A Method of Weather Recognition based on Outdoor Images

Qian Li, Yi Kong and Shi-ming Xia
College of Meteorology and Oceanography, PLA University of Science and Technology, NanJing, China
public_liqian@163.com

Keywords: Outdoor Image, Weather Recognition, Power Spectrum Slop, SVM, Decision Tree.

Abstract: To improve the quality of video surveillance in outdoor and automatic acquire of the weather situations, a method to recognize weather phenomenon based on outdoor images is presented. There are three features of our method: firstly, the features, such as the power spectrum slope, contrast, noise and saturation and so on are extracted, after analysing the effect of weather situations on image; secondly, a decision tree is constructed in accordance with the distance between the features; thirdly, when every SVM classifier on the non-leaf node of the decision tree is constructed, some features are selected by assigning the weight. The experiment results prove that the proposed method can effectively recognize the weather situations in outdoor.

1 INTRODUCTION

In many outdoor applications for computer vision, the “bad” weather situations, such as haze, fog, rain, hail and snow, are involved. And it is urgent to detect and recognize the various outdoor weather situations, especially the severe ones. Meanwhile, the observation of weather situations in meteorology is still mainly rely on manual, and weather situation is not exactly the same even within every small region. Therefore, automatic recognition of the outdoor weather situation based on image or video data gets more extensive attention in recent years.

According to the duration and extent of influence to the video or image, weather situations can be divided into static or steady weather situations category and dynamic weather situations category (Garg, 2004).In Static weather situations such as sunny, cloudy, fog, smoke, haze and so on, there is some or more stable particles in the atmosphere to attenuate and refract the ambient light, so the impact on image quality of these phenomena is relatively more stable, mainly for the blur degradation. Dynamic weather situations, such as rain, snow, dust storm, hail and so on, make ambient light attenuation and refraction for the movement of unstable particles in the atmosphere, and the image quality degradations caused in these situations are mainly motion blur, point noise and movement trace noise. Because of the differences in imaging process, for example, the influence of the size of rain and snow, the degradation effect will be different. So identifying and studying different dynamic weather phenomena in different environments and situations is one of the difficulties in current research.

This paper presents an approach to identify and classification of weather situations to use existing surveillance cameras to improve the recognition rate of outdoor image and resolve the problem of automatic weather observation. We construct classifiers with the structure of decision tree by features extracted from the sample outdoor images and acquire accurate weather situations classification results to the images captured by video camera.

2 OUR METHODS OVERVIEW

Weather recognition is a brand-new subject and only a few of previous work has addressed this issue. Narasimhan (Narasimhan, 2002; Narasimhan, 2003) improved the image quality through the establishment of the physical optics model of the atmosphere in the fog and rain and other inclement weather, however their research was mainly based on the premise of the known current weather, and did not classify the image automatically. Roser (Roser, 2008) recognized clear, light rain and heavy rain weather that exists in the image of driver assistance systems based on HSI color space histograms. Yan (Yan, 2009) analyzed the gradient and HSV color space histograms of the image data die vehicle equipment to identify the sunny, rainy and cloudy combined with road information, but their research background limited within the range of intelligent transportation and the acquired image content was simple and feature selection and recognition had been fixed. Shen (Shen, 2009) used SIFT transform to the internet images in the same scene with the different perspectives, and established the corresponding illumination model and estimated the weather according to the angle of light at the scene, but their model can only recognize sunny and cloudy weather conditions under the changing illumination. In the modeling process of the moving object of traffic surveillance video, Lagorio (Lagorio, 2008) estimated the existence of snow from the changes of parameters in the mixed of Gaussian model, and speculate fog according to the blurring of the video frame in frequency domain spatial, but the method is easily confused by similar rainfall and other weather situations.

In order to overcome the problem of the limitations of feature extraction and recognition in previous work, we present a weather classification method based on SVM, which can increase the identified weather types in the training process and select appropriate features from the candidate features according to the effect the characteristics of weather phenomena. After analyzing the influence of various weather situations to the image quality, we extract power spectrum slop, contrast, texture noise and saturation of images as the candidate features, and establish a decision-tree-based SVM classification model. The model having trained can classify the test images to get the corresponding weather situations. The common weather situations including sunny, cloudy, fog and rain are considered in our method and the process flow is as Fig 1.

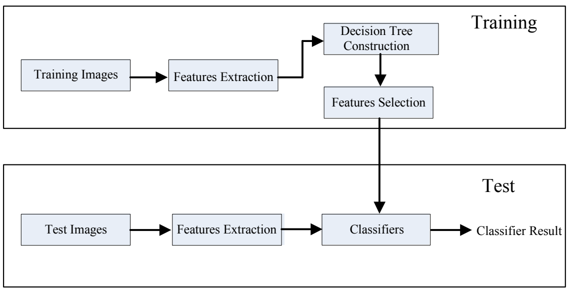


Figure 1: the Framework of Recognition of Weather.

3 FEATURE EXTRACTION

3.1 Power Spectrum Slope

According to the visual perception, the images under some inclement weather situations, such as rain, fog etc, seem to be more blurred than those in fine days, due to losing some high frequency components. Due to the different image content, so this image by extracting the slope of the power spectrum (Liu et al, 2008) information, analysis of various weather phenomena and the impact of image degradation effects.

We first compute the power spectrum of an image I with size N*N by taking the squared magnitude after Discrete Fourier Transform (DFT).

$$S(u,v) = \frac{1}{MN} | I(u,v) |^2 \tag{1}$$

where $I(u,v)$ denotes the Fourier transform image. Then we represent the two-dimensional frequency in polar coordinates, i.e., $u = f\sin\theta$ and $v = f\cos\theta$, and construct $S(f,\theta)$, f is the power spectrum image radius after shifting , and θ for the polar angle, by summing the power spectra S over all directions θ, $S(f,\theta)$, using polar coordinates, can be approximated by

$$S(f) = \sum_{\theta} S(f,\theta) \tag{2}$$

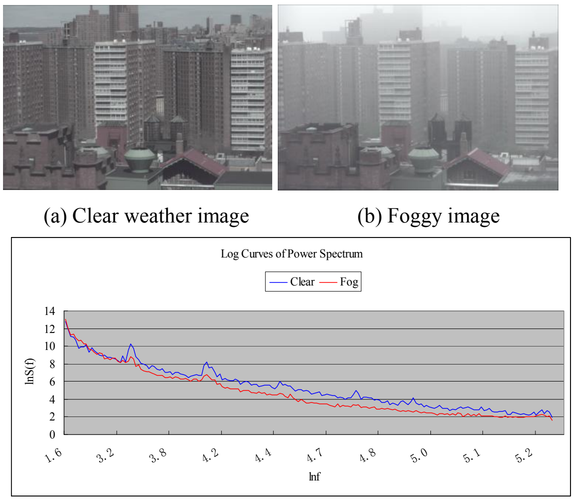
Burton (Burton, 1987) has demonstrated that $S(f)$ of most natural images is approximately decrease exponential with f, that is:

$$S(f) \approx \frac{A}{f^{\partial}} \tag{3}$$

where A is a constant, it is clear from (3) that $\partial \approx \ln A - \frac{\ln(S(f))}{\ln(f)}$, so it can fit a spline line by $\ln S(f)$ for different radius to strike the slope ∂ and show in Figure 2. While fitting the line, errors may be considerable because there are fewer points in the center of the shifted power spectrum image. Therefore we adopt $f \geq 8$ to get better fitting results.

3.2 Contrast Features

Due to attenuation and refraction of light, the contrasts of images under different weather situations are quite different, even in the same scene.



(a) Clear weather image (b) Foggy image

(c) Log Curves of Power Spectrum, with clear $\partial_1 = 2.9$,fog $\partial_2 = 3.1$

Figure 2: Analysis of outdoor image power spectrum.

Usually, image contrast is calculated by Mechelson formula as

$$C = \frac{L_{\max} - L_{\min}}{L_{\max} + L_{\min}} \tag{4}$$

where $L_{\max}$ denotes maximum pixel intensity of the image, and $L_{\min}$ is minimum pixel intensity of the image. While the intensity in image pixels will dramatic change and cause errors due to the noise pixel. To increase robustness of contrast estimation, we get image contrast in different weather situations by calculating the image intensity standard deviation (rms) (Peli, 1990)as:

$$C = \left(\frac{\sum L_{(x,y)}{}^2 - \frac{(\sum L_{(x,y)})^2}{N}}{N}\right)^{1/2} \tag{5}$$

where $L_{(x,y)}$ represents the intensity at in image (x, y), and N is the number of pixels.

3.3 Noise Features

In dynamic weather situations, the noise point with different size, shape and trajectory may appear in image, because there are various types of particles in the atmosphere and they cause the refraction and attenuation of light. So we can be effective extraction of rain, snow and other dynamic weather phenomena noise features by using fast noise estimation method (Tai and Yang, 2008). At first a Laplace noise estimation template is defined as N.

$$N = \begin{pmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{pmatrix} \tag{6}$$

The noise standard deviation of each point in image calculates with the template N and the average variance of the entire image is defined as:

$$\delta = \frac{1}{6(W-2)(H-2)} \sum_{imageI} \left| I_{(x,y)} * N \right| \tag{7}$$

where W represents the image width, H is the image height and $I_{(x,y)}$ is the intensity value at the pixel (x, y).

3.4 Saturation Features

Though grayscale features are widely used for image processing tasks that range from low level algorithms to highly sophisticated modules, there is growing attention to color information in feature extraction and tracking. In this paper, we extract saturation histogram from the HSV color space as one of classification feature input. In order to make the approach adapt to different resolution images, we set histogram as 10 bins and normalize the histogram results.

4 CLASSIFICATION

Let F be the features vector extracted from an image, and the features of n training images consist of a feature space $S = \{F_i \mid i = 0,1 \ldots n\}$. Then our aim is to find a correspondence $f : S \to C$ between the feature space S and the weather situation set C, in which there is always a weather situation label $C = f(F_{test})$ for any test image feature vector F_{test} .

As SVM method is simple, fast, and powerful, we use it to learn and classify the weather. In principle, a SVM generates a hyperplane in the feature space S and classifies a test vector by calculating on which side of the hyperplane the vector (point) lies. However, SVM classifier is mainly formulated for a two-class problems and it can not be directly used for multi-class classification. According to type of weather features relatively small, this decision tree based on multi-class SVM method for classification of weathers.

4.1 Decision Tree

In principle, decision-tree-based SVM method divides all the classes into n sub-classes (we set n as 2) with a hyperplane, and one or some classes are separated from remaining classes. In classification, starting from the top of the decision tree, we decompose the classes on the node of tree into sub-classes recursively, until all leaf nodes contains only one type of class. Then for each non-leaf node in the decision tree, there should be a SVM as the classification function. Therefore, we must construct a binary decision tree at first, as (Takahashi, 2002) proposed four decision tree constructing methods. In this paper, we bottom-up construct the decision tree with the extracted training feature vectors as follows:

Step 1: Calculate the mean feature vector of the feature vector set X_i for the ith class as:

$$\boldsymbol{u}_i = \frac{1}{|X_i|}\sum_{x \in X_i} x \tag{8}$$

Then we calculate the Euclidean distance of the mean vectors between the class i and the class j. Because each component in the feature vector is inconsistent, we normalize Euclidean distance as:

$$\overline{\boldsymbol{u}} = \frac{1}{N}\sum_{i=1}^{N}\boldsymbol{u}_i \tag{9}$$

$$d_{ij}(=d_{ji}) = \left\| \frac{\boldsymbol{u}_i}{\overline{\boldsymbol{u}}} - \frac{\boldsymbol{u}_j}{\overline{\boldsymbol{u}}} \right\| \tag{10}$$

Then all of training samples belong to different clusters with category center.

Step 2: For the classes which belong to different clusters, calculate the smallest distance and merge the associated two classes to the same cluster.

Step 3: Repeat Step 2, until all the classes are merged into the same node. For the N class problem, it is usually repeated N-1 times.

Step 4: for each combination in Step 3, a decision tree node and the corresponding vector machine function are constructed. if not all of the node's child nodes is leaf node, it should continue merge and establish the vector machines classifier.

4.2 SVM Classifier Construction

After constructing the classification decision tree as section 4.1, there should be a SVM classifier on each non-leaf node. In the classification process, different feature in feature set have different impact to different SVM classifiers. So we select features indirectly by weighting features, some features with greater impact on classification will be set larger weight, while the features with small impact will be set smaller weight even to 0. When features' weight specified, following principles should be considered (Liang, 2008): the higher inter-class variance and lower intra-class variance the feature component is, the better it is to distinguish different class. Then as discussed in section 4.1, we constructs weight vector for each component of the feature space as follow:

1) The intra-class distance vector of feature vector of training data. Since the sample is in the form of $\{X_i, \overline{X_i}'\}$ in each SVM, while X_i is the ith class of the weather situations and $\overline{X_i}'$ is the classes which is the rest classes in top-bottom classification. So the intra-class distance vector of X_i is defined as:

$$D_{\text{int}ra\_X_i} = \frac{1}{|X_i|}\sum_{x \in X_i}\frac{x - \boldsymbol{u}_i}{\boldsymbol{u}_i} \tag{11}$$

where $\boldsymbol{u}_i$ represents the ith class mean vector in (8). Consider the weather situations set $\overline{X_i}'$, which contains weather situation class $\{X_j, ..., X_m\}$, and its intra-class distance vector is:

$$D_{\text{int}ra\_\overline{X_i}'} = \frac{1}{|\overline{X_i}'|}\sum_{x \in \overline{X_i}'}\frac{x - \overline{\boldsymbol{u}}_i'}{\overline{\boldsymbol{u}}_i'} \tag{12}$$

where $\overline{\boldsymbol{u}}_i'$ denotes the mean vector of feature vector in $\overline{X_i}'$ set.

2) The inter-class distance vector of feature vector of training data. Since there are only two classes in each SVM, we define the inter-class distance vector of feature vector as the distance between the mean vectors of each weather class and the global mean vector:

$$D_{\text{int}er\_X_i} = \boldsymbol{u_i} - \overline{\boldsymbol{u}} \tag{13}$$

$$D_{\text{int}er\_\overline{X_i}'} = \frac{1}{N}\sum_{X_n \in \overline{X_i}'}\boldsymbol{u}_n - \overline{\boldsymbol{u}} \tag{14}$$

where $\overline{\boldsymbol{u}}$ is the global mean vector in (9), and in (14), $\boldsymbol{u}_n$ is the nth mean vector of class in feature set $\overline{X_i}'$.

3) The feature weight vector. Combined with the intra-class distance vector and the inter-class distance vector, then we construct the weight vector of feature vector as:

$$W = \frac{D_{\text{int}er\_X_i} + D_{\text{int}er\_\overline{X_i}'}}{D_{\text{int}ra\_X_i} + D_{\text{int}ra\_\overline{X_i}'}} \tag{15}$$

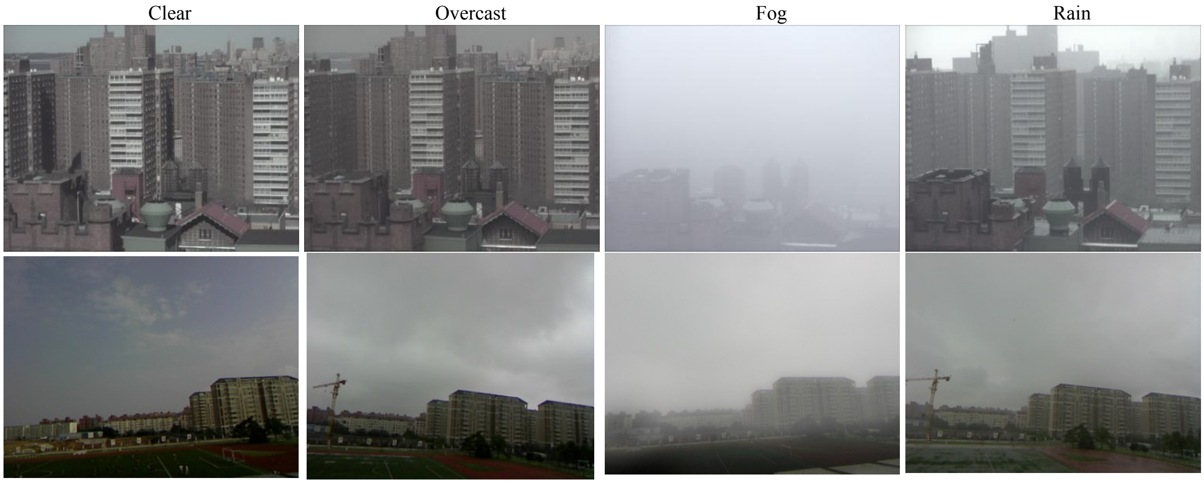


Figure 3: Some sample images.

To automatic select the features from the feature set, we sort the normalized feature weight vectors in (15) descending, that is $W' = (w_1, w_2, ..., w_n)$, then we select first jth weights with $\sum_{i=1}^{j} w_i \geq 0.95$ and set the others as zero. Then the features selection is realize.

4) The feature weight vector. Combined with the intra-class distance vector and the inter-class distance vector, then we construct the weight vector of feature vector as:

$$W = \frac{D_{inter\_X_i} + D_{inter\_\overline{X_i}'}}{D_{intra\_X_i} + D_{intra\_\overline{X_i}'}} \tag{15}$$

To automatic select the features from the feature set, we sort the normalized feature weight vectors descending, that is $W' = (w_1, w_2, ..., w_n)$, then we select first jth weights with $\sum_{i=1}^{j} w_i \geq 0.95$ and set the others as zero. Then the features selection is realize.

In our method, the radial basis function (RBF) is used as kernel functions of SVM, and the weighted feature distance between two samples' feature vectors is defined as:

$$\mathrm{d}(x, y) = \exp(-((x-y) \bullet W^T)^2 \tag{16}$$

To normalize of each component, , we replace the distance between two feature vectors with the distance between the global mean vector of training samples and the relative feature vector distance.

5 EXPERIMENTAL RESULTS

In the following, we implemented the experiments in C++ and OpenCV with Intel CoreTM2 Dual 2.99GHzCPU, 3G memory machines. WILD image dataset (Narasimhan et al., 2002) and our own image dataset are used as test data. In the WILD image dataset, the images are divided into good weather dataset (Clear Weather) and the bad weather dataset (Bad Weather), and each image in dataset has the tags about the weather situation, sky situation and visibility; the image dataset we captured from a static camera with a fixed five minutes interval, contains more than 11,000 images and it is divided into four class, that is C={clear, overcast, fog, rainy}. As all kinds of the weather is not obvious at night, we select 400 images of the day randomly in every class as training samples, the sample images shown in Figure 3.

5.1 Decision Tree Construction

After feature extraction, we can get the feature distances between any two classes in class set as the method in section 4.1, shown in Table 1.

Table 1: The distance between classes.

	Clear	**Overcast**	**Fog**	**Rain**
Clear		0.1265	0.2506	0.3171
Overcast	0.1265		0.1287	0.3465
Fog	0.25 6	0.1287		0.4414
Rain	0. 171	0.3465	0.4414	

Then the decision tree can be constructed from the feature distances and the Decision Tree construction method in section 4.1, as Figure 4. As can be seen from Table 1 and Figure 4, rainy images is most different from the other images; the feature distance between clear weather and overcast weather is smallest, and these two weather situations are selected as the bottom SVM classifier.

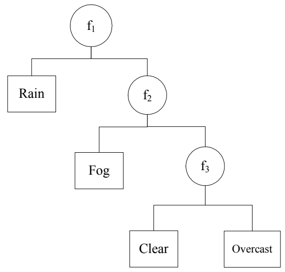


Figure 4: The structure of Decision Tree.

Where the features are {power spectrum slope, respectively, contrast, noise, saturation histogram bin1, ..., saturation, histogram bin10}.

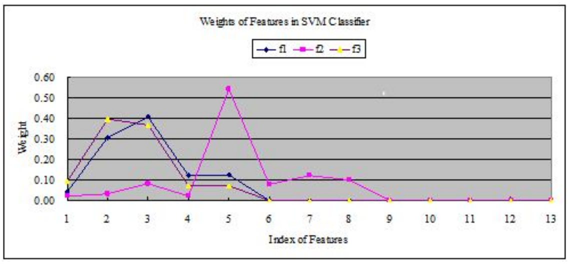


Figure 5: The Weights of SVM Features.

5.2 Classification Experimental Results

The relevant parameters in three SVMs can generate by training as the decision tree defined in Figure 4, so we randomly select two group test data from WILD and image collection we captured, the test results are shown in Table 2, where the rows of the table is the type and number of test samples, and the column represent the classifier weather result by the proposed method and the corresponding error rates.

As shown in Table 2, all kinds of weather situations can be recognized effectively, but the error rate of rainy images, especially in WILD dataset, is relatively high. We find there is mist more or less in the images of WILD labeled rain or light rain; at the same time, the images we collected are captured by the ordinary camera and the exposure time is too short to catch the raindrops trace.

Table 2: The result of weather classification.

(a) Classification Result of WILD Images

	Clear	Overcast	Fog	Rain	Error Rate
Clear(70)	65	4	1	0	*7.14%*
Overcast(60)	3	55	0	2	*8.3%*
Fog（40）	0	5	34	1	*15%*
Rain（20）	0	1	4	15	*25%*

(b) Classification Result of Our Images

	Clear	Overcast	Fog	Rain	Error Rate
Clear(200)	189	10	0	1	5%
Overcast(200)	12	182	2	4	9%
Fog(60)	0	2	57	1	5%
Rain(150)	0	2	14	134	10.7%

6 CONCLUSIONS

In this paper, we have proposed an effective approach for weather situation recognition based on outdoor images, which mainly has the following features: 1) we analysis the impact of various visual feature to outdoor images, and the power spectrum slope, contrast, noise and saturation are extracted; 2) to resolve the problem of conventional SVM multiclass, a decision-tree-based SVM weather classifier are established, in which the decision tree is set up according to the distance of the features; 3)we have resolved the problem of feature vector selection for each SVM indirectly, by weighting the features according to the distance of inter-class and intra-class in the sample dataset. Experiments show this approach can identify several common weather phenomenon from the outdoor images, and can take advantage of existing video equipment in traffic and surveillance area to automatic recognize weather phenomena, and be applied to intelligent video surveillance. In future, we will combine with semi-supervised learning with SVM to improve the learning accuracy.

ACKNOWLEDGEMENTS

This work is supported by The National Natural Scie nce Foundation of China (41305138).

REFERENCES

Bossu J., Hautiere N., Tarel J. Rain or snow detection in image sequences through use of a Histogram of Orientation of streaks. *International Journal of Computer Vision*. 2011, vol. 93(3): 348-367.

Burton G., Moorhead I., 1987. Color and spatial structure in natural scenes. *Applied Optics*. vol. 26: 157-160.
Garg, K., Nayar, Shree K., 2004. Detection and removal of rain from videos. *IEEE Conference on Computer Vision and Pattern Recognition 2004*, vol. 1:528–535.
Lagorio A., Grosso E., 2008. Automatic detection of adverse weather situations in traffic scenes” *IEEE Fifth International Conference on Advanced Video and Signal Based Surveillance*, pp. 273-279.
Liang S., Sun Z., 2008. Sketch retrieval and relevance feedback with biased SVM classification. *Pattern Recognition Letters*. vol. 29:1733-1741.
Liu R., Li Z., Jia J., 2008. Image partial blur detection and classification. *IEEE Conference on In Computer Vision and Patern Recognition*, pp. 1-8.
Narasimhan, Srinivasa G., Nayar, Shree K., 2002. Vision and the atmosphere. *International Journal of Computer Vision*, 48(3): 233-254.
Narasimhan, S., Nayar, S.. Contrast restoration of weather degraded images. *IEEE Trans. Pattern Analysis and Machine*, 2003:713-724.
Peli Eli, 1990. Contrast in complex images. *Journal of the Optical Society of America*, vol. 7: 2032-2040.
Roser M., Moosmann F., 2008. Classification of weather situations on single color images. *IEEE Intelligent Vehicles Symposium*, pp. 798-803.
Shen L., Tan P. Photometric stereo and weather estimation using internet images. *2009 IEEE Conference on Computer Vision and Pattern Recognition*, CVPR 2009, pp. 1850-1857.
Tai S., Yang S., 2008. A fast method for image noise estimation using laplacian operator and adaptive edge detection. Commnications, Control and Signal Processing, pp. 1077-1081.
Takahashi F., Abe S., 2002. Decision-tree-based multiclass support vector machines. Neural Information Processing, *ICONIP 2002*, vol.3: 1418-1422.
Yan X., Luo Y., Zheng X., 2009. Weather recognition based on images captured by vision system in vehicle. *Proceedings of the 6th International Symposium on Neural Network*: Advance in Neural Networks, vol 3:390-398.