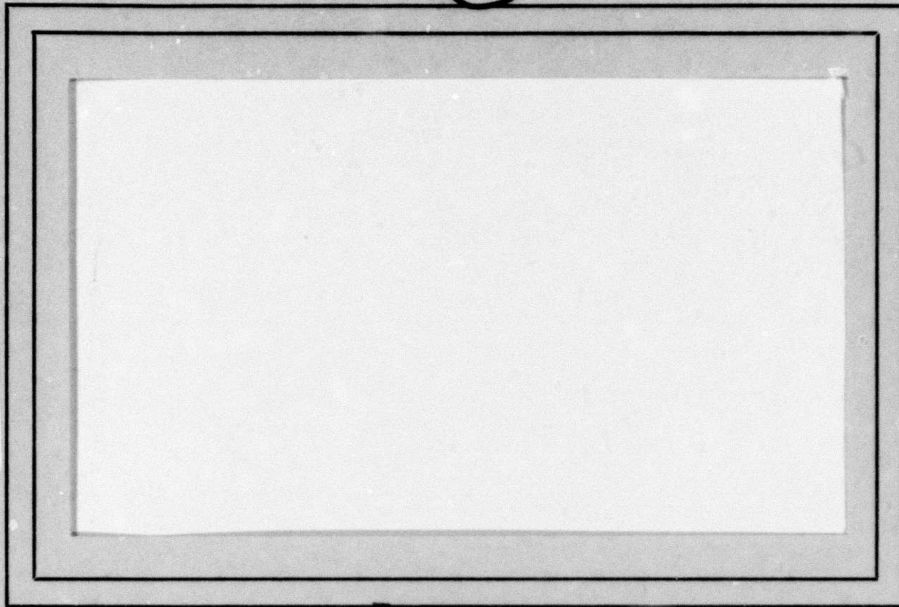


LEVEL II

(1)

ADA 076064



LEVEL II



DDC
RECEIVED
NOV 2 1972
E

DDC FILE COPY

UNIVERSITY OF MARYLAND
COMPUTER SCIENCE CENTER

403018

COLLEGE PARK, MARYLAND

20742

This document has been approved
for public release and sale; its
distribution is unlimited.

79 11 02 72

15 DAAG53-76-C-0138,
✓ DARPA Order-3206

1
12 14

14 CSC - TR-751
DAAG-53-76C-0138

11 March 1979

6 THRESHOLDING USING
THE ISODATA CLUSTERING ALGORITHM.

10 Flavio R. D. Velasco
Computer Science Center
University of Maryland
College Park, MD 20742

9 Technical rept.

DDC
RECEIVED
NOV 2 1979
E

ABSTRACT

↓
A recently proposed iterative thresholding scheme turns out to be essentially the well-known ISODATA clustering algorithm, applied to a one-dimensional feature space (the sole feature of a pixel is its gray level). We prove that in one dimension, ISODATA always converges. We also apply it to requantize images into specified numbers of gray levels.
↖

-A-

This document has been approved
for public release and sale; its
distribution is unlimited.

The support of the Defense Advanced Research Projects Agency and the U.S. Army Night Vision Laboratory under Contract DAAG-53-76C-0138 (DARPA Order 3206) is gratefully acknowledged, as is the help of Kathryn Riley in preparing this paper. The support of the CNPq is also gratefully acknowledged.

*Permanent address: INPE, C.P. 515, S.J. Campos-12200, San Paulo, Brazil.

403 018 ✓

JCB

1. Introduction

An iterative method for threshold selection has been proposed by Ridler and Calvard in [1] for object-background discrimination. After an initial guess is made, at each iteration we get a new threshold in the following way: given a threshold T_i , the next threshold T_{i+1} is the average of V_{above} and V_{below} , where V_{above} is obtained by integrating all points above T_i and V_{below} by integrating all points below T_i . T_{i+1} is, hopefully, a better threshold than T_i for object-background discrimination. The process terminates as soon as we have $T_{i+1} = T_i$, which usually requires about four iterations. The initial value, T_0 , is chosen by selecting a region in the image (its four corners) that is most likely to contain only points of the same class-background. The method is applied to thresholding a low-contrast image containing a handwritten signature.

Except for the choice of the initial threshold, the method described in [1] can be thought of as a one-dimensional application of the ISODATA algorithm (as described in [2]) where we restrict the number of classes to two. (In the ISODATA algorithm what is initially chosen are the means $\hat{\mu}_1, \dots, \hat{\mu}_c$ of the classes.)

In this note we give some other applications of the ISODATA algorithm in which we consider numbers of classes other than two. It is also proved that the algorithm for the one-dimensional, two-class case always converges.

2. The ISODATA algorithm

The basic ASODATA algorithm [2] is a procedure for classifying a set of sample vectors $x = \{\bar{x}_1, \bar{x}_2, \dots, \bar{x}_m\}$ into c distinct classes.

Algorithm 2.1 Basic ISODATA.

1. Choose some initial values for the means $\hat{\mu}_1, \hat{\mu}_2, \dots, \hat{\mu}_c$;
- Loop: 2. Classify the m samples by assigning them to the class having closest mean;
3. Recompute the means as the averages of the samples in each class,
4. If any mean has changed value, go to loop; otherwise stop.

In our case, we have an image in which each point has a "gray level" integer value in the interval $[0, L]$. Each sample is thus a point of the image. The distribution of gray levels is given by a histogram h , where $h(0), h(1), \dots, h(L)$ are the numbers of points with gray levels $0, 1, \dots, L$. Let $[LO, UP]$ be the smallest interval containing all non-zero histogram values. In this one-dimensional case, the ISODATA algorithm may be rewritten as:

Algorithm 2.2 One-dimensional ISODATA:

1. Choose some initial values for the means $\mu_1, \mu_2, \dots, \mu_c$, such that $LO \leq \mu_1 < \mu_2 < \dots < \mu_c \leq UP$;
- Loop 2. Calculate thresholds $T_1, T_2, \dots, T_{c-1}$ by the formula:
$$T_i = \lfloor (\mu_i + \mu_{i+1}) / 2 \rfloor, \quad 1 \leq i < c;$$

Assign to class i , $1 \leq i \leq c$, all gray levels in the interval $I_i = [T_{i-1} + 1, T_i]$; (we define $T_0 = LO - 1$ and $T_c = UP$)

- 3) Recompute the means: for every i make $\hat{\mu}_i$ the nearest gray level to $(\sum_{j \in I_i} j \cdot h(j)) / (\sum_{j \in I_i} h(j))$, $1 \leq i \leq c$;
- 4) If any mean has changed value, go to loop; otherwise, stop.

Observation

In step (3) of the algorithm, if it happens that $\sum_{j \in I_i} h(j) = 0$ for some i , in other words, there is no point whose gray level falls in the interval I_i , one should suppress class i and consider just the remaining classes.

For the two-class case we can show that Algorithm 2.2 converges. The proof reveals how Algorithm 2.2 works. First, however, it is necessary to prove two lemmas.

Lemma 2.1

Let μ_1^k and μ_2^k be the means of classes 1 and 2 respectively, and T^k the threshold at the k th iteration. Then we have $LO \leq \mu_1^k \leq T^k < \mu_2^k \leq UP$.

Proof:

For $k=0$ we have, by Step 1 of the algorithm, that $LO \leq \mu_1^0 < \mu_2^0 \leq UP$. As $T^0 = \lfloor (\mu_1^0 + \mu_2^0) / 2 \rfloor$, then $\mu_1^0 \leq T^0 < \mu_2^0$.

Let us suppose that the inequality is true for the $(k-1)$ st iteration. The new values for the means are based on the intervals $I_1^{k-1} = [LO, T^{k-1}]$ and $I_2^{k-1} = [T^{k-1} + 1, UP]$. Therefore $\mu_1^k \in I_1^{k-1}$ and $\mu_2^k \in I_2^{k-1}$, which implies that $LO \leq \mu_1^k < \mu_2^k \leq UP$. Again, as $T^k = \lfloor (\mu_1^k + \mu_2^k) / 2 \rfloor$ we have $\mu_1^k \leq T^k < \mu_2^k$. //

Section For	☒	☐	☐
TLC G&H			
DC TAB			
Announced			
Notification			
Y			
Classification			
Availability Codes			
Available/or			
Special			
1st			

Lemma 2.2

If $T^i \leq T^{i+1}$ then $T^{i+1} \leq T^{i+2}$. Similarly, if $T^i \geq T^{i+1}$ then $T^{i+1} \geq T^{i+2}$.

Proof:

We prove only the first part of Lemma 2.2, as the second part is analogous to the first.

If $T^i = T^{i+1}$, then $\mu_1^{i+1} = \mu_1^{i+2}$ and $\mu_2^{i+1} = \mu_2^{i+2}$ and thus $T^{i+1} = T^{i+2}$.

If $T^i < T^{i+1}$, the interval I_1^{i+1} where μ_1^{i+2} will be calculated is the union of the intervals I_1^i and $[T^{i+1}, T^{i+1}]$. So, besides the points of I_1^i that contributed to μ_1^{i+1} , we have the new gray levels of $[T^{i+1}, T^{i+1}]$ that are larger than μ_1^{i+1} . Therefore $\mu_1^{i+2} > \mu_1^{i+1}$. Similarly, the interval I_2^{i+1} where μ_2^{i+1} is calculated is the union of $[T^{i+1}, T^{i+1}]$ and I_2^{i+1} and, therefore, $\mu_2^{i+2} > \mu_2^{i+1}$. Since both means μ_1^{i+2} and μ_2^{i+2} are larger, we have $T^{i+2} > T^{i+1}$. //

Lemma 2.2 shows that the threshold, if it moves, moves only in one direction.

Theorem 2.1

Algorithm 2.2 converges in a finite number of steps.

Proof:

By Lemma 2.2, the sequence $T^0, T^1, \dots$ of thresholds forms either a non-decreasing or non-increasing sequence. By Lemma 2.1 this sequence is bounded and, therefore, there must be a k such that $T^k = T^{k+1}$. If this happens, then $T^k = T^{k+j}$ for all j .

3. Examples

Algorithm 2.2 was tested on three different pictures. Figures 1,3, and 5 show the original pictures together with their histograms. The results for numbers of classes equal to 8,4,3, and 2 for Figures 1 and 3 are shown in Figures 2 and 4 ((a),(b),(c), and (d), respectively). Figure 6 shows the result for Figure 5 when we consider only two classes.

The initial values for the means were chosen so they were evenly spread in the interval [LO,UP]. The number of iterations together with the thresholds are given in Table 1.

Figure	Number of classes	Number of iterations	LO,UP	Thresholds
1	2	5	13,49	36
	3	4		28,37
	4	4		24,31,38
	8	2		17,21,25,29,33,37,41
3	2	3	7,63	37
	3	4		28,44
	4	4		24,34,48
	8	3		15,20,26,32,40,48,55
5	2	3	3,63	37

Table 1. Number of iterations and thresholds for each figure.

Moreover, the maximum number of steps is limited by the size of the interval $[LO,UP]$. //

Observation:

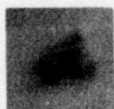
Although we can prove the convergence of the algorithm, at least for two classes, this does not mean that the algorithm always arrives at the same threshold, irrespective of the initial values for the means.

4. Comments

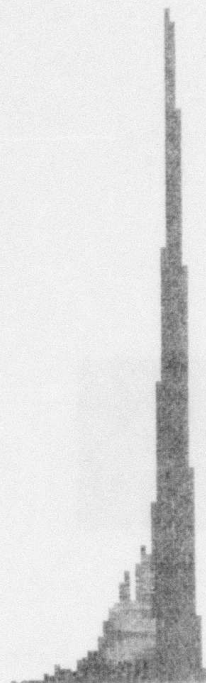
In this note we showed that the ISODATA algorithm can be used not only for thresholding a picture, as in [1], but also to requantize it into a few gray levels. In the latter application, it seems that one can achieve reasonable data compression without significant distortion of the image, as in [3]. However, an advantage over the method proposed in [3] is that one can specify a priori the number of gray levels desired.

References

- [1] T. W. Ridler and S. Calvard, Picture thresholding using an iterative selection method, IEEE Trans. on Systems, Man, and Cybernetics 8, 639-632 (1978).
- [2] R. O. Duda and P. E. Hart, Pattern Classification and Scene Analysis, John Wiley & Sons, Inc. (1973).
- [3] S. Peleg, Iterative histogram modification 2, IEEE Trans. on Systems, Man, and Cybernetics 8, 555 (1978).

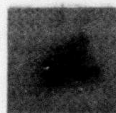


(a)

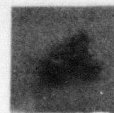


(b)

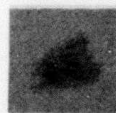
Figure 1. Original FLIR image (a) and histogram (b).



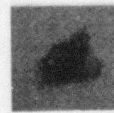
(a)



(b)



(c)



(d)

Figure 2. Results for 8 classes (a), 4 classes (b), 3 classes (c), 2 classes (d).



(a)



(b)

Figure 3. Satellite image (clouds) (a) and histogram (b).



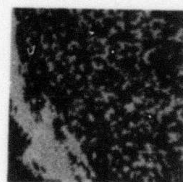
(a)



(b)

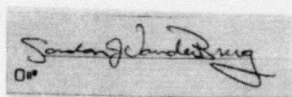


(c)

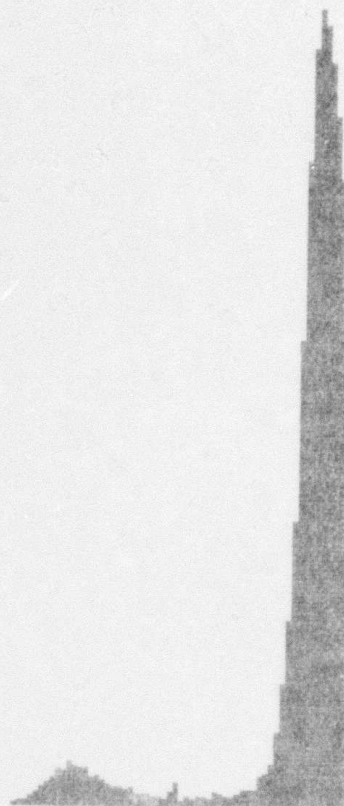


(d)

Figure 4. Results for 8 classes (a), 4 classes (d), 3 classes (c), 2 classes (d).



(a)



(b)

Figure 5. Signature (a) and histogram (b).

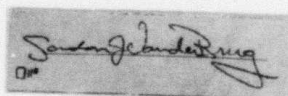


Figure 6. Result of thresholding (two classes).

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) THRESHOLDING USING THE ISODATA CLUSTERING ALGORITHM		5. TYPE OF REPORT & PERIOD COVERED Technical
		6. PERFORMING ORG. REPORT NUMBER TR-751
7. AUTHOR(s) Flavio R. D. Velasco		8. CONTRACT OR GRANT NUMBER(s) DAAG-53-76C-0138
9. PERFORMING ORGANIZATION NAME AND ADDRESS Computer Science Center University of Maryland College Park, MD 20742		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS U. S. Army Night Vision Laboratory Fort Belvoir, VA 22060		12. REPORT DATE March 1979
		13. NUMBER OF PAGES 12
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) Image Processing Thresholding Pattern Recognition Quantization Clustering ISODATA		
20. ABSTRACT (Continue on reverse side if necessary and identify by block number) A recently proposed iterative thresholding schemes turns out to be essentially the well-known ISODATA clustering algorithm, applied to a one-dimensional feature space (the sole feature of a pixel is its gray level). We prove that in one dimension, ISODATA always converges. We also apply it to requantize images into specified numbers of gray levels.		

DD FORM 1 JAN 73 1473

EDITION OF 1 NOV 65 IS OBSOLETE

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)