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A seam tracking system based on a laser vision sensor

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ABSTRACT

It is difficult to ensure robustness and accuracy when the traditional morphological method (TMM) is used to detect weld feature points, especially in an environment with a strong arc light and splash interference. In this study, a novel and robust seam tracking system based on a laser vision sensor is proposed. The feature point is obtained using the traditional morphological method before welding and can thus determine the tracked region. When the welding begins, a spatiotemporal context (STC) tracking algorithm is utilized in order to detect the weld feature points. In the welding process, the STC algorithm is adopted to determine a feature point with a strong arc light and splash interference and the morphological method is used to obtain an accurate weld feature point when the interference decays. As a result, the STC model can be updated in time, so the tracking drift problem can be solved and the robustness can be improved. A model reference adaptive control method is then adopted to improve the robustness of the robot system, which can convert the deviation between the theoretical and actual welding trajectory into a voltage to control the robot's movement. Experimental results show that the tracking error of our seam tracking system is within 0.5 mm even when the distance between the laser stripe and the welding pool is 15 mm, which can completely satisfy the industrial requirements.

1. Introduction

The arc welding process occupies a very important position in the industrial manufacturing process for industries such as car, ship, and aircraft manufacturing, which involve a good amount of arc welding. However, a large amount of dust and ultraviolet radiation in the welding process can seriously affect the health of the workers. Therefore, a large number of workers have been replaced by welding robots, which can improve the production efficiency while ensuring the welding quality. Meanwhile, the arc-welding robot essentially adopts teaching and playback modes. This always results in the weld trajectory deviating from the original teaching trajectory. The welding precision is difficult to guarantee due to workpiece errors, clamping errors and thermal deformation. Therefore, it is imperative to research real-time seam tracking technology. Laser vision seam tracking technology has been given much attention by several researchers because it can improve manufacturing accuracy and significantly reduce manufacturing costs.

Kawakara [1] designed a laser vision tracking system for a V-shaped seam. This system analyzes multiple images to remove noise and fits a straight line through an intersection to obtain the feature points of the seam track. This system is the first laser vision system designed for tracking. Wu et al. [2] designed a structured light vision sensor and used a high-performance electronic transporter image processing system to increase the image processing speed for the real-time measurement system. Although the image processing speed was improved, the results were insufficiently stable. Kim et al. [3] introduced text analysis to improve the robustness of the structured light vision tracking system, extract the raw data of a laser stripe from an image, use text analysis techniques to process the data, and detect feature points. Text analysis can resist arc and spatter interference to a certain degree. Gao et al. [4] added a Kalman filter to an image processing algorithm to solve the dynamic and nonlinear problems of laser welding. The tracking algorithm became robust because of the Kalman filter. Xu et al. [5] analyzed the welding pulse and the base current cycle while discarding the invalid image during the sensor's collection of samples. Image sensing region was divided into several small windows. In this way, the image processing range was restricted, and the processing time of the algorithm was substantially decreased. The study of laser vision seam tracking technology has had huge achievements, and most of the weld location information was obtained by morphological methods. The feature points of the weld were seriously disturbed due to the strong arc and splash noise in the image. Traditional morphological methods, such as median filtering, threshold segmentation, and various edge extraction algorithms, have been unable to obtain accurate weld feature points.

In recent years, object-tracking technology has made great progress, and many excellent object-tracking algorithms, such as MIL [6], IVT

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[7], TLD [8], IA-MCMC [9], and ANNF-SSAMC [10] have been proposed. If object-tracking technology can be used in seam tracking, the robustness of seam tracking may improve. Seam features change slowly when welding. Therefore, image context information can be considered for use to track the seam. Image contextual information for object-tracking has been well studied. Grabner et al. [11] specified some key points in the context as supporters. An association model between the object and the context motion was established to predict an object's location using the correlation. The algorithm had a relatively higher flexibility but it also increased the cost of detecting and matching. Dinh et al. [12] extracted objects with similar targets in the context as distracters and used a series of speeded up robust features (SURF) to distinguish between the true targets and the interference targets, and achieved similar target effective tracking cases. Wen et al. [13] modeled the temporal context and the spatial context, and used the SURF feature point information to establish the supporter, thus achieving the object-tracking in a complex environment. Yang et al. [14] used data mining to segment some regions around the target as auxiliary objects, and then collaboratively tracked the auxiliary objects and the target itself in order to effectively prevent the occurrence of tracking process target drift. The disadvantage of this method was the high complexity of time. Amir Saffari et al. [15] proposed a new multi-class LP Boost algorithm for object-tracking that can produce better tracking in a relatively single background environment. However, it sometimes fails in the context of more complex video environments. The algorithm proposed by Gu and Tomasi [16] is concerned with the spatial relationship between similar goals that tracks similar goals at the same time, but the algorithm ignores the temporal context information of the object. Therefore, this method causes the algorithm to be extremely sensitive to the appearance of the object. The fast object-tracking algorithm proposed by Zhang et al. [17] and based on spatiotemporal context learning (STC) is a breakthrough for the above method. The algorithm utilized a Bayesian framework to build the relationship between the object and the context information. The relationship was used to estimate the position of the object. The algorithm had strong robustness, was very efficient, and based on a Fast Fourier Transform (FFT).

In this paper, we propose a seam tracking system based on a laser vision sensor. The traditional morphological method (TMM) was used to extract weld characteristics and determine the tracking region before welding. Seam characteristics were disturbed by arc and splash noise during the welding process so the TMM was invalid. Thus, the image STC information was used to track the seam. When the interference decayed, the seam features were extracted by the TMM to correct the STC model in order to improve the tracking accuracy. Meanwhile, the model reference adaptive control method was used to control the robot's motion and improve the tracking robustness through the control voltage, which was transformed by the deviation of the actual position and the theoretical weld seam position. An identification model was created because the precise model of the system was difficult to establish, and an adaptive mechanism was used to adjust the control parameters through the model output automatically. Thus, the system could track the weld quickly and accurately (Fig. 1).

2. System structure

As shown in Fig. 2, the system was constructed using a six-DOF arc-welding robot, a robot controller, a laser vision sensor, a welding machine, a welding torch, an industrial computer, and a Beckhoff module (Fig. 3).

The working principles of the system are as follows. The laser vision sensor was mounted on the front of the torch for real-time acquisition of the weld image and image transmission to the control computer through the Ethernet. After the computer extracted the weld's feature points, it was compared to the theoretical weld position. Then, the deviation was converted into a voltage through EL4132 DA module, which was transmitted to the robot controller through the robot analog control board to direct the movement of the robot to the weld position. In addition, the robot controller also controlled the welding current and the welding speed during welding.

The laser vision sensor, which was important to the system, was constructed by a three-line laser, an industrial camera and a camera lenses. The front measurement distance d, which was between the center of the torch and the feature point formed by the laser stripe at the weld, had a significant effect on the performance of the system. When d was too small, the strong arc and splash generated by the welding could seriously pollute the image, and the tracking failed because the feature points could not be extracted. By contrast, when d was too large, although the image interference was small, the tracking error increased. The tracking error was more than 30 mm for most of the weld tracking system. To improve the tracking accuracy, d was 15 mm for our system.

3. Seam feature point detection algorithm

The precision of the weld feature extraction directly affects the accuracy of the seam tracking. The traditional morphological method (TMM) can be used to extract the weld feature points when the image has no noise. Therefore, the TMM can be used to extract the starting point before welding and determine the tracking region. However, this method is completely ineffective in the presence of strong noise. At this time, we used the STC object-tracking learning algorithm to estimate the location of weld feature points. The use of the object-tracking method produced the common problem of region drift due to the accumulation of errors in the tracking. Drifting within a certain range is acceptable in object tracking, but unacceptable in our seam tracking system, because we need to determine the location of the weld accurately in order to control the robot's movements. Drifting would also increase the tracking error and even cause the workpiece to be scrapped. Therefore, we used the TMM to extract the feature points to perform the dynamic correction of the STC model when the noise was weak.

3.1. Extracting feature points through the TMM

When the image is less polluted, the traditional morphological method (TMM) can be used to extract the feature points accurately. The TMM process is shown in Fig. 4.

First, the image was filtered to suppress the pulse interference generated during the welding process. The gray value of the pixel (c, r) of the original image I_0 is $I_0(c, r)$, and the gray value after median filtering is $I_1(c, r)$ [22],

$$I_1(c, r) = median \sum_{(i,j)\in S_{rc}} I_0(i, j) \tag{1}$$

where S_{rc} represents a rectangular filter mask, the dimensions of which are 3×3 pixels and center is (c, r), and $I_0(i, j)$ is the gray value of the pixel covered by the mask.

After filtering, threshold segmentation was performed to simplify subsequent operation since the image would contain only two gray values, 0 and 255. The threshold k was calculated using Otsu's threshold method [18] and then each pixel of the image I_0 was processed by Eq. (2) to obtain a binarized image I_1.

$$I_1(c, r) = \begin{cases} 0 & I_0(c, r) \leqslant k \\ 255 & I_0(c, r) \geqslant k \end{cases} \tag{2}$$

After the threshold segmentation, some pixels below the threshold in the laser stripe were removed, and many small holes were formed. The holes were filled via a morphological closed operation, and the burrs at the edge of the laser stripe were removed via open operation. The laser stripe region was the region of interest (ROI), and the area of the laser stripe region was larger than the noise, hence we can select the

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