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* The Weather Classification problem
  + Description

“Vision based driver assistance systems (DAS) are currently designed to perform under good-natured weather conditions. Unfortunately, limited visibility often occurs in daily life (e.g. heavy rain or fog). As this strongly affects the accuracy or even the general function of vision systems, the actual weather condition is a valuable information for assistance systems. Based on the results of weather classification, specialized approaches for each class can be invoked to improve cognition. This will form a key factor to expand the application of DAS from selected environmental conditions to an overall approach.” [1]

“The weather affects our daily lives in many ways, from solar technologies, outdoor sporting events, to the sort of clothes we wear and whether to stay indoors or not on weekend.

While current accurate weather detection technologies rely on expensive sensors, for centuries weather observing tools consisted of the human eye (and various human senses as well). If we can exploit existing surveillance cameras, which are found almost everywhere, it may be possible to turn weather observing and detection into a powerful and cost-effective computer vision application.” [2]

“The weather conditions not only strongly influence us in our daily lives [1] through the solar energy system and outdoor sporting events as examples, but also affects the functionality of many visual systems including outdoor video surveillance and vehicle assistant driving systems [2, 3] (by heavy rain, haze, etc.). It is no doubt that, judging the weather conditions by a single image, also known as weather classification task, plays a vital role in many visual and weather systems. Nowadays, the weather classification task is commonly accomplished by the human vision or expensive sensors. Since weather condition is local to an area, lack of the required human resources and/or the expensive sensors limits the avail- ability of local measurement of the weather condition. Recently, researchers argued that computer vision techniques could be developed to accurately classify weather conditions through images, which might save expensive human and instrumental resources (i.e., sensors) since economical surveillance cameras are ubiquitous and would be sufficient to accomplish weather classification. In this paper, we refer to weather classification from images as the task of predicting the class of the weather given an image (e.g., cloudy, sunny, etc.).” [3]

* + Applications
  + Approaches

Multi-Class Weather Classification

“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.” [4]

Two-Class Weather Classification

“Our first technical contribution consists of the design and implementation of the various weather cues which are used to form the *weather feature*. These everyday weather cues (such as sky, shadow, reflection, contrast and haze) are what human are still using for weather observing – a hazy or grayish sky characterizes a cloudy day, hard shadow cast on ground indicates a sunny day, as illustrated in Figure 3(a). Conversely, in the absence of any weather cues, we ourselves would lower the confidence to correctly label weather, as shown in Figure 3(b).

Given the weather feature, the next question is how to properly learn the classifier. The main issue is that not all of the weather cues are available in an image (e.g., not every outdoor image has a sky region), which is problematic to a discriminative training process adopted by traditional classifiers, such as SVM. To address this problem, our second technical contribution consists of a collaborative learning framework using homogeneous voters: we group outdoor images into clusters where images in the same cluster are similar in terms of the weather cues. This allows us to build classifiers in a conventional way thanks to the homogeneity in each cluster. The final labeling is the weighted voting result of the cluster classifier outputs. The cluster closer to the testing image is given a larger weight. As will be explained in the following, homogeneous voters are learned together in synergy under a unified optimization framework.

Despite the absence of representative work on image- based weather labeling, we perform quantitative comparison with a few common baselines including SVM, Adaboost [19, 22], and weather-related prior methods [9, 21, 16]. Perspectives on related work will be put into context when they are described.

Our final contribution consists of a 10K weather image dataset properly selected and annotated. This is used to evaluate our learning and labeling strategy.

Our learning strategy is to partition training images into disjoint clusters of homogeneous voters. Given a test image, voters closer to it are given more weights for correctly finding the weather label.” [5]

“Although the previous works provide interesting solu- tions for weather classification, the performances of these approaches are unappealing. As far as we know, the best nor- malized classification accuracy achieved in the challenging weather image dataset, which consists of 10K images, is only 53.1% (the regular accuracy is 76.5%) [1]. Figure 1 (left) shows a challenging image with sunny weather condition. It was also reported in [1] that the histogram of mean light- ness of sunny and cloudy images substantially overlap, which makes the dataset very challenging. We attribute the low performance of [1] mainly to the engineered image features adopted in this method. Compared to the typical image clas- sification task, weather classification from images is affected by various factors, e.g., illumination, reflection, scene and shadow. These factors are highly coupled with each other and therefore the categorization manifold is highly nonlinear. Al- though the previous engineered approaches can satisfy some desirable properties and mitigate some undesirable properties from these factors, they cannot well capture such nonlinearity of the categorization manifold, which makes discrimination between weather classes a hard problem.” [3]

Multi-Class Weather Classification On Single Images

“we propose a method for classifying multi-class weather from single images which is based on multiple weather features and multiple kernel learn- ing. 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 tem- plate 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 multiple 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 im- ages called MWI (Multi-class Weather Image) set.” [4]
  + Approaches with CNNs

Weather Classification With Deep Convolutional Neural Networks

“Motivated by the remarkable successes of Convolutional Neural Networks (CNNs) in computer vision and machine learning [5, 6, 7, 8, 9], we adopt CNNs to solve the weather classification task. There are three reasons for us to choose this technique: The CNN is a neural network model which captures nonlinear mapping between the different spaces, e.g.,. feature space and label space; Deep CNN has demonstrated the powerful discriminating power in extensive image representation and classification tasks; CNNs are simple and explicit end-to-end convolutional architectures, which can simplify the weather classification, without the need for engineered features (e.g. HOG [10], GIST [11]).

Most CNN works are designed for addressing the object recognition and detection tasks [5, 6, 8, 9]. However, weather classification is quite different to these issues. It is more sensitive to factors, such as lighting condition and the status of sky and shadows, rather than object-related information, such as shape and texture. This paper focuses on studying the feature spaces introduced by the different layers of CNN in the weather classification task. There are three main questions that we aim to answer:

* How good is the representation at different layers of a pre-trained CNN for addressing the weather classification problem?
* How fine-tuning of a pre-trained CNN optimized for weather classification dataset will affect the representation at each layer of the network?
* How spatial coherence is important in CNN-based weather classification?

We conducted several experiments to address all these questions over different layers of the CNNs for the weather problem. Adopting CNNs, we concluded our work by significantly outperforming the state-of-the-art by 54.8%.” [3]

# Works Cited

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| --- | --- |
| [1] | M. Roser and F. Moosmann, "Classification of Weather Situations on Single Color Images," in *2008 IEEE Intelligent Vehicles Symposium*, Eindhoven, 2008. |
| [2] | C. Lu, D. Lin, J. Jia and C.-K. Tang, "Two-Class Weather Classification," in *2014 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Columbus, 2014. |
| [3] | M. Elhoseiny, S. Huang and A. Elgammal, "Weather classification with deep convolutional neural networks," in *IEEE International Conference on Image Processing, ICIP 2015*, Quebec City, 2015. |
| [4] | Z. Zhang and H. Ma, "Multi-class weather classification on single images," in *2015 IEEE International Conference on Image Processing (ICIP)*, 2015. |
| [5] | Z. Zhu, L. Zhuo, P. Qu and K. Zhou, "Extreme Weather Recognition using Convolutional Neural Networks," in *2016 IEEE International Symposium on Multimedia*, San Jose, 2016. |
| [6] | A. Krizhevsky, I. Sutskever and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in *26th Annual Conference on Neural Information Processing Systems 2012*, Lake Tahoe, 2012. |
| [7] | C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan, V. Vanhoucke and A. Rabinovich, "Going Deeper with Convolutions," in *2015 7th International Conference on Games & Virtual Worlds for Serious Applications*, Boston, 2015. |
| [8] | K. He, X. Zhang, S. Ren and J. Sun, "Deep Residual Learning for Image Recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Las Vegas, 2016. |
| [9] | B. Zhou, A. Lapedriza, J. Xiao, A. Torralba and A. Oliva, "Learning Deep Features for Scene Recognition using Places Database," in *Advances in Neural Information Processing Systems 27 - 28th Annual Conference on Neural Information Processing Systems 2014*, Montreal, 2014. |
| [10] | K. Simonyan and A. Zisserman, "Very Deep Convolutional Networks for Large-Scale Image Recognition," in *International Conference on Learning Representations*, San Diego, 2015. |
| [11] | K. Chatfield, K. Simonyan, A. Vebaldi and A. Zisserman, "Return of the Devil in the Details: Delving Deep into Convolutional Nets," in *Proceedings of the British Machine Vision Conference 2014*, Nottingham, 2014. |
| [12] | Y. LeCun, Y. Bengio and G. Hinton, "Deep Learning," *Nature,* vol. 521, pp. 436-444, 28 May 2015. |
| [13] | J. Yan, Y. Yu, X. Zhu, Z. Lei and S. Z. Li, "Object Detection by Labeling Superpixels," in *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Boston, 2015. |