MULTI-CLASS WEATHER CLASSIFICATION ON SINGLE IMAGES

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ABSTRACT

Multi-class weather classification from single images is a fundamental operation in many outdoor computer vision applications. However, it remains difficult and the limited work is carried out for addressing the difficulty. Moreover, existing method is based on the fixed scene. In this paper we present a method for any scenario multi-class weather classification based on multiple weather features and multiple kernel learning. Our approach extracts multiple weather features and takes properly processing. By combining these features into high dimensional vectors, we utilize multiple kernel learning to learn an adaptive classifier. We collect an outdoor image set that contains 20K images called MWI (Multi-class Weather Image) set. Experimental results show that the proposed method can efficiently recognize weather on MWI dataset.

***Index Terms*—** Multi-class weather classification, multiple kernel learning, multiple weather features

1. INTRODUCTION

Most of existing methods in the field of computer vision are based on the hypothesis/assumption that the weather in outdoor images or videos are clear. However, different weather conditions such as rain, snow or haze will cause complex visual effects in images or videos, as shown in Figure 1. Such effects may significantly degrade the performances of outdoor vision systems relying on image/video feature extraction or visual attention modeling. The applications are numerous, such as the detection of critical weather conditions, the observation of weather, the reliability improvement of video-surveillance systems and rain or snow rendering. In this paper, we target at the problem of classifying multiple weather, such as sunny, rainy, snowy and haze from single images.

Despite its remarkable value, multi-class weather classification has not been thoroughly studied. Previous researches [1, 2, 3] focused on weather recognition from vehicles camera images for driver assistance. Most of these methods are only able to recognize rainy weather. Furthermore, the applications are limited due to the relatively fixed target scenes. Recently, the authors of [4, 5] focus on two-class weather recognition, include sunny and cloudy. The authors of [4] estimate the weather conditions of popular tourism from images of the same scene. The authors of [5] proposed a method for two-class weather recognition from single images, including sunny and cloudy. The authors of [6] proposed a method to label images of the same scene with three weather conditions including sunny, cloudy, and overcast. The authors of [7] proposed an approach for multi-class weather classification, which could be used for a fixed scene only. The authors of [8] proposed a method for air quality inference based on multiple image features. However, the approaches for the fix scene weather classification are weak in practice due to the following two reasons. First, it need learn different classifiers for different scenes. Second, affected by factors such as climate, it is hard to collect the training image set in anywhere.

Fig. 1. Tiananmen Square in different weather.

Different from the works above, we propose a method for classifying multi-class weather from single images which is based on multiple weather features and multiple kernel learning. Implementation of this idea, however, entails substantial challenges. First, it is difficult to find the suitable features to discriminate different weather. Second, the features might be heterogeneous and the feature vectors are high-dimensional. Aiming at the above challenges, firstly, we extract multiple features to represent different weather. For example, the sky and shadow features can indicate the sunny weather, the haze feature can indicate the haze weather, the HOG based template matching feature can indicate the rainy weather, the snowflake noise feature can indicate the snowy feature, and some global features like contrast and saturation are used to distinguish multi-class weather. Secondly, we utilize mul-

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tiple kernel learning to learn an adaptive classifier to fuse these heterogeneous and complementary features effectively. Compared with the traditional classification methods (such as SVM, Adaboost), multiple kernel learning is beneficial to learn an adaptive classifier because it can choose the best combination of kernels.

The contribution of this paper lies in four aspects:

- To the best of our knowledge, the proposed method is the first to focus on the problem of multi-class weather classification from single images in any scenario.
- We propose two methods for detecting rain and snow from single images respectively.
- We improve some existing algorithms for obtaining the weather features and take multiple kernel learning for multi-class classification.
- We collect an outdoor image set that contains 20K images called MWI (Multi-class Weather Image) set.

2. MULTIPLE WEATHER FEATURES

For any pattern recognition problem, it is important to select proper features. Weather classification from images is different from general image classification. We always implement the image classification by selecting interesting points as features or detecting the object emerging in the scene. It is impractical for our problem because there can be the same objects and interesting points under different weather conditions. Hence, it is not proper for applying the same kind of features as general image classification. We propose several low-level features by analyzing the property of images under the different weather conditions.

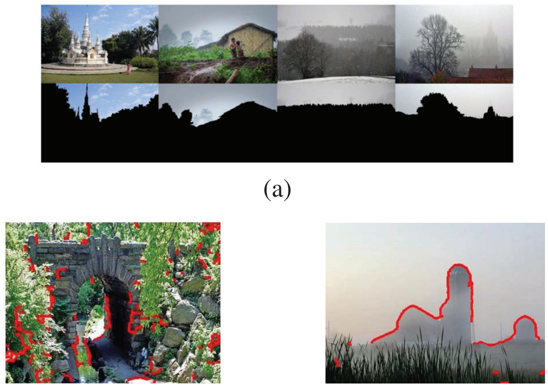
2.1. Local features

The so-called local features in this part means that each of these features is used to indicate only one class weather.

2.1.1. Sunny feature

Sky and shadow might be the most obvious features to indicate the sunny weather in images. That is to say, the minimum intensity in such a patch should have a very low value. As shown in Figure 2, the sunny images have clear sky or strong shadows, while the other weather images have gray sky or faint shadows. For the sky part, firstly, we detect the sky region in an image with the method suggested in [5, 9]. Then, we extract the a and b channels in the LAB color space of the sky region to form a 200 dimensional feature vector.

However, not all the sunny images have a sky region. For the image in which sky region is not detected, the strong ground shadows can indicate the sunny weather. We apply the shadow detection tool in [10], and follow the implementation



(a)

(b) (c)

Fig. 2. (a) Top: input images of different weather. Bottom: the detected sky regions. (b) Shadow detection result for a sunny image. (c)Shadow detection result for a haze image.

in [5]. First, we construct a sunny boundary set. For the sunny images, we extract the top 10 most confident shadow boundaries, and save them to the set. Given an image, we obtain its top 10 most confident shadow boundaries. By computing the mean distance between a boundary and its K-nearest neighbors in sunny boundary set, we can measure the boundary likelihood to be a shadow boundary of a sunny image. Then, we can form a 10 dimensional feature vector for each image.

2.1.2. Rainy feature

Rain and snow detection from single images has been rarely studied in the literature, where no temporal information among successive images can be exploited, making the problem very challenging. Some works used HOG for rain streaks removing or detecting [11, 12]. To detect the rain streaks, a Histogram of Orientation Gradients(HOG) based template matching method is used. In detail, we construct five pure rain HOG templates in different angles. For each image, we use the guided image filter to decompose it into a low-frequency part and a high-frequency part which is suggested in [13], so that the rain streaks would be in the high-frequency part with nonrain textures/edges. Then, we extract the HOG feature of the binary image from the high-frequency part. As shown in Figure 3, there is no significant difference in the bottom HOG image which is computed from the original image. We use a sliding window which size is the same with the templates to scan the whole image and compute the HOG similarity between templates and the patches. The similarity is computed by Mahalanobis distance. Then, we choose the five best matched patches, and use their HOG features to form the 180 dimensional feature vector for the image.

2.1.3. Snowy feature

As mentioned in the above section, it is difficult to detect snow, especially in single images. Snow is light and soft,

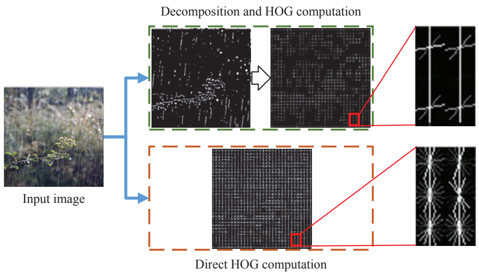


Fig. 3. The HOG figures of the high-frequency part and the original input image.

when there is wind, the snowflakes will change their original direction and fly to anywhere even to upper sky. It is hard to sum the rule of the flying snowflakes, because the trajectory of snow is disordered.

We regard snowflakes as a kind of noise. Pixels are defined as snowflake noises when they have following characteristics:

- The gray value of pixel C is $L + \varepsilon$, in which L is the mean gray value to an image, ε is a threshold and greater than zero.
- The pixels inside the circle which is centered at pixel C and with R as the radius have the same gray value with C, while the pixels on the circle do not have the same gray value with C.

For all the snowflake noise pixels in an image, we compute the histogram of intensity and hue of the patches they located in to form the 200 dimensional feature vector.

2.1.4. *Haze feature*

Dark channel prior has been well studied in the field of single image haze removal. Authors of [14] found that most local patches in haze-free outdoor images contain some pixels which have very low intensities in at least one color channel. That is to say, the minimum intensity in such a patch should have a very low value. So, we utilize dark channel to indicate the haze weather. First, we divide an input image into patches. Then, we use the median value of dark channel intensities in these patches to form a 100 dimensional feature vector.

2.2. Global features

Corresponding to the local features, the global features describe in this part mean that each feature can indicate multi-kind weather.

2.2.1. *Contrast*

Contrast is a useful cue for weather labeling as light is not the same in different weather conditions. Images captured under sufficient light always have high contrast, while the images captured under low-light have low contrast. We compute the contrast according to root mean square method as the one dimensional feature vector.

2.2.2. *Saturation*

As the saturation is independent of illumination, it can represent different images under various illumination conditions. For an image I we calculate the normalized saturation for each pixel by

$$S_{(x,y)} = \frac{S_{x,y} - \min(S_I)}{\max(S_I) - \min(S_I)}, \quad (1)$$

where $\max(S_I)$ is the maximum saturation value and $\min(S_I)$ is the minimum saturation value of image I. For convenience of calculations in the following steps, we compute the histogram of the normalized saturation of an image to form the 10 dimensional feature vector.

3. MULTIPLE KERNEL LEARNING

To fuse these features for weather classification, we utilize multiple kernel learning [15] to learn a robust classifier by using multiple kernels. Let $D_L = \{x_i, y_i\}_{i=1}^N$ be the training image dataset, where x_i denotes the $i-th$ sample and y_i denotes the corresponding class label, and N is the number of training images. We aim to train a multi-kernels based classifier with a decision function $f(x)$ to predict the weather class of an unlabeled image x. In this work, we use some linearly combined base kernel functions to determine an optimal kernel function:

$$k(x_i, x) = \sum_{m=1}^{M} \beta_m k_m(x_i, x), \quad (2)$$

where β_m is one of the linear combination coefficients, $\sum_{m=1}^{M} \beta_m = 1$ and $\beta_m \geq 0$. Given the input feature x of the image, the decision function is defined as follow:

$$f(x) = \sum_{m=1}^{M} \beta_m k_m(x)\alpha + b, \quad (3)$$

where α and b are the parameters of the standard SVM.

In this paper, we adopt the simple multiple kernel learning [16], so the objective function can be formulated as follows:

$$\min_{\beta,\alpha,b} J = \frac{1}{2} \sum_{m=1}^{M} \beta_m \alpha^T K_m \alpha + C \sum_i \xi_i, \quad (4)$$

$$s.t. \quad y_i \cdot \sum_{m=1}^{M} \beta_m K_m(x_i)\alpha + y_i b \geq 1 - \xi_i \quad \forall i,$$

$$\xi_i \geq 0, \quad \forall i \quad (5)$$

Fig. 4. Sample images in the MWI dataset.

in which $K_m(x_i) = [k_m(x_i, x_1), \cdots, k_m(x_i, x_p)]$, p is the number of weather classes. We adopt the gradient descent algorithm to solve the optimization problem in (5). For each iteration, given the weight β to obtain α and b. Then, given α and b to obtain the recomputed β. We adopt one-against-all strategy to transform the multi-class classification into two-class classification. If there are P classes, then the objective function can be rewritten as:

$$J = \sum_{p=1}^{P} J_p(\beta, \alpha_p, b_p), \tag{6}$$

where J_p is a two-class classifier, the positive samples are the samples with class label p, the negative samples are the samples with other labels. We can obtain the class label by:

$$y = \arg\max_{y_p} F_p(x). \tag{7}$$

4. DATASET AND EXPERIMENT

4.1. Dataset

We evaluate our approach on our dataset called MWI (Multi-class Weather Image) set. It contains 20K images obtained from many web albums and films, such as Flicker, Picasa, Poco, Fengniao. As shown in Figure 4, most of the images have totally different background.The images are collected by several helpers, and they choose images with their own common sense. The main purpose of this dataset is to provide an extensive testbed for the evaluation of existing appearance models, and provide insight needed to develop new appearance models.

4.2. Experiment setting

In our experiment, we set $K = 5$ for the K-nearest neighbors in the shadow feature part. For extracting rainy feature, we resize an image into 256×256, and set 8×8 as the cell size, the step is 4, the size of sliding window is 16×16. For extracting snowy feature, we set the threshold $\varepsilon = 0.3 \times L$, the radius R is $\sqrt{2}$. For extracting haze feature, we resize the input images into 450×450, and set the size of a patch as 45×45. We fuse these features to form a 701 dimensional vector for an image. In MKL, we use 5 linear base kernels respectively constructed for the multiple features. To cope with multi-class classification task using SVM, we adopt the default setting in LIBSVM.

Table 1. Classification results of different method on MWI dataset.

	SVM	Adaboost	Proposed
Accuracy	0.4280	0.2568	**0.5944**
Precision	0.8644	-	0.8889
recall	0.7586	-	0.9180
F-Measure	0.8080	-	0.7320

Table 2. Classification results of related methods on MWI dataset.

	[2]	[3]	[6]	Proposed
Accuracy	0.2267	0.1889	0.4158	**0.5944**

4.3. Experiment results

Table 1 shows the comparison results of our approach and the baseline methods. To show the best performance of all methods, every method produced multiple results using a group of reasonable parameters. The first baseline is to implement SVM directly on the 701 dimensional feature. The second baseline is the traditional Adaboost, which combines several classifiers to build a stronger classifier. We also compare our method with some related image classification methods as shown in Table 2.

From the tables, we can observe that our method achieves the best results, which demonstrates the effectiveness of fusing multiple weather features and multiple kernel learning to improve the classification performance.

5. CONCLUSION

We presented a learning-based approach for multi-class weather classification from single images in any scenario. Our approach use multiple kernel learning to learn an adaptive classifier. For training and testing our approach, we collect the MWI (Multi-class Weather Image) set. We evaluate our approach on the dataset, the results show the effective of our method. However, some features are sparse, it affects the classification performance. For the future work, we plan to enhance the weather features for improving the performance.

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