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A Novel Medical Image Fusion Method Using Multi-Channel Pulse Coupled Neural Networks

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ABSTRACT A novel method for multi-channel pulse coupled neural networks (PCNN) is proposed in order to overcome the difficulty in lack of M-PCNN and question of many images fusion and instability of double-channel PCNN due to the different fusion sequence. In this study a novel multi-channel pulse coupled neural networks is analyzed in detail from odd numbers channel PCNN and even numbers channel PCNN. Through a combination of odd numbers channel PCNN and even numbers channel PCNN this study can realize image fusion by M-PCNN. A novel calculation method about linking-weight based on gray energy is proposed in order to overcome the lack of linking-weight in M-PCNN. To effectively avoid the Laplasse operator and calculation repeatedly, this study can realize not only many images fusion, but also better time efficiency and less information loss. Experimental results show that the presented method outperforms existing methods, in both fusion effect and different performance evaluation criteria.

INDEX TERMS Image fusion, medical image, neural networks, pulse coupled neural networks.

I. INTRODUCTION

Pulse coupled neural network (PCNN) is the fourth generation of neural network model based on the pulse mechanism of the mammalian visual cortex. It is widely used in the field of multi-focus images, medical image fusion and image segmentation for its simple calculation, fewer parameters and good practicability. With the gradual deepening of research on single- and dual-channel PCNN, the method is becoming one of the most popular method in the image fusion. Compared with the wavelet transform [1] that has been applied to multi-focus image fusion, FSD [2] and Gradient pyramid [3], PCNN is still a research focus of multi-focus image fusion, medical image fusion, and the well-known works are [4]–[20].

Firstly, the relevant scholars put forward and summarized the background, principles, further development of the condition and application prospects of PCNN model [4]–[10], which laid the foundation for the further development of the model. Then, an adaptive dual-channel pulse-coupled neural network (PCNN) with triple-linking strength (ATD-PCNN) is proposed [11]. A novel fusion algorithm based on the adaptive dual-channel unit-linking pulse coupled neural network (PCNN) for infrared and visible images fusion

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in nonsubsampled contourlet transform (NSCT) domain is proposed in [12]. The flexible multi-resolution and directional expansion for images of NSCT are associated, because of the global coupling and pulse synchronization characteristic of dual-PCNN. This is the biggest advantage of this method in medical image fusion research, a fusion rule [13] based on region spatial frequency is adopted in low frequency sub-band coefficient. Dual-channel PCNN has a simpler network architecture and better adaptability. But spectral distortion and excessive introduction of noise in fused images are often a common problem. To address this issue, a dual-channel SAR-optical images fusion algorithm based on non-subsampled shearlet transform (NSST) was adopted in Literatures [14], after NSST decomposition is performed. Then, a weighted average fusion rule using the coefficient of variation according to the different imaging characteristics of SAR images in the low-frequency sub-band of the decomposition image, the effect of SAR image noise on the fused image is removed by setting the coherence coefficient threshold in the high-frequency sub-band of the decomposition image. Because the calculations in prior research are complex, model in [15] has been further improved. Side-Scan Sonar Image Fusion Based on Sum-Modified Laplacian Energy Filtering and Improved Dual-Channel Impulse Neural Network is obtained, An improved PCNN model is proposed in this paper. This is the study's greatest contribution. Many

scholars give their opinions on this question which greatly improved the computational complexity and efficiency. There are many scholars concerned about the combination of PCNN model and other models, which can foster strengths and circumvent weaknesses, and achieve the best fusion effect. Such as the combination of wavelet transform and other networks is proposed in the literature [16], [17]. We first decompose the infrared and visible image into multi-direction and multi-scale coefficient matrices by RLNSST decomposition. Then, Laplacian filter and Gaussian filter is utilized to generate the saliency map. Next, a novel weighted average based on guided filtering to retain edge detail information is used as the fusion rule. Finally, inverse RLNSST transform is used to get the fused image [16]. On this basis, a new fusion image fusion method is proposed in literature [17] based on multi-level Gaussian curvature filtering (MLGCF). We first decompose the input source images into three different layers:(small-scale, large-scale, and base layers). Then, three fusion strate giesare applied to combine the three types of layers. Finally, fusion image is reconstructed by summing the three types of fused layers. In literature [18], a novel fusion framework for infrared and visual images based on a full convolutional network (FCN) in the local non-subsampled shearlet transform (LNSST) domain is proposed. In other areas of research, such as literature [19], Visual Attention Technique (VAT) is mentioned. In PCNN models research, because both the two kind of image fusion methods above need to input the model for operations, which will bring the problem of low efficiency. To address this issue, a dual-channel PCNN model was adopted in Literatures [20], [21], using two channels to input information of two images at the same time to complete the fusion. Because the calculations in prior research are complex, model in [22] has been further improved. A new dual-channel PCNN model is obtained, with adding operation instead of multiplication, which greatly improved the computational complexity and efficiency. There are many scholars concerned about the combination of PCNN model and other models, which can foster strengths and circumvent weaknesses, and achieve the best fusion effect. Such as the combination of wavelet transform and PCNN is proposed in the literature [23]–[25]. LSWT image (Lifting Stationary Wavelet Transform) is decomposed into high and low frequency parts, using PCNN model for fusion in the high-frequency part [23]. On this basis, a new fusion image fusion method is proposed in literature [24], [25] based on non-subsampled contourlet transform (NSCT) and adaptive unit-fast-linking PCNN. This method not only improved the PCNN model, synthesizing the advantages of both unit-linking PCNN and fast-linking PCNN, but also took advantage of the clear pixels in the image as a linking weight. A image fusion method is presented in [26] by combining contourlet hidden markov tree (CHMT) and PCNN model. Firstly image is decomposed by CHWT, the rules that got the largest fusion was adopted in the low-frequency part, PCNN model was used for integration in the high frequency part, links coefficient in model was

determined by the clarity of image. This fusion method has been successfully used in remote sensing image fusion.

Image fusion method based on PCNN model has been successfully used in many areas. However, these PCNN-based algorithms are limited to dual-channel PCNN model. With the development of the application, the methods above are facing some common challenges: one of the key challenges is the methods above are only designed for two images fusion, and some problems will appear when facing the synchronous fusion of multiple images.

With the continuous advancement of technology and development of society, the problem that we need to fuse multiple images into a more informational and clear image will appear in many fields. For example, monitoring probes will record a large number of images per day, how to integrate the distributed information on multiple images into a more valuable image, is gradually becoming a new problem be solved. At present the existing PCNN models' detailed practice to solve this problem is: two images are fused firstly, and then the third image is fused with the fusion image, in turn until the final fusion image is obtained. The problems according to this method to achieve the fusion of multiple images are as follows:

(1) It's difficult to determine the order of multiple images to be fused, and different order lead to different results.

(2) A high time cost is paid.

(3) The linking weights and other information are determined by the condition of two images when they are fused. Due to lack of global considerations, without thinking about the situation of all images which will cause the loss of some valuable information.

In order to solve these problems more effectively, and for the research on multi-channel PCNN model is rarely involved recently, in this paper, a detailed study of the multi-channel image fusion model has been carried out. The major contributions of this paper are as follows:

(1) We proposed a multi-channel PCNN image fusion model to achieve the synchronous fusion of multiple images.

(2) In order to achieve a better process of the multi-channel PCNN image fusion, a suitable method for calculation of the linking weight of multi-channel image fusion model is proposed in this paper. It is not only solves the key challenge in multi-channel PCNN image fusion method, but also contacts with the gray energy of image closely, which reduces the loss of information, enhances the fusion efficiency and reduces the fusion time.

(3) The multi-channel PCNN image fusion algorithm is proposed on the basis of previous conclusions and analysis.

The rest of this paper is organized as follows. In Section 2, the multi-channel PCNN image fusion model is briefly reviewed, and then the improved method of weight calculation is introduced in Section 3. The multi-channel PCNN image fusion model algorithm from two angles of the odd channels and even channels is proposed in Section 4. Experimental results and performance evaluation are given in Section 5. Conclusions are drawn in Section 6.

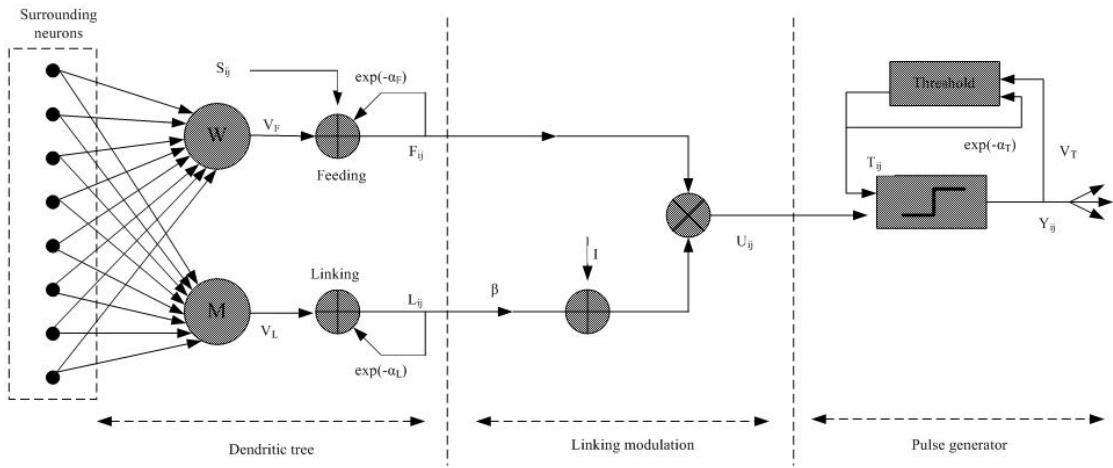


FIGURE 1. Single-channel PCNN model.

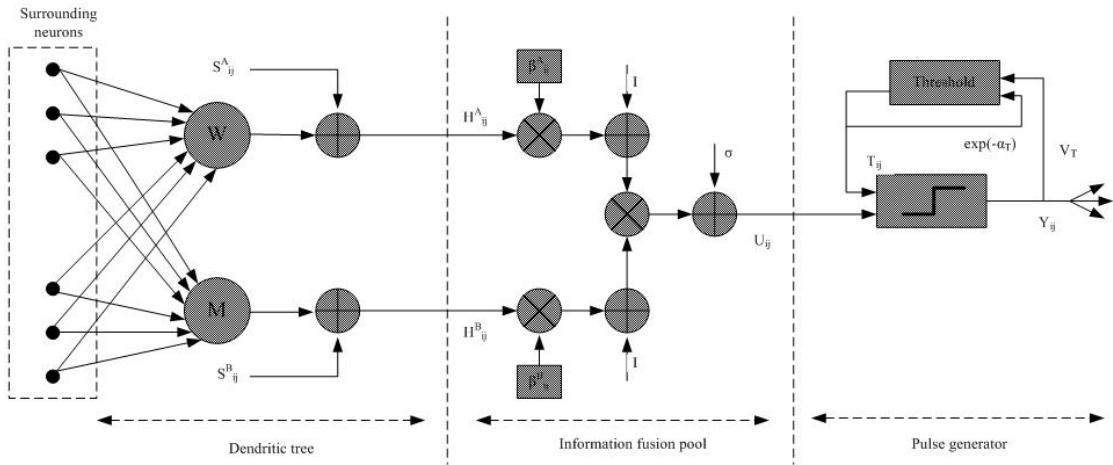


FIGURE 2. Double-channel PCNN model.

II. MULTI-CHANNEL PCNN MODEL

A. A SINGLE- AND DOUBLE-CHANNEL PCNN MODELS

A brief review for the classic single-and double-channel PCNN models are given in this section. As the model shown in Fig.1, feeding input and linking input as the input components are used for input, stimulation and feedback, resulting in a series of ignition iterative process. The model is first applied to image fusion, which was proposed in literature [11]. Two images input into model respectively for operations, then take the larger ignition times on the corresponding pixel of the two respective ignition matrix as a fusion result, which will inevitably bring the problem of computational complexity, time efficiency is low, the fusion accuracy is not high. For such problems, a improved double-channel PCNN model was proposed in literature [12], [13]. In the improved model shown in Fig.2, the feeding input and linking input are as the two equal branches to input the information of two images synchronously, and the fusion process is obtained in fusion pool after a series of operations.

B. MULTI-CHANNEL PCNN MODEL

Although the dual-channel PCNN model greatly improved the defects of the complex calculation and low accuracy in single-channel PCNN model, two input channels are not enough. At present, few researches of multiple images synchronous fusion are presented. The main idea of existing method is as follows: two source images input dual-channel PCNN model to complete the fusion firstly, and then the third image is fused with the fusion image, in turn until the final fusion image is obtained. However, according to the results of our study we found that different fusion order of multiple images would have a great impact on the fusion result. Especially the choose of first a few images is very important, if the fusion result is not ideal in the beginning, it is bound to have a great adverse effect on the final fusion result. Furthermore, it is a waste of time to achieve multiple images fusion by using dual-channel PCNN model. From the above consideration, a multi-channel PCNN model is proposed in this paper, which is better suited to the

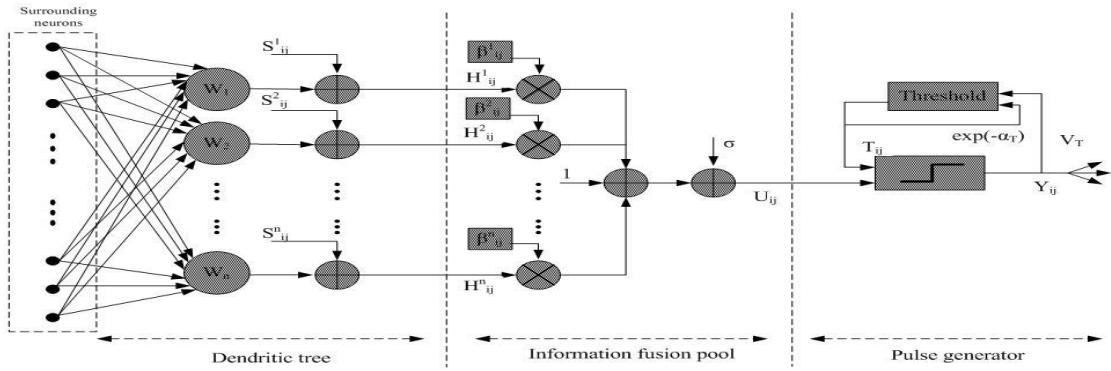


FIGURE 3. The structure of multi-channel PCNN model.

synchronous fusion of multiple images. The model is shown in Fig.3.

Fig.3 shows a multi-channel PCNN model on the basis of double-channel PCNN model by adding to N input branches, and the number of corresponding linking weighted branch is N, but the mechanism of pulse generation and ignition occurred is unchanged. In order to further improve the computational efficiency of the multi-channel PCNN model, the proposed algorithm has simplified the multiplication in Fig.2, by combining with other multiplication in fusion pool, and only the addition operator is obtained in internal output. The following expressions describe its mathematical model:

$$H_{ij}^A[n] = S_{ij}^A + \sum_{k,l} w_{ijkl}^A Y_{kl}[n-1] \quad (1)$$

.....

$$H_{ij}^N[n] = S_{ij}^N + \sum_{k,l} w_{ijkl}^N Y_{kl}[n-1] \quad (2)$$

$$U_{ij}[n] = (1 + \beta_{ij}^A H_{ij}^A[n] + \dots + \beta_{ij}^N H_{ij}^N[n]) + \sigma \quad (3)$$

$$Y_{ij}[n] = \begin{cases} U_{ij}[n] - \text{Sur}_{ij}[n] - 1, & \text{others} \\ 0, & U_{ij}[n] \leq T_{ij}[n-1] \end{cases} \quad (4)$$

$$T_{ij}[n] = \begin{cases} e^{-\alpha_T} T_{ij}[n-1], & Y_{ij}[n] = 0 \\ V_T, & \text{others} \end{cases} \quad (5)$$

where H^A, \dots, H^N refer to N images are input, $S_{ij}^A, \dots, S_{ij}^N$ are external stimuli of N channels, $Y_{ij}[n]$ refers to the output of model, β^A, \dots, β^N refer to the weighting coefficients of N channels, σ is a adjustable parameter to adjust the average level of the internal output, $U_{ij}[n]$ presents internal output, $k, W^A \dots W^N$ are internal parameters, and $k = W^A = \dots = W^N$, $T_{ij}[n]$ refers to the number of ignition, α_T is the decay time.

III. THE CALCULATION OF LINK-WEIGHT

A. THE CALCULATION AND PROBLEM OF LINK-WEIGHT IN DUAL-CHANNEL PCNN MODEL

Linking weight β presents the strength of the neurons' linking actions in the PCNN model. $\beta = 0$ presents all neurons are independent and non-interfering. $\beta \neq 0$ refers to the existence of coupling between neurons, which means a neuron has fired, adjacent neurons may lead to be fired, and

β determines the scope of the adjacent neurons. The larger β is, the greater the area of synchronous pulse method and captured neurons brightness. On the contrary, the smaller β is, the fewer images details are obtained, which means we can only achieve some coarse information of framework. In this paper, each pixel in the image gray matrix is as a neuron in the double-channel PCNN model. Let β be a large value, so that more images' information in this channel can be obtained. Therefore, β is regarded as the weight parameter between all channels in the double-channel PCNN model, and the parameter has an important impact in fusion effects.

At present, the methods to calculate the link-weight are average gradient method, Energy of Laplacian of Image [12] (EOL) and Sum Modified Laplacian [13] (SML). But all these methods have their shortcomings. For example, average gradient method gets related calculation only from the clarity of images, which is easy to overlook such as the brightness, the amount of information contained and so on. EOL method exists the problem of duplicate calculations. SML method improves Laplacian operator template on the basis of EOL method, and uses the sliding window technique to achieve the summation within local scale. But SML method still has the problem of computational complexity and duplicate calculations, in the meanwhile, the result of this method has a closely relation with the selection of Laplacian operator template and weight matrix. In addition, image energy and Laplacian operator template need to be determined firstly when computing link-weight, which introduced a lot of time for the fusion process. The methods above have demonstrated some validity in double-channel PCNN model to some extent, but they do not apply to multi-channel image fusion model.

To solve the problem above, we recalculate the image energy based on image gray matrix, and then determine the link-weight. The proposed algorithm has solved the determination of the link-weight in the multi-channel PCNN model, and has also improved the computing speed effectively with guaranteeing the accuracy of the premise.

B. IMPROVED METHOD OF THE LINKING CALCULATION

Because the gray level matrix of image can reflect the characteristics of the image in a way, such as the value of each

pixel in the image matrix can reflect the brightness of the image, usually the greater the gray value, the greater the brightness, and the brightness is the energy of an image. Replacing EOL by the gray matrix can not only obtain the energy information, but improve the computation efficiency. In this way, the information on the focus energy of the image can be computed more precisely with low computation cost. The new method are shown as Eq. (6) and Eq. (7).

$$\beta_{ij}^A = 1/(1 + e^{-\eta S_{ij}^A}) \quad (6)$$

$$\beta_{ij}^B = 1/(1 + e^{\eta S_{ij}^B}) \quad (7)$$

As shown in Eq.(6)-(7), the improved calculation method of link-weight calculated for the gray matrix of image, and the weight index of two branch links set as positive and negative respectively, which will achieve better overall coupling.

C. THE CALCULATION OF LINK-WEIGHT IN MULTI-CHANNEL PCNN IMAGE FUSION MODEL

1) THE CALCULATION OF MULTI-CHANNEL LINK-WEIGHT

Based on the above analysis, we proposed a new calculation method of link-weight in multi-channel PCNN model which is more accurate and simple, see Eq. (8)-(9).

$$\beta_{ij}^A = \frac{1}{\gamma_\alpha^{-1}(1 + e^{(-1)^{\theta_\alpha} \eta S_{ij}^\alpha})} \quad (8)$$

$$\beta_{ij}^N = \frac{1}{\gamma_\alpha^{-1}(1 + e^{(-1)^{\theta_\alpha} \eta S_{ij}^\alpha})} \quad (9)$$

where N presents the number of channels, $S_{ij}^A, \dots, S_{ij}^N$ is the N th-channel input at pixel(i, j), η is adjustable parameter. In order to couple the information in each channel effectively, factor $(-1)^{\theta_\alpha}$ is introduced to achieve positive and negative coupling. In the meanwhile, only when the sum weight of each channel is close to 1, a better overall coupling is obtained. Then we set the denominator parts in Eq. (8) and (9) be multiplied by the coefficient γ , which is used to adjust the order of magnitude of the weight in each channel to meet the overall coupling much better.

The advantages of proposed method to calculate the link-weight are as follows:

(1) By the adjustment of the denominator, the weights of all the channels are coupled and the main branch is highlighted. In this way, the effect of multiple branches can be guaranteed.

(2) Due to the direct use of the image gray level matrix instead of the results of calculations using a sliding window. The proposed method avoids the Laplacian operator template and sliding window calculation, it can greatly simplify the calculation process in ensuring the accurate calculation of the premise.

(3) A new calculation method for link-weight which applies to multi-channel image fusion model is proposed in this paper. The method lays the foundation for the further study of multi-channel image fusion.

2) ANALYSIS OF LINK-WEIGHT CALCULATION METHOD

Fig.3 shows the structure of model and Eq. (6)-(7) present the link-weight calculation method of multi-channel PCNN model. From which we find the weight of each channel in even-number channels model just shows the weight of an even number of positive and negative coupling, and a channel will can't couple if it encounters the odd-channel model. Therefore, model in both cases of odd and even channels will show the different fusion result. In this paper, we have studied the effectiveness, time efficiency and accuracy of the proposed model for image fusion from two angles of odd and even channels PCNN model.

In addition, we found under realistic conditions, whether N is odd or even, the current methods can't solve when $N \rightarrow \infty$. However, we can refer to the method of solving prime numbers in mathematics. In order to tackle multiple channel problems, a relatively simple model with fewer channel numbers are firstly investigated. The number of channels are often taken as a prime number. After that, the results are combined into the more complicated model. Because prime numbers less than 10 are 2, 3, 5 and 7, 5 is represented by $2 + 3$ in this paper. Although 7 can be represented by $2 + 5$, 5 can only be represented by a multiple of 5, and which covers a smaller range. In summary, 5-channel model will not be emphasis in the proposed method. If 7 is represented by $2 + 3 + 2$, which is also not the emphasis in our study. Firstly, the study of double-channel PCNN model is already very mature. What's more, the defects of double-channel PCNN model for multi-channel fusion such as fusion results are influenced by the fusion order vulnerably, fusion accuracy is low, time-consuming and so on are still problems need to be solved. In this paper, we let 7 be represented by $3 + 4$. 2, 3 and 4 have an important position based on the analysis above. Therefore, 3-channel model as odd-channel model and 4-channel model as even-channel model are chosen to be the basic models of the proposed multi-channel model to be studied in detail. According to the nature of prime numbers, 2, 3 and 4 as a base, other figures can be represented by their permutations and combinations. Thus, the N -channel PCNN model can be completely modeled on the 3-channel model and 4-channel model expansion to achieve. For example, when 6 images need to be synchronized fusion, 6-channel model can be obtained based on 4-channel model. Similarly, when 5 images need to be synchronized fusion, 5-channel model can be obtained based on 3-channel model.

IV. MULTI-CHANNEL PCNN IMAGE FUSION METHOD

A. FRAMEWORK OF THE PROPOSED METHOD

Fig.4 shows the structure of multi-channel PCNN image fusion model. The process of fusion can be divided into three parts: channel operations, fusion in the pool fusion and pulse generator. Firstly, input N images of gray-scale matrix, and complete the operation of each channel in accordance with Eq. (1)-Eq. (3). Then input calculations of each channel to fusion pool, and complete the process of fusion in

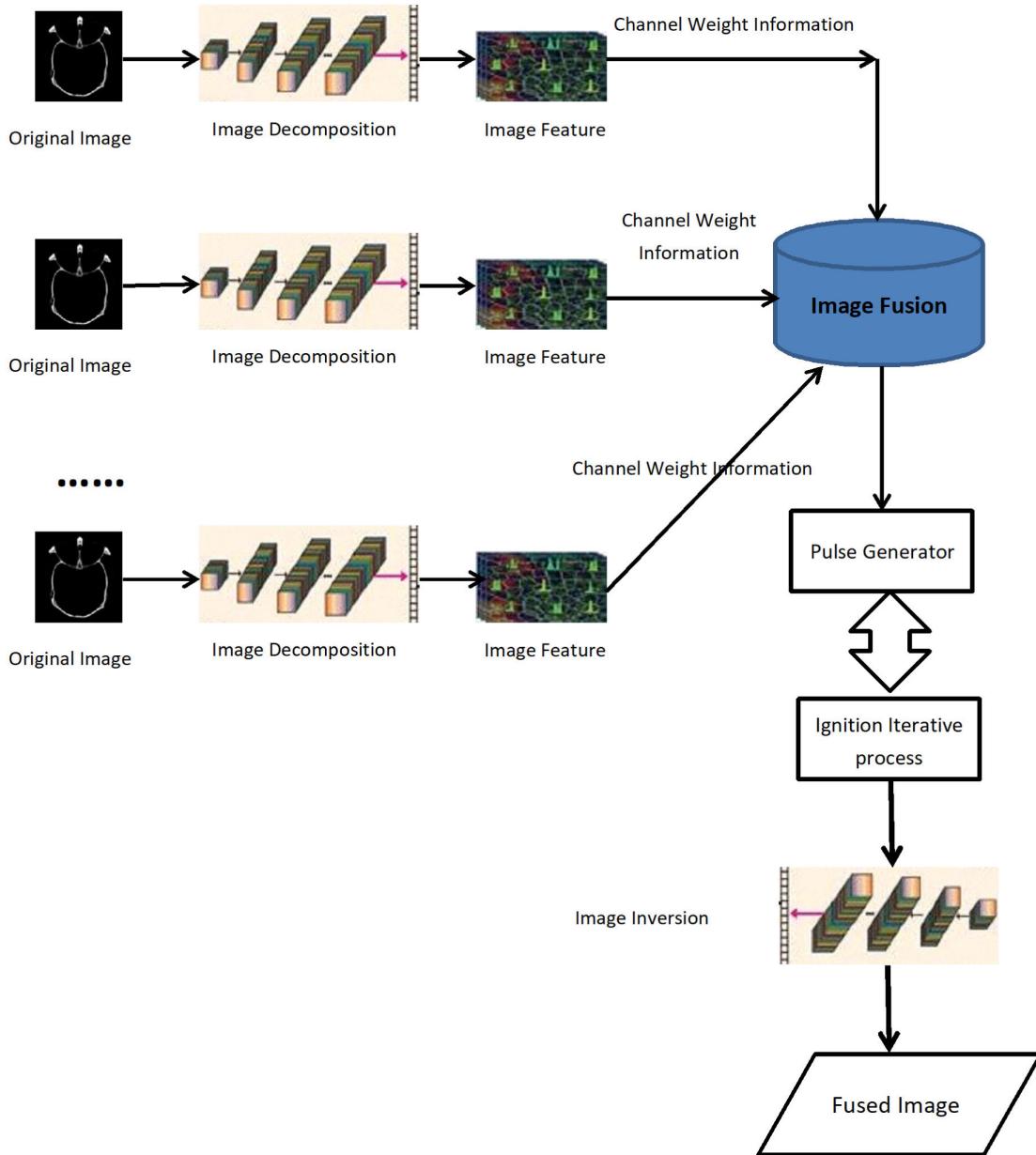


FIGURE 4. Schematic of multi-channel PCNN image fusion model.

it. Finally, pulses are stimulated by output pulse in fusion pool, and the ignition process is formed by the iterative cumulation of pulse. Ignition process matrix is approximately regarded as the gray matrix of the fused image in this paper. Multi-channel model above can be divided into Odd channels and even channels in accordance with the number of channels, 3-channel and 4-channel PCNN model are chosen in the proposed method. When the number of channel is greater than 4, odd channel model can be expansion from 3-channel model, even channel model can be expansion from 4-channel model, and any number of channel PCNN image fusion can be obtained. The process of multi-channel

PCNN image fusion: firstly, the gray matrix of image is as model input, and the normalized Sur is the external stimuli. Then, the linking weight of each channel is calculated by Eq. (8)-Eq. (9). Finally, the fusion image is obtained by the new model algorithm M-PCNN. Specific algorithm is shown as 4.2.

B. M-PCNN

The process of M-PCNN is: firstly, the gray matrix of image is as model input, and which should be normalized. Then, the linking weight of each channel is calculated by Eq. (8)-Eq. (9). Finally, the fused image is obtained by the

M-PCNN

Step1: Initialization all zero for initial state model does not produce pulses.

Step2: Normalized image matrix, finished image decomposition.

Step3: Calculate the linking weight of each channel by Eq. (8)-Eq. (9).

Step4: Fuse images using Eq. (1)- Eq. (5).

Input in accordance with Step2, obtain internal output via Eq. (3), generate pulse by the value of internal output, and obtain the ignition matrix by pulse.

Step5: Output the final fused image.

new model algorithm. The proposed fusion method M-PCNN consists of the following steps:

The calculation of linking weight and the generation of ignition matrix are two key steps in M-PCNN. The linking weight obtained by the proposed new method basically reflects the complete information of each channel, and each channel has a good fusion, which plays a crucial role in fusion algorithm. Ignition generation can completely and carefully contain the information of fused image. Therefore, the proposed M-PCNN can fuse images in a short time, which effectively avoid the defects of double-channel fusion, such as fusion results great influenced by the fusion order, low fusion accuracy and time-consuming and so on. The superiorities of M-PCNN are as follows:

(1) Synchronous fusion of multiple images can be more effective.

(2) Better to save fusion time.

(3) Maximize the good collaboration and lead to ignition from a global point of view for each channel uses reasonable and suitable method for multi-channel model to calculate weight.

V. EXPERIMENT AND ANALYSIS

To evaluate the performance of our proposed fusion method, extensive experiments with multi-focus image fusion have been performed. Note that all test images used in the experiment are downloaded on the website (<http://www.imagefusion.org> [20]) and literature [13].

A. EXPERIMENT OF ODD NUMBER CHANNEL PCNN IMAGE FUSION

As described in Section III, 5-channel PCNN model were studied in detail as the basis of the odd-channel model in this paper. Several experiments with multi-focus image fusion (one set of size 256×256 , another set of 480×360) have been performed between dual channel PCNN model and the proposed model. Fusion process of the experiment in dual-channel model is as follows: Firstly, five images were arranged in accordance with the different order. Then, dual-channel PCNN image fusion method was performed on the top two images. Finally, the final fusion result was

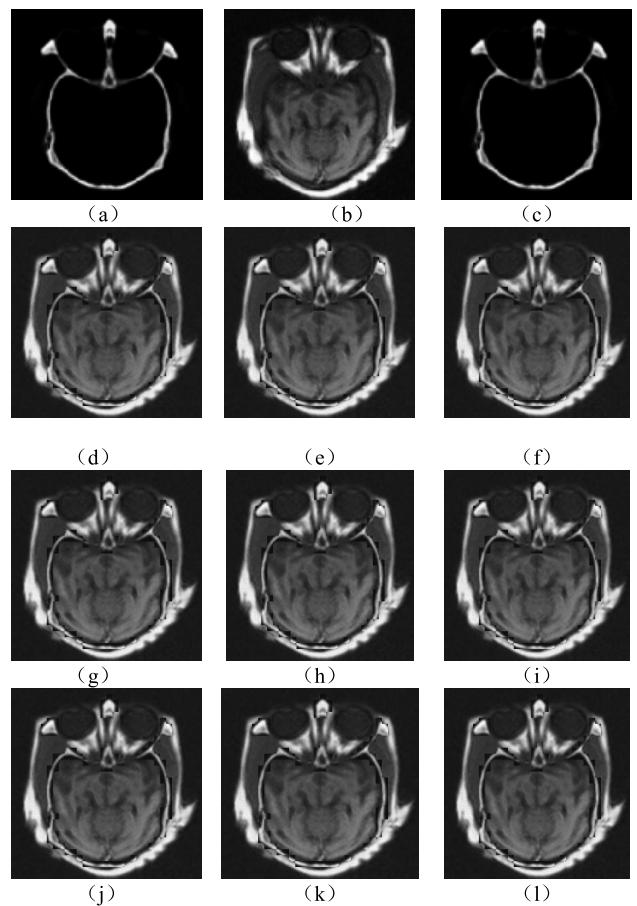


FIGURE 5. Experiment results of ct1image (a) Source image (represented by 1) (b) Source image (represented by 2) (c) Source image (represented by 4) (d) Source image (represented by 4) (e) Standard image (represented by 5) (f) The fusion result of the proposed method (g) The fusion result of dual channel model in the 1-2-4-3-5 fusion order (h) The fusion result of dual channel model in the 1-4-2-3-5 fusion order (i) The fusion result of dual channel model in the 3-5-2-1-4 fusion order (j) The fusion result of dual channel model in the 3-2-4-1-5 fusion order (k) The fusion result of dual channel model in the 5-4-3-1-2 fusion order (l) The fusion result of dual channel model in the 4-2-3-1-5 fusion order.

obtained using the same fusion method performed on the fusion result and the other source images. Fig.5- Fig.6 and Table 2-3 show the experiment result and Table 1 shows the parameter settings. Experimental datum were the average of the results obtained by running operation algorithms 100 times. The evaluation index used in the experiment: the mean (MEAN), variance (STD), entropy (H), average gradient (GRAD), time (TIME).

1) EXPERIMENT OF CT1 IMAGE

Experiment images are multi-focus images with the size of 256×256 pixel, Fig.5 and Table 2 respectively show the fusion results and comparison of results in different fusion order.

2) EXPERIMENT OF CT2 IMAGE

Experiment images are multi-focus images with the size of 480×360 pixel, Fig.6 and Table 3 respectively show the fusion results and comparison of results in different fusion order.

TABLE 1. The parameter settings of odd channel PCNN image fusion model.

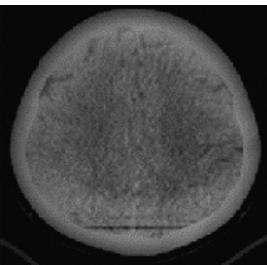
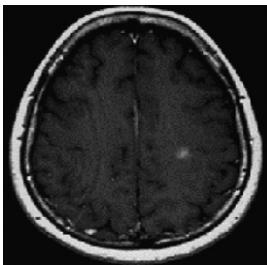
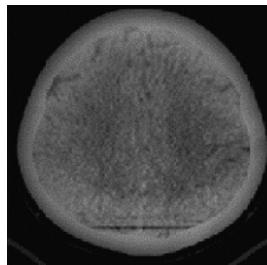
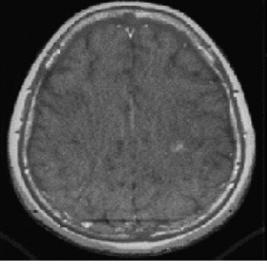
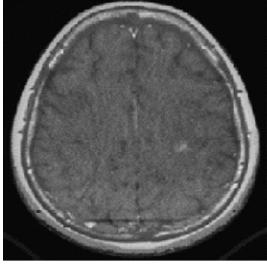
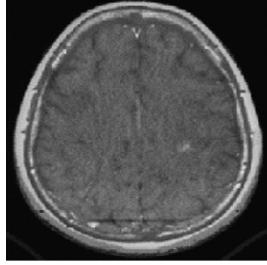
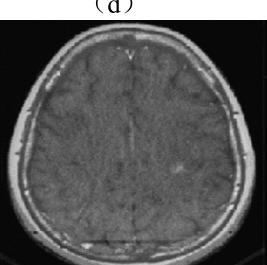
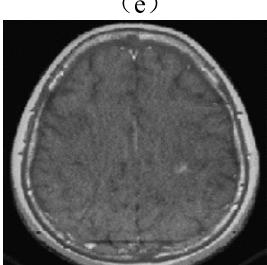
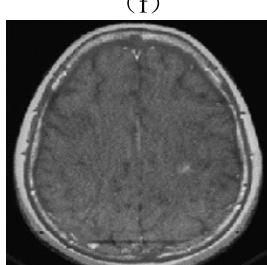
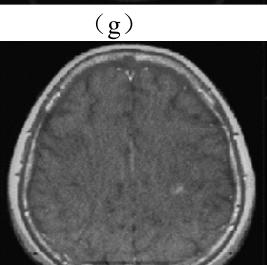
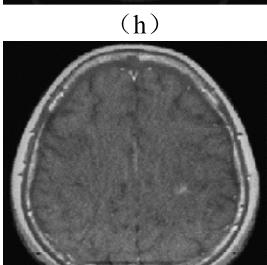
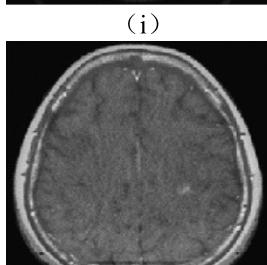
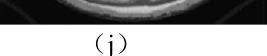
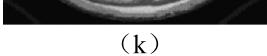
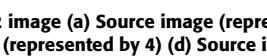
parameter	η	σ	V_T	α_T	Number of fusion	
value	<1e-2	0~1	0~1.2	0.2~1	>1000	
(a)						
(b)						
(c)						
(d)						
(e)						
(f)						
(g)						
(h)						
(i)						
(j)						
(k)						
(l)						
(m)						

FIGURE 6. Experiment results of ct2 image (a) Source image (represented by 1) (b) Source image (represented by 2) (c) Source image (represented by 4) (d) Source image (represented by 4) (e) Standard image (represented by 5) (f) The fusion result of the proposed method (g) The fusion result of dual channel model in the 1-2-4-3-5 fusion order (h) The fusion result of dual channel model in the 1-4-2-3-5 fusion order (i) The fusion result of dual channel model in the 3-5-2-1-4 fusion order (j) The fusion result of dual channel model in the 3-2-4-1-5 fusion order (k) The fusion result of dual channel model in the 5-4-3-1-2 fusion order (l) The fusion result of dual channel model in the 4-2-3-1-5 fusion order.

3) EXPERIMENTAL ANALYSIS

a: TIME PERFORMANCE ANALYSIS

Time performance analysis is very important to evaluate the performance of a fusion method. In this section, we carried

out a detailed comparative analysis for the above two sets of experiments from the time performance.

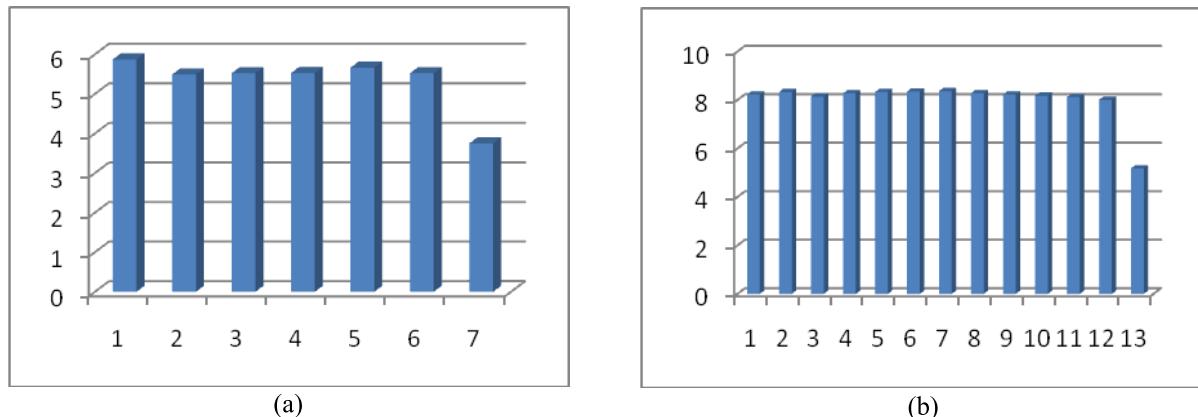
As shown in Fig.7, the proposed method has a better time performance than other methods. It spends only about

TABLE 2. Experimental results comparison of ct1 image.

method index \	The fusion order of 1- 2-4-3-5	The fusion order of 1- 4-2-3-5	The fusion order of 3- 5-2-1-4	The fusion order of 3- 2-4-1-5	The fusion order of 5- 4-3-1-2	The fusion order of 4- 2-3-1-5	The proposed method
MEAN	55.8433	55.6543	55.7664	55.6544	55.7644	55.4643	56.8043
STD	33.6553	33.7555	33.7654	33.7654	33.2567	33.8765	33.7542
ENT	6.3353	6.8665	6.3453	6.3533	6.3453	6.3532	6.4232
GRAD	4.5332	4.5322	4.8754	4.2353	4.8765	4.3453	4.4568
TIME	6.3543	6.3456	6.3456	6.8754	6.3565	6.5432	2.6543

TABLE 3. Experimental results comparison of ct2 image.

method index \	The fusion order of 1- 2-3-4-5	The fusion order of 1- 4-2-3-5	The fusion order of 2- 1-4-3-5	The fusion order of 2- 4-1-3-5	The fusion order of 4- 1-2-3-5	The fusion order of 4- 2-1-3-5	The proposed method
MEAN	41.5654	41.6424	41.7654	41.7654	41.4678	41.7654	44.8665
STD	22.7765	22.8665	22.7665	22.8765	22.7654	22.6543	22.9865
ENT	6.9443	6.8765	6.8655	6.4566	6.4544	6.3556	6.8665
GRAD	6.7654	6.877	6.5556	6.4556	6.4556	6.3556	7.5564
TIME	2.7665	2.7554	2.7654	2.8775	2.76655	2.5675	1.6544

**FIGURE 7.** Comparison of the time performance of different PCNN fusion methods: (a) 1-6 denote the double-channel PCNN methods with the different fusion sequences and 7 denotes the proposed M-PCNN method; (b) 1-12 denote the double-channel PCNN methods with the different fusion sequences and 13 denotes the proposed M-PCNN.

two-thirds time than other methods, and a fusion results with greater clarity and resolution can be obtained.

b: VISUAL EFFECT AND OBJECTIVE EVALUATION INDEX ANALYSIS

In this subsection, we had a detailed analysis of above two groups of experimental results from fusion effect and performance evaluation. From the above two sets of experimental results, we found some differences between six fusion results of different fusion order. Because different fusion order result some differences in gray-scale image, clarity, resolution and time. For example, the fusion result in the first set of experiments which is obtained by dual channel model in the 1-2-3-4-5 fusion order has a maximum average gradient, but

also more time-consuming. The fusion result in the second set of experiments which is obtained by dual channel model in the 1-2-3-4-5 fusion order has a maximum information entropy, but also more time-consuming. Fusion result according to the 4-1-2-3-5 fusion order has a minimum mean. However, the image obtained by the proposed method is significantly better than the image obtained by dual channel PCNN image fusion method in the three aspects of image mean (MEAN), variance (STD), the average gradient (GRAD). It just shows the image obtained by the proposed method has larger image contrast and higher resolution, image gray tends to disperse, and obviously reacts the tiny details contrast in the image. In this paper, a reasonable weight calculation method is adopted, each channel can

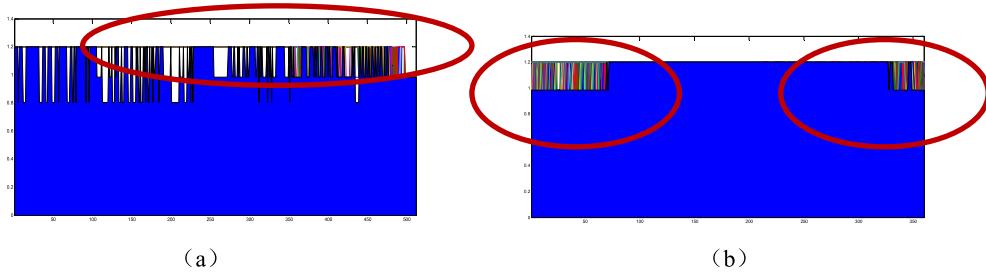


FIGURE 8. Comparison of ignition situation by the 5-channel PCNN image fusion model.: (a) Ignition situation in ct1 image (b) Ignition situation in ct2 image.

TABLE 4. The parameter settings of even channel PCNN image fusion model

parameter	η	σ	V_T	α_T	Number of fusion
value	<1e-2	0~1	0~1.2	0.2~1	>1000

TABLE 5. Experimental results comparison of ct1 image.

method index	The fusion order of 1- 2-4-5-3-6- 8-7	The fusion order of 1- 2-5-4-6-7-	The fusion order of 3- 1-6-4-8-5-	The fusion order of 6- 1-8-4-7-2-	The fusion order of 8- 7-6-1-5-2-	The fusion order of 8- 6-7-3-1-5-	The fusion order of 6- 2-7-8-4-1- 3-5
MEAN	55.3453	55.5445	55.8665	55.4566	55.4556	55.7654	55.3456
STD	33.7555	33.6544	33.4565	33.7655	33.4566	33.4567	33.3456
ENT	6.5543	6.3456	6.3444	6.4553	6.4564	6.4554	6.3554
GRAD	4.8765	4.6543	4.2456	4.7665	4.7654	4.8765	4.7654
TIME	8.4566	8.5667	8.5433	8.7653	8.4678	8.3567	8.4667
method index	The fusion order of 7- 8-6-2-4-3- 5-1	The fusion order of 4-5-8-1-7- 6-2-3	The fusion order of 4- 5-2-1-6-3- 8-7	The fusion order of 8- 2-5-1-7-4- 3-6	The fusion order of 7- 2-3-5-6-4- 8-1	The proposed method	
MEAN	55.6543	55.7765	55.4556	55.3556	55.8765		56.3456
STD	33.7555	33.5533	33.7544	33.654	33.5454		34.7654
ENT	6.6544	6.6543	6.8765	6.4556	6.6543		6.8653
GRAD	4.8765	4.4667	4.8876	4.7554	4.8766		4.8654
TIME	8.9776	8.5467	8.5456	8.5667	8.5567		2.6543

maximize the good collaboration, and information loss is less than the dual-channel pulse-coupled model. Compared to other methods, the proposed method can effectively solve the problem that different fusion orders result in differences of the fusion results. However, the proposed method is slightly worse than the dual-channel PCNN image fusion method in the aspect of information entropy (ENT).

c: IGNITION ANALYSIS

In order to further analyze the reason why 5-channel PCNN image fusion model can obtain a better result, we conducted a detailed analysis to the ignition situation caused by the 5-channel PCNN image fusion model.

The blue area in Fig.8 represents ignition area. It can be seen from two figures that the blue area in the figure is much more, which illustrate the most pixels can cause ignition phenomenon by the proposed method. Most importantly,

it reflects the method to calculate the link-weight for each channel by gray-scale energy of image grayscale matrix is much better, the energy in each channel did not loss for mutual interference, and mutual fusion can maximize the ignition effect. On the other hand, good ignition situation illustrates that the ignition matrix can completely reflect gray-scale energy information of the multiple images, which is bound to bring a better fusion effect.

B. EXPERIMENT OF EVEN NUMBER CHANNEL PCNN IMAGE FUSION

As described in Section III, 8-channel PCNN model were studied in detail as the basis of the even-channel model in this paper. Several experiments with multi-focus image fusion have been performed between dual channel PCNN model and the proposed model, and the size of multi-focus

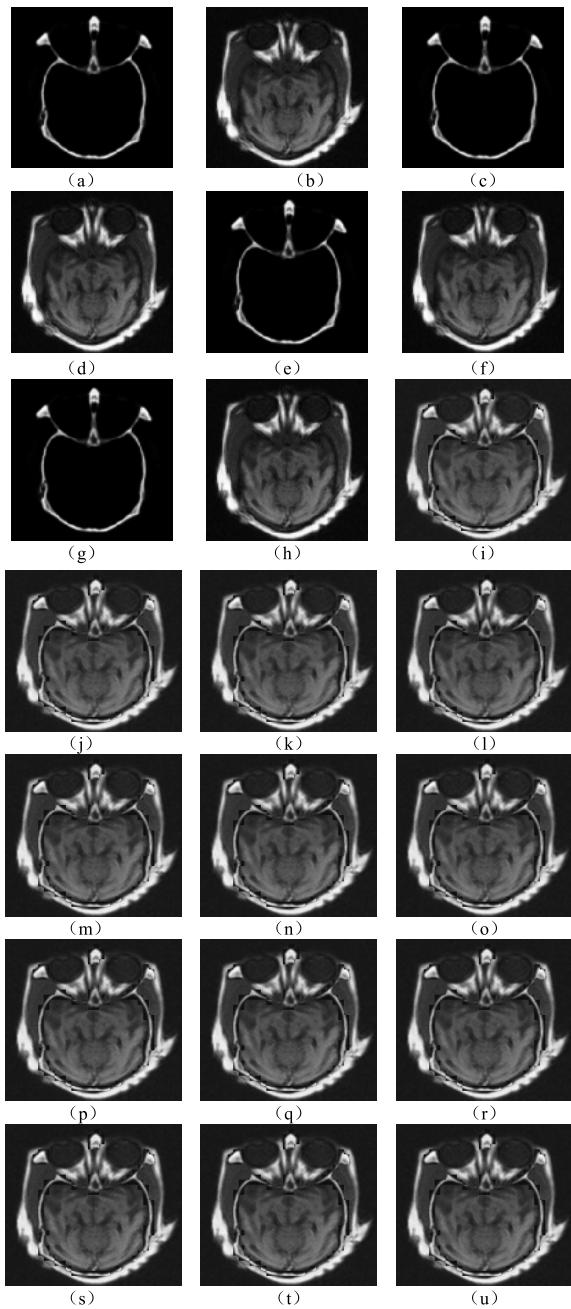


FIGURE 9. Experiment results of ct1 image (a) Source image (represented by 1) (b) Source image (represented by 2) (c) Source image (represented by 3) (d) Source image (represented by 4) (e) Source image (represented by 5) (f) Source image (represented by 6) (g) Source image (represented by 7) (h) Source image (represented by 8) (i) The fusion result of the proposed method (j) The fusion result of the dual channel model in the 1-2-4-5-3-6-8-7 fusion order (k) The fusion result of dual channel model in the 1-2-5-4-6-7-8-3 fusion order (l) The fusion result of dual channel model in the 3-1-6-4-8-5-7-2 fusion order (m) The fusion result of dual channel model in the 6-1-8-4-7-2-3-5 fusion order (n) The fusion result of dual channel model in the 8-7-6-1-5-2-4-3 fusion order (o) The fusion result of dual channel model in the 8-6-7-3-1-5-4-2 fusion order (p) The fusion result of dual channel model in the 6-2-7-8-4-1-3-5 fusion order (q) The fusion result of dual channel model in the 7-8-6-2-4-3-5-1 fusion order (r) The fusion result of dual channel model in the 4-5-8-1-7-6-2-3 fusion order (s) The fusion result of dual channel model in the 4-5-2-1-6-3-8-7 fusion order (t) The fusion result of dual channel model in the 8-2-5-1-7-4-3-6 fusion order (u) The fusion result of dual channel model in the 7-2-3-5-6-4-8-1 fusion order.

images are 256×256 , 480×360 . 196×146 . Fusion process of the experiment in proposed model is as follows: Firstly, arrange the four source images in a different order. Then, dual-channel PCNN image fusion method was performed on the top two images. Fig.9-Fig.11 and Table 5-Table 7 show the experiment result and Table 4 shows the parameter settings. Experimental datum are the average of the results obtained by running algorithms 100 times. The evaluation index used in the experiment: the mean (MEAN), variance (STD), entropy (H), average gradient (GRAD), time (TIME).

1) EXPERIMENT OF CT1 IMAGE

Experiment images are multi-focus images with the size of 256×256 pixel, Fig.9 and Table 5 respectively show the fusion results and comparison of results in different fusion order.

2) EXPERIMENT OF CT2 IMAGE

Experiment images are multi-focus images with the size of 480×360 pixel, Fig.10 and Table 6 respectively show the fusion results and comparison of results in different fusion order.

3) EXPERIMENT OF CT2 IMAGE

Experiment images are multi-focus images with the size of 196×146 pixel, Fig.11 and Table 7 respectively show the fusion results and comparison of results in different fusion order.

4) EXPERIMENTAL ANALYSIS

a: TIME PERFORMANCE ANALYSIS

In this section, we carried out a detailed comparative analysis for the above three sets of experiments from the time performance.

As shown in Fig.12, the proposed method has a better time performance than other methods.

b: VISUAL EFFECT AND OBJECTIVE EVALUATION INDEX ANALYSIS

In this subsection, we had a detailed analysis of above three groups of experimental results from fusion effect and performance evaluation. From the above three sets of experimental results, we found some differences between 12 fusion results of different fusion order. Because different fusion order of 8 source images result some differences in gray-scale image, clarity, resolution and time. For example, the fusion image in the first set of experiment which is obtained by dual channel model in the 1-2-4-5-3-6-8-7 fusion order has a maximum average variance, up to 33.7555. And the fusion image obtained by dual channel model in the 6-1-8-4-7-2-3-5 fusion order is the most time-consuming. In the second group of experiment, the fusion image obtained by dual channel model in the 6-2-7-8-4-1-3-5 fusion order has a minimum mean, smaller than the other fusion result mean 0.1 to 0.2. Fusion image obtained by dual-channel PCNN image fusion model in accordance with the 1-2-5-4-6-7-8-3 fusion order

TABLE 6. Experimental results comparison of ct2 image.

method \ index	The fusion order of 1-2-4-5-3-6-8-7	The fusion order of 1-2-5-4-6-7-8-3	The fusion order of 3-1-6-4-8-5-7-2	The fusion order of 6-1-8-4-7-2-3-5	The fusion order of 8-7-6-1-5-2-4-3	The fusion order of 8-6-7-3-1-5-4-2	The fusion order of 6-2-7-8-4-1-3-5
MEAN	41.5444	41.6544	41.7654	41.8765	41.6544	41.7544	41.4664
STD	22.7655	22.7644	22.7865	22.7554	22.7655	22.8654	22.456y
ENT	6.4577	6.5667	6.4566	6.5567	6.8765	6.4556	6.4556
GRAD	6.4556	6.4556	6.3556	6.9765	6.4453	6.3556	6.3554
TIME	3.9543	3.9766	3.7646	3.8866	3.7654	3.7565	3.7654
method \ index	The fusion order of 7-8-6-2-4-3-5-1	The fusion order of 4-5-8-1-7-6-2-3	The fusion order of 4-5-2-1-6-3-8-7	The fusion order of 8-2-5-1-7-4-3-6	The fusion order of 7-2-3-5-6-4-8-1	The proposed method	
MEAN	41.6433	41.7643	41.6535	41.6533	41.6755	44.7554	
STD	22.7544	22.7644	22.7654	22.7544	22.6754	23.6544	
ENT	6.4566	6.4566	6.4567	6.4556	6.3566	6.1566	
GRAD	6.3454	6.7655	6.8766	6.3556	6.4456	6.6443	
TIME	3.7654	3.7654	3.7665	3.7654	3.6432	2.7653	

TABLE 7. Experimental results comparison of ct3 image.

method \ index	The fusion order of 1-2-4-5-3-6-8-7	The fusion order of 1-2-5-4-6-7-8-3	The fusion order of 3-1-6-4-8-5-7-2	The fusion order of 6-1-8-4-7-2-3-5	The fusion order of 8-7-6-1-5-2-4-3	The fusion order of 8-6-7-3-1-5-4-2	The fusion order of 6-2-7-8-4-1-3-5
MEAN	25.5565	25.6644	25.7543	25.6427	25.7654	25.78654	25.5785
STD	10.6544	10.5445	10.6555	10.5445	10.7654	10.6543	10.5444
ENT	4.8758	4.9765	4.2557	4.8976	4.8654	4.8765	4.8643
GRAD	2.7654	2.8765	2.6875	2.7654	2.8766	2.7655	2.7765
TIME	1.5533	1.7654	1.0976	1.0865	0.9776	0.9443	0.9554
method \ index	The fusion order of 7-8-6-2-4-3-5-1	The fusion order of 4-5-8-1-7-6-2-3	The fusion order of 4-5-2-1-6-3-8-7	The fusion order of 8-2-5-1-7-4-3-6	The fusion order of 7-2-3-5-6-4-8-1	The proposed method	
MEAN	25.8764	25.8665	25.7654	25.7654	25.7754	27.8764	
STD	10.8765	10.8636	10.7654	10.5329	10.6543	11.8654	
ENT	4.7543	4.8765	4.7653	4.6543	4.7754	4.7654	
GRAD	2.7765	2.7654	2.5543	2.7666	2.7765	2.8976	
TIME	0.9754	0.9654	0.9664	1.0543	1.1231	0.6578	

is time-consuming 4.222765 seconds, significantly higher than the other dual-channel fusion results 0.3-0.8 seconds. However, the fusion image obtained by the proposed method is significantly better than the fusion result obtained by dual channel PCNN image fusion method in the four aspects of image mean (MEAN), variance (STD), information entropy (ENT), the average gradient (GRAD). It just shows the image obtained by the proposed method has larger image contrast and higher resolution, image gray tends to disperse, and tiny details of the image contrast are obvious. In this paper, a reasonable weight calculation method is adopted, each channel can maximize the good collaboration, and information loss is less than the dual-channel pulse-coupled model. Compared to other methods, the proposed method can effectively solve the problem that different fusion orders result in differences of the fusion results. However, the proposed method is slightly worse than the dual-channel PCNN image fusion method in the aspect of information entropy (ENT).

c: IGNITION ANALYSIS

In order to further analyze the reason why 8-channel PCNN image fusion model can obtain a better result, we conducted a detailed analysis to the ignition situation caused by the 8-channel PCNN image fusion model.

The blue area in Fig.13 represents ignition area caused by 4-channel PCNN image fusion model. Figure 13 (a), (b), (c) are virtually all of the blue region, which illustrate the most pixels can cause ignition phenomenon by the proposed method. Most importantly, it reflects the method to calculate the link-weight for each channel by gray-scale energy of image grayscale matrix is much better, the energy in each channel did not loss for mutual interference, and mutual fusion can maximize the ignition effect. On the other hand, good ignition situation illustrates that the ignition matrix can completely reflect gray-scale energy information of the multiple images, which is bound to bring a better fusion effect.

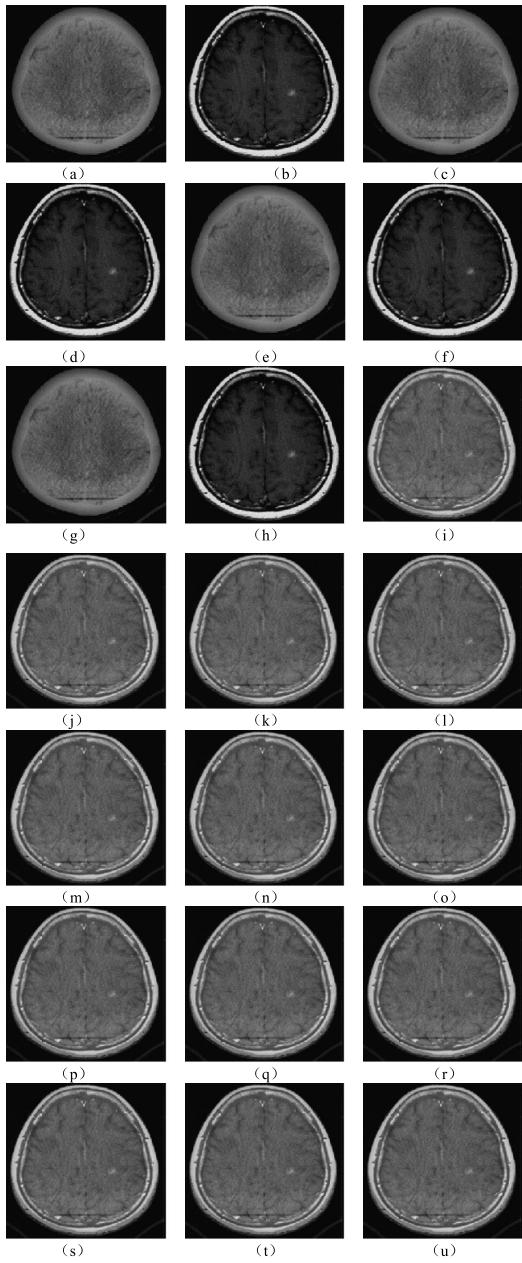


FIGURE 10. Experiment results of ct2 image (a) Source image (represented by 1) (b) Source image (represented by 2) (c) Source image (represented by 3) (d) Source image (represented by 4) (e) Source image (represented by 5) (f) Source image (represented by 6) (g) Source image (represented by 7) (h) Source image (represented by 8) (i) The fusion result of the proposed method (j) The fusion result of the dual channel model in the 1-2-4-5-3-6-8-7 fusion order (k) The fusion result of dual channel model in the 1-2-5-4-6-7-8-3 fusion order (l) The fusion result of dual channel model in the 3-1-6-4-8-5-7-2 fusion order (m) The fusion result of dual channel model in the 6-1-8-4-7-2-3-5 fusion order (n) The fusion result of dual channel model in the 8-7-6-1-5-2-4-3 fusion order (o) The fusion result of dual channel model in the 8-6-7-3-1-5-4-2 fusion order (p) The fusion result of dual channel model in the 6-2-7-8-4-1-3-5 fusion order (q) The fusion result of dual channel model in the 7-8-6-2-4-3-5-1 fusion order (r) The fusion result of dual channel model in the 4-5-8-1-7-6-2-3 fusion order (s) The fusion result of dual channel model in the 4-5-2-1-6-3-8-7 fusion order (t) The fusion result of dual channel model in the 8-2-5-1-7-4-3-6 fusion order (u) The fusion result of dual channel model in the 7-2-3-5-6-4-8-1 fusion order.

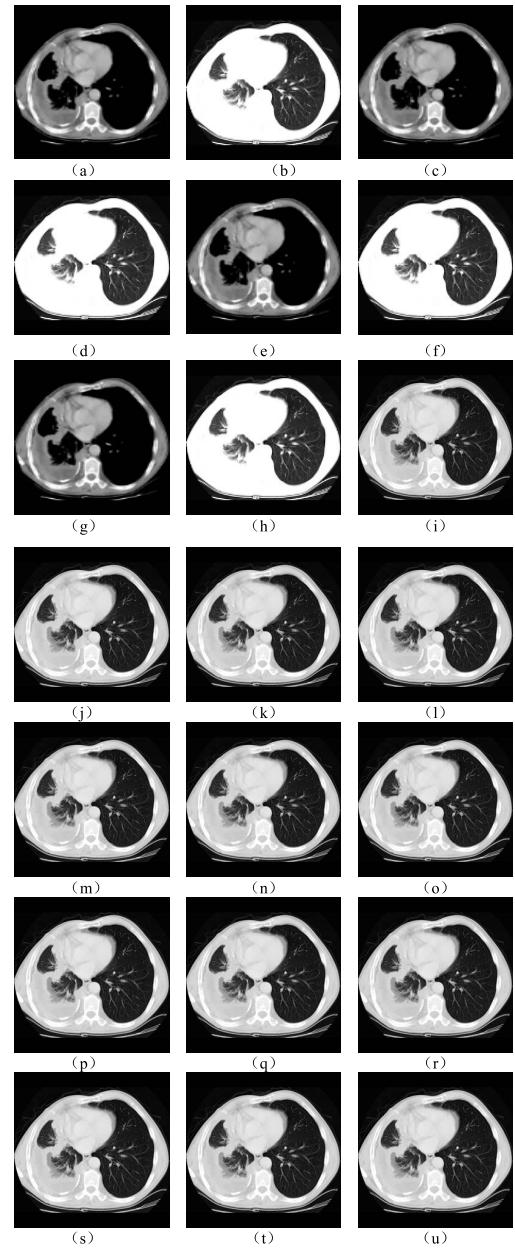


FIGURE 11. Experiment results of ct3 image (a) Source image (represented by 1) (b) Source image (represented by 2) (c) Source image (represented by 3) (d) Source image (represented by 4) (e) Source image (represented by 5) (f) Source image (represented by 6) (g) Source image (represented by 7) (h) Source image (represented by 8) (i) The fusion result of the proposed method (j) The fusion result of the dual channel model in the 1-2-4-5-3-6-8-7 fusion order (k) The fusion result of dual channel model in the 1-2-5-4-6-7-8-3 fusion order (l) The fusion result of dual channel model in the 3-1-6-4-8-5-7-2 fusion order (m) The fusion result of dual channel model in the 6-1-8-4-7-2-3-5 fusion order (n) The fusion result of dual channel model in the 8-7-6-1-5-2-4-3 fusion order (o) The fusion result of dual channel model in the 8-6-7-3-1-5-4-2 fusion order (p) The fusion result of dual channel model in the 6-2-7-8-4-1-3-5 fusion order (q) The fusion result of dual channel model in the 7-8-6-2-4-3-5-1 fusion order (r) The fusion result of dual channel model in the 4-5-8-1-7-6-2-3 fusion order (s) The fusion result of dual channel model in the 4-5-2-1-6-3-8-7 fusion order (t) The fusion result of dual channel model in the 8-2-5-1-7-4-3-6 fusion order (u) The fusion result of dual channel model in the 7-2-3-5-6-4-8-1 fusion order.

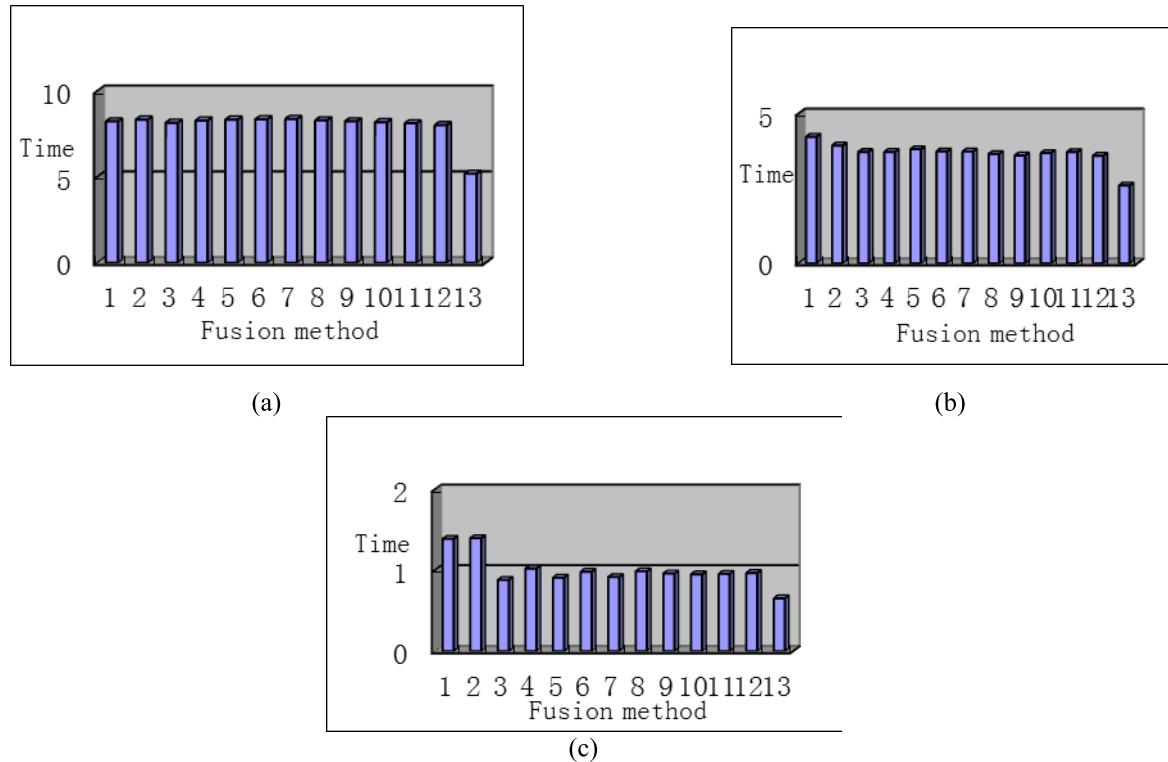


FIGURE 12. Comparison of the time performance of different PCNN fusion methods: 1-12 denote the double-channel PCNN methods with the different fusion sequences and 13 denotes the proposed M-PCNN method; (a) CT1; (b) CT2; (c) CT3.

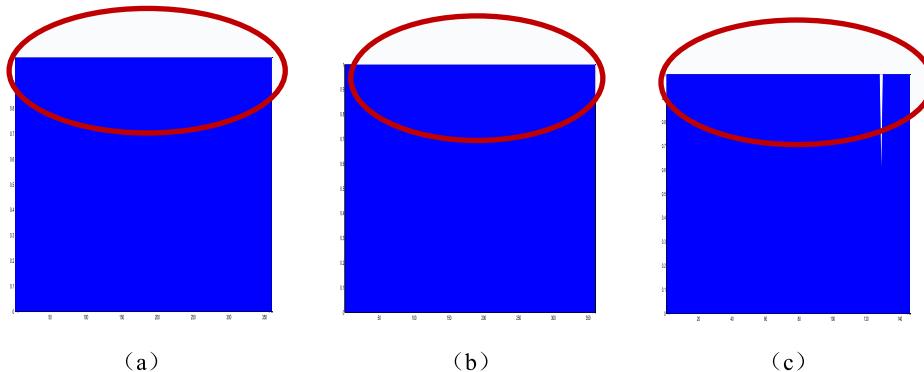


FIGURE 13. Comparison of ignition situation by the 8-channel PCNN image fusion model.: (a) Ignition situation in ct1 image (b) Ignition situation in ct2 image (c) Ignition situation in ct3 image.

In addition to this, by comparing Figure 8 (a) and Figure 13 (a), Figure 8 (b) and Figure 13(b), it is found that the pixel points could not cause ignition in Fig.8 (a) and (b) had caused ignition in Fig.13 (a) and (b), which illustrate that ignition condition caused by 8-channel PCNN model is better than 5-channel PCNN model for the same input image. This further illustrate the proposed fusion method not only does not cause loss of information, but also can maximize the fusion capabilities through collaboration between various channels when the number of channels increases. From the ignition situation analysis above, we found the ignition situation is much better when the number of channels is less than or equal to 8. And which is consistent with experience in our daily lives that more raw data collected from more valuable information.

In short, the above analysis shows that the fusion images obtained by both the odd channel model and even channel model have larger image contrast and higher resolution, image gray tends to disperse, and tiny details of the image contrast are obvious. Which verifies the proposed method can achieve multiple images synchronous fusion with less time cost, and effectively solves the problem that different fusion order results in differences fusion results.

The advantages of this paper are as follows.

- (1) As a result of a reasonable weight calculation method, each channel can maximize the good collaboration from a global perspective, the loss of valuable information is significantly less than the dual-channel PCNN model.
- (2) Multiple images synchronous fusion saves time preferably.

(3) The fusion image obtained by the proposed method has gray dispersion, large image contrast, high definition, high resolution in a certain extent.

(4) Because the proposed method is better linked with the image gray energy, fusion effect is better for images which are able to highlight the image gray information.

(5) Rarely involved in the plight of the multi-channel model has been effectively solved.

VI. CONCLUSION

In order to better solve the problems of synchronous fusion of multiple images and rarely involved in the plight of the multi-channel model, effectively overcome the problem that a great differences of result brought by dual channel PCNN model in different fusion order, a multi-channel PCNN image fusion method is proposed in this paper. Firstly, the multi-channel PCNN image fusion model is proposed. Then, calculation method of link weight has been improved. A detailed analysis of the multi-channel model from two angles of the odd channel PCNN model and even channel PCNN model is carried out, it is found that N-channel PCNN image fusion can be achieved through a combination of odd channel and dual channel. Finally, a detailed comparison with dual-channel PCNN image fusion method and non-PCNN image fusion method is carried out, which further proves the proposed method can not only solve the simultaneous integration of multiple images, but also shows certain advantages in fusion effect and time performance.

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