Image Processing, Electronics and Computers
L. Trajkovic et al. (Eds.)

doi:10.3233/ATDE240466

Research on Medical Ultrasound Image Information Extraction Model Based on Riesz Transform

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Abstract. Edge detection can greatly reduce the amount of data of the original image, eliminate many meaningless information, and retain the important structural attributes of the image. It is an important basis in the field of image analysis, such as image segmentation, region shape extraction, target detection and so on. It is also an important attribute of feature extraction in image recognition. Image edge detection based on Riesz transform is a new method of image edge detection, which has the characteristics of multi-resolution and multi-scale. In order to solve the problem of poor detection performance of traditional medical images under illumination changes, this paper proposes a medical ultrasound image information extraction model based on Riesz transform. In this paper, Riesz transform is used to replace the traditional Hilbert transform to process the image. The model uses different scale factors of Riesz transform to construct a transform space specially used to calculate phase consistency, and successfully obtains the feature image. The non-maximum suppression technique is used to detect the edge information of the image. The experimental results show that the model can effectively and quickly identify and retain the edge features in the image while suppressing the non-edge region response under uneven illumination.

Keywords. Image detection, region shape extraction, riesz transform, feature image, non-maximum suppression

1. Introduction

In image processing and analysis, edge detection has been a hot topic of concern. The first step in image analysis and understanding is often edge detection, so it has now become one of the most active research topics in machine vision. With the rapid development of modern science and technology, medical images have become an indispensable tool in modern medicine, hospitals and medical fields. Since the internal organs, tissues, blood and bones of human tissues are difficult to observe directly, medical images can accurately restore the internal structure and get a glimpse of the mystery inside the body. Through the detailed structure of medical images, physical examination can be carried out accurately, which greatly improves the efficiency of diagnosis and treatment. The wide application of medical images in modern medicine has undoubtedly brought revolutionary progress to the medical field [1].

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At present, the research methods of ultrasonic image registration at home and abroad can be divided into two categories. The first method focuses on extracting the feature information of ultrasonic images and using the operation method based on functional characteristics. Such methods achieve accurate registration by deeply analyzing specific details in the image [2]. The other method relies on statistical voxels and uses volume-based operation techniques. This kind of method realizes the registration of ultrasound images by counting and analyzing the voxel information in the image [3]. These two types of methods have their own characteristics, and researchers can choose the appropriate method according to specific needs and scenarios.

In the ultrasound image, almost all the available information is contained in the brightness value, and the brightness information is used to register the ultrasound image. Li et al. proposed a new framework for image fusion using wavelet packet transform. In this framework, the detail information in the image can be captured more finely by secondary decomposition of the high-frequency coefficients obtained by decomposition, thus significantly improving the fusion effect. This innovative method has brought new breakthroughs and progress in the field of image fusion [4]. Based on complex wavelet transform, Singh et al. proposed a fusion algorithm for multimodal medical images. The complex wavelet transform has the ability to analyze the real and imaginary parts of the image at multiple scales at the same time, which makes it have unique advantages in processing multi-modal medical images [5]. He et al. proposed the Trans FG method, which uses visual Transformer to automatically identify the most feature parts of the image. By integrating all the self-attention weights of the transformer into an attention map, this method can effectively guide the network system to select differentiated image patches, thereby enhancing the ability of image processing and improving the accuracy of feature extraction and classification [6]. Fast R-CNN is a two-stage algorithm for target detection. Object detection is an important task in the field of computer vision, which aims to identify specific objects in the image and give the location of these objects. Fast R-CNN is improved and optimized on the basis of previous R-CNN and SPPnet. Its main contribution is to improve the detection speed and accuracy, while reducing the waste of computing resources [7]. Redmon et al. first proposed a single-stage target detection algorithm YOLO-V1 [8]. Subsequently, the concept of a priori box is further introduced in the YOLO-V2 network to optimize the accuracy of target detection [9]. By 2022, YOLO-V7 was born, and it innovatively proposed the Extended End-to-End (E2E) architecture [10]. This architecture can significantly improve the self-learning ability of the network without destroying the original gradient path, thereby further improving the efficiency and accuracy of target detection.

Tang et al. proposed a target detection method called Proposal Learning, which uses a self-supervised learning strategy. By learning from unlabeled data, this method can perceive context information and generate target box features that are robust to noise [11]. Sohn et al. proposed a data distillation method called Fix Match. This method generates pseudo labels for unlabeled data by integrating various forms of prediction results, so as to effectively use unlabeled data for model training [12]. Zhang et al. proposed an innovative network architecture composed of three convolutional neural networks. The core of this network architecture is the feature extraction network, which can deeply mine the intrinsic features of FS images [13]. Lin et al. proposed a multi-task learning framework based on Faster R-CNN structure, which aims to achieve the dual tasks of standard section detection and quality assessment [14]. This framework makes full use of the advantages of Faster R-CNN in the field of target detection. By constructing a multi-task learning mechanism, it realizes the accurate detection of standard sections in images and performs quality assessment at the same time.

In many studies, phase congruency is used for image feature extraction, and remarkable results have been achieved. Compared with the traditional feature extraction method based on image amplitude gradient change, the phase congruency feature extraction method is mainly based on the phase change information in the image, so it is not easily affected by uneven illumination, thus ensuring the stability and accuracy of feature extraction.

However, it is worth noting that in the past, researchers usually calculated phase consistency in Hilbert transform space, but the operation speed of this method is relatively slow. In order to overcome this limitation, this paper introduces the phase congruency calculation into the Riesz transform space. Riesz transform has isotropic characteristics, which means that it can maintain consistency in all directions when processing images, thus helping to capture the characteristics of images more accurately.

2. Phase Consistency Calculation

Phase congruency is a method to measure the phase similarity of different frequency components in each position of the image. It is a dimensionless quantity, so theoretically its value will not be affected by changes in light and brightness. This feature makes phase congruency a very useful tool in image processing, especially in applications that require stable feature extraction.

The concept of local energy feature model is indispensable in calculating the phase congruency of images. Morrone et al. found that the local energy model is very suitable for feature extraction in computer vision. Different from the traditional feature detection method based on the local amplitude gradient change of the image, the local energy model assumes that all the phase maximum points (PCs) can be perceived in the Fourier transformed image. [15] The Fourier series expansion of the signal F (x) is:

$$F(x) = \sum_n A_n \cos(n\omega x + \varphi_{n0}) \\ = \sum_n A_n \cos(\phi_n(x)) \tag{1}$$

where An is the amplitude of the nth cosine component, ω is a constant, usually ω =2 π , Φ0 represents the phase offset of the nth cosine component, and n (x) represents the phase of the Fourier transform component at x. Correspondingly, the phase congruency function is defined as:

$$PC(x) = \max \frac{\sum_n A_n \cos(\phi_n(x) - \phi(x))}{\sum_n A_n} \tag{2}$$

Here, -(x) represents the weighted mean value of the phase, and Φ(x) ∈[-π, π] from the formula (2), it can be seen that the solution of cos [-n(x)] is very complicated. In order to simplify the calculation, another expression of local energy, the local energy formula in complex form:

$$E(x) = \sqrt{I^2(x) + H^2(x)} \tag{3}$$

Here, I(x) represents the real part, H(x) represents the imaginary part, and H(x) is the result of the Hilbert transform of the original signal F(x). This means that there are other forms to solve the phase congruency formula:

$$PC(x) = \frac{E(x)}{\sum nA_n} \tag{4}$$

It can be seen from formula (4) that the local energy is proportional to the phase [16]. When the amplitude value is constant, the local energy E(x) reaches the peak and the phase consistent PC(x) also reaches the peak. Phase congruency PC(x) is indeed an important image processing concept, which is the ratio of local energy to amplitude accumulation. This feature makes the phase consistency in feature extraction, mainly based on the speed of amplitude change, rather than just through a simple amplitude gradient change size for analysis. Therefore, phase congruency is less affected by image brightness and contrast.

3. The Riesz Transform with Log-Gabor as Scale Factor is Constructed

Riesz transform is used for signal analysis [17]. Riesz transform and Hilbert transform have many same properties. Therefore, the concept of phase congruency is introduced into Riesz transform space. The kernel of Riesz transform (Note: u signal analysis frequency domain, x image domain):

$$H(u) = -i\frac{u}{|u|} \tag{5}$$

The kernel function acts in the frequency domain. If you want to use the formula (6) to act on the image, you need a convolution template, that is:

$$h(x) = \frac{x}{2\pi |x|^3} \tag{6}$$

Among them, f(x) is the original signal. After Riesz transform, fM(x) is expressed as:

$$f_M(x) = f(x) - h(x) * f(x) \tag{7}$$

A scale variable is added to the Riesz transform space, and the one-dimensional Log-Gabor transform is used as the scale variable. The Log-Gabor transform has a relatively large coverage frequency and is similar to the human visual system. The improved Riesz kernel is:

$$H(u) = -i\frac{u}{|u|}G(|u|) \tag{8}$$

Here G (| u |) is a one-dimensional Log-Gabor function $G(\omega) = e^{\frac{-(\log(\omega/\omega_0))^2}{2(\log(\beta/\omega_0))^2}}$. In the two-dimensional frequency domain, each coordinate of u can be expressed as:

$$\begin{cases} H(u_1) = -i\dfrac{u_1}{\sqrt{u_1^2+u_2^2}}G(\sqrt{u_1^2+u_2^2}) \\ = i\cos\theta G(\omega) = H_1(\theta,\omega) \\ H(u_2) = -i\dfrac{u_2}{\sqrt{u_1^2+u_2^2}}G(\sqrt{u_1^2+u_2^2}) \\ = i\sin\theta G(\omega) = H_2(\theta,\omega) \end{cases} \tag{9}$$

In the image domain, the Riesz transform space is constructed by the ternary variable representation:

$$\begin{cases} p(x) = (f^{*}G_x)(x) \\ q_1(x) = (f^{*}h_1)(x) \\ q_2(x) = (f^{*}h_2)(x) \end{cases}$$
(10)

Here, Gx is a one-dimensional Log-Gabor transform in the image domain. h1 and h2 are the product of H(u) and convolution template h(x). Therefore, the local amplitude value A(x), local phase P(x) and local direction θ (x) of Monogenic Signal in the image can be expressed as:

$$\begin{cases} A(x) = \sqrt{p(x)^2 + q1(x)^2 + q_2(x)^2} \\ \theta(x) = \tan^{-1}\dfrac{q_2(x)}{q_1(x)} \\ P(x) = \tan^{-1}\dfrac{P(x)}{\sqrt{q_1(x)^2+q_2(x)^2}} \end{cases} \tag{11}$$

4. Riesz Transform Image Detection Method

The phase congruency algorithm under the traditional Hilbert transform mainly relies on the two-dimensional Log-Gabor transform and the real and imaginary parts to construct the signal processing space, and then calculate the local energy [18]. However, this method may be complicated in calculation, which affects the efficiency of phase congruency calculation.

In contrast, the method of obtaining local energy representation in Riesz transform space proposed in this paper provides a more efficient way to calculate phase congruency. The Riesz transform and the Hilbert transform have the same characteristics in the spectrum, which makes the Riesz transform an effective alternative to the Hilbert transform.

The filter generated by the Riesz transform constitutes a spherical quadrature filter (SQF), as shown in Figure 1. This structure helps to capture the phase information in the image more accurately.

In the Riesz transform space, the image can be processed by a series of orthogonal filters to obtain phase information in different frequencies and directions. Then, based on this information, the local energy can be calculated, and the phase consistency can be obtained. Since the operation of Riesz transform is relatively simple, this method is superior to the traditional Hilbert transform method in computational efficiency.

In Figure 1, Monogenic Signal is based on the Riesz transform as the kernel, and the one-dimensional Log-Gabor wavelet is the scale function of the Riesz transform space. Under the Riesz transform, the scale space is composed of p (x), q1 (x) and q2 (x), where θ is the local direction and p (x) is the local phase.

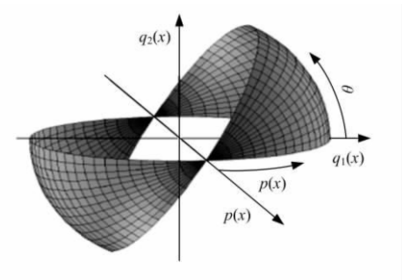

Figure 1. Riesz transformation space with respect to p (x), q1 (x) and q2 (x).

It is impossible to compute the similarity (phase congruency) of image frequencies in the Riesz transform space in a spherical orthogonal filter. Only by setting the scale factor of Riesz transform (Log-Gabor transform of scale function with different wavelength parameters), two (or more) spherical orthogonal filters can be obtained to calculate the phase consistency of the image. Assuming that the phase on the first dimension is P1, and the phase on the second dimension is P2:

$$f = A_n \cos(p)$$
(12)

Where f represents a local energy, the phase congruency definition formula is passed through:

The implementation process of the algorithm is as follows: Firstly, Fourier transform is performed on the image f (x) to obtain its FFT representation f (x). Next, in order to obtain the Riesz transform, it is necessary to perform one-dimensional Log-Gabor transform on the rows and columns of FFT f (x). Then, the FFT f (x) processed by Log-Gabor transform is convoluted with the Riesz transform. After convolution, the real and imaginary parts of the Riesz transform will constitute q1 (x) and q2 (x) of the Riesz transform space, respectively. At the same time, the real part of the one-dimensional Log-Gabor transform and FFT f (x) will be used as the p (x) of the transform space. Thus, the first set of vectors f1 for calculating phase consistency is obtained.

In order to obtain more accurate phase congruency results, the above process can be repeated by changing the wavelength of the one-dimensional Log-Gabor transform to obtain the second set of vectors f2 for calculating phase congruency. In fact, in order to obtain better low-level feature extraction results, multiple sets of vectors f can be obtained, and phase consistency can be calculated separately, and then the results of each time are fused. However, this method will increase the running time of the calculation.

Finally, the ratio of the amplitude values in the q1 (x) and q2 (x) directions can be used to calculate the local direction θ, and the non-maxima suppression method is used to extract the feature edges of the image. The flow chart of this method is shown in Figure 2.

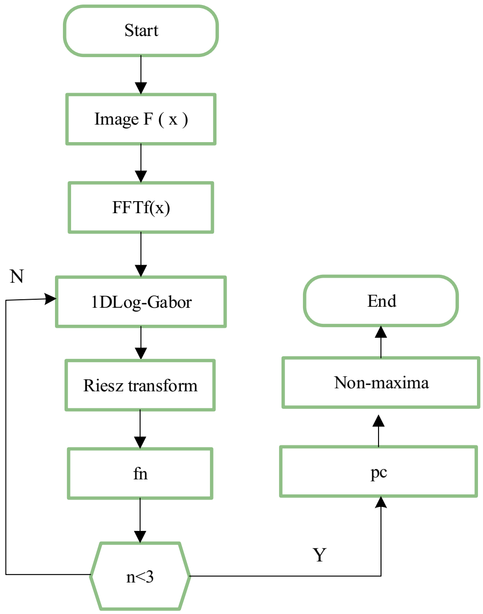

Figure 2. Flow chart of the method in this paper.

5. Simulation Experiment

5.1. Algorithm Memory Consumption and Operation Speed Comparison

Under the Windows 11 system platform, the classic Lena image is used as the test object using Matlab2023 a software. The image is an 8-bit grayscale image with a resolution of 512×512, which is often used as a test standard for image processing algorithms. In order to evaluate the memory consumption of Hilbert transform and Riesz transform in edge extraction, the Resource Monitor memory monitoring software was used to record the memory usage during the experiment.

In the experiment, the memory consumption of the two transform methods under different directional scales (nscale) and the same wavelength bandwidth is concerned. By monitoring the initial memory consumption value and the peak value at runtime during the Matlab simulation experiment, the difference in memory usage between the Hilbert transform and the Riesz transform can be compared.

Figure 3 shows the comparison of memory consumption between the edge feature extraction algorithm based on Riesz transform and the traditional Hilbert transform edge feature extraction algorithm in 6 and 4 directions. It can be clearly seen from the diagram that the method based on Riesz transform proposed in this paper has relatively small memory consumption. This advantage shows that Riesz transform may be a more efficient and practical choice in dealing with large-scale images or resource-constrained environments.

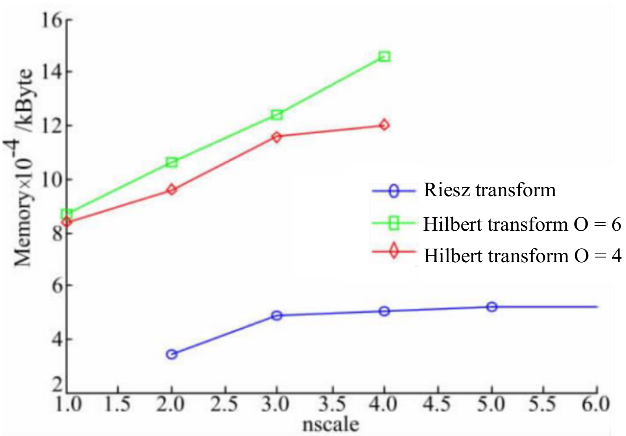

Figure 3. Comparison of memory consumption between the proposed method and the traditional method.

Compared with the traditional Hilbert transform edge extraction algorithm, the algorithm proposed in this paper has significant advantages in operation speed and efficiency. Since this algorithm does not need to consider the multi-direction problem, and avoids the cyclic operation of sine and cosine functions in the operation process, it can greatly improve the operation speed.

In order to verify this advantage, the experimental test is carried out, and the operation speed of the two algorithms is compared. The experimental samples include five grayscale images with different resolutions, which are representative in image processing. The experimental platform uses a computer equipped with Celeron 466 CPU and 128 MByte memory. The operating system is Windows 11, and Matlab 2023 a is used as the programming environment. The experimental results are shown in Table 1.

Table 1. Comparison of the speed of two algorithms.

Method	*T_1/s*	*T_2/s*	*T_3/s*	*T_4/s*	*T_5/s*	*AverageT/s*
Riesz transform	5.1	2.5	3.9	4.2	7.0	4.54
Hilbert transform	13.1	5.1	5.9	8.1	15.2	9.88

5.2. Comparison of Image Feature Extraction Effects

Figure 4 shows the experimental results of this method compared with Canny algorithm and Log-Gabor wavelet in edge extraction. Through this set of comparisons, it can be clearly seen that the performance differences of different algorithms in dealing with images with uneven illumination.

Figure 4(a) is the original image of the experimental test. Due to the influence of uneven illumination, the two straight lines of the visually segmented image gradually widen from top to bottom.

But in fact, the width of the two lines from top to bottom is uniform, but the brightness of the left line gradually becomes darker, and the brightness of the right line gradually becomes lighter. This uneven illumination is a challenge to the edge extraction algorithm.

Figure 4(b) is the result obtained by using the feature extraction method in this paper. It can be seen that the method in this paper can clearly reflect that the width of the two dividing lines is unchanged and is not affected by the change of illumination.

This is due to the robustness of the phase congruency feature extraction method in the Riesz transform space to local brightness gradient changes.

Figure 4(c) is the result of feature extraction using two-dimensional Log-Gabor wavelet with 6 directions and 3 scales. Along the left side of the image in the dark color segmentation line down, white feature segmentation line gradually become unclear, to the lower part of the image is difficult to identify white and black which is the image edge features.

This shows that the edge extraction performance of Log-Gabor wavelet is affected when dealing with images with uneven illumination.

Figure 4(d) and (e) are the results obtained by Canny edge extraction method with different parameters. It can be seen that the original vertical feature texture becomes tilted after Canny algorithm processing, and as the parameters change, the edge position of the image feature also changes.

This shows that the Canny algorithm has certain limitations in the accuracy and stability of edge extraction when dealing with images with close amplitude changes.

Figure 5 shows the comparison of edge extraction effects of different methods under different conditions. The original image (Figure 5(a)) shows the image to be processed, which contains various edge features and different lighting conditions.

Figure 5(b) and (c) are the results of edge extraction by this method, corresponding to scales n = 4 and n = 6, respectively. It can be seen that the proposed method can effectively extract the edge of the image at different scales, and the edge is continuous and clear, which is less affected by illumination.

Figure 5(d) shows the extraction effect of phase congruent edges after Hilbert transform. This method has little effect on illumination, and the edge extraction effect is relatively good. However, compared with the method in this paper, the computational complexity of Hilbert transform is higher, which may lead to lower efficiency in real-time processing or large-scale image processing.

Figure 5(e) is the image effect processed by Log-Gabor wavelet with direction O=6 and scale n=3. It can be seen that Log-Gabor wavelet has some limitations in edge extraction, especially in areas with uneven illumination, the edge extraction effect is not ideal.

Figure 5(f) and (g) are the effects of Canny operator processing, and the parameters are σ=2 and σ=5, respectively. When σ= 2, the Canny operator can extract the edge better, but when σ= 5, the effect appears obvious distortion. This shows that the Canny operator is sensitive to the selection of parameters, and the performance is unstable under different illumination conditions.

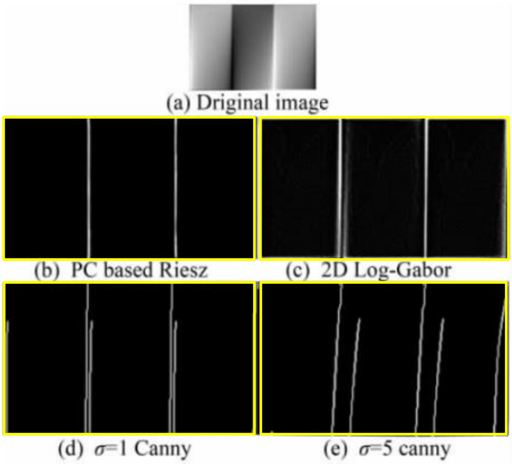

Figure 4. The experimental results of this method are compared with Canny and two-dimensional Log-Gabor changes (a)Driginal image (b)PC based Riesz (c)2D Log-Gabor (d)σ=1 Canny (e)σ=5 Canny.

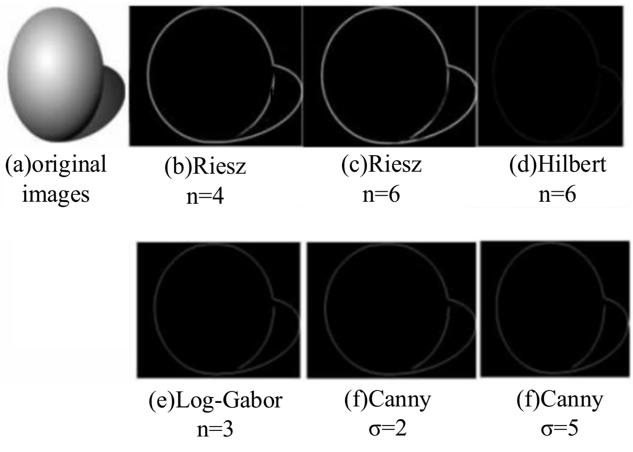

Figure 5. Comparison of this method with other edge extraction methods (a) original images (b) Riesz n=4 (c) Riesz n=6 (d) Hilbert n=6 (e) Log-Gabor n=3 (f) Canny σ=2 (f) Canny σ=5.

6. Conclusions

The application of image feature extraction has indeed received extensive attention and application in various fields. Whether it is computer vision, image recognition, or more complex machine learning and deep learning models, efficient underlying feature extraction methods are needed as support. Among many feature extraction methods, Gabor wavelet and Canny operator are favored for their fast operation speed, but their effects may not be ideal in some complex or specific application scenarios.

Although the traditional phase congruency calculation method under Hilbert transform has achieved satisfactory results in extracting image features, its operation speed often becomes a bottleneck restricting its application. In order to overcome this problem, this paper proposes a phase congruency edge extraction method based on Riesz transform.

In our method, the Riesz transform is used to replace the traditional Hilbert transform, and the Log-Gabor transform is used as the scale factor of the Riesz transform. Through the change of scale factor, a space for calculating phase consistency is constructed, so as to realize the analysis of local energy and local amplitude of the image. This method not only inherits the characteristics that the traditional phase consistency feature extraction method is less affected by light changes, but also has a more complete feature extraction effect than Gabor transform and Canny operator in an uneven illumination environment.

The simulation results show that although the proposed method is slightly more complex than Canny operator and Gabor transform in terms of operation speed, its performance is significantly better than the traditional phase consistency algorithm. This advantage makes the method of this paper have higher practical value in application scenarios that require efficient and accurate image feature extraction.

References

[1] Ali Y F, Syed W, Irfan K, et al. SeNet-I: An approach for detecting network intrusions through serialized network traffic images. Engineering Applications of Artificial Intelligence, 2023, 54(6), pp. 343-352.

[2] Salman, K A, Khalid S, and Sufyan A J. Fake Colorized Image Detection Approaches: A Review. International Journal of Image and Graphics, 2023, 23 (06), pp. 1011-1021.

[3] Mellor M, Brady M, Non-rigid multimodal image registration using local phase. Medical Image Computing and Computer-Assisted Intervention-MICCAI 2004. Springer Berlin Heidelberg, 2021, pp. 789-796.

[4] Shivakumara P, Trung Q P, Bhowmick, S, A novel ring radius transform forvideo character reconstruction. Pattern Recognition, 2012, 46(1), pp.1-6.

[5] Youssef D, Solouma N H, Accurate detection of blood vessels improves the detection of exudates in color fundus images. Computer Methods and Programs in Biomedicine, 2012, 108(3), pp. 3-5.

[6] He J, Chen J N, Liu S, et al, Transfg: A transformer architecture for fine-grained recognition. Proceedings of the AAAI Conference on Artificial Intelligence. California: AAAI Press, 2022, 36(1), pp. 852-860.

[7] Ren S, He K, Girshick R, et al, Faster r-cnn: Towards real-time object detection with region proposal networks, Advances in neural information processing systems, 2015, 28(3), pp. 19-37.

[8] Redmon J, Divvala S, Girshick R, et al, You only look once: Unified, real-time object detection, Proceedings of the lEEE conference on computer vision and pattern recognition, 2016, pp. 779-788.

[9] Redmon J, Farhadi A, YOL09000: better, faster, stronger, Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 7263-7271.

[10] Wang C Y, Bochkovskiy A, Liao H, YOLO v7: Trainable bag-of-freebies sets new state-of-the-art for real-time object detectors. arXiv Prepr, 2022, pp. 2207-2220.

[11] Sohn K, Berthelot D, Carlini N, et al, Simplifying semi-supervised Fixmatch: learning with consistency and confidence, Advances in neural information processing systems, 2020, 33(4), pp. 596-608.

[12] Xie Q, Luong M T, Hovy E, et al, Self-training with noisy student improves imagenet classification. Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 2020, pp. 10687-10698.

[13] Zhang B, Liu H, Luo H, et al, Automatic quality assessment for 2D fetal sonographic standard plane based on multitask learning. Medicine, 2021, 100(4), pp. 244-257.

[14] Lin Z, Li S, Ni D, et al, Multi-task learning for quality assessment of fetal head ultrasound images. Medical image analysis, 2019, 58(2), pp. 101-118.

[15] Saqlain R, Adeel M A, Abdul W, et al. Least complex oLSVN-based computer-aided healthcare system for brain tumor detection using MRI images. Journal of Ambient Intelligence and Humanized Computing, 2023, 15(1) pp. 683-695.

[16] Kassem M, De Kam S S, Van Velzen T J, et al. Application of mask images of contrast-enhanced MR angiography to detect carotid intraplaque hemorrhage in patients with moderate to severe symptomatic and asymptomatic carotid stenosis. European Journal of Radiology, 2023, 168, pp. 111145.

[17] Sharma K D, Singh B, Agarwal S, et al. A Survey of Detection and Mitigation for Fake Images on Social Media Platforms. Applied Sciences, 2023, 13 (19), pp. 201-204.

[18] Mirza, Shahsavar S, Rahman U, et al. Efficient Adaptive Filtering Techniques for Thoracic Electrical Bio-Impedance Analysis in Health Care Systems. Journal of Medical Imaging and Health Informatics, 2017, 7 (6), pp. 1126-1138.