Expert Systems with Applications xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Feature extraction techniques for ground-based cloud type classification

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ARTICLE INFO

Article history:
Available online xxxx

Keywords:
Image processing
Cloud classification
Ground-based images

ABSTRACT

The appearance of each cloud type can tell the different weather conditions. Clouds may tell the coming of storms, hails, or even lightning strikes. Therefore, cloud type classification can help to reduce preventable losses. This paper studies the classification of cloud types using ground-based images. Seven sky conditions are considered, namely, cirrus, cirro and altocumulus, stratocumulus, cumulus, cumulonimbus, stratus, and clear sky image. We present an algorithm that computes a matrix of feature vectors for cloud classification with five alternative ways of extracting cloud features. The five feature extraction techniques include textures, moments of two-dimensional functions, abs-FFT, log-FFT, and the new technique called Fast Fourier Transform Projection on the *x*-axis (*k*-FFTPX). We propose the *k*-FFTPX algorithm that extracts features by projecting the values of logarithmic magnitude of FFT images on the *x*-axis of the frequency domain before selecting *k* sampling values of the data as *k* dimensions of a feature vector. To the best of our knowledge, there is no research on ground-based cloud type classification using such technique before. Then, a comparison of the techniques is made through a series of five experiments and the accuracies are ranged between 80.76% and 90.40%. Our new method provides the highest accuracy. The advantages are that we can now classify more cloud types than the existing methods with further improved in accuracy, and our method requires no expensive tools, only a digital camera is used to obtain ground-based images. This suggests a variety of practical solutions in combination with other meteorological sensors to report weather conditions inexpensively.

1. Introduction

Weather conditions affect human life greatly in terms of daily life since some occupations depend on these weather conditions, for example, farmers and fishermen. In 2009, a total of 385 natural disasters have caused the damages that affected over the population of 217 million which more than 297,000 people worldwide are dead and the damage value of economic is as high as US$ 123.9 billion (Guha-Sapir, Vos, Below, & Ponserre, 2011). Therefore, the knowledge of recognition and understanding weather conditions is important for preventing the unexpected losses. One area of weather element recognition is cloud type classification since different cloud types can lead to different weather conditions.

Traditionally, classification of cloud types requires specialists to do it manually. However, it does not appear to have many specialists in this area. Moreover, the speed of manual classification is limited and human errors are sometimes introduced into the system. Each individual's experiences are also different. Hence, there have been many attempts to develop an automatic cloud type classification system (Aha & Bankert, 1994; Ambroise, Sèze, Badran, & Thiria, 2000; Bankert, 1994; Buch, Sun, & Thorne, 1995; Calbó & Sabburg, 2008; Fan, Changsheng, & Weimin, 1997; Heinle, Macke, & Srivastav, 2010; Heinzmann, 1993; Kaur & Ganju, 2008; Lee, Weger, Sengupta, & Welch, 1990, 2004; Martínez-Chico, Batlles, & Bosch, 2011; Shangguan, Hao, Lu, & Wu, 2007; Singh & Glennen, 2005; Souza-Echer, Pereira, Bins, & Andrade, 2006).

Since 1977 researchers have begun to use satellite images as the input (Parikh, 1977). However, this solution is expensive, and the images are sometimes restricted for public access. Furthermore, the satellite images are not suitable for the specific area of interests because of their lack of local details (Calbó & Sabburg, 2008; Singh & Glennen, 2005). Later, ground based imager devices were introduced (Long, Sabburg, Calbó, & Pagès, 2006). There are two types of imagers, namely the total sky imager (TSI) and the whole sky camera (WSC). Both of the imagers are expensive. Therefore, using digital camera is more suitable for smaller research groups and independent study. Moreover, the digital camera provides specific information, low cost, and less cumbersome than others.

In this paper, we will develop an automatic cloud type classification system for ground-based digital camera using image processing and pattern recognition. Seven different cloud types for

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http://dx.doi.org/10.1016/j.eswa.2015.05.016
0957-4174/

our recognition are cirrus, cirro and altocumulus, stratocumulus, cumulus, cumulonimbus, stratus, and clear sky. We extract texture features from cloud images and use these information in the training process of the classification. Artificial neural network is then used for classifying instances. Moreover, we add three types of features based on Fourier transform. The first two types use logarithmic and absolute magnitudes for extracting texture features of Fast Fourier Transform (FFT) images. The last type uses logarithmic magnitude but we project these values on the x-axis. Our main contribution is a novel feature that uses a projection of logarithmic magnitude of the FFT onto the x-axis. We call this feature k-FFTPX.

We organize the paper as follows. In Section 2, we give the literature review of cloud type classification. In Section 3, various features used in the classification are explained. In Section 4, we describe artificial neural network which is the main classifier used in the experiment. In Section 5, the methodology for cloud type classification is given. In Section 6, we apply various features for the classification and present the experimental results. Finally, in Section 7 we summarize the results.

2. Literature review

Most of automatic cloud type classifications use a set of satellite images as an input. Heinzmann (1993) provided fuzzy logic approach for classifying four cloud classes. Lee, Lin, and Wahba (2004) performed multi-category support vector machine (MSVM) to classify each pixel into three cloud classes. Lee et al. (1990) used a neural network with texture features to classify sub-regions into one of three cloud types. Bankert (1994) exploited a probabilistic neural network (PNN) to classify each area into one of ten cloud classes which give 79.80% correctly classified. Aha and Bankert (1994) introduced feature selection algorithms for classifying ten cloud classes. Forward sequential selection combined with IB1 gives the best accuracy of 88%. Fan et al. (1997) used a bispectral cloud classification method based on man-computer interactive way to classify land, water, and six types of clouds. The method has an accuracy of 87.10%. Ambroise et al. (2000) presented Probabilistic Self-Organizing Maps for classifying nine cloud types. The accuracy of the classification is 63%. Shangguan et al. (2007) proposed texture feature analysis combined with Variational theory to extract texture features. Kaur and Ganju (2008) used singular value decomposition (SVD) to extract the salient spectral and textural features to classify clouds as low, medium or high clouds. This technique gives an accuracy of 70%–90%.

Recently, ground-based images are used more in cloud type classification. Martínez-Chico et al. (2011) classified clouds according to their heights by using radiation data and images from total sky imager (TSI). The result is presented as the frequency of occurrence for each class. Buch et al. (1995) used images from two whole-sky imager (WSC) to produce three-dimensional volume. In the classification process they used the binary decision trees with three groups of features (texture measures, position information, and pixel brightness) to classify each pixel in the cloud scene as either one of the five sky conditions. The accuracy of system is 61%. Calbó and Sabburg (2008) developed a system using images from total sky imager and whole sky imager. They classified cloud types using parallelepiped technique with features that are calculated from texture, Fourier transform, and cloudy pixels. The classification accuracy is 62% when eight sky conditions are considered and increases to 76% when five different sky conditions are considered. Heinle et al. (2010) developed real-time classification cloud types using whole sky images. There are 12 features from spectral features and textural features. The k-nearest neighbor classifier is used to classify seven different sky conditions. The accuracy of the classification is as high as 97% when it is based on the Leave-One-Out Cross-Validation (LOOCV) but in the general case with unseen data, the accuracy is 75%–88%. Based on these results, Tzoumanikas, Kazantzidis, Bais, Fotopoulos, and Economou (2013) improved k-nearest neighbor classifier by considering multi-color criterion where the accuracy is increased to 78%–95%. Liu, Wang, Xiao, Zhang, and Shao (2013) developed the new feature method called salient local binary pattern based on the previous work of Heinle et al. (2010). Their accuracy classified by the nearest neighborhood using chi-square metric is at 93.65%, the best result so far for images from WSC. Taravat, Del Frate, Cornaro, and Vergari (2014) used pixel values of red, green, and blue bands of the whole-sky images for classified pixels in terms of cloud coverage or others. The overall accuracies of 95.07% using multilayer perceptron (MLP) neural networks. Cheng and Yu (2015) used block-based classification on all-sky images. Each block is extract statistical texture features and local binary pattern for six sky conditions. Then, the features are classified with Bayesian classifier which give the accuracy of 90%.

Moreover, there are several researchers started to use the input images captured from digital cameras. Souza-Echer et al. (2006) showed their new algorithm that classifies each pixel based on a criteria decision process on Illuminant-Hue-Saturate (IHS) space using images from the digital camera. The output yields accuracy of 94% for the classification of only a clear sky. Singh and Glennen (2005) used five different feature extraction methods with the k-nearest neighbor and neural network classifiers for identifying five sky conditions. The best of their classification has the accuracy of 64%. Xia et al. (2015) used texture features, color features and shape features with k-nearest neighbor for classifying four sky conditions. The average accuracy is 84.82%.

From the summary of literature survey in Table 1, the texture feature is still a popular extraction technique. However, its accuracy has been somewhat limited to around 90%. Although some authors showed more than 90% accuracy, their output classes are limited to two. In this paper, the output will be seven classes of cloud types and the input images will be from digital camera and not satellite or TSI/WSC images. Therefore, the accuracy will be compared among those digital camera images. Moreover, our new approach will incorporate the strength of texture analysis into the new technique of FFT feature extraction that focuses more on the shape of cloud. In the most recent survey, Table 2 shows various uses of FFT techniques, some are incorporated with other methods. Calbó and Sabburg (2008) used features based on Fourier transform to discriminate cloud shapes. They extracted the characteristics of the spectral power image using correlation with clear (CC) and spectral intensity (SI). Daowieng, Wongkittisuksa, Tanthanuch, and Permsirivanich (2010) used FFT and discrete wavelet transform (DWT) for word recognition. More recently, Chen (2014) extracted dual-tree complex wavelet (DTCWT) features from EEG signals and perform the FFT to the DTCWT features subbands. Soltana, Porebski, Vandenbroucke, Ahmad, and Hamad (2014) applied FFT with Local Binary Patterns (LBP) histogram to calculate features from lace images. Stępniowski, Michalska-Domańska, Norek, and Czujko (2014) calculated the radial average of FFT for arrangement analysis of the aluminum nanopores. To the best of our knowledge, there is no research on ground-based cloud type classification that performs feature extraction by projecting the values of logarithmic magnitude of FFT images on the x-axis of the frequency domain. Furthermore, the new idea of introducing the k-sampling and sorting techniques in the settings of feature vector will be incorporated into our proposed algorithms. These techniques will be explained later.

3. Features

We use a grayscale image which is computed by splitting channels of image as R, G, and B channels for extracting features. There