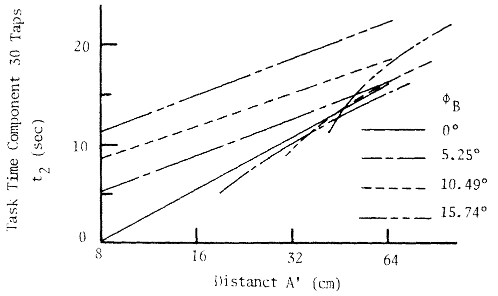

Fig. 15. Correlation of Fig. 14(a) adjusted to show increased distance due to backlash (curved lines) as well as unadjusted correlation (straight lines).

For Coulomb friction variations the gross motion times and W_{0e} are almost constant, but the fine motion (positioning) times were noticeably influenced. If the friction had decreased the maximum torque output one might expect gross motion to suffer as well. (This was not the characteristic simulated.)

The addition of backlash greatly increases fine motion time requirements. W_{0e} increases, indicating more visual feedback (available during fine motion) is necessary. The distance the master arm was required to move in order to move the slave the required amount increased with backlash. For example, $\phi_B = 5.25°$ at the "shoulder" joint corresponds to 11 cm of additional motion at the end of the arm. Shifting the curves in Fig. 14 for t_1 to the right by the distance which corresponds to the total backlash angle $2\phi_B$ places the curves for $\phi_B = 5.25°$, 10.49°, and 15.74° almost upon one another as shown in Fig. 15. (Subjects were observed to use primarily the shoulder joint with backlash.) The change in slope b_1 from the case $\phi_B = 0°$ to the case $\phi_B = 5.25°$ seems to result from the addition of small amounts of backlash.

V. Conclusion

A first attempt has been made to quantify the relationship between the performance of an experimental master–slave manipulator and each of three dynamic characteristics: natural frequency, Coulomb friction, and backlash. Performance is measured in terms of time to accomplish a simple positioning task.

The relative simplicity of the manipulator and the ability to specify the change in its closed-loop characteristics or transfer function makes it possible to relate the dynamic characteristics to measured performance for a simple task. The characteristics are those of two uncoupled second-order damped oscillators with variable Coulomb friction and backlash.

Experiments were performed to quantify the relation between manipulator performance and manipulator characteristics. A statistical analysis showed that a simple linear model could be constructed relating the task parameters of distance and width to performance measured in time to accomplish the task. This influence is also shown graphically which enables an easier interpretation to the regression results.

These results can be applied in the cost–performance trade-off of the manipulator design. This trade-off is desirable due to the increase in cost of a manipulator with improved dynamic characteristics (less backlash, less friction, etc.) and the decrease in cost of performing the task due to a better performance (less time to accomplish a task). The solution of this optimization problem will determine the minimum total cost, i.e., to what degree it will be justified to implement a better design in order to achieve a higher performance of the manipulator.

The results have been interpreted in terms of an information transmission model of the man–machine system with separate transmission rates for gross (ballistic or travel) motions and fine (positioning with visual feedback) motions and a point of transfer between the two motions. The rates and point of transfer appear to explain variations in performance in a logical and consistent manner.

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Thresholding using the ISODATA Clustering Algorithm

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***Abstract*—An investigation is made of the use of the ISODATA clustering algorithm as applied to a one-dimensional feature space. For two classes, the ISODATA turns out to be an iterative thresholding scheme,**

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which is very convenient for its simplicity. In this case (two classes) it is proved that the ISODATA algorithm always terminates. For a number of classes larger than two, ISODATA can be used to requantize images into a specified number of gray levels.

Introduction

An iterative method for threshold selection has been proposed by Ridler and Calvard [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} should be 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 (e.g., 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.

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 $\hat{\mu}_1,\cdots,\hat{\mu}_c$ of the classes.)

In this correspondence 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 terminates.

The Isodata Algorithm

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

Algorithm 1—Basic ISODATA

1) Choose some initial values for the means $\hat{\mu}_1,\hat{\mu}_2,\cdots,\hat{\mu}_c$.

Loop

2) Classify the m samples by assigning them to the class having the 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 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 $h(0),h(1),\cdots,h(L)$ are the numbers of points with gray levels $0,1,\cdots,L$. Let $[LO,UP]$ be the smallest interval containing all nonzero histogram values. In this one-dimensional case, the ISODATA algorithm may be rewritten.

Algorithm 2—One-Dimensional ISODATA

1) Choose some initial values for the means $\mu_1,\mu_2,\cdots,\mu_c$, such that $LO\leqslant\mu_1<\mu_2<\cdots<\mu_c<UP$.

Loop

2) Calculate thresholds $T_1,T_2,\cdots,T_{c-1}$ by the formula
$$T_i=\lfloor(\mu_i+\mu_{i+1})/2\rfloor,\quad 1\leqslant i<c,$$
where $\lfloor x\rfloor$ is the largest integer not greater than x. Assign to class i, $1\leqslant i\leqslant c$, 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 $(\sum_{j\in I_i} j\cdot h(j))/(\sum_{j\in I_i}h(j))$, $1\leqslant i\leqslant c$.
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 terminates. The proof reveals how Algorithm 2 works. First, however, it is necessary to prove two lemmas.

Lemma 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 kth iteration. Then we have $LO\leqslant\mu_1^k\leqslant T^k<\mu_2^k\leqslant UP$.

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

Let us suppose that the inequalities hold 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 $LO\leqslant\mu_1^k<\mu_2^k\leqslant UP$. Again, as $T^i=\lfloor(\mu_1^k+\mu_2^k)/2\rfloor$, we have $\mu_1^k\leqslant T^k<\mu_2^k$. □

Lemma 2: If $T^i\leqslant T^{i+1}$ then $T^{i+1}\leqslant T^{i+2}$. Similarly, if $T^i\geqslant T^{i+1}$ then $T^{i+1}\geqslant T^{i+2}$.

Proof: We prove only the first part of Lemma 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, $\mu_1^{i+2}\geqslant\mu_1^{i+1}$. Similarly, the interval I_2^i where μ_2^{i+1} is calculated is the union of $[T^i+1,T^{i+1}]$ and I_2^{i+1} and, therefore, $\mu_2^{i+2}\geqslant\mu_2^{i+1}$. Since both means μ_1^{i+2} and μ_2^{i+2} are at least as large, we have $T^{i+2}\geqslant T^{i+1}$. □

Lemma 2 shows that the threshold, if it moves, moves only in one direction.

Theorem: Algorithm 2 terminates in a finite number of steps.

Proof: By Lemma 2 the sequence $T^0,T^1,\cdots,$of thresholds forms either a nondecreasing or nonincreasing sequence. By Lemma 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. Moreover, the maximum number steps is limited by the size of the interval $[LO,UP]$. □

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

III. Examples

Algorithm 2 was tested on three different pictures. Figs. 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 Figs. 1 and 3 are shown in Figs. 2 and 4 ((a), (b), (c), and (d), respectively). Fig. 6 shows the result for Fig. 5 when we consider only two classes.

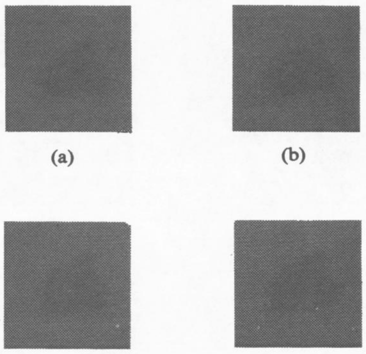
The initial values for the means were chosen so that they were evenly spread in the interval $[LO,UP]$. The number of iterations together with the thresholds are given in Table I.

IV. Comments

Although the results (Figs. 2(d), 4(d), and 6) for threshold selection were considered to be good, it is interesting to compare them with those reported in [3]–[5] for the same set of figures. In those papers, the threshold is chosen by first transforming the histogram so that the valley is deepened or converted into a peak. It is hoped that in this modified histogram the threshold is easier to select. Those methods make use of a bidimensional histogram (scatter plots) obtained by using pairs of features such as (gray level, edge value), or (gray level, average gray level).

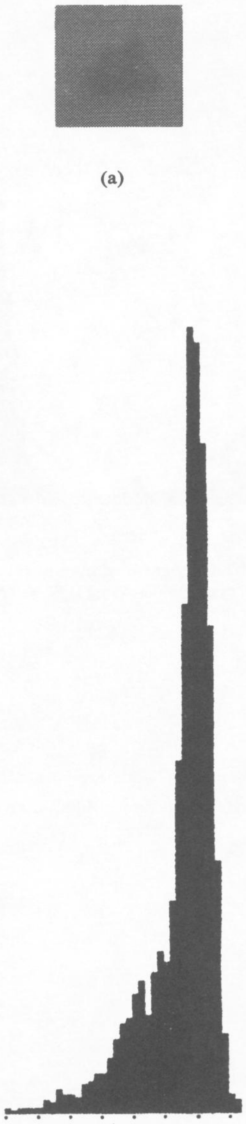
TABLE I
NUMBER OF ITERATIONS AND THRESHOLDS FOR EACH FIGURE

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



(a) (b) (c) (d)

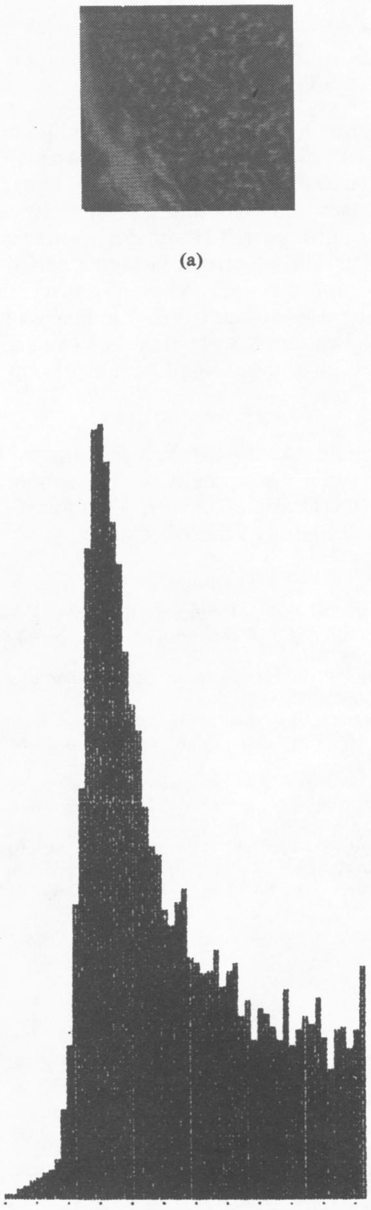
Fig. 2. Results for (a) eight classes, (b) four classes, (c) three classes, and (d) two classes.



(a)

(b)

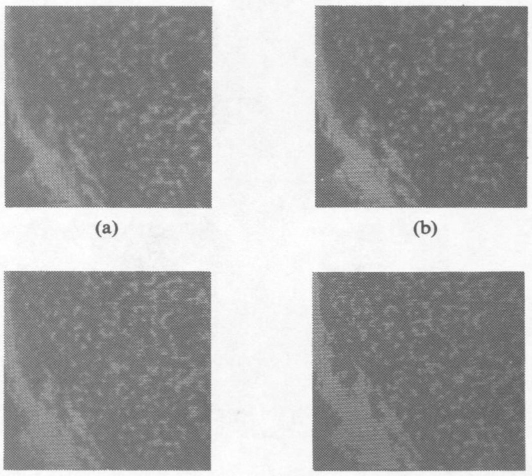
Fig. 1. (a) FLIR image. (b) Histogram. Lowest gray level—13; highest gray level—49. Mean pixel value—40.34. Scale (pixels/dot)—2.



(a)

(b)

Fig. 3. (a) Satellite image (clouds). (b) Histogram. Lowest gray level—7; highest gray level—63. Mean pixel value—33.66. Scale (pixels/dot)—2.



(a) (b) (c) (d)

Fig. 4. Results for (a) eight classes, (b) four classes, (c) three classes, and (d) two classes.

The results obtained by Kirby and Rosenfeld [5] are reported to be better than those of [3] and [4] in many cases. For Figs. 3 and 5 (clouds and signature) the thresholds obtained in [5] were similar to the ones found in this correspondence. For Fig. 1 [forward looking infrared (FLIR image)] however, the method based on the ISODATA algorithm yielded a better threshold.

If the number of classes is chosen greater than two, the ISODATA can be used to requantize the image into a few gray levels. In this application, it seems that one can achieve reasonable data compression without significant distortion of the image.

Acknowledgment

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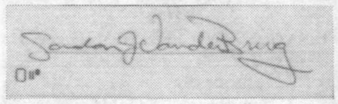
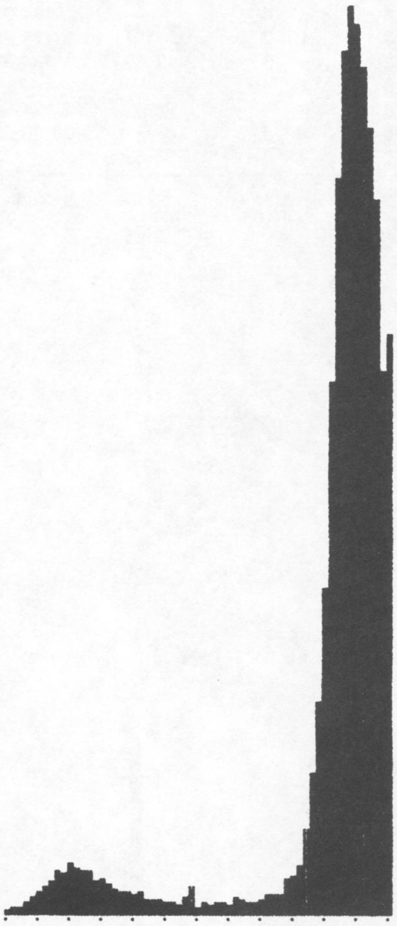


(a)



(b)

Fig. 5. (a) Signature. (b) Histogram. Lowest gray level—3; highest gray level—63. Mean pixel value—54.21. Scale (pixels/dot)—9.

Fig. 6. Result of thresholding (two classes).