

AD-A081 187

SOUTHEASTERN MASSACHUSETTS UNIV NORTH DARTMOUTH DEPT --ETC F/G 9/2
STATISTICAL IMAGE PROCESSING FOR REALTIME OPERATIONS.(U)

FEB 80 C H CHEN
SMU-EE-TR-80-2

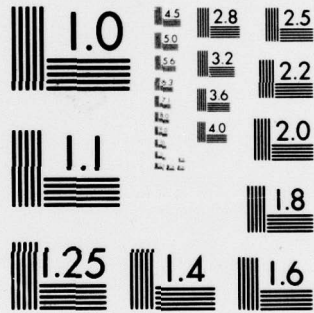
N00014-79-C-0494
NL

UNCLASSIFIED

1 OF 1
AD-
A081187



END
DATE
FILMED
3-80
DDC



MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS-1963-A

AD A 0 8 1 1 8 7

12

LEVEL



TECHNICAL REPORT SERIES IN STATISTICAL SCIENCES
(Dr. C. H. Chen, Principal Investigator)

DDC FILE COPY



DTIC
SELECTE
MAR 3 1980
A

DISTRIBUTION STATEMENT A
Approved for public release
Distribution Unlimited

**SOUTHEASTERN MASSACHUSETTS
UNIVERSITY
ELECTRICAL ENGINEERING DEPARTMENT**

NORTH DARTMOUTH, MASS. 02747 U.S.A.

80 2 28 011

15

ANNUAL REPORT

Contract Number N00014-79-C-0494

14 SMU-EE-TR-80-2

February 19, 1980

11 19 Feb 80

6 STATISTICAL IMAGE PROCESSING
FOR REALTIME OPERATIONS

12 21

9 Annual rept. Jun 80 - May 81,

Submitted to:

Statistics and Probability Program
Office of Naval Research
Arlington, Virginia 22217

Prepared by:

10 Dr. C. H. Chen

Electrical Engineering Department
Southeastern Massachusetts University
North Dartmouth, Massachusetts 02747

DTIC
ELECTE
S MAR 3 1980 D
A

DISTRIBUTION STATEMENT A
Approved for public release
Distribution Unlimited

407932

JOB

STATISTICAL IMAGE PROCESSING FOR REALTIME OPERATIONS
ANNUAL REPORT

Accession For	
NTIS GRA&I	<input checked="" type="checkbox"/>
DDC TAB	<input type="checkbox"/>
Unannounced	<input type="checkbox"/>
Justification	
By	
Distribution/	
Availability Codes	
Dist	Avail and/or special
A	

I. ABSTRACT

This report describes the results and progress for research on the topics: statistical image recognition, statistical image models, and a comparative evaluation of image processing techniques. Publications and current research activities with this project are also described in detail.

II. STATISTICAL IMAGE RECOGNITION

1. Finite Sample Classification Rules

For imagery data, the finite sample constraint includes not only the limited number of learning samples but also the finite number of quantization levels. Experimental results based on the multivariate Gaussian probability density assumption indicate that the maximum likelihood decision rule (MLDR) and the nearest neighbor decision rule (NNDR) perform very much the same at moderate sample size, say, between 100 and 400 samples. Theoretical results have demonstrated the "peaking" phenomenon between the probability of correct classification and the dimensionality, i.e. the feature number, for finite sample size in both MLDR and NNDR. For the NNDR with Gaussian patterns, we have established an empirical expression for the optimum dimensionality

$$p_{opt} = \frac{4}{9} N^{0.578} \quad (1)$$

if $k = 5$ and $2 \leq p \leq 10$. Here k is the number of nearest neighbors used, p is the dimensionality, and N is the sample size.

Decision tree or multistage classifier, if properly designed, requires much less computation time for desired accuracy in recognition or interpretation of images as compared to the conventional maximum likelihood classification. It also demonstrates theoretically the peaking phenomenon in mean recognition accuracy. Presently a nonparametric approach is used in a binary decision tree design for detection of objects in a series of aerial photographs. Theoretical error bound is also considered for the tree classifier.

The effect of quantization on the object recognition performance can be considered as follows. At 256 levels the performance is nearly the same as the continuous gray scale case. In the limiting case of two levels, i.e., the binary picture, the object is still detectable if the threshold is properly adjusted. With the assumption of the optimal quantization for all levels, the probability of correct object recognition increases exponentially. Let P_{c2} and P_{cu} be the probability of correct recognition for binary and unquantized pictures respectively, the probability of correct recognition can be written as

$$P_c = P_{c2} (1 - e^{-k\ell} + e^{-2K}) \quad (2)$$

where ℓ is the number of quantization levels and k is determined from $P_{cu} = P_{c2} (1 + e^{-2k})$.

2. Statistical Feature Extraction

Features extracted from the histograms, edges and textures, are employed in the binary decision tree classifier for object detection. The preprocessing plays an important role in extraction of effective features.

3. Statistical Contextual Analysis

Image models take into account the contextual information from nearest neighbors. Compound decision theory requires the knowledge of probability density which is usually unavailable in images.

4. Nonparametric Learning

The nonparametric approach is most suitable for image analysis as the probability densities are usually unknown. Effort is made to examine the learning algorithms using nonparametric procedures. The results will be reported in the IEEE 1980 International Conference on Cybernetics and Society (Attachment I).

III. STATISTICAL IMAGE MODELS

For many images in practical applications, statistical information is most important. Statistical image modelling provides a good approximation to image characterization and simplifies many image processing tasks (Technical Report EE-TR-79-6). The autoregressive moving-average (ARMA) model is particularly suitable for image analysis and for enhancement of noisy images. The model takes into account for each pixel the gray levels of its finite number of nearest neighbors.

Recently, we consider a two-dimensional ARMA model which is described as follows. Assume that the image is a sample from a two-dimensional homogeneous random field with the autocovariance function,

$$R_{xx}(i,j) = \sigma_x^2 \exp\{-C_1|i| - C_2|j|\}, \quad C_1, C_2 > 0 \quad (3)$$

where σ_x^2 is the variance of the images, and i and j are the spatial increments in the vertical and horizontal directions respectively. Also assume that the observable (noisy) image is given by

$$y(t,s) = x(t,s) + v(t,s), \quad t = 1, \dots, N; \quad s = 1, \dots, M \quad (4)$$

where $y(t,s)$ is the noisy observable image at (t,s) and $v(t,s)$ is a Gaussian white noise field with mean zero and variance γ . Our objective is to restore $\{x(t,s)\}$ based on the noisy observations $\{y(t,s)\}$. The two-dimensional ARMA model considered is

$$\begin{aligned} y(t+1, s+1) = & a_1 y(t, s+1) + a_2 y(t+1, s) - a_1 a_2 y(t, s) \\ & + v(t+1, s+1) + (K-1) [a_1 v(t, s+1) + a_2 v(t+1, s) \\ & - a_1 a_2 v(t, s)] \end{aligned} \quad (5)$$

where K is the stationary gain. Equation (5) represents a separable two-dimensional system. Define the sample variance of $v(t,s)$ as

$$\Lambda(\theta) = \frac{1}{NM} \sum_{t=1}^N \sum_{s=1}^M v^2(t,s) \quad (6)$$

where $\theta = (a_1, a_2, K)$. We identify the parameters a_1 , a_2 , and K such that $\Lambda(\theta)$ is minimized. The method of Steepest Descent is used in the optimization process. The minimum value of $\Lambda(\theta)$ is the estimate of the variance σ^2 of the prediction error $v(t,s)$. For a fixed θ and given observable image $\{y(t,s)\}$, the prediction error $v(t,s)$ can be computed from Equation (5) at each point. When the optimal values of a_1 , a_2 and K are obtained, we can compute the predicted image by using the expression $\hat{x}^-(t,s) = y(t,s) - v(t,s)$. For simulation study, Figure 1a shows a noisy image of size 150 x 150 with histogram given by Figure 1b. The signal-to-noise ratio is 1.73. The restored image after 6 iterations is shown in Figure 2a with initial parameter values $a_1 = 0.8$, $a_2 = 0.9$ and $K = 0.1$. Each iteration takes about

20 minutes at the PDP 11/45 minicomputer. Figure 2b is the histogram of the restored image which shows a significant improvement over Figure 1b. The computer program of the ARMA model is listed in the Appendix.

IV. COMPARATIVE EVALUATION OF IMAGE PROCESSING TECHNIQUES

A critical comparison of the median filtering, Autoregressive (AR), ARMA system, and Kalman filtering operations was reported in the Technical Report EE-TR-79-8. The Kalman filtering performs the best in images while requiring relatively less computation time. Figure 3a is the original picture with size 300 x 400 of a real image. The results of median filtering (3 x 3 window) followed by Robert's cross gradient is shown in Figure 3b. Additive Gaussian noise is added to Figure 3a with signal-to-noise ratio of 1.73. By using Kalman filtering one scan line at a time horizontally and then vertically, the restored image is shown in Figure 4a with corresponding histogram given by Figure 4b. The two peaks corresponding to background and objects are more pronounced than the histogram (not shown) of the original picture. Kalman filtering requires much less computation time than the two-dimensional ARMA model described in the previous section. For the picture size of 300 x 400 which is more than four times the size 150 x 150 considered in the previous section, Kalman filtering for both horizontal and vertical processing requires about 27 minutes. In all software implementation performed, sequential processing is used even though parallel and pipeline operations may reduce considerably the computation time. The ARMA model described in the previous section requires considerably more storage space than the Kalman filtering.

V. PUBLICATIONS AND CURRENT RESEARCH

Conference papers published thus far under the contract are:

1. C. H. Chen, "Statistical Image Processing and Recognition," COMPSAC, November 1979 (see Attachment II)
2. C. H. Chen, "Applications of Statistical Pattern Recognition," presented at the Joint Statistical Meeting in Washington, D.C. August 13-16, 1979. Full paper is published by American Statistical Association in January 1980.

Technical Reports prepared under the contract are:

1. C. H. Chen, "Statistical Image Modelling," SMU-EE-TR-79-6, October 25, 1979. To be presented at the ENAR Joint Statistical Meetings in Charleston, SC in March 1980.
2. C. H. Chen, and Jenshiun Chen, "A Comparison of Image Enhancement Techniques," SMU-EE-TR-79-8, December 26, 1979. Submitted for publication.

Current research is based on the topics described in the original proposal with emphasis on ARMA models and statistical image recognition. In addition to the principal investigator there are three graduate students participating in the research. One graduate research assistant deals with computer study of image models and processing techniques. Two graduate teaching/research assistants deal with Infrared image analysis, and statistical/structural image processing respectively.

Fig. 1b

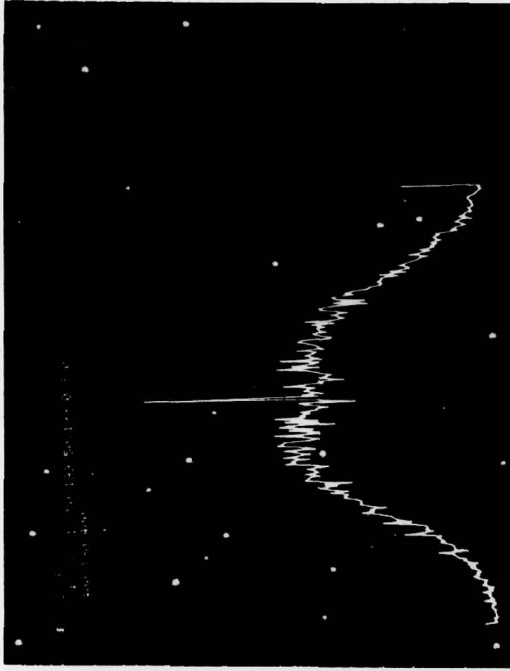


Fig. 2b

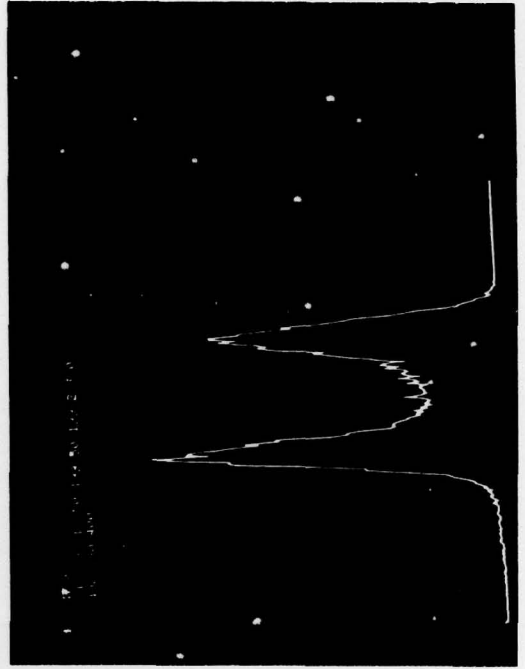


Fig. 1a

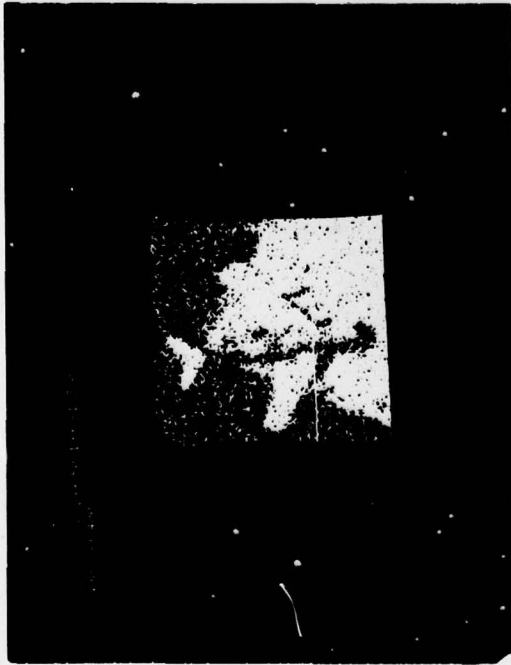


Fig. 2a



Fig. 3b



Fig. 4b

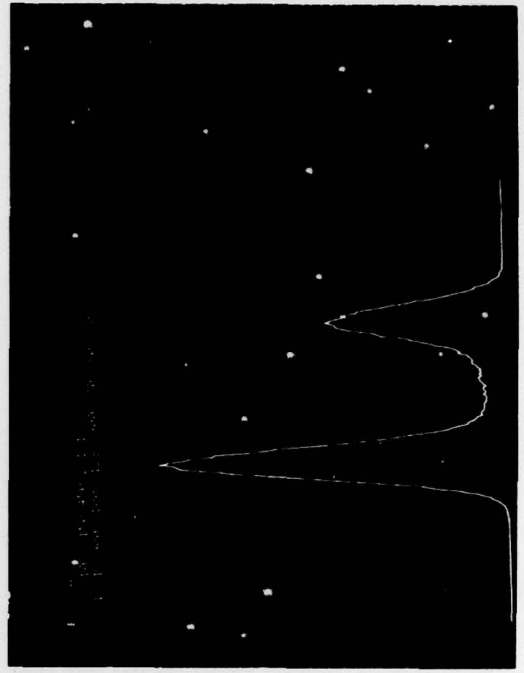


Fig. 3a



Fig. 4a



Appendix ARMA Model Computer Program

```

      BYTE B(402), C(150, 30)
      REAL Y(150)
      INTEGER OFN, OUTXC, CNT
      DOUBLE PRECISION SUM
80     READ(6, 80) IFN, OFN, IXI, IXF, IYI, IYF, I1, I2, S, FAC
      FORMAT(B15, 5F10, 4)
      IYL=IYF-IYI+1
      IXL=IXF-IXI+1
      CNT=0
      SUM=0
      DO 10 I=IYI, IYF, 30
      DEFINE FILE IFN(301, 201, U, INXC)
      DO 20 J=1, 30
      INXC=I+J-1
      READ(IFN, INXC) B
      KL=1
      DO 30 K=IXI, IXF
30     C(KL, J)=B(K)
      KL=KL+1
20     CONTINUE
      END FILE IFN
      DEFINE FILE OFN(450, 300, U, OUTXC)
      DO 40 J=1, 30
      DO 50 K=1, IXL
      CALL BY2IN(C(K, J), NT)
      CALL GAUSS(T, S, I1, I2)
50     Y(K)=FLOAT(NT)+T
      SUM=SUM+Y(K)
      OUTXC=CNT+J
      WRITE(OFN, OUTXC) Y
40     CONTINUE
      END FILE OFN
      CNT=CNT+30
10     CONTINUE
      DEFINE FILE OFN(450, 300, U, OUTXC)
      XMEAN=SUM/((IYF-IYI+1)*(IXF-IXI+1))
      DO 60 I=1, IYL
      OUTXC=I
      READ(OFN, OUTXC) Y
      DO 70 J=1, IXL
70     Y(J)=(Y(J)-XMEAN)/FAC
      OUTXC=I
      WRITE(OFN, OUTXC) Y
60     CONTINUE
      WRITE(6, 62) XMEAN
62     FORMAT('      MEAN = ', F12, 5)
      CALL BELL
      CALL .EXIT
      END
      SUBROUTINE GAUSS(T, S, I1, I2)
      T=0. 0
10     DO 10 I=1, 48
      T=T+RAN(I1, I2)
      T=T-24. 0
      T=T*0. 5
      T=T*S
      RETURN
      END

```

```

REAL Q(3), D(3)
COMMON INDEX, NFU
READ(6, 5)Q, AL, IXI, IXF, IYI, IYF, ITR, NDEV, NSF
5  FORMAT(4F12. 5, 10I5)
NFU=3
DEFINE FILE NFU(450, 300, U, INDEX)
IXL=IXF-IXI+1
IYL=IYF-IYI+1
DO 20 I=1, ITR
CALL GQ(Q, D, IXL, IYL, EF, NSF)
DO 30 J=1, 3
30  Q(J)=Q(J)-AL*D(J)
WRITE(NDEV, 35)I, Q, D, EF
35  FORMAT(1X, I4, 7F10. 4)

20  CONTINUE
70  CALL BELL
CALL EXIT
END
SUBROUTINE GQ(Q, D, IXL, IYL, EF, NSF)
REAL Q(1), D(1)
REAL K, Y(150), PY(150), V(150), PV(150), LMD(150), PLMD(150)
DOUBLE PRECISION LA1, LA2, LK, DEF
COMMON INDEX, NFU
IP=IYL-1
JP=IXL-1
IVB=150
ILB=300
LA1=0.
LA2=0.
LK=0.
DEF=0.
V(1)=0.
LMD(IXL)=0.
A1=Q(1)
A2=Q(2)
K=Q(3)
DO 5 I=1, IXL
5  PV(I)=0.
PLMD(I)=0.
INDEX=1+IVB
WRITE(NFU, INDEX)PV
INDEX=IYL+ILB
WRITE(NFU, INDEX)PLMD
INDEX=1
READ(NFU, INDEX)PY
IF(NSF. EQ. 1)WRITE(5, 41)PY
41  FORMAT(1X, 10F10. 4)
DO 10 I=2, IYL
INDEX=I
READ(NFU, INDEX)Y
DO 20 J=2, IXL
20  V(J)=Y(J)-A1*Y(J-1)-A2*PY(J)+A1*A2*PY(J-1)
V(J)=V(J)-(K-1)*(A1*V(J-1)+A2*PV(J)-A1*A2*PV(J-1))
INDEX=I+150
WRITE(NFU, INDEX)V
DO 30 J=1, IXL
30  PY(J)=Y(J)
DO 35 J=2, IXL
35  PV(J)=V(J)
IF(NSF. EQ. 1)WRITE(5, 41)Y, V
10  CONTINUE

```

```

DO 40 ISC=2, IYL
I=IYL-ISC+1
INDEX=I+IVB
READ(NFU, INDEX) V
DO 50 JSC=2, IXL
J=IXL-JSC+1
50 LMD(J)=(1-K)*(A1*LMD(J+1)+A2*PLMD(J)-A1*A2*PLMD(J+1))-2*V(J)
DO 73 J=1, JP
73 PLMD(J)=LMD(J)
INDEX=I+ILB
WRITE(NFU, INDEX) LMD
40 CONTINUE
INDEX=1
READ(NFU, INDEX) PY
INDEX=1+IVB
READ(NFU, INDEX) PV
DO 130 I=2, IP
INDEX=I
READ(NFU, INDEX) Y
INDEX=I+IVB
READ(NFU, INDEX) V
INDEX=I+ILB
READ(NFU, INDEX) LMD
DO 70 J=2, JP
LA1=LA1+LMD(J)*(Y(J-1)-A2*PY(J-1)+(K-1)*(V(J-1)-A2*PV(J-1)))
LA2=LA2+LMD(J)*(PY(J)-A1*PY(J-1)+(K-1)*(PV(J)-A1*PV(J-1)))
LK=LK+LMD(J)*(A1*V(J-1)+A2*PV(J)-A1*A2*PV(J-1))
DEF=DEF+V(J)*V(J)
70 CONTINUE
DO 80 J=1, IXL
80 PY(J)=Y(J)
DO 85 J=2, IXL
85 PV(J)=V(J)
130 CONTINUE
XY=(IP-1)*(JP-1)
D(1)=LA1/XY
D(2)=LA2/XY
D(3)=LK/XY
EF=DEF/XY
RETURN
END

```

```

REAL HX(256), HY(256), F(150)
INTEGER XMI, XEXT, YMI, YEXT
COMMON INDEX, NFU
20 READ(6, 20) TH, RMEAN, FAC, GAIN, IXI, IXF, IYI, IYF, NSF, NFU, NFC
FORMAT(4F10.5, 2O15)
21 READ(6, 21) XMI, XEXT, YMI, YEXT
FORMAT(4I5)
DEFINE FILE NFU(450, 300, U, INDEX)
IVB=150
XI=FLOAT(IXI)
XF=FLOAT(IXF)
YI=FLOAT(IYI)
YF=FLOAT(IYF)
IXL=IXF-IXI+1
IYL=IYF-IYI+1
XL=XF-XI
YL=YF-YI
CALL INITT(0)
CALL VWINDO(1, XL, 1, YL)
CALL SWINDO(XMI, XEXT, YMI, YEXT)

```

```

NF=IXL
IF(NSF.EQ.-1.OR.NSF.EQ.1)GO TO 225
190 DO 90 I=1,256
HY(I)=0.0
HX(I)=FLOAT(I)
90 CONTINUE
225 INDEX=1
DO 100 I=1,IYL
INDEX=I
READ(NFU,INDEX)F
IF(NSF)120,110,119
119 CALL IDA(I,F,NF,IVB,NFC,GAIN)
INDEX=I
IF(NSF.EQ.3)WRITE(NFU,INDEX)F
IF(NSF.EQ.3)GO TO 100
IF(NSF.GT.1)GO TO 110
120 PPY=YL-FLOAT(I)+2
CALL DSPLY(F,PPY,NF,TH)
GO TO 100
110 CALL HISTOG(F,HY,NF,RMEAN,FAC)
100 CONTINUE
CALL BELL
CALL FINITT(0.780)
IF(NSF.EQ.0.OR.NSF.EQ.2)CALL KBPLOT(HX,HY,256,0.767,10,600)
CALL EXIT
END
SUBROUTINE IDA(I,F,NF,IVB,NFC,GAIN)
REAL F(1),V(150)
COMMON INDEX,NFU
INDEX=I+IVB
READ(NFU,INDEX)V
DO 10 J=1,NF
F(J)=F(J)-V(J)
IF(NFC.EQ.1)F(J)=F(J)+GAIN*V(J)
10 CONTINUE
RETURN
END
SUBROUTINE DSPLY(F,Y,NF,TH)
REAL F(1)
DO 10 I=1,NF
IF(F(I).LT.TH)GO TO 10
FFI=FLOAT(I)
CALL POINTA(FFI,Y)
10 CONTINUE
RETURN
END
SUBROUTINE HISTOG(F,HY,IXL,RMEAN,FAC)
REAL HY(1),F(1)
DO 5 I=1,IXL
F(I)=F(I)*FAC+RMEAN
IF(F(I).GT.256.)F(I)=256.
IF(F(I).LT.1.)F(I)=1.
5 CONTINUE
DO 10 I=1,IXL
J=INT(F(I))
HY(J)=HY(J)+1.0
10 CONTINUE
RETURN
END

```

Attachment I

Submitted for the Pattern Recognition
Session of the 1980 IEEE International
Conference on Cybernetics and Society.
(invited paper)

LEARNING IN STATISTICAL PATTERN RECOGNITION

C. H. Chen
Department of Electrical Engineering
Southeastern Massachusetts University
North Dartmouth, Massachusetts 02747

ABSTRACT

Machine learning has been an area of active research interest in pattern recognition and cybernetics. A recent article by Mr. Shimura that appeared in the Proceedings of the 4IJCPR provided an excellent survey and detailed bibliography on various learning algorithms for pattern classification. In this paper which is primarily tutorial in nature, both the fundamental issues and recent development of learning in statistical pattern recognition are discussed in detail. Following an extensive review of recent progress on parametric learning that includes Bayes and maximum likelihood procedures, and the nonparametric learning particularly with the nonparametric probability density estimation, the interrelationships among learning algorithms using adaptive digital filtering, Kalman filtering, stochastic approximation and autoregressive modeling are examined. Learning algorithms for contextual analysis in imagery recognition are developed. Furthermore, the basic relationships among learning sample size, error performance and the feature number are considered. Examples are drawn from both waveform and imagery recognition studies.

STATISTICAL IMAGE PROCESSING AND RECOGNITION

C. H. Chen

Department of Electrical Engineering
 Southeastern Massachusetts University
 North Dartmouth, Mass. 02747

Abstract

This paper is concerned with the methodologies in statistical image processing and recognition. Specific areas considered are the following: (1) The decision rules in image recognition and their comparative evaluation under finite sample size condition; (2) Statistical feature extraction techniques for image segmentation with emphasis on the statistical characteristic of textural features; (3) Statistical contextual analysis algorithms for images. Emphasis is placed on the contextual pre-processing/postprocessing techniques to implement the optimum decision rules with context; (4) Statistical image modelling techniques including the nonhomogeneous models and the autoregressive models. The software problems involved in these areas are also examined in details.

I. Introduction

There has been strong demand for realtime or near realtime operations with images in practical applications. The statistical information is most important in the imagery data in many such applications. In the past two decades, the areas of statistical pattern recognition and image processing were developed simultaneously but almost independently. Thus efforts should now be made to consolidate the researches in both areas to meet the unusual requirements and the increasingly complex nature of imagery data in practical applications. This paper is semi-tutorial in nature and it covers the major methodologies and associated software implementation problems in the topics of decision rules, feature extraction contextual analysis, and image models. New results include the adaptive Kalman filtering for image enhancement.

Every image analysis algorithm should be developed with software/hardware implementation in mind. In general, local operations are faster but utilizes less contextual analysis. Global operations requires much more computation. Both software and hardware developments will be extremely important in determining the future progress in image processing and recognition.

II. Comparative Evaluation of Decision Rules

Classification is an important step in statistical information processing in general. Choice of classification (decision) rules may make a lot of difference in the recognition performance. The

comparative performance evaluation of statistical classification rules is a fundamental but unsolved problem [1] [2]. For real-time operation, the images may be received at a high data rate such that each image has to be processed within a very limited time interval. As a result a limited amount of measurements is used in actual processing. Similarly in on-board processing both time and equipments are limited. The problem of finite sample size thus becomes important. For imagery data the finite sample constraints includes not only the limited number of learning samples but also the finite number of quantization levels. Most research on statistical pattern recognition has been based on the assumption of known parameters or the availability of large or infinite number of samples to estimate the parameters or probability distributions. Under the finite sample constraints, these assumptions are not valid and the behaviors of decision rules must be re-examined.

Typical decision rules employed in image recognition are the maximum likelihood decision rule (NNDR), Fisher's linear discriminant, the sequential decision procedure, and the decision tree schemes. The MLDR is optimum in the sense of minimizing the error probability with respect to given a priori probability distributions. Under limited sample size, statistical parameters estimated may be highly inaccurate. Furthermore, the assumption of statistical distribution itself may not be valid. The use of nearest neighbor decision rule is a logical choice under these circumstances. Asymptotically, the error rate of NNDR is upper bounded by twice of the Bayes error. However, the required computation in NNDR is considerably more and the actual performance can be worse than that of the MLDR. Many researchers have reported better performance with some modifications of the MLDR and NNDR for the real data [3]. It is believed that the finite sample constraint is mainly responsible for the deviation of actual performance from theoretical performance. Recent work on the finite sample decision rules has been reported by Chen, Pau and Kittler [4,5,6]. An earlier study [7] has shown that under moderate sample size and Gaussian distribution, the performances of the MLDR and NNDR are comparable. Standard software is available to implement the MLDR.

Computationally much work has been done for the NNDR to reduce the number of distance calculations to find the nearest neighbors. Preprocessing is needed but inexpensive in all algorithms. Efficient software implementation of the NNDR, however, is

a challenging problem. By ordering the samples according to projections, Friedman et al. [8] developed an algorithm that finds the k nearest neighbors of a point, from a sample of size N in a d -dimensional space, with the expected number of distance calculations given by

$$E[n_d] \leq \pi^{-1/2} [kd \Gamma(d/2)]^{1/d} (2N)^{1-(1/d)} \quad (1)$$

Eq. 1 is the only analytical expression available for computation complexity. The brute force method would require Nd distance calculations. The amount of computational saving by the algorithm depends on k , d , and N . As a typical example of $k = 1$, $d = 2$, $N = 100$ and Gaussian sample, the algorithm requires only 10% of distance calculations for the brute force method. Another algorithm uses the branch and bound method [9]. The amount of saving is even more dramatic even though more preprocessing is required. In the maximum likelihood decision rule, consider again the Gaussian case, the equivalent number of calculations in computing the covariance matrix is also Nd . The number of calculations for the quadratic form that appears in the exponent is bound by d^4 . Thus computationally the NNDR can be made more attractive than the MLDR and thus more suitable for realtime operations. However, the memory or storage requirement definitely is in favor of the MLDR.

Among other decision rules, the Fisher linear discriminant is very effective if the second order statistics is sufficient for the data. The sequential decision procedures [10] are useful when the cost of measurements is significant enough to take into account in decision making. The decision tree classifier is most promising for realtime operation needs with the imagery data. With a pre-designed linear binary tree classifier, the overall computation time can be less than ten percent of that of a single stage classifier [11]. The combined feature selection and tree classifier design approach [12], [13] appears to be most promising for imagery recognition in terms of both computation and performance. If tree search methods are used, the software implementation will be more complicated. Theoretical evaluation of tree classifiers is generally difficult. If the memory capacity is not a major constraint, the table look-up approach [14] has been considered for the implementation of MLDR. It is also noted that the "peaking" phenomenon exists among sample size, dimensionality and error probability. It is not clear which decision rule is least sensitive to such phenomenon.

III. Statistical Feature Extraction

In statistical pattern recognition, features are usually extracted by evaluating the distance or information measures. When the sample size is limited, errors result in the computation of these measures [4]. For image classification and segmentation, textural features derived from the histogram and co-occurrence matrices of gray levels are the most useful features (see e.g. [15, 16, 17]). There are at least thirty textural features proposed so far that take into account the coarseness, contrast, directionality, line-likeness, regularity, roughness

and other properties. Information provided by grayscale histograms alone is usually not enough for classification or segmentation. Computation of co-occurrence matrices however is time consuming. Some preprocessing operations such as the spatial differentiations (e.g. gradient and modified gradient [18]) and histogram manipulation may precede the textural feature extraction and lead to more effective features. Statistical analysis of preprocessed pictures will also help to differentiate different regions in a picture, which have different statistical characteristics such as the skewness, kurtosis, and bimodality of the grayscale histograms [19], [20].

It is noted that preprocessing for feature extraction is usually less expensive than co-occurrence matrix computation. Some second order statistical property, however, is desirable or even necessary. Software development is needed for such computation. For the quantization problem, the relationship among the number of quantization levels, dimension of the vector measurement, and the number of samples has been considered. With properly chosen quantization, a small number of quantization levels can still be very effective. The binary threshold picture is a good example. As the local statistics of picture elements on both sides of an object boundary are not the same, effective algorithms can be developed for segmentation guided by statistical principles. For image classification statistical features can be effectively extracted from orthogonal transforms of the pictures. Both global and local properties can be considered in feature extraction [21].

IV. Statistical Contextual Analysis

There has been much success in using the statistical contextual information in character recognition [22]. In image recognition, interpretation and segmentation, the rich contextual information can be described statistically. There is no doubt that significant improvement over the existing results will be available if the statistical contextual information is fully utilized. One approach is to derive statistical models for the image. This is the subject of the next section. A formal statistical approach to the problem is the compound decision theory. Suppose an image is partitioned into a number of subimages (cells) and it is desired to classify each cell. The assumption of dependence on neighboring cells only is reasonable. Let x_o be the vector measurement of the cell under consideration. Then the compound decision rule is to choose the pattern class which maximizes [23],

$$p(x_o/w_k) p(w_k) \prod_{j=1}^8 p(x_j/w_k) \quad (2)$$

for 8-neighbor dependence. Here $w_k = 1, 2, \dots, m$ and m is the total number of classes. Implementation of the maximum likelihood decision rules given by Eq. (2) is straightforward provided that the probability densities are known. This information, however, is not given. It is noted that in Eq. (2) it is assumed that the true classes of neighbors are also unknown. With some manipulation, Eq. (2) can be reduced to the form which requires the transition

probabilities among the neighboring cells [23]. This problem is closely related to the probabilistic scene labeling which is a subject of scene analysis [24],[25]. Alternatively, some preclassification can be performed. The result will assist the machine to learn the probability densities for Eq. (2). After classifications, correction can be made about the knowledge of true classes of neighboring cells. The procedure may be repeated several times until consistent decisions are made for each cell. This contextual post-processing idea which was shown to be very powerful in character recognition should be effective also in statistical image recognition.

V. Statistical Image Modelling

Because of the random nature of imagery data, there have been several attempts to model the image statistically. Obviously it would be difficult to full characterize a real image by a single model. However, modelling will facilitate computer processing and will be necessary for real-time operations. Modelling takes into account the inter-pixel dependence. The Markov random field is the most typical assumption (e.g. [26,27,28]) in statistical models. Because of the object boundaries which exist in images of military applications, the homogeneous random field assumption is not appropriate. For this reason the image scan lines can be modeled as a Markov jump process [29] which leads to non-linear noise reduction. The image can also be modeled as a marked point process evolving according to a spatial parameter [30]. In another approach the image is considered as a spatially variant linear system superimposed by non-linear elements corresponding to object boundaries. Two different methods have been proposed [31][32], to perform recursive filtering of noisy images for such image models.

In our model [32] an adaptive Kalman filtering method is used for image enhancement which is recursive and suitable for real-time operation, requiring little parametric information of the image model, and adaptable to the textural and temporal variations in the image. The basic idea is that the Kalman filter is implemented on the assumption that there are no state jumps, and a second system is designed to monitor the measurement residuals of the filter to determine if a change has occurred and adjust the filter accordingly. In picture processing, state jumps correspond to the object boundaries. In order to detect and estimate the positions and amplitude of the possible state jumps, a second system is constructed which operates in parallel with the Kalman filter. The result of detection and estimation is feedback to the Kalman filter to update its operations. A generalized likelihood ratio test is used for the second system with the assumption that all the relevant densities are Gaussian. Typical computer result as illustrated in Figure 1 shows the image enhancement by adaptive Kalman filtering at low signal-to-noise ratio. The improvement is very significant as compared with the modified gradient method which is a local operation. And the computation time is not much larger.

An efficient procedure to take into account the local dependence is the statistical theory of nearest-neighbor system on a lattice [33]. Let r and s be the row number and column number associated with a picture element (pixel) x . A simultaneous model is

$$x_{rs} = \beta_1(x_{r-1,s} + x_{r+1,s}) + \beta_2(x_{r,s-1} + x_{r,s+1}) + Y_{rs} \quad (3)$$

where $i=1,2,\dots, M$; $j=1,2,\dots, N$ and $\{Y_{rs}\}$ is an uncorrelated Gaussian noise process with $E[Y_{rs}] = 0$, var. $\{Y_{rs}\} = \sigma_i^2$, $i=1,2,\dots,m$. That is, the variance of Y_{rs} differs among classes. An alternative model considered [34] is

$$x_{rs} - \mu_i = \beta_i \{ (x_{r-1,s} - \mu_i) + (x_{r,s-1} - \mu_i) \} + Y_{rs} \quad (4)$$

which may be written as

$$x_{rs} = \alpha_i + \beta_i [x_{r-1,s} + x_{r,s-1}] + Y_{rs} \quad (5)$$

the parameters (α and β) can be determined from the least squares estimates [34]. The probability density of the observations $\{x_{rs}\}$ of the image for a given class may follow the Gaussian density. Maximum likelihood decision rules can then be used for classification. For the model represented by Eq. (3), the parameters (β_1, β_2) can also be estimated from the data even though this is not a simple least squares problem. It is important to note that the first order linear autoregressive models given above can be easily extended to higher order (such as the second order) dependence. The parameter β represents spatial correlation among pixels.

Both the nonparametric adaptive filtering method and the parametric autoregressive method are very powerful and general image analysis approaches which can be efficiently implemented by software. However, the limitation is also evident. The structural properties of imagery patterns are not considered at all. It is generally difficult to incorporate any structural information in the models above. It is necessary to make sure that the assumption is at least approximately correct in using the models.

As a concluding remark, the statistical image processing and recognition presents many challenging problems to software engineers. Future software development certainly will be very helpful to the progress in this area.

Acknowledgement: This work was supported in part by the Office of Naval Research.

References

1. L. N. Kanal, "Patterns in Pattern Recognition: 1968-1974," IEEE Trans. on Information Theory, IT-20, pp. 697-722, Nov. 1974.
2. C. H. Chen, "Evaluation of Classification Rules for Imagery Recognition," Proceedings of Eighth Annual Automatic Imagery Pattern Recognition, April 1978.
3. C. H. Chen, "A Review of Statistical Pattern Recognition," in "Pattern Recognition and Signal Processing," NATO ASI E29, Sijthoff & Noordhoff International Publishers, Dec. 1978.
4. C. H. Chen, "Finite Sample Considerations in Statistical Pattern Recognition," Proceedings of IEEE Pattern Recognition and Image Processing Conference, June 1978.
5. L. F. Pau, "Finite Learning Sample Size and Problems in Pattern Recognition," in Pattern Recognition and Signal Processing," NATO ASI E 29, Sijthoff & Noordhoff International Publishers, December 1978.
6. J. Kittler and L. F. Pau, "Small Sample Properties of a Pattern Recognition System in Lot Acceptance Sampling," Fourth International Joint Conference on Pattern Recognition, Kyoto, Japan, Nov. 1978.
7. C. H. Chen "Performance Bounds of a Class of Sample-Based Classification Procedures," Proceedings of IEEE Pattern Recognition and Image Processing Conference, June 1977.
8. J. H. Friedman, F. Baskett and L. J. Shustek, "An Algorithm for Finding Nearest Neighbors," IEEE Trans. on Computers, Oct. 1974.
9. K. Fukunaga and P. M. Narendra, "A Branch and Bound Algorithm for Finding Nearest Neighbors," IEEE Trans. on Computers, vol. C-24, July 1975.
10. C. H. Chen, "Statistical Pattern Recognition," Hayden Book Co., Feb. 1973.
11. K. C. You and K. S. Fu, "An Approach to the Design of a Linear Binary Tree Classifier," Proc. of Symposium on Machine Processing of Remotely Sensed Data," June 1976.
12. C. H. Chen and C. K. Lau, "Feature Set Formulation for Reconnaissance Image Analysis," Proceedings of Seventh Annual Automatic Imagery Pattern Recognition, May 1977.
13. E. M. Rounds, "A Combined Non-Parametric Approach to Feature Selection and Binary Decision Tree Design," Proc. of IEEE Pattern Recognition and Image Processing Conference, August 1979.
14. W. G. Eppler, "An Improved Version of the Table Look-Up Algorithm for Pattern Recognition," Proc. of the 9th International Symposium on Remote Sensing of Environment, April 1974.
15. R. M. Haralick, K. Shanmugam and I. Dinstein, "Texture Features for Image Classification," IEEE Trans. on Systems, Man, and Cybernetics, vol. SMC-3, November 1973.
16. R. M. Haralick, "Statistical and Structural Approaches to Texture," Proceedings of the IEEE, vol. 67, no. 5, pp. 786-804, May 1979.
17. C. H. Chen, "A Comparative Evaluation of Texture Measures," TR-EE-75-9, Sept. 1975.
18. C. H. Chen, "A Note on a Modified Gradient Method for Image Analysis," Pattern Recognition journal, 1978.
19. C. H. Chen, "Theory and Applications of Image Pattern Recognition," TR-EE-75-3, April 1975.
20. C. J. Chow and T. Kaneko, "Automatic Boundary Detection of the Left Ventricle from Cineangiograms," Computers and Biomedical Research, vol. 5, no. 5, pp. 388-410, August 1972.
21. Y. Hsu and H. Andrews, Unpublished report 1978.
22. G. T. Toussaint, "The Use of Context in Pattern Recognition," Pattern Recognition journal, vol. 10, pp. 189-204, 1978.
23. C. H. Chen, "A New Look at the Statistical Pattern Recognition," Workshop on Pattern Recognition and Artificial Intelligence, Princeton, NJ, April 1978.
24. S. W. Zucker and J. L. Mohammed, "Analysis of Probabilistic Relaxation Labeling Processes," Proceedings of IEEE Pattern Recognition and Image Processing Conference, June 1978.
25. O. Faugeras and M. Berthod, "Scene Labeling: An Optimization Approach," Proceedings of IEEE Pattern Recognition and Image Processing Conference, August 1979.
26. E. Wong, "Two-Dimensional Random Fields and the Representation of Images," SIAM Journal of Applied Mathematics, vol. 16, pp. 756-770, 1968.
27. M. Hassner and J. Sklansky, "Markov Random Fields as Models of Digitized Image Texture," Proceedings of IEEE Conference on Pattern Recognition and Image Processing, June 1978.
28. L. N. Kanal, "The Markov Mesh Model," presented at the Workshop on Image Modeling, Chicago, IL, August 6-7, 1979.
29. P. A. Wintz and T. S. Huang, "Image Analysis and Modelling," Final Technical Report, AD-A023 633, March 1976.
30. J. W. Modestino and R. W. Fries, "Stochastic Models for Images and Applications," in "Pattern Recognition and Signal Processing," NATO ASI E 29, Sijthoff & Noordhoff International Publishers, December 1978.

31. V. K. Ingle, A. Radpour, J. W. Woods and H. Kaufman, "Recursive Estimation with Non-Homogeneous Image Models," Proceedings of IEEE Conference on Pattern Recognition and Image Processing, June 1978.
32. C. H. Chen, "Adaptive Image Filtering," Proceedings of IEEE Pattern Recognition and Image Processing Conference, August 1979.
33. M. S. Bartlett, "The Statistical Analysis of Spatial Pattern," Chapman and Hall, London and Wiley, New York, 1975.
34. S. L. Sclove, "Pattern Recognition and Image Processing Using Inter-Pixel Correlation," Technical Report 1978.

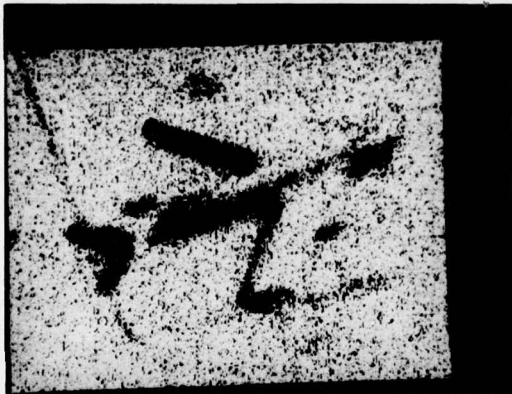


Figure 1a - Typical Aircraft Image With Signal-to-Noise Ratio of 1.8

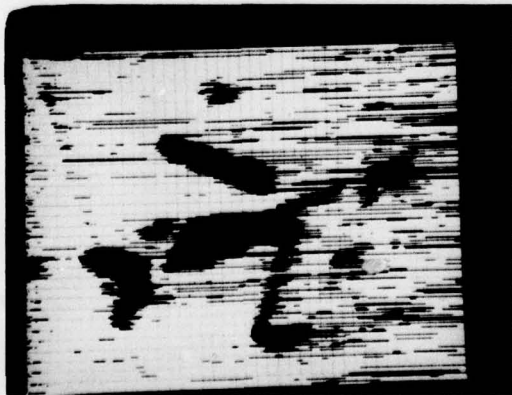


Figure 1b - Adaptively Filtered Image Corresponding to Figure 1a

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Statistical Image Processing for Realtime Operations		5. TYPE OF REPORT & PERIOD COVERED Annual Report (June 1980 - May 1981)
		6. PERFORMING ORG. REPORT NUMBER TR-EE-80-2
7. AUTHOR(s) C. H. Chen		8. CONTRACT OR GRANT NUMBER(s) N00014-79-C-0494
9. PERFORMING ORGANIZATION NAME AND ADDRESS Electrical Engineering Department Southeastern Massachusetts University North Dartmouth, MA 02747		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS Statistics and Probability Program Office of Naval Research, Code 436 Arlington, VA 22217		12. REPORT DATE February 19, 1980
		13. NUMBER OF PAGES
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; distribution 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) Statistical image recognition Statistical image models Kalman filtering		
20. ABSTRACT (Continue on reverse side if necessary and identify by block number) This report describes the results and progress for research on the topics: statistical image recognition, statistical image models, and a comparative evaluation of image processing techniques. Publications and current research activities with this project are also described in detail.		

DD FORM 1473
1 JAN 73

EDITION OF 1 NOV 65 IS OBSOLETE

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)