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Multi-model solar irradiance prediction based on automatic cloud classification

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ABSTRACT

This paper proposes a framework to automatically conduct cloud classification on all-sky images and perform short-term solar irradiance prediction according to the classification results. The all-sky images are divided into blocks to deal with the mixed cloud type conditions. Local texture patterns and statistical texture features are extracted from the image blocks for cloud classification. Different cloud types with various heights, thickness, and opacity have different impact on the variation of solar irradiance. Therefore, several regression models are trained to capture the characteristics of irradiance changes under different cloud types. The current classified cloud type is used to select a corresponding prediction model. Such design substantially increases the prediction accuracy. The experimental results verify the effectiveness of the proposed framework. Both the proposed cloud classification method and irradiance prediction mechanism outperform existing works. Adding local texture patterns in the feature vector enhance the classification performance. Compared with non-block based methods, the proposed block-based method could increase the classification rate by 5%–10%. Utilizing multiple prediction models according cloud types could lower both the mean absolute error and the root mean squared error on short-term irradiance prediction.

1. Introduction

The demand for green energy is increasing significantly as people's environmental consciousness grows. Solar energy is one type of green energy the use of which has substantially increased in recent years. PV (Photovoltaics) are installed worldwide to provide clean and renewable electricity for residential, commercial or even industrial uses. However, the main challenge of PVs is that the produced electricity is often variable and intermittent. The fluctuation of the solar supply is a problem encountered by PV grid operators. To utilize the energy more effectively, PV grid operators desire a management system that is able to schedule, dispatch, and allocate energy resources adaptively. Obtaining an accurate prediction on the resources that can be exploited is helpful for reducing storage costs and achieving better efficiency [1]. It is also helpful for planning and deployment of electricity generated by different units. Therefore, researchers have shown growing interest on the topic of short-term surface solar irradiance prediction.

Large-scale cloud information can be available from satellite images. Numerical weather prediction information or satellite cloud observations are also popular materials used for wide-range or mid-term solar irradiance prediction [2], [3]. However, the spatial and temporal resolutions provided by the weather services and satellite observations are not high enough for short-term prediction. For short-term irradiance prediction, the PV grid operators would desire more refined spatial and temporal resolution of prediction. As a consequence, devices that capture all-sky images have emerged to monitor the sun and the clouds. Devices developed more recently include the Whole Sky Imager (WSI) developed by the Scripps Institute of Oceanography at the University of California [4–6], the WSC (Whole Sky Camera) designed by the University of Girona in Spain [7], the ASI (All-Sky Imager) developed by the Japanese Communications Research Laboratory [8], and the TSI (Total Sky Imager) by Yankee Environmental Systems [9], [10]. With the all-sky images captured by these devices, it is feasible to analyze cloud activities under more refined scales.

For short-term irradiance prediction, Chaabene and Ammara [11] used meteorological measurements to predict irradiance and temperature five minutes ahead; they did not use all-sky images. Marquez and Coimbra [12] have shown that within a 15-min time frame, forecasting with the help of all-sky image information

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demonstrated obvious improvement over satellite images. They improved the cloud detection algorithms and predicted DNI (direct normal irradiance) by constructing the relationship between cloud fractions and DNI values. Cheng et al. [13] also validated that features extracted from all-sky images are helpful for more accurate irradiance prediction. Chow et al. [14] developed a forecasting system that gives cloud cover map with information extracted from 30 s up to 5 min ahead of prediction time. However, the relationship of the predicted cloud map and the solar irradiance is not clearly stated in this work. Fu and Cheng [15] utilized clearness index and a regression model to predict solar irradiance. However, none of the above mentioned short-term prediction methods utilized the knowledge of different cloud types in their methodology.

The influential factors of solar irradiance include geographic location, season, cloud cover and type, pollution particles in the air, etc. Among all, the influence of cloud is one of the main factors resulting in an unstable and intermittent nature of solar resource. The cloud types are characterized by different heights, sizes, opacities and thicknesses. Therefore, when the clouds obstruct the sun, the surface solar irradiance may vary a lot [16]. Generally speaking, higher and thinner clouds have smaller impact on the surface irradiance. On the contrary, lower and thicker clouds would cause larger irradiance drop. The motivation of this work is to automatically obtain information about current cloud type from all-sky images and incorporate this knowledge in the proposed prediction framework.

There are many existing works on cloud classification. In Ref. [17], the clouds were classified into different attenuation groups according to the levels of attenuation of the direct solar radiation reaching the surface. The authors also analyzed the annual and seasonal frequencies of each attenuation group. However, this work did not propose any automatic cloud classification method based on the image features. The research in Ref. [10] used features based on the Fourier transform along with simple statistics such as standard deviation, smoothness, moments, uniformity, and entropy. The features are extracted from the intensity images and the red-to-blue components ratio (R/B) images. The classifier used was based on supervised parallelepiped technique. In the work of Heinle et al. [18], statistical features such as mean, standard deviation, skewness, and difference were utilized. Also, textural features including energy, entropy, contrast, and homogeneity were computed from the GLCM (Gray Level Co-occurrence Matrices). Instead of extracting features from intensity images, the authors reported the color component for which each individual feature should be calculated. This work used a k-nearest neighbor (k-NN) classifier to classify the clouds into seven different types. Kazantzidis et al. [19] improved Heinle's method by a multicolor criterion which determines the total cloud coverage. Other features such as autocorrelation, edge frequency, Law's features and primitive length were also tested for cloud classification [20]. However, these works did not deal with mixed cloud type conditions in the same image. Under mixed cloud type conditions, features of different cloud types are mixed up and thus confuse the classifier. Moreover, none of the above mentioned works proposed a method for applying the cloud classification results to short-term irradiance prediction mechanism to enhance the prediction accuracy.

2. System description

In this research, we propose to automatically classify clouds into several types. Afterwards, the classification results are incorporated into the proposed prediction mechanism for more accurate results. The proposed system framework is illustrated in Fig. 1. The all-sky images are divided into blocks for automatic cloud classification. Training and classification are performed based on blocks meeting the mixed cloud type criteria. The features and classifier used are elaborated in Section 3. For irradiance prediction, several regression models are constructed to capture the characteristics of irradiance changes under different cloud types. The details of multi-model irradiance prediction are explained in Section 4. In Section 5, we demonstrate and discuss the experimental results. Finally, conclusions are deployed in Section 6.

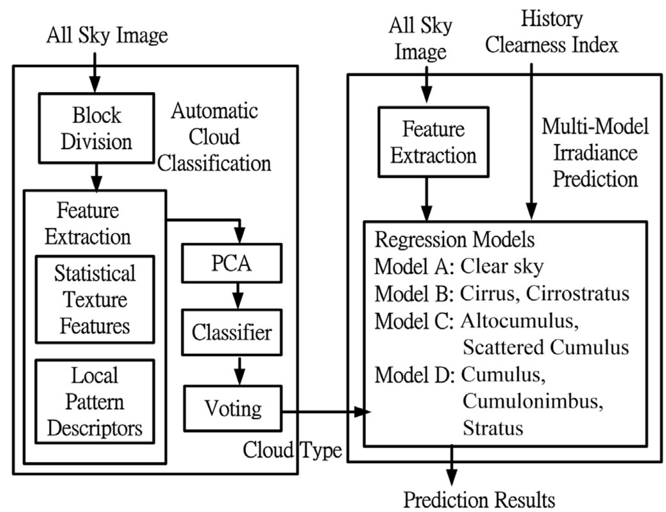

Fig. 1. Proposed system framework.

3. Automatic cloud classification

To alleviate the problem of inter-mixing features from different cloud types under mixed cloud type conditions, cloud classification is performed based on features extracted from the blocks. To extract the characteristics of textures, three different local pattern descriptors are considered in this work, including the LBP (Local Binary Pattern) [21], the LTP (Local Ternary Pattern) [22], and the LDP (Local Derivative Pattern) [23]. The local pattern descriptor is concatenated with classical statistical texture features proposed in Ref. [18] to form the feature vector. PCA (Principal Component Analysis) [24] is performed to find the principal axes of data distribution for better data representation. The high dimensional feature vector is projected onto the principal axes to reduce the dimensionality. Then, the feature vector is input into a trained classifier to determine the class label of the block. The classifier utilized in this work is the SVM (Support Vector Machine) [25] with RBF (Radial Basis Function) kernels. The classification results of all blocks in an image are gathered to obtain a summarized label for the entire image via voting. More specifically, the entire image is classified as the cloud type that appears most frequently in the blocks in the image. In this paper, we classify the images as six classes, which are cirrus (class 1), cirrostratus (class 2), scattered cumulus or altocumulus (class 3), cumulus or cumulonimbus (class 4), stratus (class 5), and clear sky (class 6). In Fig. 1, four prediction models are constructed according to the six cloud types in the system framework. We will discuss the number of prediction models in the next session.

Local pattern descriptors are widely used to represent textures and spatial structure for human faces or other objects. We apply local pattern descriptors in this application to capture the more detailed features in addition to simple statistical texture features. The three local pattern descriptors applied in this work are introduced in the following subsections.