Machine vision based sorting method for precision industrial components

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ABSTRACT

With the rapid development of industrial automation, automated sorting of precision industrial components has become the key to improve production efficiency and reduce costs. In this paper, a machine vision-based sorting method for precision industrial components is proposed, which can effectively recognize and classify iron sheets of different shapes and sizes. This study innovatively integrates image processing, pattern recognition and machine vision technologies to design an efficient automated sorting process. Designed for industrial precision components, this method integrates image preprocessing techniques optimized for industrial-grade image acquisition environments, accurate feature extraction methods for efficient identification of key component attributes, and advanced contour analysis and customized shape matching algorithms to ensure fast and accurate classification of all types of industrial components in automated sorting processes.The experimental results show that the proposed algorithm has significant advantages in improving the sorting accuracy and efficiency, and provides a new gripping and sorting technical solution for the industrial automation field.

Keywords: Machine Vision; Shape Matching; Industrial Components; Automated Sorting

1. INTRODUCTION

Automated sorting technology, as an important part of industrial automation, plays a crucial role in improving production efficiency, ensuring product quality, reducing labor costs and enhancing the level of industrial intelligence. Especially in the production line of precision industrial components, the traditional manual sorting method has been difficult to meet the requirements of modern manufacturing industry for high efficiency and high precision. Machine vision, as an effective means of automated inspection, can realize rapid identification and automatic sorting of industrial components by simulating the visual mechanism of the human eye and combining image processing and pattern recognition technology.[1]

Globally, automation technology is experiencing unprecedented rapid development, and this change has a profound impact on all areas of industrial production.[2]The development of automation technology not only represents the direction of industrial progress, but also reflects the great potential of the power of science and technology in improving production efficiency, ensuring product quality, reducing costs and enhancing production flexibility. With the evolution of technology, industrial automation has gradually transitioned from the initial manual operation to mechanized automation, and then to the intelligent automation stage that is now flourishing.[3]Despite the remarkable achievements, there are still some urgent problems and development bottlenecks in realizing highly automated and intelligent industrial sorting systems, mainly as follows:

1.1 Limitations of manual sorting

Traditional industrial component sorting relies on manual operation, this way in small-scale production, although it has a certain degree of flexibility and simplicity, but in the large-scale, high-efficiency production environment, its limitations gradually appeared. Manual sorting is inefficient, error-prone, and greatly affected by human factors, these factors together lead to sorting speed and accuracy can not meet the needs of modern industrial production. In addition, as labor costs continue to rise, the economic viability and competitiveness of manual sorting is facing serious challenges.[4]

1.2 Mechanized development

In order to overcome all the limitations of manual sorting, mechanized automation technology has emerged. By introducing various mechanical devices, such as robotic arms, mechanized automation significantly improves the speed

International Conference on Computer Vision, Robotics, and Automation Engineering (CRAE 2024),
edited by Qiang Cheng, Lei Chen, Proc. of SPIE Vol. 13249, 132490H

and power of sorting and increases the automation level of production. However, the application scope and efficiency of mechanized systems are still limited due to the lack of intelligent decision-making and fine identification capabilities when facing complex and variable sorting tasks.[5]

1.3 The rise of intelligence

The rise of intelligent automation technology is due to the rapid development of computer vision, artificial intelligence, and machine learning. By integrating advanced image processing algorithms and pattern recognition technology, the intelligent system is able to quickly and accurately identify and classify components, greatly improving the efficiency and accuracy of sorting. The development of intelligent automation technology has brought new opportunities for development in the field of industrial automation, and has provided new ideas and methods for solving the problems faced by traditional manual sorting and mechanized automation.[6]

The algorithm developed in this study addresses the limitations of existing technologies and designs three innovative steps: first, image pre-processing techniques designed for industrial environments are used to improve image quality; second, accurate feature extraction and contour analysis are performed to lay a solid foundation for subsequent shape matching; and lastly, an automated method based on shape matching and area prioritized sorting decision is introduced.[7]This method, combined with machine vision technology, significantly improves the recognition accuracy of complex shaped parts and makes sorting decisions based on an area-first intelligent strategy, thus optimizing the automatic sorting process of industrial components.[8]

2. METHODOLOGY

In the field of industrial automation, in response to the inefficiency of traditional manual sorting and the limitations of mechanized automation in handling complex tasks, this paper proposes an automated sorting method based on machine vision. The method aims to improve the accuracy of shape recognition and sorting efficiency through innovative techniques.

To support the algorithm development and experimental validation, the image dataset used in the study was captured by a high-resolution camera and finely processed to ensure the diversity and accuracy of the dataset, which covers images of iron sheets with multiple shapes.

The experimental results show that the algorithm proposed in this paper has obvious advantages in improving the sorting efficiency, reducing the cost, and enhancing the product stability. Compared with the traditional method, this method not only optimizes the sorting process, but also improves the adaptability of the system to changes in the production environment, providing an innovative technical solution for the automatic sorting of precision industrial components, and demonstrating the potential for application in the field of industrial automation and the prospect of promoting technological development.The process architecture diagram of this method is shown in Figure 1.

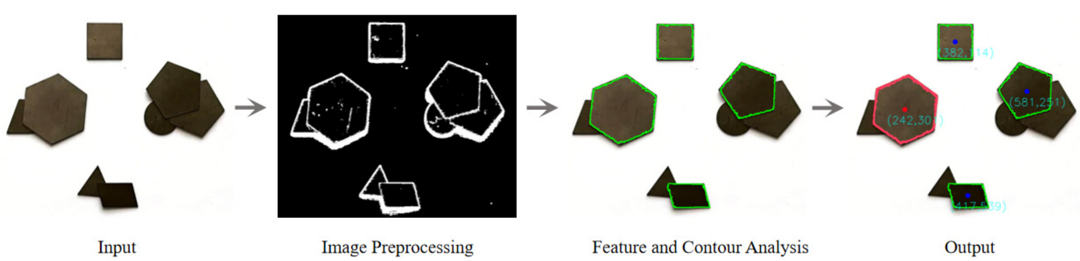

Figure 1. Method Architecture Diagram.

2.1 Industrial image acquisition optimization and preprocessing technology

Image preprocessing is the first step in the sorting algorithm, and its main purpose is to improve the image quality to make the subsequent feature extraction and contour analysis more accurate and efficient. In industrial production environments, the captured raw images usually contain various noises and complex backgrounds, which affect the recognition and sorting of target objects. Image preprocessing optimizes the raw image through a series of steps to enhance the edge features of the target object, remove noise, and simplify the image data to make it more suitable for subsequent processing. The steps typically include grayscale processing, binarization, edge detection, and morphological processing, through which the original image is transformed into a form suitable for analysis.[9]

(1) Grayscaling and edge detection

Although images captured on industrial production lines are usually in color, color information is often not a decisive factor in shape recognition. Therefore, the research in this paper first involves converting color images to grayscale images, a step that significantly reduces the amount of data and thus simplifies the subsequent image processing tasks. On the basis of the grayscale image, in order to extract the edge information, we employ the Sobel operator based on 1x3 convolution kernel for edge detection.The Sobel operator highlights the edges by calculating the first-order derivatives of the image, and is a widely used edge detection algorithm in image processing.[10]

The Sobel operator consists of convolution kernels in two directions: horizontal (x-direction) and vertical (y-direction). These two directional convolution kernels are used to calculate the gradient of the image in the horizontal and vertical directions, respectively, and their formulas are as follows: the formulas for the convolution kernel in the vertical direction (y-direction) are shown in Formula (1) and Formula (2).

a) Sobel operator in the horizontal direction (x-direction)

$$\mathrm{K_x} = \frac{1}{8}\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \tag{1}$$

b) Sobel operator in the vertical direction (y-direction)

$$\mathrm{K_y} = \frac{1}{8}\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \tag{2}$$

By applying these convolution kernels to the image, we can calculate the gradient magnitude of each pixel point in the horizontal and vertical directions, respectively. These gradient magnitudes are subsequently used to determine the edge strength and orientation of each pixel point in the image. The final strength of the edges can be calculated by synthesizing the sum as shown in Formula (3).

$$\mathrm{K} = \sqrt{\mathrm{K_x^2} + \mathrm{K_y^2}} \tag{3}$$

With this edge detection method based on 1x3 Sobel operator, we are able to effectively extract the edge information of the target object from the image, which provides a solid foundation for shape recognition and automated sorting. This process not only improves the accuracy of edge detection, but also provides strong technical support for the realization of automated sorting systems, which helps to improve the efficiency and accuracy of the entire industrial production line.

(2) Binarization and morphological processing

Binarization and morphological processing are further processing of pre-processed images to better extract the contours of the target object. Binarization converts the image to a black and white only form by setting a threshold value to make the target object more distinguishable from the background. Morphological processing, on the other hand, removes noise and fills in the voids of the target object through a series of morphological operations to obtain a clearer and more complete silhouette. The result of binarization and morphological processing is shown in Figure 2.

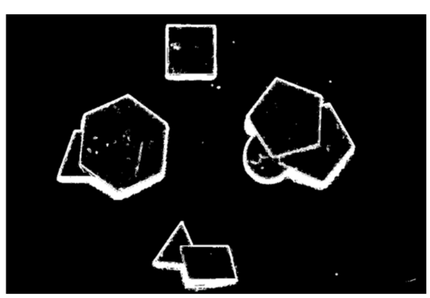

Figure 2. Binarization and morphological processing results.

2.2 Industrial component feature extraction and contour analysis methods

Feature extraction and contour analysis is the core step of the sorting algorithm, which aims to extract the contour of the target object from the preprocessed image and characterize it. This step is crucial because only when the contour of the target object is accurately extracted can subsequent shape matching and sorting decisions be made. The extraction and analysis of contours usually involves a variety of image processing techniques, such as contour detection and contour screening, through which the geometric features of the target object can be identified and characterized to provide a basis for subsequent classification and sorting.

In a preprocessed binary image, all contours need to be extracted first. Contours are continuous points (along the boundary) in the image with the same color or intensity, which can be used to describe the shape and location of the target object. In industrial sorting applications, the accurate extraction of contours is the key to the subsequent steps. After all contours have been extracted, they need to be screened and analyzed. Contour analysis mainly includes two steps of contour screening and contour feature extraction. By setting certain screening conditions, such as contour area, perimeter or shape features, irrelevant contours can be filtered out, and only valid contours of the target object can be retained, and the screening condition used in this experiment is contour area. After filtering out the valid contours, further shape feature extraction is performed on these contours in order to describe the geometric features of the target object. The filtered valid contours are shown in Fig. 3.

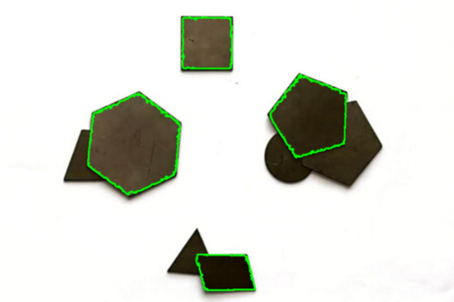

Figure 3. Images of valid contours after screening.

2.3 Customized shape matching algorithms and component sorting decisions

Shape matching and sorting decision is the last core step in the sorting method, and its goal is to achieve fast recognition and accurate classification of iron sheets of different shapes and sizes. This technology point integrates advanced technologies from several fields, such as image processing, pattern recognition and machine vision, in order to realize the automated detection and sorting of iron sheets. In the shape matching stage, the system recognizes the shape of iron sheets by analyzing their geometric features and using contour matching algorithms. And in the sorting decision stage, the system determines the priority and sorting path of each iron piece based on the results of shape matching, combined with preset rules and strategies.[11]

The key to this technology point is to be able to accurately recognize the target iron piece according to the screening conditions and determine its type, and to mark the outline of the target iron piece in red in order to prioritize it for gripping. In order to improve the accuracy and efficiency of sorting, the system will add mass points to all the surface iron sheets when handling iron sheets, and realize the precise positioning and stable gripping of the robotic arm by accurately determining the center position of the iron sheets, so as to improve the accuracy and efficiency of the operation. This step is crucial for subsequent gripping and sorting.

(1) Shape matching

In the shape matching phase, the system utilizes a contour matching algorithm to identify the shape of the iron sheet by analyzing its geometric features. Specifically, the captured image of the iron sheet is first pre-processed, including converting the image into a gray scale map to reduce the computational complexity. Then, the contour of the iron sheet is extracted using an edge detection algorithm, which can obtain the contour information of the iron sheet and exclude the background noise.[12] Next, each contour is shape-matched by calculating geometric features such as Hu moments, which are a set of image-based moment invariants that can be maintained under rotation, scaling, and flipping to provide a stable shape description. By calculating the similarity between the iron sheet contours and the predefined templates, the system is able to effectively recognize and classify different types of iron sheets. This process ensures that the method is able to accurately recognize the type of precision components in industry and is stable even in complex production environments. The preset stencil shapes are shown in Figure. 4.

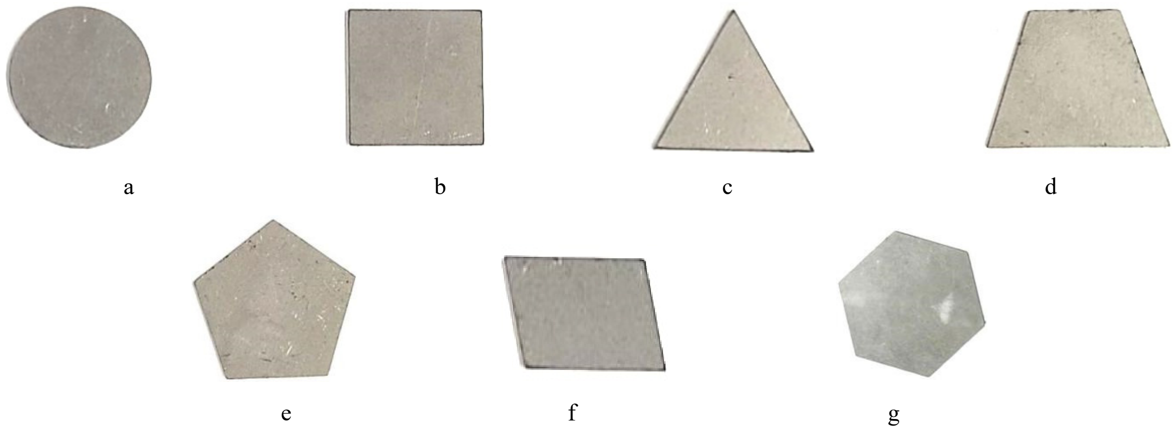

Figure 4. Images of valid contours after screening.
Note:Fig.a-g shows an example of a preset stencil shape.

(2) Sorting decision

In the sorting decision stage, the system prioritizes and sorts the path of each iron piece based on the shape matching results, combined with preset rules and strategies. First, the system prioritizes the iron pieces with the largest area to be grabbed, which is because large iron pieces may represent more critical components, and prioritizing these components can ensure that critical tasks are completed first. In addition, the removal of larger iron pieces reduces visual interference with subsequent inspection processes, improves inspection and gripping efficiency, and reduces potential safety risks on the production line. The area calculation formula is shown in Formula (4)

$$A = \sum_{i=1}^{n} x_i y_i \tag{4}$$

Note:A is the area of the iron sheet, xi and yi are the coordinates of the contour points, n is the number of contour points

By adding mass points to all the surface iron sheets, the system can accurately determine the center position of each sheet. And by calculating the position of the mass point, the robotic arm can achieve precise positioning for a stable gripping operation. This not only improves the accuracy and efficiency of gripping, but also optimizes the entire sorting process to ensure that each precision component can be accurately identified and classified. Ultimately, the system realizes automated, efficient and precise sorting of a wide range of industrial components through the processes described above, adapting to dynamically changing production needs. The effect of filtering out the iron pieces with the largest area and marking their contours and centers of mass in red is shown in Figure 5.

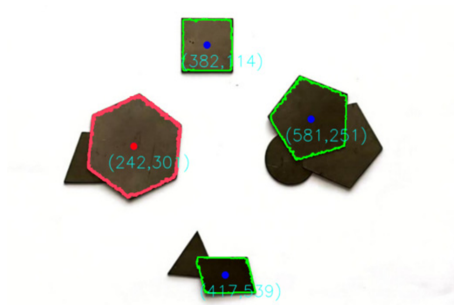

Figure 5. Filtered and labeled images of the center of mass.

3. EXPERIMENTS

In this study, we compare and analyze the performance of different edge detection algorithms in the task of iron sheet recognition and sorting. We used common edge detection operators such as Sobel with 1x3 convolution kernel, Sobel with 3x3 convolution kernel,Scharr, Laplacian, and Canny, and used the similarity between the iron piece with the largest area of the selected contour and its convex packet as an evaluation metric to quantify the performance of the different algorithms. In the evaluation criteria, the closer the similarity value is to 0 represents the higher accuracy of edge detection.[13]

In the experiments, the images were first grayscaled and then binarization was applied, where the binarization threshold of the image was set to 5, a choice made to remove noise while preserving edge information. For the predefined templates, the threshold of binarization was set to 15 to ensure that the templates have sufficient contrast during the matching process. Next, we use multiple edge detection operators based on different convolutional kernels for edge detection and smooth the edges by median filtering with a convolutional kernel size of 3 to reduce noise interference.

When filtering the internal contours, we set both the area threshold min_area_threshold and the perimeter threshold min_perimeter_threshold to 300 to ensure that only significant iron sheet contours that satisfy specific size conditions are retained. This set of filtering conditions lays the foundation for subsequent shape matching.

In the shape matching stage, we employ an advanced contour matching algorithm to recognize the shape of the iron sheet by calculating geometric features such as Hu invariant moments. These features remain invariant under image transformation, providing a stable feature description for shape matching. The similarity threshold match_threshold was set to 0.05 to evaluate the degree of match between the detected contours and the predefined templates.

To quantify the performance of the algorithm, we used the K-Select algorithm, which means that the iron with the largest contour area is selected and removed after each detection, and then the process is repeated until all the iron pieces are removed. After each removal of the largest iron, we calculate the similarity between its contour area and the convex packet to evaluate the accuracy and stability of different edge detection algorithms.

After in-depth analysis and experimental validation, we chose the Sobel operator with a 1x3 convolutional kernel as the edge detection algorithm. The experimental results show that the algorithm not only exhibits high stability and accuracy in edge detection and contour extraction, but also shows excellent performance in multiple tasks. Our choice is based on an in-depth understanding of the special needs of precision industrial components and the excellent performance of the 1x3 Sobel operator in the experiments. Therefore, we are reasonably confident that the 1x3 Sobel operator is the best choice for edge detection algorithms in the application scenarios of this study.The experimental results are shown in Table 1.

Table 1. Performance Comparison of Different Edge Detection Algorithms in Iron Sheet Recognition Tasks.

algorithm	K-Select(Similarity of convex packets of iron pieces with the largest contour area)							
	K-1	K-2	K-3	K-4	K-5	K-6	K-7	K-8
Sobel(1x3)	**0.0008**	**0.0016**	**0.0008**	0.0119	**0.0154**	**0.0002**	**0.0091**	**0.0144**
Sobel(3x3)	0.0026	0.0022	0.0716	0.0205	0.0462	0.0006	0.0137	0.0377
Scharr	0.0336	0.0030	0.0055	0.0274	0.0213	0.0004	0.0055	0.0428
Laplacian	0.0017	0.0398	0.0046	**0.0099**	0.0194	0.0016	0.0465	0.0545
Canny	×	×	×	×	×	×	×	0.0273

4. CONCLUSION

The automated sorting method proposed in this paper realizes fast identification and accurate classification of iron sheets of different shapes and sizes by integrating advanced image processing, pattern recognition and machine vision technologies. The key technologies of the system include edge detection, shape matching, convex packet algorithm, and sorting decision strategy based on area priority. Overall, the automated sorting system in this study demonstrates the potential to improve productivity, reduce labor costs and enhance sorting accuracy, and is expected to play an important role in future industrial automation.

Future work will focus on the improvement of Image pre-processing techniques, optimization of shape matching algorithms, further research on sorting decision-making strategies, and the application of machine learning techniques to improve the system's ability to generalize to new shapes and adapt to complex production environments.

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