Enhancement algorithm for color images based on improved FC-MSPCNN

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Abstract: Image enhancement has been a hot research topic in image processing in recent years, and Pulse-Coupled Neural Network (PCNN) based image processing has become one of the important channels for image processing. Recently, we have applied this network to image enhancement based on Fire-controlled Pulse-coupled NeuralNetwork (FC-MSPCNN) without changing its model structure by combining the adaptive parameter setting method to redefine the link coefficients. On the one hand, and reprocessing the mapping matrix of the extracted three channels on the other hand. The experimental results of the improved FC-MSPCNN are proved to be more effective and robust compared with the traditional classical algorithm, both in terms of competent analysis and objective comparison.

1. Introduction

In the process of information transmission, language and images are the main carriers of effective information transmission, among which, images account for 80%. In the process of image transmission, due to some unavoidable factors, the images are affected differently in the transmission process, and there is a certain amount of information interference in the images received at the receiving end, which is not conducive to extracting useful information. As a result, image enhancement has an important place in the process of effective image acquisition and transmission. Image enhancement is the process of extracting useful features from images of poor quality, and improving the quality of these images to meet the user's requirements.

Traditional image enhancement algorithms, such as linear transform method, Gamma transform method [1], and histogram equalization [2], all go through certain mapping transformations on the pixels of an image to achieve image enhancement. PCNN (Pulse-Coupled Neural Network) [3] is a neural network model developed by Eckhon. based on the mammalian visual system. PCNN is used in the field of image processing [4]. The applications are widely used, especially in the field of image enhancement, which has received much attention. Among them, Chen proposed a Simplified Impulse-Coupled Neural Network (SPCNN) [5] based on the PCNN model, simplified algorithm parameters to optimize the algorithm structure, and proposed an automatic parameter setting method. Ma Yide. further optimized the SPCNN algorithm based on the SPNN and proposed an improved Modified Simplified Pulse-Coupled Neural Network (MSPCNN) [6], which was studied and applied well in the field of image segmentation. Yang Zhen optimized the MSPCNN algorithm more recently and proposed the FC-MSPCNN algorithm [7] to apply it to the quantization application of natural images and medical images,
and the study showed that its application is effective. Based on this background, this paper develops the research of its algorithm in image enhancement methods based on FC-MSPCNN.

2. Related Work

2.1. The model of PCNN

The operation mechanism of neurons in the PCNN model is shown in Figure 1.

![Figure 1. The structure of the PCNN model](image1)

Equation (1) represents the running function of the link between the main neuron and its surrounding neurons in the L-channel. \((i,j)\) represents the position where the main neuron is located, \(W_{ijkl}\) represents the link weight between the main neuron and its surrounding neurons matrix, \(\alpha_L\) represents the decay index, and \(V_L\) is the magnitude value of the link input. \(Y_{ij}\) represents the final output.

\[
L_{ij}[n] = e^{-\alpha_L}L_{ij}[n-1] + V_L \sum_{k,l} W_{ijkl} Y_{kl}[n-1]
\]  
(1)

Equation (2) represents the running function of the signal in channel F. \(F_{ij}\) represents the feedback input of the external influence, \(S_{ij}\) represents the external influence excitation, \(M_{ijkl}\) represents the weight coefficient when the peripheral neurons are linked to each other, and \(\alpha_F\) represents the feedback input coefficient.

\[
F_{ij}[n] = e^{-\alpha_F} F_{ij}[n-1] + V_F \sum_{k,l} M_{ijkl} Y_{kl}[n-1] + S_{ij}
\]  
(2)

Equation (3) represents the function that the internal activity term runs when receiving the influence of the F channel with the L channel.

\[
U_{ij}[n] = F_{ij}[n] \left( 1 + \beta L_{ij}[n] \right)
\]  
(3)

Equation (4) represents the rule of change of dynamic thresholds, not fixed values, whose state values are closely related to the previous state and constantly changing.

\[
E_{ij}[n] = e^{-\alpha_E} E_{ij}[n-1] + V_E Y_{ij}[n]
\]  
(4)

Equation (5) represents the final output results in an excited state when the effect of the synthesized internal output is greater than the dynamic threshold, and the final output value is 1, and conversely, 0.

\[
Y_{ij}[n] = \begin{cases} 
1, & U_{ij}[n] > E_{ij}[n-1] \\
0, & U_{ij}[n] \leq E_{ij}[n-1]
\end{cases}
\]  
(5)

2.2. The model of MSPCNN

MSPCNN is based on PCNN and streamlined step by step to enhance the model structure and change the correlation coefficients. The MSPCNN structural model is shown in Figure 2. The coefficients are as follows:
\[ \alpha = \ln\left( \frac{1}{S} \right) \]  
\[ \beta = \frac{1-S'}{4S'} \]  
\[ \nu = 1 + S'^2 - S'^8 \]  

\( \alpha \) is the attenuation factor, \( S' \) is the Otsu threshold, \( \beta \) is the link strength coefficient. \( \nu \) is the magnitude value of the dynamic threshold. The MSPCNN model is based on the PCNN model, and the parameters are further modified to reduce the complexity of the computation by defining all parameters as related to \( S' \) where as the OTSU threshold. The synaptic matrix was re-modified to keep the link strengths directly connected to the main neuron unchanged, and the link strengths not directly connected to the main neuron were set to 0.

3. Image enhancement based on the improved FC-MSPCNN

3.1. The model of FC-MSPCNN

\[ U_{ij}(n) = e^{-\alpha}U_{ij}(n-1) + S_{ij}(1 + \beta \sum W_{ijkl}Y_{kl}(n-1)) \]  
\[ Y_{ij}(n) = \begin{cases} 1, & \text{if } U_{ij}(n) > E_{ij}(n-1) \\ 0, & \text{else} \end{cases} \]  
\[ E_{ij}(n) = e^{-\alpha}E_{ij}(n-1) + VR_{ij}Y_{ij}(n) \]  

\( U[n] \) represents the expression of the nth state of the internal activity term. \( Y[n] \) represents the final output result after comprehensive judgment. \( E[n] \) represents the dynamic threshold, whose value is not only related to the previous state, but also to the amplitude, the number of iterations and the output value.

3.2. Proposed the improved FC-MSPCNN

The improved FC-MSPCNN proposed in this paper, firstly, changes the relevant parameters, takes the model of FC-MSPCNN as the standard, and makes adjustments to its relevant parameters without changing the backbone network structure of FC-MSPCNN, improves the optimization parameters, streamlines the steps and simplifies the computation. In addition to making adjustments to the parameters of FC-MSPCNN, this thesis proposes an improved core flowchart of FC-MSPCNN, as shown in Figure 4, and gives the related pseudo-code according to the core flowchart. The enhancement effect is more obvious by using the algorithm proposed in this thesis through the enhancement of parameters as well as the core structure.

\[ W_{ijkl} = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \]  
\[ \alpha = -\ln\frac{S'}{P} \]  
\[ \beta = e^{-4\alpha} \]  
\[ V = e^{-\alpha}(1 + e^{-\alpha} + e^{2\alpha}) = e^{-\alpha} \frac{1 - e^{3\alpha}}{1 - e^{-\alpha}} \]
\[ R_n = \left( \frac{e^{Nu}}{1 - e^{-\alpha}} \right)^{\log_2(\beta)} \quad (16) \]

\( W_{ijkl} \) is the synaptic weight matrix, \( \alpha \) is the decay coefficient and \( P \) is the number of time iterations. \( \beta \) is the link strength. \( V \) is the amplitude of the dynamic threshold. \( R_n \) is a newly added variable, which aims to improve the accuracy of the calculation of dynamic thresholds.

Figure 4: The flowchart of the MSPCNN model

**Table 1. The pseudo-code**

| Algorithm1: The achievement steps of the color image enhancement method based on the FC-MSPCNN |
| --- |
| **Input:** A color image \( I \) and its dimensional parameter \( K \). |
| **Output:** The final quantization result. |
| For \( k = 1 \) to \( 3 \) do |
| Set the initial states of the model, including the internal activity \( U[0] = 0 \), the output pulse \( Y[0] = 0 \) and the dynamic threshold \( E[0] = 0 \). |
| Compute the setting parameters by (9)—(11) |
| Define the quantization layers as predetermined iteration times \( p = 128 \) |
| For iteration times \( n \) from 1 to \( p + 1 \) do |
| Substitute the above setting parameters into the FC-MSPCNN according to (12-16) |
| Give the computational result of the FC-MSPCNN. else Directly give the result of the FC-MSPCNN. end if |
| For \( I = 1 \) to \( 3 \) |
| Obtain the initial quantization result of each channel based on the classification rule. |
| Get The feature maps of different channels. |
| Get the average of the three extracted mapping matrices as the final feature maps |
| Combine the final result vector image with the feature matrix obtained in the previous step to obtain the final result image end if |
4. Experimental results

Three groups of experimental results image

![Image](a)
![Image](b)
![Image](c)

Figure 5. The first group of experimental results graph

![Image](d)
![Image](e)
![Image](f)

![Image](g)
![Image](h)
![Image](i)

Figure 6. The Second group of experimental results graph

![Image](j)
![Image](k)
![Image](l)

![Image](m)
![Image](n)
![Image](o)

Figure 7. The Second group of experimental results graph
Figure 8. Evaluation index of experimental results

(a) shows the original image, (b) shows the image enhancement result map obtained by gamma transformation, (c) shows the result map obtained by linear transformation, (d) is the result map obtained from logarithmic transformation, (e) is the result map obtained from histogram equalization method, and (f) is the result map obtained from this thesis.

From the subjective analysis, according to the three sets of experimental result plots, it can be obtained from the figure that, compared with the original figure, for the gamma transform, according to the characteristics of the selected figure, make the gamma value 0.3, improve the low gray area in the original figure, compress the high gray area in the original figure, the overall enhancement effect is better, but some local enhancement effect is general. Linear transformation, the gray value of each pixel point of the original image is linearly transformed, compared with the original image, the overall brightness of the image is enhanced, and the local effect is poor. Logarithmic transformation refers to the logarithmic transformation of the gray value of the pixel points in the original image, and the resulting enhancement effect is general. In this experiment, the overall effect of the image after histogram equalization transformation is better compared with the original image, but for the details in the original image, the image enhancement effect is average, especially in the edges of the image, there is still loss. Compared with other algorithms, the algorithm of this thesis is better in both overall and local effects, and the enhancement effect is better.

From the objective analysis, the five types of enhancement algorithms are compared with the original image, and evaluated in turn according to the meaning of the four evaluation indicators. Firstly, according to the experimental results of the first group of figures, the algorithm proposed in this thesis shows the results, SSIM, PSNR are significantly better than other algorithms, ABME and MSE are not the best, but their effects are in the middle, so consider several evaluation indicators in a comprehensive analysis, from the objective In terms of the experimental results, the image enhancement algorithm proposed in this paper has the best effect. Then, according to the analysis of the second group of experimental results, from the evaluation of PSNR index, the algorithm proposed in this paper has the best effect. According to the comprehensive analysis of three evaluation indexes, SSIM, ABME and
MSE, compared with other traditional algorithms, the enhancement algorithm proposed in this paper demonstrates good results with the best effect. Finally, through the third group of experimental results, the algorithm proposed in this thesis has the best effect according to PSNR shown, according to MSE, the algorithm proposed in this thesis is only second to the effect shown by logarithmic transformation, but the competent evaluation of logarithmic transformation is poorer, according to SSIM and ABME, both of which are combined, the experimental result of this thesis is better. In a comprehensive analysis, the algorithm proposed in this thesis is, to some extent, better than the traditional algorithm in terms of both subjective evaluation and objective indicators, and its enhancement effect is good.

5. Conclusion
The object of the algorithm in this paper is the color image, from the pulse-coupled neural network, to the improved simplified pulse-coupled neural network, and then to the improved pulse-coupled neural network model with controllable ignition, by simplifying the model step by step, reducing the complexity of the model and changing the relevant parameters to reduce the complexity of the calculation. Experiments are conducted through matlab platform, and the experimental results of the proposed algorithm in this thesis are compared with the results of the traditional algorithm, which are compared and analyzed from both subjective and objective perspectives. The experimental results show that the results of the proposed algorithm in this thesis are better than the traditional algorithm and have more advantages and better results.

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