d_{vis}) with onboard sensors. Proposed methods in this area can be classified according to the type of sensors they require (mono-camera, stereo rig, radar) but also to the type of precision they output (fine grained or coarse estimation):

- Mono-camera approaches with global [3] or local features [2, 4].
- Stereovision-based methods [5] analyzing obstacles segmented from the disparity map.
- Heterogeneous sensors fusion of image-based and radar detection of the preceding vehicle [6, 7].

Approaches processing images are mostly based on some kind of contrast measurement at a signal level whereas when a radar is used, the inference is made at an object level.

Mori and al [6] detect vehicle in the image and compare the ROI to a reference rear-view image of a vehicle in clear weather: the distance between the two images and the vehicle distance given by a radar are used to compute the extinction coefficient β. To overcome using a reference image, Gabb and al [7] infer visibility condition on the object level instead of the signal level. They detect preceding or oncoming vehicles in the image and, with probabilistic model, infer the visibility distance from the radar output. Our work is mostly related to the approach of Gabb and al [7]: instead of using a radar and detect obstacles, we use infrastructure landmarks encoded in a digital map and, with

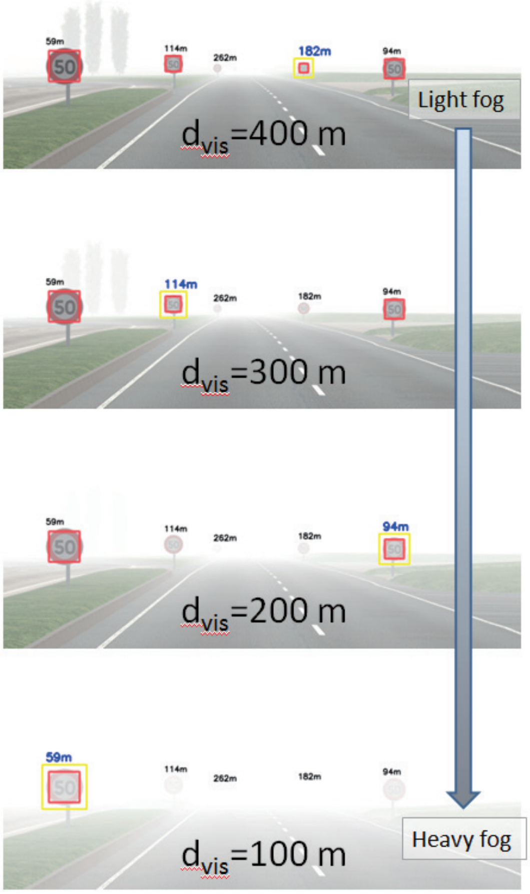

Figure 1. Traffic sign detection with increasing density of fog: BCT operating range decreases with fogginess.

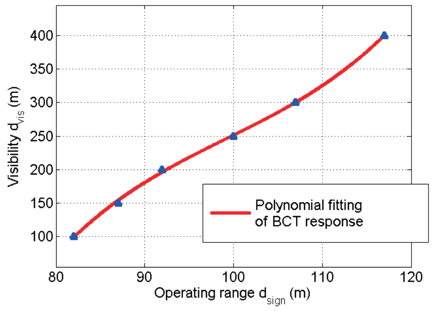

Figure 3. Detector sensitivity to the fog: visibility distance versus BCT operating range.

ego-localization, register them with camera-based detections. Our approach is especially relevant as the map information are not degraded by adverse weather conditions. We will keep the formalism close to the one proposed in [7] as much as possible.

3 Traffic sign detection under degraded condition

3.1 Traffic sign detection with BCT

In this paper, we used the Bilateral Chinese Transform BCT [8] which is well-suited for circular (prohibition and bound such as speed limit) and polygonal shapes, other than triangles. The basic of the algorithm is to evaluate the amount of symmetry between the gradient of two edgels and to increment the vote for their center points accordingly. A large literature can be found on the performance and characterization of the BCT [8].

3.2 Impact of fog on traffic sign detection

A recent study has characterized the behavior of the BCT model under foggy conditions [9]. The main results of this study is a measurement of the evolution of the operating range d_{sign} of the detector w.r.t the visibility distance d_{vis} of the fog. The operating range is a statistical measure of the maximal distance a traffic sign can be detected by BCT (its detectability distance). Let us explain the meaning of *statistical* here: a road sign placed at a distance smaller than d_{sign} has more than 80% chance to be correctly detected.

As expected, traffic signs are detected at shorter range d_{sign} when the haziness is higher, as illustrated in Fig. 1.

3.3 Visual range from operating range

Instead of studying the effect of fog density on the operating range d_{sign} as in [9], we propose to model the visibility distance as a function of the operating range:

$$d_{vis} = f\left(d_{sign}\right) = ad_{sign}^3 + bd_{sign}^2 + cd_{sign} + d \quad (1)$$

f is a third degree polynomial fitting the detector response to the fog level; it is represented in Fig. 3.

In Fig. 3, the visual range d_{vis} is plotted as a function of the operating range d_{sign}. Let us call f this function: $d_{vis} = f\left(d_{sign}\right)$. This f function enables a measurement of the visual range knowing the distance a road sign is first detected in a video sequence, when a road sign comes out of the fog close enough to be detected. For instance, if a road sign is detected at 100 m (and not before), we can presume the visibility distance to be $f\left(d_{sign}\right) = 250$ meters. Now, to know d_{sign}, we first need to associate detected ROI and the range x of traffic signs at every time.

4 Map-Aided visual estimation of visual range

4.1 Overview of the approach

Fig. 2 illustrates how the system works. Road signs are detected from a mono-camera, and associated to a set of road signs in a digital map encoding their location in the world frame coordinate. With GPS/IMU (Inertial Measurement Unit) navigation data, we are able to locate the user on the road and, with camera calibration parameters, to project ground data of map's road signs in the image. The distance x of each traffic sign to the camera can then be retrieved.

Traffic sign ROIs from the image-based detector and from the map are then associated. From the computed

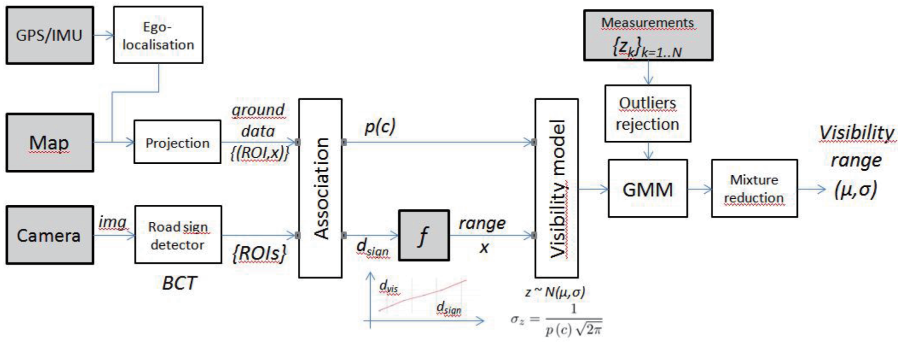

Figure 2. System overview: road signs detected in the image are matched with those encoded in the map to estimate the visibility distance using a probabilistic framework.

data association weights, detection range of each ROI can be estimated, and the visual range can be inferred as it is at least the road sign's distance (when it is first detected). Each punctual range estimation x inferred this way gives rise to an individual measurement z modeled as a i.i.d. Gaussian random variable with mean at the detected road sign's distance x. Following [7] formalism, each measurement is assigned a probability of correctness $p(c)$ reflecting the registration of a detected ROI and map data's projection in the image.

Previous measurements coming from road signs previously assessed during the vehicle journey are further combined to the current one using a Gaussian Mixture Model (GMM). A simplified mixture reduction step estimates the operating range d_{sign} of the road sign detector under current fog conditions. Using the BCT fog characteristic function f, the visibility distance can be deduced.

4.2 Visibility range from traffic sign location

When a traffic sign is on the vehicle driving environment, it is first invisible because of the fog. As the ego-vehicle is going forward, traffic sign's visibility increases until it can be detected by the BCT. The distance d_{sign} at which the road sign is first detected is extracted from the map data using the vehicle absolute localization.

Distance d_{sign} gives rise to a sample measurement of the visual range defined as $x = f\left(d_{sign}\right)$. A continuous random variable z normally distributed with a mean at range x represents this measurement: $z \sim \mathcal{N}(x, \sigma^2)$. In [7], its standard deviation is inversely proportional to a confidence level $p(c)$: $\sigma = 1/\left(\sqrt{2\pi}p(c)\right)$.

However, it is seldomly the case so, if accuracy of the lateral positioning of the vehicle cannot be ensured, a better choice is to set arbitrarily $p(c) = 1$. It is the setting in the tests of [7], and it enforces a practicability of the framework with a reasonable structure for recovering the error of both ego-localization and traffic sign detection. The method is then only sensitive to the distance d_{sign} estimation.

4.3 Filtering outliers for robust estimation

The method is sensitive to the quality of the operating range measurement d_{sign}, therefore it is sensitive to the ego-localization accuracy. The operating range measurement in itself is a variable as, with same visibility conditions, two different traffic signs are usually not detected at the exact same distance.

We propose a filtering process that allows the automatic selection of outliers visual range measurement which could be responsible for performances degradation. It temporarily isolates measurements that do not fit the current pattern of estimated visual range data in the $\mathcal{Z}$ set. In order to do so, a k-means clustering taking into account $p(c)$ values is performed with $k = 3$ clusters, as we expect that some samples are overestimated, some are underestimated and one set of measurements is correct. The two minority clusters are discarded from the GMM reduction process.

The outliers are not discarded from $\mathcal{Z}$: this set grows as new measurements are made. Former data are becoming less and less meaningful as time (or traveled distance) goes by. Their influence can be decreased by diminishing their value of $p(c)$ over time.

4.4 Gaussian Mixture Model

Each measurement made from a traffic sign is modeled by a Gaussian z. A set of N Gaussian measurements $\mathcal{Z} = \{z_k\}_1^N$ collected during time are linearly combined to create a more sophisticated density. A Gaussian Mixture Model (GMM) is formed by weighting each mode equally.

We used a simple scheme for mixture reduction, a weighted sum for final estimate μ:

$$\mu = \frac{\sum_{k\in J} p(c_k) z_k}{\sum_{k\in J} p(c_k)} \qquad \sigma^2 = \frac{\sum_{k\in J} p(c_k)\left(z_k - \mu\right)^2}{\frac{M-1}{M}\sum_{k\in J} p(c_k)} \tag{2}$$

J being the set of index of the majority cluster issued by the outliers filtering process.

5 Experiments

5.1 Foggy images test database

Due to the difficulty to collect a set of images with various level of fog, we used a database of simulated images under controlled atmospheric conditions. It is a sequence of synthetic images containing road signs (speed, pedestrian, stop) captured with a camera placed onboard a vehicle. The vehicle moves forward on a track and images are acquired every 5 meters,

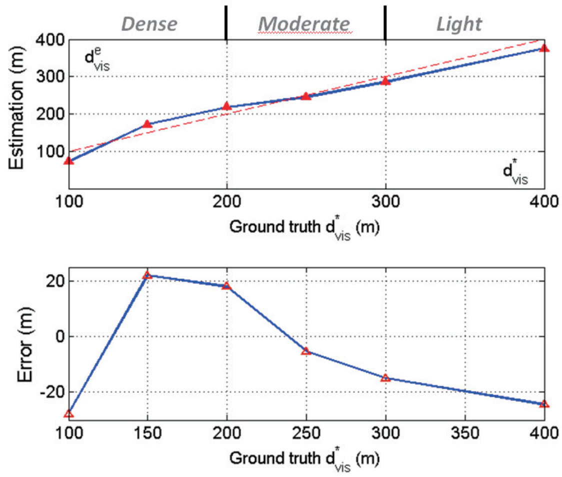

Figure 4. Visual range estimation performances: (top) estimated visibility distance d^e_{vis} versus ground truth distance d^*_{vis}; (bottom) estimation error δd_{vis}.

which is classical for ground surveys by mappers such as OpenStreetMap or Google Street.

The database features 6 density of fog , with a visibility distance ranging from 100m to 400m: dense fog $d_{vis} = [100m, 200m]$ to moderate $d_{vis} = [200m, 300m]$ to light $d_{vis} = [300m, 400m]$. For each density level, 504 images (1400×600) are available, Fig. 1 gives an example of simulated images with homogeneous fog. The ground truth of each sign was made available: sign's location and range d_{sign}.

5.2 Visibility range for various level of fog

Fig. 4 illustrates the accuracy performances of the approach. The first graphic plots the visibility distance d^e_{vis} estimated by the algorithm w.r.t. the true visibility distance d^*_{vis}. The second graph is the relative estimation error $\delta d_{vis} = (d^e_{vis} - d^*_{vis})$. Each point represents the final estimation made over 504 images.

Three domains of fogginess are identified, from dense to light. Each domain is accurately characterized by the method, since light fog is classified as light fog, moderate as moderate and dense fog as dense fog. Now going into accuracy of visibility distance estimation, the maximal error is less than 28 meters.

Light fog visibility is underestimated but its characterization is relevant with an error of less 25 meters: $\delta d_{vis} < 25m$. On the set of data with fog density $d^*_{vis} = 300m$, the estimation is very close: $d^e_{vis} = 285m$.

Estimation over a moderate fog is the more accurate with an error $\delta d_{vis} < 18m$. The estimation is $d^e_{vis} = 245m$ for $d^*_{vis} = 250m$, and $d^e_{vis} = 218m$ for $d^*_{vis} = 200m$. The algorithm is correct as moderate fog is classified as moderate, and slightly more accurate than in the light fog domain.

On the sets of heavy fog, the accuracy decreases, with an error of up to 28 m: $\delta d_{vis} < 28\ m$. The proposed algorithm overestimate the density of fog with an estimation at $d^e_{vis} = 72m$ for $d^*_{vis} = 100m$, and slightly underestimate it with $d^e_{vis} = 172m$ for $d^*_{vis} = 150m$. However, it can still be considered as an accurate measurement.

6 Conclusion and perspectives

This paper introduced a novel approach for estimating visibility condition under hazy situations, using an onboard camera and a digital map. Visual range is estimated by detecting traffic sign and using *a priori* information on their implantation on the infrastructure. Detected region of interest (ROI) are associated to the true road sign location extracted from a digital map encoding an accurate and up-to-date inventory of traffic signs. The method works on image sequences by statistically analyzing the distance a traffic sign is first detected. Exhaustive experimental tests are reported for various density of haze.

To our knowledge the reported results are the more thorough in this field of research, other papers showing results on few samples or a video sequence. Registration of the two sources of information, road sign detection and their location according to a map, leads to an accurate visual range estimation for dense to light fogginess.

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