A VISION SYSTEM WITH AUTOMATIC LEARNING CAPABILITY FOR INDUSTRIAL PARTS INSPECTION

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ABSTRACT

A vision system for automated parts inspection is proposed. The system is equipped with learning capabilities such that it automatically selects from a set of sample parts a minimum, but effective inspection region within the camera's field of view for parts discrimination. A binary template is formed within the inspection region which is then used for parts inspection by template matching. The inspection speed is enhanced by keeping the inspection region small and by making the matching task uncomplicated. A simple learning algorithm based on statistical pattern recognition theory is employed, which only requires the system to be taught by a training set of good and defective parts without specific defect identification or location. The system is applicable to most 2-D industrial parts inspection.

1. INTRODUCTION

The limitations of traditional human inspection in industrial situations are well-known. Consequently, many automatic visual inspection systems for industrial parts have been proposed and developed.[1-8] The main purposes of these systems include increased production, increased inspection accuracy, and reduced manufacturing costs. However, most inspection systems developed thus far are one-of-a-kind, each capable of only a specific inspection task. When the part to be inspected varies, a new system usually has to be developed. This need arises, in part, because the system is devoid of automated learning capabilities. In this paper we propose a versatile automatic visual inspection system which is adaptible to various parts inspection tasks through self-learning.

In two-dimensional industrial parts inspection tasks, frequently, the criterion for differentiating good and bad parts is the position and the size of some types of defects. Generally, only parts with fairly large defects at specific locations within the parts are rejected. The inherent characteristics of human observers in this kind of inspection task usually result in less than satisfactory accuracy. Thus, the high degree of precision obtainable from analysis of high-resolution images makes it attractive to construct inspection systems using video cameras. A central issue surrounding such systems is the question of how to train the system to ascertain in advance, what, where, and how large are the defects. Moreover, it is highly desirable to equip the system with some degree of self-training (i.e., automated learning).

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In this paper we describe a learning procedure by which the proposed vision system can automatically determine, within the camera's field of view, using a set of good and bad training parts, an inspection region which basically includes all the critical defects. The procedure is intelligent in that it is unnecessary to provide information about defects associated with each part in the training set. This frees the system operator from the need to identify defects during the training stage, as long as all training parts are categorized as good or bad in advance.

An appropriate inspection region also can be formed simply as the union of all the possible defective areas, as done in Perkins.[8] The present system proposes a technique that reduces the size of this roughly-formed inspection region to a minimum, as long as the two sets of good and bad parts can still be discriminated with the minimum Bayes error probability. This reduction is based on statistical pattern recognition theory and is useful for inspection speedup. There is no limit on the number of defects that may appear on a bad part.

2. SYSTEM DESCRIPTION AND INSPECTION PROCEDURE

The system is designed to inspect industrial parts using two-dimensional views. Only binary images are processed. Back lighting is adopted to produce clear parts pictures for image taking with a video camera, and simple thresholding is used to transform gray-valued images into binary ones. Pixels representing background in the binary images are assigned the value 0, while those representing machine parts are assigned the value 1, after thresholding.

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The system's inspection procedure is divided into two stages: the training stage and the operation stage. During the training stage, parts which are already labelled as "good" or "bad," or which can be determined so by an operator, are input into the system for image taking and analysis. There is no need to indicate types, numbers, locations, and sizes, of the defects associated with each input part. The result of the training stage is a minimum-sized inspection region within the image field, according to which all training parts can be discriminated as "good" or "bad" with a minimum error. An inspection template is formed within the inspection region which will be used for parts inspection by template matching in the subsequent operation stage. Based on the inspection template, a match-measure threshold is selected for later use in template matching.

During the operation stage, each part to be inspected is passed through the camera's field of view for image taking and thresholding. The resulting binary picture is then matched with the inspection template, and the number of mismatched pixels is counted and compared with the match-measure threshold for decision making. Parts with the resulting number of mismatched points larger than the threshold are rejected as bad. Since the inspection steps in the operation stage are straightforward, in the following sections we will only describe in detail the training stage.

3. TRAINING STAGE

The training stage can be divided into several steps: image registration and summation, inspection region and template formulation, sample testing and inspection region reduction.

3.1 IMAGE REGISTRATION AND SUMMATION

A basic requirement of the proposed system is that all parts to be analyzed, either in the training stage or in the operation stage, should be properly registered before image taking. Perkins[8] proposed a so-called multisector search technique for parts registration. Other approaches also are possible. For example, jigs with their positions fixed under the camera may be used. Each part to be analyzed can be fed into the jig for position registration before image taking. As it will become clear later, the partial image of a positioning jig will not have any effect on the resulting inspection rate. Necessarily, we assume that the boundaries of training parts labelled "bad" are not so severely damaged that they cannot be positioned stably within the jig. Should such parts appear during the operation stage, they can be declared simply as "bad." This approach is appropriate for those industrial parts made by casting or molding. Another approach is to register parts images by their shapes, especially their boundary shapes. This requires that each bad part be sufficiently undamaged on its boundary that it still can be matched or registered by any boundary matching methods[9] with a reference shape boundary obtained through averaging the images of all the good training parts, or from the technical drawing of a good part. This approach needs further testing.

Now assume all the images of the training parts have been taken, thresholded, and registered. Let the size of each image be I by J, and the number of good parts and bad parts be m and n, respectively. Let M(i,j) denote the pixel value (0 or 1) of an image M at position (i,j). Each pixel with value 1 is said to be an object point;otherwise, it is called a background point. Imagine all the images are 'summed up' and count the following various pixel frequencies for all $1 \le i \le I$, $1 \le j \le J$:

$f_{go}(i,j)$ = total no. of object points at (i,j) in good parts images;
$f_{gb}(i,j)$ = total no. of background points at (i,j) in good parts images;
$f_{do}(i,j)$ = total no. of object points at (i,j) in defective parts images;
$f_{db}(i,j)$ = total no. of background points at (i,j) in defective parts images.

Note that for each (i,j), we have $f_{go}(i,j) + f_{gb}(i,j) = m$ and $f_{do}(i,j) + f_{db}(i,j) = n$.

As an example, the parts shown in Fig. 1 are used to illustrate how good parts and bad parts are determined. The result of the previous summation step is shown in Fig. 2. This example will be continued through this paper to illustrate the steps of the training stage.

3.2 INSPECTION REGION AND TEMPLATE FORMULATION

The main purpose of this step is to select one by one, those 'feature points' useful for discriminating good parts from bad parts and then to generate a template for the matching operation. Obviously, at a point (i,j), where the background or object point is found in all the good parts images and the bad parts images, the information at this point (i,j) becomes useless for parts discrimination and should be ignored. That is, we exclude any point (i,j) with the frequencies satisfying

$$\frac{f_{go}(i,j)}{m} = \frac{f_{do}(i,j)}{n} = 1 \tag{1}$$

or equivalently,

$$\frac{f_{gb}(i,j)}{m} = \frac{f_{db}(i,j)}{n} = 0 \tag{2}$$

from further consideration as a point in the desired inspection region.

Conversely, we may consider each (i,j) of the remaining points as a candidate point in the desired inspection region if the frequency values at this point contain enough information for good and bad parts discrimination. If we regard the binary value at (i,j) as the only feature for discrimination, according to statistical pattern recognition theory[10], then the four terms in Eqs. (1) and (2) are just the conditional probability values with respect to the good and the defective parts "classes" (denoted as g and d, respectively), i. e.,

$$p(x_{ij}=1|g)=\frac{f_{go}(i,j)}{m},\quad p(x_{ij}=0|g)=\frac{f_{gb}(i,j)}{m},$$

$$p(x_{ij}=1|d)=\frac{f_{do}(i,j)}{n},\quad p(x_{ij}=0|d)=\frac{f_{db}(i,j)}{n}.$$

If we assign the value 0 to this point (i,j) for use in the template (i.e., the inspection template has the value 0 at (i,j)) and reclassify all the training parts, good or defective, according to the value at this point (i.e., we consider a part as "good" if it has the value 0 at (i,j)), then exactly $f_{go}(i,j)$ of the originally-labelled good parts will be misclassified as "defective" and f_{db} (i,j) of the originally-labelled defective parts will be misclassified as "good." This results in the following probability of error:

$$E_{ij}(0) = P(g)p(x_{ij}=1|g) + P(d)p(x_{ij}=0|d) = \frac{m}{m+n}\cdot\frac{f_{go}(i,j)}{m} + \frac{n}{m+n}\cdot\frac{f_{db}(i,j)}{n} = \frac{f_{go}(i,j) + f_{db}(i,j)}{m+n} \tag{3}$$

where P(g) and P(d) are the a priori probabilities of the two classes, respectively. Similarly, if we assign the value 1 to the template at position (i,j), then the probability of error will be:

$$E_{ij}(1) = P(g)p(x_{ij}=0|g) + P(d)p(x_{ij}=1|d) = \frac{f_{gb}(i,j) + f_{do}(i,j)}{m+n}. \tag{4}$$

If $E_{ij}(0) < E_{ij}(1)$, obviously we should select 0 as the template value at position (i,j), and then $E_{ij}(0)$ is the Bayes error probability. Otherwise, if $E_{ij}(0) > E_{ij}(1)$, we select 1 as the template value at (i,j) and the Bayes error probability instead is $E_{ij}(1)$. Again, for points where $E_{ij}(0) = E_{ij}(1)$, or equivalently, according to Eqs. (3) and (4),

$$f_{go}(i,j) + f_{db}(i,j) = f_{gb}(i,j) + f_{do}(i,j), \tag{5}$$

we may ignore them (i.e., exclude them from the final inspection region) because they are not useful for parts discrimination. Actually, either (1) or (2) implies (5). In short, we can precisely specify an inspection region R_o and the pixel T_o (i,j) of the corresponding inspection template T_o at each point (i,j) as follows:

$$R_o = \{(i,j) \mid 1 \le i \le I,\ 1 \le j \le J, \text{ and } f_{go}(i,j) + f_{db}(i,j) \ne f_{gb}(i,j) + f_{do}(i,j)\}, \tag{6}$$

and for all $(i,j) \in R_o$,

$$T_o(i,j) = \begin{cases} 0 & \text{if } f_{go}(i,j) + f_{db}(i,j) < f_{gb}(i,j) + f_{do}(i,j). \\ 1 & \text{if } f_{go}(i,j) + f_{db}(i,j) > f_{gb}(i,j) + f_{do}(i,j). \end{cases} \tag{7}$$

Also, define E_{ij} to be

$$E_{ij} = \min\,(E_{ij}(0),\ E_{ij}(1)) \tag{8}$$

which we call the point error probability at (i,j).

Continuing the illustrative example, we show the sums, $f_{go} + f_{db}$ (left-hand side of (5)) and $f_{gb} + f_{do}$ (right-hand side of (5)), in Fig. 3. Values for $E_{ij}(0)$ and $E_{ij}(1)$ are shown in Fig. 4, and the point error probabilities E_{ij} are shown in Fig. 5. The inspection region R_o and template T_o are shown in Fig. 6.

3.3 SAMPLE TESTING AND INSPECTION REGION REDUCTION

The inspection template T_o, obtained in the last step, can be used to match all the training parts to ascertain its utility. We call this step sample testing within the inspection region R_o. The match-measure we use is simply the number of mismatched points. For a given training sample image M, this may be simply and precisely defined as

$$y = \sum_{(i,j)\,\varepsilon R} |M(i,j) - T_o(i,j)|. \tag{9}$$

Matching each training sample image M with T_o results in a y value, which can be considered as a feature extracted out of M. Therefore, after all matchings are done, we can compute the probability densities p(y|g) and p(y|d) for all y values for both classes (good and defective) (see Fig. 7 for an illustration). From these functions and according to statistical pattern recognition, we can determine an optimal decision value y_o with minimum Bayes error probability E_o which we call the picture error probability. E_o is just the overlapping portion of the two conditional density functions as shown in Fig. 7. This error results from the use of R_o and T_o obtained in the last step. Can this error be reduced by changing R_o, or more concretely, by reducing the size of R_o so that template matching is enhanced? Further consideration reveals this is indeed possible, although not always.

Recall that each point (i,j) in R_o has a point error probability E_{ij}, which can be considered as the effectiveness of using (i,j) for class discrimination. In fact, the smaller the value of E_{ij}, the more effective the point (i,j) for discrimination. Therefore, if we delete those points with large E_{ij} values, it is possible that the remaining points could be made more effective for discriminatin, or equivalently, the corresponding picture error probability E_o would become smaller after template matching. Since the frequency values of $f_{go}(i,j)$, $f_{gb}(i,j)$, $f_{do}(i,j)$, and $f_{db}(i,j)$ are discrete with known maximums of m or n, the number of possible E_{ij} values , which can be computed from the frequency values, will be finite. Therefore, we can successively perform a sequence of inspection region reductions, each time simply deleting from the former inspection region R_i (with R_o as the initial one), those points with the largest but identical E_{ij} values, until all points in R_o are deleted. Within the resulting inspection region sequence, there must exist one region, R_N, with the minimum corresponding picture error probability E_N. This means that R_N can be regarded as a set of points which are most effective for parts discrimination. Let T_N be the corresponding template and y_N the optimal decision value (match-measuring threshold), then during the later operation stage, the image of each input part to be inspected is matched with template T_N just within the Region R_N. The part is accepted as good if the resulting mismatch points are fewer than y_N.

As a continuation of the illustrative example, the sequence of inspection regions R_o to R_5 (non "x" points) with reducing sizes, together with their inspection templates T_o to T_5, and probability density function (pdf) diagrams (including the optimal decision values y_i and picture error probabilities E_i) are shown in Figs. 7-12. As can be seen from this sequence of illustrations, when R_o is used as the inspection region, some picture error probability $E_o \neq 0$ is produced. As R_o is reduced to R_4, which includes only the four central points in the 4 x 4 picture, the two sets of parts can be fully discriminated without any error ($E_4 = 0$) at the decision value $y_4 = 1$. The fact that the four middle points alone are sufficient for parts discrimination can be verified by checking the good parts one by one. Each of the good parts includes all four middle points, but none of the bad parts include all four middle points. However, this fact is not obvious at the beginning of the learning stage.

4. LEARNING ALGORITHM

The following learning algorithm is presented to consolidate description of the proposed learning and to facilitate understanding and programming. The notations have already been defined in the previous sections.

Algorithm LEARNING

Input Sample good parts images $G_1, G_2, \ldots, G_m$ and bad parts images $D_1, D_2 \ldots D_n$ with size I x J. All images are assumed to be registered and thresholded. M(i,j) is the binary value of image M at (i,j).

Output Minimum inspection region R_N with corresponding template T_N and optimal match-measure threshold y_N.

Steps (1) "Sum up" all good parts images and count the frequencies $f_{go}(i,j)$ and $f_{gb}(i,j)$ as follows for all $1 \le i \le I, 1 \le j \le J$:

$$f_{go}(i,j) = \sum_{i=1}^{m} G_i(i,j),$$

$$f_{gb}(i,j) = m - f_{go}(i,j).$$

(2) "Sum up" all bad parts images and count the frequencies $f_{do}(i,j)$ and $f_{db}(i,j)$ as follows for all $1 \le i \le I, 1 \le j \le J$:

$$f_{do}(i,j) = \sum_{i=1}^{n} D_i(i,j),$$

$$f_{db}(i,j) = n - f_{do}(i,j).$$

(3) Set up intial inspection region R_o and template T_o according to Eqs. (6) and (7), respectively.

(4) Perform sample testing by matching each sample image M with T_o within R_o and compute the number of mismatches y according to Eq. (9).

(5) Compute optimal decision value y_o and picture error probability, E_o by the following substeps:

(5.1) Let $Y_g = \{y_g^1, y_g^2, \ldots, y_g^K\}$ be the set of all y values for good parts and let $\# y_g^k$ denote the total number of y_g^k values, $1 < k < K$. Note that

$$\sum_{k=1}^{K} \# y_g^k = m.$$

Assume $y_g^i < y_g^j$ if $i < j$, $1 \le i, j \le K$.

(5.2) Similarly, let $Y_d = \{ y_d^1, y_d^2 \ldots y_d^L\}$ be the set of all y values for bad parts with $y_d^i < y_d^j$ if $i < j$, $1 \le i, j \le L$. Let $Y = Y_g \cup Y_d = \{y^1, y^2 \ldots, y^Q\}$ with $y^i < y^j$ if $i < j$.

Note that

$$\sum_{q=1}^{Q} \# y^q = m + n.$$

(5.3) For each $1 \le q \le Q$, compute a corresponding picture error probability E_o^q which results from using y^q as the decision value (i.e., reject a part as bad if its corresponding y value is not less than y^q):

$$E_o^q = \sum_{\substack{1 \le k \le K \\ y_g^k \ge y^q}} (y_g^k/m) + \sum_{\substack{1 \le \ell \le L \\ y_d^\ell < y^q}} (y_d^\ell/n).$$

(5.4) Set the desired picture error probability E_o as

$$E_o = E_o^r = \min_{1 \le q \le Q} E_o^q$$

and the optimal decision value, y_o as y^r.

(6) Perform inspection region reduction by the following substeps:

(6.1) Compute point error probabilities, E_{ij} for all $(i,j) \in R_o$ according to eqs. (3), (4), and (8). Let $E = \{E^1, E^2 \ldots, E^P\}$ denote the resulting set of such probabilities with $E^i < E^j$ if $i < j$, $1 \le i, j \le P$.

(6.2) Associate each $E^p \in E$ with a subregion R^p and a subtemplate T^p:

$$R^p = \{ (i,j) \mid E_{ij} = E^p \},$$

$$T^p(i,j) = T_o(i,j), \ (i,j) \in R^p.$$

(6.3) For t = 1 to P - 1, perform Substeps (6.4) and (6.5) below.

(6.4) Compute $R_t = R_{t-1} - R^t$ as the new inspection region with corresponding new template $T_t(i,j) = T_o(i,j)$ for all $(i,j) \in R_t$.

(6.5) Compute new optimal decision value y_t and picture error probability E_t according to Step (5) above.

(6.6) Find E_s such that $E_s = \min_{o \le t \le p-1} E_t$ and set the desired outputs as follows:

$$R_N = R_s,$$

$$T_N(i,j) = T_o(i,j), \ (i,j) \in R_N,$$

$$y_N = y_s.$$

(7) End.

5. SUMMARY AND DISCUSSION

We have described a computer vision system with learning ability for automated parts inspection applications. The learning algorithm, as illustrated by example, has the capability of selecting the smallest but most effective inspection region within the image field for parts discrimination. This is accomplished by considering each pixel value as a feature, and through a feature selection process that reduces the viable inspection region. The system is versatile and does not require an opeartor to identify defects in the input parts during the learning stage. Because the approach is based on statistical pattern recognition theory, a sufficient number of parts should be supplied for learning so that the final inspection region is reliable. The inspection procedure during the operation stage is relatively untroublesome in that only template matching of binary pictures is required. This greatly enhances the speed of inspection, one of the most important concerns in automated industrial inspection applications.

It should be emphasized that in addition to simplified system operations, the proposed visual inspection system promises to enhance the inspection accuracy and production throughout. Moreover, the system is sufficiently general to be adaptable to a wide range of industrial parts inspection tasks. The proposed learning algorithm should be extendable to gray-valued images as well.

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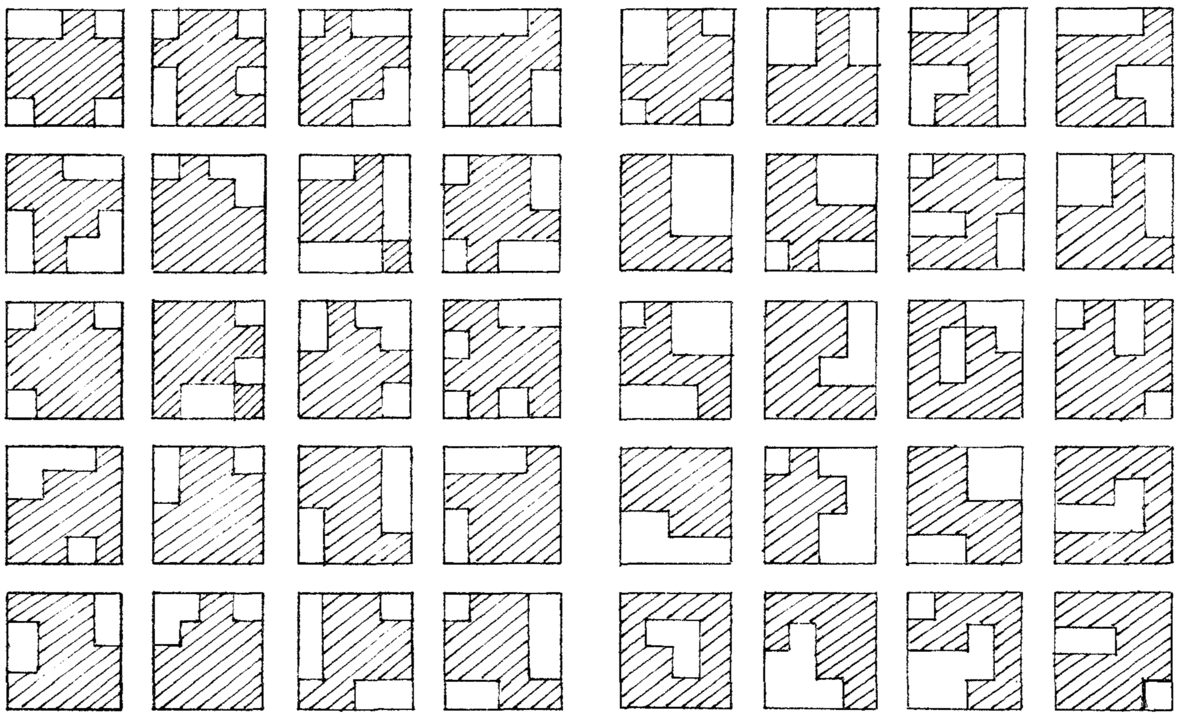


(A) Good Parts (20 Samples)

(B) Bad Parts (20 Samples)

FIG.1 Sample Parts Used For Learning In Training Stage

5	14	12	3
13	20	20	13
12	20	20	12
9	17	12	13

(A) No. of object points in Good Parts

15	6	8	17
7	0	0	7
8	0	0	8
11	3	8	7

(B) No. of background points in Good Parts

10	15	12	8
16	13	12	10
14	13	13	13
12	15	15	11

(C) No. of object points in Defective Parts

10	5	8	12
4	7	8	10
6	7	7	7
8	5	5	9

(D) No. of background points in Defective Parts

FIG. 2 Summation Results

15	19	20	15
17	27	28	23
18	27	27	19
17	22	17	22

(A) Sum of Values in FIG. 2(A) & 2(D)

25	21	20	25
23	13	12	17
22	13	13	21
23	18	23	18

(B) Sum of Values in FIG. 2(B) & 2(C)

Fig. 3 Sums For Discrimination

.375	.475	X	.375
.425	.675	.7	.575
.45	.675	.675	.475
.425	.55	.425	.55

(A) $E_{ij}(0)$ Values

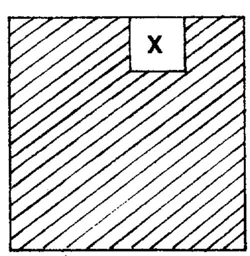
.625	.525	X	.625
.575	.325	.3	.425
.55	.325	.325	.525
.575	.45	.575	.45

(B) $E_{ij}(1)$ Values

Fig. 4 Probabilities of Error Values

.375	.475	X	.375
.425	.325	.3	.425
.45	.325	.325	.475
.425	.45	.425	.45

Fig. 5 Point Error Probability Values

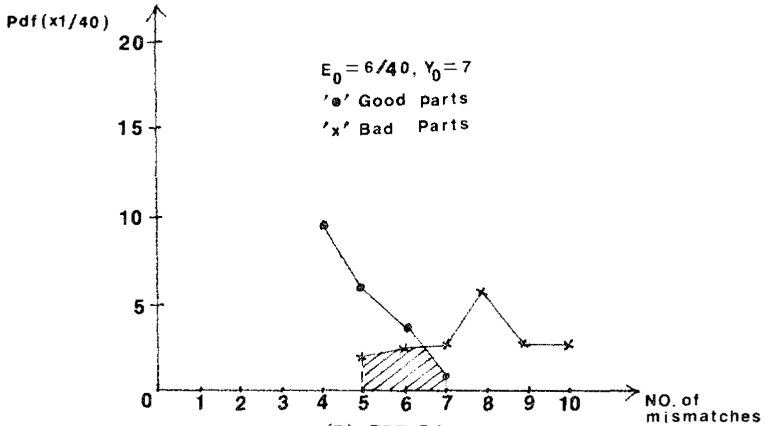


(A) R_0 With One Point (marked X) Excluded

O	O	X	O
O	I	I	I
O	I	I	O
O	I	O	I

(B) T_0 Values

Fig. 6 Initial Inspection Region & Template

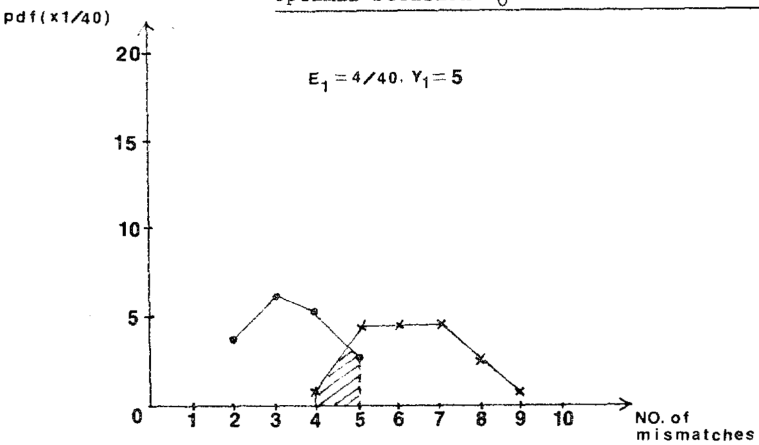


(B) PDF Diagram

O	O	X	O
O	I	I	I
O	I	I	O
O	I	O	I

(A) Inspection Region R_0 and Template T_0

FIG. 7 Sample Testing For $E_{ij} \leqslant .475$ (Picture Error Probability E_0 and Optimal Decision Y_0 Are Shown Above PDF Diagram)

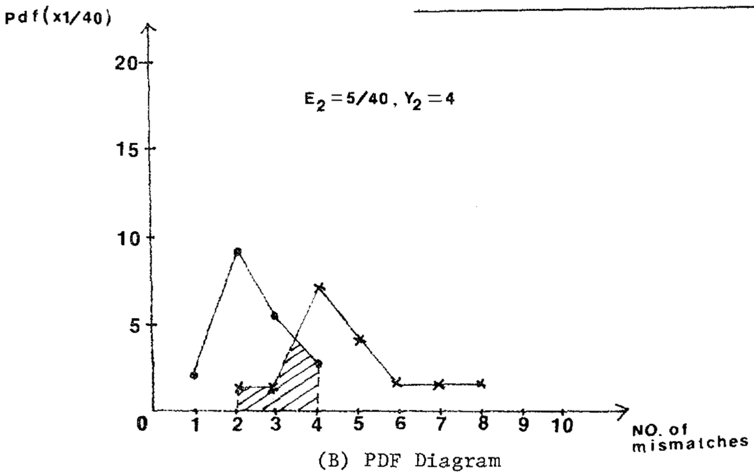


(B) PDF Diagram

O	X	X	O
O	I	I	I
O	I	I	X
O	I	O	I

(A) R_1 & T_1

FIG. 8 Same As FIG.7 Except $E_{ij} \leqslant .45$

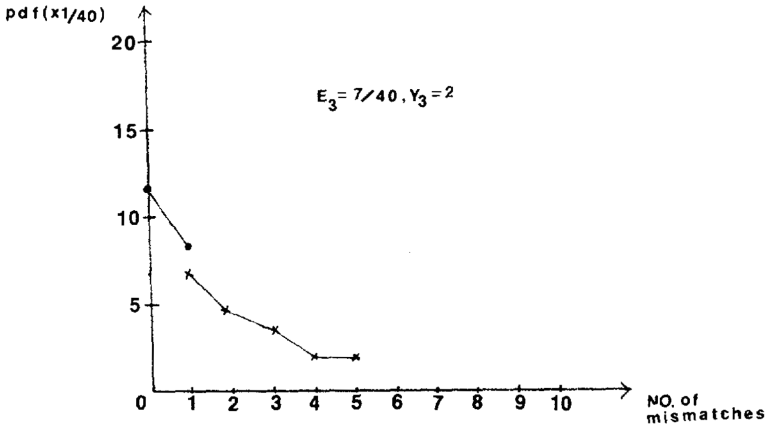


(B) PDF Diagram

O	X	X	O
O	I	I	I
X	I	I	X
O	X	O	X

(A) R_2 & T_2

FIG. 9 Same As FIG.7 Except $E_{ij} \leqslant .425$

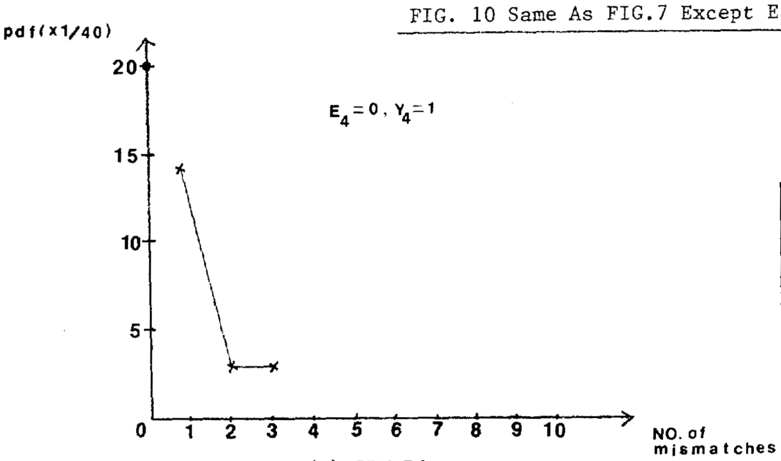


(B) PDF Diagram

O	X	X	O
X	I	I	X
X	I	I	X
X	X	X	X

(A) R_3 & T_3

FIG. 10 Same As FIG.7 Except $E_{ij} \leqslant .375$

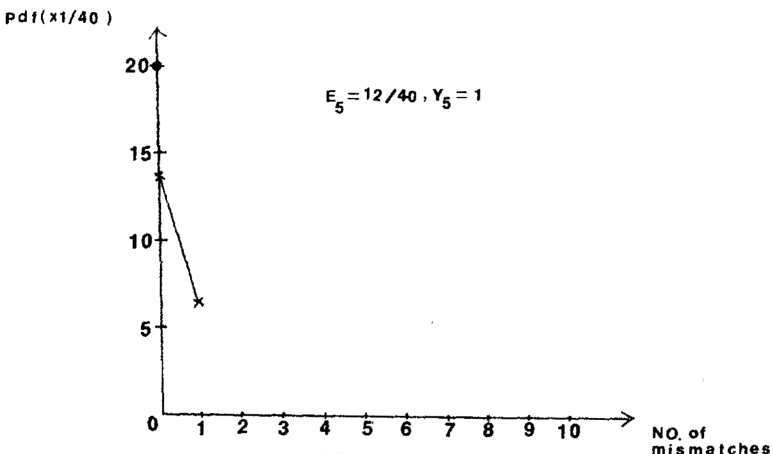


(B) PDF Diagram

X	X	X	X
X	I	I	X
X	I	I	X
X	X	X	X

(A) R_4 & T_4

FIG. 11 Same As FIG.7 Except $E_{ij} \leqslant .325$



(B) PDF Diagram

X	X	X	X
X	X	I	X
X	X	X	X
X	X	X	X

(A) R_5 & T_5

FIG. 12 Same As FIG.7 Except $E_{ij} \leqslant .3$