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Hazar Chaabani
Esprit School of Engineering

Faouzi Kamoun
Esprit School of Engineering

Hichem Bargaoui
Esprit School of Engineering

Fatma Outay
Zayed University

Ansar Ul Haque Yasar
Universiteit Hasselt

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A Neural network approach to visibility range estimation under foggy weather conditions

Hazar Chaabani[a], Faouzi Kamoun[a]*, Hichem Bargaoui[a], Fatma Outay[b], Ansar-Ul-Haque Yasar[c]

[a]*ESPRIT School of Engineering, ZI. Chotrana II, Tunis PO. Box 160, Tunisia*
[b]*Zayed University, Dubai P.O. Box 19282, U.A.E*
[c] *Hasselt University, Wetenschapspark 5 bus 6, Diepenbeek P.O. Box 3590, Belgium*

Abstract

The degradation of visibility due to foggy weather conditions is a common trigger for road accidents and, as a result, there has been a growing interest to develop intelligent fog detection and visibility range estimation systems. In this contribution, we provide a brief overview of the state-of-the-art contributions in relation to estimating visibility distance under foggy weather conditions. We then present a neural network approach for estimating visibility distances using a camera that can be fixed to a roadside unit (RSU) or mounted onboard a moving vehicle. We evaluate the proposed solution using a diverse set of images under various fog density scenarios. Our approach shows very promising results that outperform the classical method of estimating the maximum distance at which a selected target can be seen. The originality of the approach stems from the usage of a single camera and a neural network learning phase based on a hybrid global feature descriptor. The proposed method can be applied to support next-generation cooperative hazard & incident warning systems based on I2V, I2I and V2V communications.

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Keywords: visibility distance; fog detection; intelligent transportation systems; meteorologcal visibility; driving assistance; neural networks; machine learning ; Koschmieder Law; computer vision; Fourier Transform

1. Introduction

Foggy weather conditions represent an imminent threat to road safety, often leading to fatal road accidents because degraded road visibility has the potential to (1) take even experienced drivers by surprise, (2) alter the motorists' driving behavior, and (3) distort drivers' perception of depth, distance, and speed[1]. Earlier research[1,2,3]

* Corresponding author. Tel.: +216-99-423-944; fax: +216-70-685-454.
E-mail address: faouzi.kammoun@esprit.tn

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revealed that although foggy weather conditions are not very recurrent phenomena, the number of associated multiple colliding vehicles, injuries and fatalities are much higher than average. Since highway fog abatement technologies have not reached yet the desired level of maturity and economic viability, several roadway crash countermeasures and new vehicle design technologies have been proposed to assist motorists cope with foggy weather conditions. These include reflectorized paints on pavement edge striping, beaded lane delineators, blinking strobe lights, and onboard equipment including fog lights, Light Detection And Ranging (LiDAR) sensors and Autonomous Emergency Braking (AEB) systems, among many others.

Recently, there has been a growing interest in integrating variable speed limit signs (VSLMs) and Variable Message Sign (VMS) units into major highway infrastructures[4]. In addition, there has been considerable interest in cooperative situational awareness and collision avoidance systems based on I2V, V2V and I2I communications to warn drivers against low visibility and to recommend proper speeds that are adapted to the prevailing visibility conditions. The success of these solutions hinges on the ability to detect fog and estimate the visibility range in real-time. For this reason, fog detection and the estimation of visibility distance have been a major area of research study during the past few years.

In this contribution, we will begin by defining fog, outlining its associated light propagation models and introducing the notion of visibility distance. In section 3, we summarize the state-of-the-art approaches to estimating visibility distance in daytime fog. We will then present our neural network approach for visibility range estimation. In section 5, we present an experimental evaluation of the proposed solution and in section 6 we provide a summary of the key findings of this study.

2. Fog definition and visibility models

2.1. Definitions

Fog is a kind of cloud on the ground and is formed by the suspension of microscopic moisture dewdrops into airborne particles. According to the Meteorological Office 1969[5], fog is defined as the state of atmospheric obscurity where meteorological visibility falls below 1 Km. If visibility drops below 40 meters, fog is qualified as being "dense". A visibility between 40 meters and 200 meters corresponds to a thick fog situation[5]. For road safety applications, the visibility range of interest is between 0 and 400 meters. The luminous flux emanating from visible light (400 nm $\leq \lambda \leq$700 nm) gets scattered in all directions when it hits a water droplet and absorption is often negligible in this case. This scattering can severely impair drivers' depth perception and peripheral vision. The attenuation of visible light is characterized by the extinction coefficient k (m^{-1}) which is a factor of the droplets size and concentration[6]. The estimation of this coefficient has been the basis of many visibility range estimation methods.

2.2. Light propagation through fog

On the basis of Koshmieder luminance attenuation law[7], Duntley[7] proposed the attenuation law of atmospheric contrasts under uniform illuminance which states that an object with intrinsic contrast C_0 against its background will be perceived at a distance d with an apparent contrast C given by:

$$C = C_0 e^{-kd} \tag{1}$$

The above expression has been used as a basis for defining the "meteorological visibility distance" $d_{visibility}$ as the greatest horizontal distance at which a black object (C_0=1) of a moderate dimension can be seen on the horizon during daytime with a contrast threshold ε=5% , as recommended by the International Commission of Illumination (IEC[8]):

$$d_{visibility} = -\frac{1}{k}\ln(0.05) \cong \frac{3}{k} \tag{2}$$

The above simple expression suggests that, from the extinction coefficient k of the surrounding atmosphere, one can derive the perceived visual range of a black object at daytime.

3. Visibility distance estimation methods and solutions: State of the art

For most practical road safety applications, meteorological visibility is often measured as a range (e.g. below 50 meters, between 50 and 100 meters, etc...) and not as an absolute value. However, even the estimation of this range can be a daunting task given the non-uniform nature of the physical atmosphere and the intertwining factors influencing visibility which include intensity of surrounding light, physical properties of objects, light scatter and absorption among many others.

Various visibility distance estimation approaches for transportation systems have been proposed over the past years. These approaches differ in various aspects (daytime versus nighttime, fog detection and/or visibility estimation, optical versus image sensors, fixed cameras versus onboard cameras, video-based versus image-based; algorithm used for image processing and distance estimation, etc.). In general, we can classify visibility distance estimation approaches into four main categories as illustrated in figure 1.

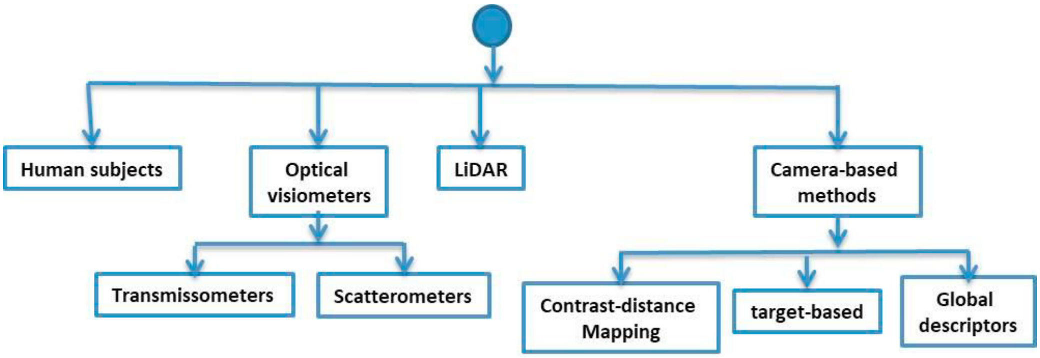

Fig.1. Classification of meteorological visibility distance estimation approaches

Manual estimation of perceived visibility range by human subjects, in the presence of designated visible targets, remains the most accurate and reliable visibility estimation method[9], despite the fact that Cavallo et al[10] reported that, under the presence of fog, drivers have tendency to overestimate the distance towards the vehicles in front them. Manual estimation is however not a practical approach for most transport safety applications. It is costly, prone to individual bias and often requires the judgement of trained experts.

Commercial instrumentation products (mainly been used at airports and weather stations) that are based on optical visiometers fall into two categories: Transmissometers and scatterometers. Transmissometers measure luminance flux received from aligned projectors to derive the extinction coefficient k, while scatterometers measure the amount of modulated light scattered at a certain angle. Instruments based on optical visiometers are expensive and have been criticized for their complexity, high sensitivity to fog non-homogeneities, low accuracy for visibilities below 50 meters or under dense foggy weather conditions, and high sensitivity to motion[11].

LiDARs have been used to estimate visibility under foggy weather conditions by analyzing the signal backscattered by fog droplets[12]. As reported by Colomb[13], this approach, however, requires fine-tuning of the LiDAR's power to adapt to the extinction coefficient k.

There has been a growing interest during the past few years in using fixed cameras (placed on the roadway) or (and to a lesser extent) onboard cameras to estimate visibility distance, as these devices are relatively cheap and are already deployed for traffic monitoring and surveillance on major highways. The main challenge with camera-based visibility estimation resides in restoring the depth information that is lost after the image transformation from the original 3-D scene. Camera-based approaches can be classified into three main categories:

The first (type-I) approach aims to measure the distance to the furthest black target in the image while still displaying a contrast greater than $\varepsilon=5\%$ as per the IEC recommendation[14,15]. This involves searching for points or regions of interest by applying thresholding and segmentation techniques to locate specified targets such as lane markings[16], road signs[17], road boundaries, or the intersection between road surface and the sky[18]. Visibility detection algorithms which belong to this category are often based on equations (1) and (2). Various approaches have also been proposed to estimate visibility distance and various types of anchor targets have been adopted. The main drawback of this approach is that it requires accurate geometric calibration of the camera and it relies on the presence of reference objects with high contrasts in the scene.

The second (type II) approach is based on computing the scene contrast and then performing a linear regression between this contrast and the visual range that is computed with the aid of additional reference sensors[19]. Various approaches have been proposed to estimate the contrast including the usage of Sobel, homomorphic or high-pass filters[20]. This approach does not require camera calibration or the presence of reference objects. However, it does involve a learning phase that requires the usage of additional meteorological sensors.

The third (type III) approach uses a global descriptor vector which is computed on the whole image, irrespective of its content. This approach does not require edge detection or knowledge of the distance to various reference targets. The global descriptor vector reflects information about the global image contrast and uses features based on the gradient sum or the Fourier coefficients sum[21] as these are invariant to illumination changes. Our proposed neural network approach falls within this category.

4. The proposed neural network approach

Our approach consists of estimating visibility range through a supervised training applied to labeled examples that are characterized by global rather than local features. Our classifier is a three-layer neural network trained with a back-propagation algorithm. The first input layer is the feature vector image descriptor. The hidden layer consists of a set of fully interconnected computational nodes whose number is determined empirically. The output layer is a vector whose size is equal to number of classes, which in our case corresponds to different visibility ranges.

For the global feature descriptor, we have opted for a Fourier Transform approach which is regarded as one of the most efficient image transformation techniques[22] and it captures the power spectrum of the image. Because of the high dimensionality of the Fourier transform magnitude descriptor, we have carried a dimensionality reduction through Principal Component Analysis (PCA). In addition to the Fourier magnitude descriptor, we have also used Shannon entropy as a second descriptor that characterizes an image texture by analyzing its gray level distribution according to the following expression:

$$E = \sum_{i=1}^{n} P_i \, log_2(P_i) \tag{3}$$

where P_i is the probability that the difference between 2 adjacent pixels is equal to i. The final aggregate descriptor is a combination of the mean squared Fourier transform vector reduced by the PCA and the image entropy.

5. Experimental evaluation and results

In this study, we have considered six classes of visibility range (< 60m, 60m - 100m, 100m - 150m, 150m - 200m, 200m - 250m, and ≥ 250m). We have used the feature vectors extracted from the images to learn the required visibility classes. Experimentally, we maintained only the first 100 eigenvectors since they represent near 99% of the cumulative percent of variance. Figure 2 depicts the general architecture of the neural network where *I*1-*I*20 represent the elements of the input descriptor vector, *H1-H12* are the hidden layer nodes and the outputs correspond to the visibility ranges.

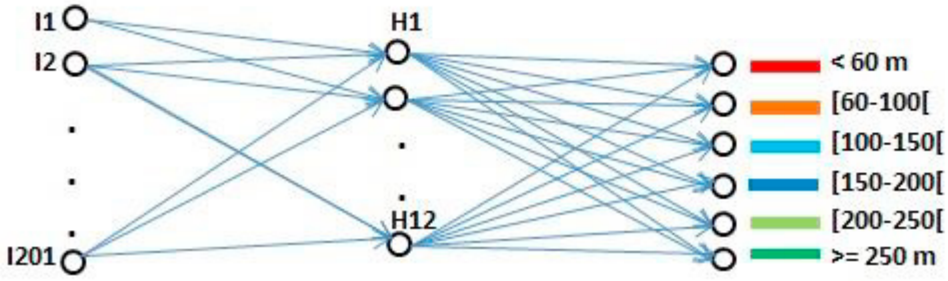

Fig. 2. Neural network layers

To evaluate our proposed approach, we have used the FROSI (Foggy ROad Sign Images) database[23]. This database contains a sequence of 504 synthetic images with 1620 road signs placed at various ranges. For each image, a set of 7 types of uniform fog density are available with visibility distances ranging from 50m (heavy fog) to 400m (slight fog), as shown in the illustrative example in figure 3.

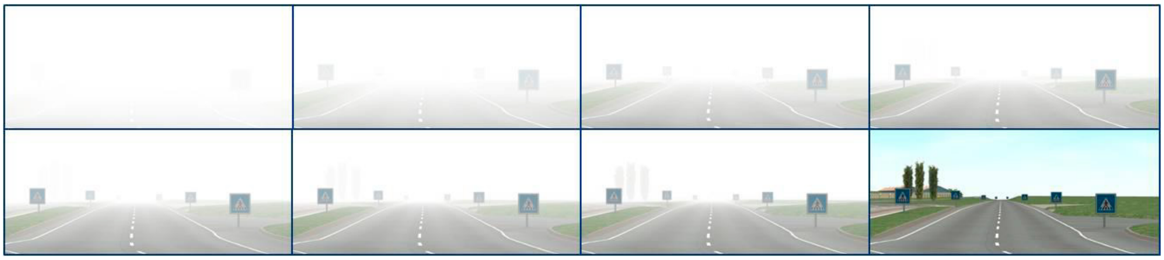

Fig. 3. Sample of images from the FROSI database

We have also compared the accuracy of our proposed solution with that based on type-I approach. In our case, no tracking/detection steps were required as traffic sign positions were known a priori. For type I approach, we have adopted Michelson contrast formula $C = (I_{max} - I_{min})/(I_{max} + I_{min})$, where I_{max} and I_{min} denote the maximum and minimum pixel intensity, respectively.

For the neural network training phase, we have used 336 images under different visibility ranges. The weighted neural network was subsequently tested using a different set of 336 images under various fog density conditions. Our results are summarized in the confusion matrix depicted in figure 4(a). Overall, a 90.2% successful classification rate was achieved, compared to a 62% success rate obtained through type I approach. As shown in figure 4(b), our approach gives better results under all visibility classes. We notice that the sixth class has the minimum probability of detection (83%) due to confusion with ranges between 150 and 250 meters.

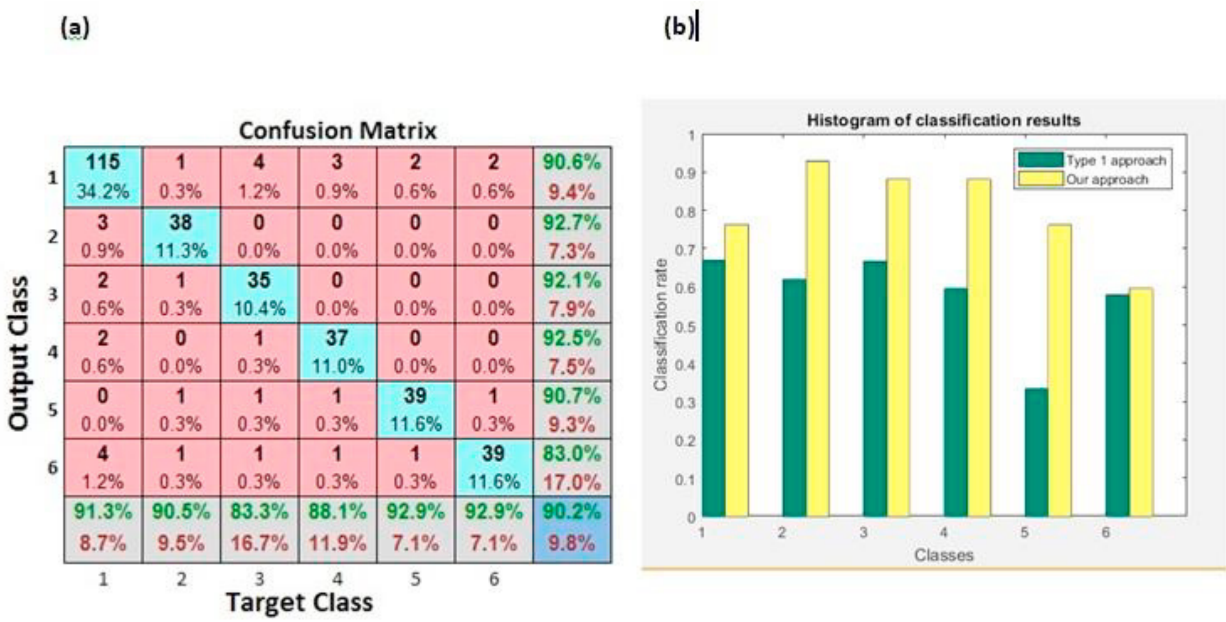

Fig. 4. (a) Confusion matrix; (b) Comparison of results

6. Conclusion

In this contribution, we have presented a neural network approach to estimate visibility range under foggy weather conditions. Our solution requires a single camera which can be fixed on the roadway side or placed onboard a vehicle. Our approach provided visibility range estimates that are close the expected values for a wide range of fog density scenarios. A key advantage of the proposed approach is that it is inherently generic and does not require special camera calibration or a prior knowledge of distances in the depth map. Our proposed algorithm can be implemented on existing camera-based traffic monitoring systems, which can serve as a driving aid to warn motorists and request them to adapt their speeds according to the estimated visibility distance. We are currently working on further refining our approach and comparing it with additional methods identified in our literature review.

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