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Sequential Similarity Detection Algorithm Based on Image Edge Feature

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Abstract: This paper proposes a new sequential similarity detection algorithm (SSDA), which can overcome matching error caused by grayscale distortion; meanwhile, time consumption is much less than that of regular algorithms based on image feature. The algorithm adopts Sobel operator to deal with subgraph and template image, and regards the region which has maximum relevance as final result. In order to solve time-consuming problem existing in original algorithm, a coarse-to-fine matching method is put forward. Besides, the location correlation keeps updating and remains the minimum value in the whole scanning process, which can significantly decrease time consumption. Experiments show that the algorithm proposed in this article can not only overcome gray distortion, but also ensure accuracy. Time consumption is at least one time orders of magnitude shorter than that of primal algorithm.

Key words: welding image, feature matching, sequential similarity detection algorithm (SSDA), self-adaption value
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0 Introduction

As to robot welding operation, motion trajectory control of intelligent welding robot mainly contains initial seam location recognition and seam tracking. The autonomous localization of initial weld position is one of the key technologies to realize intellectualized welding. Some researchers put a T type mark beside the initial position, then carried out a series of image processing procedures, such as smoothing, segmentation, edge detection and Hough transform, and eventually acquire target area[1]. Because this method is based on image taken remotely and artificial marker, its results should be improved; other researchers get an intersection of work piece edge and seam edge through disposing the whole image, and regard the area with the intersection at centre as result[2]. This means is fairly time-consuming. In the actual unstructured welding environment, interference generated by disruptive factors (such as light shade, reflection and work piece surface clearness) will hamper target area recognition. Few researchers adopt image matching method; they select a typical image as template according to prior knowledge[3-4], or define it manually[5]. Target area can be achieved through searching the whole image, and the center of initial seam position is extracted finally. In acquiring target area, this approach is much more efficient than those traditional image processing procedures. Therefore, integrated performance of the whole intelligent welding system will be promoted. Consequently, the algorithm proposed in this paper has a promising industrial application.

1 Related Work

Image matching is a fundamental task in image processing, which is used to match two or more images. It is widely used in military, industry, medical treatment, traffic and security etc. Image matching algorithms mainly fall into two categories.

(1) One category is the algorithms based on gray. It can be divided into two types according to similarity measures[6]. One is gray absolute difference which produced by subgraph and template image, i.e. absolute balance search (ABS); the other is maximal similarity, i.e. normalized correlation (NC). There are three approaches to calculate ABS value: minimum square error (MSE), minimum absolute difference (MAD) and maximum pixel count (MPC). Principles of these approaches are similar. Definition of MAD is given as

$$\mathrm{MAD}(i,j) = \frac{1}{MN}\sum_{m=1}^{M}\sum_{n=1}^{N}\left|T(m,n) - S^{(i,j)}(m,n)\right|, \qquad (1)$$

where T is an $m \times n$ template graph, S is an $M \times N$ reference graph, $S^{(i,j)}$ is a projection of T, and (i,j) is

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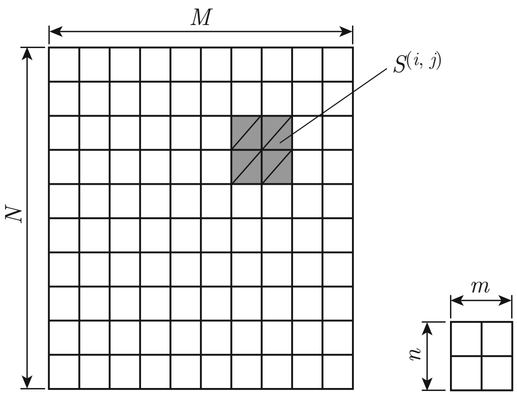
the coordinate of S which is the lower-left corner point of $S^{(i,j)}$ and also can be called reference point. The meaning of these parameters is shown in Fig. 1.



(a) Original image S (b) Template T

Fig. 1 Matching process

In these approaches discussed above, metric has the smallest value while T is just covering $S^{(i,j)}$ which is the target area, but the result has an error while processing grayscale distortion image. Therefore, ABS algorithm only can be used in the practical field in which high speed and low calculation precision are required. In order to improve the ability of resisting grayscale distortion, Nprod and NNprod have been proposed. Although they can overcome the problem created by distortion, it is time-consuming[7]. In order to improve the image matching speed, sequential similarity detection algorithm (SSDA) is put forward[8], it can discover and abandon non-matching areas in advance. Besides, the algorithm is simple. But its threshold value is fixed. Meanwhile, plenty of time will be spent if a high threshold value is set, and a low value produces low precision. Some researchers have proposed improved algorithm to solve it[9], and the time consumption is largely decreased based on a self-adaptive threshold value finally.

(2) The other is the algorithms based on feature. It utilizes spatial location relative invariant feature in matching process. These features can be edge, curve, corner point, intersection and centroid etc. Researchers proposed a new SSDA based on image edge feature[10]. Canny operator is adopted to extract characteristic points from subgraph, and to calculate those points responding pixel-value difference between subgraph and template image. The smallest value corresponding region is regarded as the target area.

In addition to those algorithm discussed above, speed algorithms also contain wavelet pyramid[11], genetic algorithm[12], various mask correlation algorithm (VMCA)[13] and invariant moments algorithm[14], etc. Detail information of image being searched and template image will be lost during the decomposing of wavelet. It is difficult to guarantee matching precision; genetic algorithm always causes the problem which coding form is difficult to be confirmed; for VMCA, the threshold is hard to choose in actual application; invariant moments algorithm is tough to achieve real-time although it has good stability.

At present, research on improved SSDA mainly chooses MAD similarity measure[9,15-16]. Its principle is simple; meanwhile, it is fast. But result of these improved algorithms which based on MAD will produce serious error for gray distortion image. Aiming at this problem, this paper proposes another new SSDA, which is based on image feature. It can avoid large time consumption problem produced by prior analogous algorithm upon image feature. A coarse-to-fine search strategy is employed. Besides, self-adaption is used to optimize the processing procedure. Experiments show that this algorithm has a well integrated performance and can be applied in intelligent welding system.

2 SSDA Based on Image Feature

Idea of the algorithm is shown as follows. Firstly edge detector is applied in subgrph and template image, and its essence is to extract edges between target and background in image. Edge is an important feature of image. Gray distortion or some other noise has little influence on it.

This paper adopts Sobel operator, which belongs to the first order differential operators. Sobel operator can not only well respond edge, but also repress noise. All of these characteristics have a strong adaptability to welding image in practical application. Calculation of Sobel gradient is based on 3 pixel×3 pixel area. Sobel operator comprises two convolution kernels. Each pixel point in image has to use kernels to get itself respond. Value in kernel equals to corresponding location value in masking T, as shown in Fig. 2. One kernel is used to detect horizontal gradient, and its result is largely affected by vertical edge; the other is to detect vertical gradient, and horizontal edge has a significant impact on its response. Two convolution kernels are shown in Fig. 2.

−1	−2	−1
0	0	0
1	2	1

(a) x-direction

−1	0	1
−2	0	2
−1	0	1

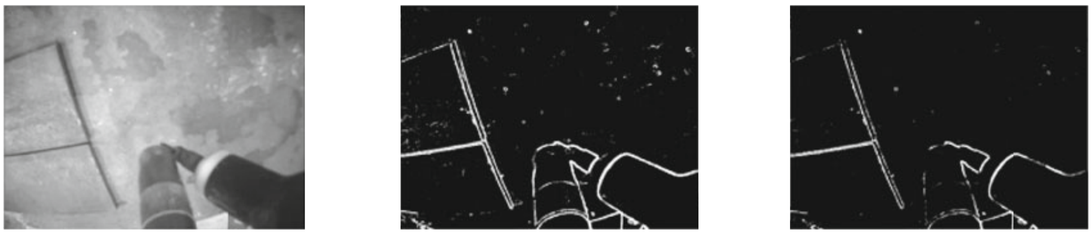
(b) y-direction

Fig. 2 Sobel convolution kernels

After the gradient is gotten, a preset constant T is used to divide pixel points into two parts: one part will be regarded as edge if its response G is greater than T, and the other will be considered as background if its response G is less than or equals to T. Relevance can be defined as

$$G = \begin{cases} 0, & G \leqslant T \\ 1, & G > T \end{cases}. \tag{2}$$

Besides, experiments show that T value can affect the result of image matching effect. By analyzing welding environment image (work piece places on left side in image; welding torch of robot lies on bottom right; target area is surrounded by an dotted box), image quality will be affected by noise engendered in image transmission, work piece surface cleanness and light conditions, etc. By the experimental analysis, plenty of small size pots appear if a small threshold value is taken (in order to emphasize the visual effect, pixel gray value of feature point is set to 255, and value of non-feature point is set to 0), which can seriously affect image matching precision and time consumption. Thresholding pictures are shown in Fig. 3.



(a) Original image (b) Processing (threshold value 75) (c) Processing (threshold value 90)

Fig. 3 Threshold processing on seam image

While threshold value is 75, there are 25 555 feature points; meanwhile, big threshold will make the target area covered by background. Consequently, an appropriate value is important; a suitable value can not only filter many useless points, but also remain the target area. When the threshold is set to 90, the number of feature points decreases to 16 119.

This algorithm is aimed at initial seam location recognition before welding operation. Initial seam location graphic contains seam, contour and surface of the workpiece, and padding (or fixture) located below workpiece, etc. All of this information can ensure that the image which is also regarded as template has obvious edge feature. Therefore, the chance that target region appears in background area is impossible.

If we directly make a location correlation detecting between subgraph feature points and template feature points, a region which has a maximum location correlation will be considered as the target area. That approach can get an accurate result, but programs will take a long time to complete. Because programs need to scan $(N-n+1)\times(M-m+1)$ points (N, M are the size of S; n, m are the size of T; the process is shown in Fig. 1), the algorithm calculates gradient of every point in each subgraph $S^{(i,j)}$ in S, and counts location correlation between subgraph $S^{(i,j)}$ and template T. Therefore, the means should be improved.

3 Algorithm Optimization and Procedures

We select feature point location non-overlapping frequency as correlation measure. An image can be equivalent to an empty two-dimensional array. Every pixel is corresponding to array element one by one. An element is set to 1 when its corresponding pixel is feature point. The relationship can be shown in

$$A = A_1 + A_2 + A_3, \tag{3}$$

where, A is the sum of feature point location non-overlapping between subgraph and template; A_1 is the number of occurrences (when one point of subgraph is 1, corresponding spot in template is 0); A_2 is number of another occurrences (one point of subgraph is 0 while corresponding spot in template is 1); A_3 is the last case (when one point of subgraph is 0, corresponding spot in template is 0).

The whole scan process adopts coarse-to-fine scanning method. In coarse matching part, an initial value A_0 which indicates the feature point location relevance between template and lower-left corner subgraph of reference graph should be acquired firstly. Then scan the rest subgraph, and compare each A_i ($i = 1, 2, 3$) produced by subgraph and template graph. When A_i is greater than A_0, scanning process of a subgraph is not finished yet, then scanning should stop immediately, and directly scan next subgraph. If A_i is less than A_0 till the end, then A_i replace A_0 before the next scanning begins. Coarse matching result, denoted as point (X, Y), can be acquired after the whole reference graph. Every subgraph of reference graph can be processed according to

$$A = \begin{cases} A_0, & A_i > A_0 \\ A_i, & A_i \leqslant A_0 \end{cases}. \tag{4}$$

In fine matching process, the scanning area is a $2m \times 2n$ rectangle area which center point is (X, Y) and its scan procedure is the same as coarse scanning.

Scanning strategy is shown as follows.

(1) One strategy is coarse matching. It is to make the feature point location relevance between lower-left

corner subgraph of reference graph and template as initial value A_0, and to keep the minimum relativity by contrast location relevance between the rest subgraphs and template graph.

(2) The other strategy is fine matching. It is to scan the rectangular area which takes the point (X, Y) as the center, has a $2m \times 2n$ size, and to repeat the same procedures in coarse matching. Eventually, the precise reference point of target area can be acquired.

Flow chart of the whole algorithm is shown in Fig. 4.

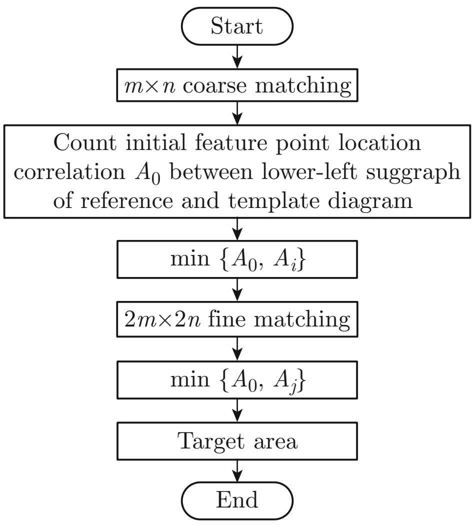


Fig. 4 Algorithm flow chart

4 Experiment Results and Analysis

Accuracy and speed are two important evaluation indexes for an algorithm. In order to prove the quality of the algorithm this paper proposes, we compare the algorithm with MAD, NC and self-adaption SSDA (its step is the same as the algorithm this paper proposes). Size of S which is being searched is 766 pixel $\times$ 578 pixel. Size of template T is 40 pixel $\times$ 30 pixel. Computer system is Windows XP Sp3, 1.73-GHz core and 1-GB RAM; image collection card is DH-VT140, and image processing software is Visual C++ 6.0. Matching result and responding data of seam image are shown in Fig. 5 and Table 1.

In order to test the ability to resist gray distortion of each algorithm, we select a template T which is suffered gray distortion. Matching data of each algorithm is shown in Table 2.

Table 1 Seam image matching data

Matching algorithm	Time consumption/s	Matching coordinate/ pixel	Matching error
MAD	9.625	(193, 209)	(0, 0)
NC	11.875	(193, 209)	(0, 0)
Self-adaption SSDA	0.078	(193, 209)	(0, 0)
This paper	0.285	(193, 209)	(0, 0)

Table 2 Matching data of seam image suffered gray distortion

Matching algorithm	Time consumption/s	Matching coordinate/ pixel	Matching error
MAD	9.390	(417, 113)	(224, 96)
NC	11.922	(193, 209)	(0, 0)
Self-adaption SSDA	0.095	(198, 516)	(5, 307)
This paper	0.311	(193, 209)	(0, 0)

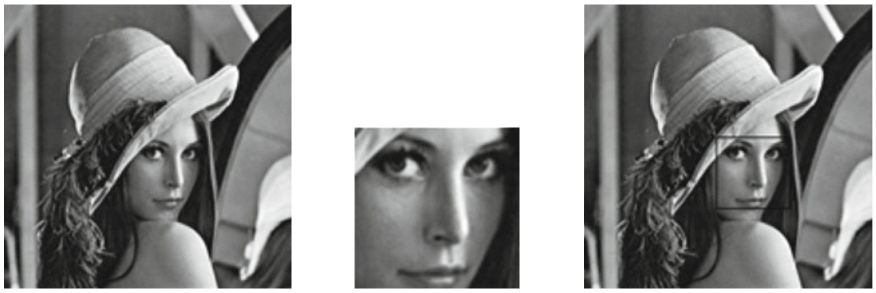
From experiments shown above we can know, results are all right while image is without gray distortion. Besides, time consumption of self-adaption SSDA is the least. From the gray distortion image, outcome of MAD and self-adaption SSDA all cause large error. Although NC algorithm has no error, it is time-consuming. The algorithm that this paper proposes not only has a precise result, but also costs less time.

Meanwhile, we select Lena image to prove the versatility of this algorithm, Lena image size is 256 pixel$\times$256 pixel, and template size is 64 pixel$\times$64 pixel. Matching result and responding data are shown respectively in Fig. 6 and Table 3.

The algorithm that this paper proposes adopts a coarse-to-fine method. Firstly, subgraph moves on original image at intervals of m rows and n columns. Besides, a self-adaption value that indicates feature points' location correlation is proposed. After get the coarse reference point of target area, then scan the region which takes the coarse reference point as the center, $2m \times 2n$ size, and repeat the same matching procedures in coarse matching. Finally, precise coordinates of target area can be acquired. Meanwhile, its time consumption is much less than that of MAD and NC algorithms. Since edge detection of every subgrph needs

(a) Seam image (b) Template T (c) Matching result

Fig. 5 Matching result of seam image



(a) Lena image (b) Template T (c) Matching result

Fig. 6 Matching result of Lena image

Table 3 Lena image matching data

Matching algorithm	Time consumption/s	Matching coordinate/ pixel	Matching error
MAD	3.375	(116, 74)	(0, 0)
NC	3.937	(116, 74)	(0, 0)
Self-adaption SSDA	0.063	(116, 74)	(0, 0)
This paper	0.225	(116, 74)	(0, 0)

plenty of time, and self-adaption SSDA only needs to count absolute differences based on pixel gray value which already exists, so SSDA is faster than the algorithm this paper proposed. But the feature algorithm can overcome the influence produced by gray distortion.

5 Conclusion

To keep the matching error minimum, algorithm that this paper proposes makes full use of the edge information, which can overcome error produced by distortion and ensure matching precision.

Adopt a self-adaption value which indicates feature points' location correlation between subgraph and template graph. This can further decrease the time consumption.

Since algorithm that this article proposes adopts a self-adaption value and coarse-to-fine scanning strategy, its matching speed is faster than that of MAD and NC. However, feature points that between template image and subgraph regions need to be detected. Traditional SSDA arithmetic just requires absolute value of gray difference which already exists. So matching speed of the algorithm this article proposes is slower than that of traditional arithmetic.

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