Sparkling Light Publisher

Sparklinglight Transactions on Artificial Intelligence and Quantum Computing (STAIQC)

Website: **https://sparklinglightpublisher.com/** **ISSN (Online):2583-0732**

A Review of the Edge Detection Technology

Shou-Ming Hou [a#], Chao-Lan Jia[a*], Ya-Bing Wang[a], Mackenzie Brown[b]

[a]*School of Computer Science and Technology, Henan Polytechnic University, Jiaozuo 454000, China*
[b]*School of Data Science, Perdana University, Serdang 43400, Selangor, Malaysia*

Abstract

The edge detection-based has profoundly inspired recent works in image classification, object detection, segmentation, et al. With the growth of computer vision, the performance of edge detection has been notably improved. In this paper, we concentrate on presenting some edge detection technologies and grouping them into two major categories: classical edge detection technology and deep learning-based edge detection technology. For every team in the classification, the fundamental thoughts are first described, and then we probe beneath into the mainly related literature in recent years. Furthermore, the evaluation indicators are entirely elaborated. In addition, this conclusion is given by a comprehensive summary which provides suggestions on future perspectives.

Keywords: Edge Detection; Computer Vision; Image Process; Deep Learning;

1. Introduction

In image processing, we regards edge detection as an essential means. Meanwhile, quickly and accurately excerpt edge data has become a complex problem for research [1, 2]. The gorgeous accessory image's data acts on the edge, a collection of pixels with a step-change in grey intensity [3]. Edge detection has defined the background of the image from the target content. In the early 20th century, edge detection technology began to be studied by humans [4]. Until the 1960s, edge detection technology has been rapidly developed [5]. Julesz firstly proposed the concept of edge detection in 1959. Since then, edge detection has been diffusely applied for various practical requests, changing from medical, industrial, and agricultural to preconditioning some computer vision assignments, such as object detection, feature extraction, and image segmentation. Currently, edge detection has been gaining a developing quantity of awareness of communities. In medical CT images [6] and X-ray images [7], many existing problems

E-mail address of authors: *corresponding author email (SMH(housm@hpu.edu.cn), CLJ(jiachaolanccq@163.com), YBW(15736796537@163.com), MB (mackbrown@ieee.org))

Please cite this article as: Shou-Ming Hou, Chao-Lan Jia, Ya-Bing Wang, & Mackenzie Brown (2021). A Review of the Edge Detection Technology. Sparklinglight Transactions on Artificial Intelligence and Quantum Computing (STAIQC), 1(2), 26-37. **ISSN (Online):2583-0732.** Received Date: 25/08/2021, Reviewed Date: 14/09/2021, Published Date: 20/09/2021.

make edge detection more difficult since separating the organs with the lesion surrounding them is difficult. And in the handle of CT image accession, noise and other factors can also cause the edges of the image to be unclear [8]. However, we cannot correctly locate the size and location of the lesion due to unclear edges, which is not auspicious to feature extraction, target detection, and image segmentation. Furthermore, the doctor's diagnosis will also be affected [9, 10]. For the industrial extraction, due to the randomness of the production processing, internal defects are often generated, such as cracks, inclusions, and pores [11, 12]. These defects will lead to unqualified parts [13]. The edge detection of the defects is helpful for the operator to identify the defect type and accurately locate the defect location.

Although diverse approaches have been recommended to improve edge detection performance, edge detection remains a primary and long-standing puzzle [14]. In our case, edge detection technology can be separated into three steps. Firstly, using filters achieves noise decrease, aims at reducing the influence of rumble. Then, the pixels with a small range of grey scale changes are enhanced [15]. Finally, judging whether pixels are edge points of the image through theories such as a threshold. We found that edge detection techniques can be split into two categories by reviewing the related literature, which is classic edge detection technology and deep learning-based edge detection technology [16]. On the one hand, pixel-based and sub-pixel-based edge detection technologies are included in classic edge detection technology. On the other hand, pixel level edge detection technology covers several differential operators (such as Prewitt [17], Sobel [18], Canny [19]), morphology, and genetic theory [20], etc. [21]. The classification of edge detection technology is shown in Fig 1.

In Section 2, we specifically review the classical edge detection algorithm. Section 3 summarized the edge detection technology with deep learning. In Section 4, we described the evaluation indexes of edge detection. And Section 4 gives the concluding remarks.

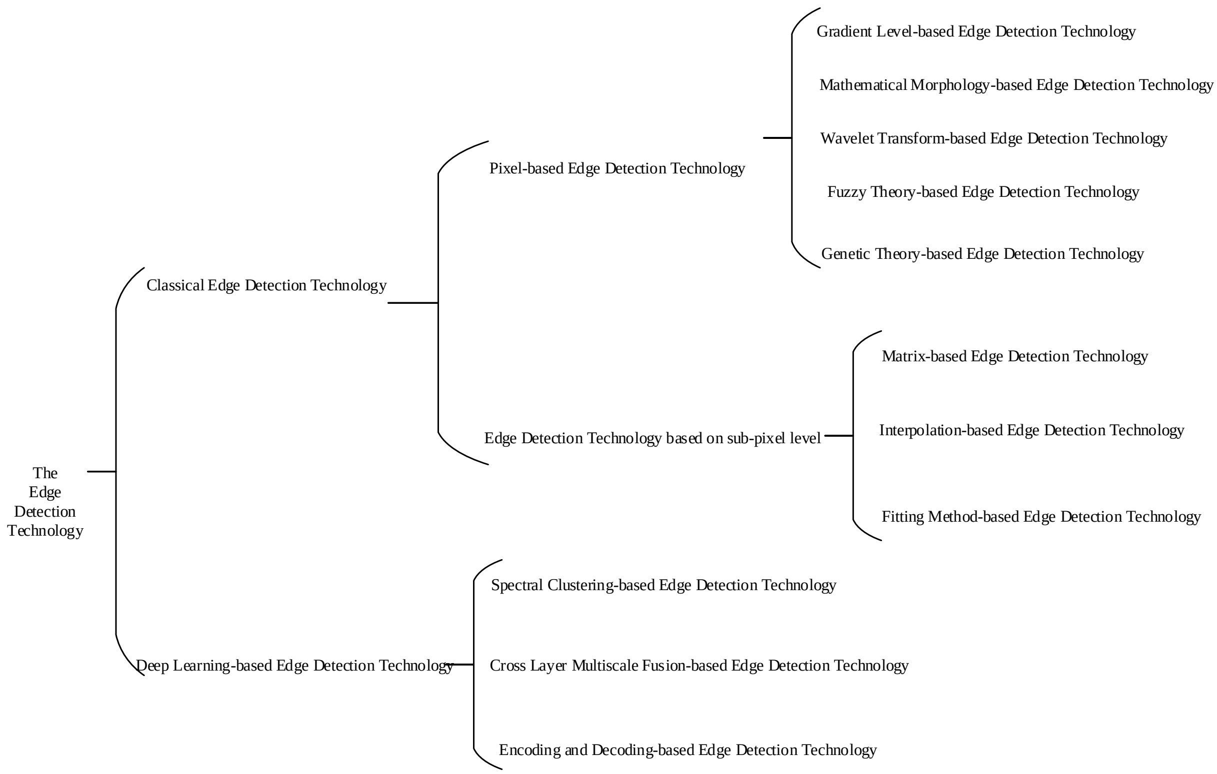

Fig 1 Edge detection technology classification

2. Classical edge detection technology

In this section, the classical edge detection technology has been introduced. The classical edge detection technology is separated into pixel-based edge detection technology and sub-pixel-based edge detection technology. In pixel level edge detection technology, the main techniques are differential operators, genetic theory, morphology, fuzzy theory, etc. In the sub-pixel edge detection technologies, matrix, interpolation, and fitting are the main techniques.

2.1. Pixel-based edge detection technology

2.1.1 Edge detection technology based on gradient level

Differential operators realize the edge detection technology given the gradient grade. The frequently accustomed differential operators include Laplacian, Canny, Sobel, Roberts, Prewitt, Log, etc. Calculating the gradient change of the original image by Canny operator, Prewitt operator, Sobel operator [22], and Roberts operator for predicting edges. However, the Laplacian operator and Log operator predict the edge by the principle of the zero crossing dot about the second derivative. In 2021, Lu et al. [23] used adaptive filter, the gradient operator and bilinear interpolation to enhance the Canny edge detection effect for improving the smartphone's performance shows the acoustic wave filter. In the same year, Shafiabadi et al. [24] used the Canny and Sobel filter to detect the outline of images' fractures for analysis the fractures in the walls. In 2010, Coleman et al. [25] found that the novel Laplacian operator is applied to irregularly distributed 3-D images.

2.1.2 Edge detection technology based on mathematical morphology

In 1995, a mathematical morphology-based fringe detection technology first was depicted. The crucial structural factors within mathematical morphology can achieve a better denoising effect while retaining image features [26], which rely on the geometric features of the image. At present, multiscale morphology-based edge detection technology [27], biased differential equations, merging with other algorithms, and mathematical morphology are included in mathematical morphology-based boundary disclosure algorithm. In 2021, Jia et al. [28] used a combination of the matched filter, the Gaussian primary-order derivative, the random forest, and mathematical morphology for obtaining the crack image quickly and accurately. In 2020, Pei et al. [29] put forward the latest multiscale edge extraction technology, which selected the optimal structural element scale by the variance of the morphological filter. In 2013, Li et al. [30] designed a new the enhanced mathematical morphology filter, which can combine to show the shallow and the deep boundaries.

2.1.3 Edge detection technology based on wavelet transform

At present, wavelet transform uses wavelet function to refine the low-frequency and high-frequency parts in signal of multiple scales [31-33], which realizes the edge detection of complex images. In 2021, Isar et al. [34] used a denoising system of the Hyper analytic Wavelet Transform before the edge detection, enhancing the robustness of edge detection. In the same year, Dwivedi et al. [35] used 2D-discrete wavelet transform for detecting lateral edges based on Haar wavelets. In 2019, Lv et al. [36] used continuous wavelet transform for detecting streamlines forming edges.

2.1.4 Fuzzy theory-based edge detection technology

Professor Zadeh from California first elaborated the edge detection technology by fuzzy theory. The core idea is that the event cannot be denied or affirmed [37, 38]. Through the enhancement of the image, we can get more detailed the image's edge. In 2021, Kumar et al. [39] added Guided L-0 smoothen function into fuzzy concept, which can control the false edges is not detected. In 2019, Dhivya et al. [40] designed an technology by fuzzy logic for edge detection, compared PSO and neural network methods, which better edges.

2.1.5 Genetic theory-based edge detection technology

In the 1970s, John Holland from the United States firstly proposed the genetic algorithm, which is a method of searching the optimal solution designed by chromosomes [41] to simulate the evolution of biology. In 2019, Fu et al. [42] combined genetic programming for Bayesian programs to extract edge features. In 2014, Xiang et al. [43] designed an edge features extracting algorithm by improving the genetic algorithm and OTSU algorithm.

Table 1 Classical technology comparison

	method	Principle	Advantage	Disadvantage	Applicable Scene
Pixel-based edge detection technology	Edge detection technology based on gradient level	Using the characteristics of differential operators for edge detection	Canny: Detect weak edges.	Canny: slow calculation speed and complicated programming	Canny: Images with weak edges.
			Robert: Good robustness to noise.	Robert: Edge positioning is not accurate, and the extracted edge is thick.	Robert: Low-noise images.
			Sobel: Good robustness to noise, and accurately locate the edge	Sobel: Inaccurate edge positioning.	Sobel: Noisy images with grayscale transformation.
			Prewitt: Good robustness to noise, accurately locate the edge, and can remove false edges.	Prewitt: The edge positioning effect is not as good as the Robert operator.	Prewitt: Noisy images with grayscale transformation.
			Laplacian: accurately locate the edge.	Laplacian: Poor robustness to noise, and easy to lose edge information.	Laplacian: Detecting edge images prone to step
	Morphology-based edge detection technology	Depending on the geometric properties of the image, filter or retain features of the image.	Good positioning effect, high edge detection accuracy, good robustness to noise.	The inspected image contains many non-target isolated points, which will greatly increase the computing time during further processing	Detection of single gray scale image with edge feature comparison
	Wavelet transform-based edge detection technology	using wavelet function to detect edges.	Good robustness to noise, image reconstruction can be realized, and more information of the image can be retained through multi-scale analysis of the image.	Higher requirements for multiple filters	Noisy images
	fuzzy theory-based edge detection technology	By enhancing the image to reduce the blur of the image, thereby forming a more layered edge	Good robustness to noise	The amount of calculation is large, and the real-time performance is not good.	Situations where the image information is unknown
	genetic theory-based on edge	Using biological evolution as a	Good global search capabilities and	Programming is complicated and slow.	Comparing multiple

	detection technology	prototype to detect image edges.	scalability.		images at the same time
sub-pixel level-based edge detection technology	Matrix-based edge detection technology	Using Zernike, Frankli and other matrices to detect sub-pixel edges.	Simple calculation	Poor robustness to noise	Images with less noise
	Interpolation-based edge detection technology	quadratic interpolation, B-spline interpolation, and polynomial interpolation.	Short calculation time and simple calculation	Susceptible to noise	Online testing
	Fitting methods -based edge detection technology	Fit the virtual edge model to obtain sub-pixel edge positioning	Good robust to noise	The model is complex and the solution speed is slow.	Images with virtual edge models

2.2. Edge detection technology based on sub-pixel level

In recent years, the sub-pixel-based edge detection technology has dragged attention of many researchers. The matrix, interpolation, and suitable methods secure the edge points' coordinates at the sub-pixel level.

2.2.1 Matrix-based edge detection technology

The Zernike, Franklin and other matrices are used to detect sub-pixel edges [44, 45]. In 2020, Bai et al. [46] proposed a non-contact vision system advancing Zernike sub-pixel edge detection. In 2020, Fang et al. [47] used the Zernike moment and Canny operator to carry on the edge sub-pixel points. In 2019, Taibi et al. [48] combined Zernike, sparse coding, Steger, and Hong transformed to identify the cracks of the imaging accounts. In 2017, Huang et al. [49] based on fuzzy means and K-means algorithms to assemble the initial images, then applying Zernike moments to detect the edge. In 2015, Du et al. [50] detected the sub-pixel natural edges by Prewitt-Zernike of the planet centroid images. In 2015, Wang et al. [51] used Harris and Zernike to locate the edges for a tremendous velocity and high accuracy vision positioning system. In 2013, Wei et al. [52] developed improved morphological and Zernike moments for measuring the accuracy of charge-coupled device metrology systems.

2.2.2 Interpolation-based edge detection technology

Identify the edge of the image by interpolating the grey value of the pixel. In 2021, Lin et al. [53] used Interpolation for evaluating whether the chips are damageable by detecting correctly incomplete defect edges. In the same year, Hu et al. [54] combined mathematical morphology and cubic spline interpolation for O-ring edge detection. In 2018, Chen et al. [55] accurately detected the edge and removed the jag of the metal image by adaptive four-order cubic convolution interpolation and gradient entropy. In 2014, Lin et al. [56] designed an automated optical investigation system by linear Interpolation to determine the microscope edge, which fits the industry field. In 2013, Wang et al. [57] proposed two sub-pixel edge interpolation methods for high-resolution images.

2.2.3 Fitting method-based edge detection technology

We were using Gaussian fitting, least-square fitting, and other functions to locate the sub-pixel fringe [58]. In 2019, Huan et al. [59] employed a sub-pixel's ellipse fitting algorithm, making the fitting ellipse accuracy not less than 50% costlier than the pixel fringe. In 2017, Li et al. [60] proposed fitting edge point curves based on the grey gravity and moving least squares. In 2016, Chen et al. [61] combined the wavelet transform and the cubic B-spline curve interpolation to get edges, which gets higher precision. In 2011, Hagara et al. [62] used the ERF function and objective image function to detect the edge of 1-D images. In 2012, Sedaghat et al. [63] improved the sub-pixel matching accuracy of two images by the Harris operator and the least-squares method.

3. Deep Learning-based edge detection technology

In this section, we will present some theories the deep learning-based edge detection technology. Due to advances in deep learning technology, we find edge discovery by means of deep learning has become a novel bearing [64]. Contrast to classical edge detection technology, the features from deep learning-based edge detection technology are learned from the big data rather than manually designed features. Generally, the edges were detected by deep learning, which are separated into three steps. Firstly, the image is inputted. Then, we need to extract the image edges. Finally, a fully connected layer is used for outputting the image's edges.

3.1. Edge detection data sets

We use the data sets to verify the technology of deep learning. At present, many data sets have been adopted to appraise the function about the profile detection technology, such as BSDS500, SBD, Pascal-Context, Cityscape, et al. Next, we specifically introduce the data sets in Table 2.

Table 2 Comparative analysis of data sets

Data Sets	Numbers image	Image size	Train set	Test set	Validation set	Image Source	Suitable for the scene
SBD	11355	-----------	8498	--------	2857	21 categories of images	Multi-classification task
Cityscape	7000	-----------	2975	1525	500	Street scenes in 50 cities	Semantic segmentation, instance segmentation
BSDS500	500	481*321	200	200	100	From the University of Berkeley	Image segmentation, contour extraction
NYUD	1449	640*480	795	654	---------	Indoor scene	segmentation, contour extraction, Edge detection
Pascal-context	19740	-----------	10103	9637	---------	Indoor scene and outdoor scene	segmentation, Edge detection
Pascal VOC 2011	17125	-----------	1112	1111	1111	21 categories of images	Segmentation, Object detection
Pascal VOC 2012	17125	-----------	1464	1449	1456	21 categories of images	Segmentation, Object detection
MDBD	-----------	1280*720	80	20	---------	Short binocular video sequence	Psychophysical Research on Edge Detection of Objects in Natural Scenes

3.2. Edge detection technology based on deep learning

At present, the classical edge detection technology has made significant progress, but there are still certain defects due to the complexity of the manual design. In view of the deep learning evolution [65-67], deep learning-based edge detection technology also acquires notable progress [68].

3.2.1 Edge detection technology based on spectral clustering

Based on spectral clustering, edge detection technology, which will convert edge detection into an image classification problem. Due to the various traits of the edge and noise, we can detect the images' edge while removing the noise. In 2018, Liu et al. [69] believed that the image classification could help achieve contour detection (such as letting the edge divide into Contour and non-contour). Then the sliding window is used to detect and classify contours. Furthermore, the random forest foretells whether the centre of a local block is connected to the Contour. According to the detection results on the BSDS500 data set, this method improves contour detection performance. In 2015, Shen et al. [70] proposed an edge detection technology, namely Deep Contour. Clustering and model parameters are fitted to form the contours of the image in this technology. Moreover, the images' contour features are further obtained by conquering strategy and structure forest. The algorithm is tested on BSDS500, and the ODS value is 0.757.

3.2.2 Edge detection technology based on cross-layer multiscale fusion

The receptive field of the deep features of the image is more boundless, and the semantic information is more prosperous. In contrast, the receptive field of the shallow features of the image is smaller, and the position information is more petite. In the edge detection technology by multiscale and cross-layer fusion, the shallow and deep features of the image are fused into one result, which can make the detected image have richer edge information. In 2021, Cao et al. [71] put forward a novel refined the network in depth that combined many refinement aspects for getting substantial features for edge detection. In the same year, Huan et al. [72] proposed a context-aware tracing strategy (CATS) to detect the edges evaluated by VGG16 in BSDS500. In 2019, Qu et al. [73] used Visual Geometry Group (VCF) to detect edges based on Caffe and VGG16. VCF used a fully connected layer parameter dimensionality reduction, then cross fusion and cross-layer fusion were applied to extract and refine the edges of the image. The experiment results show that ODS is 0.808 in the BSDS500 dataset. In 2018, Lin et al. [74] proposed a lateral refinement network algorithm, which is based on CNN and refinement module, using VGG19 network obtained ODS is 0.816 and 0.761 in the BSDS500 and NYUD-V2 date sets, moreover, using ResNet network obtained ODS is 0.820 and 0.760 in BSDS500 and NYUD-V2 date sets. In 2016, Liu et al. [75] designed a fully convolutional neural network based on the structural characteristics of each layer, which can let ODS is 0.806.

3.2.3 Edge detection technology based on encoding and decoding

Through encoding and decoding to discover the image's edge is the main idea of the edge detection technology utilizing encoding and decoding. The encoding and decoding structure firstly uses operations such as convolution and pooling, forming an encoder to encode the image's contour data, and then forming a decoder by operations such as up-sampling or de-convolution decode the image information. In 2021, Tan et al. [76] used encoder and decoder, forming a best-seller end-to-end path segmentation system. The encoder gets trait of unequal levels and scales. The decoder fused and evaluated image features by scale fusion and scale sensitivity. In 2019, Wang et al. [77] designed multiscale trait detection methods based on encoding and decoding structure for fusing two different phases (such as low-level and high-level) denotative data.

Table 3 Comparison of edge detection methods based on deep learning

Methods	Principle	Advantage	Disadvantage	Key technology
Edge detection technology based on spectral clustering	Turn the edge detection problem into an image classification problem	The idea is simple, easy to implement, and has the ability to identify non-Gaussian distributions	The choice of spectral clustering parameters lacks adaptability.	Clustering, divide and conquer strategy
Edge detection technology based on cross-layer multi-scale fusion	Obtain richer semantic information by combining the shallow and deep features of the image	Improve image resolution	The edge information of the image is easy to lose, and the amount of calculation is	Edge detector, multi-scale acquisition and fusion

			large	
Edge detection technology based on encoding and decoding	Design a codec to detect image edges	Improve the image resolution after pooling	The increase in parameters leads to a large amount of calculation	Codec

4. Edge detection evaluation index

In this section, the edge detection evaluation index has been elaborated. The meaning of edge detection accuracy is the probability of whether an edge point is accurately detected. In image processing, edge detection function is estimated by MSE, SNR, PSNR, SSIM, Recall, Precision, and Accuracy [78]. SNR is used to respond to the noise, and SNR is more considerable, representing more noise in the images [79]. PSNR is the quotient of the medium voltage about the peak omen to the noise [80]. MSE shows the average of the sum of squares of the divergence amid the pixel equivalent of the detected image and the pixel equivalent of the original image [81]. We mark the structural correlation together the detected data with the initial data by SSIM. Recall refers to the number of actual positive sample pixels in the original sample that are still predicted as positive samples in deep learning prediction. Precision shows the eventuality that the edge pixels generated by the computer are actual pixels [82].

$$\mathrm{MSE}=\frac{1}{\mathrm{MN}}\sum_{i=1}^{\mathrm{M}}\sum_{j=1}^{\mathrm{N}}(g(i,j)-f(i,j))^{2} \tag{1}$$

$$\mathrm{SNR}=10\log_{10}\left(\frac{\mathrm{MAX}_{g(i,j)}^{2}}{\frac{1}{\mathrm{MN}}\sum_{i=1}^{\mathrm{M}}\sum_{j=1}^{\mathrm{N}}(g(i,j)-f(i,j))^{2}}\right) \tag{2}$$

$$\mathrm{PSNR}=10\log_{10}\frac{(2^{n}-1)^{2}}{MSE} \tag{3}$$

$$\mathrm{SSIM}=\frac{2\alpha_x\alpha_y+\beta_1}{\alpha_x^2+\alpha_y^2+\beta_1}*\frac{2\delta_x\delta_y+\beta_2}{\delta_x^2+\delta_y^2+\beta_2}*\frac{\delta_{xy}+\beta_3}{\delta_{xy}+\beta_3} \tag{4}$$

$$\mathrm{Recall}=\frac{\mathrm{TP}}{\mathrm{TP+FN}} \tag{5}$$

$$\mathrm{Accuracy}=\frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FT+FN}} \tag{6}$$

$$\mathrm{Precision}=\frac{TP}{TP+FP} \tag{7}$$

Where, M and N are the image's width and height, respectively, and n represents the amount of bits each pixel. And α_x as well as α_{y} are the mean of image x and image y, respectively. δ_x as well as δ_{y} express the variance of x and y, respectively. δ_{xy} means the covariance of image x and image y. β_1, β_2, and β_3 are constants. TP indicates the number of concrete conditions divined being positive aspects, FN means the amount of front situation divined being negative aspects, TN indicates the amount of adverse conditions divined being negative aspects, and FP expresses the amount of negative aspects positive classes.

5 Conclusion

At present, the classical edge detection technologies have begun to merge into edge detection technology based on deep learning. In this paper, we mainly review and summarize classical edge detection technology and deep learning-based edge detection technology and classify and summarize them in detail. However, although edge detection technology has made meaningful progress, there are still some challenges and research directions in this field.

1) There are fewer data sets for edge detection, and different directions require different data sets.

2) In deep learning, manually labeling data sets requires a lot of staffing and material resources.

3) At present, although edge detection operators have begun to be fused in deep learning, the degree of fusion is not good enough. In the future, we should further explore adding classical edge detection technology to deep learning-based edge detection technology.

Online license transfer

All authors are required to complete the STAIQC exclusive license transfer agreement before the article can be published, which they can do online. This transfer agreement enables to protect the copyrighted material for the authors, but does not relinquish the authors' proprietary rights. The copyright transfer covers the exclusive rights to reproduce and distribute the article, including reprints, photographic reproductions, microfilm or any other reproductions of similar nature and translations. Authors are responsible for obtaining from the copyright holder, the permission to reproduce any figures for which copyright exists.

Acknowledgements

We thank everyone who contributed to the article.

References

[1] Kim, G., Jung, H. G., & Lee, S. W. (2021). Spatial reasoning for few-shot object detection. *Pattern Recognition*, *120*, 108118.

[2] Sajid, A., Thygesen, K. S., Reimers, J. R., & Ford, M. J. (2020). Edge effects on optically detected magnetic resonance of vacancy defects in hexagonal boron nitride. *Communications Physics*, *3*(1), 1-8.

[3] Kim, Y., Choi, Y., Kim, K. B., Leem, H., & Jung, J. H. (2021). Serial Line Multiplexing Method Based on Bipolar Pulse for PET. *Nuclear Engineering and Technology*.

[4] Barnawi, A., Chhikara, P., Tekchandani, R., Kumar, N., & Alzahrani, B. (2021). Artificial intelligence-enabled Internet of Things-based system for COVID-19 screening using aerial thermal imaging. *Future Generation Computer Systems*.

[5] Hutli, E., Petrović, P. B., Nedeljkovic, M., & Legrady, D. (2021). Automatic Edge Detection Applied to Cavitating Flow Analysis: Cavitation Cloud Dynamics and Properties Measured through Detected Image Regions. *Flow, Turbulence and Combustion*, 1-29.

[6] Zhang, Y. D., Khan, M. A., Zhu, Z. Q., & Wang, S. H. (2021). Pseudo Zernike Moment and Deep Stacked Sparse Autoencoder for COVID-19 Diagnosis. *Cmc-Computers Materials & Continua*, 3145-3162.

[7] Zhang, Y. D., Zhang, Z., Zhang, X., & Wang, S. H. (2021). MIDCAN: A multiple input deep convolutional attention network for Covid-19 diagnosis based on chest CT and chest X-ray. *Pattern Recognition Letters*, *150*, 8-16.

[8] Heidary, H., Mehrpouya, M. A., Ghalee, A., & Oskouei, A. R. (2021). A design for a yoke to detect a notch on edge by using magnetic flux leakage method. *The European Physical Journal Plus*, *136*(4), 1-20.

[9] Ghanbari, B., & Atangana, A. (2020). Some new edge detecting techniques based on fractional derivatives with non-local and non-singular kernels. *Advances in Difference Equations*, *2020*(1), 1-19.

[10] Grycuk, R., Wojciechowski, A., Wei, W., & Siwocha, A. (2020). Detecting visual objects by edge crawling. *Journal of Artificial Intelligence and Soft Computing Research*, *10*.

[11] Jenkins, B. M., London, A. J., Riddle, N., Hyde, J. M., Bagot, P. A., & Moody, M. P. (2020). Using alpha hulls to automatically and reproducibly detect edge clusters in atom probe tomography datasets. *Materials Characterization*, *160*, 110078.

[12] Barua, A., Dong, C., Al-Turjman, F., & Yang, X. (2020). Edge Computing-Based Localization Technique to Detecting Behavior of Dementia. *IEEE Access*, *8*, 82108-82119.

[13] Tomaniak, M., Zandvoort, L. J., Forero, M. N. T., Masdjedi, K., Visseren, L., Witberg, K., ... & Daemen, J. (2019). PROGNOSIS BASED ON CHARACTERISTICS OF NON-TREATED EDGE DISSECTIONS AS DETECTED BY OPTICAL COHERENCE TOMOGRAPHY. *Journal of the American College of Cardiology*, *73*(9S1), 1386-1386.

[14] Adil, M., Almaiah, M. A., Omar Alsayed, A., & Almomani, O. (2020). An anonymous channel categorization scheme of edge nodes to detect jamming attacks in wireless sensor networks. *Sensors*, *20*(8), 2311.

[15] van Zandvoort, L. J., Tomaniak, M., Tovar Forero, M. N., Masdjedi, K., Visseren, L., Witberg, K., ... & Daemen, J. (2020). Predictors for Clinical Outcome of Untreated Stent Edge Dissections as Detected by Optical Coherence Tomography. *Circulation: Cardiovascular Interventions*, *13*(3), e008685.

[16] Goodwin, C. A., Réant, B. L., Kragskow, J. G., DiMucci, I. M., Lancaster, K. M., Mills, D. P., & Sproules, S. (2018). Heteroleptic samarium (iii) halide complexes probed by fluorescence-detected L 3-edge X-ray absorption spectroscopy. *Dalton Transactions*, *47*(31), 10613-10625.

[17] Nair, S. K., Chinnappan, S. K., Dubey, A. K., Subburaj, A., Subramaniam, S., Balasubramaniam, V., & Sengan, S. (2021). Prewitt Logistic Deep Recurrent Neural Learning for Face Log Detection by Extracting Features from Images. *Arabian Journal for Science and Engineering*, 1-12.

[18] Lyu, C., Chen, Y., Alimasi, A., Liu, Y., Wang, X., & Jin, J. (2021). Seeing the Vibration: Visual-Based Detection of Low Frequency Vibration Environment Pollution. *IEEE Sensors Journal*, *21*(8), 10073-10081.

[19] Patil, R. V., & Reddy, Y. P. (2021). An Autonomous Technique for Multi Class Weld Imperfections Detection and Classification by Support Vector Machine. *Journal of Nondestructive Evaluation*, *40*(3), 1-33.

[20] Wang, S., Yang, M., Li, J., Wu, X., Wang, H., Liu, B., ... & Zhang, Y. (2017). Texture analysis method based on fractional Fourier entropy and fitness-scaling adaptive genetic algorithm for detecting left-sided and right-sided sensorineural hearing loss. *Fundamenta Informaticae*, *151*(1-4), 505-521.

[21] Yezerska, O., Butenko, S., & Boginski, V. L. (2018). Detecting robust cliques in graphs subject to uncertain edge failures. *Annals of Operations Research*, *262*(1), 109-132.

[22] Zhang, Y., & Wu, L. (2008). Improved image filter based on SPCNN. *Science in China Series F: Information Sciences*, *51*(12), 2115-2125.

[23] Lu, X., Liu, Z., & Li, H. (2021). Parameter detection for surface acoustic wave filter based on image processing. *Measurement Science and Technology*, *32*(11), 115014.

[24] Shafiabadi, M., Kamkar-Rouhani, A., Riabi, S. R. G., Kahoo, A. R., & Tokhmechi, B. (2021). Identification of reservoir fractures on FMI image logs using Canny and Sobel edge detection algorithms. *Oil & Gas Science and Technology–Revue d'IFP Energies nouvelles*, *76*, 10.

[25] Coleman, S. A., Scotney, B. W., & Suganthan, S. (2010). Edge detecting for range data using laplacian operators. *IEEE Transactions on Image Processing*, *19*(11), 2814-2824.

[26] Zhang, Y., & Wu, L. (2009). Segment-based coding of color images. *Science in China Series F: Information Sciences*, *52*(6), 914-925.

[27] Zhang, Y., Wu, L., Wang, S., & Wei, G. (2010). Color image enhancement based on HVS and PCNN. *Science China Information Sciences*, *53*(10), 1963-1976.

[28] Jia, H., Wei, B., Liu, G., Zhang, R., Yu, B., & Wu, S. (2021). A Semi-Automatic Method for Extracting Small Ground Fissures from Loess Areas Using Unmanned Aerial Vehicle Images. *Remote Sensing*, *13*(9), 1784.

[29] Pei, Y., Liu, C., & Lou, R. (2020). Multi-scale edge detection method for potential field data based on two-dimensional variation mode decomposition and mathematical morphology. *IEEE access*, *8*, 161138-161156.

[30] Li, L., Ma, G., & Du, X. (2013). Edge detection in potential-field data by enhanced mathematical morphology filter. *Pure and Applied Geophysics*, *170*(4), 645-653.

[31] Zhang, Y., Wang, S., Huo, Y., Wu, L., & Liu, A. (2010). Feature extraction of brain MRI by stationary wavelet transform and its applications. *Journal of Biological Systems*, *18*(spec01), 115-132.

[32] Wang, S. H., Wu, X., Zhang, Y. D., Tang, C., & Zhang, X. (2020). Diagnosis of COVID-19 by Wavelet Renyi entropy and three-segment biogeography-based optimization. *International Journal of Computational Intelligence Systems*, *13*(1), 1332-1344.

[33] Wang, S. H., Zhang, Y. D., Yang, M., Liu, B., Ramirez, J., & Gorriz, J. M. (2019). Unilateral sensorineural hearing loss identification based on double-density dual-tree complex wavelet transform and multinomial logistic regression. *Integrated Computer-Aided Engineering, 26*(4), 411-426.

[34] Isar, A., Nafornita, C., & Magu, G. (2021). Hyperanalytic Wavelet-Based Robust Edge Detection. *Remote Sensing*, *13*(15), 2888.

[35] Dwivedi, D., & Chamoli, A. (2021). Source Edge Detection of Potential Field Data Using Wavelet Decomposition. *Pure and Applied Geophysics*, *178*(3), 919-938.

[36] Lv, Congcong, Kaifu Wang, Guoqing Gu, and Yun Pan. "Edge detection of internal defects based on the hidden singularity of gradient streamlines obtained by continuous wavelet transform." *Optical Engineering* 58, no. 3 (2019): 033105.

[37] Wang, S., Li, Y., Shao, Y., Cattani, C., Zhang, Y., & Du, S. (2017). Detection of dendritic spines using wavelet packet entropy and fuzzy support vector machine. *CNS & Neurological Disorders-Drug Targets (Formerly Current Drug Targets-CNS & Neurological Disorders)*, *16*(2), 116-121.

[38] Zhang, Y. D., Yang, Z. J., Lu, H. M., Zhou, X. X., Phillips, P., Liu, Q. M., & Wang, S. H. (2016). Facial emotion recognition based on biorthogonal wavelet entropy, fuzzy support vector machine, and stratified cross validation. *IEEE Access*, *4*, 8375-8385.

[39] Kumar, A., & Raheja, S. (2021). Edge Detection in Digital Images Using Guided L0 Smoothen Filter and Fuzzy Logic. *Wireless Personal Communications*, 1-19.

[40] Dhivya, R., & Prakash, R. (2019). Edge detection of satellite image using fuzzy logic. *Cluster Computing*, *22*(5), 11891-11898.

[41] Zhang, Y., Wang, S., & Ji, G. (2013). A rule-based model for bankruptcy prediction based on an improved genetic ant colony algorithm. *Mathematical Problems in Engineering*, *2013*.

[42] Fu, W., Zhang, M., & Johnston, M. (2019). Bayesian genetic programming for edge detection. *Soft Computing*, *23*(12), 4097-4112.

[43] Dang, X. Y. (2014). A new image edge detection method based on GAP predictor and genetic algorithm. In *Applied Mechanics and Materials* (Vol. 644, pp. 912-915). Trans Tech Publications Ltd.

[44] Zhang, Y. D., Jiang, Y., Zhu, W., Lu, S., & Zhao, G. (2018). Exploring a smart pathological brain detection method on pseudo Zernike moment. *Multimedia Tools and Applications*, *77*(17), 22589-22604.

[45] Wang, S. H., Du, S., Zhang, Y., Phillips, P., Wu, L. N., Chen, X. Q., & Zhang, Y. D. (2017). Alzheimer's disease detection by pseudo Zernike moment and linear regression classification. *CNS & Neurological Disorders-Drug Targets (Formerly Current Drug Targets-CNS & Neurological Disorders)*, *16*(1), 11-15.

[46] Bai, X., Yang, M., & Ajmera, B. (2020). An Advanced Edge-Detection Method for Noncontact Structural Displacement Monitoring. *Sensors*, *20*(17), 4941.

[47] Fang, J., Xu, S., Yang, Y., & Wang, Y. (2020). Localization and measurement method of continuous casting slab model based on binocular vision. *Microwave and Optical Technology Letters*, *62*(1), 53-59.

[48] Taibi, F., Akbarizadeh, G., & Farshidi, E. (2019). Robust reservoir rock fracture recognition based on a new sparse feature learning and data training method. *Multidimensional Systems and Signal Processing*, *30*(4), 2113-2146.

[49] Huang, L., Yu, X., & Zuo, X. (2017). Edge detection in UAV remote sensing images using the method integrating Zernike moments with clustering algorithms. *International Journal of Aerospace Engineering*, *2017*.

[50] Du, S., Wang, M., Chen, X., Fang, S., & Su, H. (2016). A high-accuracy extraction algorithm of planet centroid image in deep-space autonomous optical navigation. *The Journal of Navigation*, *69*(4), 828-844.

[51] Wang, Z. J., & Huang, X. D. (2015). Visual positioning of rectangular lead components based on Harris corners and Zernike moments. *Journal of Central South University*, *22*(7), 2586-2595.

[52] Wei, B. Z., & Zhao, Z. M. (2013). A sub-pixel edge detection algorithm based on Zernike moments. *The Imaging Science Journal*, *61*(5), 436-446.

[53] Lin, B., Wang, J., Yang, X., Tang, Z., Li, X., Duan, C., & Zhang, X. (2021). Defect Contour Detection of Complex Structural Chips. *Mathematical Problems in Engineering*, *2021*.

[54] Xiong, S., Wu, X., Chen, H., Qing, L., Chen, T., & He, X. (2021). Bi-directional skip connection feature pyramid network and sub-pixel convolution for high-quality object detection. *Neurocomputing*, *440*, 185-196.

[55] Chen, Z. G., Li, Y. G., Chen, X. F., Yang, C. H., & Gui, W. H. (2018). Edge and texture detection of metal image under high temperature and dynamic solidification condition. *Journal of Central South University*, *25*(6), 1501-1512.

[56] Lin, S. K., & Yang, S. W. (2014). Lens sag and diameter measurement of large-size microlenses using sub-pixel algorithm and optical interferometry. *Optics & Laser Technology*, *57*, 293-303.

[57] Wang, L. G., Wang, Z. Y., Dou, Z., & Wang, Y. (2013). Edge-directed interpolation-based sub-pixel mapping. *Remote sensing letters*, *4*(12), 1195-1203.

[58] Si-Mohamed, S. A., Sigovan, M., Hsu, J. C., Tatard-Leitman, V., Chalabreysse, L., Naha, P. C., ... & Douek, P. C. (2021). In Vivo Molecular K-Edge Imaging of Atherosclerotic Plaque Using Photon-counting CT. *Radiology*, 203968.

[59] Zhang, H., Meng, C., Bai, X., & Li, Z. (2019). Rock-ring detection accuracy improvement in infrared satellite image with sub-pixel edge detection. *IET Image Processing*, *13*(5), 729-735.

[60] Li, Y., Zhou, J., Huang, F., & Liu, L. (2017). Sub-pixel extraction of laser stripe center using an improved gray-gravity method. *Sensors*, *17*(4), 814.

[61] Chen, Y., Li, Y., & Zhao, Y. (2016). Sub-pixel detection algorithm based on cubic B-spline curve and multi-scale adaptive wavelet transform. *Optik*, *127*(1), 11-14.

[62] Hagara, M., & Kulla, P. (2011). Edge detection with sub-pixel accuracy based on approximation of edge with Erf function. *Radioengineering*, *20*(2), 516-524.

[63] Sedaghat, A., Ebadi, H., & Mokhtarzade, M. (2012). Image matching of satellite data based on quadrilateral control networks. *The Photogrammetric Record*, *27*(140), 423-442.

[64] Pranata, Y. D., Wang, K. C., Wang, J. C., Idram, I., Lai, J. Y., Liu, J. W., & Hsieh, I. H. (2019). Deep learning and SURF for automated classification and detection of calcaneus fractures in CT images. *Computer methods and programs in biomedicine*, *171*, 27-37.

[65] Wang, S. H., Lv, Y. D., Sui, Y., Liu, S., Wang, S. J., & Zhang, Y. D. (2018). Alcoholism detection by data augmentation and convolutional neural network with stochastic pooling. *Journal of medical systems*, *42*(1), 1-11.

[66] Zhang, Y. D., Muhammad, K., & Tang, C. (2018). Twelve-layer deep convolutional neural network with stochastic pooling for tea category classification on GPU platform. *Multimedia Tools and Applications*, *77*(17), 22821-22839.

[67] Wang, S. H., Wu, K., Chu, T., Fernandes, S. L., Zhou, Q., Zhang, Y. D., & Sun, J. (2021). SOSPCNN: Structurally Optimized Stochastic Pooling Convolutional Neural Network for Tetralogy of Fallot Recognition. *Wireless Communications and Mobile Computing*, *2021*.

[68] Kieu, S. T. H., Bade, A., Hijazi, M. H. A., & Kolivand, H. (2021). COVID-19 Detection Using Integration of Deep Learning Classifiers and Contrast-Enhanced Canny Edge Detected X-Ray Images. *It Professional*, *23*(4), 51-56.

[69] Liu, N., Yuan, Y., Wan, L., Huo, H., & Fang, T. (2018, February). A comparative study for contour detection using deep convolutional neural networks. In *Proceedings of the 2018 10th International Conference on Machine Learning and Computing* (pp. 203-208).

[70] Shen, W., Wang, X., Wang, Y., Bai, X., & Zhang, Z. (2015). Deepcontour: A deep convolutional feature learned by positive-sharing loss for contour detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 3982-3991).

[71] Cao, Y. J., Lin, C., & Li, Y. J. (2020). Learning Crisp Boundaries Using Deep Refinement Network and Adaptive Weighting Loss. *IEEE Transactions on Multimedia*, *23*, 761-771.

[72] Huan, L., Xue, N., Zheng, X., He, W., Gong, J., & Xia, G. S. (2021). Unmixing Convolutional Features for Crisp Edge Detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*.

[73] Qu, Z., Wang, S. Y., Liu, L., & Zhou, D. Y. (2019). Visual cross-image fusion using deep neural networks for image edge detection. *IEEE Access*, *7*, 57604-57615.

[74] Lin, C., Cui, L., Li, F., & Cao, Y. (2020). Lateral refinement network for contour detection. *Neurocomputing*, *409*, 361-371.

[75] Liu, Y., Cheng, M. M., Hu, X., Wang, K., & Bai, X. (2017). Richer convolutional features for edge detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 3000-3009).

[76] Tan, X., Xiao, Z., Wan, Q., & Shao, W. (2020). Scale sensitive neural network for road segmentation in high-resolution remote sensing images. *IEEE Geoscience and Remote Sensing Letters*, *18*(3), 533-537.

[77] Wang, E., Jiang, Y., Li, Y., Yang, J., Ren, M., & Zhang, Q. (2019). MFCSNet: Multi-scale deep features fusion and cost-sensitive loss function based segmentation network for remote sensing images. *Applied Sciences*, *9*(19), 4043.

[78] Kim, W. S., Lee, D. H., Kim, T., Kim, H., Sim, T., & Kim, Y. J. (2021). Weakly Supervised Crop Area Segmentation for an Autonomous Combine Harvester. *Sensors*, *21*(14), 4801.

[79] Dhiman, B., Y. Kumar, and Y.-C. Hu, *A general purpose multi-fruit system for assessing the quality of fruits with the application of recurrent neural network.* Soft Computing, 2021. 25(14): p. 9255-9272.

[80] Kazemi, M. F., & Mazinan, A. H. (2021). Neural network based CT-Canny edge detector considering watermarking framework. *Evolving Systems*, 1-13.

[81] Ono, Y., Yoshimura, M., Ono, T., Fujimoto, T., Miyabe, Y., Matsuo, Y., & Mizowaki, T. (2021). Appropriate margin for planning target volume for breast radiotherapy during deep inspiration breath-hold by variance component analysis. *Radiation Oncology*, *16*(1), 1-8.

[82] Darma, P. N., & Takei, M. (2021). High-Speed and Accurate Meat Composition Imaging by Mechanically-Flexible Electrical Impedance Tomography With k-Nearest Neighbor and Fuzzy k-Means Machine Learning Approaches. *IEEE Access*, *9*, 38792-38801.

****