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Estimating meteorological visibility range under foggy weather conditions: A deep learning approach

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Abstract

Systems capable of estimating visibility distances under foggy weather conditions are extremely useful for next-generation cooperative situational awareness and collision avoidance systems. In this paper, we present a brief review of noticeable approaches for determining visibility distance under foggy weather conditions. We then propose a novel approach based on the combination of a deep learning method for feature extraction and an SVM classifier. We present a quantitative evaluation of the proposed solution and show that our approach provides better performance results compared to an earlier approach that was based on the combination of an ANN model and a set of global feature descriptors. Our experimental results show that the proposed solution presents very promising results in support for next-generation situational awareness and cooperative collision avoidance systems. Hence it can potentially contribute towards safer driving conditions in the presence of fog.

Keywords: Visibility distance; intelligent transportation systems; meteorologcal visibility; neural networks; deep learning, convolution neural networks; machine learning; computer vision.

1. Introduction

According to the U.S. Federal Highway Administration (FHA), fog is a significant cause of fatal road accidents as

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it represents the most hazardous type of adverse weather conditions for motorists. In fact, fog can take drivers by surprise, impair their driving behavior and distort their perception of depth, distance and speed [1]. Fog can be defined as a dense cloud of microscopic moisture dewdrops that are suspended into airborne particles at ground level. It represents a state of atmospheric obscurity where visibility falls below one Kilometer. A dense fog corresponds to a visibility distance less than 40 meters, whereas a thick fog condition is associated with a visibility range between 40 and 200 meters.

There has been a growing number of research initiatives towards connected vehicular systems based on V2V, I2V and I2I technologies that would allow intelligent road-side units (RSUs) and vehicles to cooperate for enhanced awareness of driving conditions and for a more proactive approach to counter low visibility due to foggy weather conditions. However, as highlighted by Hautière et al [2], in order to act on their surrounding environment, these assistance systems depend on efficient mechanisms to detect the presence of fog and, accordingly, estimate the visibility distance or range.

In this paper, we propose a new method to estimate visibility range under foggy weather conditions which is based on a deep learning approach. To the best of our knowledge, this is the first contribution that aims to explore the application of deep learning approaches to estimate visibility range in the presence of fog.

The remaining of this paper is organized as follows: Section 2 presents a brief overview of earlier approaches to estimate visibility distance in the presence of daytime fog. Section 3 presents our proposed deep learning approach for feature extraction while section 4 outlines the SVM classifier approach to visibility distance estimation. In section 5, we present some experimental evaluation results of the proposed approach and finally, in section 6, we conclude with a summary of the main findings of the paper.

2. Visibility distance estimation approaches: A brief overview

As shown in figure 1, visibility distance estimation approaches can be classified into four main categories. Methods based on human subjects, Lidars and optical visiometers are presented in [3] and will not be further discussed herein. In the present contribution, we focus on camera-based visibility estimation methods. These methods can be classified into two categories, depending on whether we have to localize some region of interest (target-based methods) or whether we will act directly on the full image (overall image-based methods).

The first (target-based) approach has been used with fixed cameras setups such is the case in [4, 5], as well as with onboard cameras such is the case of the RALPH system [6]. The contributions that fall under this approach differ in many aspects including the choice of (1) edge detection techniques, (2) descriptors, (3) target points (region) of interest, (4) target localization technique, and the methods used to estimate the distance. Various targets have been explored, including Lane markings [6], road signs [7], road shoulders [4], the intersection between a portion of the road surface and the sky [8-10], fixed landmarks [11], the vanishing point of the image where parallel road lines merge [9], the highest visible point in the driving space area [12], known targets based on a 2-dimensional map [13] and Lambertian surfaces [14-16]. The main drawbacks of target-based methods reside in the need for accurate geometric calibration of the camera in some proposed approaches and the reliance on reference objects with high contrasts in others [8, 15]. Target-based methods are also not effective in dealing with real-life situations associated with occlusion problems, curved roads, faded lane markers, and nonpermanent targets. The additional cost of installing and/or maintaining visibility markers also needs to be taken into consideration.

The second approach is based on extracting a global image descriptor vector which is computed on the whole image, independently of its content. The proposed algorithms under this approach rely on the overall features that are present in the image rather than on the explicit knowledge of the distance to various targets [17]. Examples of feature descriptors include the Fourier Transform [3, 18], the power spectrum [19], the combination of various geometric descriptors [17], and the combination of sharpen image and homomorphic filter [20].

Classification approaches have commonly been associated with overall image-based methods. The proposed classification solutions are based on:

- Power Spectrum approach based on the Fourier Transform and Fisher's Linear Discriminant Analysis (LDA) [19].
- Combination of Sobel algorithm for edge extraction and Fuzzy logic scoring system for classification [17].

- A 3-layer ANN classifier, combined with a global feature vector descriptor which is a combination of the mean squared Fourier transform vector, reduced by the Principal Component Analysis (PCA), and Shannon's image entropy [3].

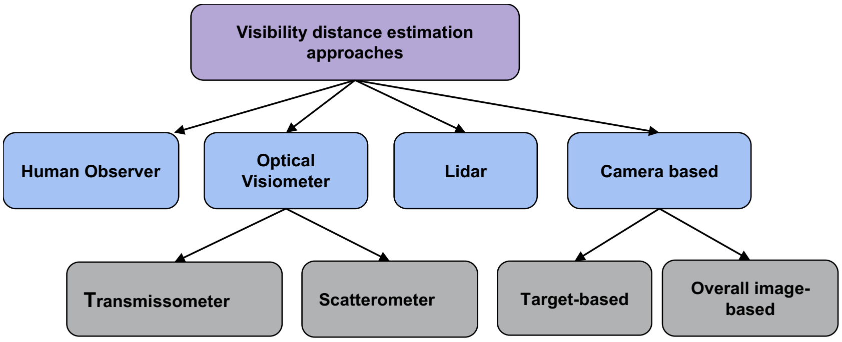

Fig.1. Classification of meteorological visibility distance estimation approaches

The present contribution which is discussed in the next section falls under this "classification approach" based on overall image-based method.

3. Feature extraction: Convolution neural network

In this work we propose a deep learning approach in which a Convolution Neural Network (CNN) is used as a feature extractor. The derived features will be used as input to a given standard classifier.

Basically, a CNN deep learning architecture is composed of a sequence of cascading layers performing basic operations such as convolution, sub-sampling, followed by another sequence of fully connected layers, which act similarly to a classic ANN. These architectures have been known since the '80s, but they have now been rediscovered thanks to the availability of adequate computational power and training data [21]. Since 2012, when a CNN architecture resulted in the best ranked method in the ImageNet Large Scale Visual Recognition Challenge, CNNs have become, *de-facto*, the standard tool to address a large spectrum of problems in the fields of Computer Vision, Pattern Recognition and Image Processing. On the other hand, training a CNN network from scratch requires a large dataset, which is a tedious process for most practical applications. Further, and in addition to requiring considerable computational resources, there are no systematic guidelines as for the optimal choice of the architecture in terms of depth (number of layers) and structure. A good strategy to circumvent this challenge is to use pre-trained CNN architectures, that are proven to have good performance through training and validation over a huge database, and then tune, via training conducted on a specific application dataset, the pre-trained weights of the architecture. This technique, known as fine-tuning, can be performed either across the whole CNN or at specific layers. In this contribution, we propose to use the standard AlexNet architecture [22]. The AlexNet architecture consists of five convolutional layers, three maxpool layers and three fully connected layers. More details about AlexNet architecture can be found in [22].

4. Support vector machine

We used one-vs-rest multi class SVM for the classification of five discrete classes. More precisely, 5 binary SVM models are learnt by training the images of one class as positive and the remaining classes as negative.

The aim of a binary SVM classifier is to learn a hyperplane that optimally discriminates between the two classes according to the following equation:

$$min_{w} \quad \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} + C.\sum_t(\max(0,1-l_t\boldsymbol{w}^T x_t))^2 \tag{1}$$

where $l_t = \{1,-1\}$. Unlike other classifiers such ANN, SVM classifier has the ability to manage a high-dimensional feature input without increasing the computational complexity. Hence it can handle the mapping of a huge number of features obtained from different layers of the CNN.

5. Quantitative evaluation and results

In this section, we present our experimental evaluation of the proposed deep learning approach for visibility range estimation in the presence of daylight fog. Considered ranges are <100, [100 200[, [200 300[, [300 400] and >400. First we will describe the dataset used in this study and then we will give details about our experiments and present some quantitative results.

5.1. Data description

In this study, we used the FROSI (Foggy ROad Sign Images) database [23] which contains as set of 4032 (1400*600) synthetic images of static outdoor scenes at various visibility ranges, namely 50m, 100m, 150m, 200m, 250m, 300m, 400m, and original scenes with visibility range above 400 meters. In each range, FROSI provides 168 images of three road sign panels (stop, speed and pedestrian).

While in the previous work of Chaabani et al [3], experiments were conducted on a sample of 336 images taken from the FROSI database, in this contribution, and for a better comparative analysis, the entire database was used instead. 70% of the image database was used for training and the remaining 30 % was used for testing.

Since deep learning is greedy in terms of its need for a huge amount of data for training, the size of the database was increased using different data augmentation techniques in order to avoid over-fitting. Recall that data augmentation is the process of enlarging a database utilizing information only from the original training set by applying transformations that preserve the label or the class identity. Due to the sensitivity of the images only two types of data augmentation techniques were implemented which operate on the shape and the noise level of the images, respectively. More precisely, we applied horizontal flipping (Fig 2-c) of the images and the addition of Additive White Gaussian Noise (AWGN) (Fig 2 -c). The mean and the variance parameters used for the noise addition are 0 and 0.005, respectively.

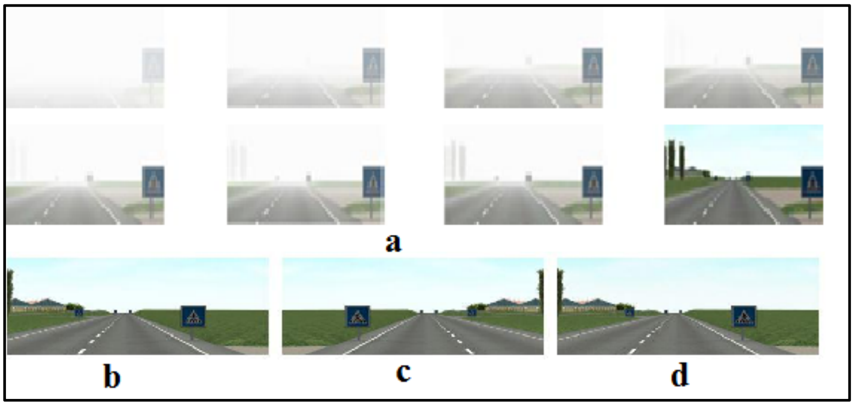

Fig. 2. a: Sample of each class in the data base, b: original image, c: horizontal flip, d: noisy image

5.2. Experimentation

A series of extensive experiments were performed for five class classification problem which aim to evaluate the effectiveness of the proposed approach. The performance results of our proposed method were also compared with those of Chaabani et al [3], which was based on using an ANN as classifier and a global descriptor based on Fast Fourier Transform and Shanon entropy. Here we also adopted the 70%, 30% rule for training and testing, respectively. The main focus is on encoding the foggy images in terms of activations of a pre-trained convolutional neural network. The features were employed from different layers from the pre-trained CNN. Therefore, AlexNet activations were used since this architecture consists of simple but effective structure composed of five convolution layers (***Conv***) and three fully connected layers (***FC***). The network was trained using the ImageNet database which consists of natural images; therefore the activations learned by this architecture exhibited diverse and discriminative features that could be utilized for our specific classification problem. We observed that activations from the first layers learned generic representations which failed to provide sufficient discriminative power. As a result, we investigated feature representations from the middle layers and onward, namely Conv4 till FC7.

5.3. Results

We evaluated the performance of the proposed approach in terms of three performance metrics, namely recall, precision and accuracy. The findings for training the SVM classifier with different features encoded from different layers of AlexNet are reported in Table 1, where the best reported performances are highlighted in bold.

Table 1: Average recall, precision and accuracy values for 5-class classification obtained from our approach and the ANN approach [3]

Descriptor	Classifier	Recall	Precision	Accuracy
CNN (Conv4)	**SVM**	**99.11%**	**99.17%**	**99.02%**
CNN (Conv5)	SVM	98.22%	98.69%	98.42%
CNN (FC6)	SVM	96.51%	96.89%	95.83%
CNN (FC7)	SVM	95.49%	96.28%	95.31%
Fourier Transform + Shanon Entropy	**ANN**	**77.54%**	**75.86%**	**72.30%**

The results shown in Table 1 indicate that for our 5-class classification, the best performance is achieved when the features are encoded from conv4 layer with scores of 99.11%, 99.17% and 99.02% for recall, precision and accuracy, respectively. This can be explained by the fact that deeper activations coming from deeper layers are more abstract and specific to the training data.

The results presented in Table 1 also show that the proposed deep learning approach outperforms the previous ANN approach of Chaabani et al [3] which provided scores of 77.54%, 75.86% and 72.30% for recall, precision and accuracy, respectively.

6. Conclusion

In this paper, we presented a novel deep learning-based approach to estimate the meteorological visibility range in the presence of daytime fog. We also presented a quantitative evaluation of the proposed method. Our proposed solution can support next-generation variable message signs and onboard Advanced Driver Assistance Systems (ADAS) to inform drivers about the visibility range and suggest the proper speed, thus contributing towards safer driving conditions in the presence of fog. In future, we plan to perform further experiments and test our approach with additional image sequences.

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