Information Compensation Based on Pulse Coupled Neural Network

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ABSTRACT

Image Fusion is an enhancement technique, which aims to combine the images acquired by different sensors and generate informative images in order to make the subsequent processing easier or to help make decisions. The image fusion mission is done by the image fusion algorithm which is based on Pulse Coupled Neural Network and Discrete Cosine Transform. After the image fusion, information loss appears in part of fusion results, so some positions become empty. To solve this problem, this paper designs a compensation framework for image fusion. This framework aims to obtain better subjective effects and objective indicators. By comparing with the image information compensation methods of different parameters and different frames, the image after the image information compensation of the pulse coupled neural network has got a good visual effect, and the index is relatively excellent.

CCS CONCEPTS

• **Software and its engineering**; • **Software creation and management**; • **Designing software**; • **Software design engineering**;

KEYWORDS

Image Fusion, Image Information Loss, Pulse Coupled Neural Network, Image Information Compensation

ACM Reference Format:

Juntong Jing. 2021. Information Compensation Based on Pulse Coupled Neural Network. In *2021 6th International Conference on Biomedical Imaging, Signal Processing (ICBSP '21), October 29–31, 2021, Xiamen, China*. ACM, New York, NY, USA, 5 pages. <https://doi.org/10.1145/3502803.3502805>

1 INTRODUCTION

With the rapid development of brain science, medicine, neuroscience, and organizational behavior, humans have carried out fruitful research on their own visual system from the macroscopic structure and working methods to the microscopic nerve cells and working mechanism, and a series of gratifying achievements have been made. Since the mid-1970s, many scholars have combined the above research results to carry out research work on computer vision and image processing technology based on the mechanism of human vision [1-5], seeking new technologies and new methods to

break the bottleneck of existing computer vision and image processing technologies in order to improve and enhance the performance of computer vision technology and image processing technology. At present, bionic and computer vision and image processing technology that combines human visual characteristics have become a hot research direction.

In 1987, Gray et al. discovered a biological phenomenon in which neurons in the cerebral cortex of mammals stimulate oscillations. Later, Eckhorn et al. constructed a mathematical model showing the oscillating behavior of visual cortex neurons based on this phenomenon, that is, Pulse Coupled Neural Network (PCNN), which becomes a Typical representative of the visual cortex neuron model. Since the working mechanism of the PCNN model is similar to that of the human visual cortex neurons (such as the pulse firing phenomenon of the visual cortex neurons after being stimulated and the refractory period characteristics of the human visual cortex neurons), the model has become one of the means of doing researches of image processing method that is based on human vision mechanism.

Gray et al. found through experiments on cat visual cortex that the generation of oscillatory response is a cerebral cortex phenomenon. This supports Eckhorn's synchronization hypothesis that synchronization is the mechanism by which local visual features can explain global perception. Therefore, they divided synchronization into two different types: stimulus-compulsive type and stimulus-induced type. Subsequently, some other researchers proposed a connection field model to simulate the synchronized activities of the cat's visual cortex [6, 7]. Johnson implemented a pulse-coupled neural network in the field of image processing for the first time, and analyzed the wave mechanism of information propagation [8, 9]. Ranganath and other studies have shown that PCNN is an effective tool for image smoothing, image segmentation and feature extraction [10]. In 1996, Kinser introduced a more effective impulse network, which produced results similar to the original network [11]. Since then, people have proposed a series of improved models of PCNN, aiming to adjust its performance to image processing algorithms [12]. The Intersecting Cortical Model (ICM) is one of the most representative simplified versions of the PCNN model, which is used to enhance the features in the image [13]. In 2009, Zhan et al. [14] introduced the Spike Cortical Model (SCM), which made a compromise between ICM and the original PCNN, that is, SCM is a simplified system of PCNN equations, but retains the connection field, while ICM only includes feeding enter. In recent years, heterogeneous PCNN [15-17] and non-full-step models [18] have been proposed and improved one after another, enriching the classification of PCNN models.

In this paper, the pulse-coupled neural network algorithm is used to achieve information compensation for the fused image with information loss, and a better visual effect is obtained. The article

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ICBSP '21, October 29–31, 2021, Xiamen, China
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ACM ISBN 978-1-4503-8581-7/21/10.
<https://doi.org/10.1145/3502803.3502805>

Figure 1: Image fusion algorithm flow based on improved pulse coupled neural network and discrete cosine transform.

includes three parts: introduction, pulse-coupled neural network information compensation, and conclusion.

2 PULSE COUPLED NEURAL NETWORK IMAGE INFORMATION COMPENSATION

2.1 Image Fusion Algorithm

Assuming that there is a source image that has been registered, the image fusion is divided into three steps. The first step is the initial fusion of the image. First, two-scale decomposition is performed. The source image is decomposed into a base layer image and a detail layer image through a low-pass filter, and then different fusion strategies are designed according to the characteristics of the base layer image and the detail layer image. The base layer image is fused using the average fusion strategy, and the detail layer image is fused using discrete cosine transform, and then the base layer image and the detail layer image are initially fused and reconstructed; The second step is to process the preliminary fused image through a pulse-coupled neural network optimized based on the sine-cosine objective optimization, so that the final result is more in line with the perception habits of the human eye. The algorithm flow based on improved pulse coupled neural network and discrete cosine transform is shown in Figure 1

Figure 2: Image schematic diagram of cavity

2.2 Image Information Compensation Algorithm Framework

After image fusion, information loss occurred in part of the fusion result, and holes appeared in some locations, as shown in Figure 2,

Figure 3: Block diagram of image information compensation mechanism

which is not possible for the final result of image fusion. Therefore, in order to avoid this unexpected situation, a compensation framework for image fusion is designed. This framework is designed for the purpose of obtaining better subjective effects and objective indicators. Obtain the difference image, $Diff F$, of the fusion image and the mean value of I_1 and I_2 from Formula (1),

$$Diff F = Fusion - \frac{I_1 + I_2}{2} \quad (1)$$

The difference image $Diff F$ is morphologically dilated as the input of the improved pulse-coupled neural network to obtain the different image $Diff F_{PCNN}$, and then normalize $Diff F_{PCNN}$. Finally, as shown in Figure 3, the difference image $Diff F$ is processed according to formula (2) and combined with $Fusion$ to obtain the final fused image,

$$Finish = Fusion + Diff F_{dilate} \times Diff F_{PCNN} \quad (2)$$

where $Diff F_{dilate}$ is the image obtained by morphological dilation of $Diff F$.

In order to clearly explain the algorithm flow of the information compensation mechanism, the algorithm frame of the entire compensation mechanism is shown in Figure 3. The pseudocode is as follows:

```

Begin
Input Fusion, I1, I2;
Diff F = Fusion - (I1 + I2) / 2;
Diff F_dilate = indilate(Diff F); Diff F_PCNN =
PCNN(Diff F_dilate);
Normalized treatment of Diff F_PCNN;
Finish = Fusion + Diff F_dilate × Diff F_PCNN;
End

```

3 IMAGE INFORMATION COMPENSATION EFFECT VERIFICATION

This part uses five evaluation indicators, including information entropy (EN), mutual information (MI), structural correlation degree (SCD), edge strength (Edge), and average gradient (AVG) for evaluation. The comparison objects are image information compensation methods with different parameters and different frames. The results of different compensation methods are shown in Table 1. Figure 2 is the image obtained by the two-scale fusion algorithm based on discrete cosine. Although the objective indicators are very good, the subjective effect is not good. It can be seen from the image that there are obvious holes. Figure 4(a) is the image obtained by adding the pixel points greater than 0.9 after normalization of the difference image $Diff F$ on the basis of the pseudo fusion image, $Fusion$. Figure 4(b) is the image obtained by adding the pixel points greater than 0.95 after normalization of the difference image $Diff F$ on the basis of $Fusion$. The effect is not very good either. In addition, there is a problem with this method, that is, each image needs to be tried artificially to get an appropriate pixel threshold, such as 0.9 and 0.95. Figure 4(c) is the image obtained by multiplying the difference image with the image of the improved pulse-coupled neural network and adding it to $Fusion$. This method does not require artificial selection of parameters, but holes can still be seen from the figure. Figure 4(d) is the method proposed in this paper. The difference image $Diff F$ is morphologically dilated, and then the dilated image $Diff F$ is used as the input of the improved simple pulse-coupled neural network, and then multiplied by $Diff F_{dilate}$, and the result is added to $Fusion$. It can be seen from the image that a good visual effect is obtained, and the indicators are relatively excellent.

Table 1: Results Table of Different Compensation Methods

	$Diff F > 0.9$	$Diff F > 0.95$	$Diff F \times Diff F_{PCNN}$	$Diff F_{dilate} \times Diff F_{PCNN}$
EN	0.99	0.99	0.99	0.99
MI	1.99	1.99	1.99	1.99
SCD	1.381	1.3789	1.3736	1.392
Edge	91.87	91.83	92.669	90.890
AVG	9.072	9.0608	9.145	8.962

(a) $Diff F > 0.9$ (b) $Diff F > 0.95$ (c) $Diff F \times Diff F_{PCNN}$ (d) $Diff F_{dilate} \times Diff F_{PCNN}$ **Figure 4: Results of different compensation methods**

4 CONCLUSION

In order to solve the problem of fusion information loss in some images after image fusion based on pulse coupled neural network and discrete cosine transform image fusion algorithm, this paper proposes a pulse coupled neural network image information compensation mechanism. Compared with other methods, the compensated image in this method are basically the same in objective indicators, and at the same time, a fusion image that is more in line with the human vision law is obtained. The proposed algorithm introduces the pulse coupled neural network model in the image information compensation framework, improves robustness, and while improving the image quality, makes the image more in line with human visual perception. But there are also some shortcomings. When the image contrast is low, the processing effect is poor. In the next step, we will continue to improve the algorithm and develop a more robust and applicable algorithm.

ACKNOWLEDGMENTS

This research was supported by the NSFC (No. 61572159) and the Natural Science Foundation of Heilongjiang Province of China (ZD2019E007).

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