A method of workpiece location based on improved generalized Hough transform

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Abstract. In order to solve the problem that the workpiece is not easy to identify in the complex environment in the industrial processing, sorting and other automatic production links, a workpiece positioning method based on Improved Generalized Hough transform, also known as eif-ght, is proposed. In order to solve the problem of large time consumption and high memory consumption of traditional generalized Hough transform in target detection, this paper uses the rotation invariant feature angle formed by any two edge points in the image as the R table index under the condition of image preprocessing to realize the representation of target shape, and uses particle swarm intelligent evolutionary algorithm to speed up the search. The final target is determined by similarity measurement. The experimental results show that when the workpiece rotates and shifts, and in the complex environment with noise, local occlusion, nonlinear illumination and so on, it can achieve stable and efficient positioning.

1. Introduction

With the concept of "industry 4.0" put forward by European and American countries with Germany as the main body, China has also put forward the industrial development direction with the concept of "made in China 2025". Under the continuous drive of national policies, the whole environment shows that China's industry is changing from the industrial manufacturing system driven by human labor to the direction driven by intelligent technology. In the traditional factory machining, sorting and other automatic production links, the introduction of vision technology, through machine vision to the workpiece non-contact identification and positioning[1-3], can greatly improve the efficiency of industrial production. At present, the commonly used target location method is template matching. The traditional template matching methods include gray-scale matching and feature-based matching. The gray-scale matching generally uses the template image to slide on the tested image, and uses the similarity measurement formula to calculate the image matching degree. For example, absolute error sum algorithm (SAD), error sum of squares algorithm (SSD), etc., this kind of method is only different similarity measurement formula, because it needs to slide the whole image, it will cause a lot of time consumption, and it is not easy to detect the target with rotation transformation. [4]A GPU based NCC template matching algorithm is proposed for seismic detection. Feature based matching algorithm mainly uses edge, corner, contour and other features for matching. [5]An automatic robust image matching method based on local features is proposed, which realizes fast, dense and robust feature points through improved accelerated robust feature (SURF) detector and adaptive block size invariant feature transform (AB-SIFT) descriptor Extraction. Aiming at the slow speed of traditional SIFT algorithm in feature extraction and matching, Liu[6] proposed an improved RANSAC feature image matching method based on fast robust feature (SURF). In addition to these two methods, many
researchers have proposed some new methods, such as [6] proposed a template matching algorithm based on blob analysis technology to achieve LED chip positioning. [7] In order to solve the complex template matching problem, a hybrid method of wolf colony algorithm (GWO) and side inhibition mechanism (LI) is proposed.

Based on the above analysis, in order to improve the speed of template matching, and in order to adapt to the interference of complex environment, an image matching method based on Improved Generalized Hough transform is proposed, which is applied to workpiece positioning.

2. Materials and Methods

2.1. Improved generalized Hough transform

The traditional generalized Hough transform uses the gradient feature of a single edge point to establish the r-table. When the target has rotation and translation, it will generate three-dimensional parameter space to vote, resulting in large storage capacity and high computational complexity. In order to solve the above problems, this paper proposes an improved generalized Hough transform, called EIF-GHT, according to the invariant features of the edge points. This method uses the rotation invariant feature angle formed by any two edge points in the template image to establish r-table, which solves the influence of the parameter space of target rotation and reduces the traditional three-dimensional parameter space to two-dimensional parameter space in order to achieve the image object representation.

![Figure 1 geometric diagram of EIF-GHT](image)

Where $\alpha$ and $\beta$ are the gradient angles of the two edge points $P(x_p, y_p)$ and $Q(x_q, y_q)$ respectively, and $\theta$ is the characteristic angle. The characteristic angle is composed of the difference of the gradient angles of the two edge points on the target edge, which has rotation invariance, it can be obtained from formula 1.

$$\theta = \beta - \alpha$$  \hspace{1cm} (1)

$\gamma$ is the azimuth angle from point $P$ to point $Q$, and $\varphi$ is the index angle at point $P$, which is rotationally invariant. It can be calculated by formula 2 and formula 3.

$$\gamma = \tan^{-1}\left(\frac{y_q - y_p}{x_q - x_p}\right)$$  \hspace{1cm} (2)

$$\varphi = \gamma - \alpha$$  \hspace{1cm} (3)

It consists of two phases: offline phase and online phase. In the offline stage, r-table is created, and the feature angle is set according to the shape of the target. Only when the feature angle formed by any two edge points meets the setting conditions, the parameter information is recorded to R-Tabel. The local invariant feature $\varphi$ is selected as the index of R-Tabel, and the corresponding parameter information is $\alpha$. R-table is shown in Table 1.
Table 1 R-Table of EIF-GHT

| $\theta$ | $I$ | $\varphi$ | $\alpha^i$ |
|----------|-----|-----------|------------|
| $\theta$ | 0   | 0         | $\alpha^1_1$, $\alpha^2_2$, $\cdots$ |
| $\theta$ | 1   | $\varphi$ | $\alpha^2_2$, $\alpha^3_3$, $\cdots$ |
| $\theta$ | 2   | $\varphi$ | $\alpha^3_3$, $\alpha^4_4$, $\cdots$ |

Where $I$ is the index number, $\Delta \varphi$ is the index angle quantization interval, the superscript $i$ is the corresponding index number, and the subscript $j$ is the number of entries corresponding to the same index.

In the online phase, the rotation angle and translation position of the target are solved in two steps.

Setp1: when the characteristic angle of any two edge points in the target image is equal to the set parameter $\theta$, look up the table, use formula (4) to calculate the rotation angle $R$, and conduct voting statistics on $R$. The rotation angle of the target has the largest number of votes.

$$R = \alpha' - \alpha$$  \hspace{1cm} (4)

Setp2: after correcting the angle of the target, look up the table, use formula (5) to calculate the translation position $(x_c, y_c)$, and make voting statistics on $(x_c, y_c)$. Finally, the translation position of the target has the largest number of votes.

$$\begin{align*}
x_c &= x_p - (x_p \cos R - y_p \sin R) \\
y_c &= y_p - (x_p \sin R + y_p \cos R)
\end{align*}$$  \hspace{1cm} (5)

### 2.2. Particle swarm optimization strategy

Particle swarm optimization (PSO) is a random search algorithm based on swarm intelligence cooperation, which was invented by Eberhart and Kennedy according to the foraging behavior of birds. The PSO algorithm designs a kind of particle with only two attributes of speed and position to represent the birds in the bird swarm, in which the particle speed represents the bird's moving speed ($v$), the particle position represents the bird's moving direction ($x$), and the food captured by each bird is expressed as the individual optimal solution searched by each individual particle in the search range, which is also called individual extreme value (pbest) Each particle shares the current search individual extremum with the whole particle swarm, and obtains the optimal individual extremum. All particles in the particle swarm adjust their position and speed according to the optimal individual extremum, and find the optimal solution (gbest) in the whole search space through iterative operation. When the iteration reaches a certain number of times and gbest is in a relatively stable range, the iteration ends Generation.

The velocity and position of particles are updated as shown in formulas (6) and (7):

$$v_i = v_i + c_1 \times rand() \times (pbest_i - x_i) + c_2 \times rand() \times (gbest_i - x_i)$$  \hspace{1cm} (6)

$$x_i = x_i + v_i$$  \hspace{1cm} (7)

Among them, $i$ in formula (6) represents the current particle, $c1$ and $c2$ represent the learning factors, formula (6) updates the next speed according to the current speed of the particle combined with the experience of the previous particle searching for individual extreme value and the experience of the group searching for local extreme value, and formula (7) updates the next position according to the current position and speed of the particle.

### 3. Results & Discussion

#### 3.1. Target location method

The generalized Hough transform based on edge invariant features is used to represent the shape and features of the target. In the voting process of R table, particle swarm optimization algorithm is
combined to speed up the search of the best matching position of the target. SSD similarity calculation is carried out for the found target to further determine the final target position.

The flow chart of workpiece positioning method based on EIF-GHT is shown in Fig. 2.

3.2. Experimental results and analysis

In order to verify the correctness and effectiveness of the proposed method, a computer (CPU 1.7GHz, RAM) is used 8GB), in which the detected image contains noise, local occlusion, nonlinear illumination and other interference factors, and the target has rotation, translation and other position transformation, as shown in Fig. 3, the screw and other targets in the workpiece image are positioned 1:1 respectively.
Compared with the traditional ght algorithm, the experimental results are shown in Table 2.

|                     | Average time of EIF-GHT algorithm/ms | Average time of GHT algorithm/ms |
|---------------------|-------------------------------------|----------------------------------|
| Noise               | 16.2                                | 174                              |
| Partial occlusion   | 16.4                                | 172                              |
| Nonlinear illumination | 14.9                          | 144.24                           |
| rotate              | 15.2                                | 148                              |

It can be seen from Fig. 3 that the proposed localization method has a relatively stable performance in a variety of complex environments. It can be seen from table 2 that the speed of the proposed algorithm is improved by at least 9 times. At the same time, it is improved more in complex
environments with noise or partial occlusion, and the processing speed is faster in cases of non-linear illumination and target rotation.

4. Conclusions
Aiming at the problem of poor positioning effect in complex environment, this paper proposes a workpiece positioning algorithm based on Improved Generalized Hough transform. Through the above experiments, it is proved that the proposed method still maintains good robustness and high computing speed in complex environment such as target workpiece rotation and translation, strong noise, local occlusion, nonlinear illumination and so on.

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