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COVID-19 CT image denoising algorithm based on adaptive threshold and optimized weighted median filter

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\textbf{ARTICLE INFO}

\textbf{Keywords:}
Median filter  
COVID-19 CT image  
Adaptive threshold  
Weighting parameters  
Hybrid genetic algorithm

\textbf{ABSTRACT}

CT image of COVID-19 is disturbed by impulse noise during transmission and acquisition. Aiming at the problem that the early lesions of COVID-19 are not obvious and the density is low, which is easy to confuse with noise. A median filtering algorithm based on adaptive two-stage threshold is proposed to improve the accuracy for noise detection. In the advanced stage of ground-glass lesion, the density is uneven and the boundary is unclear. It has similar gray value to the CT images of suspected COVID-19 cases such as adenovirus pneumonia and mycoplasma pneumonia (reticular shadow and strip shadow). Aiming at the problem that the traditional weighted median filter has low contrast and fuzzy boundary, an adaptive weighted median filter image denoising method based on hybrid genetic algorithm is proposed. The weighted denoising parameters can adaptively change according to the detailed information of lung lobes and ground-glass lesions, and it can adaptively match the cross and mutation probability of genetic combined with the steady-state regional population density, so as to obtain a more accurate COVID-19 denoised image with relatively few iterations. The simulation results show that the improved algorithm under different density of impulse noise is significantly better than other algorithms in peak signal-to-noise ratio (PSNR), image enhancement factor (IEF) and mean absolute error (MSE). While protecting the details of lesions, it enhances the ability of image denoising.

1. Introduction

1.1. Background & problem domain

Since December 2019, COVID-19 has spread widely around the world. According to the data released by the Johns Hopkins University, as of September 18, 2020, there were 30065728 confirmed cases in the world. The disease is highly infectious and it can cause severe acute dyspnea. Studies have shown that computed tomography (CT), as a non-invasive imaging method, is of great value in detecting lung lesions in patients with COVID-19. Therefore, CT can be used for detection and diagnosis of COVID-19. However, CT images will produce high-dose radiation in the process of acquisition, which will pose a great threat to the patient’s health. Therefore, at present, the damage to the patient’s body is usually reduced by decreasing the CT dose. But CT images taken with low dose usually have noise. The generation of noise will affect the quality of CT images, which will seriously affect the doctor’s diagnosis for the patient’s condition. Lung CT images are inevitably disturbed by various noises in the process of acquisition, transmission and storage, which will cause some random, discrete and isolated pixels on the image, that is, image noise will bring bad interference to lesion image segmentation and doctors’ judgment of patients’ condition.

1.2. Review of literature

At present, nucleic acid detection is the most common method to diagnose COVID-19 \cite{1}. This method combines RNA reverse transcription and polymerase chain reaction (RT-PCR) to detect the viral RNA fragments \cite{2,3}, and the diagnosis can be confirmed by the positive nucleic acid test. However, the screening of RT-PCR has the problem of low sensitivity. Even if the RT-PCR result of suspected patient is negative, the possibility of SARS-Cov-2 infection cannot be completely ruled out \cite{4}. In addition, nucleic acid testing has the disadvantage of time-consuming and it requires a special test kits. Therefore, it is necessary to further accelerate the detection speed and reduce the cost \cite{5}. Through the comparative experimental analysis of CT and RT-PCR, Ai

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\url{https://doi.org/10.1016/j.bspc.2022.103552}
Received 22 October 2021; Received in revised form 7 January 2022; Accepted 2 February 2022
Available online 16 February 2022
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This method can suppress the image noise, the subtraction operation is inverse Fourier transform is used to obtain the saliency map. Although according to logarithmic amplitude spectrum of the image, and then the be quantified. It helps to reduce manual operation and improve the efficiency of accurate quantitative analysis. Standard median filter can preferably filter impulse noise. However, the traditional median filter takes the median value of the neighborhood pixels, the information points in the image may be filtered out and replaced by noise points, which will lead to the loss of some details in the image. Therefore, many scholars have proposed some improved algorithms. Verma [15] proposed adaptive median filter (AMF) algorithm, which shows good filtering performance in low-intensity noise, but when the noise density is too high, a large number of noises needs to be filtered, and the filtering window will expand. The current pixel and the replaced median may lack correlation, resulting in information loss and image blur. Sheela [16] proposed the switching median filter (SMF) method. This method determines whether each pixel is noisy. Due to the threshold needs to be defined in advance when judging the noise, the threshold remains unchanged in the processing process, the final filtering effect is not very ideal. Gupta [17] proposed a discrimination-based dual threshold median filter (DBF) method to judge whether the pixel is noisy by comparing the current pixel with the dual threshold. However, when dealing with high-intensity noise, this method is easy to produce "tailing effect", and the filtering performance is greatly reduced. Ahmed [18] proposed an improved discriminant-based asymmetric clipping median filter algorithm. This method can obtain good filtering effect under low-intensity noise, but under high-intensity, the filtering effect is very poor and some details are lost. There are some state-of-the-art methods about denoising algorithm reported. Zhao [19] obtains the residual spectrum according to logarithmic amplitude spectrum of the image, and then the inverse Fourier transform is used to obtain the saliency map. Although this method can suppress the image noise, the subtraction operation is used in the process of calculating the log amplitude. It not only suppresses the noise, but also restrains the detail information, which is not conducive to the denoising of the COVID-19 image. The CNN denoising method [20] can effectively use the global features of the image to significantly improve the denoising effect. The lower the number of CNN layers, the more primitive the extracted low-level features, such as color and edge lines. However, with the deepening of the network, the features extracted by the CNN method become more advanced, and a large number of low-level features will be lost. Yan [21] proposed a K-SVD image denoising algorithm based on K-means and singular value decomposition (SVD). This method is based on the bayesian reconstruction theory, and it uses the K-means clustering to obtain an optimal signal sparse representation dictionary set. Through the linear combination of the dictionary elements, various signals are constructed to remove the noise in the CT image. However, dictionary learning brings high computational cost, resulting in too long time for image denoising. In addition, the KSVD method is also insufficient for denoising of high-proportion noisy images. Yahya [22] proposed block-matching and 3D filtering (BM3D) algorithm, which has achieved good results in various image denoising processes, but it is easy to cause tissue contour blur when denoising low-dose CT image. Moreover, there are a lot of parameters in the BM3D algorithm that need to be set manually, which severely limits the effect of the practical application. Gu [23] proposed a weighted kernel norm minimization (WNNM) denoising algorithm. This method can characterize the difference of image effect according to the matrix singular value, given different weights, and it highlights the important information for the image. However, this algorithm needs time-consuming SVD calculation and iterative approximation, which is slow and inefficient.

1.3. Gaps identified from review

The above improved algorithms have great improvements in filtering performance, but there are still some deficiencies in dealing with image detail blur. The lesions of COVID-19 mainly show various forms of ground-glass or consolidation shadow. In the early imaging of COVID-19, the change of lesions is not obvious, and the density is low, which is easy to confuse the early lesions of COVID-19 with noise. On the other hand, the lesions of ground-glass in the advanced stage are uneven and it have similar gray values to the CT images of suspected COVID-19 cases such as adenovirus pneumonia and mycoplasma pneumonia. The traditional weighted median filter denoising algorithm has the problems of low contrast and fuzzy boundary.
2. Multi-level threshold center weighted adaptive median filtering algorithm

The CT image of early COVID-19 is easily confused by noise. The traditional extreme noise points judgment [24-27] can easily cause misdiagnosis of COVID-19 lesion signals. For the single threshold filtering method, the pixel whose value exceeds the preset threshold will be judged as noise [28-30]. Therefore, using a single threshold method may increase the probability of error detection for noise. Hence, a median filtering method based on adaptive multi threshold discrimination is proposed. In this method, the noise pixels will be discriminated in a relatively narrow interval. Thus, this will improve the accuracy of noise detection.

2.1. Multi-level threshold calculation method

Calculation of threshold $T_0$: this threshold is the first step of noise point detection. The purpose is to find suspected noise points. It can calculate the gray value of each pixel, the median gray value of the filter window, the gray average value of the four rectangular neighborhood windows on the top, bottom, left and right of the point $(i,j)$. The calculation of threshold $T_0$ is:

$$
T_0 = \frac{1}{n} \sum_{m=-2}^{2} \sum_{n=-2}^{2} \left| f(i+m,j+n) - f_{med} \right|^\dagger + \frac{1}{n} \sum_{m=-2}^{2} \sum_{n=-2}^{2} \left| f(i+m,j+n) - f_{ave} \right|^\dagger + \frac{1}{n} \sum_{m=-2}^{2} \sum_{n=-2}^{2} \left| f(i+m,j+n) - M_D \right|^\dagger + \frac{1}{n} \sum_{m=-2}^{2} \sum_{n=-2}^{2} \left| f(i+m,j+n) - M_L \right|^\dagger + \frac{1}{n} \sum_{m=-2}^{2} \sum_{n=-2}^{2} \left| f(i+m,j+n) - M_D \right|^\dagger + \frac{1}{n} \sum_{m=-2}^{2} \sum_{n=-2}^{2} \left| f(i+m,j+n) - M_R \right|^\dagger + \frac{1}{n} \sum_{m=-2}^{2} \sum_{n=-2}^{2} \left| f(i+m,j+n) - M_D \right|^\dagger + \frac{1}{n} \sum_{m=-2}^{2} \sum_{n=-2}^{2} \left| f(i+m,j+n) - M_R \right|^\dagger.
$$

(1)

The variable $n$ and $m$ represent the length and the width of the filter window respectively(the length and width are equal), and $f(i,j)$ represents the gray value of the current pixel. $f_{med}$ is the median gray value of all pixels in the filter window, and $f_{ave}$ is the average gray value of all pixels in the filter window. Four neighborhood rectangular windows of $5 \times 2$ and $2 \times 5$ are defined on the top, bottom, left and right directions of the point $(i,j)$, and the gray average values corresponding to the four neighborhood windows are defined as $M_D$, $M_D$, $M_L$, and $M_R$, as shown in Fig. 3.

![Fig. 3. Weighting operator based on 5 * 5 image plane.](image)
Fig. 4. Flow chart of median filtering based on adaptive threshold and optimized weighting parameters.

Fig. 5. Adaptive hybrid cross operation.

Fig. 6. Adaptive hybrid mutation operation.
Fig. 2. The value calculation formula is:

\[
\mathcal{M}_U = \frac{1}{2} \sum_{i=-2}^{2} \sum_{j=-2}^{2} f(i, j)
\]

(2)

\[
\mathcal{M}_D = \frac{1}{2} \sum_{i=-2}^{2} \sum_{j=-2}^{2} f(i, j)
\]

(3)

\[
\mathcal{M}_L = \frac{1}{2} \sum_{i=-2}^{2} \sum_{j=-2}^{2} f(i, j)
\]

(4)

\[
\mathcal{M}_L = \frac{1}{2} \sum_{i=-2}^{2} \sum_{j=-2}^{2} f(i, j)
\]

(5)

Calculation of the second threshold T_1: this threshold is the second step for noise point detection. When the point is determined to be a suspected noise point, the average gray value of all pixels in the filter window is calculated. If the gray value of the point is significantly different from the average value, it can be determined that the current point is a noise point and needs to be replaced by the median value. Through the further accurate judgment for the suspected noise point by the second threshold T_1, the calculation of T_1 is:

\[
T_1 = \varphi p = \left( F_1 + F_2 \right) \times \frac{N_{w}}{n \times n}
\]

(6)

The variable \( \varphi \) is the regulatory factor of threshold T_1, \( \varphi = F_1 + F_2 \), the expression of F_1 and F_2 is:

\[
F_1 = \frac{n}{N} \sum_{i=-2}^{2} \sum_{j=-2}^{2} f(i, j) - f_{med}
\]

(7)

\[
F_2 = \frac{n}{N} \sum_{i=-2}^{2} \sum_{j=-2}^{2} \left[ f(i, j) - F_1 \right]
\]

(8)

p is the image noise density, the expression is \( p = \frac{N_p}{N_{w}} \), \( N_p \) represents the number of noise points in the window. The threshold T_1 increases with the increase of noise density, and the threshold value is related to the noise density, so as to realize the adaptive selection of the threshold in the same image under different noise density.

2.2. Adaptive weighted median filter algorithm

The lesions of ground-glass in the advanced COVID-19 show non-uniformity, which is similar to the CT images of COVID-19 suspected cases such as adenovirus pneumonia and mycoplasma pneumonia. Aiming at the problems of low contrast and fuzzy boundary in the traditional median filter denoising algorithm, a weighted median filter image denoising method based on adaptive hybrid genetic algorithm is proposed, so that the weighted denoising parameters can adapt to the changes according to the details of lung lobes and ground-glass lesions. Based on the steady-state regional population density, the cross and the mutation probability of genetic is adaptively matched to obtain a more accurate denoised CT image of COVID-19 with relatively few iterations.

The calculation of the center weighted filtering [31–34] is:

\[
f(i, j)_{cwM} = \text{median} \left\{ w(i, j) \times f(i, j) \times f(r, s) \times f(r, s) \in N_p(i, j) \right\}
\]

(9)

w(i, j) \times f(i, j) represents the gray value when the weight of f(i, j) is w(i, j), f(i, j)_{cwM} is the center weighted median gray value, f(i, j) represents the gray value of pixel p(i, j), N_p(i, j) represents the hollow neighborhood of pixel p(i, j), and f(r, s) represents the gray value corresponding to all pixels in N_p(i, j). The improved weight of the center weighted filtering is:

\[
w(i, j) = a_1 w_1(i, j) + a_2 w_2(i, j)
\]

(10)

\( a_1 \) and \( a_2 \) are weight parameters, which is optimized by the adaptive
hybrid genetic algorithm. The weighted sub coefficient $w_1(i,j)$ is set in the weighted coefficient $w(i,j)$, and $w_1(i,j)$ is used to characterize the similarity between the current pixel and the median pixel $f_{med}$ (representing uncontaminated point). The smaller the similarity value, the greater the correlation. The calculation of the weighted sub coefficient $w_1(i,j)$ is:

$$w_1(i,j) = \frac{1}{\sum_{(i-x,j-y)|W_r} \max\{f_{med}((i-x)+(j-y)-f_{med})^2\}}$$  \hspace{1cm} (11)

$T_{mean}$ represents the average value for the square of the difference between each pixel value and its average value, which is calculated as following:

$$T_{mean} = \frac{\sum_{(i-x,j-y)|W_r} (f(i-x,j-y)-f_{mean})^2}{N_r}$$  \hspace{1cm} (12)

$N_r$ is the total number of window pixels and $f_{mean}$ is the average value of all pixels in the current window. A weighted sub coefficient $w_2(i,j)$ is set in the weighted coefficient $w(i,j)$, and $w_2(i,j)$ is used to characterize the similarity between the current pixel and the nearest noise point. According to the pixel space distance value, a distance correlation function $Q(i,j)$ is designed to characterize the correlation between the current pixel and the noise points. The weighted coefficient $w_2(i,j)$ should meet the following conditions: (1) $w_2(i,j)$ is a non-decreasing function with $Q(i,j)$, that is, the greater the $Q(i,j)$, the greater the weight value to be added; (2) $w_2(i,j)$ should increase slightly when $Q(i,j)$ is small, and when $Q(i,j)$ is large, $w(i,j)$ should increase greatly, that is, $w(i,j)$ is positively correlated with $Q(i,j)$. Setting the current pixel as $f(i,j)$, and $f(s,t)$ is the noise point pixel nearest to the current pixel. Combined with the weighted distance and its normalization, the following weighted function is obtained, which meets positive correlation and the requirement of human vision. Setting the weighted function is:

$$w_2(i,j) = \frac{Q(i,j)}{\sum_{(i-x,j-y)|W_r} Q(i-x,j-y)}$$  \hspace{1cm} (13)

Table 1

Comparison of TWMF with different methods for CT image of early COVID-19.

| Denoising method | MSE/\(\text{db}\) | PSNR/\(\text{db}\) | IEF |
|------------------|-----------------|-----------------|-----|
| TDMF             | 288.5           | 23.5            | 129.4 |
| MMF              | 256.3           | 24.0            | 131.6 |
| SMF              | 166.7           | 26.3            | 135.6 |
| DBACMF           | 154.6           | 26.8            | 139.5 |
| CWMF             | 130.3           | 27.0            | 142.7 |
| AMF              | 112.8           | 27.6            | 145.4 |
| TWMF             | 81.6            | 29.0            | 173.7 |

Fig. 8. CT image of early COVID-19 (a) impulse (40%) noise; (b) original CT image; (c) denoised image by TDMF; (d) denoised image by MMF; (e) denoised image by SMF; (f) denoised image by DBACMF; (g) denoised image by CWMF; (h) denoised image by AMF; (i) denoised image by TWMF.
\[
\begin{align*}
\begin{array}{ccc}
\text{Noise Index} & \text{TWMF} & \text{TDMF} \\
10\% & \text{MSE/IEF} & 59.3/196.5 \\
20\% & \text{MSE/IEF} & 64.6/184.4 \\
30\% & \text{MSE/IEF} & 75.3/180.7 \\
40\% & \text{MSE/IEF} & 81.6/173.7 \\
50\% & \text{MSE/IEF} & 87.6/168.3 \\
60\% & \text{MSE/IEF} & 96.9/162.6 \\
70\% & \text{MSE/IEF} & 107.2/158.7 \\
\end{array}
\end{align*}
\]

Table 6
Comparison of TWMF with different methods for CT image of early COVID-19 with different noise density.

\[
\begin{align*}
\text{Noise} & \quad \text{Index} & \quad \text{TWMF} & \quad \text{TDMF} & \quad \text{MMF} & \quad \text{SMF} & \quad \text{DBACMF} & \quad \text{CWMF} & \quad \text{AMF} \\
10\% & \text{MSE/IEF} & 59.3/196.5 & 245.7/145.5 & 201.3/144.8 & 125.1/152.8 & 131.9/154.1 & 116.2/156.8 & 103.7/160.8 \\
20\% & \text{MSE/IEF} & 64.6/184.4 & 254.9/137.1 & 174.8/148.6 & 115.3/156.7 & 121.6/161.8 & 101.8/168.6 & 97.6/172.4 \\
30\% & \text{MSE/IEF} & 75.3/180.7 & 273.7/133.8 & 222.9/134.1 & 155.6/145.8 & 144.9/144.6 & 123.5/144.6 & 106.9/155.5 \\
40\% & \text{MSE/IEF} & 81.6/173.7 & 288.5/129.4 & 256.3/131.6 & 166.7/135.6 & 154.6/139.5 & 130.3/142.7 & 112.8/145.4 \\
50\% & \text{MSE/IEF} & 87.6/168.3 & 301.4/126.8 & 266.7/126.5 & 184.9/132.4 & 176.2/132.7 & 136.7/138.8 & 123.2/141.6 \\
60\% & \text{MSE/IEF} & 96.9/162.6 & 323.9/121.2 & 280.7/122.2 & 195.9/126.5 & 180.7/128.5 & 143.2/133.5 & 131.4/135.8 \\
70\% & \text{MSE/IEF} & 107.2/158.7 & 341.9/116.3 & 301.8/117.6 & 207.2/120.5 & 189.2/125.7 & 153.6/129.2 & 139.3/130.7
\end{align*}
\]

\[
\begin{align*}
\begin{align*}
Q(i,j) & = \frac{\sqrt{(s-i)^2 + (t-j)^2}}{n} \\
\end{align*}
\end{align*}
\]

Fig. 13. Early COVID-19 with different noise density: (a) comparison of the MSE; (b) comparison of the IEF. Advanced COVID-19 with different noise density: (a) comparison of the MSE; (b) comparison of the IEF. Adenovirus pneumonia with different noise density: (a) comparison of the MSE; (b) comparison of the IEF. Early COVID-19 with non-symptom by different noise density: (a) comparison of the MSE; (b) comparison of the IEF. Advanced COVID-19 with non-symptom by different noise density: (a) comparison of the MSE; (b) comparison of the IEF.
Where, $c$ is the distance constant, which is related to the size of the filter window, $c = \frac{1}{(n \times n + 1)/2}$. Therefore, the $c$ value of 5x5 detection window used in this paper is $c = \frac{1}{(5 \times 5 + 1)/2} = \frac{1}{13}$. Through the optimal combination for $(\alpha_1, \alpha_2)$, the relatively optimal denoising effect in the spatial domain can be obtained. The pixel weighted coefficient is represented as shown in Fig. 3.

### 2.3. Improvement steps

Step 1: find out the maximum gray value $f_{\text{max}}$ and minimum gray value $f_{\text{min}}$ in the filter window, which is compared with the current pixel value $f_i$.

![CT image of advanced COVID-19](image)

**Fig. 9.** CT image of advanced COVID-19 (a) impulse (40%) noise; (b) original CT image; (c) denoised image by TDMF; (d) denoised image by MMF; (e) denoised image by SMF; (f) denoised image by DBACMF; (g) denoised image by CWMF; (h) denoised image by AMP; (i) denoised image by TWMF.

| Table 2 | Comparison of TWMF with different methods for CT image of advanced COVID-19 |
|---------|--------------------------------------------------------------------------|
| Denoising method | MSE/DB | PSNR/DB | IEF |
| TDMF | 324.4 | 23.0 | 127.1 |
| MMF | 274.7 | 23.7 | 138.0 |
| SMF | 198.7 | 25.2 | 142.9 |
| DBACMF | 174.8 | 25.7 | 148.5 |
| CWMF | 149.4 | 26.4 | 152.8 |
| AMF | 123.7 | 27.2 | 159.5 |
| TWMF | 87.1 | 28.7 | 172.4 |

| Table 7 | Comparison of TWMF with different methods for CT image of advanced COVID-19 with different noise density |
|---------|------------------------------------------------|
| Noise Index | TWMF | TDMF | MMF | SMF | DBACMF | CWMF | AMF |
| 10% MSE/IEF | 60.1/193.3 | 130.5/147.7 | 123.5/152.6 | 115.3/158.6 | 108.5/163.3 | 102.2/165.6 | 93.5/170.3 |
| 20% MSE/IEF | 72.5/182.5 | 201.7/140.7 | 173.4/145.8 | 140.4/150.8 | 136.7/158.2 | 127.3/159.9 | 104.8/166.3 |
| 30% MSE/IEF | 80.7/176.5 | 276.3/135.6 | 224.3/140.6 | 174.3/146.9 | 159.9/153.2 | 136.3/154.2 | 114.2/162.9 |
| 40% MSE/IEF | 87.1/172.4 | 324.4/127.1 | 274.7/138.0 | 198.7/142.9 | 174.8/148.5 | 149.4/152.8 | 123.7/159.5 |
| 50% MSE/IEF | 94.4/166.7 | 350.7/122.5 | 302.8/133.3 | 222.3/135.5 | 201.9/140.3 | 162.4/146.7 | 142.5/151.9 |
| 60% MSE/IEF | 100.5/160.8 | 376.8/118.8 | 341.2/128.9 | 254.3/131.8 | 225.5/135.7 | 198.3/140.6 | 168.2/146.8 |
| 70% MSE/IEF | 108.5/150.9 | 399.4/112.6 | 362.2/120.7 | 296.3/125.3 | 253.3/128.9 | 234.8/132.1 | 201.3/140.0 |
If $f_{\text{max}} - T_0 < f(i,j) < f_{\text{max}}$ or $f_{\text{min}} < f(i,j) < f_{\text{min}} + T_0$, this point may be a noise point, and skip to step 2. Step 2: calculate the average gray value $f_{\text{ave}}$ of all pixels in the filter window. Step 3: set the second threshold $T_1$, if $\|f(i,j) - f_{\text{ave}}\| > T_1$, replace the weighted median value with the current point and repeat the above steps. The algorithm flow chart is shown in Fig. 4.

3. Parameters optimization of weighted median filter based on adaptive hybrid genetic algorithm

The principle of the adaptive hybrid genetic optimization is as following: (i) Initializing the search space of $X_{\alpha_1, \alpha_2}$, leading the genetic operators to search with $r_{\text{m}}X = X + \varphi(\Delta x)$ to obtain the new solution $r_{\text{m}}V_{\alpha_1, \alpha_2}$; (ii) Using the parameter factors $\alpha_1$ and $\alpha_2$ to carry

### Table 3
Comparison of TWMF with different methods for CT image of adenovirus pneumonia

| Denoising method | MSE/IEF | PSNR/IEF | IEF  |
|------------------|---------|----------|------|
| TDMF             | 289.7/23.5 | 117.4/150.7 | 108.5/53.8 |
| MMF              | 247.8/24.2 | 165.4/145.8 | 148.5/148.3 |
| SMF              | 198.2/25.2 | 211.8/141.5 | 176.8/44.6 |
| DBACMF           | 156.9/26.2 | 277.5/132.6 | 178.5/141.6 |
| CWMF             | 145.0/26.5 | 221.6/125.4 | 175.5/144.3 |
| AMF              | 123.3/27.2 | 356.8/119.0 | 287.8/131.5 |
| TWMF             | 83.6/28.9  | 344.5/121.9 | 324.4/125.3 |

### Table 8
Comparison of TWMF with different methods for CT image of adenovirus pneumonia with different noise density

| Noise | MSE/IEF | TWMF | TDMF | MMF | SMF | DBACMF | CWMF | AMF |
|-------|---------|------|------|-----|-----|--------|------|-----|
| 10%   | 58.1/194.4 | 124.5/148.8 | 117.4/150.7 | 108.5/53.8 | 100.7/159.8 | 96.4/164.7 | 88.2/168.4 |
| 20%   | 65.4/186.7 | 186.4/142.8 | 165.4/145.8 | 148.5/148.3 | 123.4/156.8 | 114.4/158.7 | 101.6/162.7 |
| 30%   | 72.4/179.8 | 226.5/137.9 | 211.8/141.5 | 176.8/44.6 | 144.6/151.5 | 129.5/153.8 | 116.4/156.9 |
| 40%   | 83.6/172.5 | 289.7/131.2 | 247.8/137.5 | 198.2/42.6 | 156.9/149.9 | 145.0/148.1 | 123.3/151.7 |
| 50%   | 89.2/164.5 | 221.6/125.4 | 277.5/132.6 | 221.5/37.6 | 178.5/141.6 | 175.5/144.3 | 138.6/148.7 |
| 60%   | 97.4/158.7 | 356.8/119.0 | 307.3/126.7 | 287.8/131.5 | 204.4/136.7 | 198.5/138.6 | 154.3/142.3 |
| 70%   | 105.5/150.6 | 388.6/116.4 | 344.5/121.9 | 324.4/125.3 | 236.4/131.7 | 226.8/135.3 | 178.6/137.7 |
out the optimal weighted median filter; (iii) Calculating the value of PSNR as the fitness of the genetic algorithm; (iv) Using simulated annealing to cover the solution with high fitness over the low fitness as the current optimal solution. In this way, the cycle stops until the termination condition is established to obtain the optimal solution \( X^{*} (a_1, a_2) \) corresponding to the highest fitness.

### 3.1. Improved operator strategy of adaptive hybrid genetic

In this paper, an adaptive hybrid genetic operator is proposed. In addition to retaining the “excellent” individuals in the parents to the next generation, individuals with close to average fitness in the parents should also be considered. If the fitness value of the offspring generation extracted in the "steady-state region" is higher than the average and close to the upper bound, it indicates that such parent individuals contain excellent gene patterns, it should be retained to the next generation. The diameter \( D = f_{\text{max}} - f_{\text{min}} \) of the population is defined. The expression of the distance from the individual fitness value to the average value is \( d = |f - f_{\text{avg}}| \). The neighborhood radius is defined as \( \delta = \frac{D}{M} \) (\( M \) is the population number). If the number of populations in the steady-state region is \( N \), the density of populations in the steady-state region is \( \rho = \frac{N}{M} \). We use the population density \( \rho \) to correct the crossover and mutation probability (Eqs. 19 and 20). The adaptive hybrid crossover probability can be expressed as:
### Table 9
Comparison of TWMF with different methods for early COVID-19 with non-symptom by different noise density

| Noise Index | TWMF     | TDMF     | MMF      | SMF      | DBACMF   | CWMF     | AMF      |
|------------|----------|----------|----------|----------|----------|----------|----------|
| 10%        | 72.1/200.4 | 107.6/159.4 | 104.5/163.4 | 103.4/168.5 | 101.5/173.7 | 97.2/175.4 | 95.2/178.5 |
| 20%        | 80.6/192.9 | 164.7/150.4 | 155.7/152.8 | 157.4/160.8 | 156.4/161.6 | 121.5/162.6 | 112.3/165.5 |
| 30%        | 85.5/185.4 | 225.3/143.7 | 202.4/145.7 | 199.3/150.6 | 188.4/150.7 | 154.6/153.4 | 128.7/156.6 |
| 40%        | 92.8/179.2 | 292.7/132.2 | 248.8/138.9 | 232.3/140.8 | 214.8/143.4 | 178.5/146.7 | 149.2/149.6 |
| 50%        | 98.3/172.7 | 328.4/125.7 | 286.5/132.7 | 267.5/132.8 | 243.2/135.7 | 206.4/138.6 | 175.4/142.8 |
| 60%        | 104.5/167.4 | 378.4/118.6 | 312.4/125.6 | 301.3/125.7 | 288.9/128.4 | 235.5/132.7 | 202.5/136.6 |
| 70%        | 112.7/159.4 | 404.4/110.5 | 355.7/116.3 | 342.8/118.3 | 312.6/120.4 | 265.5/126.8 | 248.3/128.6 |

---

**Fig. 12.** CT image of advanced COVID-19 with non-symptom (a) impulse (40%) noise; (b) original CT image; (c) denoised image by TDMF; (d) denoised image by MMF; (e) denoised image by SMF; (f) denoised image by DBACMF; (g) denoised image by CWMF; (h) denoised image by AMF; (i) denoised image by TWMF.

### Table 5
Comparison of TWMF with different methods for CT image of advanced COVID-19 with non-symptom.

| Denoising method | MSE/dB | PSNR/dB | IEF |
|------------------|--------|---------|-----|
| TDMF             | 285.7  | 23.6    | 121.6 |
| MMF              | 261.7  | 24.0    | 129.4 |
| SMF              | 233.3  | 25.1    | 137.7 |
| DBACMF           | 196.5  | 25.2    | 142.1 |
| CWMF             | 156.6  | 26.2    | 154.8 |
| AMF              | 149.4  | 26.4    | 168.5 |
| TWMF             | 89.2   | 28.6    | 181.8 |
Pc = \begin{align*}
\rho \leq \delta \left(1 + \frac{k_1}{\rho} f' \right), \\
\rho > \delta \left(1 - \rho \right) \sqrt{f' \rho}, \\
\rho > \delta \left(1 - \rho \right) \frac{1}{\rho},
\end{align*}

where \( k_1, k_2 \) are coefficients and \( k_1, k_2 \leq 1 \).

The adaptive hybrid cross operation is shown in Fig. 5, and the adaptive hybrid mutation operation is shown in Fig. 6.

### Table 10
Comparison of TWMF with different methods for advanced COVID-19 with non-symptom by different noise density

| Noise Index | TWMF | TDMF | MMF | SMF | DBACMF | CVMF | AMF |
|-------------|------|------|-----|-----|--------|------|-----|
| 10%         | MSE/IEF | 60.1/207.3 | 124.6/148.9 | 114.1/152.5 | 105.5/158.4 | 94.2/169.4 | 89.5/177.7 | 80.3/192.5 |
| 20%         | MSE/IEF | 73.3/196.6 | 187.4/138.5 | 175.3/143.7 | 168.2/150.6 | 150.5/158.9 | 126.9/168.4 | 113.2/185.6 |
| 30%         | MSE/IEF | 82.6/188.8 | 234.4/129.7 | 228.4/135.8 | 190.2/142.7 | 174.2/149.5 | 140.3/160.5 | 129.3/177.7 |
| 40%         | MSE/IEF | 89.2/181.8 | 285.7/121.6 | 261.7/129.4 | 233.3/137.7 | 196.5/142.1 | 156.6/154.8 | 149.4/168.5 |
| 50%         | MSE/IEF | 96.4/172.8 | 325.2/116.5 | 315.2/122.7 | 305.6/128.4 | 245.3/135.6 | 211.1/142.2 | 186.2/155.8 |
| 60%         | MSE/IEF | 103.4/162.8 | 359.7/112.3 | 345.5/117.9 | 327.7/122.2 | 288.3/129.7 | 256.5/133.8 | 215.1/143.4 |
| 70%         | MSE/IEF | 114.3/150.1 | 398.6/108.8 | 382.2/112.4 | 366.5/118.9 | 334.7/124.1 | 298.4/128.2 | 264.2/135.0 |

Fig. 14. Fitness evolution curve of denoising parameters optimization for different CT images. (a) CT image of early COVID-19; (b) CT image of advanced COVID-19; (c) CT image with non-symptom of early COVID-19; (d) CT image with non-symptom of advanced COVID-19; (e) CT image of adenovirus pneumonia.
3.2. Improved simulated annealing algorithm

Derek [35] proposed metropolis simulated annealing algorithm criterion. This paper further improves the cooling function and designs an expression similar to the doppler effect temperature decline curve:

\[
T = T_2 \alpha \left( \cos\left( \frac{\pi}{2} \left( 1 - \frac{k}{K} \right) \right) + \cos\left( \frac{\pi}{2T_0} \left( 1 - \frac{k}{K} \right) \right) \right)
\]  
(17)

The traditional exponential simulated annealing is difficult to reach the low temperature state when the number of iterations is small; the rapid simulated annealing drops to the low temperature state prematurely, making the subsequent iterative solution unchanged. The "doppler" curve takes the advantages of the two algorithms and eliminates their defects. It not only tends to the low temperature urgency, but also

| CT image                        | AHG + ESA | OAG + RSA | TAG + ESA | AHG + DESA |
|--------------------------------|-----------|-----------|-----------|------------|
| Early COVID-19                 | 3.46      | 3.52      | 4.76      | 2.66       |
| Advanced COVID-19              | 3.78      | 3.82      | 4.91      | 2.83       |
| Non-symptom of early COVID-19  | 3.71      | 3.76      | 4.88      | 2.81       |
| Non-symptom of advanced COVID-19| 3.79      | 3.86      | 4.96      | 2.87       |
| Adenovirus pneumonia           | 3.90      | 3.94      | 5.03      | 2.97       |
continuously "tempering and heating up" in the second half of annealing, so that the algorithm has multiple opportunities to jump out of the local optimum during the optimization process, making it easier to find out the global optimal solution. K is the total number of iterations, and k is the current number of iterations. The flow chart of the adaptive hybrid genetic combined with the doppler effect simulated annealing algorithm is shown in Fig.7.

4. Experimental results

4.1. Parameters setting

Aiming at the different kinds of COVID-19 CT images including early COVID-19, advanced COVID-19, early COVID-19 with non-symptom, advanced COVID-19 with non-symptom, adenovirus pneumonia added into the density 40% of the impulse noise are tested by the Intel E8200 CPU 2.5 GHz, RAM 8G, Matlab 2016a.Two dimensional median filter (TDMF) [36], multiple median filter (MMF) [37], switching median filter (SMF) [38], discriminant-based asymmetric cropping median filter (DBACMF) [39], center weighted median filter (CWMF) [40], adaptive median filter (AMF) [15], adaptive threshold and optimized weighted median filter (paper method, TWMF) are used for simulation comparison tests. Then, impulse noise with different density (10%,20%,30%,40%,50%,60%,70%) is selected to add noise in the tested images, and finally the above methods are used for simulation

| Denoising method | MSE/dB  | PSNR/dB  | IEF     |
|------------------|---------|----------|---------|
| TWSC             | 108.5   | 27.8     | 152.5   |
| KSVD             | 106.5   | 27.8     | 154.7   |
| ATIF             | 103.3   | 27.9     | 156.3   |
| WNNM             | 100.8   | 27.9     | 158.8   |
| BMED             | 98.3    | 28.0     | 160.2   |
| SAINT            | 97.8    | 28.0     | 162.5   |
| DAAM             | 96.2    | 28.1     | 163.0   |
| TNRD             | 95.9    | 28.2     | 164.4   |
| DnCNN            | 94.2    | 28.3     | 165.1   |
| TWMF             | 81.6    | 29.0     | 173.7   |

Table 12: Comparison of TWMF with denoising SOTA methods for CT image of early COVID-19

The expression of IEF is:

\[
IEF = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left| x(i,j) - \hat{x}(i,j) \right|^2
\]  

The expression of PSNR is:

\[
PSNR = 10 \times \log \left( \frac{255^2}{MSE} \right)
\]  

The evaluation index values are shown in Table 2.

4.3. Denoising simulation experiments

Using the paper method and the comparison methods to do denoising simulations on the CT image of early COVID-19, and further comparing and analyzing the MSE, PSNR and IEF under different denoising methods. The comparative CT image denoising simulations of early COVID-19 are shown in Fig.8. The evaluation index values are shown in Table 1.

From the change trend of the data in the Table 1, compared with the comparative denoising methods, TWMF has increased the value of PSNR by about 5.5 dB, the value of MSE has been greatly reduced, the value of IEF has been increased by about 42 dB. It can be seen that the denoising effect for the CT image of early COVID-19 under TWMF is the best. There is no obvious change in the CT image of early COVID-19, the number of the lesion is small and the density is low. The traditional CT image denoising algorithms have the higher value of MSE and the lower value of IEF. It is easy to cause the CT image of early COVID-19 to be contaminated with noise, and it is easy to cause mistake diagnosis for patients with early COVID-19. The TWMF method improves the denoising accuracy for the CT image of early COVID-19. The CT image of early COVID-19 is simulated by denoising tests with different density (10%-70%) of impulse noise. The comparison for the MSE and IEF among different denoising methods by different density of the impulse noise is shown in Fig.13(a)(b). The evaluation index values are shown in Table 6.

When the value of MSE is smaller and the value of IEF is larger, it means that the denoised image is closer to the original image. It can be seen from the Fig.13(a)(b) that with the increase of the impulse noisy density, the PSNR is gradually reduced and the MSE is gradually increased under different denoising methods. Compared with the different traditional denoising methods, the IEF of TWMF is still the largest, and the MSE of TWMF is still the smallest. In conclusion, compared with the traditional denoising methods, the improved median filter denoising algorithm in this paper increases the IEF and reduces the MSE for CT image of early COVID-19 to a certain extent with different noise density. It significantly improves the denoised effect. Using the TWMF and the comparison methods to do denoising simulations on the CT image of advanced COVID-19. The comparative CT image denoising simulations of advanced COVID-19 are shown in Fig.9. The evaluation index values are shown in Table 2.

From the change trend of the data in the Table 2, compared with the comparative denoising methods, TWMF has increased the value of PSNR by about 5.7 dB, the value of MSE has been greatly reduced, the value of IEF has been increased by about 45 dB. It can be seen that the denoising effect for the CT image of advanced COVID-19 under TWMF is best. The advanced stage of COVID-19 is characterized by increased number of lesions and increased density. The TWMF method improves the denoising accuracy for the CT image of advanced COVID-19 and it reduces the misdiagnosis rate for the advanced lesions. The CT image of advanced COVID-19 is simulated by denoising tests with different density(10%-70%) of impulse noise. The comparison for the MSE and IEF among different denoising methods with different density of the impulse noise is shown in Fig.13(c)(d). The evaluation index values are shown in Table 7.

It can be seen from the Fig.13(c)(d) and Table 7 that with the increase of the impulse noisy density, the IEF is gradually reduced and the MSE is gradually increased under different denoising methods. Compared with the different traditional denoising methods, the IEF of TWMF is still the largest, and the MSE of TWMF is still the smallest. In conclusion, the TWMF significantly improves the denoised effect for CT image of advanced COVID-19 to a certain extent with different noisy density. Using the TWMF and the comparison methods to do denoising simulation experiments.
simulations on the CT image of adenovirus pneumonia (suspected cases of COVID-19). The comparative CT image denoising simulations of adenovirus pneumonia are shown in Fig.10. The evaluation index values are shown in Table 3.

From the change trend of the data in the Table 3, compared with the comparative denoising methods, TWMF has increased the value of PSNR by about 5.4 dB, the value of MSE has been greatly reduced, the value of IEF has been increased by about 41 dB. It can be seen that the denoising effect for the CT image of adenovirus pneumonia under TWMF is the best. The CT image of adenovirus pneumonia is patchy, small nodular ground-glass shadow, and then developing into consolidation shadow, bronchial wall thickening, visible mesh or strip shadow. The TWMF improves the denoising accuracy for the CT image of adenovirus pneumonia and reduces the misdiagnosis rate for the lesions. The CT image of adenovirus pneumonia are simulated by denoising tests with different density (10%-70%) of impulse noise. The comparison for the MSE and IEF among different methods with different density of the impulse noise is shown in Fig.13(e)(f). The evaluation index values are shown in Table 8.

It can be seen from the Fig.10 and Table 3 that with the increase of the impulse noisy density, the IEF is gradually reduced and the MES is gradually increased under different denoising methods. Compared with the different traditional denoising methods, the IEF of TWMF is still the largest, and the MSE of TWMF is still the smallest. In conclusion, the TWMF method significantly improves the denoised effect for CT image of adenovirus pneumonia to a certain extent with different noisy density. Using the TWMF and the comparison methods to do denoising simulations on the CT image with non-symptom of early COVID-19. The comparative CT image denoising simulations are shown in Fig.11. The evaluation index values are shown in Table 4.

From the change trend of the data in the Table 4, compared with the comparative denoising methods, TWMF has increased the value of PSNR by about 5 dB, the value of MSE has been greatly reduced, the value of IEF has been increased by about 47 dB. It can be seen that the denoising effect for the CT image of early COVID-19 with non-symptom under TWMF is the best. The CT image of early COVID-19 with non-symptom are simulated by denoising test with different density (10%-70%) of impulse noise. The comparison for the MSE and IEF among different denoising methods with different density of the impulse noise is shown in Fig.13(g)(h). The evaluation index values are shown in Table 9.

It can be seen from the Fig.13(g)(h) and Table 9 that with the increase of the impulse noisy density, the IEF is gradually reduced and the MES is gradually reduced under different denoising methods. Compared with the different traditional denoising methods, the IEF of TWMF is still the largest, and the MSE of TWMF is still the smallest. In conclusion, the TWMF significantly improves the denoised effect for CT image of adenovirus pneumonia under different noisy density. Using the TWMF and the comparison methods to do denoising simulations on the CT image of non-symptom of early COVID-19. The evaluation index values are shown in Table 10.

From the change trend of the data in the Table 5, compared with the comparative denoising methods, TWMF has increased the value of PSNR by about 5.0 dB, the value of MSE has been greatly reduced, the value of IEF has been increased by about 60 dB. It can be seen that the denoising effect for the CT image of advanced COVID-19 with non-symptom under TWMF is the best. The CT image of advanced COVID-19 with non-symptom is simulated by denoising test with different density (10%-70%) of impulse noise. The comparison for the MSE and IEF among different denoising methods with different density of the impulse noise is shown in Fig.13(i)(j). The evaluation index values are shown in Table 10.

It can be seen from the Fig.13(i)(j) and Table 10 that with the increase of the impulse noisy density, the IEF is gradually reduced and the MES is gradually increased under different denoising methods.

Compared with the different traditional denoising methods, the IEF of TWMF is still the largest, and the MSE of TWMF is still the smallest. In conclusion, the paper method significantly improves the denoised effect for CT image of advanced COVID-19 with non-symptom to a certain extent by different noisy density. Aiming at the different kinds of COVID-19 CT images adaptive hybrid genetic combined with exponential simulated annealing [41] (AHG + ESA) orthogonal adaptive genetic [42] combined with rapid simulated annealing [43] (OAG + RSA) traditional adaptive genetic [44] combined with exponential simulated annealing (TAG + ESA) adaptive hybrid genetic combined with doppler effect simulated annealing (AHG + DESA, paper method) are used for simulation comparison tests of denoising parameters optimization. The fitness evolution curve for different COVID-19 CT images are shown in Fig.14. The evaluation index values of time processing under different methods are shown in Table 11.

It can be seen from the Fig.14 and Table 11 that with the increase of the number of iterations, the standard deviation of the objective function value is gradually reduced and the processing time is gradually increased under different parameters optimization methods. Compared with the different comparison methods, the number of iterations of “HG + DESA” is still the smallest, and the processing time of “AHG + DESA” is still the fastest. In conclusion, the paper method (AHG + DESA) significantly improves the denoised effect for different kinds of COVID-19 CT images of parameters optimization.

4.4. Comparison to state-of-the-art methods

We compared the TWMF with 9 state-of-the-art approaches including TWSC [45], KSVD [21], activity-tuned image filtering (ATIF) [19], WNNM [23], BM3D [22], SAINT [46], DAAM [47], TNRD [48], DnCNN [20] to do denoising simulations on the CT image of early COVID-19, and further comparing and analyzing the MSE, PSNR and IEF under different denoising methods. The comparative CT image denoising simulations of early COVID-19 are shown in Fig.15. The evaluation index values are shown in Table 12. From the change trend of the data in the Table 12, compared with the comparative denoising methods, TWMF has increased the value of PSNR by about 1.2 dB, the value of MSE has been reduced by about 27 dB, the value of IEF has been increased by about 21 dB. It can be seen that the denoising effect for the CT image of early COVID-19 under TWMF is the best. The early stage of COVID-19 is characterized by less number of lesions and less density. The TWMF method improves the denoising accuracy for the CT image of early COVID-19 and reduces the missed diagnosis for the early lesions.

5. Conclusion

In this paper, a median filtering method based on multi-level threshold and parameters optimization is proposed. In this method, the pixels in the horizontal and vertical directions of the pixels to be processed, the multi-level threshold for detecting impulse noise is selected by comprehensive estimation, because the threshold changes with the movement of the window, which reflects the adaptability of threshold selection. In this paper, the algorithm gives different weight values to each pixel according to the gray distance between the pixel and the central pixel and the spatial distance between the pixel and the noise point to filter out the noise. The adaptive hybrid genetic algorithm combined with the doppler effect simulated annealing algorithm is used to determine the weight value of the improved median filter. The simulation results show that this method has greater advantages in denoising ability than other filtering methods of the iteration and the processing time, and the performance of detail protection is also greatly improved.

CRediT authorship contribution statement

Shuli Guo: Conceptualization, Methodology. Guowei Wang:
Writing & original draft, Data curation, Software. Lina Han: Writing - review & editing. Xiaowei Song: Investigation. Wentao Yang: Validation.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research has been partially funded by National Key R&D Program of China (2017YFF0207400) and project supported by Beijing Municipal Science and Technology Commission-Beijing Natural Science Foundation (M21018) and Beijing Natural Science Foundation-haidian District Joint Fund for original innovation (L192064).

References

[1] Chenyao Lin, Jie Xiong, Mingze Yan, Hongze Li, Shuang Huang, Changxin Shen, Comparison of throat swabs and sputum specimens for viral nucleic acid detection in 52 cases of novel coronavirus (sars-cov-2)-infected pneumonia (COVID-19), Clinical Chemistry and Laboratory Medicine (CCLM) 58 (2020) 1089-1094.

[2] Yafen Li, Lin Yao, Jiawei Li, Lei Chen, Yitian Sun, Zhengfeng Cai, Chunhua Yang, Stability issues of rt-PCR testing of sars-cov-2 for hospitalized patients clinically diagnosed with covid-19. J. Med. Virol. (2020).

[3] Joanna Smyrlaki, Marcin Ekmam, Andrea Lentini, Nuno Rufino de Sousa, Natali Papanicolau, Miroslav Podhajsky, Samah Marwan, Antonino Gigliotti Rothfuchs, Jan Albert, Bjørn Hogberg, and Bjørn Reinius. Massive and rapid covid-19 testing is feasible by extraction-free sars-cov-2 rt-pcr. Nature Commun., 11, 2020.

[4] Rajab Mardani, Abbas Ahmadi Vasheghani, Fatemeh Zali, Ali Rezaei Gholami, Seyed Davoudi Mouavi, Nurmahamad Haghigh, Mehdi Kaviani, and Nasey Ahmadi. Laboratory parameters in detection of covid-19 patients with positive rt-pcr; a diagnostic accuracy study. Arch. Acad. Emergency Med., 8, 2020.

[5] Ali Rezaei Tahamtan, Abdullah Ardebili, Real-time rt-pcr in covid-19 detection: issues affecting the results, Expert Rev. Mol. Diagn. (2020) 1-2.

[6] Tao A, Zheliu Yang, Hongyan Hou, Chenzhao Zhang, Chong Wensi, Qian Tao, Ziyong Sun, Liming Xia, Correlation of chest ct and rt-pcr testing in coronavirus disease 2019 (covid-19) in china. A report of 1014 cases, Radiology (2020).

[7] Adam Bernheim, Xueyan Mei, Mingqian Huang, Yang Yang, Zahi A. Fayad, Ning Huang, and Andrea Lentini. Massive and rapid covid-19 testing is feasible by extraction-free sars-cov-2 rt-pcr. Nature Commun., 11, 2020.

[8] Farid Mardani, Abbas Ahmadi Vasheghani, Fatemeh Zali, Ali Rezaei Gholami, Seyed Davoudi Mouavi, Nurmahamad Haghigh, Mehdi Kaviani, and Nasey Ahmadi. Laboratory parameters in detection of covid-19 patients with positive rt-pcr; a diagnostic accuracy study. Arch. Acad. Emergency Med., 8, 2020.

[9] Yu. Xiang, Shuihua Wang, Yudong Zhang, Cgnet: A graph-knowledge embedded convolutional neural network for detection of pneumonia, Inform. Process. Manage. 58 (2021), 102411.

[10] Yongkui Sun, Wen Tan, Tongwen Chen, A method to remove chattering alarms using median filters, ISA Trans. 73 (2018) 201-207.

[11] Jun Xu, Lei Zhang, David Dian Zhang, A trilateral weighted sparse coding scheme for impulse noise reduction with pre-detection based on evidential reasoning, Inform. Process. Image Commun. 53 (2017) 65-72.

[12] Jun Xu, Lei Zhang, David Dian Zhang, A trilateral weighted sparse coding scheme for impulse noise reduction with pre-detection based on evidential reasoning, Inform. Process. Image Commun. 53 (2017) 65-72.

[13] Yongkui Sun, Wen Tan, Tongwen Chen, Using artificial intelligence to diagnose with covid-19, J. Med. Virol. (2020).

[14] Wenyu Wang, Xiaowan Chen, Shangxue Huang, Yiding Zhao, Yafang Li, Lin Yao, Jiawei Li, Lei Chen, Yitian Sun, Chunhua Yang, Stability issues of rt-PCR testing of sars-cov-2 for hospitalized patients clinically diagnosed with covid-19. J. Med. Virol. (2020).

[15] Lie Yu, Tzu-Chao Lin, Chao Lin, Mu-Kun Liu, Chien-Ting Yeh, Partition-based fuzzy median filter based on adaptive resonance theory, Comput. Stand. Interfaces 36 (2014) 631-640.

[16] Derek M. Shore, Dow P. Hurst, Diane L. Lynch, Patricia H. Reggio, Identification of an endogenous allosteric modulator’s binding site on the human cannabinoid-1 receptor, using forced-biased metropolis monte carlo simulated annealing method (mcmc) and molecular dynamics, Biophys. J. 108 (2015).

[17] Yongkui Sun, Wen Tan, Tongwen Chen, A method to remove clattering alarms using median filters, ISA Trans. 73 (2018) 201-207.

[18] Weisheng Dong, Guangming Shi, Xin Li, Nonlocal image restoration with bilateral and non-local total variation, Int. J. Imaging Syst. Technol. 26 (2016) 314-323.

[19] Xiaowei Song: Investigation. Wentao Yang: Validation.