AD-A128 394 PRELIMINARY RADAR FEATURE EXTRACTION AND RECOGNITION 1/1
USING TEXTURE MEASUREMENT(U) ARMY ENGINEER TOPOGRAPHIC
LABS FORT BELVOIR VA P CHEN JAN 83 ETL-0315

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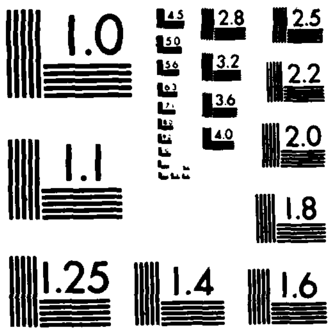

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Preliminary radar feature extraction and recognition using texture measurement

Pi-Fuay Chen

FEBRUARY 1983

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U.S. ARMY CORPS OF ENGINEERS
ENGINEER TOPOGRAPHIC LABORATORIES
FORT BELVOIR, VIRGINIA 22060

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REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER ETL-0315	2. GOVT ACCESSION NO. A128 394	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Preliminary Radar Feature Extraction and Recognition Using Texture Measurement		5. TYPE OF REPORT & PERIOD COVERED Research Note 6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) Pi--Fuay Chen		8. CONTRACT OR GRANT NUMBER(s)
9. PERFORMING ORGANIZATION NAME AND ADDRESS U.S. Army Engineer Topographic Laboratories Fort Belvoir, Virginia 22060		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS 6.11.02.A 4A161102B52C B 012
11. CONTROLLING OFFICE NAME AND ADDRESS U.S. Army Engineer Topographic Laboratories Fort Belvoir, Virginia 22060		12. REPORT DATE January 1983 13. NUMBER OF PAGES 22
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified 15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for Public Release; Districution Unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Classifiers
Feature Extraction
Image Texture
Radar Images
Solid-State Arrays

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

Preliminary results are presented for the automated extraction and classification of a selected set of radar imagery containing city, field, water, and forest images. A sensing array minicomputer system with image texture processing algorithm was employed for the scanning and conversion of radar images into digital signals and also for the extraction of a feature vector from the images. A sequential template-matching classifier was used for the classification of the set of radar imagery into preassigned categories. Slightly better than 90 percent classification accuracy was obtained.

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PREFACE

This work was authorized by U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, under FY 82 DA Project Task Area Work Unit Number 4A161102B 52C B 012, "Electronic Image Analysis for Feature Extraction."

The work was done under the supervision of Dr. F. Rohde, Team Leader, Center for Theoretical and Applied Physical Sciences; and Mr. M. Crowell, Jr., Director, Research Institute.

COL Edward K. Wintz, CE, was Commander and Director and Mr. Robert P. Macchia was Technical Director of the Engineer Topographic Laboratories during the study period.

A

CONTENTS

ILLUSTRATIONS

PRELIMINARY RADAR FEATURE EXTRACTION
AND
RECOGNITION USING TEXTURE MEASUREMENT

INTRODUCTION

Recently an image-domain processing technique was investigated and implemented with an experimental solid-state sensor array-minicomputer system at the U.S. Army Engineer Topographic Laboratories (ETL).[1] The system employs a 32-element by 32-element solid-state sensor array to convert images into electronic signals and a minicomputer to process the signals for extracting and classifying the cartographic features from the imagery into preassigned categories based on a feature vector. The images under test and investigation were selected aerial photographs.

The purpose of this effort was to modify and verify the above system for extracting and recognizing features from a selected set of radar imagery of the Huntsville, Alabama, area. Description of the system modification is followed by a discussion of the selection of feature vector components and classification strategy. Classification results for a set of selected radar imagery are presented. Finally, conclusions are given together with comments regarding extensions of this work.

SYSTEM DESCRIPTION

The hardware portion of the system used for this experimentation is essentially the same as the one reported previously.[2] The voltage of the light source was increased because most of the radar imagery was rather dark. A new software program was developed for the extraction of radar features because radar signatures of terrain features are quite different from their counterparts, the cartographic features from aerial photographs.

---

[1]P.F. Chen, *A Sensing Array System with Image Statistics Processing,* U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, ETL-0297, May 1982, AD-A119 259.

[2]*Ibid.*

The block diagram of the system is shown in figure 1. A 9-inch by 9-inch glass plate mounted with strips of radar imagery is illuminated by a white light source, and a section of the image is projected onto a Reticon 32-element by 32-element, solid-state array through an imaging lens. The array converts the optical energy of the image into a video signal. The video signal is quantized into 10 bits of digital signals and sent to the Hewlett-Packard 2108 minicomputer for processing. The computer first takes in the quantized signals of 32 pixels by 32 pixels of 1,024 gray levels array. With the brightest and darkest pixels within a frame as the maximum and minimum, this quantized image array is next scaled down to become 32 pixels by 32 pixels of 16 gray levels. The joint probability matrix of this scale array is then obtained. The next step is to compute a feature vector based on the joint probability matrix. Although nine feature vector components were computed, only two are needed for classification of the selected radar imagery. A sequential template-matching classifier is used to classify the input images into one of the preassigned image categories; an image is recognized as a reject if it does not belong to any of these categories. The classification result is then indicated on a CRT console. At the end of classification a signal is sent to the translational stage controllers to move the stages in the predetermined X and Y positions, and a new section of image is projected onto the surface of the solid-state array. The procedure described repeats until all preselected image sections are classified.

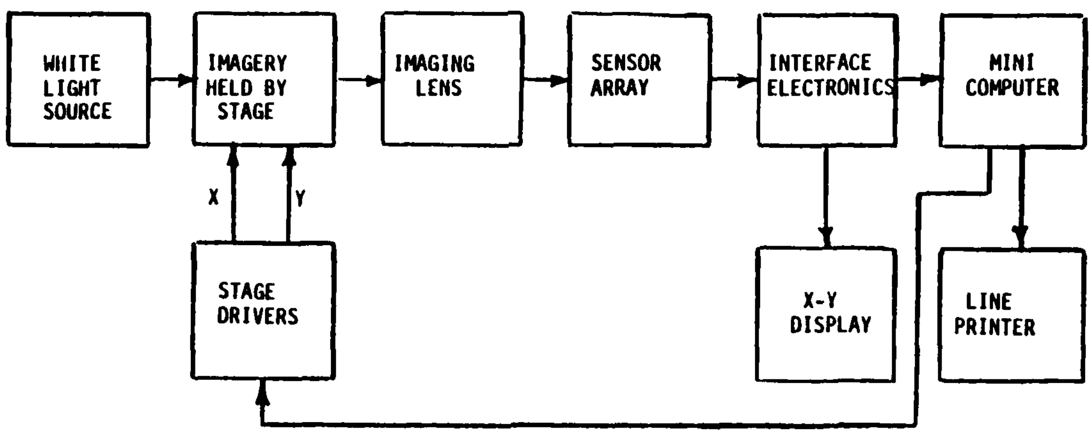


FIGURE 1. System Block Diagram.

RADAR FEATURE EXTRACTION

The system described in the previous report uses image histogram and image texture as the bases for developing a feature vector.[3] Only the image-texture technique was considered for the extraction of radar features from a selected set of radar imagery because the image categories of interest are easier to separate.[4]

Image-texture features (second-order image statistics) are based on the definition of the joint probability distribution of pairs of pixels. Pratt stated that the two-dimensional histogram can be considered as an estimate of joint probability distribution.[5] Consider a pair of pixels $F(j, k)$ and $F(m, n)$ that are separated by γ radial units, and are at an angle θ with respect to the x-axis of the measurement window. The histogram estimate of the second-order distribution is given by Pratt[6] as

$$P(a, b) = \frac{N(a, b)}{M} \tag{1}$$

Where M is the total number of all occurrences in the measurement window and $N(a, b)$ denotes the number of occurrences for which $F(j, k) = a$, $F(m, n) = b$. Various texture measures that have been used in this study are listed in appendix A (and also in ETL-0297).[7] These measures are as follows:

1. Mean
2. Variance
3. Covariance
4. Autocorrelation
5. Absolute Value
6. Energy
7. Inverse Difference
8. Inertia
9. Entropy

---

[3]P.F. Chen, *A Sensing Array System with Image Statistics Processing*, U.S. Army Engineer Topographic Laboratories, Fort Belvoir, Virginia, ETL-0297, May 1982, AD-A119 259.

[4]W.K. Pratt, *Digital Image Processing*, New York, John Wiley and Sons, Inc., 1978.

[5]*Ibid.*

[6]*Ibid.*

[7]Chen, *op. cit.*

For our application, P(a, b) was made to be symmetrical so that $\bar{a} = \bar{b}$, and $V_a = V_b$ (see appendix A). Each input image was first scaled down from 1,024 to 16 gray levels (L = 16). Nine components of the feature vector based on these equations given in appendix A and equation (1) were then computed. Equation (1) was evaluated for θ values of 0, 45, 90, and 135 degrees. The corresponding feature vector components of different θ's for each image category of interest were compared. It was discovered that only two components of the feature vector, namely the covariance and the autocorrelation, and the number of pixels within the measurement window that are above a specific threshold value (NPATV) were required for classification purposes.

CLASSIFIER

For the selected set of radar imagery, only two components of the feature vecto computed in the previous section plus the number of pixels above a threshold value (NPATV) were used to constitute a three-dimensional sequential template-matching classifier. These three components are as follows:

1. Covariance
2. Autocorrelation
3. The number of pixels above the threshold value (NPATV).

Many prototype image samples were obtained from a set of radar imagery to determine the upper and lower limits of the template values for each image category. Three template ranges for the covariance were defined as follows: water, −2.0 to 1.5; field, 0 to 1.5; and city and forest, 1.5 to 6. The template ranges for the autocorrelation were designated to be city, 0 to 40 and forest, above 40 to 150. Likewise, the template ranges for the NPATV were set to be water, 0 to 500 and field, above 501 to 1023 (see figure 2).

The covariance of the unknown incoming input image is first compared to the template ranges of the covariance template. If its value is within the range of −2.0 to 1.5, then the NPATV of the input image is compared to its corresponding template. If it is equal to or less than 500, the input image is classified as "water." If NPATV is greater than 500 or the covariance is not within the range of −2.0 to 1.5, then the next test will be performed. The sequence of tests is always from "water" to "field" to "forest" and finally to "city" as listed in appendix B. The covariance template is used as the preliminary template for all four image categories of interest. The autocorrelation template is selected as the final decision template for "forest" and "city," while the NPATV template is employed as the final decision template for "water" and "field." Finally, if the unknown image does not belong to any step of the test described, it is then classified as "not recognized."

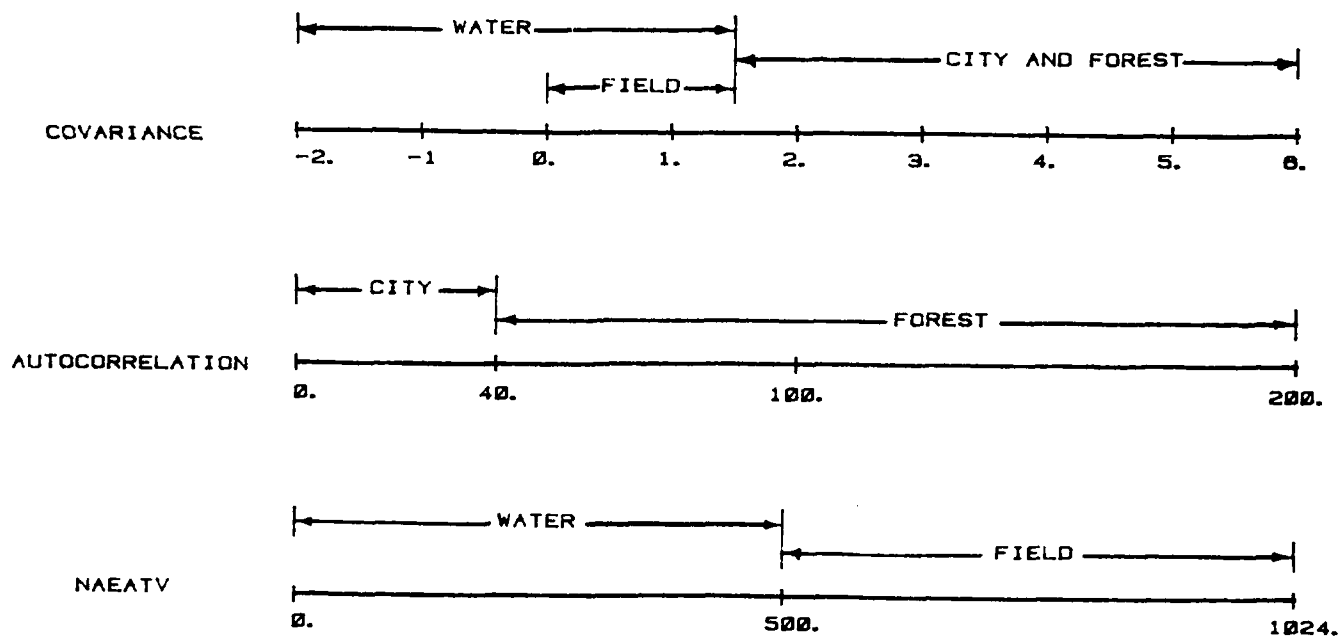


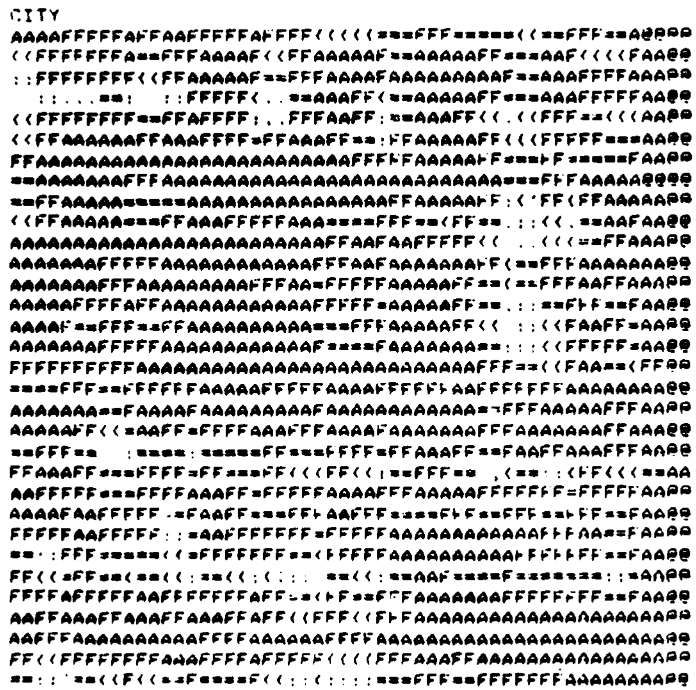
FIGURE 2. Template Ranges for Feature Vector Used for Radar Image Classification.

TEST RESULTS

A set of high-quality, scale of 1 to 100,000, X-band, synthetic aperture radar imagery from the Huntsville, Alabama, area was used for this experimentation. The set consisted of image categories such as city (combination of commercial and residential structures, DLMS categories #504 FIC 301 and #505 FIC 401), field (agriculture, used primarily for crop and pasture land, DLMS category #510 FIC 950), water (river, smooth fresh water, DLMS category #501 FIC 941), and forest (deciduous, DLMS category #510 FIC 952). Figures 3(a) to 6(a) show the line printer output of the typical radar image categories of city, field, water, and forest respectively. Each is printed in 16 gray shades by line printing. In figures 3(b) to 6(b), the nine feature vector components computed by using equations in appendix A and equation (1) and the NPATV are shown for each image category.

Approximately 100 images covering all four categories were scanned. These images were used as input to evaluate the classification accuracy of the sequential template-matching classifier. The result is illustrated in figure 7. An overall classification accuracy of approximately 92 percent was obtained. The category determination of prototype (or reference) images that were used for this classifier was based on the ground truth located from a map of the same area.

The variations of the feature vector components with respect to the texture-measurement angle, θ, for the selected radar-image categories of city, field, water, and forest are illustrated in figures 8 through 11, respectively. The covariance measure for city is highly directional, as indicated in figure 8. The covariance for the horizontal and vertical (θ = 0 and 90 degrees) directions is almost twice that measured in the diagonal sense (θ = 45 and 135 degrees). The big jump in covariance of water for the measurement direction, θ = 90 degrees, was due to a thin, long bright object running through in the vertical direction in that particular measurement window. Other variations are relatively small and insignificant. The classification accuracy shown in figure 7 was obtained by using the texture-measurement angle, θ = 0 degree.



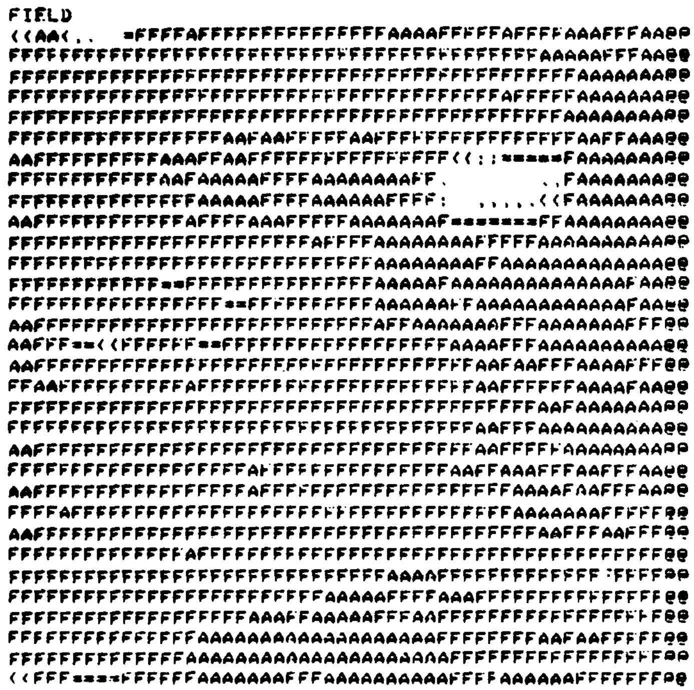
(a)

```
CITY

 SUM PROBABILITY=   1.000
 AVE=    5.593  VAR=    5.132  COV=    3.26358
 ANGULAR SECOND ORDER MOMENT =     .04341
 INVERSE SECOND ORDER MOMENT =     .51052
 ENTROPY=   3.75808
 CONTRAST=   3.73589
 ABSOLUTE VALUE=   1.39315
 AUTOCORRELATION=  34.54231
 NO. OF ELEMENTS>IT=   817
SECOND ORDER STATISTICS
```

(b)

FIGURE 3. (a) Pictorial Print of Input Image, and (b) Feature Vector Components for City.



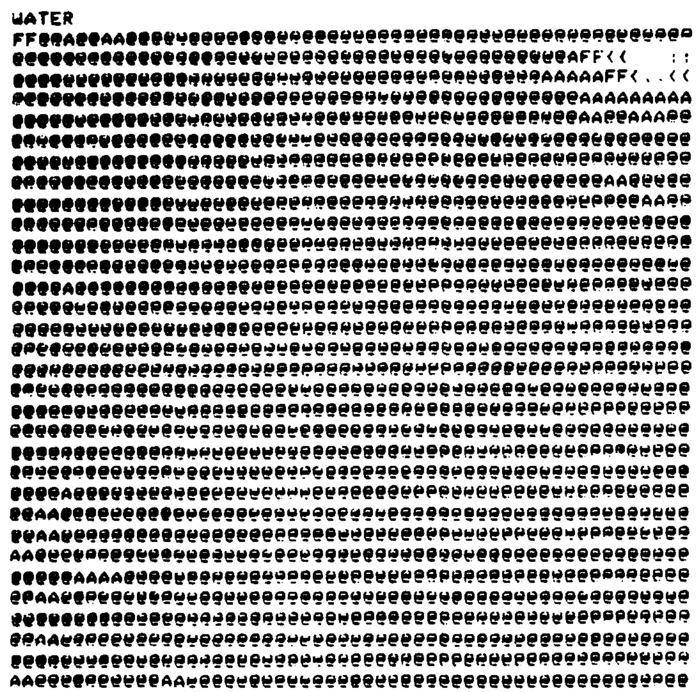
(a)

```
FIELD

 SUM PROBABILITY=   1.000
 AVE=   5.200  VAR=   1.965  COV=   1.37649
 ANGULAR SECOND ORDER MOMENT =     .26248
 INVERSE SECOND ORDER MOMENT =     .78760
 ENTROPY=   2.02791
 CONTRAST=   1.17742
 ABSOLUTE VALUE=    .53024
 AUTOCORRELATION=  28.41228
 NO. OF ELEMENTS>IT=   192
SECOND ORDER STATISTICS
```

(b)

FIGURE 4. (a) Pictorial Print of Input Image, and (b) Feature Vector Components for Field.



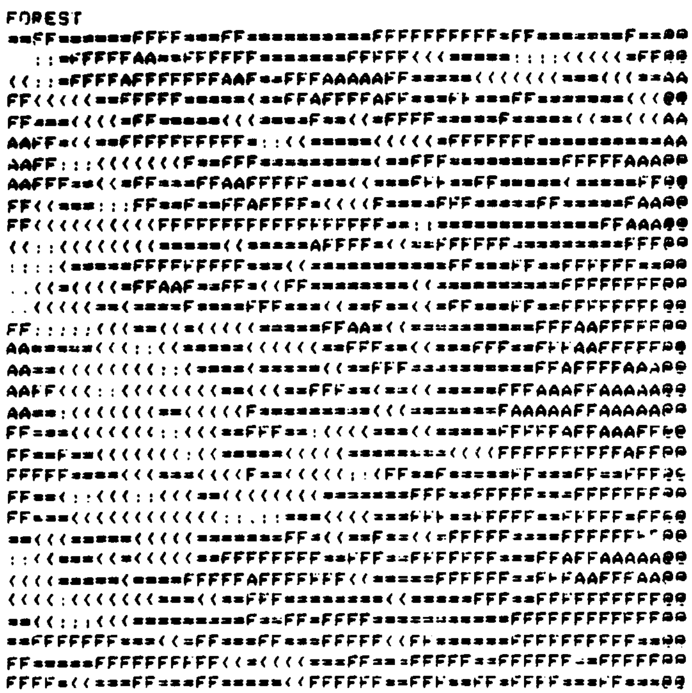
(a)

```
WATER

 SUM PROBABILITY=    1.000
 AVE=    2.606  VAR=     .955  COV=     .66863
 ANGULAR SECOND ORDER MOMENT =     .25228
 INVERSE SECOND ORDER MOMENT =     .79592
 ENTROPY=    1.56895
 CONTRAST=     .57359
 ABSOLUTE VALUE=     .43246
 AUTOCORRELATION=    7.46169
 NO. OF ELEMENTS>IT=     12
SECOND ORDER STATISTICS
```

(b)

FIGURE 5. (a) Pictorial Print of Input Image, and (b) Feature Vector Components for Water.



(a)

```
FOREST

 SUM PROBABILITY=   1.000
 AVE=   7.151  VAR=   3.363  COV=   2.16176
 ANGULAR SECOND ORDER MOMENT =    .03948
 INVERSE SECOND ORDER MOMENT =    .56595
 ENTROPY=   3.58451
 CONTRAST=   2.40222
 ABSOLUTE VALUE=   1.09980
 AUTOCORRELATION=  53.29433
 NO. OF ELEMENTS>IT=   973
SECOND ORDER STATISTICS
```

(b)

FIGURE 6. (a) Pictorial Print of Input Image, and (b) Feature Vector Components for Forest.

CLASSIFIED CATAGORY

TRUE IMAGE CATAGORY	WATER	FIELD	FOREST	CITY	NOT RECOGNIZED
WATER	25	Ø	Ø	Ø	Ø
FIELD	2	23	Ø	Ø	Ø
FOREST	Ø	Ø	23	2	Ø
CITY	Ø	Ø	3	22	Ø

NUMBER OF OVERALL IMAGES: 100
NUMBER OF OVERALL CORRECT CLASSIFICATION: 92
PERCENTAGE OF OVERALL CORRECT CLASSIFICATION: 92.Ø

FIGURE 7. Classification Results for Sequential Template Matching Classifier.

```
WED JUL  1 1981 15:25

CITY(0=0 DEGREE)

 SUM PROBABILITY=   1.000
 AVE=   5.483  VAR=   4.852  COV=   3.19426
 ANGULAR SECOND ORDER MOMENT =     .04563
 INVERSE SECOND ORDER MOMENT =     .52381
 ENTROPY=   3.68050
 CONTRAST=   3.31452
 ABSOLUTE VALUE=   1.30645
 AUTOCORRELATION=  32.38914
 NO. OF ELEMENTS>IT=   816
SECOND ORDER STATISTICS
WED JUL  1 1981 15:26

CITY(0=45 DEGREES)

 SUM PROBABILITY=   1.000
 AVE=   5.455  VAR=   5.005  COV=   1.74535
 ANGULAR SECOND ORDER MOMENT =     .03322
 INVERSE SECOND ORDER MOMENT =     .43073
 ENTROPY=   3.91361
 CONTRAST=   6.52029
 ABSOLUTE VALUE=   1.83767
 AUTOCORRELATION=  31.49950
 NO. OF ELEMENTS>IT=   815
SECOND ORDER STATISTICS
WED JUL  1 1981 15:26

CITY(0=90 DEGREES)

 SUM PROBABILITY=   1.000
 AVE=   5.374  VAR=   5.164  COV=   3.08291
 ANGULAR SECOND ORDER MOMENT =     .04282
 INVERSE SECOND ORDER MOMENT =     .52379
 ENTROPY=   3.71620
 CONTRAST=   4.16129
 ABSOLUTE VALUE=   1.40323
 AUTOCORRELATION=  31.96271
 NO. OF ELEMENTS>IT=   814
SECOND ORDER STATISTICS
WED JUL  1 1981 15:27

CITY(0=135 DEGREES)

 SUM PROBABILITY=   1.000
 AVE=   5.454  VAR=   4.929  COV=   1.77023
 ANGULAR SECOND ORDER MOMENT =     .03506
 INVERSE SECOND ORDER MOMENT =     .44541
 ENTROPY=   3.88526
 CONTRAST=   6.31842
 ABSOLUTE VALUE=   1.79605
 AUTOCORRELATION=  31.51303
 NO. OF ELEMENTS>IT=   819
SECOND ORDER STATISTICS
```

FIGURE 8. Variation of Feature Vector Components with Respect to θ for City.

```
WED JUL  1 1981 15:28

FIELD(θ=0 DEGREE)

 SUM PROBABILITY=    1.000
 AVE=    4.667  VAR=    1.443  COV=     .96662
 ANGULAR SECOND ORDER MOMENT =     .21235
 INVERSE SECOND ORDER MOMENT =     .78491
 ENTROPY=    1.94701
 CONTRAST=     .95262
 ABSOLUTE VALUE=     .50706
 AUTOCORRELATION=  22.74597
 NO. OF ELEMENTS>IT=    139
SECOND ORDER STATISTICS
WED JUL  1 1981 15:29

FIELD(θ=45 DEGREES)

 SUM PROBABILITY=    1.000
 AVE=    4.608  VAR=    1.450  COV=     .69209
 ANGULAR SECOND ORDER MOMENT =     .20567
 INVERSE SECOND ORDER MOMENT =     .76567
 ENTROPY=    2.01150
 CONTRAST=    1.51909
 ABSOLUTE VALUE=     .60146
 AUTOCORRELATION=  21.92299
 NO. OF ELEMENTS>IT=    139
SECOND ORDER STATISTICS
WED JUL  1 1981 15:29

FIELD(θ=90 DEGREES)

 SUM PROBABILITY=    1.000
 AVE=    4.614  VAR=    1.619  COV=    1.13963
 ANGULAR SECOND ORDER MOMENT =     .20983
 INVERSE SECOND ORDER MOMENT =     .80782
 ENTROPY=    1.95769
 CONTRAST=     .95867
 ABSOLUTE VALUE=     .45867
 AUTOCORRELATION=  22.43244
 NO. OF ELEMENTS>IT=    139
SECOND ORDER STATISTICS
WED JUL  1 1981 15:30

FIELD(θ=135 DEGREES)

 SUM PROBABILITY=    1.000
 AVE=    4.589  VAR=    1.447  COV=     .69994
 ANGULAR SECOND ORDER MOMENT =     .20528
 INVERSE SECOND ORDER MOMENT =     .75907
 ENTROPY=    1.99932
 CONTRAST=    1.49428
 ABSOLUTE VALUE=     .61186
 AUTOCORRELATION=  21.75858
 NO. OF ELEMENTS>IT=    142
SECOND ORDER STATISTICS
```

FIGURE 9. Variation of Feature Vector Components with Respect to θ for Field.

```
WED JUL  1 1981 15:18

WATER(0=0 DEGREE)

 SUM PROBABILITY=    1.000
 AVE=  11.611  VAR=    4.900  COV=     .89838
 ANGULAR SECOND ORDER MOMENT =      .11266
 INVERSE SECOND ORDER MOMENT =      .51204
 ENTROPY=    2.66173
 CONTRAST=    8.00303
 ABSOLUTE VALUE=    1.69456
 AUTOCORRELATION= 135.72278
 NO. OF ELEMENTS>IT=       0
SECOND ORDER STATISTICS
WED JUL  1 1981 15:19

WATER(0=45 DEGREES)

 SUM PROBABILITY=    1.000
 AVE=  12.200  VAR=    5.371  COV=    1.23459
 ANGULAR SECOND ORDER MOMENT =      .10252
 INVERSE SECOND ORDER MOMENT =      .50183
 ENTROPY=    2.73039
 CONTRAST=    8.27367
 ABSOLUTE VALUE=    1.76795
 AUTOCORRELATION= 150.08224
 NO. OF ELEMENTS>IT=       0
SECOND ORDER STATISTICS
WED JUL  1 1981 15:1-

WATER(0=90 DEGREES)

 SUM PROBABILITY=    1.000
 AVE=  10.641  VAR=    6.124  COV=    3.51939
 ANGULAR SECOND ORDER MOMENT =      .11007
 INVERSE SECOND ORDER MOMENT =      55014
 ENTROPY=    2.70480
 CONTRAST=    5.20968
 ABSOLUTE VALUE=    1.40776
 AUTOCORRELATION= 116.75305
 NO. OF ELEMENTS>IT=       0
SECOND ORDER STATISTICS
WED JUL  1 1981 15:20

WATER(0=135 DEGREES)

 SUM PROBABILITY=    1.000
 AVE=  11.523  VAR=    4.786  COV=     .85403
 ANGULAR SECOND ORDER MOMENT =      .10713
 INVERSE SECOND ORDER MOMENT =      .47410
 ENTROPY=    2.67107
 CONTRAST=    7.70447
 ABSOLUTE VALUE=    1.77940
 AUTOCORRELATION= 133.64310
 NO. OF ELEMENTS>IT=       0
SECOND ORDER STATISTICS
```

FIGURE 10. Variation of Feature Vector Components with Respect to θ for Water.

```
WED JUL  1 1981 15:22

FOREST(0=0 DEGREE)

 SUM PROBABILITY=   1.000
 AVE=   7.046  VAR=   3.585  COV=   2.33354
 ANGULAR SECUND ORDER MOMENT =    .03534
 INVERSE SECOND ORDER MOMENT =    .55526
 ENTROPY=   3.67226
 CONTRAST=   2.50282
 ABSOLUTE VALUE=   1.13306
 AUTOCORRELATION=  51.98490
 NO. OF ELEMENTS)IT=   966
SECOND ORDER STATISTICS
WED JUL  1 1981 15:23

FOREST(0=45 DEGREES)

 SUM PROBABILITY=   1.000
 AVE=   7.051  VAR=   3.647  COV=   1.84860
 ANGULAR SECUND ORDER MOMENT =    .02832
 INVERSE SECOND ORDER MOMENT =    .47812
 ENTROPY=   3.86469
 CONTRAST=   3.59625
 ABSOLUTE VALUE=   1.43392
 AUTOCORRELATION=  51.56502
 NO. OF ELEMENTS)IT=   966
SECOND ORDER STATISTICS
WED JUL  1 1981 15:24

FOREST(0=90 DEGREES)

 SUM PROBABILITY=   1.000
 AVE=   6.983  VAR=   4.224  COV=   2.79106
 ANGULAR SECOND ORDER MOMENT =    .02904
 INVERSE SECOND ORDER MOMENT =    .51132
 ENTROPY=   3.81064
 CONTRAST=   2.86593
 ABSOLUTE VALUE=   1.27319
 AUTOCORRELATION=  51.55849
 NO. OF ELEMENTS)IT=   966
SECOND ORDER STATISTICS
WED JUL  1 1981 15:24

FOREST(0=135 DEGREES)

 SUM PROBABILITY=   1.000
 AVE=   7.072  VAR=   3.639  COV=   1.58790
 ANGULAR SECUND ORDER MOMENT =    .02770
 INVERSE SECOND ORDER MOMENT =    .46320
 ENTROPY=   3.80963
 CONTRAST=   4.10190
 ABSOLUTE VALUE=   1.52341
 AUTOCORRELATION=  51.59837
 NO. OF ELEMENTS)IT=   965
SECOND ORDER STATISTICS
```

FIGURE 11. Variation of Feature Vector Components with Respect to θ for Forest.

CONCLUSIONS

1. The image-texture technique provides an effective means for evaluating texture and coarseness of radar area features.

2. The technique is most applicable for extracting and classifying if the search window contains only a single category of radar features such as city, forest, water, or field. Multiple categories of radar features contained in a search window were mostly misclassified or rejected as not recognized. Determination and detection of boundaries between different radar features are subjects of future research.

3. A preliminary classification accuracy of slightly better than 90 percent was obtained for a selected set of radar imagery from the Huntsville, Alabama, area.

4. The technique will be extended, and similar experiments will be conducted for a wide range of radar imagery from various locations and for imagery taken with different radar depression angles.

APPENDIX A. Feature Vector Components

Mean: $$\bar{a} = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} a\, P(a, b)$$

$$\bar{b} = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} b\, P(a, b)$$

Variance: $$V_a = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} (a - \bar{a})^2\, P(a, b)$$

$$V_b = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} (b - \bar{b})^2\, P(a, b)$$

Covariance: $$C_o = \sum_{a=0}^{L-1} \sum_{a=0}^{L-1} (a - \bar{a})\, (b - \bar{b})\, P(a, b)$$

Autocorrelation: $$A_u = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} a\, b\, P(a, b)$$

Absolute Value: $$A_b = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} |a - b|\, P(a, b)$$

Energy: $$E_g = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} [P(a, b)]^2$$

APPENDIX A. Feature Vector Components (Continued)

Inverse Difference: $$I_d = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} \frac{P(a, b)}{1 + (a - b)^2}$$

Inertia: $$I_n = \sum_{a=0}^{L-1} \sum_{b=0}^{L-1} (a - b)^2 \; P(a, b)$$

Entropy: $$E_n = -\sum_{a=0}^{L-1} \sum_{a=0}^{L-1} P(a, b) \; \log_2 \; [P(a, b)]$$

APPENDIX B. Computer Printout

```
&FDCT3 T=00004 IS ON CR00009 USING 00006 BLKS R=0000

FTN4,L
C
C************SUBROUTINE "FDCT3" -- REV 07/25/80***************
C
C       SUBROUTINE TO PERFORM FEATURE CLASSIFICATION FOR PROGRAM
C       "FDTX1"
C
        SUBROUTINE FDCT3(COV,AU,ITS,LUOT)
        IF(COV.LT.-2.OR.COV.GT.1.50)GO TO 810
        IF(ITS.LT.0.OR.ITS.GT.500)GO TO 810
        WRITE(LUOT,80)
        GO TO 888
  810   IF(COV.LT.0.OR.COV.GT.1.50)GO TO 820
        IF(ITS.LT.500.OR.ITS.GT.1024)GO TO 820
        WRITE(LUOT,81)
        GO TO 888
  820   IF(COV.LT.1.50.OR.COV.GT.6.0)GO TO 830
        IF(AU.LT.40.OR.AU.GT.200)GO TO 830
        WRITE(LUOT,82)
        GO TO 888
  830   IF(COV.LT.1.50.OR.COV.GT.6)GO TO 840
        IF(AU.LT.00.OR.AU.GT.40)GO TO 840
        WRITE(LUOT,83)
        GO TO 888
  840   WRITE(LUOT,84)
        GO TO 888
  80    FORMAT(1X,"WATER")
  81    FORMAT(1X,"FIELD")
  82    FORMAT(1X,"FOREST")
  83    FORMAT(1X,"CITY")
  84    FORMAT(1X,"THIS CARTOGRAPHIC FEATURE IS NOT SPECIFIED")
  888   IF(LUOT.EQ.6)WRITE(LUOT,880)
  880   FORMAT("1")
        RETURN
        END
        END$
```

END

FILMED

6-83

DTIC