

The Research of Automatic Registering Detection of Rotary Screen Printing Machine Based on MeanShift and Fast Block-Matching Algorithm

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Abstract—With the register detection problem, the color textile image segmentation algorithm based on MeanShift and the block matching algorithm based on Harris corner detection were proposed. The extended MeanShift algorithm was used to segment the textile image, and then different color regions were extracted from the segmented standard image; then the feature points were detected by Harris operator, and with these feature points as the centers, the standard matching blocks were selected; finally the best matching block in the dealt target image were found to calculate register errors. The experiment results show that MeanShift algorithm is not sensitive to the texture of the fabric image, so the algorithm is good for the segmentation of it. And the matching accuracy and speed are improved, because the feature block-matching algorithm combines the point pattern matching with the feature matching algorithm. The research in this paper will lay the foundation for the closed-loop control of online register detection.

Index Terms—rotary screen printing, registering detection, MeanShift, Harris, matching

I. INTRODUCTION

The registering accuracy is a key factor which affects the fabric printing quality. In order to guarantee the printing accuracy, and to ensure that there is no off-pattern appearance, all cylinders of rotary screen printing machine must keep the same pace with the conduction band precisely. In the actual production process, as the rotary screen printing machine is affected easily by the wear of transmission parts, gear loose and fabric deformation and other factors, the relative position between the cylinders and the bands changes easily. And if it is not adjusted timely, the off-pattern phenomenon will appear. To solve this problem, the manufacturers of rotary screen printing machine at home and abroad, do continuous improvements on the textile registering link.

Most of the strategies they take are about the improvement of the mechanical structure and updating of electrical actuators; or detecting the register error by color mark method [1]. Overall, to this problem, it still remains in the manual judgment and adjust phase, and the closed-loop control has not been implemented [2].

In recent years, the on-line detection systems based on machine vision are widely applied in industry. If the auto-registering detection system based on machine vision [3], [4], [5], replaces the manual detection, it will not only eliminate the human subjective errors and improve registering accuracy, but reduce the labour burden, raise the per unit quality and productivity. In Ref.[6], a theoretical model of rotary screen printing machine automatic registering detection system based on machine vision was presented, but the specific image processing algorithms were not given. In Ref.[7], the print pattern location information was extracted by hardware and was compared with the standard image, and the error information was got; but in most cases it is very difficult to extract out the complete print pattern. In this paper, the MeanShift algorithm with strong adaptability was used to segment the color printing and dyeing textile image with texture noise, and the block matching algorithm based on Harris corner detection was used to match the standard and target image.

II. ROTARY SCREEN PRINTING MACHINE AUTOMATIC REGISTERING DETECTION SYSTEM BASED ON INTELLIGENT CAMERA

The non-contact automatic registering detection system based on machine vision was put forward, combined technological process of rotary screen printing machine with the requirements of detection accuracy 0.1 mm. The system uses image processing technology to analyse and process the printing and dyeing textile image [8], and get the register error; and it provides real-time feedback data for the closed-loop control. The system mainly consists of optical imaging part, image acquisition and processing

Project number: 11JK0910

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part, and communication interface part. The structure diagram of the system is as follows:

The installation is as follows Fig.1. The light source 1 and visual sensor 2 is placed above the region which is behind the last the cylinder in the forward direction of the conduction band of rotary screen printing machine. The position control and detection device 4 is mounted on the rolling roller, and drive the roller rolling, and count the pulses according to the rotating location.

When the rotary screen printing machine started working, it adjusts the position and speed of each cylinder. When the speed of the conduction band and the relative position between the cylinders and the bands is adjusted well and there is no off-pattern appeared, the location of the pattern on the fabric is unchanged. The CCD camera 2 is mounted on the fixed point above the conduction band. When the conduction band carrying the fabric runs across the entire times of take back, the device 4 sends the trigger signal to the PLC, and PLC generates trigger pulse and sends it to the smart camera to acquire image. And then the smart camera calls the image processing procedure stored inside to do chromatic segmentation, extract and match each topping, and to calculate the error and compare it with the threshold seted before, and at last, to adjust the rotary screen or the conduction band according to the result.

III. MEANSHIFT ALGORITHM INTRODUCTION

MeanShift algorithm is an effective iterative clustering algorithm based on feature space, which was originally proposed by Fukunaga and others in 1975[9],[10]. MeanShift algorithm does analysis entirely depending on the sample points in feature space, and do not need to artificially set too many parameters. It is not sensitive to texture of the image, so it has a strong adaptability. In this paper, the extended MeanShift algorithm was used to segment the fabric image. It segment the fabric image well, combining the colour and spacial feature clustering.

The basic form of algorithm:

$x_i, i=1,2,3,\dots,n$ is n sample points in d -dimensional space R^d , and the basic form of the MeanShift vector on the x point can be defined as following:

$$M_h(x) = \frac{1}{k} \sum_{x_i \in S_h} (x_i - x) \tag{1}$$

In equation (1), S_h is a high-dimensional ball area with the radius h , and it is the collection of y -points meeting following condition.

$$S_h(x) = \{y : (y - x)^T (y - x) \leq h^2\} \tag{2}$$

In equation (2), among the n sample points $\{x_i\}$, there are k points in the area of S_h .

In equation (1), the MeanShift vector $M_h(x)$ is the average value of all the k sample points offset vector to x . $(x_i - x)$ is the offset vector of the sample point x_i to x . If the sample points x_i is sampled from a probability density function $f(x)$, the sample points within the region S_h will

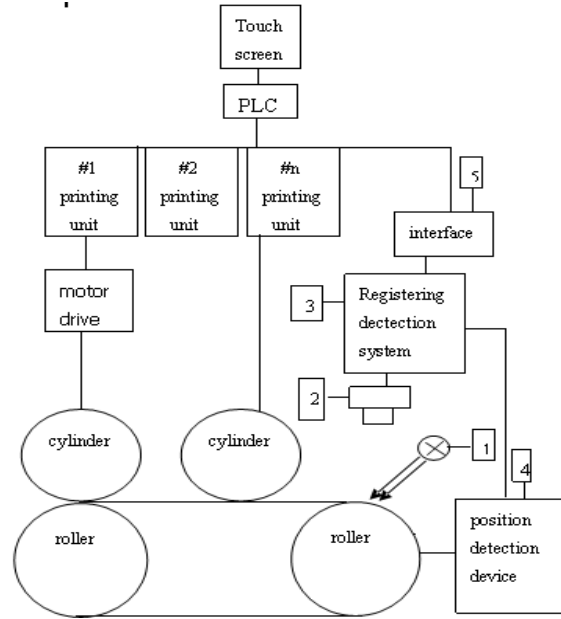


Figure 1. The diagram of printing image detection system

be more possibly along the gradient direction, as the non-zero probability density gradient points to the direction of the probability density largest increase. So the corresponding MeanShift vector $M_h(x)$ should point to the direction of the probability density gradient.

The extended MeanShift vector is as follows:

$$M_h(x) = \frac{\sum_{i=1}^n G(\frac{x_i - x}{h}) w(x_i) (x_i - x)}{\sum_{i=1}^n G(\frac{x_i - x}{h}) w(x_i)} \tag{3}$$

that is:

$$M_h(x) = \frac{\sum_{i=1}^n G(\frac{x_i - x}{h}) w(x_i) x_i}{\sum_{i=1}^n G(\frac{x_i - x}{h}) w(x_i)} - x \tag{4}$$

order:

$$m_h(x) = \frac{\sum_{i=1}^n G(\frac{x_i - x}{h}) w(x_i) x_i}{\sum_{i=1}^n G(\frac{x_i - x}{h}) w(x_i)} \tag{5}$$

In equation (3),(4),(5) above, $G(x)$ is a unit kernel function. Unit uniform kernel function and Epanechnikov kernel function are as follows:

$$F(x) = \begin{cases} 1 & \text{if } \|x\| < 1 \\ 0 & \text{if } \|x\| \geq 1 \end{cases} \tag{6}$$

$$K_E(x) = \begin{cases} C_E (1 - \|x\|^2)^2 & \text{if } \|x\| \leq 1 \\ 0 & \text{if } \|x\| > 1 \end{cases} \tag{7}$$

In equation(7), C_E is a constant to ensure $\int_{R^d} |K_E(x)| dx = 1$ achieved.

From (1)~(3), h is a window width parameter which is greater than zero, $w(x_i) \geq 0$ is the weight assigned to the sampling points x_i . The reason why the introduction of the weight $w(x_i)$ of the sampling points x_i is that as long as the sampling points are into S_h , the nearer to x , the greater impact on the statistical characteristic of estimating x .

The estimate relationship about MeanShift vector and density gradient is as follows:

$$m_{h,g}(x) = \frac{1}{2} h^2 c \frac{\hat{\nabla} f_{h,k(x)}}{\hat{f}_{h,G(x)}} \quad (8)$$

In equation(8), $c > 0$, $g(x)$ is the profile function of the kernel function $G(X)$. At the x -point, MeanShift vector calculated by a kernel function $G(X)$ and the density gradient estimate calculated by a standardized kernel function $K(X)$ are proportional. Therefore, this vector points to the density increase direction. Here the standardization was calculated through the probability density estimate being calculated by the kernel $G(X)$. As MeanShift vector $m_{h,g}(x)$ moves to the density increased direction, the moving step may changed. When the density is small, the step is long; and when the density is big, closer to the peak, the step is short. Under the certain condition, MeanShift algorithm will converge to the peak near x point. The Fig.2 is about the searching process of MeanShift algorithm.

IV. MEANSHIFT ALGORITHM USED TO SEGEMENT THE TEXTILE IMAGE

A. MeanShift Image Filtering

$x_i, i = 1, \dots, n$ can be used to present n pixels in a color printing image. Start from a certain pixel point $x_j (j \in (1, n))$, calculate the MeanShift vector $m_{h,g}(x)$, and then move kernel vector $G(x)$ in accordance with this vector. According to the nature of MeanShift algorithm, $m_{h,g}(x)$ will eventually converge to a local maximum density point, which is marked as mode. All points through the testing process are recorded to be related to the mode. Their values can be changed required by the cluster. That is, the value of the mode is assigned to it, and the process is just a filtering. In the processing of MeanShift iteration to the remaining pixel points, if a pixel's projection coordinate coincides with that of the pixel recorded by the mode before, the iteration will be stopped, and the pixels in the iterative process will be recorded by the mode mentioned before. During a new iterative, if no pixel coincides with that recorded before, but finally converges to another pixel, then a new mode point is found, as shown in Fig. 2.

In order to get a better understanding the role of kernel function $G(x)$ in the MeanShift iterative process, we use $\{y_j\} j = 1, 2, \dots$ to present a series of center position during the moving of $G(x)$. According to MeanShift expression [3], the equation (9) can be achieved:

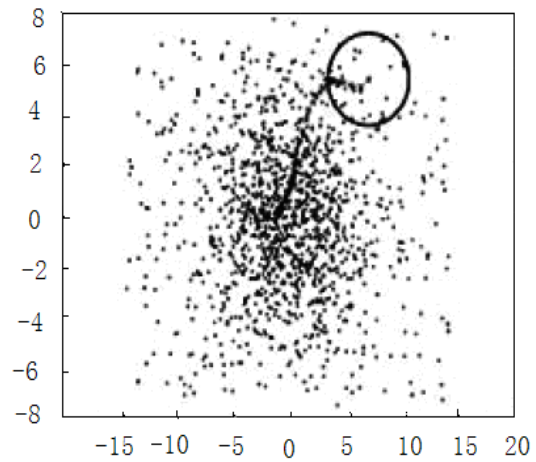


Figure 2. The diagram of MeanShift algorithm searching mode

$$y_{j+1} = \frac{\sum_{i=1}^n G\left(\frac{x_i - y_j}{h}\right) w(x_i) x_i}{\sum_{i=1}^n G\left(\frac{x_i - y_j}{h}\right) w(x_i)} \quad (9)$$

y_{j+1} is the weighted average calculated by $G(x)$ at y_j and it is also the next continuous point calculated at y_j point. The corresponding density estimate at these points can form one sequence, which is recorded as $\{\hat{f}_{h,K}(j)\}_{j=1,2,\dots}$, and:

$$\{\hat{f}_{h,K}(j)\} = \hat{f}_{h,K}(y_j), j = 1, 2, \dots \quad (10)$$

In equation(10), $\hat{f}_{h,K}(y_j)$ is a series of probability density estimation calculated by kernel K . Because the MeanShift algorithm is convergent [2], the sequence $\{y_j\} j = 1, 2, \dots$ will be convergent. With the starting point

y_1 , the density estimation sequence $\{\hat{f}_{h,K}(j)\}_{j=1,2,\dots}$ corresponding to the sequence $\{y_j\}_{j=1,2,\dots}$ increases accordingly. That is: the density constantly increases, until it is convergent to the intensity maximum. The Filtering specific steps are described as below: $(x_i) i = 1, 2, \dots, n$ and $(z_i) i = 1, 2, \dots, n$ represent the original pixels and those after filtering in 5-dimensional joint domain. For each pixel:

- (1) Initialization: $j=1, y_{1,1} = x_i$;
- (2) According to the formula (10), calculate $y_{i,j+1}$ in the kernel whose center is $y_{i,j}$ until it is convergent, and record $y = y_{i,c}$
- (3) Order $z_i = (x_i^s, y_{i,c}^r)$, the superscripts s and r denote the spatial and color parts of a vector.

In Step 2, the kernel function is Epanechnikov in this paper, and the profile function of Epanechnikov is uniform distribution function. In the feature space, the kernel is a multi-dimensional unit super-ball, which is the simplest kernel function, with the highest computing speed, so such kernel is used with the highest frequency.

User can control the size of the kernel by setting the bandwidth parameters h . And this can determine the mode detection, namely, filtering resolution. Here, the bandwidth parameters h includes spatial bandwidth h_x , h_y and color domain bandwidth h_l , h_u , h_v . Generally, assume that $h_s = h_x = h_y$ presents space bandwidth, $h_r = h_l = h_u = h_v$ presents color bandwidth.

The filtered data at x_i will use color domain component of convergence point y_c , that is: the spatial component is x_i , and color component is y_c . The color value of convergence point is given to the point to be processed.

B. MeanShift Image Segmentation

The image processed by MeanShift filtering, color information of n pixels is replaced by that of a limited number of mode points, but there are too many color kind. And it is not conducive to the image clustering segmentation, so it is essential to combine the regions where pixels difference is small.

Image region is defined as all the pixels associated with the same mode in the joint domain. First of all, the very prominent modes were found, and the less prominent ones were deleted. And then record those pixels marked by deleted modes, with prominent modes. So each pixel can be linked with the prominent modes of the joint domain density located in its neighbourhood, that is, these regions merge into a large area. When all of the modes are screened, the merger will complete, and so does the cluster of 5-dimensional space. The target to be processed in this article is textile images, whose texture varied. And the weft colors of its same region mixes up with other colors. However, from the user view, mixed color should be classified to the pixel colors of this region. Therefore, in the process of clustering, it should also be bound together with a number of man-made constraints, and set the size of the smallest regional as M .

Clustering algorithm steps are as follows:

$\{z_i\} i = 1, 2, \dots, n$, represents pixels after filtering in joint 5-dimensional domain. L_i refers to the label of the pixel i in the image segmented.

- (1) After a MeanShift filtering to textile image, all the mode information in the 5-dimensional joint domain, are stored in z_i , that is, $z_i = y_{i,c}$;
- (2) A cluster is made to the filtered 5-dimensional joint is through a cluster. Assuming the obtained sequence is $\{K_p\} p = 1, 2, \dots, m$. Euler measure is made to the air space and color gamut of z_i in the joint domain, and combine all the z_i whose spatial distance less than h_s and color gamut distance less than h_r , that is, to link all the regions of the corresponding convergence points (mode).
- (3) Order $L_i = (p | z_i \in K_p)$, for arbitrary $i = 1, 2, \dots, n$;
- (4) According to the nature of the image, set size restrictions parameter M of the minimum zone, to remove those regions less than M pixels.

C. The Segment Results

There are three parameters affecting MeanShift segmentation, and they are airspace bandwidth parameter h_s , color bandwidth parameter h_r and minimum region

parameter M . many color fabric images were chosen to be segmented to verify MeanShift algorithm.

Fig. 3 (a) is the original image, and Fig. 3 (d) is the segmentation result, with parameters set $[h_s, h_r, M] = [7, 7, 1100]$. Fig.3 (b) and Fig.3 (c) gives the experimental results obtained by changing bandwidth parameters. From the results, the selection of bandwidth parameters have a significant effect on the textile printing image. In Fig. 3 (b), make a change of the air domain bandwidth h_s , maintain the color domain bandwidth h_r and minimum region parameter M unchanged, the segmentation results were obtained that the red region was divided into two parts, light red and dark red. The reason to cause over-segmentation can be got from the original Fig.3 (a), and the right side of the red area of which, is obviously lighter than the left side. When the image converted into the Luv space, the brightness values in the right region is greater than that of the left. So with bandwidth h_s increasing, the filtering resolution of its kernel function reduces, resulting in regions over-segmentation. Fig. 3 (c), the reduce of color gamut parameters h_r caused the increase of the kernel function's resolution, which leads to the gray area over-segmentation. From the segment results, we can see h_s has larger impact.

Fig. 4 (a) is the original image, and Fig. 4(c) is the segmentation result, with parameters set $[h_s, h_r, M] = [86, 7, 1000]$. Fig. 4(c) gives the experimental results obtained by changing bandwidth parameters. From the results, we can see the selection of bandwidth parameters have a significant effect on the textile printing image. In Fig. 4 (b), because of the parameter were not appropriate, the segmentation results were so bad that the texture was still left. Compared to the Fig. 3(b), Fig. 4(b) is over-segmentation. But when the parameters $[h_s, h_r, M]$ were changed to be $[9, 7, 1300]$ in Fig. 4(c), the segment results is good.

The difficulty of segmenting color textile image lies in the existence of other variegated colors in the weft gap. To prove the algorithm's superiority, Select a higher resolution image shown in Fig. 5(a) which is the original image with a size of 640×480 , and a resolution of 96 dpi. From the image, a large number of variegated color information can be found in the weft gap of all regions. Fig.5(b) shows the segmentation results, with the parameter $[h_s, h_r, M] = [9, 7, 2500]$. And the results show that the algorithm can overcome the effect of variegated color in regional gap.

The following research chooses 24-bit color fabric image, whose size is 228×176 , and resolution is 96dpi shown in Fig. 6(a). The segment effects were controlled by three parameters, which are spatial bandwidth h_s , color bandwidth h_r and the minimum region M . Set $[h_s, h_r, M] = [8.5, 8, 1000]$, the segmentation result shown in Fig. 6(b). And the segment cost 3.57 seconds. In that case, the chromatic extraction from Fig.6(b) can be directly done.

The block matching process in the part V will take the Fig. 6 (a) as an example.

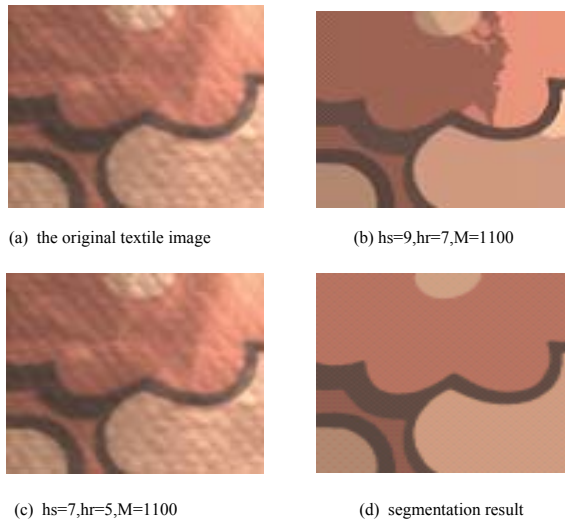


Figure 3. The segmentation of the printing image by MeanShift

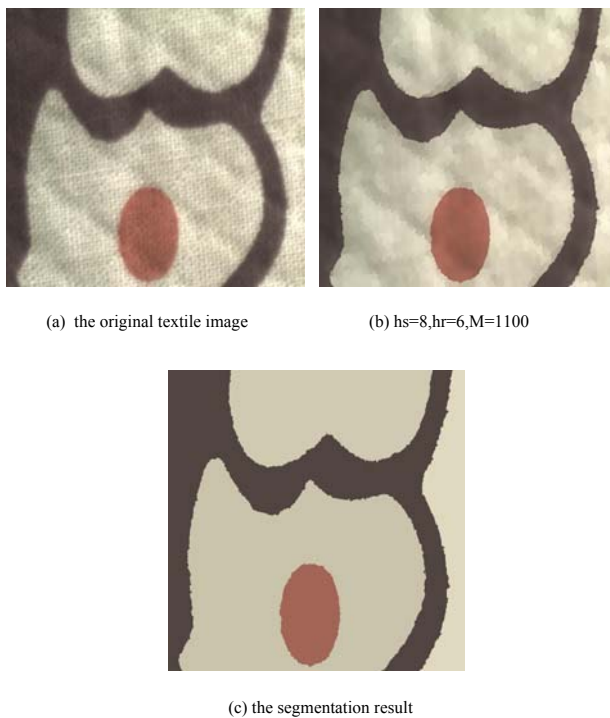


Figure 4. The segmentation of the printing image by MeanShift

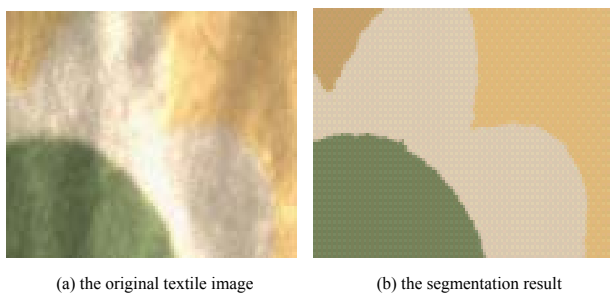


Figure 5. The segmentation of the printing image by MeanShift

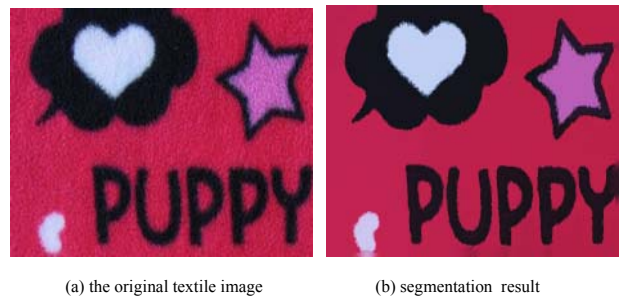


Figure 6. The segmentation results of the printing image by MeanShift

V. CHARACTERISTIC BLOCK-MATCHING DETECTING REGISTER ERROR VECTOR

The block matching process is illustrated with a chromatography in this paper. The chromatically printing is a technology of 2-color or more being printed on the fabric, and a cylinder of rotary screen printing machine prints only one color. When the n-chromatography is under detection, the previous n-1 chromatography are viewed as background and have no off-pattern. In the following, Harris corner detection[11] is first introduced, and later the block matching based on it is introduced.

A. The Corner Extractinon Based on Harris Operater

Intuitively, corner is the point that contain enough information and can be extracted from the current frame and the next frame. Harris operator is a stable operator based on signal feature point extraction, and it was proposed by Harris C and Stephens MJ. It is characted by simple calculation and the reasonable and uniform corner extracted.

The process is as follows:

$$M = Gauss(s) \otimes I \tag{11}$$

In equation(11): $I = \begin{bmatrix} I^2_x & I_x I_y \\ I_x I_y & I^2_y \end{bmatrix}$ is the dual gradient Matrix; I_x and I_y are the first-order partial derivatives of the image in the direction of the x, y ; $Gauss(s)$ is Gaussian model; I was smoothed with Gaussfilter, and the result is M .

$$\tag{12}$$

$$R = det(M) - k(trace(M))^2, \\ k = 0.04 \sim 0.06$$

In equation(12), det is the determinant of matrix, $trace$ is the matrix trace, k is a free parameters of the corner detection. Each pixel value of the matrix corresponds to the corner point value in the original image. And only when the corner is greater than a certain threshold, it is considered the corner point value. As the small threshold increases the number of feature points and the amount of subsequent matching calculation and the big threshold increases the leakage election likelihood, you can select the appropriate threshold according to experience.

In order to achieve fast matching, the feature points should be screened first. Screening principles is as following: first, the distance between two feature points not smaller than the size of the cut; second, select a square area with the length B_s and the feature points as center. Do matching on the standard image first, if two or more matching regions are found, the feature point should be excluded.

In Fig. 7, take the chromatic pink as example to indicate the extraction process of the Harris corner point. Fig. 7 (a) is chromatic pink extracted from the segmented image, and Fig. 7 (b) is the binary image of Fig. 7 (a). After corner point detection, the corner points selected are marked in the Fig. 7 (c).

B. The Fast Block-Matching Algorithm

Image matching is a process of searching the area with the highest similarity to the template image in the target image area. It can be divided into the matching algorithms based on gray and based on feature. The former has a large calculation amount. Although its processing time varies for different searching strategies, generally it is very difficult to meet real-time requirements. The feature-based matching algorithm has some robustness for image distortion, noise and shelter, but its matching accuracy is low, and the matching performance greatly depends on the quality of feature extracted. The fast matching algorithm proposed in this paper combines the advantages of these two kinds of algorithms. Get the interesting block through the off-line learning, and then take the block as the center to search the relevant matching block in the smaller "+" shaped area with the radius as SearchSize. As shown in Fig. 8, it can not only achieve high precision, but increase the operation speed through greatly reducing computation.

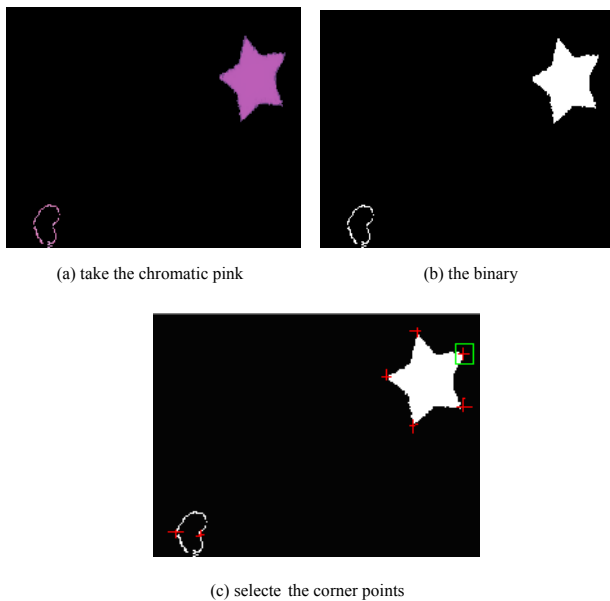


Figure 7. The corner points detection on the parted different color region

Generally the block matching is used in motion estimation algorithm. And because the method is simple, effective and is easy to integrate in large scale, it is widely used in video coding [12]. It is used in the estimation of motion vector of the current frame and the previous frame. ES, fatigue algorithm (also called global searching algorithm), three-step search algorithm (TSS), four-step search algorithm (FSS), and new three step search algorithm (NTSS), etc. [13],[14] are the searching algorithm often used. The principle is: the two-dimensional image is divided into many sub-blocks of a certain size, and then search the best matching to these pixel blocks around the corresponding place in its neighbouring frames according to BMA guidelines. (dx, dy) , which is the relative position to the current block, is the motion vector.

This paper refers to the above ideas, take each point $P_i(x_i, y_i)$ of the feature points set selected from the standard image as the center, and chose the small area whose size is $B_s \times B_s$ as the feature block. And in the target image, take the point $O_i(x_i, y_i)$ corresponding to P_i as the center, chose "+" shaped area whose length is $S_s (> B_s)$ to find the best matching block. Take the corner point marked in the upper right of figure 7(c) for example, expressing the matching process in the target image of the selected block.

In this paper, the matching criteria is NCCF [15], that is, to seek the cross correlation coefficient:

$$R(i, j) = \frac{Rst}{\sqrt{Rss \times Rtt}}$$

$$i, j \in (P(i, j) - S_s/2, P(i, j) + S_s/2) \tag{13}$$

In equation (13):

$$Rtt = \sqrt{\sum_x \sum_y^{B_s} (T(x, y) - \bar{T})^2} \tag{14}$$

$$Rss = \sqrt{\sum_x \sum_y^{B_s} (S(x+i, y+j) - \bar{S}(i, j))^2} \tag{15}$$

$$Rst = \sum_x \sum_y^{B_s} (T(x, y) - \bar{T}) \times (S(x+i, y+j) - \bar{S}(i, j)) \tag{16}$$

The steps :1) calculate the Rtt of matching block ; 2) calculate Rst and Rss in the searching region respectively; 3) compare the correlation coefficient, then compare the maximum absolute value with the seted threshold value, if $\max(|R(i, j)|) > Threshold$, the coordinates is the best matching.

C. The Matching Result

When the matching was finished, you can get the average of the seven points $dx=0.142857mm$, $dy=0.928572mm$, as shown in Table 1. That means that the pink color area of the image turned $0.928572mm$ in the right, turned down $0.142857mm$. Because we have selected the feature points before, and put the searching region to "+" shaped area, so the matching efficiency was improved.

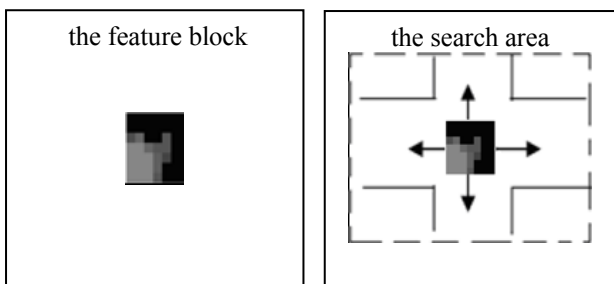


Figure 8. The diagram of feature blocks searching and matching

Tab.1 Coordinate standard points and matching point

Corner points	Corner points in Standard image	Corner points in target image
1	(5,83)	(6,85)
2	(15,72)	(15,73)
3	(36,80)	(36,82)
4	(33,93)	(34,94)
5	(16,94)	(16,96)
6	(69,9)	(69,12)
7	(69,19)	(69,21)

VI. CONCLUSION

In this paper, the MeanShift segmentation algorithm and the fast block-matching algorithm based on Harris operator were applied to fabric image. The extended MeanShift algorithm can overcome the fabric texture noise, and obtain a good segmentation result; the matching efficiency of the block-matching algorithm was increased, extracting the feature points and then matching the feature block. Experiments show that it is a feasible strategy to combine these two kinds of algorithms to do registering detection.

ACKNOWLEDGEMENT

The authors would like to thank for the support of Scientific Research Program Funded by Shaanxi Provincial Education Department (Program No. 11JK0910); Research and Development Project of Jscience and technology(Project NO. 2010K09-17), Shaanxi, PRC.

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