Multi-class weather classification based on multi-feature weighted fusion method

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Abstract. Weather classification, which aims to prevent extreme weather from affecting people's life and property, has recently become a significant interest in image classification. The traditional weather recognition methods always adopt expensive sensors and human vision as auxiliary. However, they perform not very well. Although the Convolutional Neural Networks (CNNs) have shown the state of the art performance on image classification recently, for weather classification, it is a challenging task because it relies on weather-sensitive cues such as the various illumination, contrast and the clutter background of the weather images. To address this issue, a method named multi-feature weighted fusion is presented in this paper. Firstly, we extract the well-chosen weather-specific features such as haze, contrast, brightness, etc., and then fuse these features with data-driven CNNs feature to form high dimensional vectors. Moreover, to increase the recognition performance, various weights are adopted for weather-specific features and CNNs feature to learn an adaptive five-class weather conditions classifier. The extensive experimental results demonstrate that the proposed method obtains better performance than the method using CNNs feature alone.

1. Introduction

According to the existing surveys, inclement weather conditions often lead to catastrophic events such as ship wreck, forest fires, power grids, trains derailment and aviation accidents. Moreover, it also has potential risks to the vehicle, for example, frequent road traffic accidents which is a serious threat to personal safety. Undoubtedly, the identification of weather conditions through outdoor images, also known as multi-class weather classification, plays an important role in many visual and weather systems.

Some researchers have studied the methods of weather classification, but there are still many difficulties and challenges. Early studies about weather classification mainly relied on special sensors (Special Sensor Microwave or Imager Satellite Sensor) or the human eyes to distinguish weather categories [1-3]. However, the weather situation is regional, in addition to the lack of human resources and expensive sensors, which limits the availability of assessing local weather conditions. Since economical surveillance cameras were ubiquitous enough to cope with weather classification[4], motivated by the remarkable success of CNNs in computer vision and machine learning [15, 25-28], researchers have argued that CNNs can be applied to accurately classify weather conditions through images, which might save the costs in labor and equipment (i.e., sensors). Nevertheless, when it is directly used in weather classification, they perform not very well. Because not all CNNs feature is directly related to weather conditions, and weather classification relies on weather-sensitive cues such
as the various illumination, contrast and the clutter background of the weather images. It is indispensable to exploit the synergies between CNNs feature and weather-specific features.

This paper attempts to address the above issues, we focus on fusing the weather-specific features and CNNs feature in the multi-class weather classification task. The contribution of our work lies in three aspects. The first one is extracting the well-chosen weather-specific features (six low-dimensional features such as haze, contrast, brightness, white pixels, sharpness and CHs), then analyzing the effects of these features on classifying outdoor weather images individually. Secondly, the feed-forward, end-to-end CNNs classifier which fused the weather-specific features and CNN features has been trained to perform the five-class classification. Finally, the multi-feature weighted fusion method is proposed to improve the classification accuracy by adopting various weights for weather-specific features and CNNs feature.

This paper is organized as follows. In Sec. 2, the related work is introduced. Weather-specific features are introduced in Sec. 3. Section 4 reports a description of the methodology, emphasizing on the multi-feature weighted fusion method that was used. Section 5 describes a concise presentation of the weather image dataset, details of the experimental process and results. Finally, we conclude this paper in Sec. 6.

2. Related Work
In recent years, significant researches have been made as an attempt to deal with the weather classification problem. However, the existing works still have some limitations. The weather identification was initially carried out in the road detection system, but only the relatively single rain [5-7], fog [8-10] weather conditions were identified. Most of the weather images used to train this classifier were captured by In-Vehicle Multipurpose Cameras, which in the car on the highway, but these captured images are fixed and share a set of similar features, which implies the classifier cannot be generalized for the images with different backgrounds and viewpoints [11].

Practically, domain specific engineered features play an important role in building a weather classification model. Most recent works [29-31] have utilized sky and shadow to constitute weather-specific features for weather classification model. Lu et al. [12] presented a two-class weather classification framework that classified images based on SVM and five weather-specific features such as sky, haze, contrast, reflection and shadow. Zhang et al. [13] proposed a method to label images with four weather conditions including sunny, cloudy, and snowy and haze. They trained a SVM as weather classifier which combined the global and local features. Martin et al. [14] estimated weather conditions by extracting five features of images (such as brightness, contrast, sharpness, saturation and hue) and training a classifier base on SVM.

Recently, CNN is one of the most advanced and very widely used classification models in image classification. Krichevsky et al. [15] proposed a particular CNN structure called AlexNet and obtained the champion of the ILSVRC-2012 ImageNet challenge. Elhoseiny et al. [4] proposed a method to label the image as either sunny or cloudy based on AlexNet. Lu et al. [16] performed a similar series of experiments to extend their work of two-class weather recognition based on [15]. The study by Zhu [17] offered a comprehensive empirical analysis of the four class weather classification algorithms through fine-tuning the Google Net. Di Lin et al. [18] proposed a deep learning framework named the region selection and concurrency model (RSCM) which used regional cues to identify the weather category.

Different from these methods, we extracted six well-chosen weather-specific features to represent different weather types and fused data-driven CNNs feature to train classification models.

3. Weather-specific Features
In traditional image classification task, interest points or object edges in the image are generally selected as features. While there are some same objects and points under different weather image simultaneously, it is impractical for weather-based image classification. Therefore, it is inappropriate to utilize the same kind of features as general image classification [13]. We collect six well-chosen weather-specific features by evaluating the characteristic of images under different weather conditions.
3.1. Brightness

Brightness is one of the most significant pixel properties. The brightness can explain weather images well. For example, the brightness of sunny image is generally higher, while cloud and fog usually are lower. Actually, there is no customary formula to calculate brightness. Sergey Bezryadin et al. [19] proposed an effective method to calculate brightness substitutions: Luma Brightness, which is widely used in image processing algorithms imitating performance of corresponding Color-TV adjusting knobs and brightness equivalent in MPEG and JPEG algorithms. Photoshop uses this metric in contrast editing algorithms to calculate average brightness as well. The method is adopted in this paper, and the formula is shown in Eq. (1):

\[ Y' = 0.299r + 0.587g + 0.114b, \]  

(1)

Where Y’ is Luma brightness value, r, g, and b are stimulus sRGB coordinates [19].

3.2. Contrast

Contrast can be commonly explained as the variation between the maximum and minimum pixel intensity in an image. The larger the difference range, the higher the contrast, otherwise the contrast is smaller. Images captured under sufficient light always have high contrast, while images captured under low-light have low contrast. For example, the sunny images have high contrast, and the rainy images have low contrast. To calculate the contrast, the encoded contrast are utilized as the percentile in image saturation. Clearly, if all saturation percentiles are the same for a given image, the saturation contrast is low [17], we measure contrast metric simply as Eq. (2, 3, 4):

\[ d^l(x) = \min_{n \in [r, g, b]} I^n(x), \quad b^l(x) = \max_{n \in [r, g, b]} I^n(x), \]  

(2)

\[ d = \frac{\sum_{x \in X} d^l(x)}{S_x \times S_y}, \quad b = \frac{\sum_{x \in X} b^l(x)}{S_x \times S_y}, \]  

(3)

\[ c = d - b, \]  

(4)

Where \( d^l(x) \) is the minimum pixel value in pixel r, g, b three channels, \( b^l(x) \) is the maximum value, d and b are the mean of \( d^l(x) \) and \( b^l(x) \) respectively, \( S_x \times S_y \) is total pixel count. C is contrast value.

3.3. Haze Factor

Haze may come from cloudy or foggy weather. For most fog weather images, the lowest and highest value in color channels tends to be the same value of atmospheric light [20]. We need a haze function to detect cloudy and foggy images.

For a fuzzy fog weather image, special methods such as defogging can be used to improve the recognition accuracy. However, recognizing weather condition from a single outdoor image has not been thoroughly studied. Jun Mao et al. developed a stable algorithm to estimate different haze automatically. The formula is as follows (Eq. (5) and Eq. (6)):

\[ \omega = \exp\left\{ -\frac{1}{2}\left(\mu x_1 + \nu x_2 + \sigma \right) \right\}, \quad x_1 = \frac{A_0 - d}{A_0}, \quad x_2 = \frac{c}{A_0}, \]  

(5)

\[ A_0 = \lambda \min_{x \in X} b^l(x) + (1 - \lambda) \overline{b}, 0 \leq \lambda \leq 1, \]  

(6)
Where \( \lambda \) is set to 1/3, \( \omega \) is haze value, \( A_0 \) is the global atmosphere light.

Obviously, the calculation of haze uses the values as mentioned above of contrast value (c), d, b, etc. According to the experience, we recommend \( \mu = 5.1 \), \( \nu = 2.9 \), \( \sigma = 0.2461 \). Finally, the calculated haze value between 0 and 1, the degree of haze is divided into six levels. As shown in Table 1.

| Haze-degree | Corresponding value | Haze area proportion | Haze density |
|-------------|---------------------|----------------------|-------------|
| 0           | 0.1                 | 0                    | clear       |
| 1           | 0.3                 | 0-80%                | thin        |
| 2           | 0.5                 | 0-80%                | Normal or thick |
| 3           | 0.7                 | 80%-100%             | thin        |
| 4           | 0.8                 | 80%-100%             | normal      |
| 5           | 0.9                 | 80%-100%             | thick       |

3.4. Sharpness

Sharpness is defined by the boundaries between zones of different tones or colors [21]. Distinguishable objects under several weather conditions are expected to have sharp edges with substantial contrast differences, so the sharpness is suggested to proposed weather types. We observed that sunny, cloudy and rainy weather images are sharper than the snowy and foggy weather images.

To measure sharpness of an image, a method named “sharpness estimation from image gradients” was proposed, which reads an image and iteratively smooths it more and more to present how sharpness reduces [22]. The method is tested against mean and unsharp (sharpen) filtering. It is based on an average determination of the Sobel gradient magnitude. The formula is as follows Eq. (7):

\[
T = \frac{\sum_{i} s_x^2(i) + s_y^2(i)}{\sum_{i}}.
\]

Where \( i = [1 \ldots \text{all pixels}] \), \( S_x \) and \( S_y \) response the sobel filter, \( T \) is sharpness value.

3.5. White Pixel

According to researchers observation, snowy or sunny weather could come with the white pixel, and it is high in snowy and sunny images, low in foggy and rainy images. But in a grayscale image white pixels are not only represented with 255 value of gray level but also 150, 200, 250 and higher pixel values are relatively white. Based on this situation, we test snowy, cloudy and other types of weather images and choose 175 and higher valued pixels as white pixels, others are black. Lastly, we count white pixels in given image. To put calculated intensity value between (0, 1), the count of white pixel divided by the total pixel number of given image.
Algorithm 1 Pseudo code of white pixel extraction algorithm
1: initialize image: transfer image from RGB to GRAY
2: white_pixels ← 0
3: black_pixels ← 0
4: white_threshold ← 175
5: for i ← 0 to row of the image
6: for j ← 0 to columns of the image
7: if item of the image(i, j) < white_threshold
8: then black_pixels ← black_pixels + 1
9: else
10: then white_pixels ← white_pixels + 1
11: call CalValue(white_pixels / (black_pixels + white_pixels))

3.6. Color Histograms
Color histograms (Chs) are significant color features, which are widely used in image classification and target detection. It describes the proportion of different colors in the entire image, that is, the number of colors in the image, and does not care about the spatial position of each color. Since different types of weather images have very varied and distinctive colors, Chs can be used for weather condition recognition. We calculate the values of images histogram of RGB three channels, and then concatenate them to get a flattened image descriptor array.

4. Methodology
Recently, CNN has been widely used in computer vision, bringing inspiration to many image classification models. Different from the related works above, we propose a method to classify multi-class weather, which fuses weighted well-chosen weather-specific features and CNNs feature. To begin this process, we properly encode kinds of weather-specific features (such as haze factor, sharpness, contrast, and brightness, and white pixel and color histograms) which can encode different type of weather images into feature vectors. To the best of our knowledge, the haze feature can indicate the foggy or cloudy images; contrast and brightness can indicate sunny images; sharpness can indicate snowy or foggy images; the color histogram can indicate rainy images; the white pixels can indicate snowy images.

CNN mainly realizes displacement scaling through three methods—local receptive field, shared weights, and down-sampling. It retains most of the useful information of image and has powerful capability of recognition and classification. Moreover, it also greatly reduces the amount of parameters and avoids over-fitting by receptive field and shared weights. The implementation of CNNs is shown in Fig.1.

Figure 1. CNN training process
By analyzing weather-specific features and CNNs feature, we are able to find two reasons to support using fusion methods.

a) The weather-specific features were employed to gain a further understanding of multi-class weather images. But it does not represent most of the content in images.

b) The CNN feature is capable of capturing global image characteristics, if we combine the data-driven CNN feature and well-chosen weather-specific features to overall weather feature, the accuracy may be improved.

So we incorporate the powerful CNN feature and weather-specific features into the overall weather feature to recognize weather types. It can represent image information more comprehensively so that improving classification accuracy. Specifically, we train a classifier by concatenating the flattened output of CNNs frame and weather-specific features in a single array as the description of an image. To verify the classification performance, we consider the features with three types of concatenating way: a) concatenate none of it; b) concatenate part of it; c) concatenate all of it. Figure 2 presents a detailed implementation of the fusing method.

![Figure 2](image)

**Figure 2.** The concatenation weather-specific features and CNNs.

To further improve the accuracy of the model, we adopt various weights for weather-specific features and CNNs feature, and named it multi-feature weighted fusion method. As the illustration in Fig.3. The final fused feature is concatenated with two parts: one part is the weather-specific feature; the other part is the output of the CNN. Additionally, a set of weighting coefficients are adopted for each part. The final output is the sum of the two parts’ weighted output. From the aspect of quantity and dimension, the weather-specific features differ from the features extracted by the CNNs. We adopted two weighted features to obtain the best-weighted combination, and it allows these two features to perform best on the classifier. Moreover, this weight was initialized to a random value between (0, 1), and it can be learned and updated continuously through back propagation during optimizing the loss function.
5. Dataset and Experiment

5.1. Weather image dataset
In this paper, the weather image dataset used in J. C. V. Guerra’s paper [11] was adopted to evaluate our proposed model, which is mainly divided into two parts: the first part is the RFS dataset which contains three types of weather categories such as rainy, foggy and snowy. Additionally, each category contains 1100 images collected from the Internet. The second part is the two types of weather dataset (sunny and cloudy), which is collected by Lu et al. as a part of their work. In the course of experiments, we used a total of 5,500 images of the five categories described above to divide them into a 70% training set and a 30% test set to evaluate weather classification models. Both of the training set and the test set are selected randomly. Figure 4 shows some example images.

![Figure 4](image-url)

**Figure 4.** Some example images from the weather image dataset. It includes five weather categories, i.e., (a) cloudy, (b) foggy, (c) rainy, (d) snowy and (e) sunny.

5.2. Experiment and results
The method proposed in this paper is implemented based on Keras and Python. Experiments have been performed on four different CNN structures: VGGNet16, VGGNet19, ResNet50 and ResNet101. All

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1 RFS can be accessed online using the link: https://github.com/ZebaKhanam91/SP-Weather
the models are initialized with learning rate of 0.001 and this value is reduced by 10% after each two thousand iterations. Termination of training after 60,000 iterations. The momentum and the weight decay were assigned to 0.9 and 0.0005 respectively. The experiment is as follows:

a. Concatenating none of the weather-specific features

The whole images in weather dataset were inputted directly, and obtained the five-class weather recognition result through different CNN function alone, as Table 2 shows. The results of the experiment are similarly with J. C. V. Guerra’s experiment [11] and it performs not well, because not all CNNs feature is directly related to the weather conditions. This is an effective but not the best way in this task, so it is requisite to exploit the synergies between CNNs feature and weather-specific features.

| Model         | Without weather features | Fusing multi-feature | Fusing weighted multi-feature | Weight value |
|---------------|--------------------------|----------------------|-------------------------------|--------------|
| VGGNet16      | 0.7204                   | 0.7580               | 0.7863                        | 0.83         |
| VGGNet19      | 0.6901                   | 0.7204               | 0.7576                        | 0.87         |
| ResNet50      | 0.7725                   | 0.7995               | 0.8379                        | 0.76         |
| ResNet101     | 0.7616                   | 0.7897               | 0.8352                        | 0.68         |

b. Concatenating five groups of the weather-specific features

Five groups of weather-specific features were concatenated with the output of flatten layer of CNNs models respectively to classify each category, like cloudy, foggy, sunny, snowy, rainy. For each of the categories, 770 were used for the training phase, and 330 were used in the testing phase. The analysis of the results category wise (Fig. 5-9) indicates that the best architecture to tackle the weather classification problem is ResNet50 architecture, and for each category, after concatenating the corresponding weather-specific feature, the obtained improvements are in the range of 2-3%. Among them, the contribution of haze factors in the identification of fog weather is particularly obvious. White pixels are also important weather cue among the five weather-specific features for identifying snowy weather. And the brightness and contrast weather cue also work well.

![Figure 5](image_url)
Figure 6. Evaluations for sunny Category.

Figure 7. Evaluations for Snowy Category.
The whole flattened weather-specific features and the output of the flatten layer of CNNs model were fused into a high-dimensional single array called the overall features to train the classifiers. We evaluated its performance through various CNNs which is shown in Table 2. The result shows that this method can significantly improve the performance of the classifier, mainly due to the overall features, which not only contains most of the basic functions of the image, but more importantly, it also contains specific-weather features that can present the characteristics of the weather category.

d. Weighting

We adopted a weighted way to encode the overall feature vector. The weight mentioned here can be continuously learned and updated by back propagation during optimizing the loss function.
reported the best performance and achieved higher accuracy than the other two experiments. And the results are about 6%-7% higher than J. C. V. Guerra’s experiment [11]. The result and obtained weight values are shown in Table 2. Obviously, we adopted two weighted features to obtain the best-weighted combination, which significantly improved the impact of these two features on the classifier to minimize the loss function. Figure 10 shows some detection results.

![Detection Results](image)

**Figure 10.** Some detection results for online images. The first column to the fifth column are (a) cloudy, (b) foggy, (c) rainy, (d) snowy and (e) sunny respectively.

### 6. Conclusion
In this paper, we proposed a practical deep learning-based model for classifying five types of weather, the main work are: 1) we extracted the well-chosen weather-specific features and analyzed the impact of them to weather situation recognition; 2) we fused weather-specific features and CNNs feature to learn adaptive classifiers; 3) we generally improve the classification accuracy, by multi-feature weighted fusion. Experimental results proved that this is a fairly effective and inspiring strategy that could identify common weather conditions from a single color image, and can take advantage of existing video equipment in traffic and surveillance area to automatic recognize them. In the future, the weather images dataset constructed in this paper will be extended with more categories, such as hailstone, light rain, etc. and we will continue to optimize the model through enhancing the weather features which can affect the classification performance.

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Zhiqiang Li received his BS degrees in Communication Engineering from Chengdu University of Information Technology (CUIT) in 2017. He is currently studying for a master's degree in the College of Communication Engineering, CUIT, majoring in computer vision and machine learning.

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