Journal of Cases on Information Technology
Volume 25 • Issue 1

Research on Hot Operation of a Petrochemical Plant Based on Compound Edge Operator

Zhipeng Liu, SINOPEC Qilu Petrochemical Company, China*

ABSTRACT

In the operation of petrochemical plants, safety operation is the top priority, especially for the control of fire operation. In this paper, based on the real hot work in petrochemical plants, based on the extraction methods of different edge operators, the compound analysis of different edge operators can be carried out to visually detect the hot work of petrochemical workers in petrochemical plants, and based on the neural network algorithm, the convolution operation of edge data is carried out, and the data is input into the hot work database to build the hot work database and identify the flame. Remind the hot operation, according to the size of the flame to make a preliminary judgment on whether the danger, combined with the characteristics of the petrochemical device itself to add smoke identification. This method is of great significance to improve the thermal safety monitoring level of petrochemical plant.

KEYWORDS

Compound Edge Operator, Convolutional Neural Network, Edge Operators, Risky State Monitoring

INTRODUCTION

The refinery mainly produces gasoline, aviation coal, diesel oil, asphalt, polyethylene, polypropylene, polyvinyl chloride, acrylonitrile, butanol, caustic soda, benzene, and other chemicals, and a focus has been placed on the safety of personnel working in hot work. At present, enterprises mainly use mobile individual soldiers (Abdi & Williams, 2010; Azami et al., 2019) supplemented by cameras to shoot on-site operations and arrange inspectors for on-site supervision, which can realize real-time uploading of construction site videos. However, the amount of surveillance videos is huge, and the time and energy of inspection team personnel are limited, so they cannot supervise for extended lengths of time (Barz & Denzler, 2021). Because of this, they can only adopt centralized random inspection for supervision. It is difficult to detect violations and find hidden risks through manual screening. The video platform is also unable to provide early warning and real-time communication, and there is no early warning means at the operation site to remind the construction personnel in time(Bo & Jiulun, 2022). It can only be traced after the fact, which increases the workload of inspectors and the probability of safety hazards.

DOI: 10.4018/JCIT.328768
*Corresponding Author

With the development of computer technology, artificial intelligence technology has become more and more mature (Díaz et al., 2021; Feng et al., 2019; Gordo et al., 2016; Huang et al., 2015). Deep learning consists of deep neural networks, which consist of an input layer, multiple hidden layers, and an output layer. Each layer has several neurons, and there is a connection weight between neurons. Each neuron mimics a human nerve cell, and the connections between nodes mimic those between nerve cells (Krizhevsky et al., 2012; Lai & Chen, 2011). Deep learning uses layer by layer training mechanisms to get the initial values of the parameters of each layer. Then, backpropagation is used to compute the gradient of the target function. In deep networks (above 7 layers), the spread of residuals to the first layer will become small, in what is called gradient diffusion. The deep neural network model is complex and requires a large amount of training data and computation. On the one hand, deep neural networks are a simulation of the human brain, and mathematically, every neuron in a deep neural network is including activation functions (such as Sigmoid, ReLU, or Softmax functions). The number of parameters to estimate is also extremely large. In speech recognition and image recognition applications, there are tens of thousands of neurons and tens of millions of parameters. Such a model is very complex, and it requires a large amount of computation to solve such a model. Deep neural networks, on the other hand, require large amounts of data to train models with high accuracy (Li et al., 2021; Lowe, 2004; Manjunath & Ma, 1996; Menghao & Hongwei, 2019).

The deep neural network has a large number of parameters and a complex model. To avoid overfitting, massive training data is needed. Based on these two factors, training a model takes an incredible amount of time. Deep neural network training convergence is difficult and needs repeated experiments. The deep neural network is a nonlinear model, with a cost function that is non-convex, and it is easy to converge to the local optimal solution. At the same time, the model structure, input data processing method, weight initialization scheme, parameter configuration, activation function selection, weight optimization method, etc. of the deep neural network may have a great influence on the final result (Mohamed et al., 2021). In addition, the mathematical basic research of deep neural networks is, at present, insufficient. Although the network model can be initialized by production modeling methods, such as a constrained Boltzmann machine or denoising autoencoder to reduce the risk of obtaining local optimal, it still cannot solve the problem completely. When a deep neural network is used in practice, it is necessary to make reasonable use of massive data and choose an optimization mode. Piras and Giacinto (2017) improved the deep learning algorithm, and combined with transfer learning, focused on image preprocessing and other methods to detect hot spots in infrared images of photovoltaic modules, and achieved an algorithm model with high detection accuracy. Wang et al. (2020) proposed the use of data transfer to enhance heat source data, and a multi-scale feature learning module added into Faster-RCNN to further improve the detection accuracy.

Wang et al. (2021) proposed the deep transfer learning model to solve the problem of sample scarcity and achieved a better network model. Xicheng et al. (2021) realized effective detection of common defects in substations by adding a feature pyramid network and adjusting loss function and non-maximum suppression appropriately. Yin (2018) used an improved convolutional neural network combined with a pattern recognition strategy to detect 7 types of equipment defects in infrared images of substation equipment, such as current transformers, isolation switches, and arresters. Ying (2021) used the improved SSD network to identify transformer equipment, and then used the adversarial generation network to improve the defect detection ability of the model, and finally realized the effective detection of voltage transformers, dials, cabinet doors, insulators, and other defects. In Ye et al. (2023), image enhancement and restoration methods, based on filtering and generative adversarial network, are used to process images based on data sets, and the influence of underwater image enhancement and restoration on deep learning target detection accuracy is discussed. In Hei Ng et al. (2015), the data set is processed by the underwater image enhancement and restoration method, and the influence of the enhancement and restoration method on the target detection accuracy is studied. Zhang et al. (2021) extracted the traditional image processing technology and applied the depth global features. Zhang (2021) proposed the use of noiseless data sets containing annotation boxes for training and added the target detection network to improve the model's ability to describe the global features of images. Zhang et al. (2021) used the end-to-end two-path network model to learn clothing features in different scenarios, and, at the same time, introduced metric learning to make retrieval features more compact.

In this paper, a method based on a compound edge operator is proposed to detect the dangerous state monitoring method of fire operation in a petrochemical plant. The original monitoring image of the petrochemical plant is called to monitor whether there is a flame in the fire operation area, determine the dangerous state of fire operation in the petrochemical plant, and realize the real-time analysis and early warning of the operation site. The main line is, "monitoring violations, identifying risks, eliminating hidden dangers, and preventing accidents." This research gives full play to the role of the existing security video surveillance system to achieve the goal of improving the level of enterprise security control and effectively improve the existing disadvantages and improve the quality of site construction.

In this paper, the innovative extraction methods based on different edge operators are used for compound analysis. The use of different edge operators improves the accuracy compared with the previous single-edge operator extraction method.

This paper focuses on the hot operation of a petrochemical plant, carries out convolution operation on the edge data based on a neural network algorithm, inputs it into the hot operation database, identifies the flame, determines whether it is initially dangerous according to the size of the flame, and adds smoke identification in combination with the characteristics of the petrochemical plant itself. This method is of great significance to improve the monitoring of safe hot work in petrochemical plants.

The unique contribution of this study lies in the innovative use of a compound edge algorithm to analyze the hot operation of petrochemical plants, which can predict the occurrence time of accidents earlier and plays a key role in improving the safety of petrochemical plants.

PRINCIPLE OF THE EDGE DETECTION ALGORITHM

The edge detection algorithm is based on the edge of the flame in hot operation and is distinguished by the local characteristics of the discontinuity of the flame in hot operation. The edge of the object is the standard to distinguish each object, and the brightness degree, different shapes, and smooth effect of the edge of the object are the standards to judge the object. The edge detection technology takes advantage of the different light and dark degrees of the object edge as the premise to detect the discontinuous points of the object edge, and then connects these discontinuous points to get a complete edge line so that the effect of separating the image can be obtained.

Edge Detection Algorithm Based on the Canny Operator

The edge detection operator uses the reciprocal of the first-order direction in any direction of the two-dimensional Gaussian function as the noise filter. After image intensity convolution filtering, the local maximum of the image gradient is found and the image edge is determined.

Edge Detection Algorithm Based on the Roberts Operator

The operator first calculates the gradient of the diagonal deviation around the pixel point, and the intensity of the pixel is represented by the gradient size. The direction perpendicular to the gradient direction is the edge. In the pixel coordinate system, gradient Gx and Gy in horizontal and vertical directions are obtained, respectively, and g(x, y) is defined to represent the gray value of the calculated image, as shown in the formula.

$$g\left(x,y\right)=\sqrt{G_x^2+G_y^2} \tag{1}$$

$$g\left(x,y\right)=\left|G_x\right|+\left|G_y\right| \tag{2}$$

$$\left|G_x\right|=\left|\left[f\left(x,y\right)-f\left(x+1,y+1\right)\right]^2\right| \tag{3}$$

$$\left|G_y\right| = \left|\left[f\left(x+1,y\right) - f\left(x+1,y\right)\right]^2\right| \tag{4}$$

Edge Detection Algorithm Based on the Prewitt Operator

This kind of detection operator utilizes the fact that the gray difference between the upper and lower pixel points and the left and right adjacent points reaches the extreme at the edge, to smooth the image noise more effectively. Differential operator and template matching methods are usually used to detect the edge of the image with hot work.

Edge Detection Algorithm Based on the Sobel Operator

The Sobel operator is a kind of transmission edge detection method, which combines Gaussian filter smoothing noise and first-order differentiation and calculates the pixel gradient value of the image brightness function by the horizontal edge and vertical edge operators. The algorithm principle is as follows: Gaussian filter is used to de-noise the original image, and the Gaussian smoothing function is shown as follows:

$$G\left(x,y\right) = \frac{1}{2\pi\sigma^2}\mathrm{e}^{-\frac{x^2+y^2}{2\sigma^2}} \tag{5}$$

Among them, σ is the standard deviation of Gaussian filter parameters, which affects the quality of denoising. The original image f (x,y) and Gausse filter are rolled to obtain the image. The image I(x,y) is differentiated in the x and y directions, respectively, to obtain Gx and Gy:

$$g\left(x,y\right) = \sqrt{G_x^2 + G_y^2} \tag{6}$$

The approximate gradient of each point of the image is calculated, and the edge point can be obtained by setting the appropriate threshold. Table 1 shows the threshold value and direction of the edge detection operator. Table 1 shows the Canny operator, Roberts operator, Prewitt operator, and quantitative analysis of the Sobel operator.

EDGE DETECTION ALGORITHM BASED ON DEEP LEARNING

Neural Network Algorithm Analysis

Constructing the objective function of the neural network algorithm looks as follows:

Table 1. Threshold and direction of edge detection operators

Edge Detection Operator	Threshold	Direction	Selected Threshold
Canny operator	[0.0250,0.0625]		0.0800
Roberts operator	0.1127	Horizontal, vertical	0.0800
Prewitt operator	0.099		0.0800
Sobel operator	0.1126	Horizontal, vertical	0.0800

$$\min \Delta f\left(\Delta X_f\right) = \frac{\partial f}{\partial C}\cdot\Delta C + \frac{\partial f}{\partial R}\cdot\Delta R + \frac{\partial f}{\partial P}\cdot\Delta P + \frac{\partial f}{\partial S}\cdot\Delta S \tag{7}$$

ΔX_f represents the error value of different edge operators relative to the actual edge, namely, the compound error increment of the edge detection algorithm based on the Canny operator, the edge detection algorithm based on the Roberts operator, the edge detection algorithm based on Prewitt operator and edge detection algorithm based on Sobel operator.

$\frac{\partial f}{\partial C}, \frac{\partial f}{\partial R}, \frac{\partial f}{\partial P}, \frac{\partial f}{\partial S}$ means that the edge detection algorithm based on the Canny operator obtains partial differentiation concerning the actual edge error value. The edge detection algorithm based on the Roberts operator obtains partial differentiation concerning the actual edge error value, and the edge detection algorithm based on the Prewitt operator obtains partial differentiation concerning the actual edge error value. Figure 1 is the Composite Edge Operator

ΔC represents the error value of the edge detection algorithm based on the Canny operator relative to the actual edge.

ΔR represents the error value of the edge detection algorithm based on the Roberts operator relative to the actual edge.

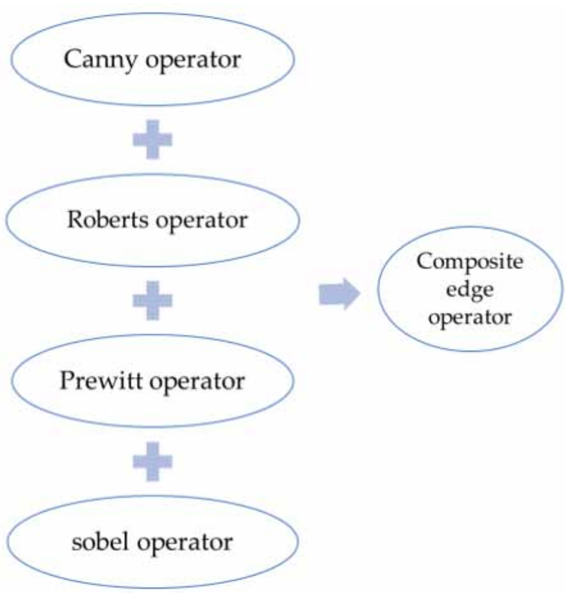
ΔP represents the error value of the edge detection algorithm based on the Prewitt operator relative to the actual edge.

ΔS represents the error value of the edge detection algorithm based on the Sobel operator relative to the actual edge.

Edge Detection Algorithm Based on Deep Learning

The convolutional neural network proposed in this paper is based on the complex edge operator, that is, the edge detection algorithm based on the Canny operator, Roberts operator, Prewitt operator, and Sobel operator. The eigenvalues extracted by the convolutional neural network are input into

Figure 1. The composite edge operator



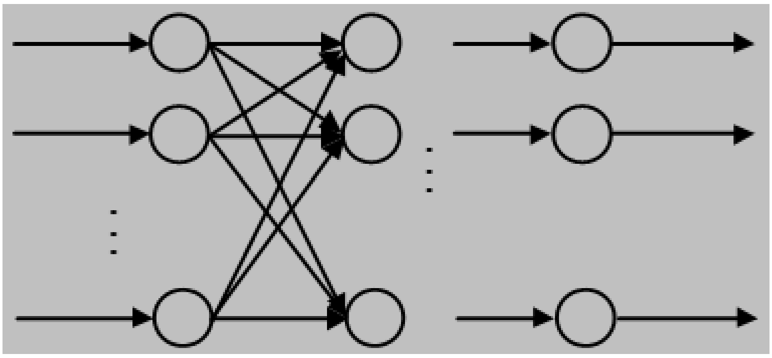
the first convolution layer. Considering that the input data are quite different in different time series, the first convolution layer is set as 1D-CNN considering the timing. Once 1D-CNN receives the input information, it will carry out the convolution operation immediately, start the initial transient timing feature extraction, and then reduce the dimension of time dimension through the pooling operation. Subsequently, multiple rounds of convolution operation are carried out until the characteristic value of the data signal is extracted. Once the specific feature of the original input is determined, its specific position is not as important as its position relative to other features. Feature extraction operation of convolutional neural network completely reduces the spatial dimension, which is limited to length and width, but does not include depth. Its main significance includes the number of weight coefficients being reduced to reduce the amount of calculation. Another significance is that it effectively controls the risk of overfitting. This item is mainly used in the case that the model overfits the training sample and the generalization ability of the verification set and the test set is insufficient.

Usually, neural networks are trained to make a specific input lead to a specific output. The neural network is trained by constantly comparing the output and target values until the output and target values of the network are the same. Usually, the network contains many of these input-output pairs in this supervised training mode.

The forward convolutional neural network topology diagram is adopted in this paper, as shown in Figure 2. The input layer, hidden layer, and output layer are the main components of the topology. Among them, the hidden layer can be a single-layer or multi-layer structure, and the neurons of each layer can only have input and output contact with the neurons of the adjacent two layers before and after, and cannot function across layers. The relevant parameters of the input layer reach the output layer through the function of several hidden layer neural networks, and the output layer is carried out. The neurons of each layer are independent and do not affect each other. The most commonly used forward network models are BP neural network and radial basis function network.

After the convolution calculation, a standard layer is added to process each batch of data of the convolutional neural network training, to reduce the training time of the neural network. Then, the data passing through the standard layer is randomly deactivated by the neural network, and a node retention probability is set for each layer of the neural network. In a forward iteration process, some neurons are randomly discarded, that is, the nodes of all data layers have a probability to be retained, and then the weight of each node is optimized so that the probability of each node is not too large. To reduce the overfitting of the god convolution through the network, considering that this digital twin platform considers the transient signal timely order characteristics and has a strong diversity of data, the Softmax classifier is selected to carry out multi-classification processing and gradient derivation for the digital twin system of the high-voltage circuit breaker operating mechanism with

Figure 2. Forward convolutional neural network topology



multi-dimensional parameter digital acquisition, and multiple neurons can be mapped. The data can be backpropagated according to the training method of a convolutional neural network, and the database of typical hot work can be constantly updated to improve the accuracy of hot work identification. Figure 3 shows the flow chart of neural network analysis. Figure 4 is the flow chart of hot work identification in petrochemical plants.

Figure 3. The flow chart of the neural network analysis

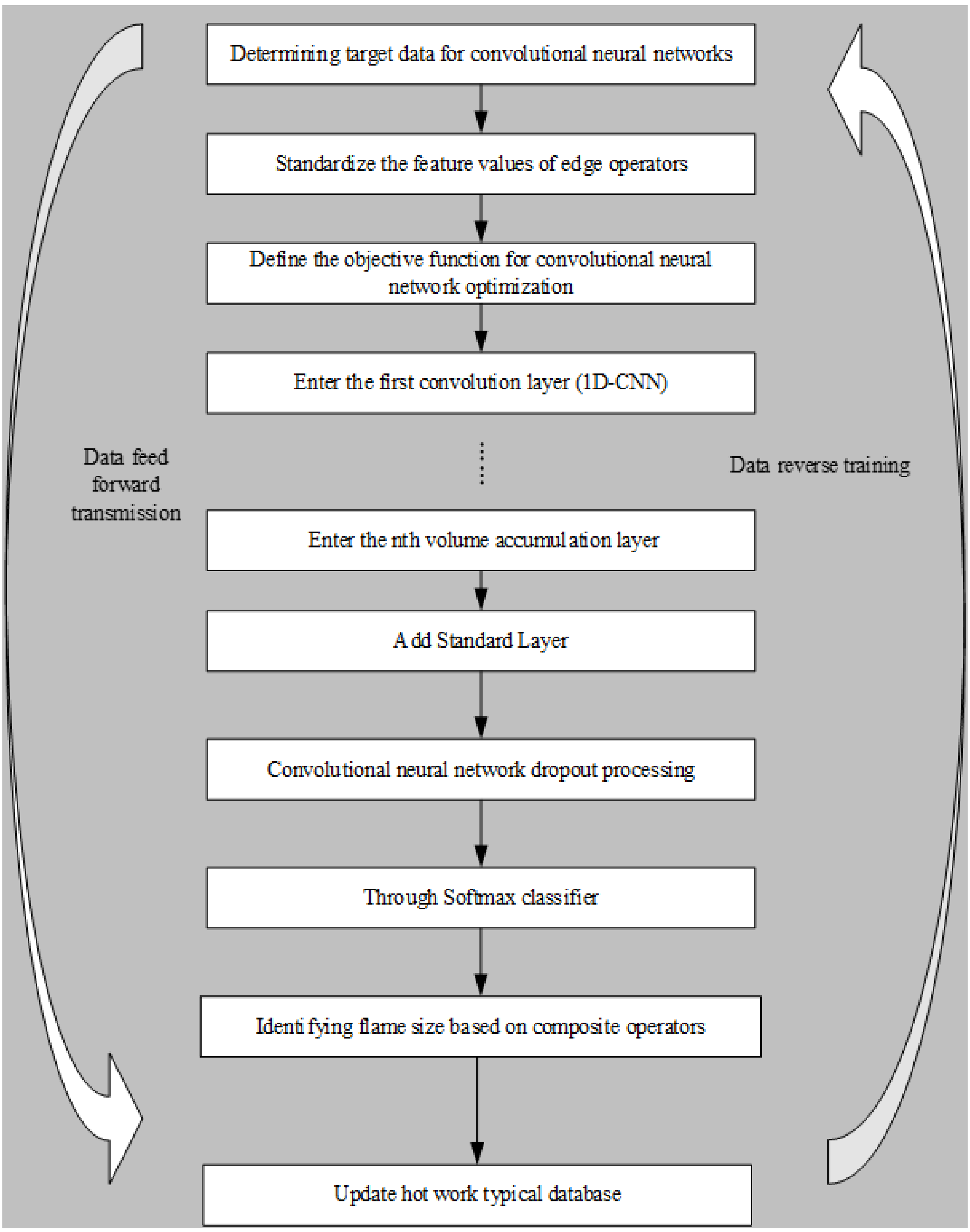
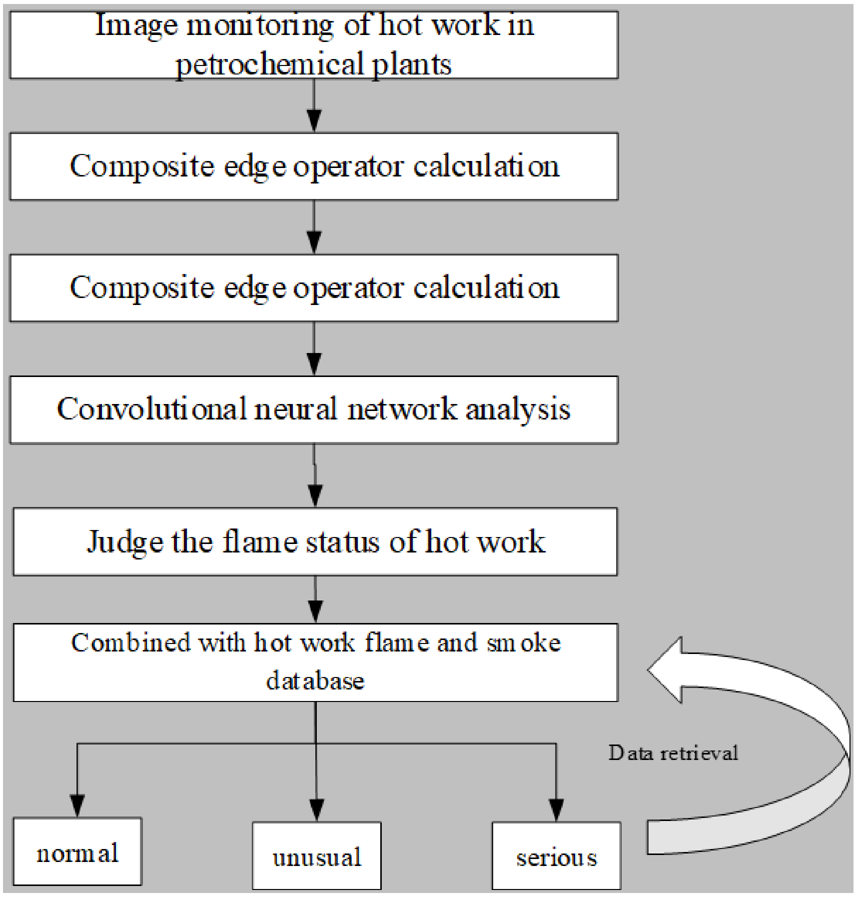


Figure 4. The flow chart of hot work identification in petrochemical plants



COMPOUND EDGE OPERATOR BASED ON DEEP LEARNING TO IDENTIFY HOT JOB FLAME

Given the original image, Figure 5, of active operation in petrochemical plants, image recognition in this figure focuses on the identification of the flame itself and edge extraction is carried out based on the Canny operator, Roberts operator, Prewitt operator, and Sobel operator. Figure 6 shows the edge extraction diagram based on the Canny operator. Figure 7 is the edge extraction diagram based on the Roberts operator. Figure 8 is the edge extraction diagram based on the Prewitt operator, and Figure 9 is the edge extraction diagram based on the Sobel operator. Figure 10 shows the flame identification image of a hot operation in a petrochemical plant based on an optical flow field.

It can be seen from Figures 5-9 that the Canny operator has the best effect based on edge extraction of hot operations in petrochemical plants. It can be seen from Figure 10 that a deep learning algorithm based on a compound edge operator has a good effect on flame identification in hot operations in petrochemical plants.

Given the original image of a hot operation in a petrochemical plant in Figure 11, image recognition in this figure focuses on the identification and flame edge of the hot operation, and edge extraction is carried out based on the Canny operator, Roberts operator, Prewitt operator, and Sobel operator. Figure 12 shows the edge extraction diagram based on the Canny operator. Figure 13 is the edge extraction diagram based on the Roberts operator. Figure 14 is the edge extraction diagram based

Figure 5. Original image of hot operation in a petrochemical plant

Figure 6. Edge extraction diagram based on the canny operator

on the Prewitt operator, and Figure 15 is the edge extraction diagram based on the Sobel operator. Figure 16 shows the flame identification image of a hot operation in a petrochemical plant based on an optical flow field.

Figure 7. Edge extraction based on the roberts operator

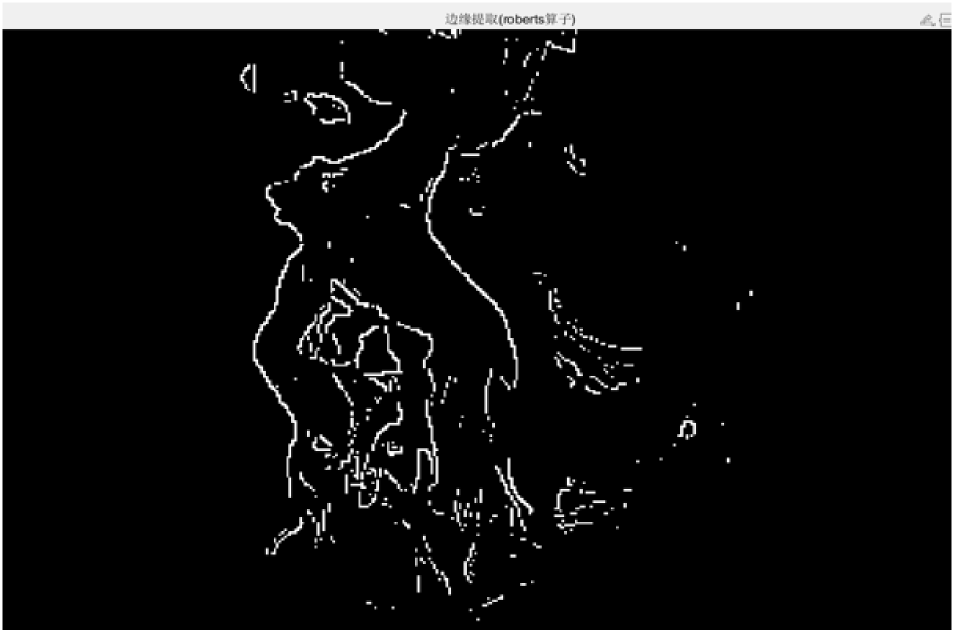
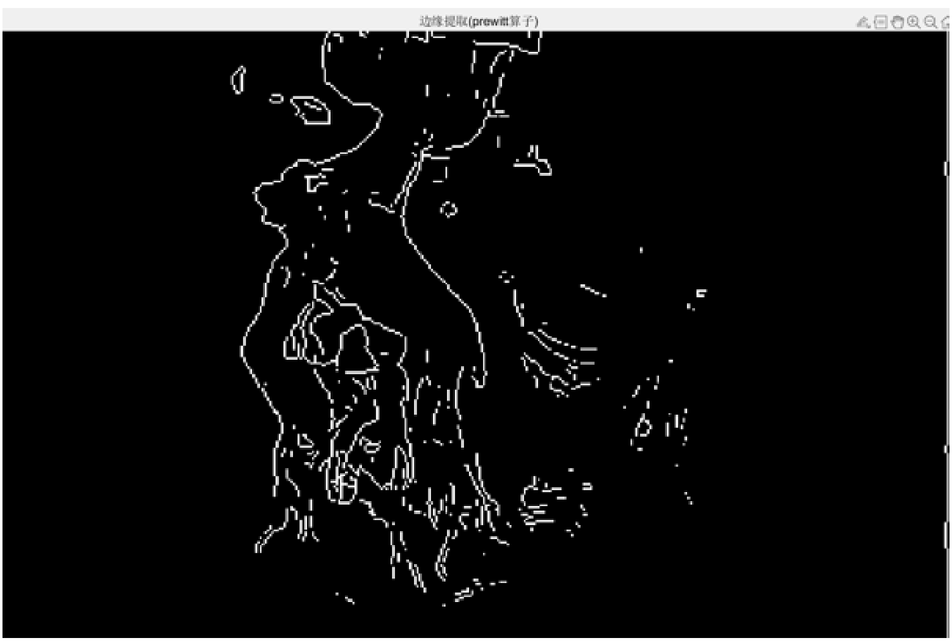


Figure 8. Edge extraction graph based on the prewitt operator



It can be seen from Figures 11-15 that the Canny operator has the best effect on edge extraction based on hot operations in petrochemical plants. It can be seen from Figure 16 that a deep learning algorithm based on a compound edge operator has a good effect on flame edge recognition in hot operations in petrochemical plants.

Figure 9. Edge extraction diagram based on the sobel operator

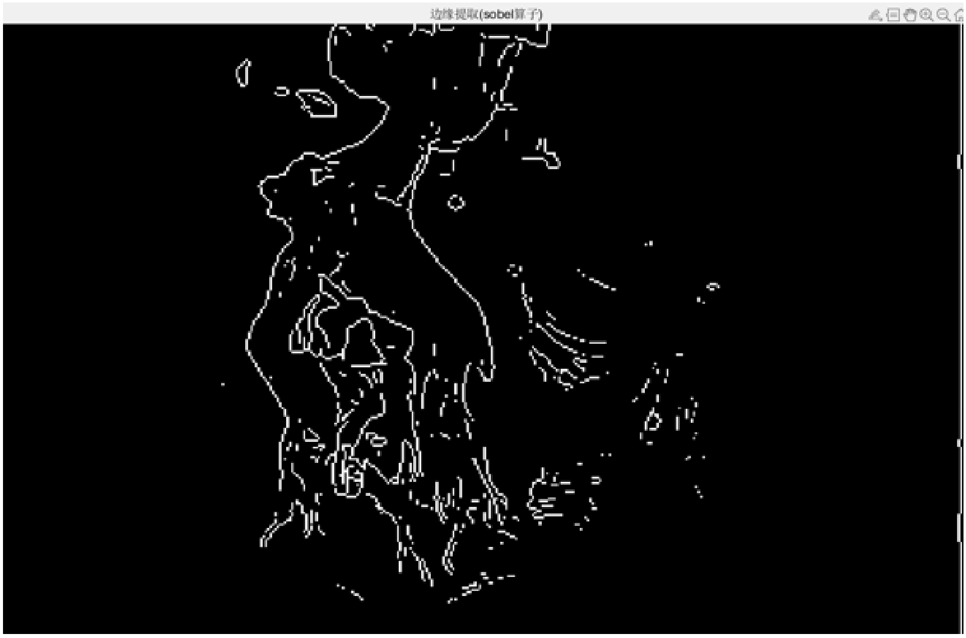
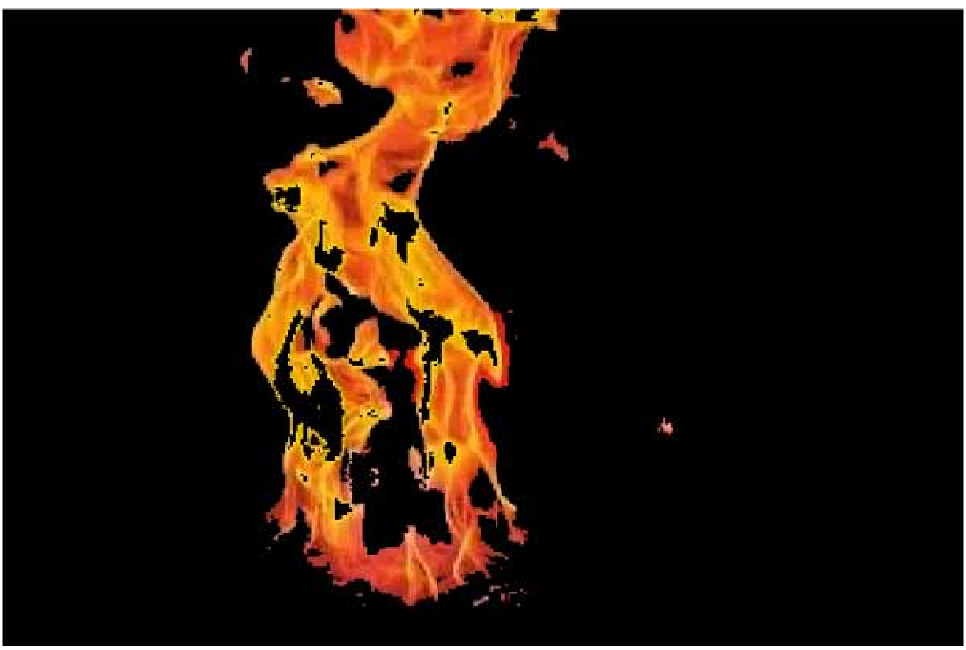


Figure 10. Flame identification image of hot operation in a petrochemical plant



Given the original image of hot operation in petrochemical plants, Figure 16, image recognition in this figure focuses on the identification of non-ground flame and edge extraction is carried out based on the Canny operator, Roberts operator, Prewitt operator, and Sobel operator. Figure 17 shows

Figure 11. Original image of hot work

Figure 12. Edge extraction diagram based on the canny operator

the edge extraction diagram based on the Canny operator. Figure 18 is the edge extraction diagram based on the Roberts operator, and Figure 19 is the edge extraction diagram based on the Prewitt operator. Figure 20 is the edge extraction diagram based on the Sobel operator, and Figure 21 shows

Figure 13. Edge extraction based on the roberts operator

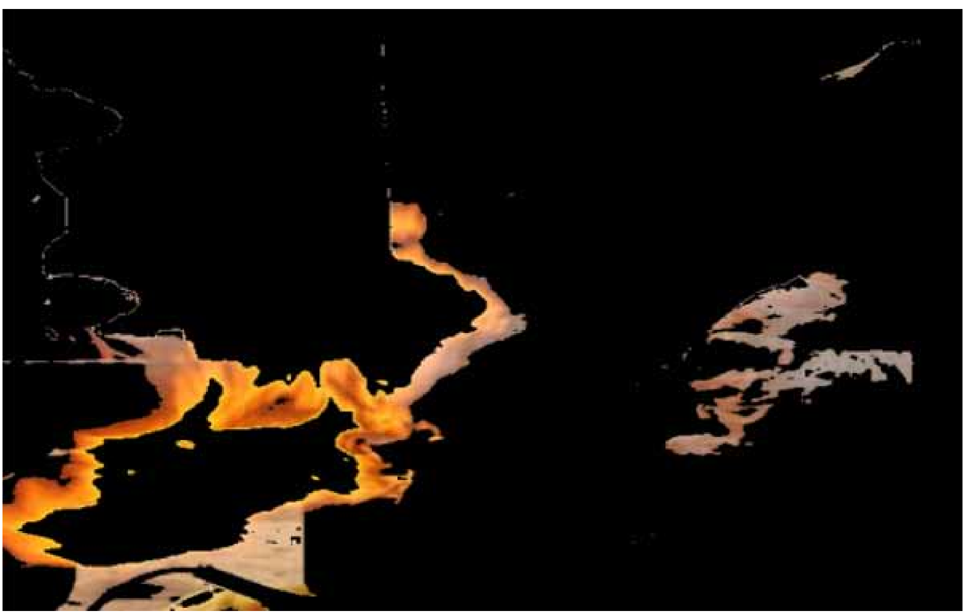
Figure 14. Edge extraction graph based on the prewitt operator

the flame recognition image of hot operations in petrochemical plants by a deep learning algorithm based on a compound edge operator.

It can be seen from Figures 17-21 that the Canny operator has the best effect on edge extraction based on hot operations in petrochemical plants. It can be seen from Figure 22 that a deep learning

Figure 15. Edge extraction diagram of the sobel operator

Figure 16. Flame identification image of hot work



algorithm based on a compound edge operator has a good effect on flame edge identification for high-altitude hot operations in petrochemical plants.

Given the original image of fire smoke in a petrochemical plant, Figures 23 and 25, image recognition in these figures focuses on the identification of fire smoke in a petrochemical plant. It

Figure 17. Original image of the flame in a petrochemical plant

Figure 18. Edge extraction diagram based on the canny operator

can be seen from Figures 24 and 26 that the deep learning algorithm based on an optical flow field has a good effect on flame edge recognition in high-altitude hot work in a petrochemical plant.

Figure 19. Edge extraction based on the roberts operator

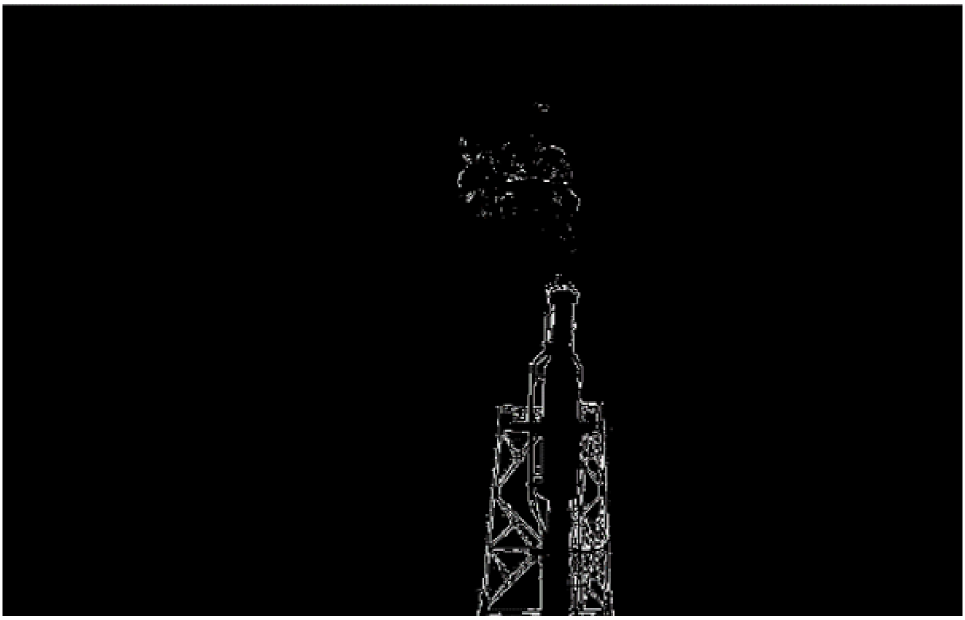


Figure 20. Edge extraction graph based on the prewitt operator

CONCLUSION

In this paper, based on the Canny operator, Roberts operator, Prewitt operator, and Sobel operator, we extract the edge of the flame in the hot operation of a petrochemical plant, improve the accuracy of flame edge extraction in the hot operation of a petrochemical plant, and identify the fire smoke in the

Figure 21. Edge extraction diagram based on the sobel operator

Figure 22. Flame identification image of hot work

petrochemical plant, and, therefore, help to improve the safety of the hot operation of a petrochemical plant. The unique contribution of this study lies in the innovative use of a compound edge algorithm to analyze the hot operation of petrochemical plants, which can predict the occurrence time of accidents earlier and plays a key role in improving the safety of petrochemical plants. In the application scenario of the particularity of hot fire operation in petrochemical plants, smoke identification and hot fire

Figure 23. Original image of smoke from a petrochemical plant fire

Figure 24. Fire smoke identification map of a petrochemical plant

operation analysis databases are added based on flame identification, which better improves the safety of factory operations.

Figure 25. Original image of smoke from a petrochemical plant fire

Figure 26. Fire smoke identification diagram of a petrochemical plant

FUTURE WORK

In this paper, the innovative extraction methods based on different edge operators are used for compound analysis according to different edge operators, which improves the accuracy compared with the previous single-edge operator extraction method. Focusing on the hot operation of a petrochemical plant, the neural network algorithm is used to carry out a convolution operation on the edge data, input it into the hot operation database, identify the flame, make a preliminary judgment on whether the flame is dangerous according to the size of the flame, and add smoke identification combined with the characteristics of the petrochemical plant itself. This method is of great significance to improve the monitoring of safe hot work in petrochemical plants. In future studies, more pictures will be collected and further analysis of hot fire operations in petrochemical plants will be carried out.

DATA AVAILABILITY

The data used to support the findings of this study are available from the corresponding author upon request.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING STATEMENT

This research was supported by the Qilu Branch of SINOPE.

REFERENCES

Abdi, H., & Williams, L. J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, *2*(4), 433–459. doi:10.1002/wics.101

Azami, H., Eduardo, L., da Silva, V., Carolina, A., & Omoto, M. (2019). Two-dimensional dispersion entropy: An information-theoretic method for irregularity analysis of images. *Signal Processing Image Communication*, *75*, 75. doi:10.1016/j.image.2019.04.013

Barz, B., & Denzler, J. (2021). Content-based image retrieval and the semantic gap in the deep learning era. In *International Conference on Pattern Recognition*. Springer. doi:10.1007/978-3-030-68790-8_20

Bo, L., & Jiulun, F. (2022). Adaptive granulation Renyi rough entropy image thresholding method with nested optimization. *Expert Systems with Applications,* 203.

Chunling, L., Wenxiu, W., & Wenlin, G. (2021). Single-pixel imaging for dynamic targets via a non-diffracting beam. *Optics and Lasers in Engineering*, 139.

Díaz, A., Mahu, R., & Novoa, J. (2021). Assessing the effect of visual serving on the performance of linear microphone arrays in moving human-robot interaction scenarios. *Computer Speech & Language*, 65.

Feng, Q., Wei, Y., Yi, Y., Hao, Q., & Dai, J. (2019). Local ternary cross structure pattern: A color LBP feature extraction with applications in CBIR. *Applied Sciences (Basel, Switzerland)*, *9*(11), 2211. doi:10.3390/app9112211

Gordo, A., Almazán, J., & Revaud, J. (2016). Deep image retrieval: Learning global representations for image search. In *Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part VI 14.* Springer International Publishing.

Huang, J., Feris, R. S., & Chen, Q. (2015). Cross-domain image retrieval with a dual attribute-aware ranking network. In *Proceedings of the IEEE International Conference on Computer Vision*. IEEE. doi:10.1109/ICCV.2015.127

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classifcation with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25.

Lai, C. C., & Chen, Y. C. (2011). A user-oriented image retrieval system based on an interactive genetic algorithm. *IEEE Transactions on Instrumentation and Measurement*, *60*(10), 3318–3325. doi:10.1109/TIM.2011.2135010

Li, G., Zhu, W., Dong, H., & Ke, Y. (2021). Stiffness-oriented performance indices defined on two-dimensional manifold for 6-DOF industrial robot. *Robotics and Computer-integrated Manufacturing*, *68*, 68. doi:10.1016/j.rcim.2020.102076

Lowe, D. G. (2004). Distinctive image features from scale-invariant key points. *International Journal of Computer Vision*, *60*(2), 91–110. doi:10.1023/B:VISI.0000029664.99615.94

Manjunath, B. S., & Ma, W. Y. (1996). Texture features for browsing and retrieval of image data. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *18*(8), 837–842. doi:10.1109/34.531803

Menghao, G., & Hongwei, X. (2019). Hot spot defect detection based on infrared thermal image and faster R-CNN. *Computer Systems & Applications*, *28*(11), 265–270.

Mohamed, A., Peel, H., & Cohn, A. G. (2021). Combining block-based and pixel-based approaches to improve crack detection and localization. *Automation in Construction*, 122.

Piras, L., & Giacinto, G. (2017). Information fusion in content-based image retrieval: A comprehensive overview. *Information Fusion*, *37*, 50–60. doi:10.1016/j.inffus.2017.01.003

Wang, D.,Li, C.,& Li, M. (2020). *Solar photovoltaic modules hotspot detection based on deep convolutional neural networks*. Academic Press.

Wang, X., Wu, J., & Wang, Y. (2021). Dynamics evaluation of 2UPU/SP parallel mechanism for a 5-DOF hybrid robot considering gravity. *Robotics and Autonomous Systems*, *135*, 135. doi:10.1016/j.robot.2020.103675

Xicheng, G., Huaxia, D., & Mengchao, M. l. (2021). Removing light interference to improve character recognition rate by using single-pixel imaging. *Optics and Lasers in Engineering*, 140.

Ye, T., Ying, F., & Jun, Z. (2023). Joint supervised and unsupervised deep learning method for single-pixel imaging. *Optics & Laser Technology*, 162.

Yin, S. (2018). *A Research on the Application of Deep Learning in Defect Detection of Power Equipment in Substations*. Chengdu University of Electronic Science and Technology.

Ying, Y. (2021). *Research on Defects Detection Algorithm of Substation Equipment Based on Improved Faster R-CNN*. Zhejiang University.

Yue-Hei Ng, J., Yang, F., & Davis, L. S. (2015). Exploiting local features from deep networks for image retrieval. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops*. IEEE.

Zhang, H., Cheng, L., Zhang, J., Huang, W., Liu, X., & Yu, J. (2021). Structural pixel-wise target attention for robust object tracking. *Digital Signal Processing*, *117*, 103139. doi:10.1016/j.dsp.2021.103139

Zhang, X. (2021). Center pixel weight based on Wiener filter for non-local means image denoising. *Optik (Stuttgart)*, *244*, 244. doi:10.1016/j.ijleo.2021.167557

Zhang, Y., Zhang, C. H., & Shao, X. (2021). User preference-aware navigation for mobile robot in domestic via defined virtual area. *Journal of Network and Computer Applications*, *173*, 173. doi:10.1016/j.jnca.2020.102885

APPENDIX

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of the editor(s). The editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.