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AD-A231 419

REPORT DOCUMENTATION PAGE

Form Approved OMB No. 0704-0188

DTIC ELECTE JAN 11 1991 S B D

1a. REPORT SECURITY CLASSIFICATION Unclassified		1b. RESTRICTIVE MARKINGS	
2a. SECURITY CLASSIFICATION AUTHORITY		3. DISTRIBUTION/AVAILABILITY OF REPORT Approved for public release; Distribution unlimited	
2b. DECLASSIFICATION/DOWNGRADING SCHEDULE			
4. PERFORMING ORGANIZATION REPORT NUMBER(S) GL-TR-90-0326		5. MONITORING ORGANIZATION REPORT NUMBER(S)	
6a. NAME OF PERFORMING ORGANIZATION Geophysics Laboratory	6b. OFFICE SYMBOL (If applicable) LYS	7a. NAME OF MONITORING ORGANIZATION	
6c. ADDRESS (City, State, and ZIP Code) Hanscom AFB Massachusetts 01731-5000		7b. ADDRESS (City, State, and ZIP Code)	
8a. NAME OF FUNDING/SPONSORING ORGANIZATION	8b. OFFICE SYMBOL (If applicable)	9. PROCUREMENT INSTRUMENT IDENTIFICATION NUMBER	
8c. ADDRESS (City, State, and ZIP Code)		10. SOURCE OF FUNDING NUMBERS	

PROGRAM ELEMENT NO	PROJECT NO	TASK NO	WORK UNIT ACCESSION NO
62101F	6670	17	12

11. TITLE (Include Security Classification)
Automated Cloud Typing Using Satellite Imagery

12. PERSONAL AUTHOR(S)
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13a. TYPE OF REPORT	13b. TIME COVERED	14. DATE OF REPORT (Year, Month, Day)	15. PAGE COUNT
Reprint	FROM ____ TO ____	1990 December 14	6

16. SUPPLEMENTARY NOTATION
Presented at the Proceedings of the Cloud Impacts on DoD Operations and Systems (CIDOS) - 1989/1990 Conference, Naval Postgraduate School, Monterey CA 9-11 January 1991

17. COSATI CODES			18. SUBJECT TERMS (Continue on reverse if necessary and identify by block number)
FIELD	GROUP	SUB-GROUP	Satellite Cloud Analysis; Cloud Typing; Satellite Image Processing

19. ABSTRACT (Continue on reverse if necessary and identify by block number)

An automated cloud typing algorithm is presented and described whereby 1 km visible and infrared Defense Meteorological Satellite Program (DMSP) data are classified into one of 18 cloud types, including clear. The cloud typing algorithm first converts a satellite visual image into a one-bit binary image that has pixel values at one of two possible grayshades. Spectral and spatial information from the original image is retained in this process; once the one-bit image is constructed it is then analyzed for features that relate to the spatial variations of the clouds in the original satellite image.

Overall, cloud type classification results were reasonable; some disturbing failures resulted as well as some success attained. More work is needed before an extensive, globally robust classifier can be developed and implemented in an operational sense into cloud analysis models such as the Air Force Real-time Nephanalysis (RTNEPH).

20. DISTRIBUTION/AVAILABILITY OF ABSTRACT ☐ UNCLASSIFIED/UNLIMITED ☒ SAME AS RPT ☐ DTIC USERS	21. ABSTRACT SECURITY CLASSIFICATION Unclassified	
22a. NAME OF RESPONSIBLE INDIVIDUAL R.P. d'Entremont	22b. TELEPHONE (Include Area Code) (617) 377-2983	22c. OFFICE SYMBOL LYS

DD Form 1473, JUN 86 Previous editions are obsolete. SECURITY CLASSIFICATION OF THIS PAGE
Unclassified

0 024

GL-TR-90-0326

Automated Cloud Typing Using Satellite Imagery

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1. Introduction

The automated analysis of cloud types from satellite imagery has proven to be an enigma for almost two decades. Success does not appear on the horizon. The cloud typing problem is certainly very difficult and has no unique solutions. Like the clouds themselves, cloud images from satellite are enormously complicated and much is unknown about them. High resolution data and multiple channels do help but only to a point, and do not remove existing problems of analysis.

There have been several approaches to the problem of automated analysis of cloud types from satellites. Cloud type analyses can be viewed as shorthand encrypted ways of specifying what information resides in the imagery. Most often the approaches to cloud type analysis calculate spectral features of the imagery and use these features in classification schemes. Other approaches calculate and work with statistical features of the image grayshades.

The Air Force Global Weather Center at Offutt AFB, Nebraska has operated an automated imagery analysis program known as the Real-Time Nephanalysis (RTNEPH) since the early seventies that makes assessments of 11 cloud types using satellite imagery. Those types are cumulus, altocumulus, stratocumulus, stratus, altostratus, nimbostratus, cirrus, cirrocumulus, cirrostratus, cumulonimbus, and clear, along with unknown. The cloud typing technique makes use of statistical sample means and variances of satellite grayshade data, and is limited in its usefulness when visible and infrared (IR) data are not simultaneously available. The RTNEPH can make use of improved cloud typing techniques.

While a great amount of effort is being placed into automated extraction of many types of meteorological information from satellite data, little effort is being directed to the area of automated cloud typing.

Parikh (1977) made a statistical study of classification techniques for a four-group cloud model (low, mixed, cirrus, and cumulonimbus) and a three-group cloud model ("mix" excluded). She showed a preference toward design parameters for the automatic classification of cloud systems. The major problem was identification of mixed cloud types when low and high clouds are present. Four cloud type classes may be too few except for the most crude of requirements, but this is yet to be determined. Certainly, high resolution data satisfy more demands for accurate cloud information, and can likely support a scheme that classifies more than four cloud types.

Harris and Barrett (1978) show a method for the automatic determination of cloud types and cloud amounts. Textural measures such as standard deviations of brightness and vector dispersion of grayshade density values are evaluated. A discriminant analysis scheme makes decisions as to one of the cloud categories and to a no-cloud category.

Garand (1988) developed a classification procedure for oceanic cloud patterns. The classification scheme consisted of 20 classes. The data he used were from coarse-resolution GOES imagery. His approach yielded very favorable results, and more effort should be directed along these lines because most satellite image resolutions will remain coarse for the forseeable future. High resolution data (0.5 km and finer) may be years down the road for operational purposes. There is need for cloud typing techniques that use both fine and coarse resolution satellite data. In our study we use high resolution data.

Ebert (1987) developed a technique for recognizing 18 cloud types over polar regions. This is a statistical recognition technique that uses 66 features of visible, near-infrared, and infrared Advanced Very High Resolution (AVHRR) satellite data. The algorithm classified data into one of seven surface categories or one of 11 cloud categories.

The algorithm classified 870 training samples with a skill of 84%. Some difficulty was had in classifying stratus over snow and ice and thin cirrus over land and water. When tested on independent data the algorithm showed a skill of 83%.

Satellite imagery is enormously complicated. Even in data of highest resolution there are questions that cannot be answered satisfactorily. We must accept the fact that a good assessment is all that is possible and not perfection. It is important to plot out a route toward a useful analysis system. That such is possible is known, for enormously meaningful assessments of imagery can be made by highly trained analysts. There is no doubt therefore that good results are attainable. The challenge is to formulate computer algorithms that can do what a trained analyst can do as well as things he cannot do. The traditional approach of the human analyst is to separate cloud regions into specific areas and then characterize them with adjectives and descriptions that give a good assessment of the cloud field within the region.

There is great value to be gained from an automated cloud typing scheme. First, it would provide a framework for extensive analysis of cloud imagery. It would allow the processing and evaluation of large amounts of data and would provide a framework for incorporating other types of data into the analyses. A good automated cloud typing scheme would make it possible to obtain extensive climatological cloud type summaries from global RTNEPH analyses. Most of all it would provide a basic analysis scheme for incorporation into operational systems.

We approach the problem from the direct angle: that which the analyst uses. Regions with similar kinds of clouds are first identified in an image. After areas are separated out, the problem of typing the clouds in the image follows. That is the problem we attack here. Once homogeneous areas in an image are selected for analysis, specific typing is done. The cloud typing algorithm we present here is fully automatic.

There are enormous details which have to be worked out before we get to a final product. Better results will undoubtedly come from higher resolution data since clouds occur in all scales and great detail often occurs. Any technique will depend greatly on the resolution of the imagery and the spectral channels used. Here we are thinking in terms of visual and longwave IR data and resolutions of the order of 1 km. Imagery data used in this study are 1 km Defense Meteorological Satellite Program (DMSP) visible and IR DMSP data. It is of great consolation to know that good answers are attainable since the expert analyst can, with great labor, produce very impressive cloud typing results using this imagery. We like to think that the computer on its own can come up to at least the "useful" mark on the skill scale.

2. Background Information

Several years ago Hawkins (1977) developed an algorithm for converting satellite visual images to one-bit binary arrays while preserving image information. At that time it was realized that run-length spectra of that data might be useful in computerized analysis. Unpublished results indicated that, to an extent, different cloud types exhibited different run-length spectra. Images reduced to one bit have pixels at one gray shade or another. Bright areas are mostly the high level, dark areas are mostly the low level, and intermediate area of brightness are modulations of both levels. The number of consecutive pixels of the same level is referred to as a run length. We refer to these run lengths as "zeros" and "ones" or "blacks" and "whites" while in fact they represent selected and fixed levels of brightness which are "high" and "low" as referenced to gray shades.

The algorithm for converting a picture to a one-bit image array is very simple and its flowchart is given in Figure 1. Scans are made through a visual image bit array. We have found that four scans are fully adequate. The algorithm checks to see if a pixel grayshade value point is relatively high or relatively low compared to its surrounding points. If it is high it is made still higher at the expense of the surrounding values. If is is low it is made still lower by subtracting from it and giving those values to the surrounding points. You can see that brightness values are conserved locally and that high values are built up and low values are taken down relatively speaking. Constants for limits to build up and tear down pixel values (a and b in the diagram) are selected by trial and error to give what appears to the user to be an optimum balance. The incremental amount, c, is taken as 4. For our data we found best results in trials for a=60 and b=192. After four iterations of the algorithm, truncation was made at grayshade level 120. In other words, the algorithm manipulates an eight-bit visual image so that the picture is made "black" or "white" on the pixel level while conserving local brightness over small areas. When this is finished the high pixel values are labeled "one" and represent some bright grayshade, while the low pixel values are labeled "zero" and represent some dark grayshade. The grayshade level of separation is called the "truncation" level. Images seen on display devices approximate original images in the same way as dots in newspaper pictures approximate photographs (halftone pictures). The former has all dots the same size and the latter uses variable dot size. In both cases the image pixels are either black or white at fine resolution.

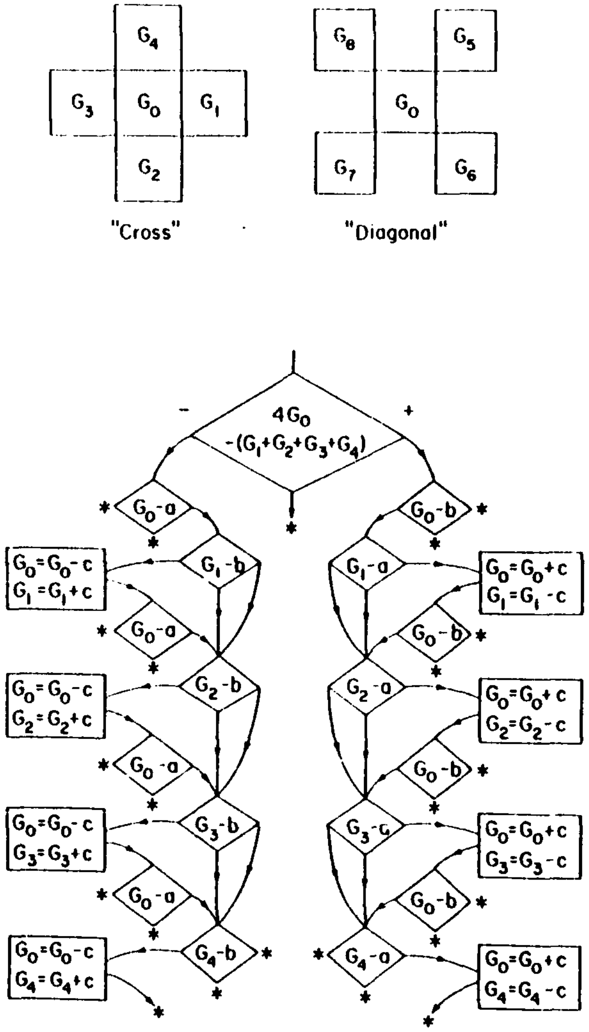

Figure 1. Algorithm for transforming a visible satellite image sample into a "one-bit" image. On the top are representations of the "cross" and "diagonal" gridpoint designations. On the bottom is the flowchart for the binary algorithm. The G's refer to the gridpoint designations. Asterisks (*) mean Exit; "a" is the lower bound, "b" the upper bound, and "c" is an increment of brightness count (see the text).

3. Method of Experiment

A cloud classification scheme developed earlier (Hawkins 1980) is used. See Figure 2 for details. Years of experience at interpreting satellite pictures has shown us that cloud arrangements are very complicated in space and time. And for this reason classification schemes are steps boldly taken. We have preferred working with this rather comprehensive scheme realizing that simplifications can be made later. There is only one classification for clear areas. There are four kinds of cumulus regions plus cumulonimbus. There are five different stratiform-cumuliform cloud types. And finally there are seven kinds of cirriform types. Even for the human analyst this is a comprehensive classification system. Our experiment was with 0.5 km DMSP visual and IR imagery. This scheme of course would not be appropriate, say, for 5 km imagery because the characteristics of each cloud type will change as the resolution gets more coarse.

In order to expedite calculations a computer program was written on our AIMS image analysis computer system at the Geophysics Laboratory. This program allows for the interactive automation of cloud typing for both "training (dependent)" and "classification (independent)" image samples.

A set of DMSP data at 1 km resolution was used in this study. A 30×30 cursor box was implemented that fits over an array of grayshades that represents a single cloud type. Figure 3 shows a visual image and a sample of a 30×30 one-bit image inside it. From the one-bit image a run-length spectrum can be computed. Run-length spectra were obtained and averaged for the various cloud classes. The object was to select as much DMSP data as possible for the dependent training set while leaving some for independent classification. Run lengths were converted to cumulative run

Cloud Classification System		
Cumuliform	*Cirriform*	*Stratiform*
1. Small Scattered (CUSC)	5. Thin (CITN)	12. Stratus (ST)
2. Small (CUSM)	6. Moderate (CIMD)	13. Stratocumulus (SC)
3. Moderate (CUMD)	7. Thick (CITK)	14. Altocumulus (AC)
4. Large (CULG)	8. Thin Over CU (CITC)	15. Altostratus (AS)
	9. Mod Over CU (CIMC)	16. Nimbostratus (NS)
	10. Thin Over ST (CITS)	
	11. Mod Over ST (CIMS)	
17. Cumulonimbus (CB)		
18. Clear (CLR)		

Figure 2. Cloud types used in the automated cloud typing procedure.

lengths for classification purposes. Average cumulative run length spectra were then obtained, weighted by corresponding average infrared values for the image sample in question. The computer implemented a minimum distance classifier in the classification process. Whichever cloud type's average run length spectrum was the closest to the sample spectrum in a least-squares sense is chosen to be that sample's cloud type.

It should be mentioned that imagery even on these fine scales is very complicated and that much work will be needed before we can turn the computer loose on an image. The analyst who did the training classifications was struck by the complexity of the imagery. At this point we do not know how many cloud types can be successfully distinguished using this technique. However, it is doubtful that simpler schemes will be as good. Even for crude climatological models it is hard to see how simple schemes of cloud types will be satisfactory.

4. Conclusions

The results of this experiment are given in Figure 4. A total of 299 samples were taken from 25 pictures. Both sets of samples exhaust our 1 km DMSP data collection. The data are over Southeastern Europe and the Mediterranean region. It was found that bright desert interfered with most classifications and therefore it was avoided. Ice and snow backgrounds were also avoided for the same reason. However, we feel that most other darker terrain backgrounds are no problem. Clear backgrounds are one area that will have to be improved on, perhaps using background brightness data.

It can be seen in Figure 4 that some success was attained and some disturbing failures resulted. Some of the clear (CLR) failures which fell in the small cumulus (CUSM) category were a result of land looking like clouds. The cumulus

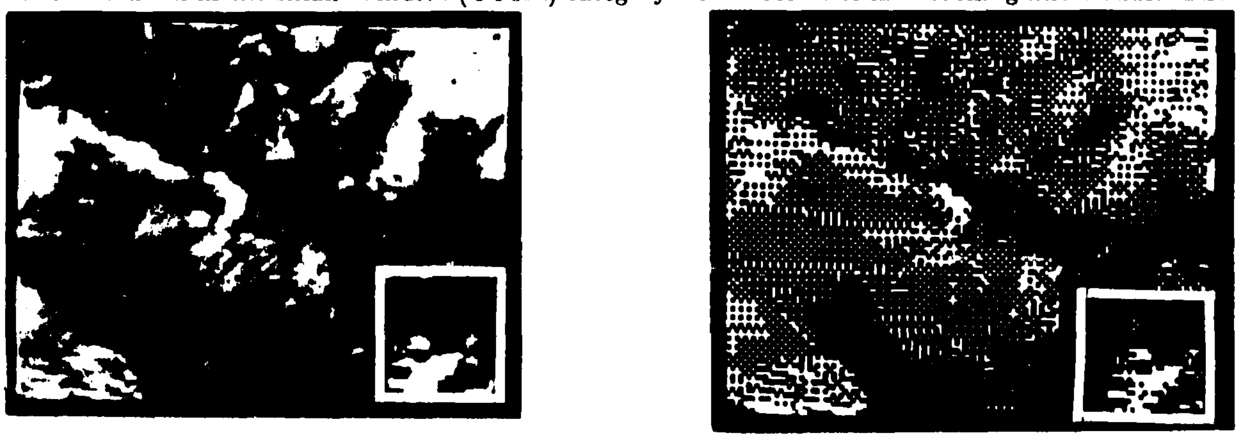

Figure 3. Sample visible image (left) and its corresponding one-bit binary image (right). The white box is 30 pixels on a side.

categories were successful if you can be a little forgiving. Large cumulus (CULG) was very successful. For the most part, the high cloud cloud types are not confused with the cumulus categories.

Examination of Figure 4 shows that much of the "error" of specification is forgiveable in that when misclassifications are made, other cloud types are often selected that are not such a bad choice. It should also be remembered that the analyst can make some judgement errors. All in all we think these results show promise for this approach.

Figure 5 shows the results summarized in terms of five major categories: clear, cumuliform, stratiform, cirriform, and cumulonimbus. Clear was misclassified frequently as cumuliform and less so as stratiform. There were no errors in the cirriform or cumulonimbus categories. In the other categories the greatest error is the misclassification of cirriform as stratiform. Cumulonimbus classed as cirriform is somewhat forgiveable.

In the future CLR ought to be separated into at least "land" and into "water" and perhaps an even greater division reflecting the background brightness. It is best, we feel, to work with imagery resolutions that allow accurate cloud typing, that is to say, resolutions of 1 km or better.

TRUTH \ CLASSIFICATION	CLR	CU SC	CU SM	CU MD	CU LG	AC	ST	SC	AS	NS	CI TN	CI MD	CI TK	CI TC	CI MC	CI TS	CI MS	CB
CLR	32	2	17	3	1				8									
CUSC	6		3	1														
CUSM	2	1	4	1														
CUMD	1	1	2	4	2													
CULG				2	15													
AC								1	1	1						2		
ST							15	1	3	1		1				1		
SC					3		6	16	2	4						1		
AS							1	2	7			1		1		2		3
NS									2									
CITN			3						1		7	6						
CIMD					1		1	1	1		3	9	2	1		2	6	
CITK							1	2	10	3		1	1			2	3	
CITC																		
CIMC																		
CITS																2	2	
CIMS									3				1			3	4	
CB									5	2	1					5	6	12

Figure 4. Truth table results for the 18-cloud-type automated classifier. Numbers along the main diagonal indicate correct classifications.

CLASSIFICATION

		Clear	Cumuliform	Stratiform	Cirriform	Cumulonimbus
T	Clear	32	23	8		
R	Cumuliform	9	36	3	2	
U	Stratiform		3	60	7	3
T	Cirriform		4	23	55	
H	Cumulonimbus			7	12	12

Figure 5. Truth table results for the 5-cloud-type automated classifier. Numbers along the main diagonal indicate correct classifications.

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