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Improved cloud phase retrieval approaches for China's FY-3A/VIRR multi-channel data using Artificial Neural Networks

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ABSTRACT

Retrieving cloud phase accurately is important for cloud parameter studies, weather forecasting, and climate change research. Consequently, the purpose of this study is to develop better and more accurate cloud phase retrieval approaches to upgrade the current threshold technique used for China's second-generation polar-orbit meteorological satellite FengYun-3A (FY-3A). In this paper, improved cloud phase retrieval approaches using a supervised Back-Propagation Neural Network (BP-NN), and an unsupervised Self-Organizing Feature Map Neural Network (SOFM-NN) were proposed and investigated. The results of this study indicated that the two ANN approaches are satisfactory in discriminating cloud phase using FY-3A/Visible and InfRared Radiometer (VIRR) multi-channel data, and the average accuracy rates for the BP-NN approach are 93.50%, 93.81%, 94.25%, and 93.38% for the winter, spring, summer, and fall season categories, respectively, while for the SOFM-NN approach, rates are 91.93%, 92.08%, 92.63%, and 91.97%, respectively. The BP-NN approach performs slightly better than the SOFM-NN approach. Moreover, the two ANN approaches are found to perform more accurately than the current FY-3A operational product. Therefore, our work demonstrated that the ANN approaches provide an attractive alternative for cloud phase retrieval that could potentially be used to upgrade the current threshold technique used for the FY-3A operational product.

1. Introduction

Owing to the development and advantages of satellite remote sensing technology, retrieving cloud phase from satellite observations has become an important topic in satellite meteorology and atmospheric physics [1]. Cloud phase refers to its thermodynamic phase, and the categories include water cloud, ice cloud, thin cirrus, and mixed-phase cloud. Clouds with different thermodynamic phases have very different absorption and scattering properties; thus, the accurate determination of cloud phase is a critical first step in retrievals of cloud microphysical parameters, such as cloud optical depth, cloud particle size, and cloud-top temperature, because the inversion quality is dependent on accurate cloud phase information [2]. In addition, cloud phase has a significant influence on the formation and evolution of weather systems. Therefore, retrieving cloud phase accurately is not only important for cloud parameter studies, but also critical in weather forecasting and climate change research.

Currently, the most widely utilized method for cloud phase retrieval is the threshold technique, and many studies employ this technique to discriminate cloud phase using satellite observation data from various sensors (e.g., Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), and SCanning Imaging Absorption spectroMeter for Atmospheric CHartographY (SCIAMACHY)) [3–5]. The technique is based on the different absorption and scattering properties of water and ice particles at certain wavelengths, and uses satellite observation data from a single channel or channel combinations by applying a set of thresholds for reflectance, reflectance ratio, brightness temperature, and brightness temperature difference to identify cloud phase [6]. Evidently, the determination of these thresholds is a key factor for the technique; in other words, an inherent weakness of the technique is that the cloud phase retrieval accuracy is affected by various specific thresholds, meaning that once improper thresholds are determined and employed, misclassifications will occur and the retrieval accuracy will undoubtedly decrease. This problem often occurs, especially when two different classes have similar spectral characteristics in some channels. FengYun-3A (FY-3A) is China's second-generation polar-orbiting meteorological satellite, which was launched successfully from Taiyuan city, Shanxi province, China, on May 27, 2008 [7]. The

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cloud phase retrieval algorithm of the present FY-3A operational product is developed based on the threshold technique. Unfortunately, owing to the inherent weakness of the threshold technique, misclassification often occurs in the FY-3A operational product. Therefore, in order to improve the retrieval accuracy and avoid this inherent weakness of the threshold technique, it is desirable to develop novel and improved cloud phase retrieval approaches that are independent of various specific thresholds.

In recent years, Artificial Neural Networks (ANNs) have been adopted in the fields of cloud detection and cloud classification, and their relatively superior performance has been acknowledged in many studies [8,9]. ANNs are computational models, inspired by animal's central nervous systems (in particular the brain), which have strong non-linear processing capacity. ANN approaches have a distinct advantage over other traditional methods in that they are non-parametric and require little or no a priori knowledge of the input data. These factors make ANN approaches applicable to pattern recognition, intelligent control, combinatorial optimization, forecasting, and other fields. ANN approaches offer an attractive alternative for cloud phase retrieval owing to their adaptive learning nature; however, cloud phase retrieval using ANN approaches, and their performance when used with multi-channel satellite data, have been inadequately studied. Consequently, automated cloud phase retrieval approaches were developed using ANNs in this study, and their performance when used with FY-3A/VIRR multi-channel data was investigated. Among the dozens of ANNs available to date, the present research chose a supervised Back-Propagation Neural Network (BP-NN), and an unsupervised Self-Organizing Feature Map Neural Network (SOFM-NN), as they are some of the most successfully applied ANNs that excel at pattern recognition and classification tasks. This paper focuses on two primary questions: Are the ANN approaches suitable for cloud phase retrieval applications using FY-3A/VIRR multi-channel data? Can the ANN approaches perform more accurately than the current FY-3A operational product that adopts the threshold technique?

The results of this study demonstrated that the ANN approaches are satisfactory in discriminating cloud phase using FY-3A/VIRR multi-channel data, and they are found to perform more accurately than the current FY-3A operational product; they not only improved the retrieval accuracy at the pixel level but also at the cloud patch level. Furthermore, the novel approaches developed in this study have several distinct advantages compared with the threshold technique adopted by the current FY-3A operational product. Firstly, a separate cloud detection step is not needed when using ANNs; the ANN approaches can automatically deliver the retrieval results of clear (cloud-free), water cloud, ice cloud, thin cirrus, and mixed-phase cloud, since the networks have been well trained with pixel samples of different cloud phases (including cloud-free pixels of various underlying surface types). Secondly, the ANN approaches are able to identify cloud phase accurately without determining various specific thresholds, because ANNs are non-parametric and have a strong capability to estimate non-linear relationships between the input data and the desired outputs. This work will also provide insights to aid the choice of automated cloud phase retrieval approach for the upcoming launch of the FY-4 series [10]. The organization of this paper is as follows. Section 2 introduces the FY-3A/VIRR multi-channel data. Section 3 provides a brief description of the two ANNs and describes their use in cloud phase retrieval. Section 4 presents the capability and performance of the two ANN approaches compared with the current FY-3A operational product. Finally, the conclusions are given in Sec. 5.

2. FY-3A/VIRR multi-channel data

FY-3A, as the first satellite of the FY-3 series, carries 11 sets of instruments and has more than a hundred spectral channels,

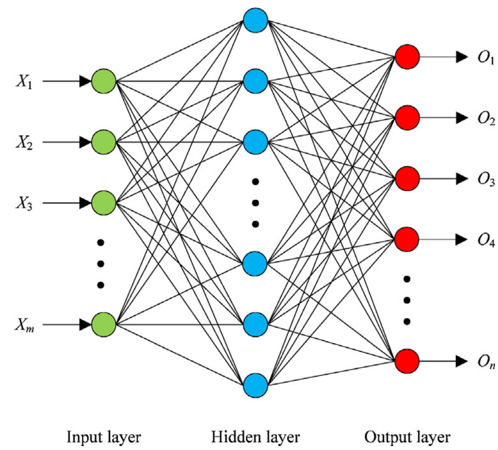

Fig. 1. The architecture of the Back-Propagation Neural Network (BP-NN): green circles on the left are input neurons, blue circles in the middle are hidden neurons, and red circles on the right are output neurons. $X_i(i = 1, 2, \ldots, m)$ are input patterns 1 to m, and $O_j(j = 1, 2, \ldots, n)$ are output patterns 1 to n. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

covering a wide spectral range from ultraviolet to microwave. Among them, the VIRR has 10 spectral channels (0.43–12.5 μm) with a spatial resolution of 1.1 km, making it particularly suitable for cloud phase retrieval. According to the remote sensing characteristics, the reflectance of channel 1 (R(0.63)) is related to cloud optical depth; greater (smaller) values of R(0.63) indicate a larger (smaller) cloud optical depth. The reflectance of channel 6 (R(1.60)) is sensitive to cloud particle size and cloud phase; clouds with larger (smaller) particle size usually show smaller (larger) values of R(1.60), and the value of R(1.60) for ice cloud is generally smaller than that for water cloud. The reflectance of channel 10 (R(1.36)) is utilized, as it is a much more effective channel both for thin cirrus detection and for discriminating between ice cloud and water cloud, because this channel covers the water absorption band, and the values of R(1.36) for the underlying surface, low-level water cloud, and mixed-phase cloud are smaller than that for ice cloud and thin cirrus. The brightness temperature of channel 4 (BT(10.8)) carries information on the cloud-top height, smaller values of BT(10.8) indicate a higher cloud-top. Additionally, the split-window brightness temperature difference ($SWBTD$(10.8–12)) can competently discriminate between underlying surface and cloud areas.

In summary, this study uses data from five VIRR channels for cloud phase retrieval: the reflectance of channel 1, channel 6, and channel 10, and the brightness temperature of channel 4 and channel 5.

3. Methods

3.1. Back-Propagation Neural Network

The Back-Propagation Neural Network (BP-NN), proposed by Rumelhart and McClelland in 1986 [11], is a multi-layer feed-forward network trained according to error back-propagation, and its architecture is shown in Fig. 1.

The BP-NN consists of three parts: an input layer, an output layer, and one or more hidden layers, and each layer contains a number of neurons. These neurons receive input signals from external sources or neurons in the previous layers, and convert the input signals to an output signal used by the neurons in the next layer. The BP-NN uses a supervised learning method that can be divided into two phases. (1) The input signal passes through the neural network from the input layer to the output layer and generates