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Development of a support vector machine based cloud detection method for MODIS with the adjustability to various conditions

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ABSTRACT

Common requirements for cloud detection methods including the adjustability with respect to incorrect results are clarified, and a method is proposed that satisfies the requirements by applying the support vector machine (SVM). Because the conditions of clouds and Earth's surfaces vary widely, incorrect results in actual cloud detection operations are unavoidable. Cloud detection methods therefore should be adjustable to easily reduce the frequency of incorrect results under certain conditions, without causing new incorrect results under other conditions. Cloud detection methods are also required to resolve a characteristic issue: the boundary between clear-sky and cloudy-sky areas in nature is vague, because the density of the cloud particles continuously varies. This vagueness makes the cloud definition subjective. Furthermore, the training dataset preparation for machine learning should avoid circular arguments. The SVM learning is generally less likely to result in overfitting: this study suggests that only typical data are sufficient for the SVM training dataset. By incorporating the discriminant analysis (DA), it is possible to subjectively determine the definition of typical cloudy and clear sky and to obtain typical cloud data without direct cloud detection. In an approach to adjust the classifier, data typical of certain conditions that lead to incorrect results are added to the training dataset. In this study, an adjustment procedure is proposed, which quantitatively judges, whether an addition is actually effective for reduction of the frequency of incorrect results. Another approach for the adjustment is improving feature space used for cloud detection. Indices as quantitative guidance to estimate whether an addition or elimination of a feature actually reduces the frequency of incorrect results can be obtained from the analysis of the support vectors. The cloud detection method incorporating the SVM is therefore able to integrate practical adjustment procedures. Applications of this method to Moderate Resolution Imaging Spectroradiometer (MODIS) data demonstrate that the concept of the method satisfies the requirements and the adjustability to various conditions can be realized.

1. Introduction

Cloud detection (or cloud screening) is a fundamental and important process in satellite remote sensing. It is widely used not only for cloud observations (such as cloud amount) but also to eliminate cloud contamination when retrieving surface and atmosphere properties, such as the sea (e.g., Sakaida et al., 2006) and land (e.g., Bulgin et al., 2014) surface temperature. Much advancement of the satellite sensor, such as high spatial and temporal resolution, more wavelengths, and hyperspectral imaging, has enabled the collection of detailed and unprecedented data about the environment of Earth. Cloud detection methods have also been improved to obtain more accurate and useful remote sensing products. Such as for a hyper–spectral sensor (e.g., Thompson et al., 2014), a cloud radar (e.g., Marchand et al., 2010), and targeting a specific type of cloud such as cirrus (e.g., Ewald et al., 2013), fog/low stratus (e.g., Cermak and Bendix, 2008).

Even when focusing on multichannel passive imagers, various algorithms have been proposed for each application and purpose. With respect to the current status of algorithm development, Bulgin et al. (2014) summarized the performance of several cloud detection methods in the land surface temperature retrieval using the Advanced Along–Track Scanning Radiometer (AATSR), a 7-channel imager with a resolution of 1 km. These methods apply the dynamic threshold or Bayesian technique. Mei et al. (2017) proposed a cloud detection method adapted to aerosol observation using the MEdium Resolution Imaging Spectrometer (MERIS), an imager for visible to near IR wavelengths. This method consists of an integration of many threshold tests. These studies indicate difficulties inherent to cloud detection. One

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is that the cloud definition (or the judgment criteria of the cloud detection correctness) depends on purposes and targets, highlighting the "subjectivity" of the cloud. For example, aerosol observation requires a discrimination of clouds better than land surface temperature does (Mei et al., 2017). Another is that it is difficult to consider all possible conditions with respect to the threshold determination. In particular, extreme conditions and complicated scenarios are likely to be omitted. On one hand, cloud detection methods should be adjusted and specialized to adapt to certain requirements of cloud detection result users. The adjustment may make it impossible to be suitable for all applications. On the other hand, the methods should also be improved to be able to deal with various conditions, forced to become "universal".

Because cloud detection is a type of classification that involves multivariate analysis, it is well suited for machine-learning techniques. Several supervised and unsupervised learning methods, such as unsupervised clustering (e.g., Simpson and Gobat, 1995), the Bayesian algorithm (e.g., Uddstrom and Gray, 1996), discriminant analysis (DA: e.g., Murino et al., 2014), and neural network (e.g., Welch et al., 1992), have been incorporated into data classification including cloud detection in various satellite data. In particular, use of Support Vector Machines (SVMs) has become popular, because they are expected to have a high capability of generalization to avoid overfitting. Bai et al. (2016) applied the SVM to the cloud detection in high-resolution (about 16 m) imager data, which can derive not only spectral but also richer texture information. The SVMs were also applied to cloud type classification using the Moderate Resolution Imaging Spectroradiometer (MODIS), a multichannel passive sensor with a resolution of about 1 km (Lee et al., 2004). Mazzoni et al. (2007) incorporated the SVM for cloud–aerosol discrimination, using an interactive training process to collect sufficient training data. Gomez-Chova et al. (2008, 2010) introduced semi-supervised SVM algorithms to reduce the bias of training data.

Incorporation of machine-learning techniques into cloud detection methods, however, also involves the difficulties mentioned above, the subjectivity and adjustability, especially when preparing training datasets (or "truth data"). Therefore, it is necessary to first clarify requirements to overcome the difficulties, particularly, how to deal with various conditions of the atmosphere and surface, or how to realize the adjustability with respect to incorrect cloud detection results. We then propose a cloud detection method that incorporates SVM with a training data preparation procedure by applying DA. We finally prove that the concept of this method satisfies the requirements. In this study, we focus on cloud detection methods for passive multichannel satellite imagers. We discuss common requirements for cloud detection methods in detail in Section 2. We describe the principles of DA and SVM in Section 3 and explain how the proposed method satisfies the requirements. An example of classifier construction and its application is demonstrated in Section 4 to prove that the proposed method can obtain appropriate cloud detection results. The adjustment procedures are provided in Section 5. Section 6 describes the summary and conclusions.

2. Requirements of cloud detection via satellite observations

In this section, we discuss common requirements for cloud detection methods including the adjustability. Cloud detection is necessary to achieve an adequate "accuracy", which means that (almost) all of the data classified as cloudy satisfy the cloud definition. Here, we think back to the cloud definition, or what scene a user considers as a cloud. Because the density of cloud particles (or optical thickness) continuously varies in nature, the boundary between clear sky and cloudy sky is intrinsically vague. The sensitivity to clouds also depends on the type of sensor (e.g., Wang et al., 2016). In actual satellite observations, mixed pixels of clear sky and cloudy sky occur, and three–dimensional radiative effects (Yang and Di Girolamo, 2008) tend to enhance the ambiguity at the boundary. We suggest that the cloud definition (and the criteria for "correct" discrimination) should be determined subjectively (or arbitrarily) and dependently on purposes of observations. Cloud detection algorithms should consider the subjectivity of the cloud definition.

The adequacy of supervised learning methods for cloud detection depends in part on, whether an appropriate training dataset, which is a set of labeled (clear or cloudy) samples, is prepared to construct the classifier. A simulation based on a radiative transfer model is one approach. It is, however, difficult to know all parameters determining the (spectral) reflectance and bidirectional reflectance distribution function (BRDF), especially of surfaces for which observations of radiative properties are scarce. Another approach to obtain a training dataset is to acquire collocated observation data on the cloud occurrence in situ or using other satellites. However, a cloud detection process is required to label clouds in the collocated data, and is likely to fall into a circular argument. Furthermore, the subjectivity of the cloud definition makes it difficult to determine what training data (especially for clouds) are "appropriate" for observation purposes, whichever the approaches (theoretical or empirical) are applied.

Incorrect results are unavoidable in actual cloud detection. A difficulty in cloud detection arises from the confusion between clouds and surfaces whose radiative appearance is similar to that of clouds, such as snow, sunglint at the water surface, and arid salt lakes. Heavy aerosol loadings, caused by dust transport, forest fires, and human activities, sometimes cause confusion. The radiative appearance of clouds varies widely, depending on the particle phase and size, altitude of the cloud top and bottom, and other physical properties. Cloud detection methods, especially for global observations, are necessary to deal with a variety of conditions, such as cloud and surface types. It is, however, very difficult to consider all situations in advance of constructing a classifier, partly because some conditions rarely occur and others are locally restricted. In other words, it is almost impossible for cloud detection by supervised learning to prepare a perfect training dataset that is sufficient for correctly detecting clouds everywhere. For some actual cloud detection operations, a cloud detection method is required to correctly discriminate a rare type of cloud within a localized area rather than to achieve high performance in a comprehensive validation. Therefore, cloud detection methods should integrate adjustment procedures, which can easily reduce the frequency of incorrect results each time they occur. In addition, the adjustment should also treat the subjectivity of the cloud definition.

An approach for the adjustment of supervised learning methods is to add incorrect cloud detection data to the training dataset to reconstruct a new classifier. However, if the radiative properties of the condition in which the incorrect results frequently occur are similar to some types of cloud, it is likely that the addition not only fails to improve the incorrect results, but also causes new incorrect discriminations. In order to avoid haphazard approaches, it is necessary to judge, whether an addition is actually effective for the reduction of the frequency of incorrect results before constructing a new classifier, and to quantitatively estimate the impact of a changed classifier on the results in other conditions. On the other hand, to change the feature space is another approach. This approach consists of finding features that can reduce the frequency of incorrect discriminations but do not cause new incorrect results. No appropriate feature might exist because of limited sensor performance (e.g., lack of critical wavelengths). On the approach, quantitative guidance to estimate the effects of a feature addition to cloud detection is useful for the adjustment.

We summarize the common requirements for machine-learning based cloud detection methods:

(i) To treat the subjectivity of the cloud definition,
(ii) A procedure for training data preparation to avoid a circular argument,
(iii) To integrate adjustment procedures for reducing the frequency of incorrect results, avoiding haphazard approaches.