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ORIGINAL PAPER

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Novel fuzzy test patterns and their application in the measurement of geometric characteristics of displays

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Abstract One of the final steps in a display production line is the image alignment that includes the visual adjustment of the geometric parameters and the color of the image. Measurement of geometric characteristics using machine vision is a necessary function in the automatic alignment of displays' image in the factory. A critical part in the measurement of the geometric attributes is to precisely locate a test pattern position on the display screen. In this paper we introduce novel patterns as fuzzy test patterns and present a novel algorithm to precisely locate the fuzzy test pattern in captured images of the display screen. We experimentally show that the application of the proposed fuzzy test pattern and its associated locating algorithm increases the precision and robustness of the geometric measurements of a display like a TV display. The use of this new measurement method in an auto-alignment system increases the adjustment accuracy, improves the reliability of the alignment system, and improves the quality of images on the display of the adjusted display sets.

Keywords Fuzzy test pattern · Precise localization algorithm · Geometric characteristics of displays · Visual measurement · Sub-pixel edge detection

1 Introduction

There are many practical solutions for automatic precision measurement and inspection that can provide assurance in industrial manufacturing. The use of contact sensors may not be feasible to perform the measurements for some of the parameters [1]. One of the significant non-contact measuring tools are provided by machine vision that can be used to measure observable parameters. The parameters related to the geometric characteristics of a display are among the class of parameters that can only be measured using a vision system.

Obviously, there are some uncertainties and errors in any measurement system which affect the accuracy of the results. The source of uncertainties and errors in visual measurements include the following.

- The displacement of the relative pose between camera and the object under test.
- The quantization error in image digitization.
- Errors due to improper illumination.
- CCD noise.
- A/D converter or video capture noise (that is more sensible in analog frame grabbers) [2].
- The distortion of the camera lens [3].
- Ambient light noise (that is a Poisson process).

Work has been carried out in order to overcome the aforementioned error sources by developing both software and hardware. Edge detection is one of the most widely used visual measurement tools. Edge detection and localization in an image are used for dimensional measurements and localization of objects in industrial applications [4]. In order to obtain accurate edge measurements, it is necessary to determine the location of an edge with a resolution greater than the quantization of the CCD that is at sub-pixel resolution [5].

Up to now, many sub-pixel edge detection techniques such as first derivative algorithm [6–9], second derivative algorithm [9, 10], estimation of derivatives using Gaussian smoothing kernel [11], template matching [12, 13], edge fitting [9, 14], statistical approach [15, 16], analog-based approach [17], moment-based method [5, 18, 19], approximation of geometrical primitives [16, 20] with genetic algorithm [21] or with least square error [19, 22] have been proposed. A series of performance criteria have also been developed to evaluate the accuracy, the quality and the robustness of sub-pixel edge detection methods [2, 23–25].

Previous works that have been carried out to simplify and automate the alignment of the geometric characteristics of displays [26–31] show that the automatic precision

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measurements of the geometrical characteristics of the display's image is a necessary condition for the proper operation of the display alignment.

In this paper, we introduce a new method for the automatic precision measurement of the geometric characteristics of a display. We present a novel fuzzy test pattern and a new algorithm to measure the precise position of the fuzzy test pattern in captured images of the display screen. Among existing methods, Meade and Webb edge fitting method is one of the most accurate test pattern localization techniques [9]. The experimental results of applying a modified version of Meade and Webb method, Steger's method and our proposed fuzzy pattern localization algorithm to find the pattern's position on the TV screen in various states of ambient light and image focus, confirm the superior performance of our proposed method.

2 Fuzzy test pattern

For the measurement of the geometric attributes of a display, we have the freedom to design the shape of the test patterns that are displayed on the display under test. Therefore, using simple shapes in the test patterns, we generally do not need to find the edges of complex shapes on the display screen. Usually, test patterns are created on a dark background. The darkness of the display screen due to the display of a test pattern with a dark background causes the reflection of ambient light from the display screen glass just like a mirror. In order to reduce the reflection effect in captured images using a camera with an auto-iris system, we have designed our test patterns with a set of narrow dark lines on a bright background. Thickness of the pattern's dark lines must be greater than a minimum value since thin lines may be not clearly captured in the images of the display. This depends on the resolution of the camera CCD and the display.

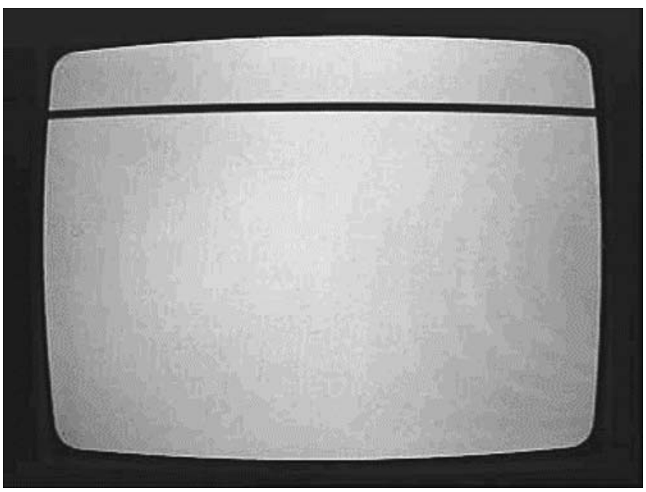

Fig. 1 The captured image of TV screen with a horizontal crisp test pattern for vertical measurements

A test pattern with two gray levels is called a crisp test pattern. In crisp test patterns, one gray level is devoted to background and the other gray level is devoted to foreground. Figure 1 shows a typical crisp test pattern on TV screen that can be used for some vertical measurements.

The average gray level variations in the captured image of Fig. 1 from the top to the bottom of the TV screen are shown in Fig. 2. As can be seen in Fig. 2, the sampling effects of the CCD sensor during the capturing process cause the crisp test pattern that was displayed on the screen lose its original crispness such that it no longer has its original flat bar profile [11].

A fuzzy test pattern includes a set of parallel thin lines (actually more than two) with different gray levels. This set of thin lines altogether forms a thick line. Figure 3 shows an enlarged part of the crisp test pattern and its fuzzy equivalent derived by zooming in.

Our designed fuzzy test pattern is formed on a bright uniform background. We place the aforementioned set of parallel thin lines at the test pattern position. Starting from either side of the created test pattern that is displayed on the

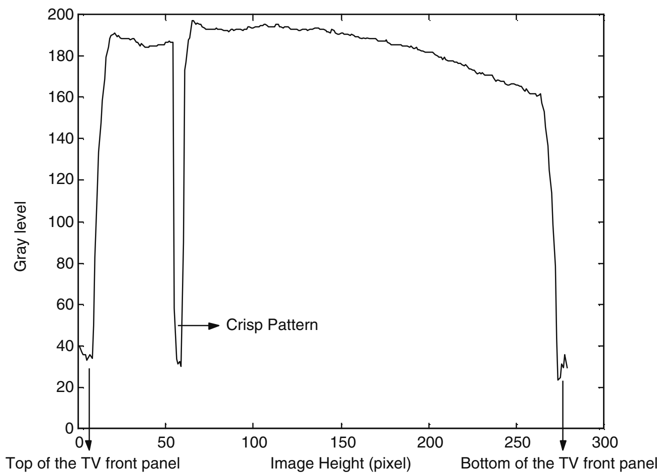

Fig. 2 The average gray level variations (the average profile) of the captured image of Fig. 1 from the top of the TV screen to the bottom

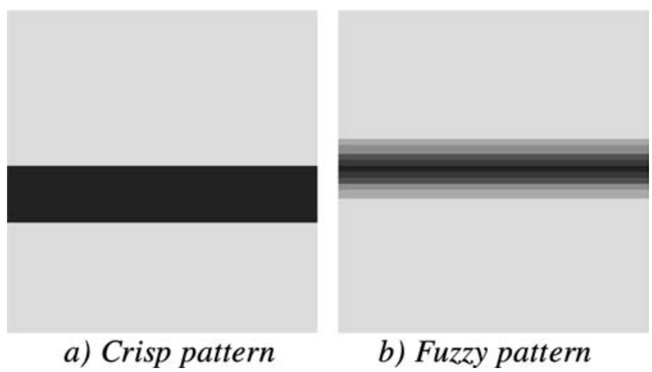

Fig. 3 An enlarged part of the crisp test pattern and its fuzzy equivalent derived by zooming in

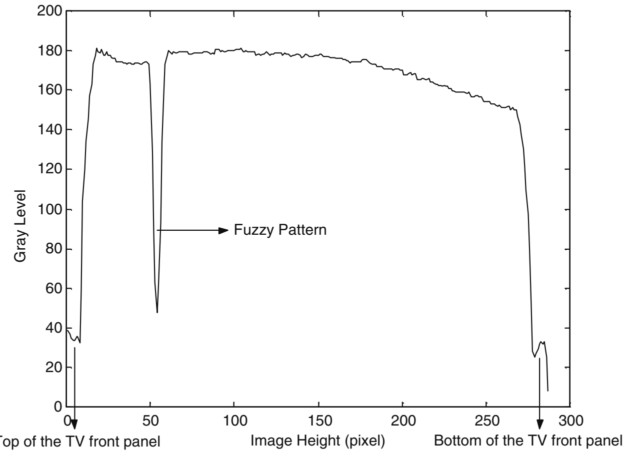

Fig. 4 The average gray level variations (the average profile) of the captured image of a horizontal fuzzy test pattern displayed on TV screen from the top to the bottom

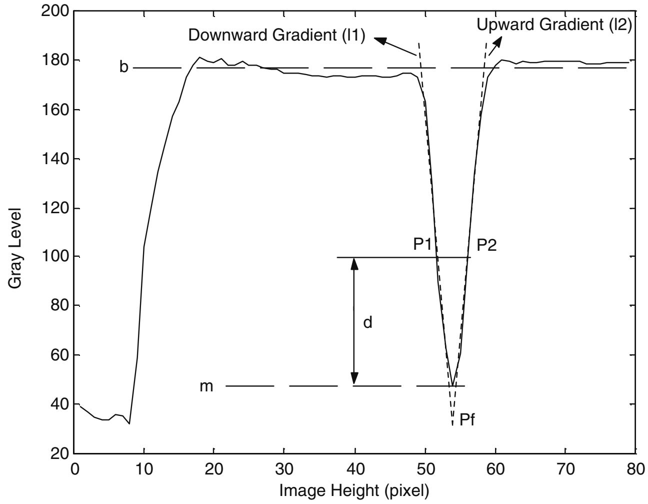

Fig. 5 Details of our proposed localization algorithm for the fuzzy test pattern

screen horizontally and moving across the pattern in the vertical direction, the gray level of the bright background linearly changes to the darkest gray level at the center of the fuzzy pattern position and then it changes back to the bright gray level of the background in a linear fashion. Therefore, the number of gray levels used for creating the fuzzy test pattern is determined by the given width of the pattern. For example, if the width of the fuzzy pattern is w pixels, the number of used gray levels would be $(w + 3)/2$ (w determines the number of used parallel thin lines in the fuzzy test pattern and must be selected as an odd number). The maximum gray level difference between two adjacent pixels in the captured image of our designed fuzzy test pattern is a definite value that is related to the slope of the linear variations of the gray level in the designed fuzzy test pattern. The average gray level variations or average profile of a fuzzy test pattern displayed on TV from the top to the bottom is shown in Fig. 4.

3 Precise localization algorithm for the center of fuzzy test patterns

To find the precise location of the fuzzy test pattern in the captured image of a display screen, we need the average gray level variations or the average profile across the fuzzy test pattern. In order to reduce the intensive computation of the average profile in the whole image, we compute the average profile of the displayed horizontal fuzzy test pattern on several equally spaced vertical lines of pixels across the test pattern in the captured image. On the obtained average profile, we find the pixel with the local minimum as the starting point of our localization algorithm. We take:

$$m = \text{local minimum gray level} \quad (1)$$

$$b = \text{mean value of bright background gray level} \quad (2)$$

Consider Fig. 5 to clarify how our proposed localization algorithm for the fuzzy test pattern works. Next, we use the least-square fit of the line to the points that belong to the upward and downward slopes of the two sides of the local minimum on the average gray level variations (the average profile) diagram of the test pattern. Then on the basis of the slope of the two fitted lines, we obtain the upward and downward gradients of the two sides of the local minimum.

$$g^+ = \text{upward gradient} \quad (3)$$

$$g^- = \text{downward gradient} \quad (4)$$

On the average profile of the fuzzy test pattern, we must find the coordinates of two points $P1$ and $P2$ on the two sides of the local minimum both with the gray levels equal to $(m+b)/2$. On the basis of our empirical results, the value of $(m+b)/2$ corresponds to the minimum variance of the measurement error of the fuzzy test pattern position. Therefore, in order to find the points $P1$ and $P2$, we use interpolation on the coordinates of the points with gray levels just above and below $(m + b)/2$ on the average profile of the fuzzy test pattern.

Finally, we pass a line ($l1$) from the point $P1$ with the slope g^- and similarly pass a line ($l2$) from the point $P2$ with the slope g^+. The position of point P_f that is the intersection of the two lines $l1$ and $l2$ is the precise location of the center of the fuzzy test pattern in the captured image of the display screen.

4 Description of the measurement system

To implement real measurement, we use a High-Sharp color video camera with a resolution of 768 × 576 and a 233 MHz Intel-Pentium PC with two display graphics cards, one used as a test pattern generator and the other used as a user interface. Also, an FPS60 video card with the maximum resolution of 768 × 576 has been installed in the PC as a frame grabber. The experimental results of this paper have been obtained on a 14″ color television set, but this does not reduce the generality of our solution. The PC produces a designed test pattern on the TV screen being tested through the specified graphics card, and then the video camera transfers the image of the TV display through the frame grabber to the measurement algorithm that runs on the PC. All actual measurements in this paper are carried out by capturing at a resolution of 328 × 288.

In the next section, we compare the performance of our proposed fuzzy test pattern localization algorithm with an efficient version of Meade's method [9] for crisp test pattern localization and also with Steger's method [11] to locate both crisp and fuzzy test pattern by the described measurement system.

5 Comparison of experimental results

In order to compare the localization accuracy and the measurement robustness of the test pattern position, we repeatedly applied the crisp and the fuzzy test pattern measurements on the TV display. The sub-pixel edge detection method introduced by Meade and Webb [9] is one of the most precise methods to localize a crisp test pattern on the display screen. In this method, a Taylor series expansion of the intensity around the estimated edge position is used in order to locate the sub-pixel position of the edge. In addition, we examine Steger's method [11] as a precise sub-pixel edge detector to measure the test pattern position. Steger's method applies Gaussian masks to estimate the derivatives of the image and uses the second-order Taylor polynomial to determine the test pattern position with sub-pixel accuracy.

We generate a crisp test pattern with a horizontal dark line and a bright background on the TV display as previously shown in Fig. 1. Test patterns like this are often used to measure vertical attributes of TV displays. Starting from the top side of the screen, Meade's algorithm is applied on several equally spaced vertical lines of pixels across the displayed test pattern on the TV screen in the captured image. Averaging the obtained sub-pixel edge position of the negative edge – from bright pixels to the dark ones – over these vertical lines results in the location of the used test pattern. In order to increase the localization accuracy of this method, we eliminate the classification error points with the least variance criterion called Random Samples Determination with the Least Variance Criterion (RSDLV) introduced by Xu and Wendel [16]. In this way, the exact position of the crisp test pattern in the captured images of the TV display is obtained.

Similarly, we apply Steger's method on the aforementioned equally spaced vertical lines of image pixels and average the obtained sub-pixel edge position to locate the crisp or bar-shaped test pattern in the captured image of the TV display.

We define a separability parameter S_{GP} in order to evaluate the localization precision of a test pattern's position in captured images of the TV display based on the repeatability of the extracted results (i.e. their variance) and their absolute errors [32] as follows:

$$S_{\mathrm{GP}} = \frac{\min_k(|\Delta \mathrm{mp}_k|)}{\max_k(\sigma_k^2)} \tag{5}$$

where

$$\Delta \mathrm{mp}_k = \mathrm{mp}_k - \mathrm{mp}_{k-1}$$

$$\sigma_k^2 = \frac{1}{n}\sum_{i=1}^{n}\left(p_k^i - \mathrm{mp}_k\right)^2$$

$$\mathrm{mp}_k = \frac{1}{n}\sum_{i=1}^{n} p_k^i$$

where

p_k^i

is the measured value of the test pattern position in the ith iteration when the geometrical parameter equals k, k the value of the geometrical parameter GP and n the number of iterations.

The greater value of the separability parameter S_{GP} shows the higher precision in test pattern position measurements. Now, we generate a crisp test pattern on the TV screen like that shown in Fig. 1 and use Meade's method on 20 equally spaced vertical lines of pixels with RSDLV to measure the pattern's position at sub-pixel accuracy. This measurement process is repeated for 60 iterations at a given value of the considered geometrical parameter of the TV under test. Typically, in this paper we consider the vertical size (*V-Size*) parameter – a parameter for adjusting vertical size of the display image – as the varying geometrical attribute of the TV display and repeat the aforementioned measurements for 10 consecutive values of the *V-Size* parameter. The selection of the *V-Size* parameter does not decrease the generality of the experimental results.

Since one of the major performance criteria of an algorithm is the dependence of the extracted features on the input noise level, the measurement results are experimented for different ambient light conditions. Therefore, we have established five different conditions of ambient light including: L1 = 0.2 Lux, L2 = 100 Lux, L3 = 500 Lux, L4 = 1000 Lux and L5 = 10,000 Lux. These illuminances of ambient light for our experimental conditions have been measured approximately. The measurement error in the worst case of the crisp test pattern localizations at 10 consecutive values of the *V-Size* parameter for (a) suitable (L1 = 0.2 Lux), (b) unsuitable (L3 = 500 Lux), and (c) ill conditions (L5 = 10,000 Lux) of ambient light using Meade's method and RSDLV are shown in Fig. 6.

The figure below illustrates the effects of ambient light conditions on the measurement error of the crisp test pattern position in captured images of TV screen. The numerical statistics including mean and variance of the measured crisp test pattern positions for each consecutive value of the *V-Size* parameter in the aforementioned conditions of ambient light using Meade's method and RSDLV are shown in Table 1.

Table 1 The numerical statistics of the measured crisp test pattern position for 10 consecutive values of the V-Size parameter using Meade's method and RSDLV in three different conditions of ambient light

	Value (k)									
V-Size Parameter	0	1	2	3	4	5	6	7	8	9
Suitable conditions of ambient light (L1=0.2 Lux)										
Mean (mp_k)	57.44	56.89	56.24	55.81	55.02	54.45	54.01	53.23	52.78	51.99
Var (σ_k^2)	0.0033	0.0008	0.0009	0.0016	0.0021	0.0015	0.0011	0.0015	0.0045	0.0015
Unsuitable conditions of ambient light (L3=500 Lux)										
Mean (mp_k)	59.31	58.83	58.08	57.54	56.08	56.20	55.64	54.85	54.37	53.72
Var (σ_k^2)	0.0013	0.0011	0.0051	0.0131	0.0038	0.0035	0.0056	0.0043	0.0088	0.0085
Ill conditions of ambient light (L5=10000 Lux)										
Mean (mp_k)	59.11	58.51	57.74	57.21	56.63	55.93	55.46	54.70	53.85	53.37
Var (σ_k^2)	0.0051	0.0032	0.0021	0.0052	0.0040	0.0082	0.0051	0.0065	0.0135	0.0177

Table 2 The separability parameter values of the crisp pattern and the fuzzy pattern methods in three different conditions of ambient light

	(a) Suitable conditions of amb ient light (L1 = 0.2 Lux)	(b) Unsuitable conditions of ambient light (L3 = 500 Lux)	(c) Ill conditions of ambient light (L5 = 10000 Lux)
Crisp test pattern			
Meade's method	96.6	36.3	26.2
Steger's method	73.2	27.9	19.4
Fuzzy test pattern			
Our proposed method	219.9	161.4	134.6
Steger's method	146.0	92.3	67.5

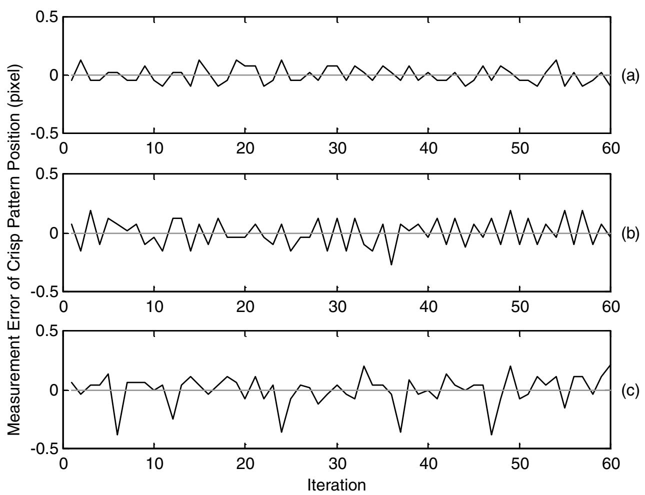

Fig. 6 The measurement errors in the worst case of the crisp test pattern localization for different values of the V-Size parameter in, **a** suitable (L1 = 0.2 Lux), **b** unsuitable (L3 = 500 Lux), and **c** ill conditions (L5 = 10000 Lux) of ambient light using Meade's method and the RSDLV

The values in Table 1 and Eq. (6) are used to compute the separability parameter $S_{V\text{-}Size}$ values of these test pattern position measurements. The results are tabulated in Table 2.

The separability parameter is a measure of detection robustness between two consecutive values of an image geometrical parameter. A small value of the separability parameter displays weakness of resolving and detecting rate between two consecutive values of a geometrical parameter. This shows a low robustness in detecting two consecutive values of a geometrical parameter. The computed values of the separability parameter, therefore, show the weakness of the crisp test pattern localization using Meade's algorithm and RSDLV under various ambient light conditions.

Similarly, we repeat the last experiments using Steger's method on 10 equally spaced vertical lines of pixels to localize the crisp test pattern at sub-pixel accuracy. Using 10 vertical lines of pixels in Steger's method is equivalent to using 20 vertical lines of pixels in Meade's method since Steger's method uses the edges on both sides of the bar-shaped test pattern to determine the test pattern position in captured images, but Meade's method extracts a single edge.

The results of the crisp test pattern localization using Steger's method for (a) suitable (L1 = 0.2 Lux), (b) unsuitable (L3 = 500 Lux) and (c) ill conditions (L5 = 10,000 Lux) of ambient light that are equivalent to the conditions of the last experiments of Meade's method are summarized in the computed values of the separability parameter of the second row in Table 2. The separability parameter values of Steger's method (second row) are smaller than those of Meade's method (first row) and this illustrate preferable measurements using Meade's method.

Now, we repeat our experiments for an equivalent fuzzy test pattern and apply our localization algorithm on the average profile of 10 equally spaced vertical lines of pixels, since our localization algorithm uses the edges on both sides of the fuzzy pattern. The worse case of the fuzzy test pattern localizations at 10 consecutive values of the *V-Size* parameter using our proposed localization algorithm for (a) suitable (L1 = 0.2 Lux), (b) unsuitable (L3 = 500 Lux) and (c) ill conditions (L5 = 10,000 Lux) of ambient light that are equivalent to the conditions of Fig. 6 are illustrated in Fig. 7.

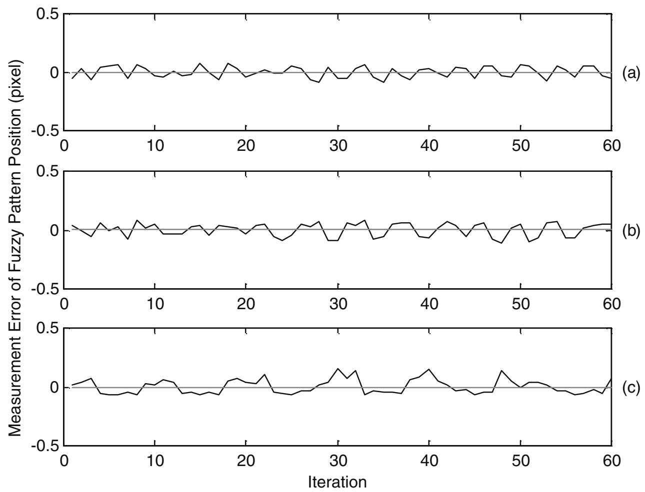

Fig. 7 The measurement errors in the worst case of the fuzzy test pattern localization for different values of V-Size parameter in, **a** suitable (L1 = 0.2 Lux), **b** unsuitable (L3 = 500 Lux), and **c** ill conditions (L5 = 10000 Lux) of ambient light using our proposed localization method

Figures 6 and 7 show the absolute error of the position measurements of the crisp and fuzzy test patterns using Meade's method and our proposed localization algorithm, respectively. It is clear that the absolute accuracy of the position measurements of the fuzzy test pattern is higher than the crisp test pattern.

The numerical statistics including mean and variance of the measured fuzzy test pattern position for each consecutive value of the *V-Size* parameter in the aforementioned three different conditions of ambient light using our proposed localization algorithm are shown in Table 3. Using Table 3 and Eq. (6), the separability parameter values for these measurements can be obtained. The resulted are also tabulated in the third row of Table 2.

Since Steger's method can be applied on parabolic shaped test patterns, we also repeat the last experiments using Steger's method to localize the fuzzy test pattern at subpixel accuracy. The results of the fuzzy test pattern localization using Steger's method in the three conditions of ambient light that are equivalent to the applied conditions of the last experiments are summarized in the separability parameter values of the fourth row in Table 2. In this manner, we have applied two precise localization methods on crisp test patterns and two precise localization methods on fuzzy test patterns.

The values shown in Table 2 show that in every case of ambient light, the separability parameter values of the fuzzy test pattern methods (third and fourth rows) are greater than the separability parameter values of the crisp test pattern methods (first and second rows). Therefore, the measurements of the fuzzy test pattern methods are more precise and more robust than the measurements of the crisp test pattern methods for equivalent conditions of ambient light. In addition, the obtained results clearly display the superiority of our proposed fuzzy test pattern method.

Another useful criterion which proves our claim is the error histogram. The error histogram for $n = 600$ measured samples of test pattern positions using the crisp and the fuzzy methods for five different conditions of ambient light are shown in Figs. 8 and 9, respectively.

Increasing the ambient light disturbance gradually from L1 to L5, the measurement error histograms of the crisp and the fuzzy test pattern methods are widened and the measurement error variances are increased. Comparing the measurement error histograms and variances of the crisp pattern methods (Fig. 8) and the fuzzy pattern methods (Fig. 9), we can see that the measurement results of the fuzzy test patterns are better than those of the crisp test patterns. Also, it is obvious from Figs. 8 and 9 that the measurement performance of our fuzzy pattern method under different conditions of ambient light is better than the other applied crisp and fuzzy pattern methods.

In addition to the last experiments, we repeat the comparison of the fuzzy test pattern and the crisp test pattern measurements for various states of image focus. In order to create equivalent conditions in measurement experiments, we define five definite states of image focus F1 through F5. F1 corresponds with complete focus while F5 corresponds with the blurriest used state. States F2, F3 and F4 equally partition the space between states F1 and F5. The separability parameter values in three states of image focus for the crisp test pattern using Meade and Steger methods are

Table 3 The numerical statistics of the measured fuzzy test pattern position for 10 consecutive values of the V-Size parameter using our proposed method in three different conditions of ambient light

	Value (k)									
V-Size Parameter	0	1	2	3	4	5	6	7	8	9
Suitable conditions of ambient light (L1=0.2 Lux)										
Mean (mp_k)	57.75	57.15	56.57	56.01	55.46	54.87	54.25	53.64	53.03	52.49
Var (σ_k^2)	0.0016	0.0016	0.0016	0.0012	0.0011	0.0015	0.0025	0.0019	0.0014	0.0009
Unsuitable conditions of ambient light (L3 = 500 Lux)										
Mean (mp_k)	59.86	59.26	58.67	58.11	57.51	56.96	56.31	55.72	55.09	54.56
Var (σ_k^2)	0.0008	0.0022	0.0023	0.0015	0.0017	0.0016	0.0033	0.0016	0.0014	0.0013
Ill conditions of ambient light (L5 = 10000 Lux)										
Mean (mp_k)	59.86	59.32	58.73	58.18	57.60	57.01	56.37	55.75	55.14	54.58
Var (σ_k^2)	0.0025	0.0022	0.0034	0.0008	0.0007	0.0011	0.0040	0.0020	0.0032	0.0019

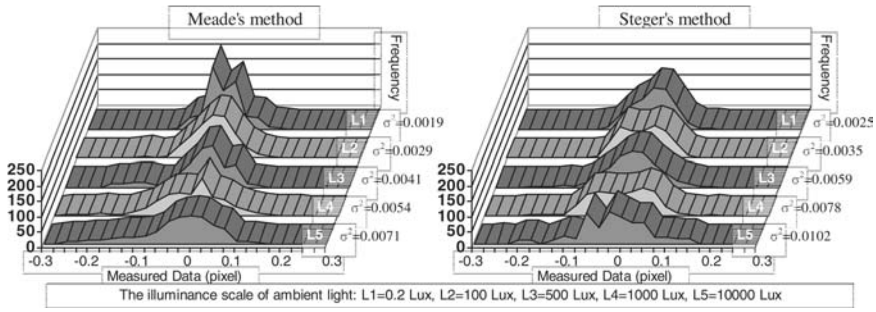

Fig. 8 The measurement error histograms of the crisp test pattern position using Meade and Steger methods in five different conditions of ambient light disturbances which gradually increase from L1 to L5

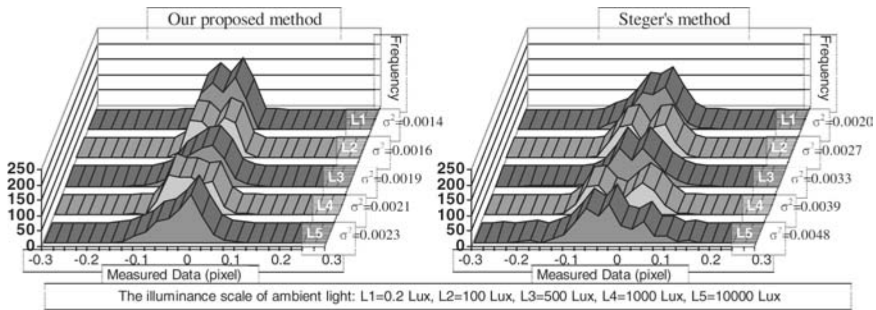

Fig. 9 The measurement error histograms of the fuzzy test pattern position using our proposed and Steger methods in five different conditions of ambient light disturbances which gradually increase from L1 to L5

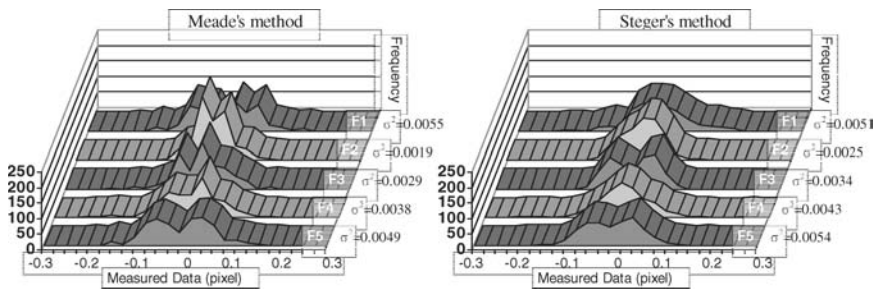

Fig. 10 The measurement error histograms of the crisp test pattern position using Meade and Steger methods in five different conditions of image focus which the complete focus gradually degrades from F1 to F5

shown in the first and second rows of Table 4, respectively, and those for the fuzzy test pattern using our proposed and Steger methods are shown in the third and fourth rows of Table 4, respectively. A small deviation from the complete focus situation (F2) operates as a smoothing optical filter by eliminating the discrete pixels of the display screen in the captured images. Moreover, it can be seen that the best results are obtained in the near complete focus condition for all methods. In all focus conditions, the fuzzy test pattern measurements indicate that we have better results than when using the crisp test pattern methods and the best measurement results belong to our proposed localization algorithm for fuzzy test patterns.

Table 4 The separability parameter values of the crisp pattern and the fuzzy pattern methods in three different status of image focus

	(a) Complete focus = F1	(b) Near complete focus = F2	(c) Blur = F5
Crisp test pattern			
Meade's method	30.2	94.7	59.9
Steger's method	57.4	72.2	52.7
Fuzzy test pattern			
Our proposed method	108.2	231.8	132.0
Steger's method	91.0	168.4	85.7

The error histograms of $n = 600$ measured samples of test pattern position using the crisp and the fuzzy methods for five different states of image focus from (F1) complete focus to (F5) the blurriest used state are shown in Figs. 10 and 11, respectively. These measurement error histograms also verify the advantage of our proposed fuzzy pattern method.

The ambient light of a manufacturing house varies at different times during production. On the other hand,

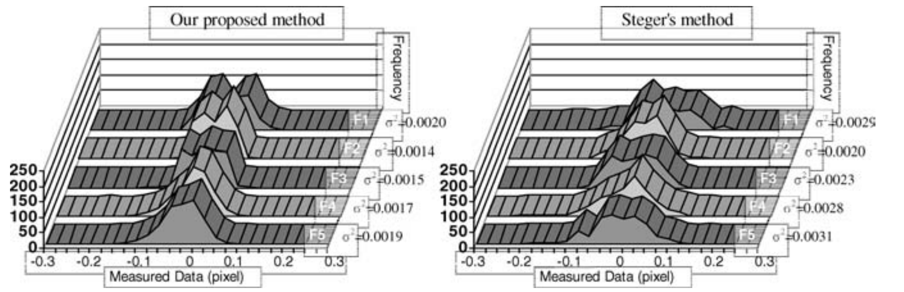

Fig. 11 The measurement error histograms of the fuzzy test pattern position using our proposed and Steger methods in five different conditions of image focus which the complete focus gradually degrades from F1 to F5

varying distances of display screens on the production line from a fixed camera viewpoint introduce uncertainties in the accurate focus of the camera lens. Therefore, the different conditions of ambient light and image focus are critical issues when evaluating the performance of automatic measurements algorithms.

Comparing the experimental results including the separability parameter values and the measurement error histograms of the four applied methods under different conditions of ambient light and image focus imply that our proposed localization algorithm for fuzzy test patterns is more precise and robust than the other test pattern localization methods. The time consumed by the measurement process for our fuzzy test pattern localization algorithm is 110 ms, for Meade's localization algorithm is 155 ms and for Steger's localization algorithm is 175 ms on our platform. So, the speed of the measurement process of our localization algorithm for fuzzy test pattern is approximately 1.4 times that of the speed of Meade's localization algorithm and 1.6 times that of the speed of Steger's localization algorithm. All algorithms were efficiently programmed in C++ and were run on the same platform to make these comparisons.

6 Conclusions

In this paper, we have introduced a novel type of test pattern as fuzzy test patterns which can be useful in designing the geometrical measurement algorithms of a display auto-alignment system. Also, we have proposed a new precise localization algorithm for fuzzy test patterns in captured images of the display screen. Our fuzzy test pattern localization method has been compared on real images with a modified version of Meade's localization algorithm for crisp test patterns and with Steger's localization algorithm for crisp (bar-shaped) and fuzzy (parabolic-shaped) test patterns under different states of ambient light and image focus.

The experimental results show that our proposed measurement algorithm for fuzzy test pattern position on the display screen is more precise and robust than the other used localization algorithm for crisp and fuzzy test patterns that are some of the most efficient methods in bar-shaped and parabolic-shaped test pattern localization. This paper indicates that the use of fuzzy test patterns increases the repeatability of the extracted results and decreases their absolute measurement errors in various levels of input noise.

Finally, the application of our proposed fuzzy test pattern method to measure a display geometrical attributes in an auto alignment system increases the alignment reliability and the quality of the displays coming out of the factory.

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