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CLASSIFICATION OF POLAR SATELLITE DATA USING MINIMUM DISTANCE METHOD

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Abstract: Detection of Antarctic clouds is important because of their strong radiation influence on energy balance of the snow and ice surface. In this paper, a method to classify cloud, sea ice and ground is proposed. This study is based upon analysis of the NOAA/AVHRR infrared images in Antarctica. The algorithm consists of two major approaches: extraction of image features and a classification algorithm. A minimum distance classifier was used to classify that region into one of three categories using five image features. To reduce the error rate of the classification, threshold boundaries for minimum distance classifiers have been changed. Both classified and misclassified areas were decreased with increased threshold levels.

1. Introduction

Clouds have a major role in radiative processes in planetary atmospheres, both in the absorption and reflection of solar radiation and in the emission of thermal energy (CHAHINE, 1982; HARTMANN and SHORT, 1980; KEY and BARRY, 1989; SALTZMAN and MORITZ, 1980). A meteorological satellite gives considerable information about the surface of the earth. Several studies have been attempted for detecting cloud cover from visible and infrared satellite-measured radiance. Since, however, in the polar region, cloud, snow and ice have almost the same albedo in the visible channel and the same brightness temperature in the infrared channel, it is difficult to distinguish among these regions using only the gray level threshold of a satellite image (COAKLEY and BRETHERTON, 1982; DESBOIS *et al.*, 1982). In addition, because of high latitude, visible channels cannot be used during winter. To classify the areas from satellite images in all seasons, we have to use only the infrared channel.

In this paper, techniques for classifying Antarctic satellite images into cloud, sea ice and ground using single channel data are proposed. The algorithm consists of two major approaches: extraction of image features and a classification algorithms. A minimum distance classifier is applied to classify the region into one of three categories using five image features. To reduce the error rate of the classification, threshold boundaries for minimum distance classifiers were changed.

2. Data

NOAA/AVHRR data with a spatial resolution of 2.2 km are used in this study (YAMANOUCHI *et al.*, 1991). Each scene is composed of 512×512 pixels covering a land area of 1100×1100 km. At each pixel location, the image brightness was quantified into 256 gray levels for computer graphics display.

3. Image Features

3.1. Subregion

All of the features to be expressed in this work were template techniques in which a subregion was defined as a (32×32)-pixel block area. The input pixels within the subregion were calculated and output pixels created at its central. The subregion then moved over one pixel in the same line and the process was repeated using the original input pixels.

3.2. Image features

3.2.1. Average and standard deviation of the brightness temperature of each pixel in a subregion

Averaging of the brightness temperatures of the pixels is one of the most effective approaches to image classification. The standard deviation provides one measure of the variability, these values are much easier to compute than the fractal and textural feature.

3.2.2. Fractal feature

Fractal feature can be used to describe structural similarities independent of scale in nature. The fractal dimension is a quantitative property of self-similar structures (PENTLAND, 1984). The gray level in the region is defined by brightness. This method relies on the assumption that regions of an image having a particular structure will usually produce a fractal gray level surface, with a particular fractal dimension. The details of our image processing and analysis techniques of fractal dimension are given elsewhere (MURAMOTO and YAMANOUCHI, 1996). Briefly, we used a three-dimensional cube to measure the fractal surface's dimension by covering the surface with a minimal number of cubes.

3.2.3. Textural feature

Texture is usually defined as a function of the spatial variation in pixel gray levels. One approach to texture feature extraction is based on the spatial gray level co-occurrence matrix $P(i, j)$ (HARALICK *et al.*, 1973). Each element of the gray level co-occurrence matrix is a measure of the probability of occurrence of two gray scale values separated by a given distance in a given direction. Generally, four angular matrices for directions separated by 90 degrees will be computed for given pixel distances whose gray levels are i and j, respectively. The co-occurrence matrix reveals certain properties about the spatial distribution of gray levels in the texture image. HARALICK *et al.* (1973) defines fourteen measures of texture feature from the four angular matrices. The following equations describe the two of these features.

$$uni = \sum_{i=1}^{N} \sum_{j=1}^{N} \left\{ \frac{P(i,j)}{R} \right\}^2,$$

$$cor = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} \{ i \cdot j \cdot P(i,j)/R \} - \mu_x \cdot \mu_y}{\sigma_x \cdot \sigma_y},$$

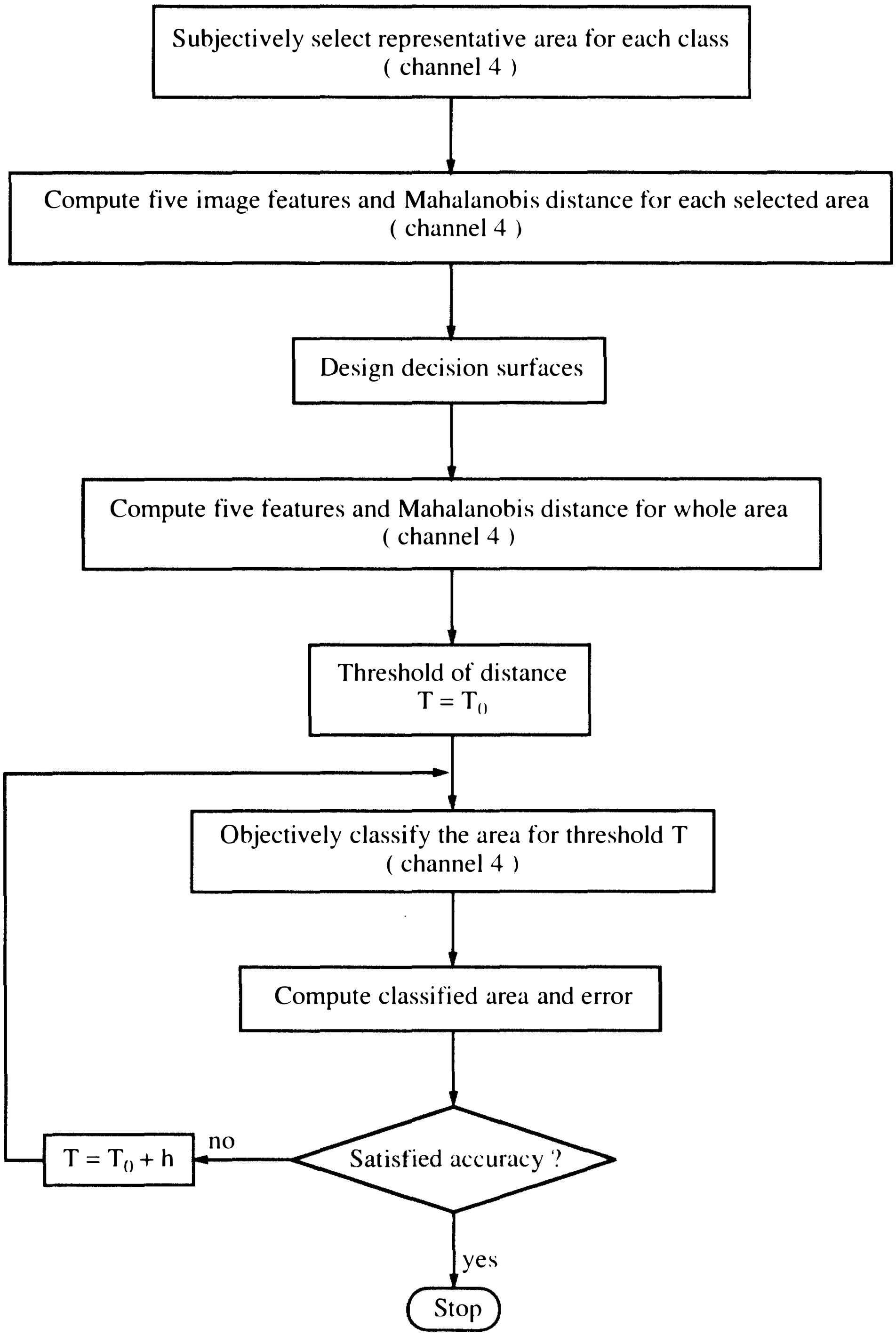

Fig. 1. Flow chart of the classification procedure.

where N is the number of gray levels, R is a renormalizing constant equal to the total number of pixel pairs in a subregion, and μ and σ are the mean and standard deviation of the distributions of gray scale values accumulated in the x and y directions. The *uni* is a measure of uniformity using a second moment. Since the terms are squared, a few large differences will contribute more than many small ones. The *cor* is a measure of the linear dependency of gray level obtained by correlation.

4. Classification

4.1. Classifying process

A flow chart of the iterative procedure is summarized in Fig. 1. In order to classify clouds, sea ice and ground, a representative area for each desired class was selected subjectively using infrared imagery (channel 4). More than one training area per class was used to include the range of variability. Five features of image data of the selected areas were computed for training samples. Those were, (1) average of brightness temperature, (2) standard deviation of brightness temperature, (3) fractal dimension, (3) uniformity of texture, and (5) correlation of texture. Image features of all pixels of infrared imagery and the parameters of the Mahalanobis distance method were calculated. The whole area of visible imagery (channel 1) was also classified manually to obtain test samples for estimating the classification results. Every pixel in the scene was classified into one of the classes using the Mahalanobis distance method. Classification accuracy was changed by an iterative procedure which moves the threshold boundary.

4.2. Minimum distance classifier

Minimum distance classifier is a commonly used algorithm for image classification. Values of image features of each subregion are plotted in multi-dimensional feature

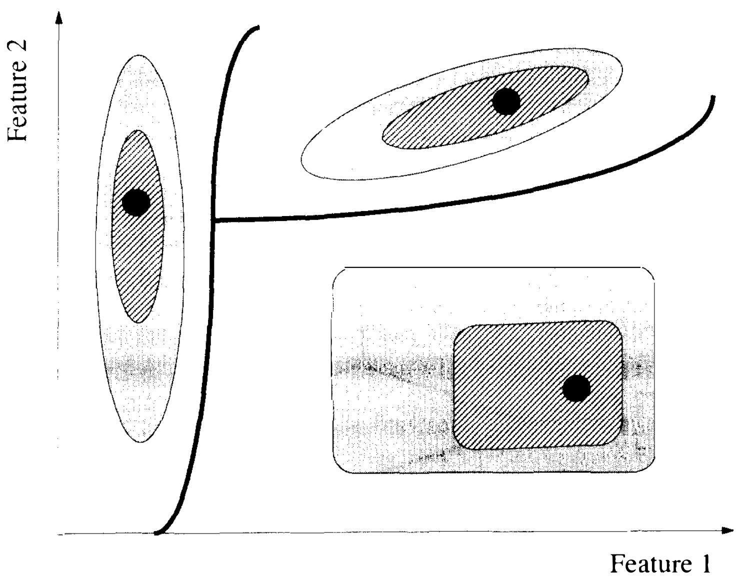

Fig. 2. Minimum distance classifier. Threshold boundaries are applied to limit the extent of each group.

space. The mean value for each feature is determined. A pixel of unknown is classified by computing the distance between the unknown pixel and each of the class means. After computing the distances, the unknown pixels are assigned to the closest class. The discriminant function for the minimum distance classifier is defined using covariance matrices (DUDA and HART, 1973). If the covariance matrices of all the candidate classes are equal, the discriminant distance is called the Mahalanobis distance. If the covariance matrices are diagonal and have equal variance along each feature axis, the discriminant distance is called Euclidean distance. In this study, the Mahalanobis distance method was used. Every pixel is classified by this method, irrespective of how small the classification actual accuracy is. A modification to this method was adopted to prevent misclassification. Figure 2 shows geometric representation of a simple case

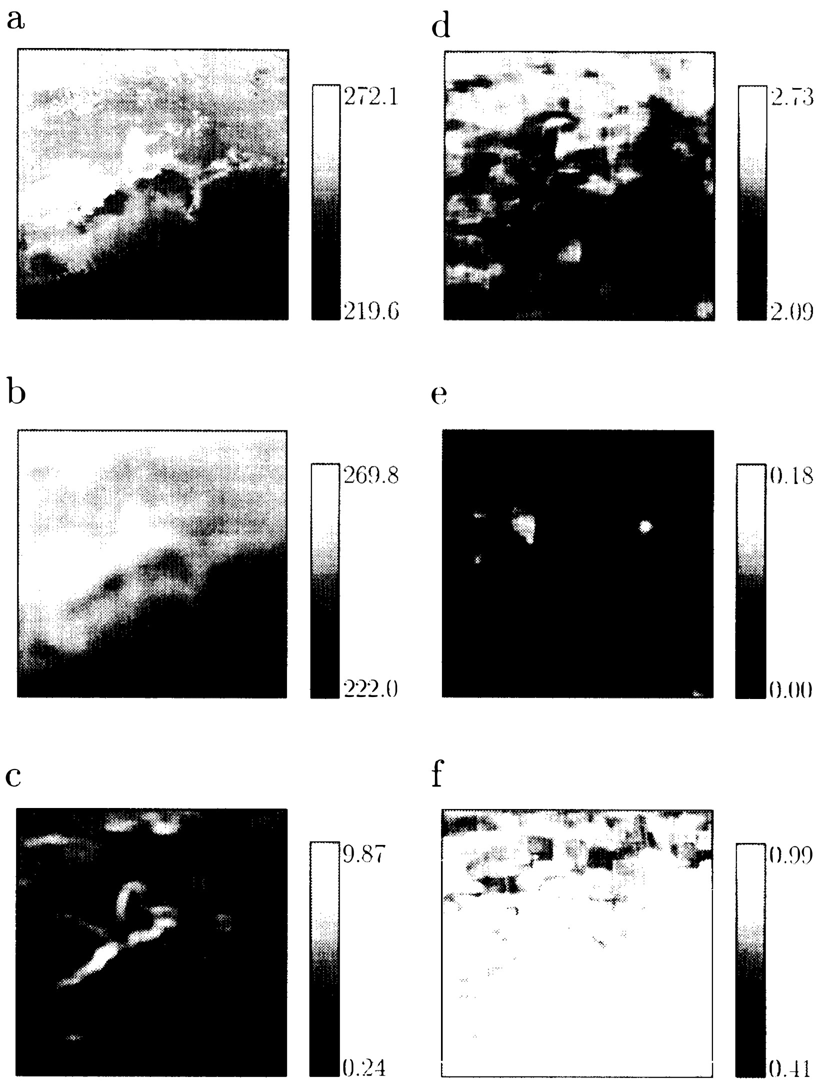

Fig. 3. Image features of NOAA satellite displayed by gray scale.
(a) AVHRR image of channel 4. (b) Average of brightness temperature.
(c) Standard deviation of brightness temperature. (d) Fractal dimension.
(e) Uniformity of texture. (f) Correlation of texture.

illustrating threshold boundaries in two dimensions for a distribution of feature values. Thresholds are applied to limit the extent of each group. Any pixel further away than the boundary distance is left unclassified. Thresholds prevent misclassification of pixels outside the boundary. Though classified areas are decreased with decreasing distance from mean value to boundary, misclassified areas are also excluded.

5. Results and Discussion

First, five features for cloud, sea ice and ground in the satellite image were calculated using subjectively selected representative areas. These data were used to calculate a decision boundary for the minimum distance classifier. Figure 3 shows examples of five image features of NOAA satellite displayed by gray scale. Figure 4 shows a histogram of the image features. It can be seen that many area of sea ice can be separated from others on the basis of average brightness temperature, and many areas

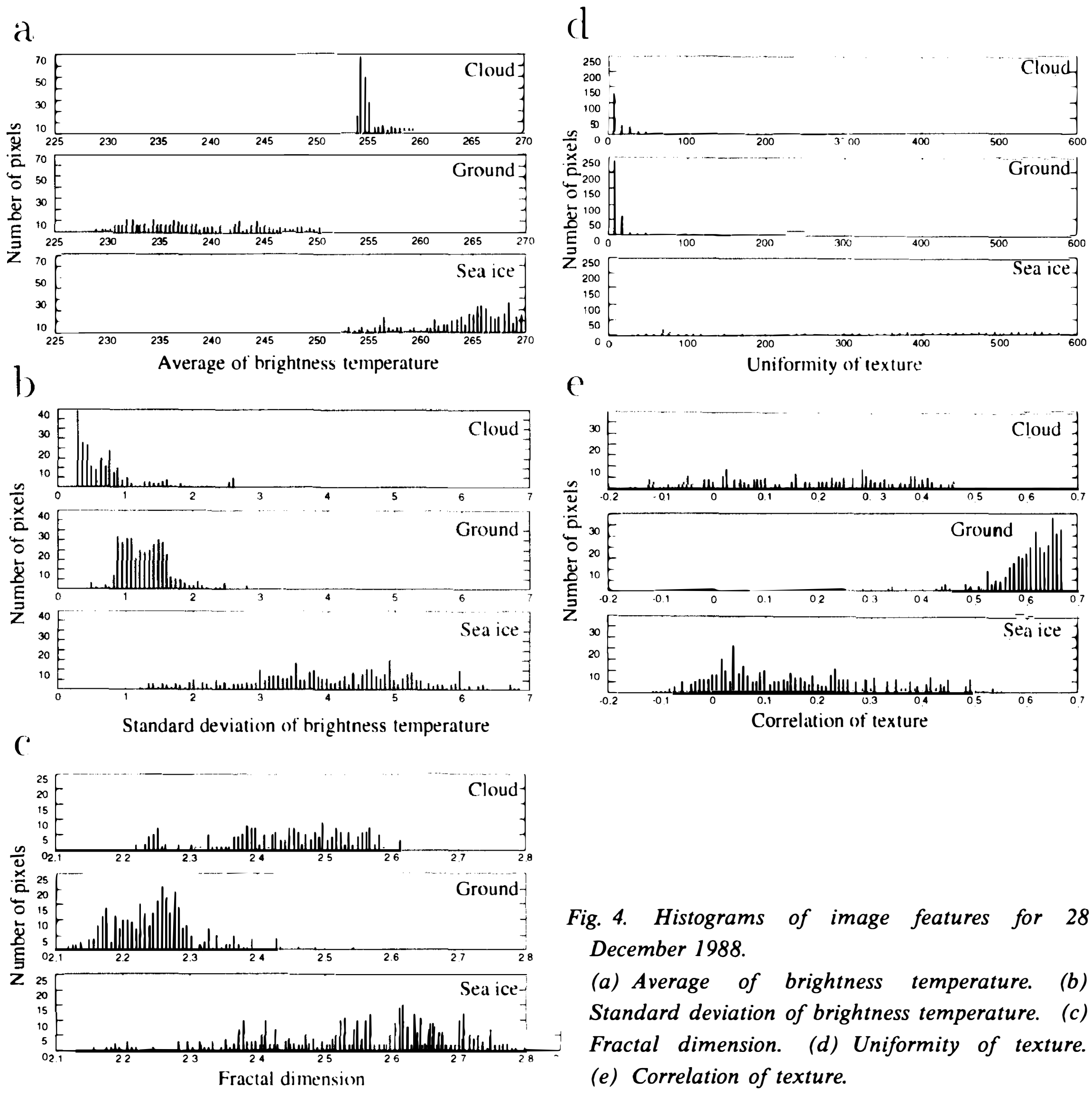

Fig. 4. Histograms of image features for 28 December 1988.
(a) Average of brightness temperature. (b) Standard deviation of brightness temperature. (c) Fractal dimension. (d) Uniformity of texture. (e) Correlation of texture.

of ground can be separated from others on the basis of correlation of texture feature. However, it was impossible to segment the image into three regions with only one feature. More than two features have to be used to separate all regions. Classified areas and their estimations were examined by changing decision boundaries. In this study, stages 1, 2, 3, 4 and 5 were used, corresponding to percentages of error in the classified area of 36.7%, 30%, 25%, 20% and 15%, respectively.

Figure 5 illustrates the effect of threshold of boundaries on the classification. In stage 1, the upper right part was misclassified as a cloud class because of feature similarity between that part of the sea ice and the cloud training class. The application of thresholds (stages from 2 to 5) could exclude these misclassified pixels, but sometimes originally correctly classified pixels were similarly eliminated. The accuracy for each stage was estimated by dividing the number of correctly classified pixels by the total number of classified pixels in that stage. Figure 6 shows the percentage of classified area and its estimation of stages from 1 to 5. Classified areas and error rates were decreased with increasing number of stages. When all pixels were classified, the classification error was 36.7%. In general, a compromise threshold that eliminates the maximum number of misclassified pixels throughout the scene without significantly

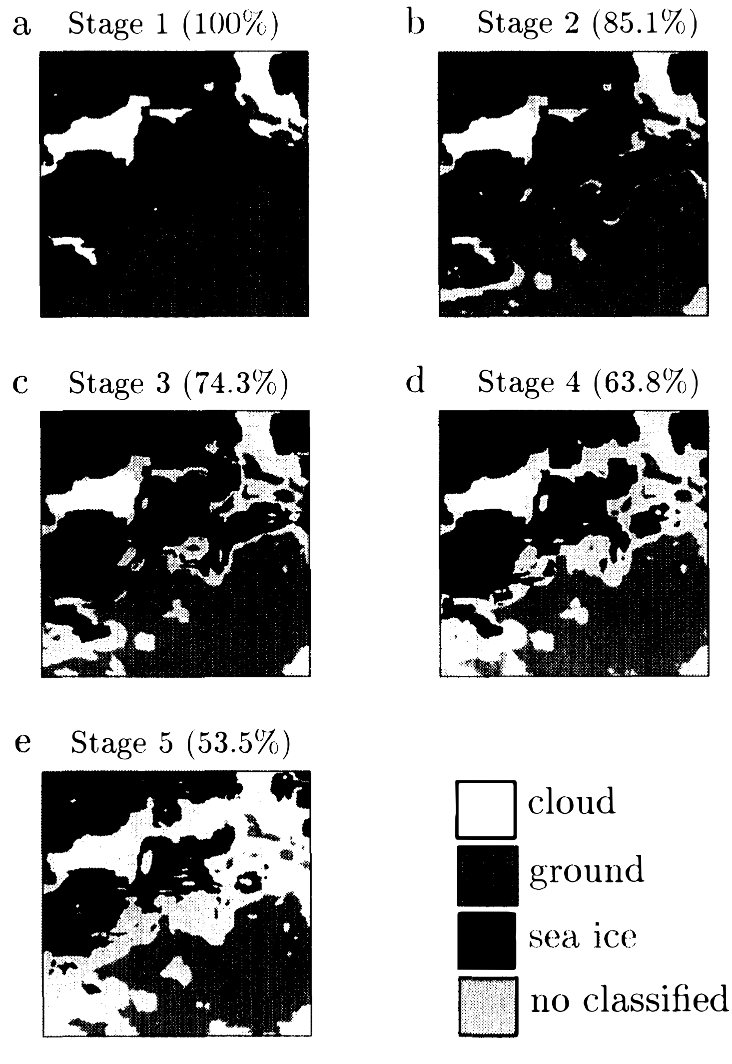

Fig. 5. Classified satellite image for five stages. When all pixels were classified (stage 1), the classification error was 36.7%. To decrease the error rate of classification, thresholds were applied. When the desired error rate was 30%, 85.1% of all pixels were classified (i.e., the 14.9% of all pixels were not classified). Thus, classified areas decreased with decreasing error rate.

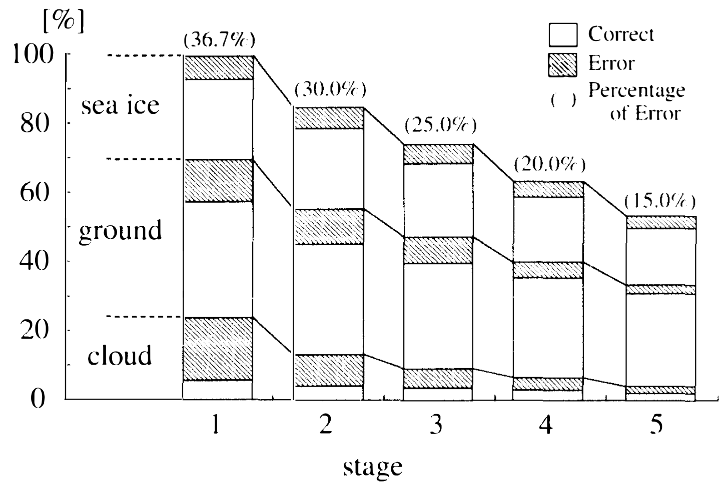

Fig. 6. Percentage of classified area and estimation stages from 1 to 5.

affecting the correctly classified pixels is desired.

6. Conclusions

Detection of Antarctic clouds is important because of their strong radiation influence on the snow and ice surface energy balance. A method to classify cloud, sea ice and ground from an Antarctic satellite image using a single AVHRR infrared channel is proposed. Average and standard deviations of brightness temperature, fractal dimension and textural features of the image data were used to classify each pixel into one of three regions. When all pixels were classified, the error rate was large. To decrease the error rate of the classification, the extent of each group was limited by changing decision boundaries. The decision boundaries do not improve the classification accuracy of pixels within the class boundary. They only prevent misclassification of pixels outside the boundary.

The decision boundaries can be useful, however, in limiting maximum error rate. Error rate decreased with decreasing classified area. In practice, thresholds are applied to limit the percentage of misclassification.

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