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13. Abstract (Maximum 200 words). Cloud features have an important impact on global Navy activities, ranging from the effects of clouds on surface ship and aircraft operations to the limitation and enhancement of surveillance activities. We have been developing an automated system for the recognition of operationally important cloud types using data obtained from the Defense Meteorological Satellite Program (DMSP) satellite system. The satellite is deployed in a sun-synchronous morning orbit, and carries a variety of sensors, including the Optical Line Scanner (OLS). This paper describes ongoing work in the use of physical and textural measures for the automatic recognition of cloud classes. We have found the physical measures to be relatively computer intensive, and dependent on visible and IR satellite data. The addition of textural measures shows promise for enhancing the classification capability by using only a single channel and by reducing computer processing time. <i>AD 25; 7007</i> <i>Cloud Classification of DMSP visible and IR Imagery Using Physical and Textural Features</i>					
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Cloud Classification of DMSP visible and IR Imagery
Using Physical and Textural Features

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1 Summary

Cloud features have an important impact on global Navy activities, ranging from the effects of clouds on surface ship and aircraft operations to the limitation and enhancement of surveillance activities. We have been developing an automated system for the recognition of operationally important cloud types using data obtained from the Defense Meteorological Satellite Program (DMSP) satellite system. The satellite is deployed in a sun-synchronous morning orbit, and carries a variety of sensors, including the Optical Line Scanner (OLS). This paper describes ongoing work in the use of physical and textural measures for the automatic recognition of cloud classes. We have found the physical measures to be relatively computer intensive, and dependent on visible and IR satellite data. The addition of textural measures shows promise for enhancing the classification capability by using only a single channel and by reducing computer processing time.

2 DMSP Data analysis

Satellite image data from the DMSP Optical Lines Scanner are received at FNOC within two hours of observation. The OLS data are measured in two spectral bands, visible and thermal infrared, with constant ground resolution across the satellite swath. The data are immediately transformed to the Quadrilateralized Spherical Cube coordinate system (Chan and O'Neill, 1978). This coordinate system is particularly suited to objective image analysis, since the coordinate system is area preserving, providing a constant ground resolution anywhere on the globe. The satellite data are stored in 64 by 64 pixel interpolation blocks (IB). overlaps from different orbits are permitted among IB's, but within each IB data are guaranteed to be obtained from the same orbit.

The coordinate system is ideal for multispectral analysis since the data are located on a equal area projection, with the same resolution for visible and IR channels

3 Image feature derivation

The digital imagery are analyzed within each interpolation block. The earlier physical image analysis (Garand, 1988, Goroch, 1988) have been found to be computer intensive, and inefficient on the Cyber 175 computer system in use at FNOC. The analysis was expanded to include textural measures (Welch, 1986) in an effort to provide a graded system of cloud classification. The current objective is to analyze the image with progressively more complex classification measures, until a required confidence level is attained.

4 Physical features

The physical features of the visible and infrared image have been described by Garand and Weinman (1986) and Ebert (1988) and are summarized in table 1. The features are combined into an image

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vector which is normalized and used in later feature discrimination. The physical meaning of the feature vector is determined by its use in the function discriminating among cloud types. In the current use of a Gaussian multivariate type of discriminant function, the elements of the feature vector of a category provide the following information

Element negative - feature reduces class membership

Element zero - class membership distributed around mean

Element positive - feature increases class membership

The Garand cloud classes were obtained from a training set of GOES data during the winter of 1984 in the northwest Atlantic. The classifications are shown in Table 2, together with objective characteristics of each cloud type. Figure 1 shows the characteristic feature vectors associated with low layered cloud types. Note, for example, the importance of the MC, multilayer, element in differentiating the altocumulus cloud type from the two multilayered cloud types, Cumulus with Altocumulus and Stratocumulus with Altocumulus.

Table 1
Physical characteristic vectors

Description	Limits
Crosscorrelation (ST.)	(0, 1)
Spectral Intensity between 20-40 km (SE)	(0, 1)
mean cloud albedo (AL)	(0, 1)
Cloud top height (HT)	0 - 14 km
Background connectivity (BC)	(0, 1)
IR low cloud fraction (LO)	(0, 1)
IR middle cloud fraction (MI)	(0, 1)
Multilayer index (ML)	(0, 1)
Total cloud fraction (CF)	(0, 1)
Number of clouds (NC)	
Fraction of cirrus clouds (LR)	(0, 1)
Cloud Connectivity (CC)	(0, 1)
High Cloud fraction (HI)	(0, 1)

5 Textural features

To supplement the physical features, we have added the textural features used by Welch (1986) and others for class discrimination. The textural features are shown in Table 3. The textural features provide a rapid textural analysis which it was considered would add to useful measures, which would not use every much computer time.

Table 2 - Physical class characteristics

Type	Cloud Fraction			Texture	Character	Visible Albedo			IR Height		
	Min	Typ	Max			Min	Typ	Max	Min	Typ	Max
Clear			< 1								
Stratus				Smooth	Uniform	50		80	1.4	2.5	
Scattered Cumulus		< 50		Grainy		30		45	1.8	3.5	
Broken Cumulus		> 50		Grainy			43		2.5	5	
Scattered Stratocumulus		< 50		few clouds, large units	Highly connected		40	60	2.4	3.5	
Broken to Overcast Stratocumulus		> 50		few clouds, large units	Highly connected		46	60	2.7		
Cloud Streets	15	50	90	grainy, composed of cumulus	Clear directionality		43		2.3		
Rolls		60	93	Thick, little grain	Mid level directionality		75		4	6	
Polygonal Open Cells				Honeycombed character	Sizeable holes		55		3.5	5.5	
Strongly convective open cells	60	93		toroidal cloud elements, lumpy	holes several km in diameter		63		4.4	6	
Bright Closed Cells	30	80	95	Large clumps	may have towering Cu			63	3.4		
Nimbostratus	85	90		lumpy	smooth, at mid-level		77		2.5	4	6
AltoCumulus	1	45	100	Uniform	single mid layer		34		3.5	4.2	6
Cumulus with AltoCumulus				low - grainy mid - patchy	low cumulus with mid level deck		47		4.8	6	
Strato-Cumulus with AltoCumulus		72			low - StCu multi-layered		47		5.5	6	
Thin Cirrus				Fibrous, in IR	Semi-transparent		25	35			
Multilayers with Cirrus	high - 5	87	high < 85	IR structure	multiple layers	35	41	55	8.7		
Bright multilayer with Ci/CuNi		94		IR structure	Multiple-layers		72		8.9		
Dense Cirrostratus	90	97			high clouds > 85% of total		50		10.3		
Overcast Cumulonimbus	90	100			Deep CuNi in cyclone		87		10.7		

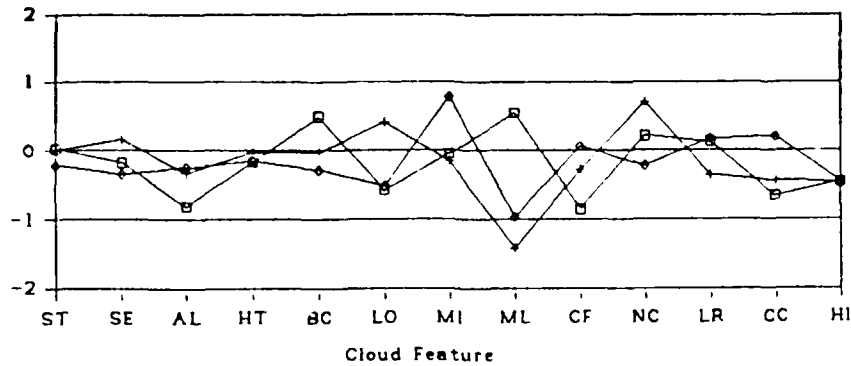


Figure 1, Low layer cloud feature vectors, Altocumulus(square), Cumulus with Altocumulus (plus), Strato cumulus with Altocumulus (diamond)

Table 3 Textural Feature Analysis
Grey Shade Co-Occurrence Calculation Functions

$$D_{f,H(l,p,d)} = f(V(l,p), V(l,p+d))$$

$$D_{f,V(l,p,d)} = f(V(l,p), V(l+d,p))$$

where f = sum, difference, Absolute value of difference

$$P_d(D) = \frac{N(D_H = D, D_V = D)}{N(D_V, D_H)}$$

Grey Shade Co-occurrence Texture Measures

$$Mean = \frac{1}{N_{shades}} \sum_i^{N_{shades}} i * P(i)$$

$$Second\ Moment = \frac{1}{N_{shades}} \sum_i^{N_{shades}} (i - Mean)^2 P(i)$$

$$Distribution\ Square = \frac{1}{N_{shades}} \sum_i^{N_{shades}} P(i) \cdot P(i)$$

$$Entropy = - \frac{1}{N_{shades}} \sum_i^{N_{shades}} P(i) \log(P(i))$$

$$Contrast = \frac{1}{N_{shades}} \sum_i^{N_{shades}} i^2 P(i)$$

$$Homogeneity = \frac{1}{N_{shades}} \sum_i^{N_{shades}} \frac{P(i)}{1 + i^2}$$

$$Shading = \frac{1}{N_{shades}} \sum_i^{N_{shades}} (i - Mean)^3$$

$$Prominence = \frac{1}{N_{shades}} \sum_i^{N_{shades}} (i - Mean)^4$$

The textural features were calculated by determining the frequency of occurrences of differences, sums and absolute differences in pixel values between pixels separated by d pixels. The current analysis was conducted for separations of d=0, adjacent cells, and d= 1, separated by one intervening pixel. only vertical and horizontal separations were used.

The textural features were calculated over each IB with a difference of 1 and 2. In addition the textural features were calculated over sub blocks within the IB. The means and standard deviations of the sub block statistics were saved for the analysis.

6 Feature Discrimination

The feature discrimination function is required to separate class types reliably. Our current classification function is the Mahalanobis distance, which is the multidimensional analogue of the Gaussian distribution function. The category means and correlations are those determined by Garand (1986) and Garand and Weinman (1986).

An example of the feature classification is the classification of the West Coast on Oct 5, 1989. The general region chosen for classification was between 30N and 40 N in latitude and 122W and 128W in longitude. Near simultaneous GOES imagery of the region are shown for the visible (Figure 2) and the infrared (Fig. 3). The region chosen was the area behind a frontal passage, characterized by a variety of stratus and stratocumulus features.

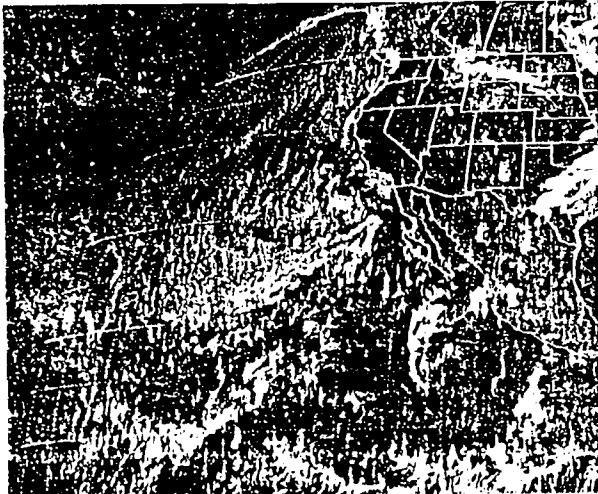


Figure 2 - GOES Visible
Image of Analysis



Figure 3 - IR image of analysis

The physical classifier was used to classify 24 regions within the image. Each IB was separated into 4 32 x 32 pixel squares which were used for individual analysis. The initial predictions were found to be highly skewed to clear classifications. The classifier was changed to eliminate clear values. The resulting first, second, and third choices are shown in Table 4.

The visible image was also analyzed for textural features. Each 64 x 64 pixel region was analyzed for sum, difference and absolute difference vectors using the formulation of Eq 2. The three grey level distributions for each distance were used to find the scene texture characteristics of each image.

The 64x64 pixel array was further divided into separate 8x8 pixel blocks. Similar gray shade distributions were calculated for each subregion. The mean and standard deviation of the texture characteristics were calculated, and are shown in Table 5.

Table 4
Physical Classification of DMSP image

Lat N	Lon W	Choice 1	Choice 2	Choice 3
40.0	134.0	Scattered St	Dense CiSt	Bkn/Ovcst St
40.0	132.0	Scattered St	Broken Cu	Dense CiSt
36.0	132.0	Scattered St	Dense CiSt	Bkn/Ovcst St
40.0	130.0	Scattered St	Broken Cu	Dense CiSt
38.0	130.0	Scattered St	Broken Cu	Dense CiSt
36.0	130.0	Scattered St	Dense CiSt	Bkn/Ovcst St
34.0	130.0	Dense CiSt	Poly Open Ce	Scattered St
40.0	128.0	Scattered St	Broken Cu	Dense CiSt
38.0	128.0	Scattered St	Broken Cu	Dense CiSt
36.0	128.0	Dense CiSt	Scattered St	Poly Open Ce
34.0	128.0	Scattered St	Dense CiSt	Bkn/Ovcst St
38.0	126.0	Dense CiSt	Stratus	Scattered St
36.0	126.0	Scattered St	Broken Cu	Dense CiSt
34.0	126.0	Scattered St	Broken Cu	Bkn/Ovcst St
40.0	124.0	Broken Cu	Scattered St	Bkn/Ovcst St
38.0	124.0	Scattered St	Broken Cu	Bkn/Ovcst St
36.0	124.0	Scattered St	Broken Cu	Bkn/Ovcst St
34.0	124.0	Scattered St	Dense CiSt	Bkn/Ovcst St
36.0	122.0	Broken Cu	Scattered St	Bkn/Ovcst St
34.0	122.0	Scattered St	Dense CiSt	Ovcst CuNi
36.0	120.0	Poly Open Ce	Dense CiSt	Scattered St
34.0	120.0	Broken Cu	Scattered St	Bkn/Ovcst St

Table 5
Textural characteristics of DMSP visible image

Summary Statistics	Sum	Difference	Absolute Difference
Mean	1.30e-001	5.04e-001	6.95e-002
2nd Moment	2.35e+000	3.19e+001	4.16e-001
P ²	4.05e-004	5.29e-004	1.90e-003
Entropy	1.07e-002	9.87e-003	1.57e-002
Contrast	2.38e+000	3.24e+001	2.38e+000
Homogeneity	4.82e-005	1.95e-006	4.82e-005
Shading	4.67e+001	2.05e+003	4.67e+001
Prominence	1.00e+003	1.32e+005	1.00e+003
The subarea means are			
Mean	1.30e-001	5.04e-001	6.94e-002
2nd Moment	2.35e+000	3.19e+001	4.16e-001
P ²	5.00e-004	6.01e-004	2.06e-003
Entropy	9.96e-003	9.42e-003	1.52e-002
Contrast	2.38e+000	3.24e+001	2.38e+000
Homogeneity	4.85e-005	1.95e-006	4.85e-005
Shading	4.67e+001	2.05e+003	4.67e+001
Prominence	9.97e+002	1.32e+005	9.97e+002
The subarea standard deviations are :			
Mean	1.46e-002	1.66e-003	6.74e-003
2nd Moment	5.00e-001	2.08e-001	9.25e-002
P ²	6.46e-005	7.07e-005	2.30e-004
Entropy	4.18e-004	3.89e-004	7.80e-004
Contrast	5.08e-001	2.12e-001	5.08e-001
Homogeneity	1.85e-005	1.60e-008	1.85e-005
Shading	1.43e+001	2.06e+001	1.43e+001
Prominence	3.95e+002	1.08e+003	3.95e+002