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THE DEVELOPMENT OF MACHINE TECHNOLOGY PROCESSING FOR EARTH RESOURCE SURVEY

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INTRODUCTION

Two earlier papers by R. B. MacDonald have described some of the research being pursued at LARS/Purdue directed toward the applications of remote sensing. The purpose of this presentation is to describe research in the development of new technology. Several projects to be discussed are of several years duration; current progress will be described in these cases. In addition, several new programs have begun and preliminary results will be presented.

THE REGISTRATION OF MULTISPECTRAL AND MULTITEMPORAL IMAGES

The first study to be described has to do with the registration of multispectral images. This work began several years ago and has passed through graded steps of increasing technological difficulty. The ultimate objective is to develop a capability for accurately aligning data in image form gathered from different parts of the spectrum and on different flight missions.

This first step in this process several years ago was to achieve the capability to register image data from two different sensors mounted aboard the same platform. Figure 1 serves to illustrate the problem. Shown is a printout from a channel of data in the visible portion of the spectrum (center) and data gathered at the same time but with a different scanner operating in the thermal region. A conventional panchromatic air photo is shown on the left for comparison. Registration accuracy to better than plus or minus 1 resolution element is desired.

Since the two scanners may be running at slightly different speeds, and creating other distortions of a local nature, a scheme which assures correct registration on both a global and local basis is necessary. The general approach chosen was to use two-dimensional correlation as a basis for finding points of correspondence in the two images. This approach provides the maximum flexibility which is required by a research situation as compared to an operational one. However, it quickly became apparent that images from widely separated parts of the spectrum may not correlate well since the spectral separation leads to fundamental differences in the data. It was found desirable to preceed the correlation process by enhancing all the boundaries in both images and then correlating to the boundary-enhanced image.

Thus, the first useful system contained three steps: a boundary enhancement step; a two-dimensional correlation to determine the points of coincidence in the two images; and finally, the overlaying of the two data sets to form a new data set of dimensionality equal to the sum of the previous two.

The next step in the development of the system was to provide it with a measure of adaptability to the type of data being registered. The registration process utilizing two-dimensional correlation as a basis is clearly very scene-dependent. A different sized correlation window is required when registering data over an agricultural scene, for example, as compared to data from natural vegetation. Figure 2 shows the organization of the system after incorporating this capability. A means for estimating the complexity of the image in terms of the degree of difficulty in obtaining a proper two-dimensional correlation measure has been added to the system. This results in a picture complexity index from which the correlation window size is determined. Developments to this point were reported in this meeting a year ago (see reference 1).

Since that time, a number of additional capabilities have been added to the system. Chief among these has been the development of a capability for accomplishing rotation and scale change in the imagery. The current system diagram is shown in Figure 3 (see reference 2). The system now is organized to permit the overlay of two "slave" images onto a master. There is an opportunity to input scale and rotational corrections of a global nature manually into the system. After suitable buffering, the image boundary enhancement and complexity estimation step is next. Then follows the image correlation step in which the points of correspondence between the three images are determined. At this point the more precise local scale and rotational correction factors are determined and a capability for updating the global scale and rotation factors is provided. The final step is that of utilizing the scene correspondence points to achieve a single data tape on which have been properly registered the three previous images.

Two different methods of boundary enhancement techniques are available. Figure 4 shows examples of each. The simplest and computationally fastest means is a gradient technique utilizing the magnitude of the first difference of adjacent scene points to determine if a boundary exists. The result of such a computation is shown in the center of Figure 4. On the right is shown the result of using a clustering technique operating in a multivariant fashion to determine boundaries (see reference 3).

The use of Temporal Information

The new capability which the modifications have provided enabled initial studies in the use of multi-temporal multi-spectral data analysis. Figure 5 shows printouts of single channels of the two data sets utilized. On the left is a printout of a channel of data from the June, 1969 mission. Due to a cross wind, an average yaw distortion of 11.7 degrees exists in the data. The August, 1969 data shown on the right contains very little yaw distortion. It is readily apparent from these two printouts that changes in the scene have taken place between June and August, and this provides a graphic example of the considerable scene dependence which exists in attempting to use two dimensional correlation directly for registration of images. Note in the June data that since the vegetation canopy does not fully cover the ground soil patterns are readily apparent in this display; by August this is no longer the case.

In the multi-temporal analysis experiment, a control classification was run utilizing the June data only. A classifier was trained using classes corn, soybeans, wheat and oats. The best four of the 12 channels of data were selected for this classification. Data from the August mission was registered onto the June data. The classification using the same classes, training, and spectral bands of this August data was then run for comparison. Next, the best four of the 8 channels (4 from June, the same 4 from August) were selected and the same classification was again carried out. The results of this experiment are shown in Figure 6. Note that the capability to discriminate between corn and soybeans does improve over that available from either of the data sets alone. It should also be noted that by the August mission all wheat and oats in the flightline had been harvested; these classes therefore did not exist by the time of that mission.

This classification test, while preliminary in nature, does tend to verify the expected increase in accuracy one should obtain by having multi-temporal data available. It seems reasonable to speculate that even greater accuracy should be possible if one permits oneself to select the best four of the total number of channels available (24 in this case) rather than constraining to the spectral bands which were favored for the June data set. The above procedure was used, however, in order to simulate the situation which might exist for a satellite sensor system in which the spectral bands to be used throughout must be selected a priori.

On the Value of Image Data Registration

There are at least four major reasons why image data registration is important. These are indicated in Figure 7. The desirability of registration in the case of multiple sensors has already been discussed. This was discussed within the context of visible and thermal data; however, the problem is similar in the case of data from the microwave portion of the spectrum. In general, each new part of the spectrum available in registered form should provide additional information about the contents of the scene.

The above example tended to illustrate the importance of the use of temporal information. However, not nearly enough experimentation has been possible to date in order to develop the full importance of this area.

A third reason for the importance of image data registration is that it permits the automatic correction of various types of distortion in image data. If a good quality image (from a photogrammetric standpoint) exists of an area, this image could be made to serve as a master upon which data from other sensors e.g. scanner, radar, television, etc. could be registered; in this fashion, rectification and geometric correction of all types could take place as a normal part of achieving multiband multi-temporal information.

Finally, the through-put rate for this type of information processing is limited as much as anywhere at points at which ground data and ancillary information must be merged into the multispectral image data stream itself. Data registration can, in many cases, tend to alleviate this difficulty. For example, in the case of an agricultural problem, one need only establish field boundaries etc. once during a growing season in order to have ground truth information referenced to the appropriate fields in this image data. Since the registration process establishes scene point coincidences in the images it established this same coincidence and referencing for all ground truth associated with given scene points. Thus, training sample coordinates need be selected only once during a season.

DIGITAL IMAGE DISPLAY SYSTEM

A second project underway for some time is the specification, design, procurement, and implementation of a digital image display system. A pacing item in the development of a capability to rapidly collect, analyze and disseminate information by remote sensing means is the capability for the human operator to rapidly interact with the image data stream and collate with it literal or other information from other sources. The purpose of the digital image display is to enable research into techniques to alleviate this limitation.

The need for such a system and the general outline of its specifications was first identified in March, 1966. After a long series of delays, the project was finally funded and a contract awarded for its construction by the IBM Federal Systems Division in August, 1969. The system has recently arrived on location at Purdue and is currently undergoing acceptance tests. It consists of three major elements: a control unit containing logic circuitry, interfacing circuitry, and a disk image buffer; the display console including a light pen and function keyboard for controlling software packages, and a photocopy unit used to generate hard copy versions of images being displayed.

Figure 8 shows a photograph of the photocopy unit (right) and display console (left). The display system provides an image of 768 elements and 577 lines with a 16-step grayscale and a 30-frame-per-second (with interlace) refresh rate. Figure 13 shows the output of image data produced by the photocopy unit. Upon final acceptance of the system from the manufacturer, work will begin on techniques for allowing the human operator to use very large quantities of remote sensing data.

DATA SYSTEMS PARAMETER STUDY

Figure 9 is a block diagram of a satellite-based remote sensing system. Shown are the major elements of such a system, such as the sensor, onboard processing and telementry, ground processing and data reduction, and information consumption. In considering the design of such a system, it is immediately apparent that there are a great number of parameters to be chosen. Parameters such as the spectral and spatial resolution of the sensor, the detector signal-to-noise ratio, the type of telemetry, data compression scheme, etc. must all be selected.

Heretofore, research on individual elements of the system had not proceeded far enough to permit the consideration of overall performance relative to these parameters. It now appears, however, that this point has been reached. As a result, a data system parameter study has been defined. The approach to be used is to test the overall system sensitivity to various key parameters. Generally, the index of performance to be used is the pattern recognition classification performance on test data sets. Preliminary results in several of these parameter studies will now be described.

Classification Sensitivity to Additive Noise

A parameter of considerable importance to the design of new sensor systems is the signal-to-noise ratio of the detector. For a sensor material of given sensitivity the signal-to-noise ratio of the data produced can generally be improved by degrading either the spectral or spatial resolution or both. However, data analysts are generally not anxious to see this done and a trade-off must be made. Quantitative information about desired signal-to-noise ratios for specific analysis tests has previously been scarce.

In order to increase the understanding of the necessary signal-to-noise ratio for various classification tests it was decided to carry out a single test classification on a data set to which varying amounts of noise have been added. Figure 10 shows a small portion of a scene from which the data was selected. Shown are a panchromatic air photo of the area and below it a printout of the original undegraded signal. Printouts of the same data with two different levels of noise added are shown on the right. Digital data of eight-bit precision was used. Thus, a gray scale of 256 possible steps is available. The magnitude of the noise (which was Gaussian and uncorrelated between channels) is measured in terms of the number of bins out of 256 per standard deviation.

The noise was generated using a software-implemented random number generator within the computer. It was decided to choose Gaussian noise, uncorrelated from spectral band to spectral band, as this most nearly approximates the type of noise generated within the sensor detector. Figure 11 is a classification of a segment of the data for the no-noise case and the two noise levels shown in Figure 10. The degradation of accuracy is visibly apparent.

The graph of Figure 12 summarizes the overall results for the study. This is a plot of the percent correct recognition for the classification task as a function of the magnitude of noise added to the data. The shapes of the curves which are in the form of the complement of the Gaussian error function could easily be predicted. It is also not surprising that the results for the training samples stayed consistently above the results for the overall test samples.

An interesting result can be seen from the two individual classes which are plotted. The data used for this test was of an agricultural scene in Tippecanoe County in June, early in the growing season. At this point in the season wheat is ready for harvest and, being golden brown at this stage, is a relatively easy class to separate from the rest of the scene. Thus, in the graph of Figure 12 the accuracy is high. More importantly at this point though, it degrades relatively slowly. On the other hand, soybeans provides a much more challenging classification since the percent of ground cover at this stage of the season is very low. While the accuracy in the no-noise case is quite high, one sees that the additive noise quickly degrades this accuracy to a low value. These results tend to bear out the statement that as the signal-to-noise ratio degrades, the more difficult classifications will be affected most. That is, for simple classifications the signal-to-noise ratio is not too important; however, it becomes so for more difficult ones.

The classification used was a nine class classification. One would assume that in an extrapolation to the right, these curves would become asymptotic to chance performance which is 11 percent in this case. One can also consider an extrapolation of these curves to the left. This extrapolation should provide curves which become asymptotic to 100 percent accuracy. Since the original data did not have an infinite signal-to-noise ratio, it may be supposed that these curves provide an indication of the true original signal-to-noise ratio.

Data Compression based on Spatial Redundancy

The General Electric Company was awarded a contract some time ago by NASA to study the possibility of using data compression techniques on a sensor system of the type to be flown on the Earth Resources Technology Satellite. The techniques to be studied apparently are to be those based primarily on the fact that a great deal of redundancy exists in an image due to spatial correlation in the data. As a result of the application of efficient data compression techniques, it is possible to reconstruct the image transmitted to good but not perfect precision. It is, therefore, desirable to learn the degree to which the data compression technique will affect the ability of the data analyist to achieve good results.

It is desirable to determine these effects on both photointerpretative based analysis systems and pattern recognition (machine oriented) schemes. A co-operative program between LARS and GE was agreed upon in order to accomplish a portion of this evaluation. Test data was selected jointly by LARS and GE from among flightlines of data which had been flown by the Michigan scanner system and digitized at LARS. The data was provided to GE for the purpose of compressing and re-expanding it using compression algorithms of General Electric Company design. The four channels of the Michigan scanner system most nearly coinciding with the four channels of the ERTS multispectral scanner were to be used. After compression and re-expansion the data was returned to LARS and a test classification run upon it.

The joint study has now progressed to the point that the first compression algorithm has been tested. Figure 13 shows images generated from a small portion of the original data and the same data having been processed by the compression algorithm. The algorithm is a preliminary one for base line tests and is simply a procedure whereby only every fourth sample of each channel is transmitted. Intermediate points not transmitted are assumed on the ground to have been the same gray scale intensity as the last previously transmitted point in that spectral band.

Figure 14 shows the results of the test classification on the two different data sets. Also shown is the results of the classification of the same data but using the set of spectral bands which are preferred for this classification. Notice that the degradation provided by the compression as compared with the uncompressed data is not major. Full analysis of results must await the conclusion of the study including the use of other compression schemes. These will be reported in due course. However, some further comments about these results will be made after having reported the results of another data compression study in progress.

DATA COMPRESSION TECHNIQUES BASED ON SPECTRAL REDUNDANCY

A second data compression study has been underway for some time based on the use of the redundancy between spectral bands. This study is being conducted entirely by LARS. The point of departure of this study is somewhat different than the one previously described in that a larger number of spectral bands are assumed. An overview of the view point is contained in Figure 15. We see on the left a multispectral scanner sensor which produces data in M different channels. The technique here would be to design a data compression system which converts the M channels into N features, $N < M$. The original data could be recovered to within some prescribed accuracy by processing the data at this point through a reconstruction algorithm after which data analysis could take place.

However, imagery could be generated in each of the N features in exactly the same way that it could be generated in each of the M channels. In any case, the measure of the degree of compression in this case is the ratio of M to N.

The compression algorithm tested is a type based upon a Karhunen-Loeve expansion. It amounts, in fact, to a linear transformation in M-dimensional space and, more specifically, a linear transformation which is a rotation to principal co-ordinates. The same data and classification was used to test this scheme as used in the LARS/GE Data Compression Study and the Additive Noise Study. The results of this classification are shown in Figure 16. The first line gives the results of the control classification, that is, classification directly on the original data.

When the 12 original channels were transformed and then half deleted so that only six features remained in the N-dimensional feature space, the accuracy of the classification did not change significantly. The test was repeated for a 12- to 3-dimensional transformation and again the accuracy was essentially unaffected. Not until all but two bands in feature space were deleted did the accuracy begin to seriously deteriorate. The percent of mean square difference between the reconstructed and the original image is shown on the right. These results have been judged to be very encouraging and the scheme is now being extended to include both spectral and spatial redundancy.

SOME COMMENTS ON SPECTRAL BAND SELECTION

Some of the results above raise some points that have to do with the relative importance of a band selection capability. Notice from Figure 14 that the overall classification accuracy for the preferred channels (i.e. the best of the 12 available) was approximately 90%. This is more than 10% higher than the performance figure for the same data but using the ERTS channels. Thus, one may say from the data analyst's viewpoint that being required to give up the capability to tailor the band selection to the particuliar classification being carried out is a more serious effect than accepting the degrading effects in the data due to a data compression algorithm. This can be seen and understood more clearly as follows:

Assume this case to be typical. Here, 12-channel data was available; the band limits of the particular bands are shown in Figure 17. The problem of band selection comes to finding the four best channels[1] of the 12 to use for the particular classification. The feature selection algorithm implemented in the LARSYSAA programming system computes the relative separability of each class pair for each possible four-tuple of spectral bands. The classes used in the test classification are shown on Figure 18. Beside each is indicated a single symbol used to designate that class in two following figures. Figure 19 shows the results of applying this algorithm to this classification task. The numbers on the right of this figure are the numbers indicating the relative separability of the class pairs. Class pairs are indicated by two symbols (SC for soybeans and corn, SW for soybeans and wheat) at the head of each of these columns. The four-

[1] A preliminary determination as to the number of channels to be used must, of course, be made. Four have been assumed.

tuple of features (spectral bands) are then rank-ordered based upon the average of these interclass separability measures. Thus, it can be seen that bands 1, 9, 11 and 12 were selected as the best feature set and bands number 6, 9, 11 and 12 which are the ones most nearly matching the ERTS channels are second.[1]

However, by using additional options available with the feature selection algorithm it is possible to further tailor the band selection to the classification task. Note that in Figure 19 some of the interclass pair separabilities are very large, indicating very obvious separability; on the other hand, other interclass separability measures are quite small. It would be desirable to select feature sets so as to increase the separability of the more difficult interclass pairs at the expense of the classes with the more obvious separability. In order to do this the feature selection algorithm has been provided with an option permitting the imposing of a maximum interclass separability measure which will be considered for the purpose of rank-ordering the four-tuples. Figure 20 shows the results of using a maximum of 200. Note that the preferred feature set now becomes 1, 6, 10 and 12 and that the ERTS simulated channels 6, 9, 11 and 12 become 55th in ranking.

The validity of this re-ranking is borne out in the difference in overall accuracy ultimately obtained in the two classifications. Approximately 90% for the preferred channels 1, 6, 10 and 12 as compared to approximately 80% for the ERTS channels 6, 9, 11 and 12.[2]

Thus, by being forced to a sub-optimum choice of spectral bands an overall 10% accuracy loss occured and the increased loss in accuracy due to data compressions was only an additional 2 or 3 percent.

These results tend to suggest aht the capability to make a proper selection of sepctral bands from a large set may indeed be far more important than the effects of a perhaps lower signal-to-noise ratio, a data compression scheme, and conceivably other system parameters. As a matter of fact the scheme indicated in Figure 15 whereby in the spacecraft a scanner with many channels is operating but a compression algorithm reduces the dimensionality for transmission to earth may provide a more useful approach. Further investigations into this type of scheme are under way.

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[1] In the case of an actual satellite however, channel 1 would probably not be as useful as it appears to be here, since it is well into the blue portion of the spectrum and from space there would be considerable blue scattering. These results tend to bear out the choice that the 4 ERTS spectral bands are generally a good set.

[2] From these results one might tend to conclude that the ERTS channels which are the best set of bands <u>in general</u> may be considerably suboptimum <u>in specific cases</u>.

Reference 1 - Anuta, P. E. "Digital Registration of Multispectral Video Imagery" Society of Photo-Optical Instrumentation Engineers Journal, Volume 7, Number 6, September 1969.

Reference 2 - Anuta, P. E. "Spatial Registration of Multispectral and Multitemporal Digital Imagery Using Fast Fourier Transform Techniques", IEEE Transactions on Geoscience Electronics, Volume GE-8, Number 4, October 1970.

Reference 3 - Wacker, A. G. and Landgrebe, D. A. "Boundaries in Multispectral Imagery by Clustering" 1970 IEEE Symposium on Adaptive Processes, December 7-9, 1970, University of Texas at Austin.

Visible and Thermal IR Imagery

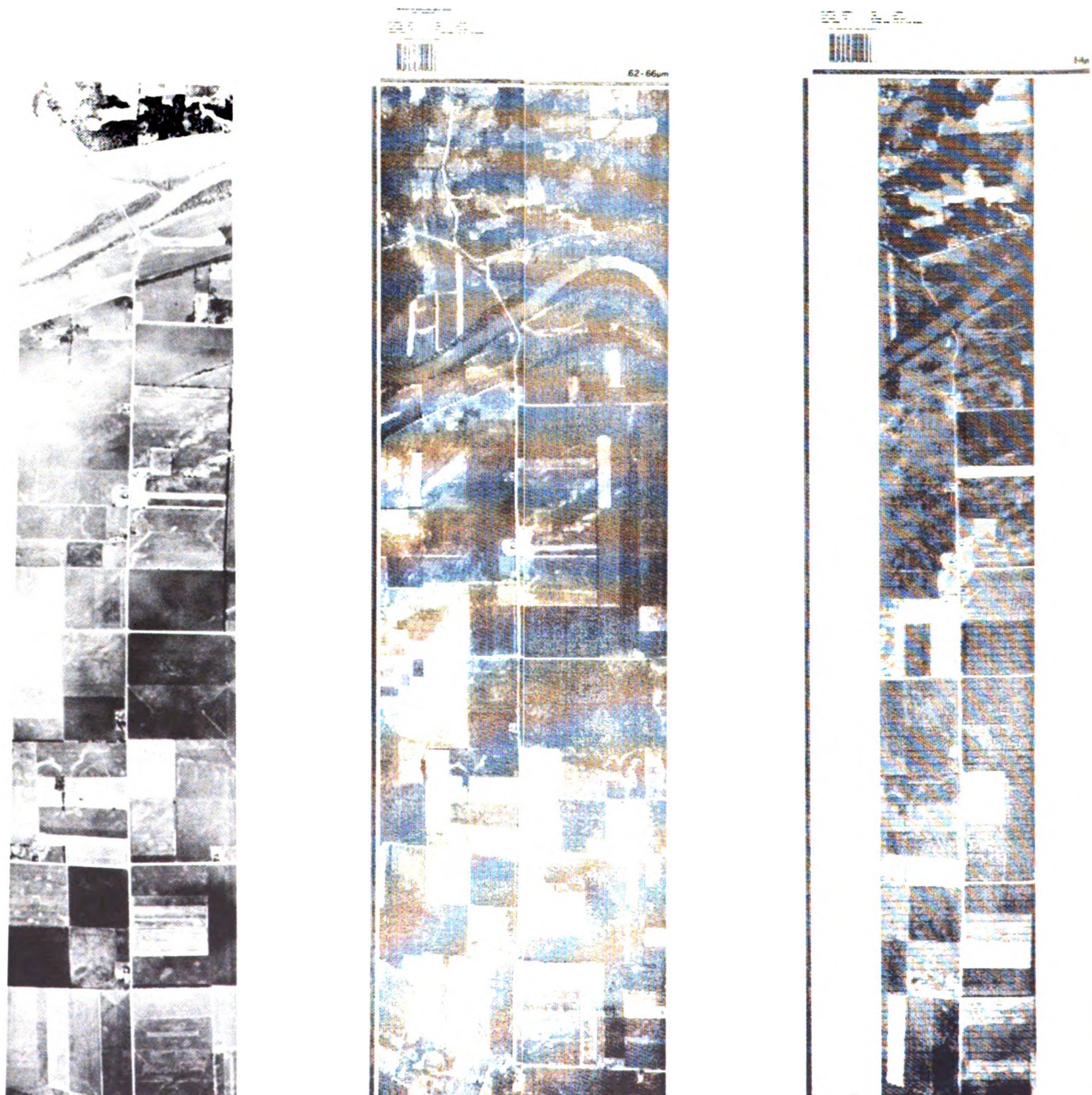
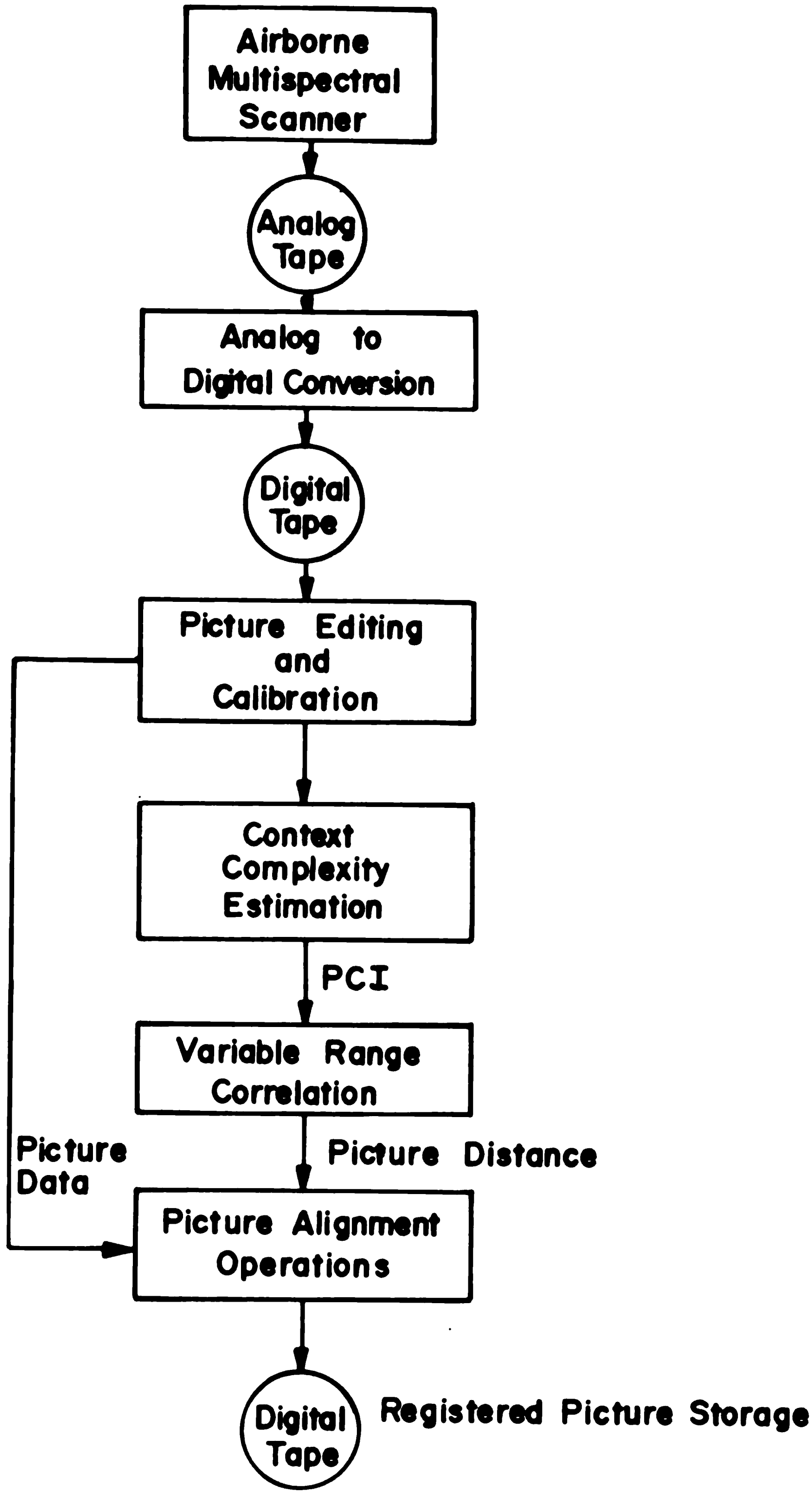
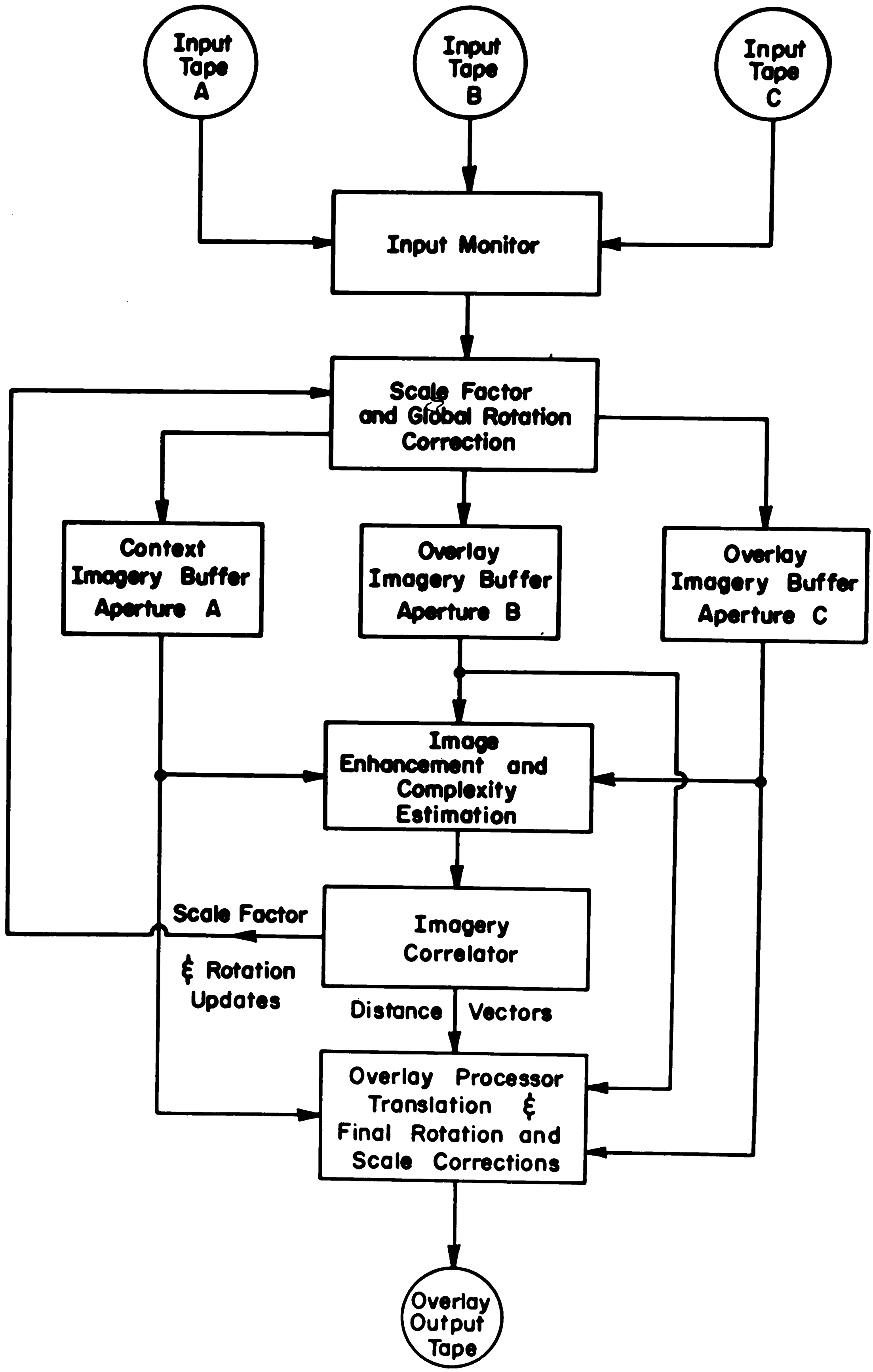


Figure 1



ADAPTIVE MULTISPECTRAL PICTURE REGISTRATION SYSTEM

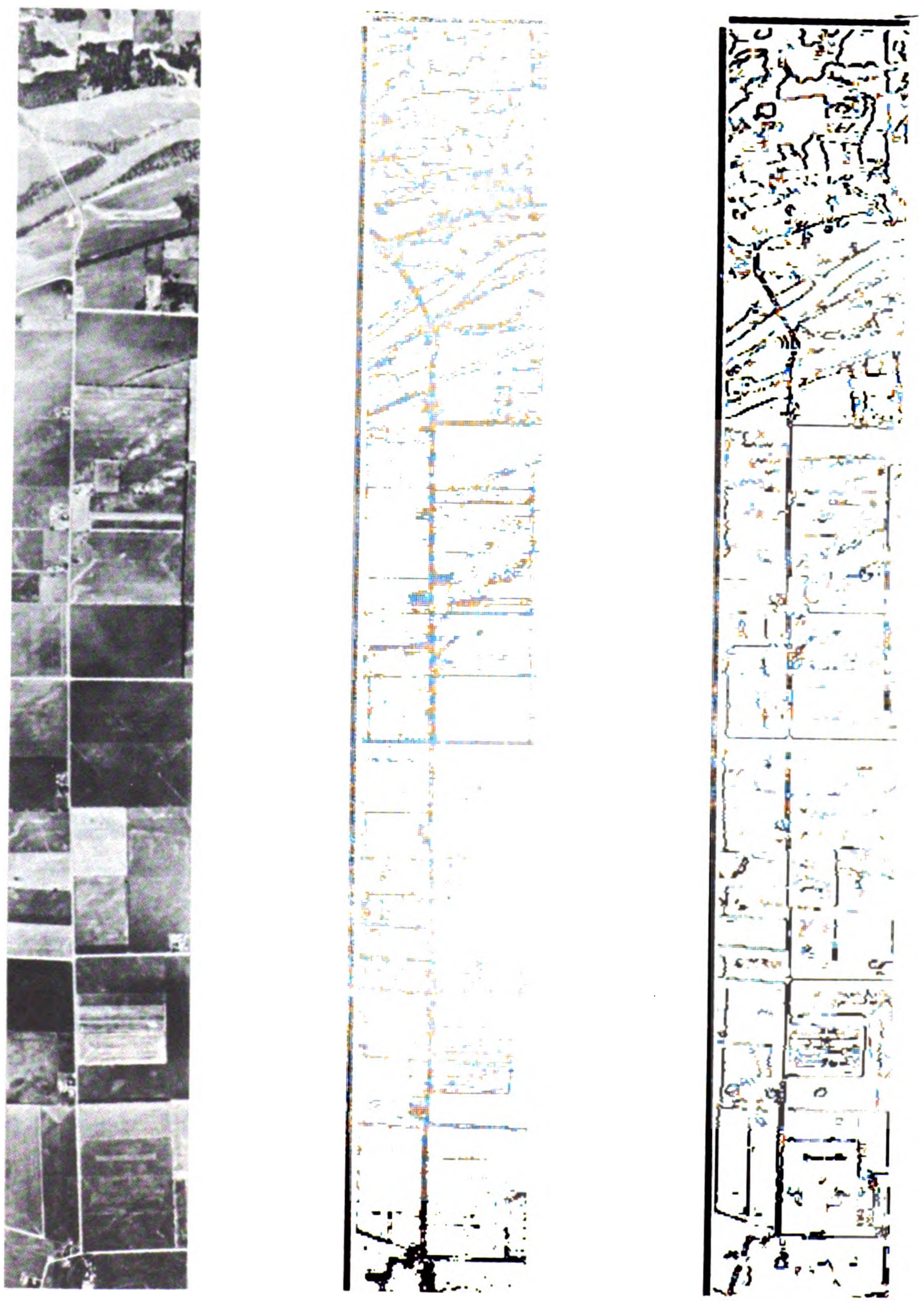
Figure 2



DIGITAL IMAGERY REGISTRATION SYSTEM

Figure 3

Border Enhancement Techniques



Air Photo

Gradient Borders

Cluster Borders

Figure 4

June 1969
11.7° Yaw Distortion

August 1969
0° Yaw Distortion

Flightline PF24
Altitude 5000 ft.
Band .66-.72 microns

Example of Rotational Distortion in Multispectral Airborne Scanner Imagery

Figure 5

MULTI-TEMPORAL ANALYSIS

Scanner Data from June & August, 1969

PF24 Run 69004801

Test Field Classification Accuracy

	No. of Samples	June (Ch 3,6,9,12)	August (3,6,9,12)	June/Aug. (6,9,12 June; 12 Aug.)*
Corn	3281	80.2%	53.6%	86.4%
Soybeans	1738	83.3%	89.6%	91.8%
Wheat	396	71.5%	———	75.5%
Oats	693	78.1%	———	67.5%
OVERALL		80.3%	57.4%	85.8%

Channel	Band
3	.52 - .55μ
6	.62 - .66μ
9	.80 - 1.0μ
12	2.0 - 2.6μ

*Best 4 of the 8 Available by the Divergence Analyser

Figure 6

Image Data Registration

- Non-single Aperature Sensors
- Temporal Information
- Distortion Correction
- Ground-Data Merge

Figure 7.

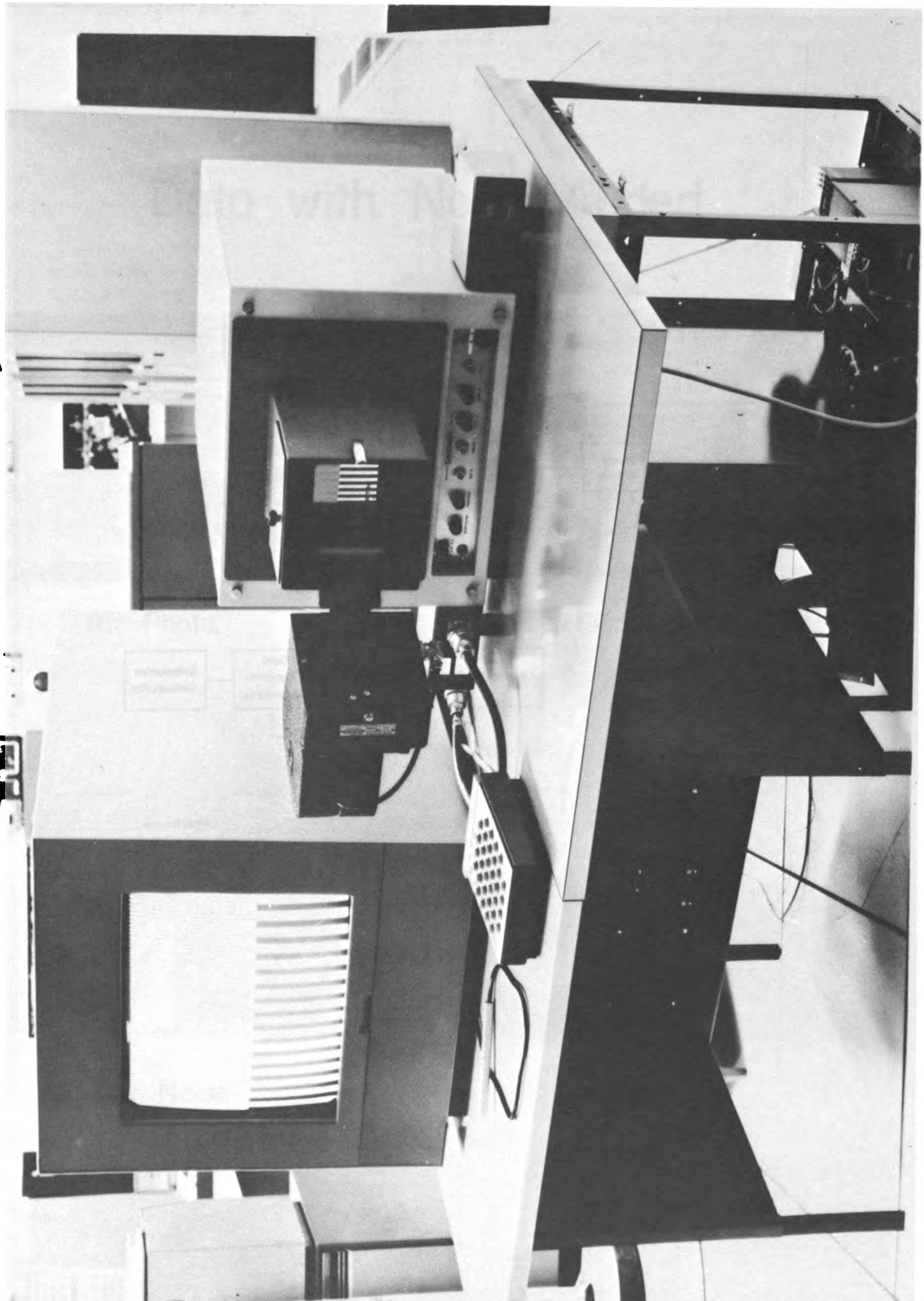


Figure 8

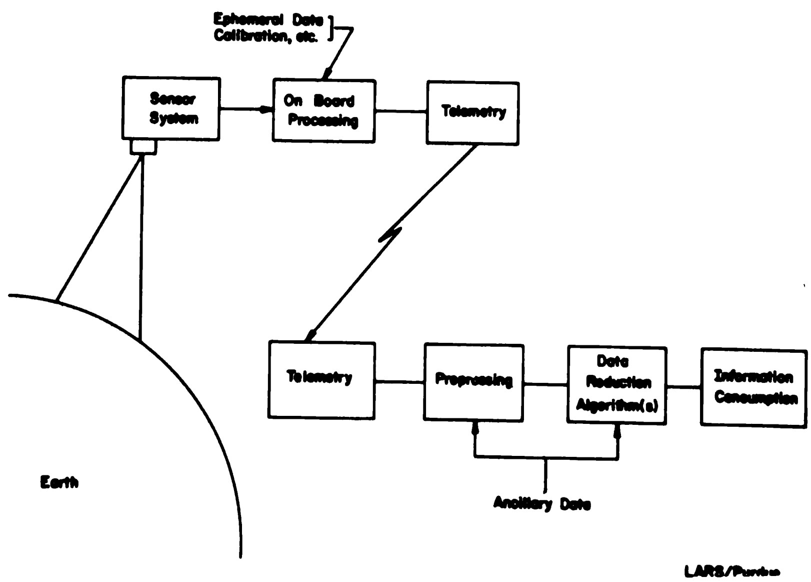
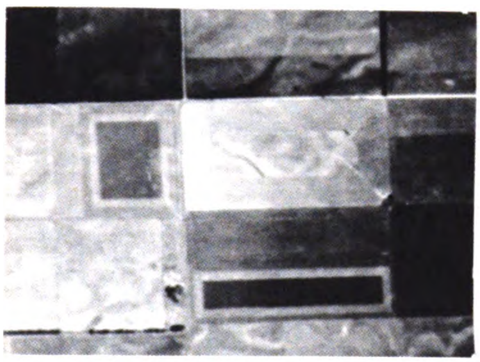
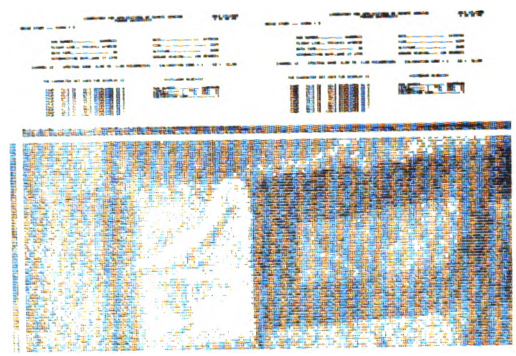

Ephemeral Data
Calibration, etc.
Sensor System
On Board Processing
Telemetry
Telemetry
Preprocessing
Data Reduction Algorithm(s)
Information Consumption
Ancillary Data
Earth
LARS/Purdue

Figure 9

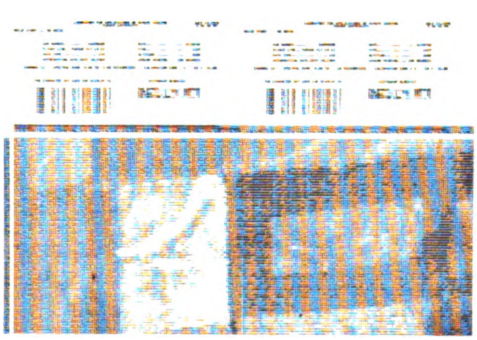
Data with Noise Added



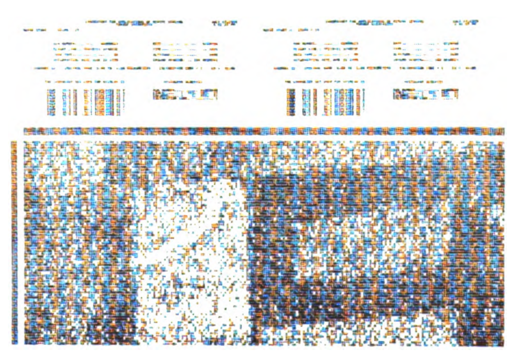
Air Photo



Sigma = 5



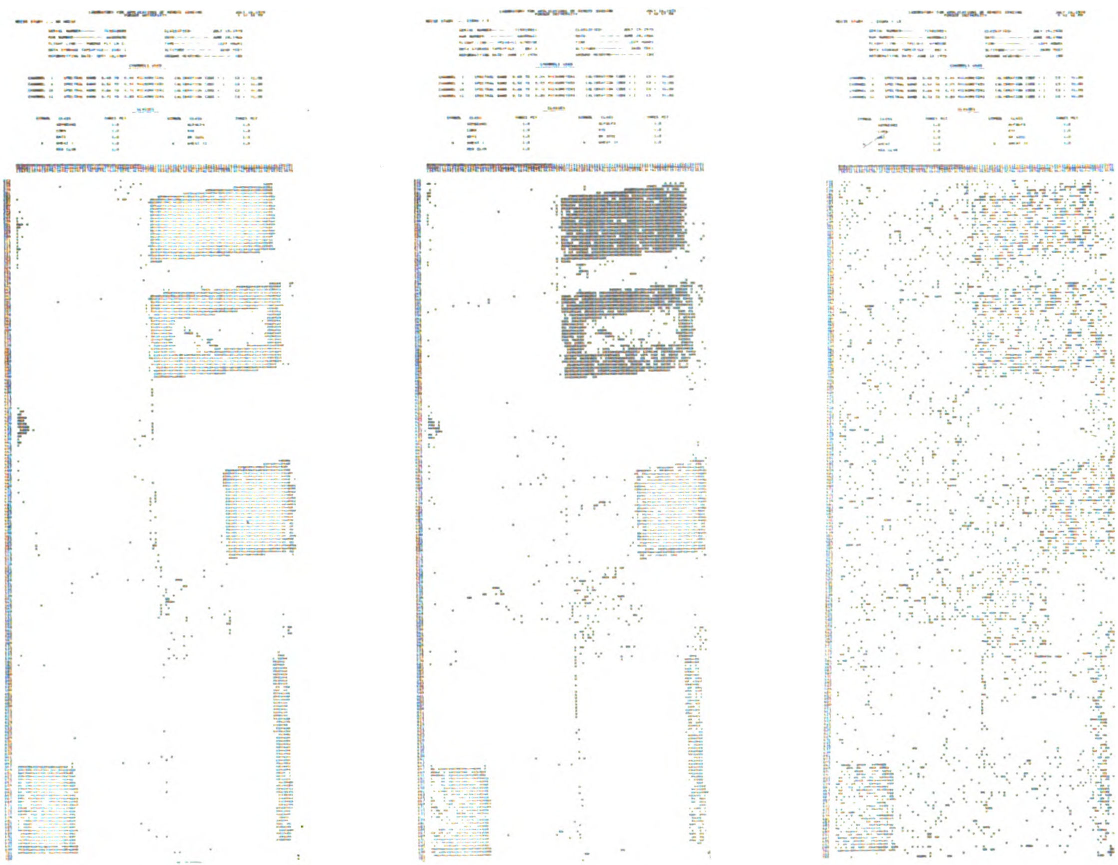
No Noise



Sigma = 15

Figure 10

Classification Results, Wheat Only



No Added Noise Sigma = 5 Sigma = 15

Figure 11

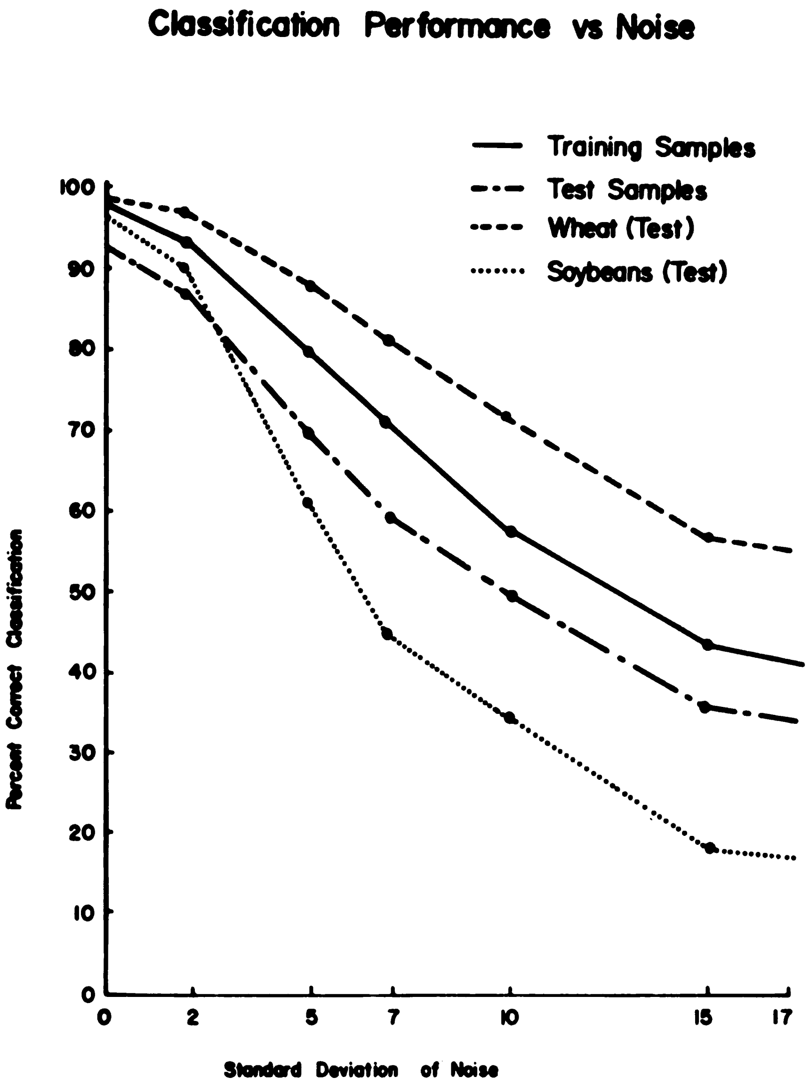
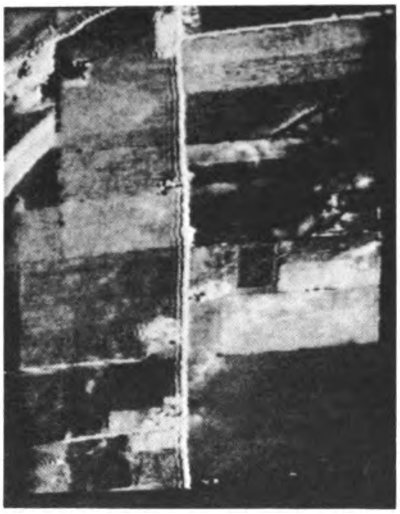
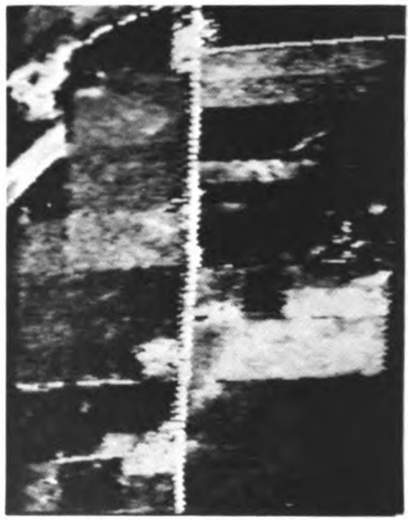

Classification Performance vs Noise
Training Samples
Test Samples
Wheat (Test)
Soybeans (Test)
100
90
80
70
60
50
40
30
20
10
0
Percent Correct Classification
0
2
5
7
10
15
17
Standard Deviation of Noise

Figure 12

GE/LARS Data Compression Study



Original Data



Compressed

Figure 13

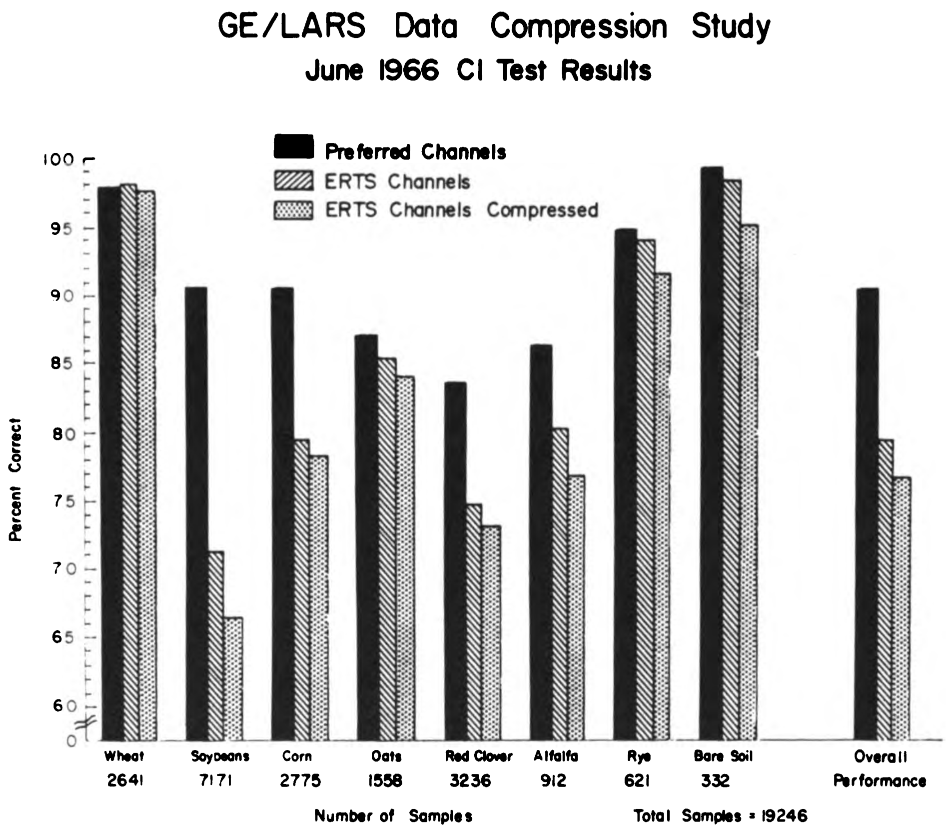

GE/LARS Data Compression Study
June 1966 CI Test Results
Preferred Channels
ERTS Channels
ERTS Channels Compressed
Percent Correct
100
95
90
85
80
75
70
65
60
0
Wheat 2641
Soybeans 7171
Corn 2775
Oats 1558
Red Clover 3236
Alfalfa 912
Rye 621
Bare Soil 332
Overall Performance
Number of Samples
Total Samples = 19246

Figure 14

MSS Data Compression
Based on Spectral Correlation

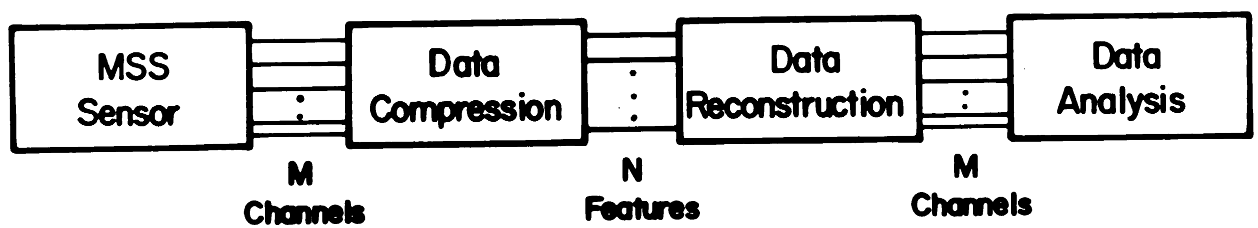


Figure 15

MSS Data Compression
Based on Spectral Correlation

Compression Ratio M/N	Overall Performance in %	Mean Square Error in %
12/12	90.1	0
12/6	88.6	1.1
12/3	89.5	2.2
12/2	60.7	6.6

Spectral Bands for Classification: .40-.44, .52-.55, .66-.72 and .80-1.0μm

Figure 16

Spectral Band Selection

Spectral Bands

1	.40–.44	7	.55–.58
2	.44–.46	8	.58–.62
3	.46–.48	9	.62–.66 –ERTS
4	.48–.50	10	.66–.72
5	.50–.52	11	.72–.80 –ERTS
6	.52–.55 ERTS	12	.80–1.00 –ERTS

Figure 17

Spectral Band Selection

Classes	R - Red Clover
S - Soybeans	A - Alfalfa
O - Oats	W - Wheat 1
C - Corn	Y - Rye
M - Wheat 2	X - Bare Soil

Figure 18

Class Separability Measure
(No Maximum)

Rank	Spectral Bands	Average Separability	Individual Class Separability				
			SC	SW	SA	WR	WY . . .
1	1, 9, 11, 12	444	25	190	188	620	58
-ERTS- 2	6, 9, 11, 12	428	26	177	299	630	208
3	2, 9, 11, 12	423	24	151	182	619	58
4	5, 9, 11, 12	420	.	.	.	.	.
5	8, 9, 11, 12	418	.	.	.	.	.
	.	.	.	.	.	.	.

Figure 19

Class Separability Measure
(Maximum = 200)

Rank	Spectral Bands	Average Separability	Individual Class Separability				
			SC	SW	SA	WP	WY
1	1, 6, 10, 12	155	34	200	196	200	180
2	1, 6, 10, 11	154	34	200	192	200	183
3	1, 6, 9, 12	153	26	200	193	200	200
4	1, 6, 9, 11	153	27	200	190	200	200
	⋮	⋮	⋮	⋮	⋮	⋮	⋮
-ERTS- 55	6, 9, 11, 12	145	26	177	200	200	200
	⋮	⋮	⋮	⋮	⋮	⋮	⋮

Figure 20