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Block based cloud classification with statistical features and distribution of local texture features

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that can be exploited is helpful for reducing costs and achieving better efficiency. Therefore, the ability to perform accurate short-term forecast on surface solar irradiance is desired.

The unstable and intermittent nature of solar resource is due to the influences of cloud cover and cloud types. The height and the thickness of the clouds vary for different types of clouds. Therefore, the impact on the irradiance caused by different types of clouds also varies a lot (Martínez-Chico et al., 2011; Fu and Cheng, 2013). Large-scale cloud information can be available from satellite images. However, the spatial and temporal resolutions provided by satellite images are not high enough for short-term prediction. As a consequence, devices that capture all-sky images are designed to monitor the sun and the clouds. Devices developed more recently include Whole Sky Imager (WSI) developed by Scripps Institute of Oceanography at the University of California (Li et al., 2004; Kassianov et al., 2005), Whole Sky Camera (WSC) designed by Spain's University of Girona (Long et al., 2006), All Sky Imager (ASI) developed by Japanese Communications Research Laboratory (Kubota et al., 2003), and Total Sky Imager (TSI) by Yankee Environmental Systems (Pfister et al., 2003; Calbo and Sabburg, 2008). With the all-sky images captured by these devices, analyzing the cloud activities on a basis of more refined scales is feasible. Such analysis on cloud activities include cloud cover detection, cloud tracking, and cloud classification. The purpose of cloud classification is to distinguish the cloud types and hopefully figure out their impacts on the change of irradiance.

In the work of Martínez-Chico et al. (2011), the clouds were classified into different attenuation groups according to different levels of attenuation of the direct solar radiation reaching the surface. The authors also analyzed the annual and seasonal frequencies of each cloud group. However, this work did not propose any method for extracting features from images and performing classification based on image features. For works of cloud classification using sky image features, we review the following existing methods. The research by Calbo and Sabburg (Calbo and Sabburg, 2008) used features based on Fourier transform along with simple statistics such as SD, smoothness, mo-

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ments, uniformity, and entropy. The features are extracted from intensity images and red-to-blue components ratio (R/B) images. The classifier they used was based on supervised parallelepiped technique.

In the work of Heinle et al. (2010), statistical features such as mean, SD, skewness, and difference are also utilized. Also, textural features including energy, entropy, contrast, and homogeneity are computed from the Grey Level Co-occurrence Matrices (GLCM). 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. Other features such as autocorrelation, edge frequency, Law's features and primitive length are also tested for cloud classification (Singh and Glennen, 2010).

The statistical features utilized in these works are basic and simplified descriptors. The abilities of these descriptors are more restricted since a certain amount of information is lost in the simplification process. In addition to the simple statistical features, we extract the local texture features using Local Binary Patterns (LBP) (Suruliandi et al., 2012). The texture information encoded by LBP forms higher dimensional feature vectors compared with traditional statistical features. Therefore, we perform dimension reduction on the extracted feature vector before performing classification.

Figure 1 illustrates the proposed system framework. An all-sky image is divided into blocks before the features are extracted. The existing works classified the clouds based on the entire scene. However, very often there are mixed cloud types in the scene of an all-sky image as can be observed in Fig. 2. Therefore, we divide the scene into blocks and perform classification based on the feature of each block. After block division, the system extracts statistical feature and texture features based on local patterns from each block. Then, Principal Component Analysis (PCA) (Duda et al., 2001) is performed to reduce the dimensionality of the extracted feature vectors. For classification, we compare several classifiers, including k -NN, Bayesian classifier with regularized discriminant analysis (Cheng et al., 2010), and Support Vector Machine (SVM) (Cristianini and Shawe-Taylor, 2000). In this work, the blocks are classified into cirrus, cir-

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rostratus, scattered cumulus or altocumulus, cumulus or cumulonimbus, stratus, and clear sky. In the post processing step, the classification results from the classifier is examined using the cloud cover information. Furthermore, a voting scheme is proposed to summarize the classified label of the entire image from the class labels of all the blocks.

2 Data and methodology

This section outlines the data sources and samples as well as the methodology used for classification.

2.1 All sky images

The all sky images used in this research are captured by the all sky camera manufactured by the Santa Barbara Instrument Group (SBIG). The charge-coupled device (CCD) is Kodak KAI-0340. The lens of the camera is Fujinon FE185C046HA-1. The focal length is 1.4 mm and focal ratio range is $f/1.4$ to $f/16$. The device covers a field of view (FOV) of 185° . The RGB images are stored in bitmap format with resolution 640×480 . The dataset is provided by the Industrial Technology Research Institute of Taiwan.

Figure 3 displays the six types of clouds that the system will perform classification. Cirrus clouds and cirrostratus clouds are high and thin clouds. The main difference between cirrus clouds and cirrostratus clouds is that the area of cirrostratus is larger. Scattered cumulus or altocumulus clouds are middle-altitude clouds, which look like blobs of cotton. Cumulus or cumulonimbus clouds are lower- altitude clouds which have noticeable vertical development and are often darker and larger. Stratus clouds are flat and wide-area clouds at lower altitude.

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2.2 Block division

In practice, there might be more than one cloud types in one sky image as shown in Fig. 2. In Fig. 2a, some cumulus clouds present in the scene, and there are some cirrostratus clouds around the sun area. In Fig. 2b, a cumulus cloud blocks the sun, and some altocumulus and cirrus clouds also exist in other regions of the image. Mixing up the features of cumulus, altocumulus, and cirrostratus tends to confuse the classifier. Therefore, under such conditions of mixed cloud types, it is not appropriate to use the features of the entire image and classify the whole image as a certain cloud type. To solve this problem, we divide the entire scene into blocks and perform classification based on blocks. An example of the divided block is shown in Fig. 4 with block size 60×80 pixels. The feature vector of a block represents the characteristics of the cloud type in the block only. Such design will reduce the confusing conditions of mixing up features of different cloud types. And we can obtain more detailed information about the location of each cloud type. This information is very helpful since the clouds in the regions closer to the sun have higher impact on the irradiance changes.

2.3 Feature extraction

This work combines the statistical features proposed in the work by Heinle et al. (2010) and the distribution of local texture features using Local Binary Pattern (LBP) codes (Suruliandi et al., 2012). The statistical features represent the spectral and texture information in a global view. On the contrary, the LBP codes encode the local characteristics of the gradient and texture features.

2.3.1 Statistical features

The statistical feature vector used in the work by Heinle et al. (2010) includes statistical spectral features and statistical textual features. The statistical spectral features include the following dimensions: mean of R components, mean of B components, standard

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deviation of B component, skewness of B component, differences of R-G, R-B and G-B components. The statistical textual features are statistical measures computed from Grey Level Co-occurrence Matrices (GLCM) (Haralick et al., 1973), including energy, entropy, contrast and homogeneity of the GLCM. Also, the cloud cover ratio is considered as a feature. The details of these statistical features can be found in the work by Heinle et al. (2010).

2.3.2 Distribution of Local texture features

In addition to the above-mentioned statistical features, we enhance the texture features by applying Local Binary Pattern (LBP) (Suruliandi et al., 2012). The $LBP_{P,R}$ code for a pixel (x_c, y_c) is defined in Eq. (1). In this equation, g_c denotes the gray level value of the center pixel (x_c, y_c) , and g_p denotes the gray level value of its neighboring pixel. The parameter P sets the number of neighboring pixels that are considered when computing the binary codes. The parameter R sets the distance between the center pixel and its neighbors. For $LBP_{8,1}$ codes, we consider the 8 neighboring pixels whose distance with the center pixel is 1. The code represents the local texture characteristics around (x_c, y_c) .

$$LBP_{P,R}(x_c, y_c) = \sum_{p=0}^{P-1} s(g_p - g_c) 2^p \quad (1)$$

$$s(g_p - g_c) = \begin{cases} 1 & g_p - g_c \geq 0 \\ 0 & g_p - g_c < 0 \end{cases} \quad (2)$$

For each pixel in the image, a P-bit binary number is computed. When representing the LBP texture feature of a region using a feature vector, the convention is to construct an LBP histogram by voting with the codes of all the pixels in the region. The LBP histogram characterizes the distribution of local texture features of the region.

We apply the $LBP_{P,R}$ codes with $P = 8$ and $R = 1$ to extract local texture features in this work. For $LBP_{8,1}$ codes, there are 256 distinct values since the code is an 8-bit

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binary number. Therefore, 256 histogram bins are required for all the distinct codes. However, it has been shown that some codes appear more frequently than others, making the votes in the histogram being concentrated in a few bins. The codes that appear with higher frequencies are the uniform LBP codes. Researches have shown that uniform LBP codes account for over 90 % of all LBP codes. The uniform LBP codes are the codes that have at most two zero-to-one or one-to-zero transitions. Among the 256 distinct LBP codes, 58 LBP codes are uniform. As a consequence, we can use 58 bins for the uniform LBP codes and one extra bin for all the non-uniform LBP codes in the histogram. In total, the number of histogram bins is reduced to 59 instead of 256.

Because clouds of a certain type might be rotated, we further consider rotation invariant LBP code. To make the LBP code invariant to rotation, the code is circularly shifted to a minimum code number. In Eq. (3), $\text{ROR}(\text{LBP}_{P,R}, i)$ performs a circular bit-wise right shift on $\text{LBP}_{P,R}$ for i times. For rotation invariant LBP, there are 9 uniform patterns. Therefore, only 10 bins are required for the histogram of uniform rotation invariant LBP.

$$\text{LBP}_{P,R}^{\text{RI}} = \min\{\text{ROR}(\text{LBP}_{P,R}, i) | i = 0, 1, \dots, P - 1\} \quad (3)$$

To obtain the distribution of the local texture patterns and to retain the localized information as well, we divide each block into N_{cell} cells when constructing the feature vector. One LBP histogram is generated for each cell. And then the N_{cell} histograms are concatenated to form the feature vector. In other words, for each image block, we generate a $59 \times N_{\text{cell}}$ dimensional feature vector for uniform LBP. And we generate a $10 \times N_{\text{cell}}$ dimensional feature vector for uniform rotation invariant LBP.

2.3.3 Combining statistical features and distribution of local texture features

The feature vectors described in Sects. 2.3.1 and 2.3.2 can be concatenated to obtain the combined feature vector. We denote combined feature A as the vector obtained by concatenating statistical features and uniform LBP histogram. We denote combined

feature B as the vector obtained by concatenating statistical features and uniform rotation invariant LBP histogram. Since the statistical feature vector has 12 dimensions, combined feature A and combined feature B have $12 + 59 \times N_{\text{cell}}$ and $12 + 10 \times N_{\text{cell}}$ dimensions, respectively.

2.4 Dimension reduction

Principal Component Analysis (PCA) (Duda et al., 2001) is a commonly used way to reduce the dimensions of the feature vectors. To reduce the dependency among different feature dimensions, PCA seeks to find a set of new orthogonal bases to re-express the data more effectively. The new orthogonal bases, which are called principal components, are linear combinations of the original bases. Considering the variability in the data as an important and desired characteristic, PCA will preserve most of the data variability to the first (often few) principal components. Suppose that the original dataset \mathbf{X} has D_1 dimensions and there are N samples in the dataset. The matrix \mathbf{X} is a D_1 by N matrix whose columns are the original feature vectors. The PCA will select the first D_2 Eigenvectors corresponding to the first largest D_2 Eigenvalues of the matrix $\mathbf{X}^T \mathbf{X}$, which is proportional to the empirical sample covariance matrix of the original dataset \mathbf{X} . These D_2 Eigenvectors define the principal component directions. Then the original data is projected on to the principal components to obtain the data with reduced dimensions in the new coordinate system. The criterion to select D_2 is usually based on the following equation. In Eq. (4), λ_k denotes the k th Eigenvalue of the matrix $\mathbf{X}^T \mathbf{X}$. In other words, we preserve the first D_2 Eigenvectors so that ratio between the sum of the absolute values of the first D_2 Eigenvalues and the sum of the absolute values of

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all the Eigenvalues is larger than a threshold Thr_{PCA} .

$$\frac{\sum_{k=1}^{D_2} |\lambda_k|}{\sum_{k=1}^{D_1} |\lambda_k|} > \text{Thr}_{\text{PCA}} \quad (4)$$

2.5 Classifiers

In addition to the basic k -NN classifier, this work also utilizes Bayesian classifier with regularized discriminant analysis and Support Vector Machine in the experiments.

2.5.1 Bayesian classifier with regularized discriminant analysis

Given an unknown sample x , the Bayesian classifier will classify it as the most probable class ω_k with the highest posterior probability $P(\omega_k|x)$. According to Bayes' theorem, the posterior probability can be decomposed into several terms as shown in Eq. (5).

In Eq. (5), the denominator is the probability of the sample $P(x)$, which does not depend on the class label and thus does not affect the decision process. The numerator includes the prior probability $P(\omega_k)$ and class conditional probability $P(x|\omega_k)$. The prior probability is the probability of observing a certain class before the feature of unknown sample x is taken into account. The class conditional probability is learned from the training samples. It is usually modeled using Gaussian functions, as defined in Eq. (6). For simplicity, we can assume that all the classes have the same prior probabilities. It is also possible to set the prior probabilities according to the frequency of appearance

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of each class in the training dataset.

$$P(\omega_k|x) = \frac{P(\omega_k)P(x|\omega_k)}{P(x)} \quad (5)$$

$$P(x|\omega_k) = \frac{1}{(2\pi)^{p/2}|\Sigma_k|^{1/2}} e^{-\frac{1}{2}(x-\mu_k)\Sigma_k^{-1}(x-\mu_k)^T} \quad (6)$$

To model class conditional probabilities as Gaussians, we need to estimate the parameters of the Gaussians from the training data. Regularization techniques help reduce variance without adding too much model bias when estimating the parameters for high dimensional data (Cheng et al., 2010). In Eigenvalue Decomposition Regularized Discriminant Analysis (EDRDA) (Bensmail and Celeux, 1996) the covariance matrix Σ_k for the k^{th} class is re-parameterized in terms of its eigenvalue decomposition $\Sigma_k = \alpha_k \mathbf{D}_k \mathbf{A}_k \mathbf{A}_k^T$, where $\alpha_k = |\Sigma_k|^{1/p}$ and \mathbf{D}_k is the matrix of eigenvectors of Σ_k . The matrix \mathbf{A}_k is a diagonal matrix such that $|\mathbf{A}_k| = 1$ with the normalized eigenvalues of Σ_k on the diagonal in a decreasing order. By allowing each of the parameters α_k , \mathbf{A}_k , \mathbf{D}_k to be either the same or different among different classes, eight discriminant models can be obtained. Furthermore, six more models are obtained by modelling the covariance matrix as a diagonal matrix or a scalar multiple of the identity matrix. More specifically, $\Sigma_k = \alpha_k \mathbf{B}_k$ leads to four more less complex models, where \mathbf{B}_k is a diagonal matrix with $|\mathbf{B}_k| = 1$. The models requiring the smallest numbers of parameters are to assume spherical shapes, i.e., \mathbf{A}_k is identity matrix, which lead to model $\alpha_k I$ and model αI . Among the 14 models, there are 9 models whose maximum likelihood (M.L.) estimation of the covariance matrix can be computed in closed form. For other models, the M.L. estimation needs to be computed through an iterative procedure. To accelerate the model selection process, this work only considers the nine EDRDA models that have closed-form solutions for M.L. parameter estimation.

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entire image. A simple way to summarize the labels in an image is to perform voting. From the classification results in Fig. 6, we have the knowledge that clouds of class 3 and 4 dominate this all-sky image.

3 Experiments and discussions

In this section, we report experimental results and discuss the performance of the proposed block-based cloud classification framework. For the training purpose, we select 1800 blocks from the images and manually label the ground truth of these blocks. Selected training blocks for the six classes are shown in Fig. 7. Note that the block size used in our experiments is 60×80 pixels. We manually classified the ground truth of 3000 images in the dataset in order to calculate the summarized classification accuracy for whole images. Since there are mixed cloud conditions in many images, each image can be associated with at most two ground truth labels. For a mixed cloud type image, the voting result is considered correct if the classified label matches any of the two ground truth labels. Figure 8 displays some examples of images that are associated with two ground truth labels. Figure 8a is labeled as both class 1 and 4. Figure 8b is labeled as both class 1 and 3.

To select the proper threshold Thr_{PCA} for dimension reduction, we plot the accuracy using different Thr_{PCA} in Fig. 9. We use the 1800 blocks with ground truth labels and perform 10-fold cross validation (CV) when conducting this experiment. Note that the CV accuracy in Fig. 9 is based on the classification result of Bayesian classifier. We can observe that when Thr_{PCA} ranges from $93 \sim 94\%$, the CV accuracy is higher for both uniform LBP and combined feature A. Therefore, we select $\text{Thr}_{\text{PCA}} = 93\%$ for uniform LBP and combined feature A in the rest of the experiments. According to Fig. 9, we select $\text{Thr}_{\text{PCA}} = 95\%$ for uniform rotational invariant LBP and combined feature B. In Fig. 9, when Thr_{PCA} equals to 100% , it is equivalent to not applying dimensionality reduction. For combined feature A and combined feature B, the advantage of applying PCA is more obvious since the dimensionality is higher. The statistical feature vector

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has only 12 dimensions. Therefore, there is no need to apply PCA on the statistical feature vector.

To compare the effect of various features and classifiers, Fig. 10 shows the 10-fold cross validated classification accuracy on the 1800 blocks with ground truth labels using different features and classifiers. Compared with the statistical features and k -NN classifier used in the work by Heinle et al. (2010), the proposed combined features with Bayesian classifier or SVM demonstrate higher classification rates. It is clear that local texture feature alone does not perform better than statistical features. However, when combined with statistical features, additional information provided by distribution of local texture features can significantly improve the classification accuracy. We can observe that combined feature A slightly outperforms combined feature B when using Bayesian Classifier and SVM. Although intuitively we think that features with rotation invariant characteristics should be preferable for cloud classification, combined feature A performs slightly better in practice. It might be due to the small dimensionality of combined feature B. Overall speaking, the method using combined feature A and Bayesian classifier with regularized discriminant analysis has the highest cross validated classification accuracy in our experiments. Figure 11 displays selected classification results using combined feature A and Bayesian classifier with regularized discriminant analysis. Although there are inevitably some misclassified blocks, most blocks are correctly classified in Fig. 11. Note that classification labels are not displayed on incomplete blocks and the block where the sun resides in Fig. 11.

To observe the advantage of block based classification, Fig. 12 shows the classification accuracy on the 3000 images in the dataset with and without block voting scheme. In this experiment, the classifier is Bayesian classifier. Since features from mixed cloud conditions will not be mixed up in a single feature vector, the classification rates using block voting schemes are higher. Moreover, another advantage of block based classification is that the classification result of each individual block with the knowledge of the block location can be utilized by subsequent application modules.

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4 Conclusions

Cloud classification is an important task for improving short-term solar irradiance prediction since different types of clouds have different effects on the change of solar irradiance. In this work, an automatic cloud classification method for all-sky images is proposed. The classification is performed based on fixed-size blocks in the all-sky images. In addition to the statistical features in the literature, we combine the histogram of local texture patterns in the feature vector. With more discriminate features provided by local texture patterns, the proposed combined feature can improve the classification accuracy. Replacing k -NN classifier with more sophisticated supervised learning methods can further enhance the recognition results. Bayesian classifier with regularized discriminant analysis outperforms other classifiers on this dataset in our experiments. This work also compares the classification accuracy with and without the voting scheme. With block based classification and the voting scheme, the classification results on images with mixed cloud type conditions were shown to be better. For future work, we would like to integrate the proposed cloud classification method in a short-term irradiance prediction system to obtain more accurate prediction results.

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References

- Bensmail, H. and Celeux, G.: Regularized Gaussian discriminant analysis through Eigenvalue decomposition, *J. Am. Stat. Assoc.*, 91, 1743–1748, 1996.
- Calbo, J. and Sabburg, J.: Feature extraction from whole-sky ground-based images for cloud-type recognition, *J. Atmos. Ocean. Tech.*, 25, 3–14, 2008.
- Cheng, H. Y., Yu, C. C., Tseng, C. C., Fan, K. C., Hwang, J. N., and Jeng, B. S.: Environment classification and hierarchical lane detection for structured and unstructured roads, *IET Comput. Vis.*, 4, 37–49, 2010.

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Cristianini, N. and Shawe-Taylor, J.: An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods, Cambridge University Press, Cambridge, 2000.

Duda, R. O., Hart, P. E., and Stork, D. G.: Pattern Classification, 2nd Edn., John Wiley & Sons, New York, 2001.

5 Fu, C. L. and Cheng, H. Y.: Predicting solar irradiance with all-sky image features via regression, Sol. Energy, 97, 537–550, 2013.

Haralick, R. M., Shanmugam, K., and Dinstein, I.: Textural features for image classification, IEEE T. Syst. Man Cyb., 3, 610–621, 1973.

10 Heinle, A., Macke, A., and Srivastav, A.: Automatic cloud classification of whole sky images, Atmos. Meas. Tech., 3, 557–567, doi:10.5194/amt-3-557-2010, 2010.

Kassianov, E., Long, C. N., and Ovtchinnikov, M.: Cloud sky cover vs. cloud fraction: whole-sky simulations and observations, J. Appl. Meteorol., 44, 86–98, 2005.

15 Kubota, M., Nagatsuma, T., and Murayama, Y.: Evening corotating patches: a new type of aurora observed by high sensitivity all-sky cameras in Alaska, Geophys. Res. Lett., 30, 1612, doi:10.1029/2002GL016652, 2003.

Li, Z., Cribb, M. C., Chang, F. L., and Trishchenko, A. P.: Validation of MODIS-retrieved cloud fractions using whole sky imager measurements at the three ARM sites. Proc. 14th ARM-Science Team Meeting, Albuquerque, NM, Atmospheric Radiation Measurement Program, vol. 6, 2–6, 2004.

20 Long, C. N., Sabburg, J., Calbó, J., and Pagès, D.: Retrieving cloud characteristics from ground-based daytime color all-sky images, J. Atmos. Ocean. Tech., 23, 633–652, 2006.

Martínez-Chico, M., Battles, F. J., and Bosch, J. L.: Cloud classification in a mediterranean location using radiation data and sky images, Energy, 36, 4055–4062, 2011.

25 Pfister, G., McKenzie, R. L., Liley, J. B., Thomas, A., Forgan, B. W., and Long, C. N.: Cloud coverage based on all-sky imaging and its impact on surface solar irradiance, J. Appl. Meteorol., 42, 1421–1434, 2003.

Singh, M. and Glennen, M.: Automated ground-based cloud recognition, Pattern Anal. Appl., 8, 258–271, 2005.

30 Suruliandi, A., Meena, K., and Reena Rose, R.: Local binary pattern and its derivatives for face recognition, IET Comput. Vis., 6, 480–488, 2012.

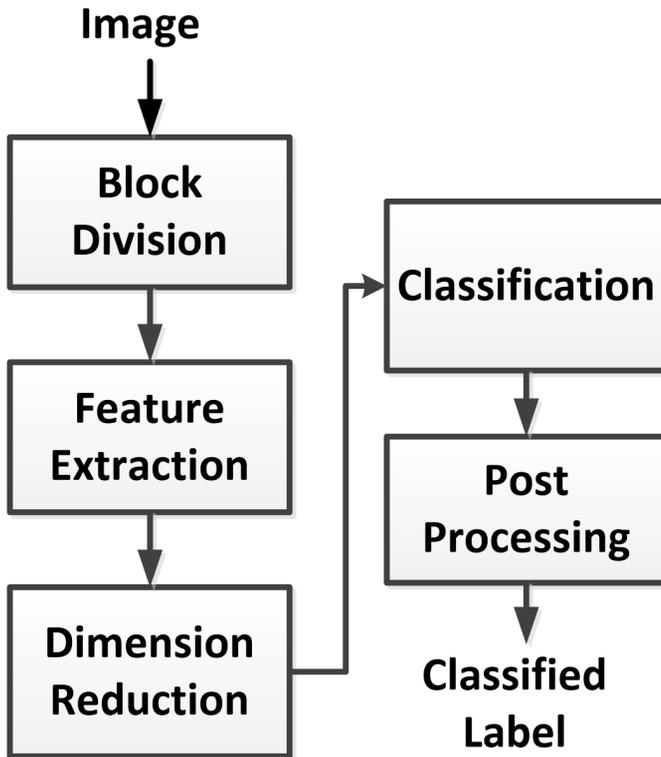


Figure 1. System framework.

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Figure 2. Conditions of mixed cloud types.

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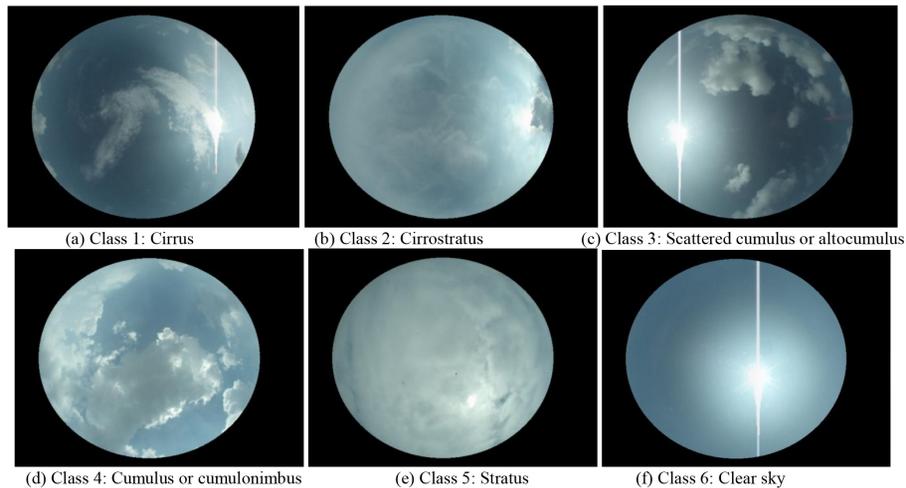


Figure 3. Six different types.

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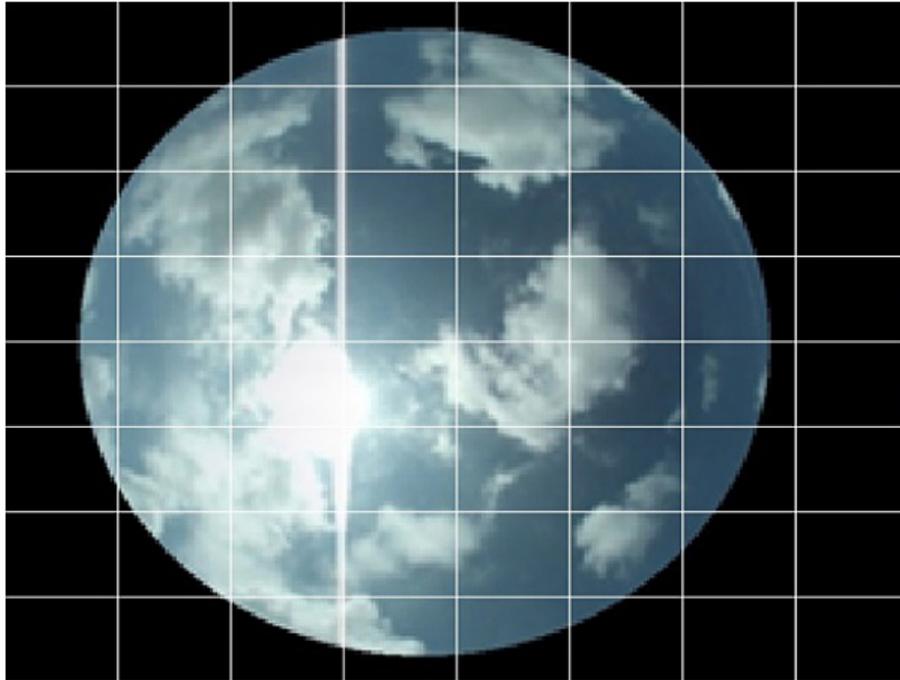


Figure 4. Block division example.

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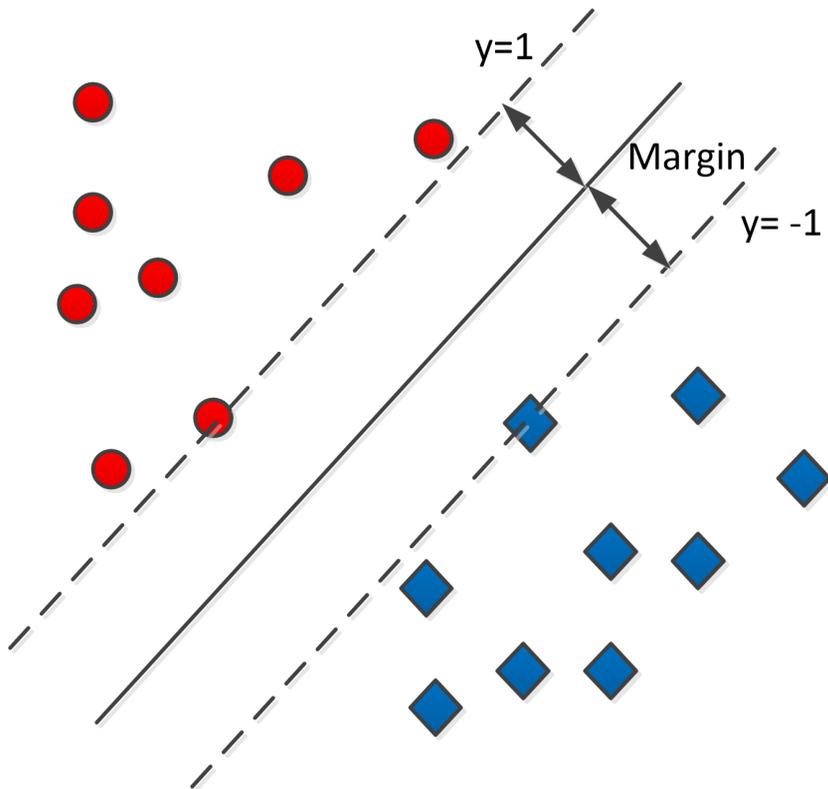


Figure 5. Decision boundary of support vector machine.

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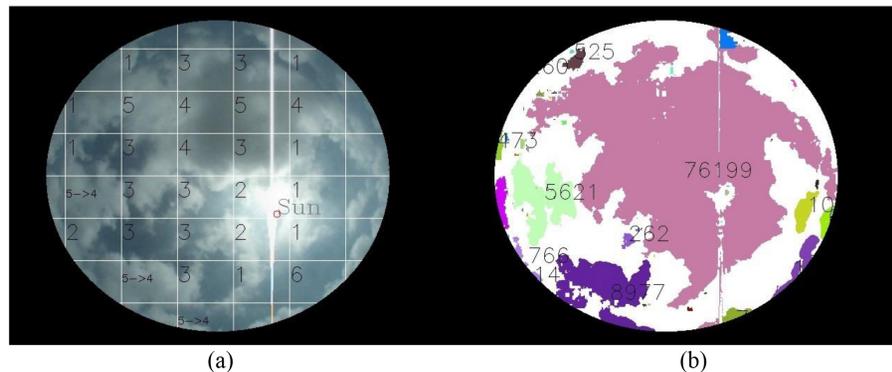


Figure 6. Example of correcting a stratus block as cumulus.

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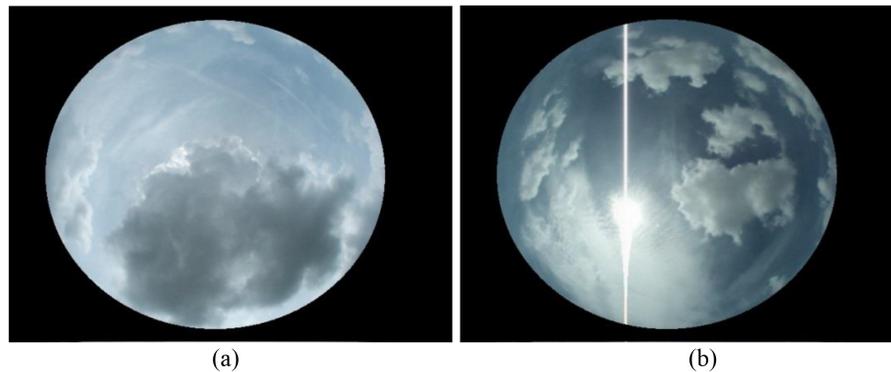
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**Figure 8.** Examples of images with two ground truth labels.[Title Page](#)[Abstract](#)[Introduction](#)[Conclusions](#)[References](#)[Tables](#)[Figures](#)[◀](#)[▶](#)[◀](#)[▶](#)[Back](#)[Close](#)[Full Screen / Esc](#)[Printer-friendly Version](#)[Interactive Discussion](#)

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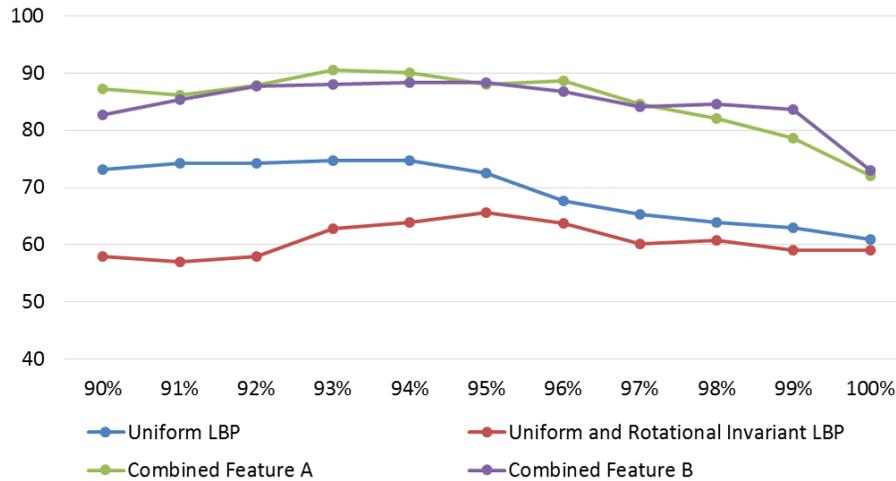


Figure 9. Selection of the threshold Thr_{PCA} for dimension reduction.

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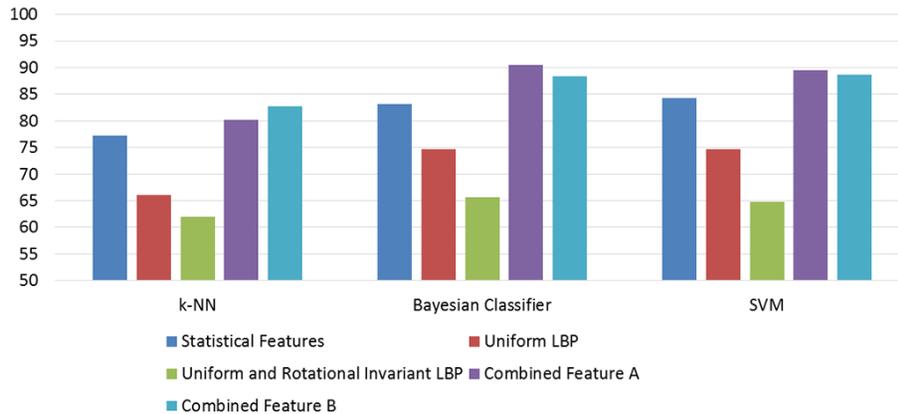


Figure 10. Classification accuracy on blocks using different feature and classifier combinations.

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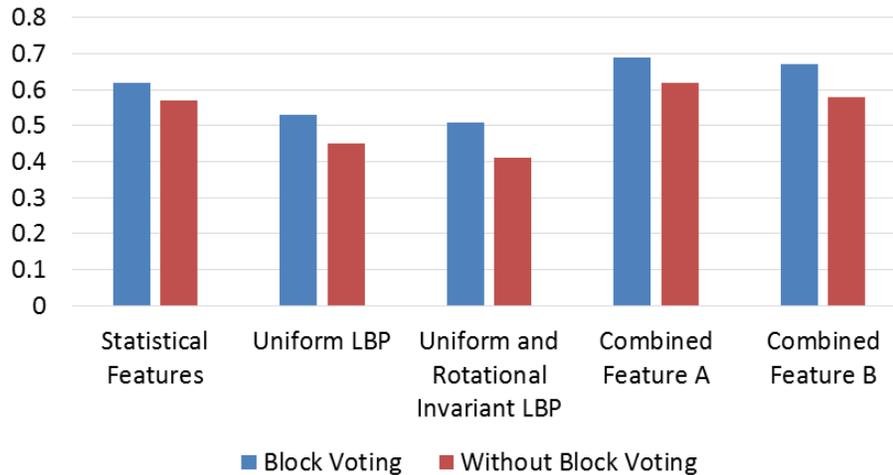


Figure 12. Comparison of whole-image classification and block-based classification with voting scheme.

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