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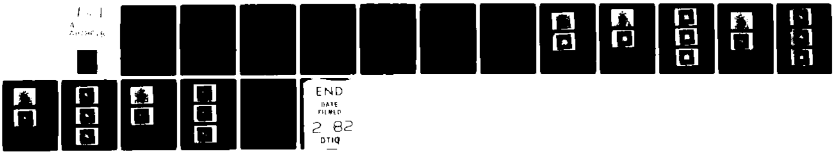

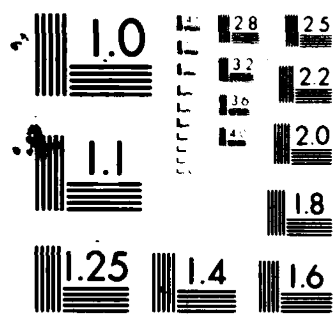

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Fisher's linear discriminant, image segmentation, pixel classification, target detection; target tracking, Gaussian statistics, time-varying images.

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

A target tracking and detection experiment is reported that uses the Fisher's linear discriminant for pixel classification to segment simulated static and dynamic scenes. The results clearly demonstrate that the segmentation method performs better than other work on the same static scene. Detection performance versus the learning sample sizes for dynamic scenes is empirically determined. It indicates that a small target can still be detected if a sufficiently large learning sample size is available.

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(1)

An Experiment on Target Tracking Via Image Segmentation*

by
C. H. Chen
Wen-Hsing Yang
Department of Electrical Engineering
Southeastern Massachusetts University
North Dartmouth, Massachusetts 02747

* The support of the Statistics and Probability Program of the Office of Naval Research on this work is gratefully acknowledged.

An Experiment on Target Tracking Via Image Segmentation

1. Introduction

In surveillance and tracking using imagery sensors, targets must be detected and tracked at various signal-to-noise ratios for a fixed or varying target size. Although the scenes considered may be quite simple consisting of one or multiple targets in a noisy background, the computational algorithms must be also simple and effective to meet the real-time or near real-time requirements. Our previous study [1] has demonstrated such capability by using the Fisher's linear discriminant to segment the infrared images. Recently, a Bayes classifier was proposed [2] for the pixel classification to segment a scene with a box of different Gaussian statistics from the noisy background. In their approach, object (target) parameters such as size, location etc. calculated from projections are used to iteratively improve the decision rule. A cost function is used to derive the final segmentation. An entirely different approach [3] is to use a semi-causal recursive filter for the enhancement of image such that the target can be detected and tracked.

In this paper, the approach taken in Ref. 1 is used to examine the same example in Ref. 2 for a comparative study. Furthermore, the experiment is extended to a dynamic simulation of a moving object by varying the size of the target sequentially. A comparison is made with the theoretical performance. The effect of the learning sample size on detection performance is also determined empirically.

2. Algorithm for Static Scenes

The first part of the algorithm is for a static scene as considered in Ref. 2. The full picture is of 32x32 pixels while the target box with size 11x11 is in the center of the scene. Extensive experimental study shows that the feature vector consisting of two components: the gray level of the pixel, and the average gray level of the 3x3 neighborhood performs the best. This feature vector is then used throughout the target tracking study. For the learning samples, 100 pixels from the target region (class 1) and 100 pixels from the background (class 2) are selected. The target region has a Gaussian distribution with mean 10 and variance 2 while the background region has a Gaussian distribution with mean 8 and variance 2. The Fisher's linear discriminant is used for pixel classification to segment the image into target region and background region. The experimental probability of pixel misclassification can then be compared with the theoretical value given by [1]

$$P_e = \frac{1}{\sqrt{2\pi}} \int_{\frac{\sqrt{u}}{2}}^{\infty} \exp - \frac{y^2}{2} \, dy$$

where u is the "norm" which in this case is the Mahalanobis distance between the two classes based on the pooled scattered matrix. Fig. 1 shows the experimental and theoretical errors in a reasonable aggreement, as a function of u. The larger the error, the more difficult is the target detection.

Fig. 2a is the original artificial 32x32 image as generated and displayed on the AED-512 terminal in 256 gray levels. Fig. 2b shows the Fisher's linear discriminant result. 10 errors are detected in the target, which is slightly better than the result reported in Ref. 2.

3. Algorithm for the Time-Varying Images

The main part of the algorithm is used to segment the time-varying images. We select four 32x32 pictures with the target sizes 10x10, 8x8, 6x6 and 4x4 respectively. The results are as follows.

(1) The picture with 10x10 target (Fig. 3)

learning sample size	error percentage
10x10	4.00 (Fig. 3b)
8x8	4.88 (Fig. 3c)
6x6	7.81 (Fig. 3d)
4x4	9.67 (Fig. 3e)

(2) The picture with 8x8 target (Fig. 4)

learning sample size	error percentage
10x10	3.91 (Fig. 4b)
8x8	4.79 (Fig. 4c)
6x6	8.10 (Fig. 4d)
4x4	9.96 (Fig. 4e)

(3) The picture with 6x6 target (Fig. 5)

learning sample size	error percentage
10x10	3.71 (Fig. 5b)
8x8	4.69 (Fig. 5c)
6x6	8.01 (Fig. 5d)
4x4	10.06 (Fig. 5e)

(4) The picture with 4x4 target (Fig. 6)

learning sample size	error percentage
10x10	2.83 (Fig. 6b)
8x8	3.71 (Fig. 6c)
6x6	7.32 (Fig. 6d)
4x4	9.38 (Fig. 6e)

From the above results, it is concluded that for a given target size, better detection is available with a larger learning sample size. Fig. 7 is a plot of empirical relationship between the percentage error and the learning sample size. We also notice that even when the target is small as it just appears on the scene, good detection is possible by taking a large size learning sample.

References

1. C. H. Chen and C. Yen, "Object isolation in FLIR images using Fisher's linear discriminant," Pattern Recognition Journal, December 1981.

2. C. Skevington, G. M. Flachs and B. Schaming, "A statistical approach to image segmentation," Proc. of IEEE Pattern Recognition and Image Processing Conference, pp. 267-272, Aug. 1981.

3. H. A. Titus and J. L. Pereira, "A comparison of digital image filters and hybrid smoother," Proc. of the IEEE Asilomar Conference, pp. 345-348, Pacific Grove, CA 1979.

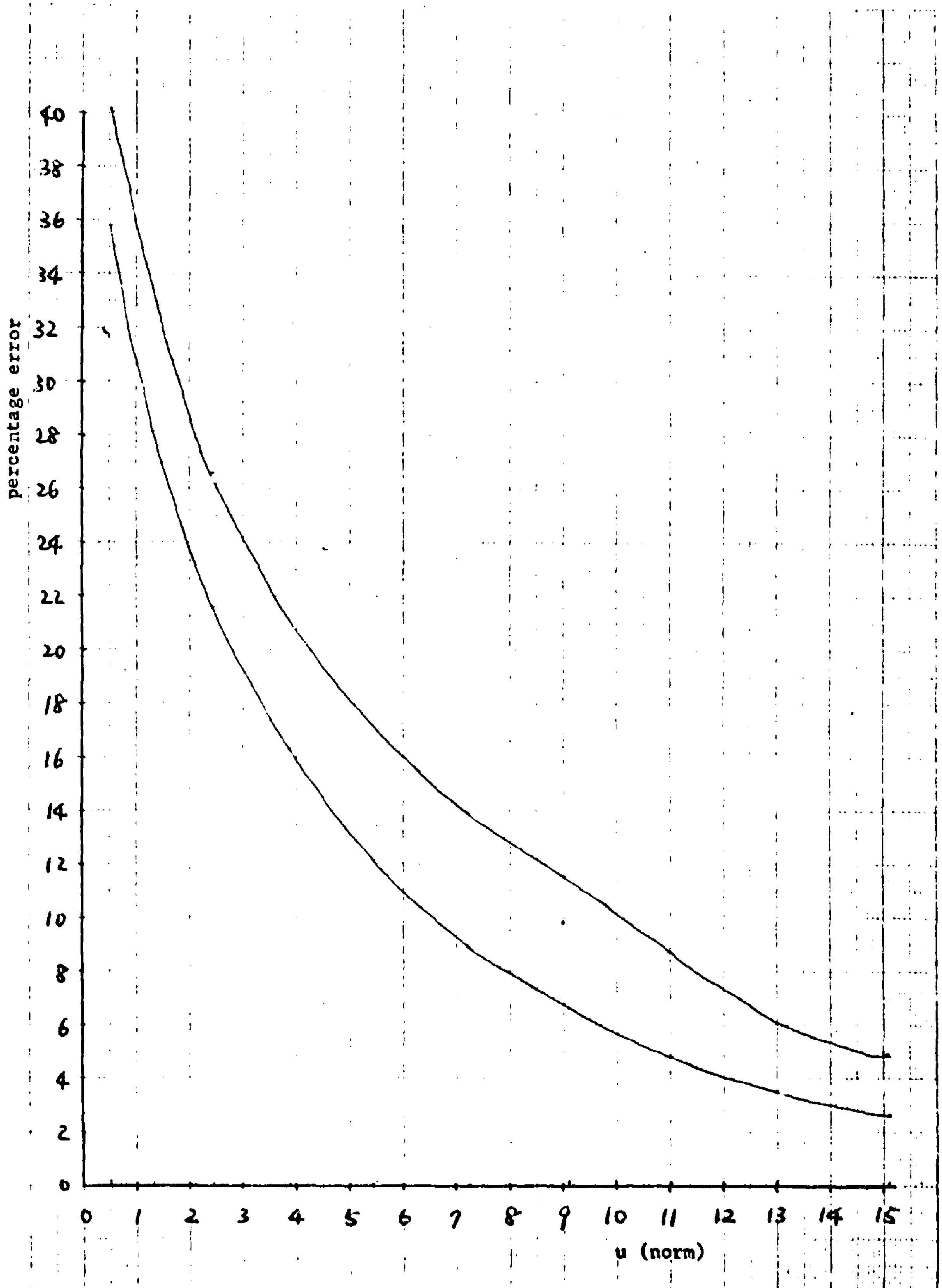
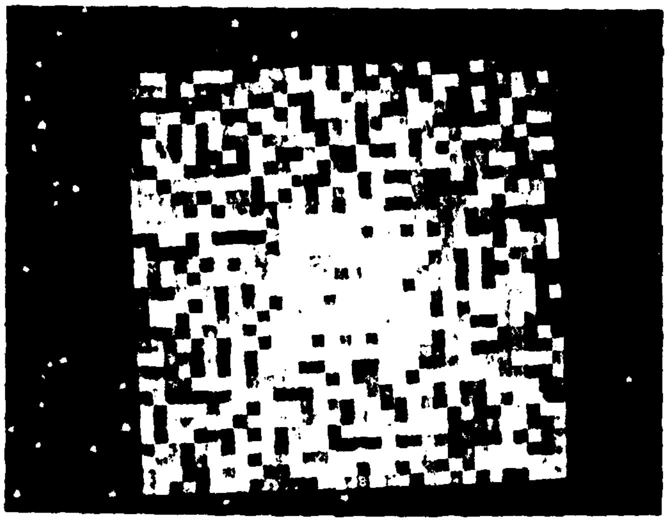
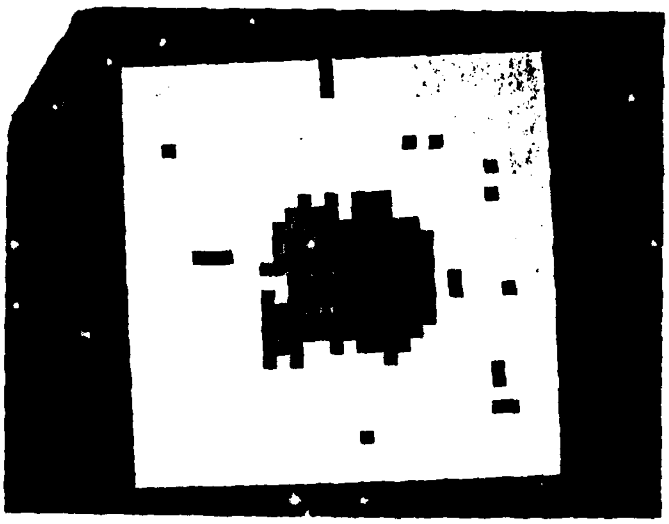


Fig. 1 Experimental and theoretical errors

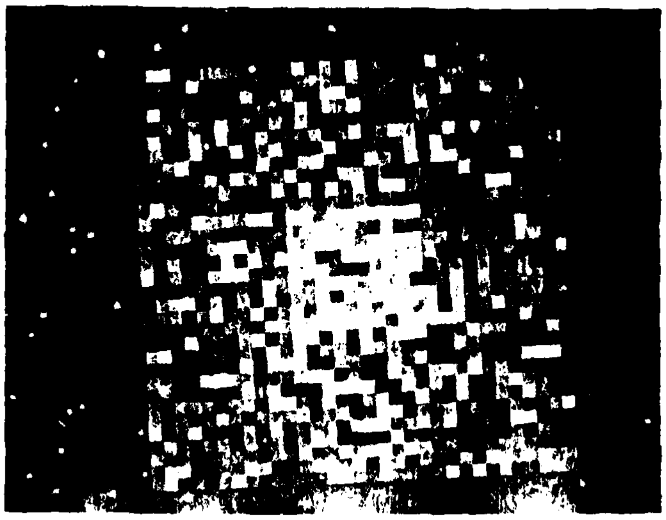


(a) original artificial picture with target (11 x 11) box of N(10,2) and background of N(8,2)

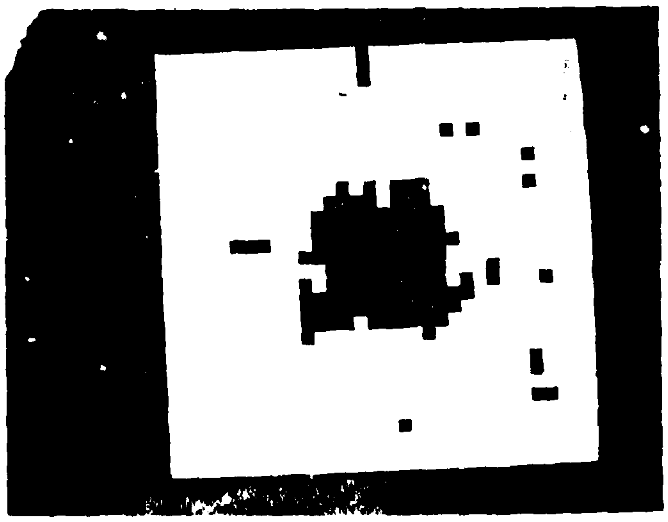


(b) result of using Fisher's linear discriminant, with 10 errors in the target box.

Figure 2

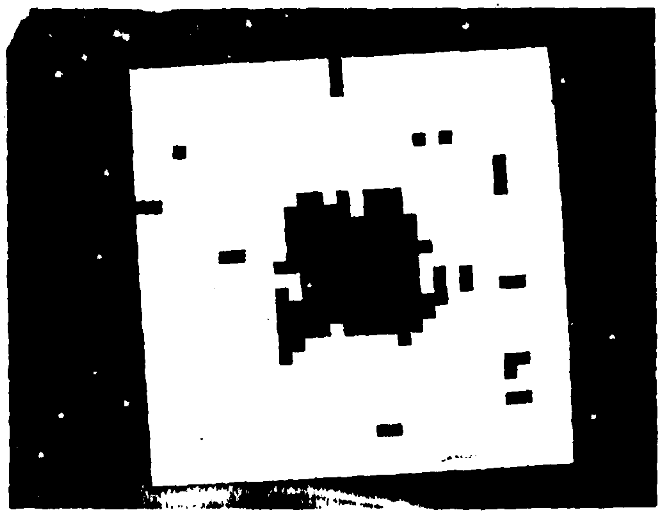


(a) original picture with 10x10 object box

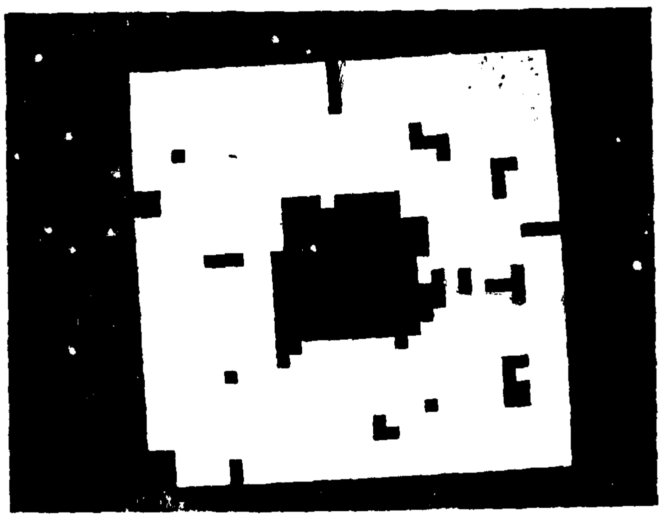


(b) detection result using 100 learning samples

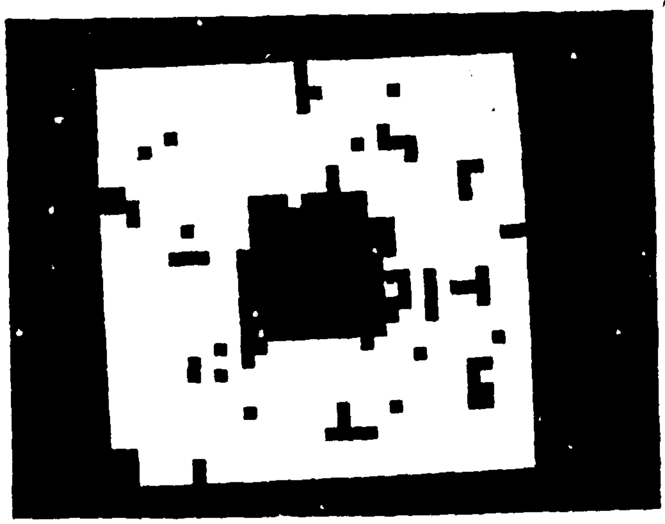
Figure 3



(c) detection result using 64 learning samples

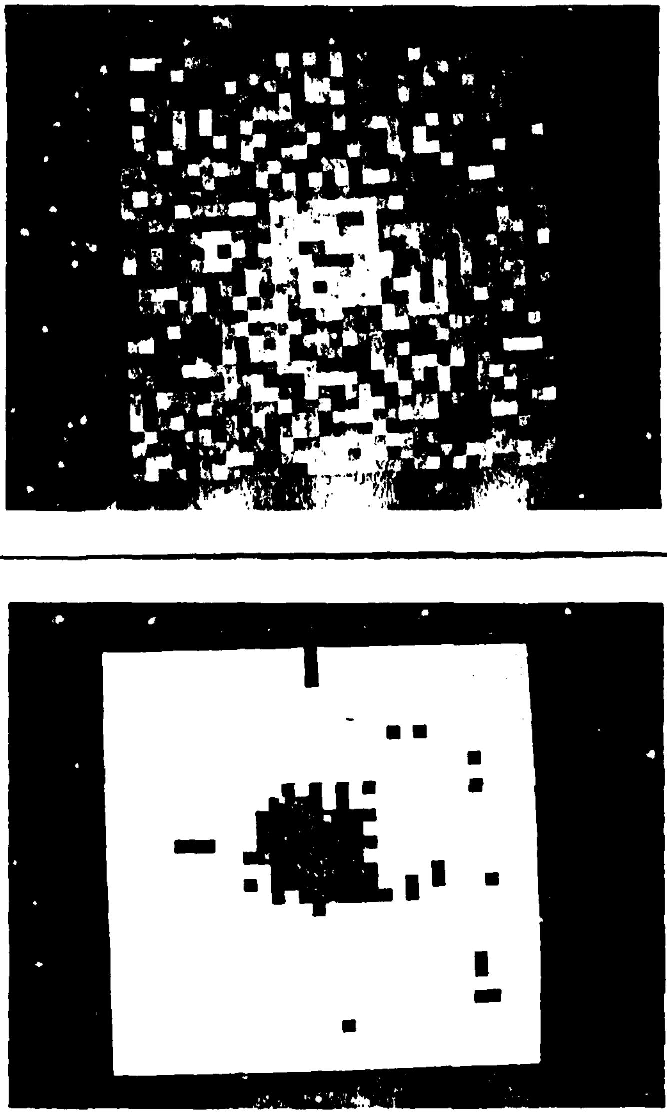


(d) detection result using 36 learning samples



(e) detection result using 16 learning samples

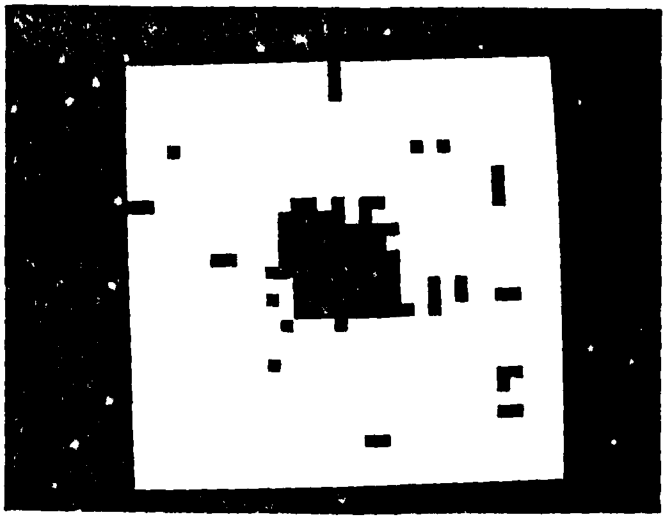
Fig. 3 (continued)



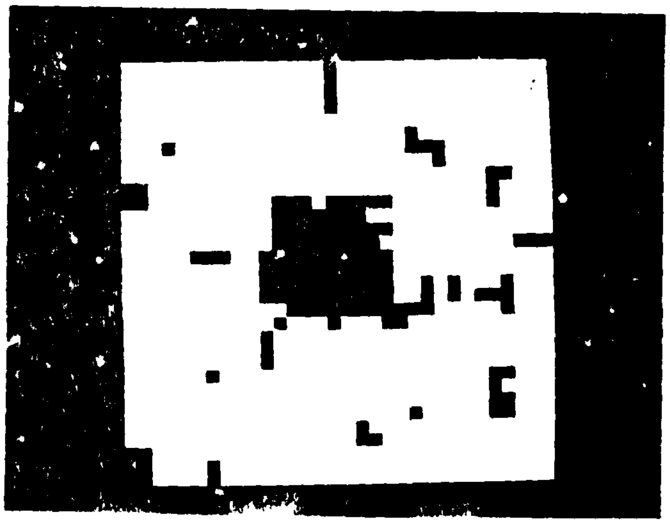
(a) the 32x32 picture with 8x8 object box

(b) detection result using 100 learning samples

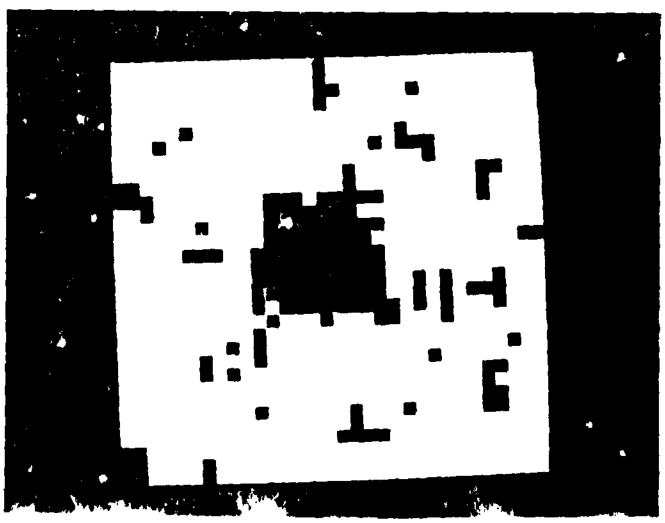
Figure 4



(c) detection result using 64 learning samples

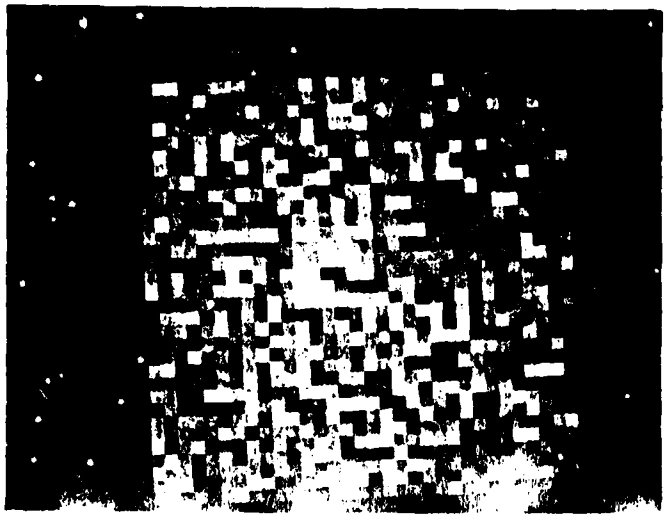


(d) detection result using 36 learning samples

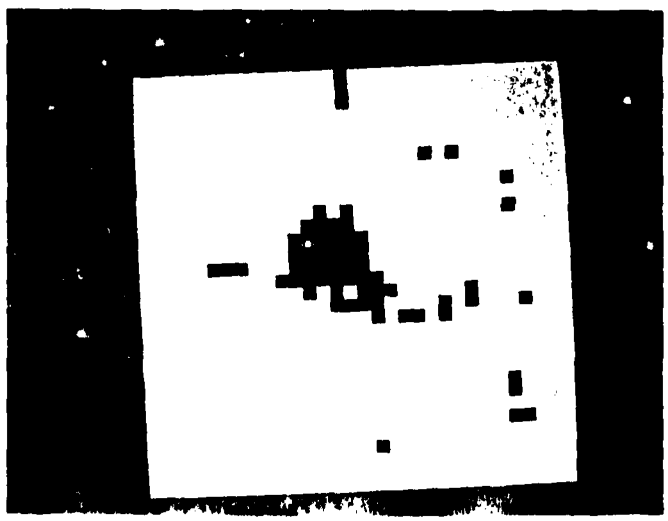


(e) detection result using 16 learning samples

Fig. 4 (continued)

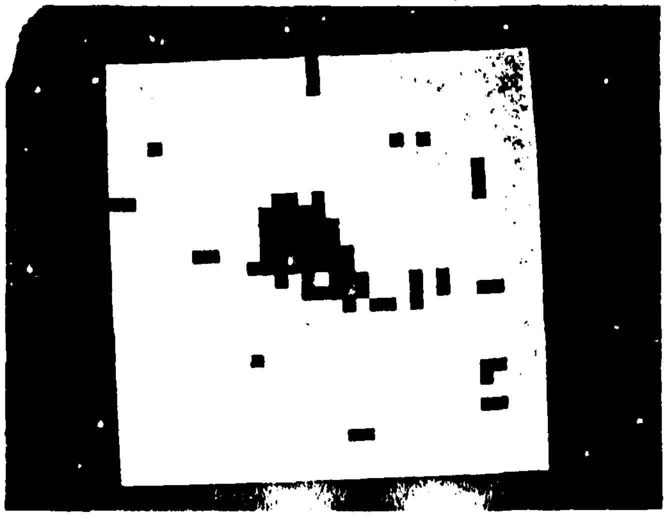


(a) the 32x32 picture
with 6x6 object box



(b) detection result
using 10x10 learning
samples

Figure 5

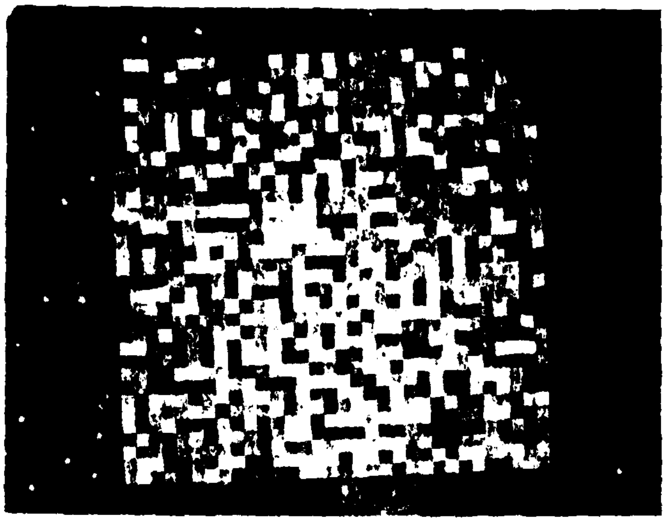


(c) detection result using 64 learning samples

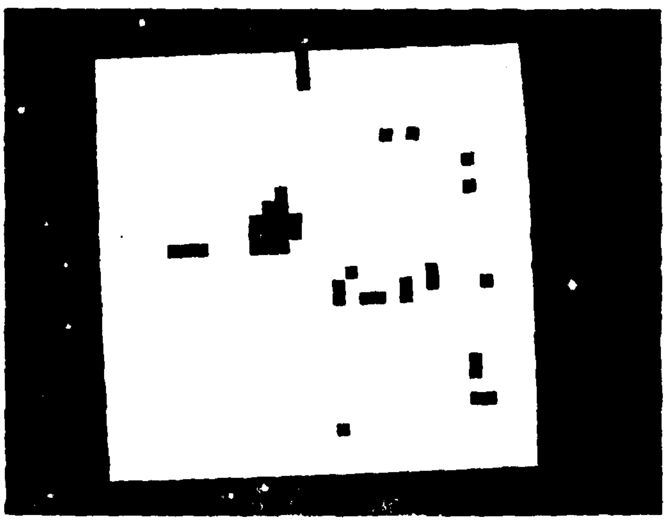
(d) detection result using 36 learning samples

(e) detection result using 16 learning samples

Fig. 5 (continued)

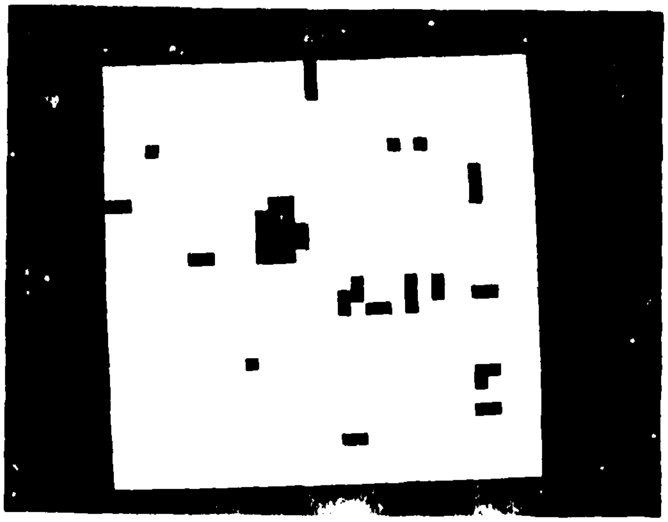


(a) the 32x32 picture with 4x4 object box



(b) detection result using 100 learning samples

Figure 6



(c) detection result using 64 learning samples

(d) detection result using 36 learning samples

(e) detection result using 16 learning samples

Fig. 6 (continued)

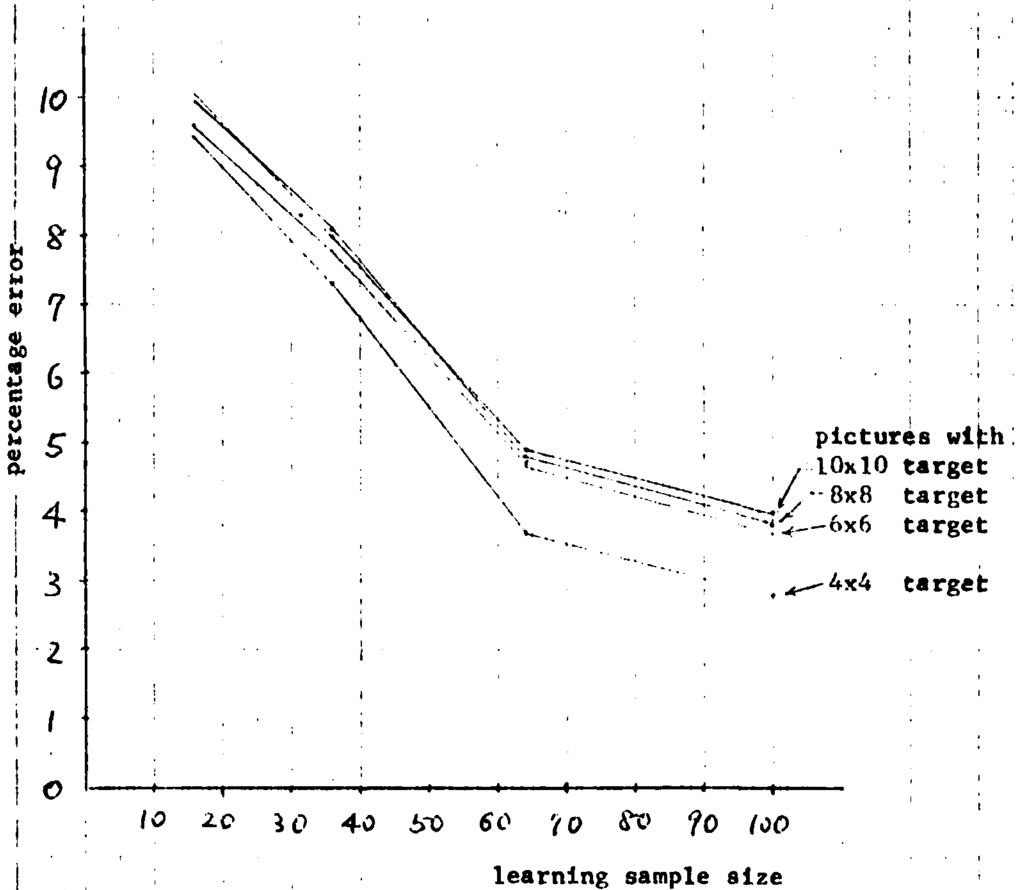


Fig. 7 percentage error versus learning sample size for various target sizes.