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Automatic Identification of Casting Part Numbers based on Machine Vision

Jinqi Ge *

School of Mechanical and Electrical Engineering, Nanjing Forestry University, Huai'an, 223001, China
* Corresponding author Email: 2210304105@njfu.edu.cn

ABSTRACT

For the casting of the workpiece number characters are small, and the blade surface reflection, the target and the background of the contrast is low, resulting in the human eye recognition difficulties, low efficiency and other issues. In this paper, a machine vision-based casting workpiece number automatic identification system is designed. First of all, through the high-resolution industrial camera to obtain the image to be recognized, and to be recognized image preprocessing; and then according to the target area characteristics to determine the region of interest, extract the character features to establish a character library; and finally the application of character templates in the character library to achieve automatic recognition of characters in the image to be measured. After the actual test shows that the system can meet the casting workpiece number automatic identification needs, and stable performance, has good practicality and feasibility, thus proposed to improve the identification system. Whether in the generation of the manufacturing process, or testing and maintenance process, need to be organized according to the workpiece number, workpiece number is equivalent to each casting ID, can be convenient to record and query the casting in the generation of the manufacturing process of the relevant information as well as testing and maintenance of defects found in the process of information.

KEYWORDS

Workpiece Casting; Character Recognition; Machine Vision.

1. INTRODUCTION

With the continuous development of industrial production automation and intelligent manufacturing technology, the automatic identification of casting part number becomes more and more important in the production process. Casting workpiece number is the unique identification of each casting, can record the casting in the manufacturing process of the relevant information as well as inspection and maintenance process defects found in the information. However, the traditional casting workpiece number identification work mainly rely on manual vision, there are low efficiency, easy to fatigue, easy to error and other problems. Especially in the casting surface is smooth, the reflectivity of light is strong, the target and the background contrast is low, the human eye recognition becomes more difficult.

In recent years, machine vision technology has been rapidly developed, because of its intelligent and efficient advantages gradually favored by people. Machine vision technology can automatically identify the casting workpiece number, improve work efficiency, avoid identification errors, and realize the automatic identification of casting workpiece number. Therefore, the casting workpiece number recognition technology based on machine vision has important research background and application value.

Machine vision-based casting workpiece number identification technology can improve work efficiency, reduce the time and labor intensity of manual identification, reduce production costs. At the same time, the technology can accurately identify the casting workpiece number, to avoid errors and omissions of manual identification, improve production quality and reliability. In addition, based on machine vision casting workpiece number recognition technology can be combined with automated production lines to realize the automated production and management of castings, improve production efficiency and competitiveness. At the same time, this technology is also an important part of intelligent manufacturing technology, which helps to promote the development and application of intelligent manufacturing technology. Finally, the research and application of casting workpiece number recognition technology based on machine vision can expand the application scope of machine vision technology in industrial production, medical education and other fields.

In summary, the casting workpiece number recognition technology based on machine vision has important research background and significance. It plays an important role in improving production efficiency, reducing production cost, realizing automated production, promoting the development of intelligent manufacturing technology and expanding the application fields of machine vision technology.

2. LITERATURE REVIEW

The casting workpiece number recognition technology based on machine vision has received extensive attention and research in recent years. This technology realizes the automatic identification of casting workpiece number by using machine vision algorithm and deep learning model, so as to improve the production efficiency and identification accuracy.

Image preprocessing technology is one of the key steps in the process of casting part number recognition. Researchers have proposed a variety of image preprocessing techniques, such as filtering, binarization, edge detection, etc., in order to improve the image quality, enhance the contrast between the target and the background, so as to improve the recognition accuracy[1]. In addition, feature extraction and matching technology is also an important means to realize the casting workpiece number recognition[2]. These techniques include morphological features, texture features, color features and so on. Automatic recognition is achieved by extracting the features of the casting part number image and matching them with the pre-established character library. The researchers used deep learning models such as convolutional neural network (CNN) for feature extraction and classification, and achieved better recognition results. These deep learning models can automatically learn image features, thus improving recognition accuracy and robustness[3]. In order to improve the practicality and reliability of the casting workpiece number recognition system, researchers have integrated and optimized the system. This includes industrial cameras, light sources, lenses and other hardware equipment selection and configuration, as well as software algorithm optimization and adjustment. The current status of research on casting workpiece number recognition technology shows the importance and potential of this technology in the field of industrial automation and intelligent manufacturing. Machine vision technology through computer algorithms and models to simulate human vision, can automatically capture and process image information, so as to achieve accurate identification of casting workpiece number [4].

3. THE MAIN RESEARCH ELEMENTS OF THIS PAPER

For the casting of the workpiece number characters are small, and the blade surface reflection, the target and the background of the contrast is low, resulting in the human eye recognition difficulties, low efficiency and other issues. In this paper, a machine vision-based casting workpiece number automatic identification system is designed. First of all, the designer needs to analyze the characteristics of the casting workpiece number in detail, including its font, color, size, location and possible background interference. This analysis will guide the subsequent image acquisition, pre-processing and feature extraction steps.

In terms of hardware configuration, choosing the right industrial camera is the key, its resolution and frame rate need to meet the needs of casting image acquisition. At the same time, the design or selection of a suitable light source to ensure that the workpiece number area to provide uniform and appropriate lighting, reduce shadows and reflections. The choice of robot arm or robot should also consider its flexibility and stability, in order to adjust the camera angle and distance, to obtain the best image.

The image acquisition system should be able to automatically or manually control the camera for image acquisition and ensure that the acquired images are of sufficiently high quality. Next, the image is pre-processed, including denoising, contrast enhancement and image segmentation to separate the part number from the background.

In the feature extraction stage, the designer needs to extract the shape, color, texture and other features of the part number. For complex part numbers, advanced feature extraction methods such as SIFT or SURF may be required. Subsequently, depending on the type and complexity of the part number, OCR technology or deep learning models are selected for character recognition.

In the algorithm optimization stage, methods such as cross-validation and grid search are used to optimize the model parameters, and data enhancement techniques are used to improve the generalization ability of the model [5]. At the same time, a recognition model is designed to be able to handle workpiece numbers with different fonts, sizes and angles.

The system acquires high-resolution and clear images through the industrial camera, then preprocesses the images, then draws the ROI area, then extracts characters according to the character texture features and establishes the character library, then completes the workpiece number recognition of the image to be measured, and finally completes the design of the upper computer interface through the C# and the Vision Master (directly referred to as the VM in the back).

The feature extraction of CNN is mainly realized through the convolutional layer. The convolutional layer mimics the biological visual perception mechanism by sliding a filter over the image to calculate the dot product and generate the feature map [6]. The input of the convolutional layer is the pixel matrix of the image, and the output is the feature map, in which each element represents the intensity of the feature at that location. The convolutional layer can extract the local features of the image, such as edges, corner points, texture, etc On the basis of feature extraction, CNN uses activation functions to increase nonlinearity and help the model learn more complex features [7]. Commonly used activation functions are ReLU, Sigmoid, Tanh and so on. The introduction of activation function makes CNN able to capture more complex image features and improve the recognition accuracy.

In order to reduce the feature dimensionality and improve the computational efficiency, CNN introduces a pooling layer (also known as aggregation layer)[8]. The pooling layer reduces the dimensionality of the feature map and retains the important feature information. Commonly used pooling operations include maximum pooling, average pooling and so on.

After feature extraction and dimensionality reduction processing, the CNN uses a fully connected layer for the classification or regression task [9]. The fully connected layer maps the extracted features to the output space of the classification or regression task. The feature extraction and classification process of convolutional neural networks (CNN) is a complex but efficient learning task. In the convolutional layer, feature maps are generated by sliding a filter (or convolutional kernel) over the image and computing dot products [7]. These feature maps capture the local features of the image, such as edges, corner points, textures, etc. Subsequently, activation functions (e.g., ReLU, Sigmoid, Tanh) are used to increase the nonlinearity, thus helping the model to capture more complex features[6].

In order to reduce the feature dimension and improve the computational efficiency, CNN introduces a pooling layer[8]. The pooling layer reduces the dimensionality of the feature map through operations such as maximum pooling or average pooling to retain important feature information.

After feature extraction and dimensionality reduction, the CNN uses a fully connected layer for the final classification or regression task [9]. The fully connected layer maps the extracted features to the output space of the classification or regression task. Here, classification algorithms such as softmax regression or support vector machine (SVM) are used to compare the similarity between the output vectors of the fully-connected layer and the predefined category labels to achieve classification [6].

The application of convolutional neural networks (CNNs) in the field of deep learning has yielded remarkable results, especially in image processing tasks.CNNs are unique in their ability to learn the features of an image automatically, end-to-end, without human intervention [6].

4. THE APPLICATION PROCESS OF THE VM PLATFORM

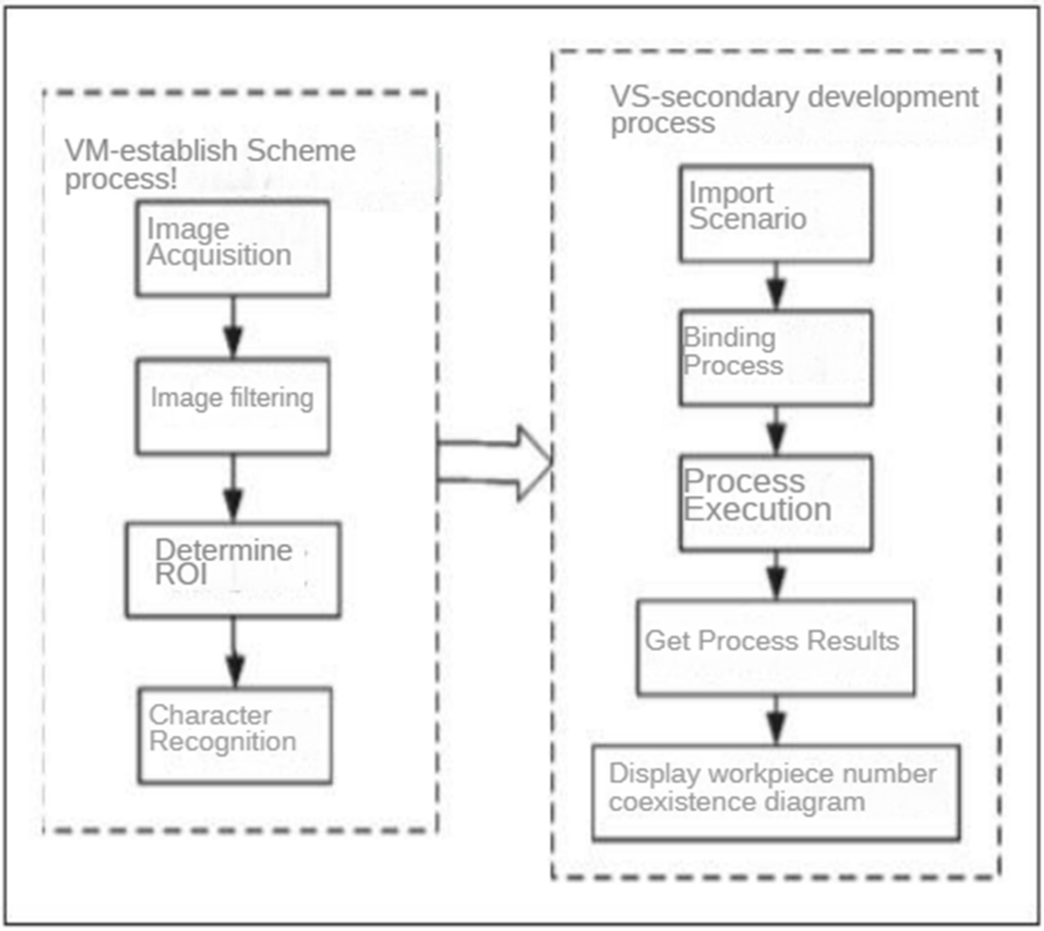

Figure 1. The application process of the VM platform

Automatic identification of casting workpiece number using Vision Master is a comprehensive process, involving image processing, feature extraction, machine learning and system integration and other aspects.

First, an image of the cast part needs to be captured by a high-resolution camera. The quality and clarity of the image is critical to the subsequent recognition process, so it is necessary to ensure that the light source is appropriate, that the camera is at the right distance from the workpiece, and that the workpiece is consistently positioned and oriented in the image.

Next, the captured images are preprocessed. The preprocessing may include steps such as denoising, contrast enhancement, gray scale conversion, etc. These processes help to eliminate the disturbing factors in the image and improve the accuracy and robustness of the recognition. These processes help to eliminate the interfering factors in the image and improve the accuracy and robustness of the recognition.

Then, Vision Master's image processing functions are used to locate the position of the artifact number. This may involve algorithms such as edge detection and morphological processing. Through these algorithms, the location of the part number can be accurately extracted from the image, preparing it for subsequent feature extraction and recognition.

After locating the position of the artifact number, the next step is to extract the features. This may include the use of image moments, HOG (Histogram of Orientation Gradients) features, Local Binary Patterns (LBP), and other methods. These features can effectively represent the visual characteristics of the part number and are essential for the subsequent recognition process.

With the extracted features, machine learning algorithms can be used to learn the features, thus realizing the recognition of workpiece numbers.Vision Master may have built-in algorithms such as Support Vector Machines (SVMs), Random Forests, etc., or it can be integrated with external models. Choosing the right algorithm and training the model is a critical step in the recognition process, which needs to be adjusted and optimized according to the actual application scenarios and requirements.

Recognition results need to be validated to ensure that the accuracy rate meets the requirements. This may involve methods such as comparison with known labels, confusion matrix analysis, and so on. Once validated, the results can be exported to a database or used in further automated processes, such as automated access control, quality control, etc.

Finally, Vision Master's part number recognition system is integrated into the production line to realize real-time automatic part number recognition. This may involve connecting and communicating with PLCs, databases, etc., as well as coordinating and cooperating with other systems on the production line.

Figure 2. vision master

4.1. Capture an Image of the Cast Workpiece

Utilizing a high-resolution camera to capture the image of the casting workpiece is a critical step, which directly affects the quality and effect of the subsequent image processing and feature extraction. In this step, it is necessary to select a suitable high-resolution camera, ensure proper lighting conditions, and adjust the position and focus of the camera to obtain a clear image. The captured images may contain noise, shadows or other interfering factors, so it is necessary to use preprocessing techniques, such as filtering, denoising, contrast enhancement, etc., to process the images in order to improve the accuracy of the subsequent processing. Finally, the pre-processed images are transferred to a computer system and stored in a suitable database or file system.

Image processing and feature extraction are key steps after capturing an image of the casting using a high-resolution camera. The goal of this step is to extract useful information from the image for subsequent analysis and recognition. First, image preprocessing, such as filtering, denoising, contrast enhancement, etc., is needed to improve the accuracy of subsequent processing. Then, the image is segmented to extract the region of interest. Commonly used image segmentation methods include threshold segmentation, region growing, edge detection and so on. Next, useful features, such as edge features, texture features, shape features, etc., are extracted from the segmented image. The result of feature extraction will directly affect the accuracy of subsequent target recognition and classification. In addition, feature selection and dimensionality reduction are also needed to improve the efficiency and accuracy of subsequent target recognition and classification. Finally, the extracted features are utilized for target recognition and classification. Commonly used target recognition and classification methods include support vector machine, neural network, deep learning and so on. The results of target recognition and classification will directly affect the quality assessment and defect detection of casting workpieces.

4.2. Pre-processing of Images

Pre-processing of acquired images is a key step in image analysis, which aims to improve image quality, reduce noise and interference, and enhance the features of interest in the image. This step is crucial for subsequent image processing and analysis [10]. Noise cancellation, contrast enhancement, image deblurring, image segmentation, feature extraction and data enhancement are common preprocessing methods. These techniques can be selected according to the specific application requirements and image quality. The effect of preprocessing directly affects the accuracy and efficiency of subsequent image analysis and processing.

For example, K. Ramchandran et al. proposed nonlinear filtering in 1985 for image quality improvement. B. Parvin et al. proposed image segmentation using water thresholding in 1991, which is a commonly used technique for image segmentation [11]. T. F. Chan and L. A. Vese proposed the active profile model for image segmentation [12]. K. He et al. proposed DeepLab model for semantic segmentation in 2016 [13]. R. Girshick et al. proposed Rich Feature Hierarchies model for accurate object detection and semantic segmentation in 2014 [14]. A. Zisserman and L. van Gool proposed a statistical approach for shape matching in 1997 [15].

4.3. Using the Image Processing Function of Vision Master to Locate the Position of the Workpiece Number

When using Vision Master to perform image processing to locate the position of a part number, you can first use the camera to capture an image containing the part number and ensure that the image is of high quality and the part number is clearly visible. Subsequently, Vision Master's Noise Removal tool removes noise from the image, improves the contrast of the part number, and uses the Image Deblurring tool to deal with blurred images.

Next, Vision Master's image segmentation function can be utilized to separate the artifact number from the background, which can be achieved by threshold segmentation, region growing, etc. The key features of the artifact number are then extracted, such as edges and corner points, which will be used for subsequent localization operations. Then, the key features of the part number, such as edges, corners, etc., are extracted, and these features will be used for subsequent localization operations.

After feature extraction, Vision Master's template matching function can be used to match part numbers to pre-defined templates. This requires a template image with a known part number. Template matching helps to find the location of the part number and determine its coordinates in the image.

Based on the results of the template matching, the position of the center point of the part number can be calculated and the distance and angle between the center point of the part number and other reference points in the image can be calculated using Vision Master's measurement tools. These calculated part number position coordinates can be used in the control system or for further image processing.

In order to obtain the best positioning accuracy, the pre-processing and image processing parameters are optimized according to the actual application requirements. Finally, the image processing program of Vision Master is deployed to the corresponding hardware platform to ensure real-time image processing and workpiece positioning.

4.4. How to Extract Features That

After image processing with Vision Master to locate the position of the part number, the next step is to extract the key features of the part number. This step is crucial for subsequent recognition and analysis. The process of feature extraction includes image segmentation, feature extraction, feature description, and feature matching. Image segmentation is to separate the workpiece number from the background, which can be realized by threshold segmentation, region growing and other methods. Feature extraction is to extract key information, such as edges, corners, textures, etc., from the artifacts, which can be achieved by using the tools provided by Vision Master, such as edge detection, corner detection, texture analysis, etc. Feature description is to extract features from the artifacts. Feature description is to describe the extracted features to provide more information for subsequent recognition and analysis, which can be realized by histogram, shape descriptor, texture descriptor and other methods. Feature matching is to match the extracted features with predefined templates or features in the database, which can help to identify the specific type or shape of the part number. The matching result can be used for control system or further image processing. According to the actual application requirements, the parameters of feature extraction and matching are optimized to obtain the best recognition and analysis results. Finally, the image processing program of Vision Master is deployed to the corresponding hardware platform to ensure real-time image processing and workpiece feature extraction.

4.5. Validation of Identification Results

After image processing with Vision Master to locate the position of the part number and extract its key features, the next step is to verify the correctness of the recognition results. This typically involves a series of verification steps to ensure the authenticity, accuracy, consistency and robustness of the recognition results. Verification of trueness is usually accomplished by comparison with known correct part numbers, which may include manual inspection or comparison with standard part numbers in a database. Accuracy validation involves assessing the difference between the identification result and the actual part number, which may be measured by calculating the identification error. Consistency validation ensures that the recognition system consistently produces correct results at different points in time and under different conditions. Robustness validation tests the performance of the system in the face of various disturbances and part number deformations [16].

Performance metrics such as accuracy, recall, and F1 scores are also used to evaluate the overall performance of the recognition system. In addition, obtaining operator feedback is critical to understanding how the recognition system performs in real-world applications, which can help identify potential problems and provide suggestions for improvement [16].

Based on the validation results and user feedback, the recognition system should be iteratively optimized, which may include adjusting the algorithm parameters, updating the feature extraction methods or introducing new recognition algorithms. This process is usually evolving and improving to adapt to technological advances and changes in application requirements [16].

4.6. ntegration of Vision Master's Workpiece Number Identification System into the Production Line

Integrating Vision Master's part number recognition system into a production line involves several steps to ensure that the system works seamlessly with existing line equipment and processes. First, a requirements analysis was performed to determine the specific needs of the production line for the part number recognition system, including speed, accuracy, reliability and compatibility with other systems. Based on the results of the needs analysis, a part number identification system was designed to meet the requirements of the production environment and the required hardware components, such as industrial cameras, data acquisition cards, light sources and computer systems, were identified.

Next, the application is developed using Vision Master SDK and programming languages such as C# to realize the recognition and extraction of the workpiece number, and the interface with the production line control system (e.g. PLC) is developed so that the recognition results can be transmitted to the corresponding production line link. During the development process, we ensure that the system can withstand the conditions of temperature, humidity and vibration in the production environment, and configure the industrial camera and light source to obtain the best image quality and recognition effect.

Once the software was developed, the system was tested in a controlled environment to ensure that it could accurately recognize part numbers under a variety of conditions and to test the robustness of the system, including its ability to cope with interference, light variations and part number distortion. Subsequently, the recognition system was integrated into the production line, commissioned and its performance monitored to ensure that it worked seamlessly with the rest of the production line.

Based on the feedback from the trial run, the system was adjusted and optimized as necessary to improve the recognition algorithm, increase accuracy and reduce false recognition. The production line operators are trained to ensure that they can skillfully use the new system, and technical support is provided to solve any problems that may arise in the process of using the system. Finally, after confirming that the system performance is stable, the workpiece number identification system is formally deployed to the production line, and the system performance is continuously monitored to ensure that it meets the needs of the production line.

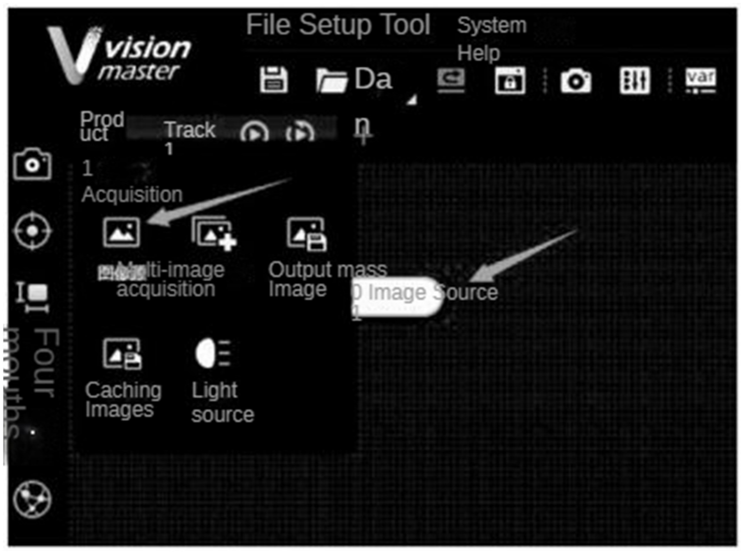

Figure 3. vision master

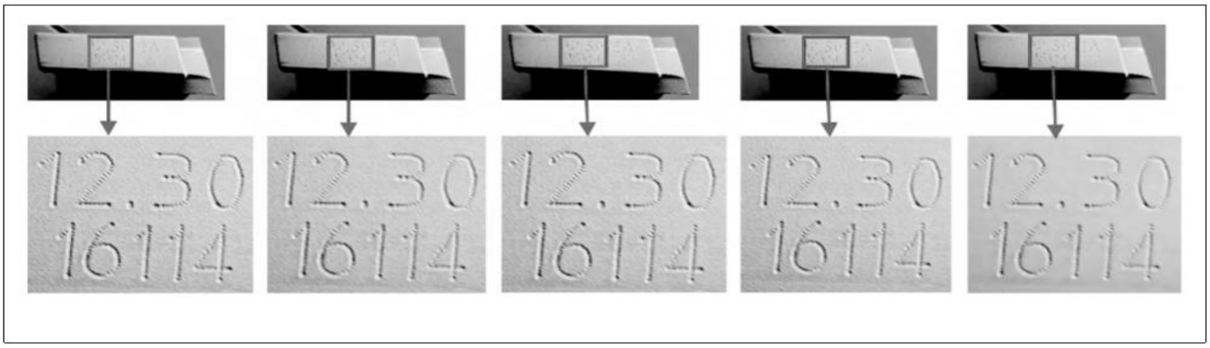

Figure 4. Photo retouching

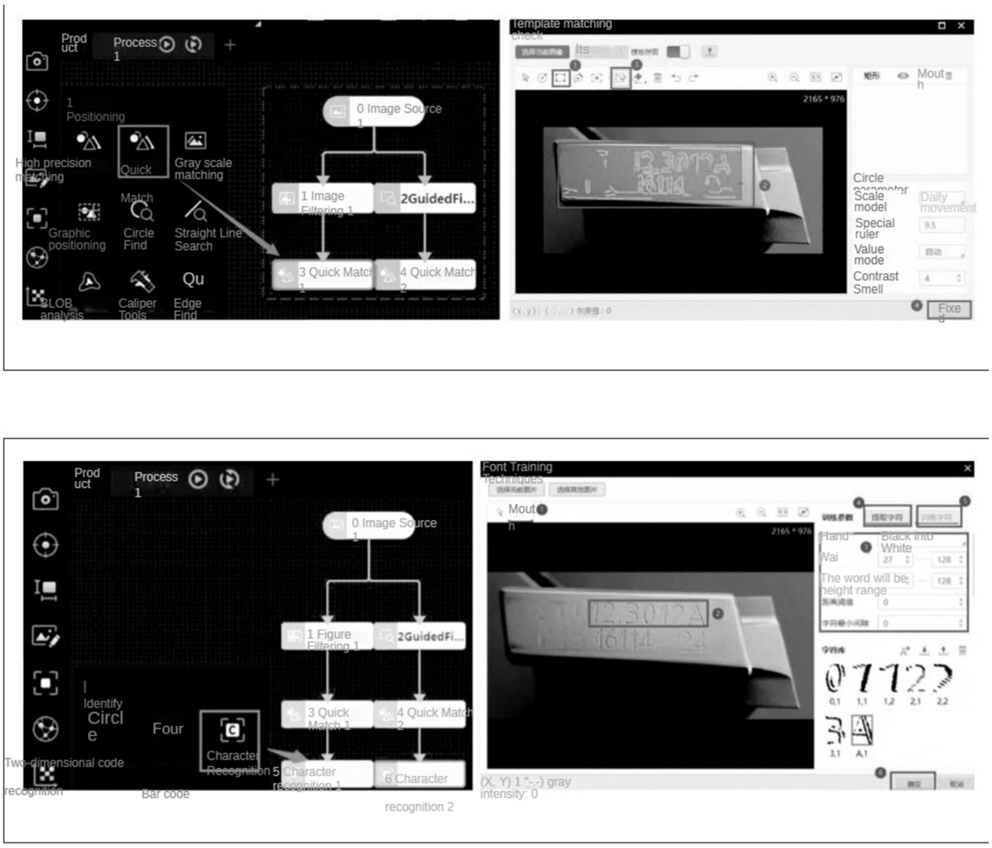

Figure 5. Steps

Figure 6. Save

5. CONCLUSION

Through in-depth research and practice, this thesis successfully applies machine vision technology to the automatic identification of casting part number, and proposes a recognition method based on deep learning and image processing algorithms. We use high-performance image processing equipment and advanced machine vision algorithms to realize the real-time recognition and extraction of casting workpiece number. The experimental results show that the system has high accuracy, high real-time performance and good robustness, and can meet the demand of workpiece number recognition in the production line.

Although we have achieved some research results, there are still some challenges and potential research directions. First, as the production line continues to grow and change, the recognition system may need to adapt to new part number specifications and shapes. Therefore, future research can focus on developing more flexible and scalable recognition algorithms to adapt to different part number shapes and sizes. Secondly, with the continuous advancement of deep learning technology, the use of more advanced neural network models can be further explored to improve the performance of the recognition system. In addition, machine vision technology can be combined with other intelligent technologies, such as the Internet of Things and big data analytics, to realize more efficient and intelligent production line management.

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