Intelligent analysis of hot stamping production process based on image recognition

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Hot stamping is an energy-efficient and low-cost way to produce automotive parts. The hot stamping production line has a high degree of automation and a good digitalization foundation. Due to the lack of a complete information system in most workshops, the digitalized production process data often lacks detailed information on recipes, molds, and parts. In this paper, the infrared temperature field of hot blanks on moulds is obtained using an infrared imaging detection system, and an abnormal blank position detection method based on locating pin finding is proposed, which is experimentally investigated in order to achieve the stability and accuracy. Based on the target detection model to predict the pin position, the correct rate of abnormal position detection of the Faster R-CNN model is analyzed under the conditions of coarse and fine judgments.

Keywords: Intelligent analysis; Image recognition; Hot stamping.

1. Introduction

With the new round of global scientific and technological revolution and industrial transformation advancing rapidly, the great power strategic game further focus on manufacturing industry, the United States “Advanced manufacturing leadership strategy”, Germany “National industrial strategy 2030”, Japan “Social 5.0” and other development strategies are centered on revitalizing the manufacturing industry, all based on the principle of "smart manufacturing", trying to seize the high ground of the new round of global manufacturing competition [1]. On the basis of manufacturing automation, the auto parts manufacturing industry is rapidly adopting big data, image recognition, deep learning and other methods towards in-depth informatization and intelligence [2].

Hot stamping is an energy-efficient and low-cost way to produce automotive parts. Hot stamping production lines are highly automated and have a good foundation for digitization [3, 4]. In the workshop that lacks a complete information system, the production process data often lacks detailed information of recipes, moulds and parts. To address this situation, this paper proposes an intelligent analysis method of hot stamping production process based on image recognition, which uses image data from infrared thermal camera and adopts image recognition method to identify the features of the parts,

†This study was supported by National Key Research and Development Program of China (Grant No. 2022YFB3706903) and the National Science and Technology Major Project of China (Grant No. 2018ZX04023001).

Y. Zhang and M. Ma (eds.), *Proceedings of the 7th International Conference on Advanced High Strength Steel and Press Hardening (ICHSU 2024)*, Atlantis Highlights in Materials Science and Technology 3,
https://doi.org/10.2991/978-94-6463-581-2_63

so as to compare and evaluate the production process and production process of the parts, and to give suggestions for production improvement.

2. An infrared imaging detection system

Existing hot stamping lines are unable to directly detect and evaluate the temperature and position of parts in the forming area. In the hot stamping process, the temperature of the material entering and exiting the mould determines the forming performance and quality, and the instability of the robot loading and unloading leads to the possible deviation of the positioning of the blanks transported into the mould, which affects the safety of the mould and the production quality. Based on these needs, an infrared imaging detection system [5] is designed for the forming area of the production line to detect the temperature and position of the incoming blanks and the outgoing parts online, and use the long-cycle big data to mine the information of part types, production cycle, etc., to achieve the online assessment and troubleshooting of the production process.

The infrared imaging detection system focuses on the forming area on the mould, uses the infrared camera to obtain the temperature field of the area at a specific process time point, identifies the temperature, location and characteristics of the blank from the temperature field, integrates the process requirements, the short-term production data, and adopts an intelligent method to discern the operation status of the production process and flow, and issues a timely warning for production faults. The system consists of an infrared camera and an industrial computer, which obtains recipe and material delivery process data from the process control system of the production line and the press transportation robot, and outputs analysis results and production warnings to the process control system and the press, as shown in Figure 2-1.

The system becomes part of the production line as a stand-alone process detection unit and generally needs to be driven by the production line's process control data. To ensure the timeliness and reliability of critical control signals, the system exchanges control signals directly with the press and transportation robots. When faults with abnormal blank positions are detected, due to the limitation of the means of fault processing, it is the only way to automatically stop the production line and manually handle the faults.

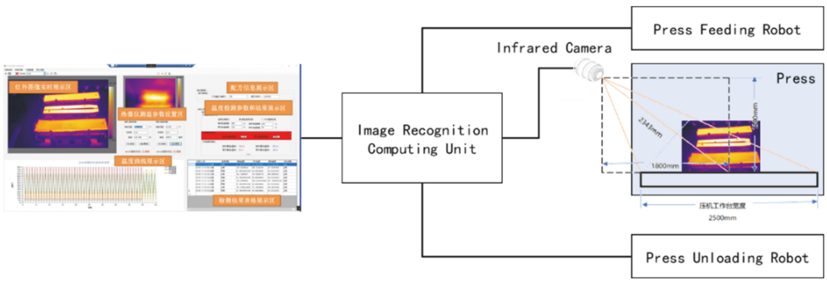

Figure 2-1 The composition of infrared imaging detection system.

3. Abnormal position detection methods of high temperature blanks

This chapter proposes an abnormal position detection algorithm based on blank locating pin finding, which predicts the position of the locating pin in the infrared image by training a target detection network model, matches the predicted position with the standard locating pin position, and determines whether the blank and the locating pin fit together or not, and obtains the position detection results (Figure 3-1).

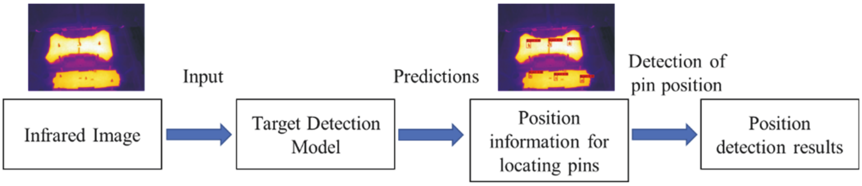

Figure 3-1 Positional anomaly detection method based on locating pin finding.

In the production process, the abnormal position of the blank is generally considered to be caused by a number of factors, one of which is the slight shrinkage of the blank size caused by the temperature reduction, and another is the accumulated position deviation during the transport of cold and hot blanks. Cumulative position deviation in cold stamping is generally corrected by positioning tapping, but in hot stamping, due to the softer blanks, the tapping effect is poor and is generally corrected by setting positioning pins on the mould. Due to the temperature difference, the pin and the blank can be well distinguished on infrared images. When the position is abnormal, the locating pin fails to fit with the locating hole on the sheet, supports the sheet, and the sheet obscures the locating pin.

Therefore, it can be assumed that the position of the blank is abnormal when the number of locating pins detected in the infrared image is less than the standard number of locating pins, as shown in Equation (3-1). num_{pre} is the number of locating pins predicted by the model, and num_{gt} is the number of locating pins in the standard of the mould.

$$num_{\mathrm{pre}} < num_{\mathrm{gt}} \tag{3-1}$$

A more accurate judgement should incorporate consideration of pin's location on the infrared image. IoU is the ratio of the area of the intersecting portion of two 2D planar regions to the area of the concatenation of the two regions, which reflects the degree of intersection of the two regions, and is computed as shown in Equation (3-2).

$$IoU = \frac{Predict \cap Ground-truth}{Predict \cup Ground-truth} \tag{3-2}$$

Predict is the region generated by the network and *Ground-truth* is the calibrated region containing the locating pin of the mould. When all Ground-truth regions intersect with the corresponding predicted locating pin regions, all the locating pins are considered to be correctly located and the blanks are correctly located.

Faster R-CNN (Region Convolutional Neural Network) is a representative network model of two-stage target detection network model (Figure 3-2). Faster R-CNN network model consists of pre-trained Convolutional Neural Network as feature extractor, Region Proposal Network (RPN), ROI Pooling and Classification Network. Faster R-CNN uses a two-stage approach of candidate frame generation and classification regression. RPN is responsible for generating candidate frames and the classification network is responsible for classifying the candidate frames and regressing the bounding frames. This two-stage design allows Faster R-CNN to achieve a better balance between accuracy and speed. The basic structure of Faster R-CNN is shown in Figure 3-2. Resnet (residual network) [6] introduces the jump connection of the original inputs to the original structure of convolutional and activation layers, which changes the output of the original structure, H(x)=F(x), to H(x) = F(x) + x, realizing a constant mapping from input to output, solving the problem of gradient vanishing that occurs during the training of the traditional multilayer neural network model, accelerating the convergence speed of the model, and further extending the depth of the neural network.

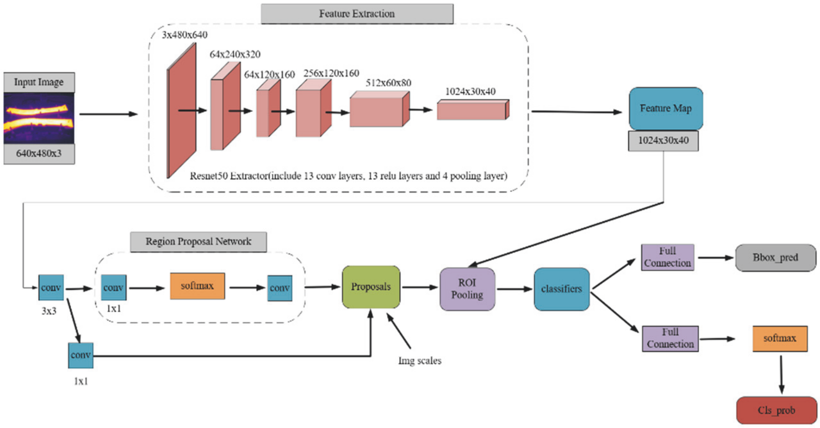

Figure 3-2 Faster R-CNN network model.

To obtain a realistic test dataset, an infrared imaging detection system is installed to a hot stamping production line in an automotive parts production workshop, using infrared camera to collect online infrared image of hot blanks from several moulds to establish infrared image dataset. All locating pins were manually labelled in infrared images [Figure 3-3]. The model is trained using GeForce RTX 3070Ti GPU with Pytorch 1.7.1.

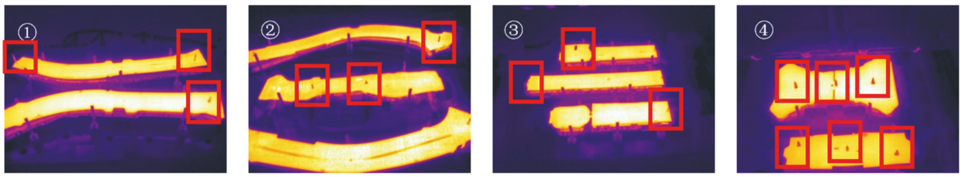

Figure 3-3 infrared image of hot blanks with locating pins labeled.

4. Results and analyses

4.1. *Prediction accuracy analysis*

Model validation was carried out for 9 sets of moulds, of which 8 sets of moulds training sets were used for training and 1 training set (mould #9) for model validation, the results of calculating IoU for each set of moulds are shown in Table 4-1.

Table 4-1 IoU for prediction results

Mould No.	1	2	3	4	5	6	7	8	9	Average
Faster R-CNN	0.81	0.74	0.63	0.81	0.67	0.72	0.43	0.69	0.64	0.68

Due to the large scale of the extracted features relative to the original image at the time of ROI pooling, Faster R-CNN performs 4 times down-sampling, a 4×4 anchor corresponds to a 64×64 region of the original image. For extracting features from small targets, this resolution is slightly less than satisfactory, but still achieves a prediction accuracy of 68%.

4.2. *Location identification analysis*

The model is able to predict the number and position of locating pins from the infrared image. The position boxes of locating pins predicted by the model usually have duplicate boxes, and the duplicate boxes are removed by calculating the IoU. A coarse blank position prediction is made by the number of locating pins, as shown in Table 4-2.

Further locating pin-position finding improves the detection accuracy, especially for impurities mistakenly detected as positioning pins. Take mould #9 as an example, as can be seen in Table 4-2, the correct rate is directly increased to 77.5% after fine judgement and the detection accuracy is increased by 13.14%. After the fine judgement, the accuracy of the Faster R-CNN network model has reached about 88.9%, which basically solves the engineering problem of detecting the abnormal position of hot blanks.

Table 4-2 Prediction correctness (%) of coarse judgement/fine judgement for target detection model.

Mould No.	1	2	3	4	5	6	7	8	9	Average
Faster R-CNN coarse judgement	92.4	96.7	71.7	100	100	89.6	91.4	81.3	68.5	88
Faster R-CNN fine judgement	95.6	96.4	63.7	100	100	91.4	93.2	82.6	77.5	88.9

4.3. *Time-consuming analysis*

In practical application scenarios, the whole process for the blanks being put into the mould to the press being fully pressed down is only 1~1.5s, which requires the temperature detection and position detection of the blank to be rapid. It is necessary to judge the abnormality and give an abnormal signal to stop the press before the press is fully pressed down. The time analysis of the whole process is taken on the images of 9 sets of moulds, a total of 450 images for the entire position detection. The average time required for each process is shown in Figure 4-1.

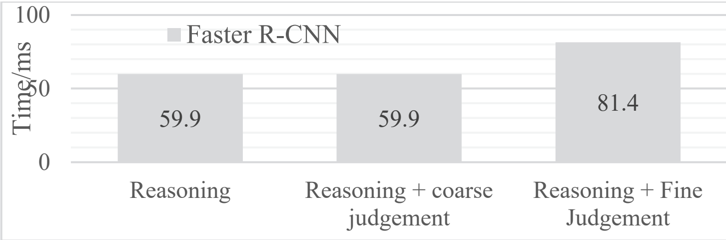

Figure 4-1 Comparison of time spent on the whole process of model detecting.

5. Conclusion and prospects

In this paper, the infrared temperature field of hot blanks on moulds is obtained using an infrared imaging detection system, and an abnormal blank position detection method based on locating pin finding is proposed, which is experimentally investigated in order to achieve the stability and accuracy.

Based on the target detection model to predict the pin position, the correct rate of abnormal position detection of the Faster R-CNN model is analyzed under the conditions of coarse and fine judgments. The result proves that Faster R-CNN has the high correct rate, with more than 88% for coarse judgement and more than 88.9% for fine judgement. The Faster R-CNN model takes 59.9 ms for reasoning and 81.4 ms for position detection, which is able to satisfy the demand of engineering applications that require the detection time of less than 100 ms.

This study adopts a target detection approach using image data, which provides corroboration for obtaining the type and shape characteristics of blanks. Based on this study, it is possible to continue to improve the identification and judgment accuracy by building a richer and more comprehensive data set, which will achieve the purpose of replacing manual recognition and detecting blank-positioning faults in advance.

References

1. Yisheng Zhang, Yilin Wang, Bin Zhu, et al. Research progress in hot stamping forming technology based on multi-component integration, *Journal of Plastic Engineering* **30**,1(2023).
2. Y. S. Zhang, Z. J. Wang and L. Wang. Progress in hot stamping process and equipment for high strength steel sheet, *Journal of Plasticity Engineering* **25**, 11 (2018).
3. L. Wang, B. Zhu, Q. Wang, J. Meng and Y. S. Zhang. Production control and optimization of hot stamping line, in *Proceedings of 5th International Conference on Hot Sheet Metal Forming of High-performance Steel*, (Toronto, Canada, 2015).
4. L. Wang, B. Zhu, Q. Wang and Y. S. Zhang. Modeling of hot stamping process procedure based on finite state machine (FSM), *The International Journal of Advanced Manufacturing Technology* 89, 857 (2017).
5. X. Q. Zhang, F. Zhang. Research and Application of Temperature Monitoring and Error Correction System for High-Strength Steel Hot Stamping Parts. in *Proceedings of the 6th International Conference on Advanced High Strength Steel and Press Hardening (ICHSU 2022)*.