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Advancing Driver Assistance Systems: Multi-Class Weather Classification using Supervised Learning for Enhanced Traffic Safety

M. Ramana Kumar,

Assistant Professor, Dept. of CSE, Shadan Women's College of Engineering & Technology, Hyderabad, Telangana.
drmrkumar2020@rediffmail.com

Abstract
Traffic accidents present considerable hazards in adverse weather conditions, including rain, nighttime, icy surfaces, and locations with insufficient street lighting. Modern driver assistance systems are predominantly engineered for functionality in optimal weather conditions. The classification of weather conditions, which entails the recognition of optical characteristics within visual data, represents a viable method to enhance computer vision capabilities in adverse weather scenarios. This study presents a multi-class weather classification system that utilizes various weather features and supervised learning techniques to improve the effectiveness of computer vision in challenging weather conditions. The procedure involves extracting essential visual characteristics from various traffic images, which are subsequently converted into an eight-dimensional feature space. Five distinct supervised learning techniques are subsequently employed for model training. The analysis of the extracted features indicates that the proposed approach enhances the accuracy and adaptability of weather classification, establishing a foundation for improvements in vehicular safety. This innovation enhances its functionality in scenarios characterized by low visibility at night and on icy surfaces, thereby improving the driver's field of vision. Feature extraction serves as a vital component in pattern recognition, providing an effective approach to streamline high-dimensional image data and isolate key information necessary for interpreting multi-traffic scenarios.

Keywords: Traffic Accident Prediction, Weather Classification, Computer Vision, Feature Extraction, Supervised Learning, Vehicular Safety**.**

1. Introduction
Traffic scene recognition is an important and challenging issue in Intelligent Transportation Systems (ITS). Recently, Convolutional Neural Network (CNN) models have achieved great success in many applications, including scene classification. The remarkable representational learning capability of CNN remains to be further explored for solving real-world problems. Vector of Locally Aggregated Descriptors (VLAD) encoding has also proved to be a powerful method in catching global contextual information. In this paper, we attempted to solve the traffic scene recognition problem by combining the features representational capabilities of CNN with the VLAD encoding scheme. More specifically, the CNN features of image patches generated by a region proposal algorithm are encoded by applying VLAD, which subsequently represent an image in a compact representation. To catch the

spatial information, spatial pyramids are exploited to encode CNN features. We experimented with a dataset of 10 categories of traffic scenes, with satisfactory categorization performances.

Humans have the remarkable ability to categorize complex traffic scenes very accurately and rapidly, which is important for the inference of the traffic situation and subsequent navigation in the complex and varying driving environment. It will be major achievement to implement an automatic traffic scene recognition system which imitates the human capability to understand traffic scenes. Such a system will play a crucial role toward the success of numerous applications, such as self-driving car/driverless car, traffic mapping and traffic surveillance [1]. Automatic acquisition of information from real-world traffic scenes will also be pivotal to optimize current traffic management system, for example, by improving traffic flow during busy periods [1]. Image representation has been studied for more than two decades, with a number of efficient hand-designed algorithms previously proposed for feature extraction. Among them, bag-of-features (BOF) methods represent an image as bags of locally extracted visual features, such as HoG (Histogram of Oriented Gradient) [2] and SIFT (Scale Invariant Feature Transform) [3]. Despite some limited success, hand-crafted features cannot reflect the rich variabilities hidden in the data. In recent years, Convolutional Neural Networks (CNN) [3][4] have brought breakthroughs in learning image representations. By training multiple layers of convolutional filters in an end-to-end network, CNNs are capable of detecting complex features automatically, which is a prerequisite for many of the computer vision tasks such as scene recognition. In many benchmark examples like image classification with the ImageNet dataset, superior performance have been reported comparing to earlier work which relied on hand-crafted features [5].

2. Literature Survey

Little work has been done on weather related issues for in-vehicle camera systems so far. Payne et al. propose classifying indoor and outdoor images by edge intensity [1]. Lu et al. propose a sunny and cloudy weather classification method for single outdoor image [2]. Lee and Kim propose intensity curves arranged to classify four fog levels by a neural network [3]. Zheng et al. present a novel framework for recognizing different weather conditions [4]. Milford et al. present vision-based simultaneous localization and mapping in changing outdoor environments [5]. Detecting critical changes of environments while driving is an important task in driver assistance systems [6], Liu et al. propose a vision-based skyline detection algorithm under image brightness variations [7]. Fu et al. propose automatic traffic data collection under varying lighting conditions [8]. Fritsch et al. use classifiers for detecting road area under multi-traffic scene [9]. Wang et al. propose a multi-vehicle detection and tracking system and it is evaluated by roadway video captured in a variety of illumination and weather conditions [10]. Satzoda et al. propose a vehicle detection method on seven different datasets that captured varying road, traffic, and weather conditions [11].

3. Proposed Method

In this section, we will describe the main method we propose, which includes the extraction of region-based features based on the region proposal algorithm EdgeBoxes, VLAD encoding and Spatial Pyramid VLAD encoding. Fig.1 shows this system workflow.Each window is generated by a region proposal algorithm and represented by FC6 features, the dimension reduction method: Principle Component Analysis (PCA) is applied, followed by K-means clustering for centroid learning (The blue dots). Traffic scene can then be classified with VLAD code and a SVM classifier.

Although VLAD encoding performs well in preserving local features, VLAD coding does not preserve spatial information. To deal with this problem, several recent papers have proposed spatial pyramid VLAD as a solution [4]. In this research, we implemented this method for traffic scene classification. As shown in Fig.2, the level of the spatial pyramid is 2x2. Regions are allocated into each spatial grid, with an assignment determined by the distribution of the region's centers.

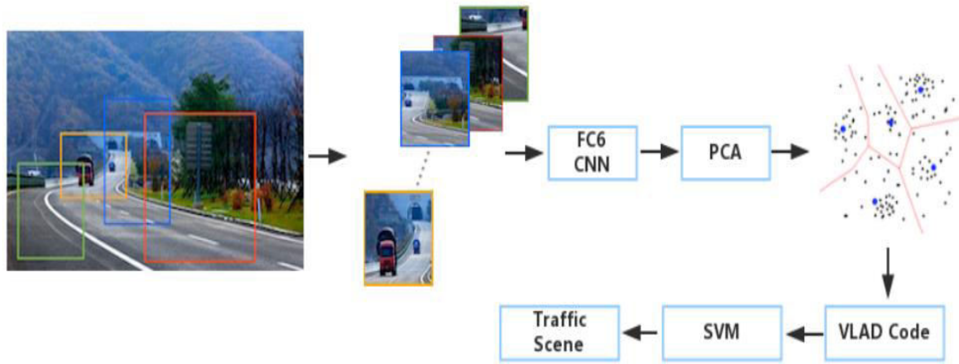

Figure 1. Illustration of the proposed method.

In many vision tasks involving object detection as a component, region proposals have been regarded as standard practice. In our work, we will also start with a set of region proposals from the images. Among the approaches published, Edgeboxes was applied in our work to produce high-quality region proposal, because of its high-level capability and computational efficiency. The pre-trained Image Net model VGG16 was directly applied for feature extraction. For the task of traffic scene recognition, we used the Softmax Loss layer from the MatConvnet platform. Based on our experience, we found that 1000 regions are adequate for image representation. We use the CNN model to extract CNN features from the first fully connection layer (FC6) for the 1000 high-quality region proposals by EdgeBoxes for each image. Since the algorithm of Edgeboxes provides ranking list for region proposal that have confidence values, the top 1000 region proposal have higher probabilities, which means most probably they contain a traffic scene. The number of clusters multiplied by the dimension of CNN features after PCA dimensionality reduction is the final dimension of the VLAD.As has being pointed out in [7], appropriate dimension reduction on original features would further improve the performance of VLAD encoding. Therefore, we use Principal Component Analysis (PCA) [20] to perform dimensionality reduction on the CNN features extracted from these regions. However, as the number of features is large, training conventional PCA on all of the features would be unrealistic. We firstly randomly select 220K sampled regions for training and reduced the CNN features from 4096 dimensions to 256. Then we perform PCA on all of the remaining features.

In this work, firstly, owing to classify multi-traffic scene road images, underlying visual features (color features, texture features, edge features) are extracted from multi-traffic scene images, and then the features expressed as eight-dimension feature matrix. The traffic scene classification problem is becoming the supervised learning problems. Secondly, BP neural network, support vector machine, probabilistic neural network, S_Kohonen network and extreme learning machine algorithms are used to train classifiers. In order to achieve weather images automatic classification, the main steps are shown in Fig.2.Image feature extraction is the premise step of supervised learning. It is divided into global feature extraction and local feature extraction. In the work, we are interested in the entire image, the global feature descriptions are suitable and conducive to understand complex image. Therefore, multi-traffic scene perception more concerned about global features, such as color distribution, texture features.

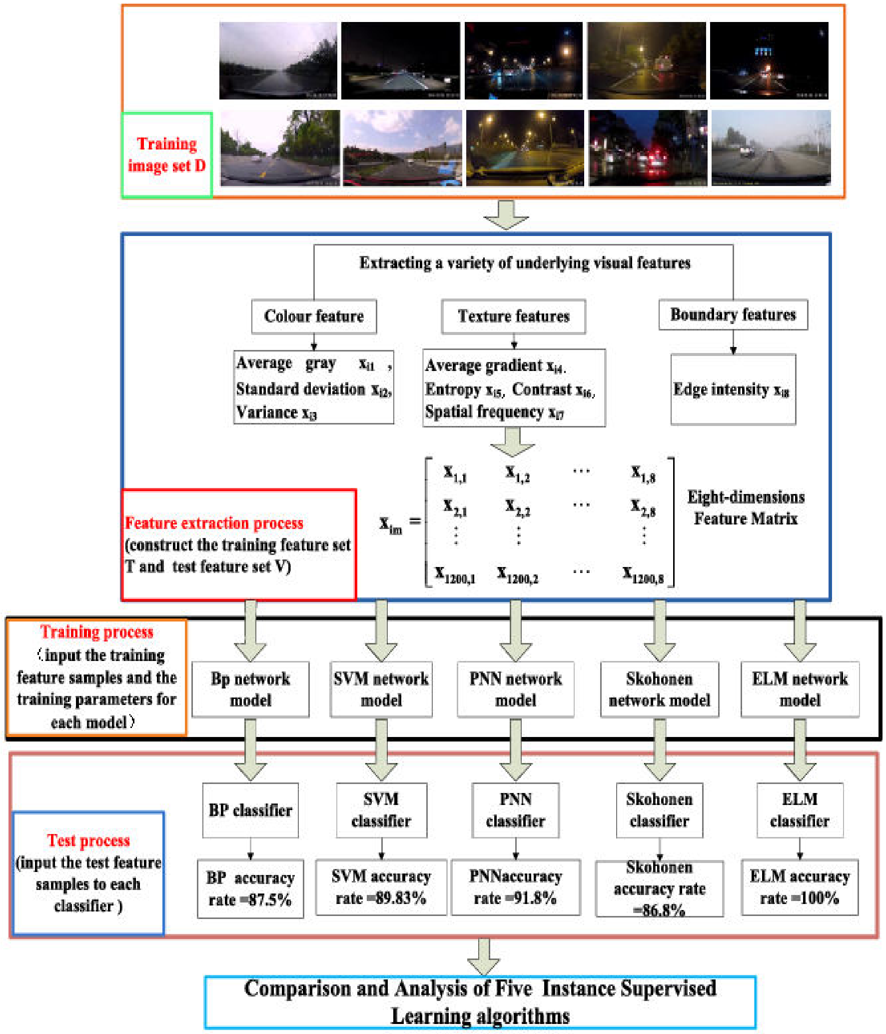

Figure 2. VLAD encoding with a spatial pyramid

Image feature extraction is the most important process in pattern recognition and it is the most efficient way to simplify high-dimensional image data. Because it is hard to obtain some information from the M × N × 3 dimensional image matrix. Therefore, owing to perceive multi-traffic scene, the key information must be extracted from the image.

In the work, there are 1200 images are collected by use of driving recorder and the image set D is established for training and test. There are 10 categories traffic scene images are classified in the work, 120 images are chosen from each category at random. The camera system provides images with a resolution of 856 * 480 pixels. The images are obtained respectively under rainy day, night without street lamp, night with street lamp, overcast, sunlight, rainy night , foggy day and other low visibility road environment images, the classification labels is 1-10, sub-sample set is shown in Fig. 2. In order to train classifier, underlying visual features are extracted that can describe color distribution and structure of image. Such as, color features, texture features, and edge features. Han et al. propose a road detection method by extracting image features. Zhou et al. propose a automatic detection of road regions by extract distinct road feature. Bakhtiari et al. propose a semi automatic road extraction from digital images method. Chowdhury et al propose a novel texture feature based multiple classifier technique and applies it to roadside vegetation classification. In this work, average gray i1 x , standard deviation i2 x , variance i3 x , average gradient i4 x , entropy i5 x , contrast i6 x , spatial frequency i7 x and edge intensity i8 x are extracted and they are as shown in formula(1). The feature sample set with labels can be expressed as C [ ] i1 i2 im 1,2,3 8= 1, 2,3 , m = x ,x , x , i N = ,where, i represents the number of images in the image set. The process that extracted eight underlying visual features is simple, time saving and eight underlying visual can comprehensively describe the visual information of the image.

4. Experiment Results

In the following section, we will first introduce the traffic scene dataset, and then the experimental set up will be briefly outlined including performance comparison, followed by the details of experiments on the database for traffic scene recognition.Our dataset contains 2000 images assigned to 10 categories of traffic scenes with 200 images belonging to each category (Fig.3): bridges, gas station, highway, indoor parking, outdoor parking, roundabout, toll station, traffic jams, train station and tunnel. The average size of each image is approximately 450*500 pixels. The images of the 10 categories were obtained by us from both the Google imagesearch engine as well as personal photographs. Each category of scenes was split randomly into two separate sets of images, 135 for training and the rest for testing.

Figure 3. Sub-sample of 10 categories traffic road scene (from left to right, from top to bottom, the labels are 1-10)

Figure 4.Proposed traffic detection.upload test image (left). detection of traffic (middle). Classification (right).

We evaluated our method on the traffic scene dataset, which is split into training and testing sets of 1350 and 650 instances respectively to evaluate the system performance. The images within each class have large variations in backgrounds and images angles. We followed the Spatial Pyramid VLAD encoding of CNN features as previously explained, and applied a SVM classifier for the final prediction. Specifically, the VGG16 model was utilized for feature extraction. The region proposal algorithm EdgeBoxes was applied on each image, and FC6 features were then extracted for each region. The VLAD encoding was accomplished after PCA dimensionality reduction and codewords learning with clustering. More details about the experiment procedure and three comparative settings are described as follows: To evaluate the stand-alone performance of VGG16, the CNN features from the first fully connected layers (FC6) corresponding to each image are directly applied for traffic scene classification as a comparative baseline. The accuracy is 93.54%, which implies that CNN features for traffic scene recognition are sufficient. The images were directly input to the CNN without candidate objects extraction by a region proposal algorithm.

5. Conclusion

In this paper, we presented a novel traffic scene recognition system with demonstrated satisfactory performance on a traffic scene dataset of 10 categories. Experimental results indicate that information from local patches and the global contextual information are significant contributing factors to improve the performance of traffic scene recognition. This is substantiated by our reimplementation of the Vector of Locally Aggregated Descriptors (VLAD) on top of a spatial pyramid for CNN features to catch local information and global spatial information simultaneously. Experiments were conducted for different settings, with results confirmed that the VLAD codes brings performance gains for traffic scene recognition. The beneficial effect of spatial pyramids has also been demonstrated with performance enhancement.

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