

Interactive Entertainment Image Restoration Method Based on Hopfield Neural Network

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Abstract. The traditional image restoration methods of interactive entertainment are based on the original data. This paper proposes an interactive entertainment image restoration method based on Hopfield neural network. Firstly, the nonlinear mapping relationship between the degraded image and the real image is preliminarily established through the network, and then optimized by the algorithm. Finally, the image restoration can be achieved through the network. The experiments show that it has higher feasibility and the recovery effect on small-scale blur is better than the existing method.

1 Introduction

In 2018, the market of online game in China are growing steadily, with a market size of 64.33 billion yuan, which has a growth of 6.5% from the previous month and a 10.3% increase from the same period last year. The number of mobile game users was 475 million, which has an increase of 5.5% from the previous month; the number of PC game users was 416 million, which has an increase of 4.1% from the previous month. The mobile game market has reached 42.48 billion yuan, and the quarterly market has exceeded 40 billion for the first time.

The Hopfield neural network was proposed by Professor J. J. Hopfield, a physicist at the California Institute of Technology in 1982. The concept of "energy function" was introduced into the neural network and is the most famous and widely used feedback neural network. The feedback neural network is a looped neural network in the topology. The existence of the feedback loop causes the output part of the network to affect the input acting on the network, so that the network generates dynamic characteristics, which has a profound impact on the learning ability and performance of the network. All nodes are computational nodes and at same time accept inputs and deliver outputs to the outside world. It means that in the feedback network, the information is forwarded and forward feedback and this information feedback can occur between neurons in different network layers, or it can be limited to only one layer of neurons.

The technology of Image restoration has a wide range of applications. There are many factors in the process of obtaining interactive entertainment images that cause image quality degradation, such as optical aberrations, defocus and system noise, which can cause blurring and distortion of the image.

The purpose of interactive entertainment image restoration is to degrade the image, select the appropriate optimization criteria, and try to be close to the original image to improve the image. There are Wiener filtering, constrained least squares (CLS), iterative blind deconvolution (IBD) and other methods, the classical filtering methods of which often assume that the point spread function is known, and comprehensively apply the point spread function, the original image and the statistical characteristics of noise and other information. It can achieve the purpose of noise reduction and restoration, but the point spread function is not certain thus the need for blind recovery technology is urgent. The Hopfield neural network constructs the corresponding optimization objective function from the constraint relationship between the real image and the point spread function, and solves the clear image in a progressive manner, which can avoid the difficulty of directly estimating the point spread function. The disadvantage is that the calculation amount is large and the noise is sensitive. Fahmy applies a variety of prior data knowledge and constraints to the Hopfield neural network, thus search direction of the solution is better guided, but the convergence of the solution is related to the initial condition and the uniqueness of the solution is uncertain. Zhang et al. further used adaptive sparseness to verify the estimated point spread function and noise model, so as to better guide the method of optimization problem solving. The algorithm smoothes the image with rich details and the recovery result is more distorted. In addition, Cao et al. used a depth map of a single image to estimate the point spread function to implement Hopfield neural network quickly and efficiently. The disadvantage of that is that the attenuation and diffusion of light in the algorithm have the same degradation rule hypothesis and cannot satisfy edge regions that the the depths of scenes are not continuous which results in loss of edge detail and noise residue. In summary, the interactive entertainment Hopfield neural network needs to solve the estimated point spread function and reduce the amount of calculation.

2 Hopfield neural network

For interactive entertainment feedback neural network if the summing point (neuron) number is M , each node has M inputs and one output and all nodes are interconnected. It is a feedback dynamics system that takes a while to stabilize. In the feedback neural network structure, the input value y_i , $i \in [1, M]$ of the entire neural network is calculated by its output through some feedback mechanism.

Hopfield neural network is a fully connected feedback network, which means that every evolution result of the network is re-introduced as the input of the network. For example, the evolution result of A is re-evolved as the input of C. This process is mainly used for associative memory and optimization calculation.

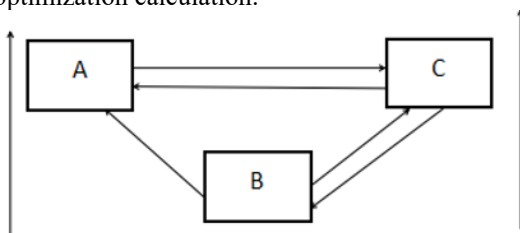


Figure 1. Topology of Hopfield neural network.

Associative memory is that when the network has obtained a vector the network evolves through feedback and another vector is obtained from the network output. Such an output vector becomes a stable memory of the network from the initial input vector association which is a balance point of the network.

3 Interactive entertainment Hopfield neural network image algorithm

The interactive entertainment Hopfield neural network image algorithm uses $X(t)$ to represent the state of the network at time t . If starting from any initial state $X(0)$ of $t=0$, there is a finite time t that from this moment, the neural network state does not change anymore:

$$X(t + \Delta t) = X(t), \Delta t > 0 \quad (1)$$

Therefore the network is stable. The neural network of interactive Hopfield will have the following characteristics: a symmetric neuron connection weight matrix W has no self-feedback, which means that the system has a stable solution and different states may converge to a stable state, which also known as a fixed point attractor; or oscillation occurs, that is converge on the period two attractors. Marcus et al. demonstrate that systems with symmetric weight matrices only have solutions of the two attractors and attractors of the fixed-point period.

The image algorithm network model of interactive entertainment Hopfield neural network is a discrete time system. Each neuron has only two states, which can be represented by 1 or 0. The

matrix composed of connection weights is a symmetric matrix with a diagonal of 0, which is

$$W_{ij} = \begin{cases} W_{ji}, & i \neq j \\ 0, & i = j \end{cases} \quad (2)$$

If $X(t)$ is used to represent the state of the entire network at time t , then X represents the state of each artificial neuron in the network. The number of components in the state vector X is the number of artificial neurons in the network. The number of pixels in the network is n , then the composition of vector X is as follows:

$$X^T(t) = [x_1(t), x_2(t), \dots, x_i(t)] \quad (3)$$

$x_i(t)$ indicates the state of pixel i at time t , and the state of the pixel at time $t+1$ is determined by:

$$X_i(t + 1) = \begin{cases} 1, & H_i(t) \geq 0 \\ 0, & H_i(t) < 0 \end{cases} \quad (4)$$

Here, $H_i(t) = \sum_{j=1}^n W_{ij}X_j(t) - \theta_j$, W_{ij} is the connection weight of the i pixel point to the j pixel point which is the threshold value of the pixel point j . There are two modes of operation in this way: the serial mode is that only one neuron i has a state change at any time t , while the remaining neurons remain in the same state; the parallel mode has a partial or total at any time t The neurons change state at the same time.

4 The structure of interactive entertainment Hopfield neural network

The network proposed by the interactive entertainment Hopfield neural network is composed of a 4-layer network structure (as shown in Fig. 2). Firstly the image is grayscaled and normalized, and then the dices are delivered as a training sample into the network. At the application layer, the input is quickly operated using 10 pixel collation and a feature map of 10 sizes is obtained. In the sub-sampling layer, the feature map of the upper layer of pixels is sampled by the mean of the size to obtain 10 feature maps. Although the feature extracted by the operation is reduced in size, the performance of the feature can still be guaranteed. At the output layer, the full connection method is used and finally the pixel values of the image are obtained through a linear regression network. The structure of network topology is 10:20:1. The hidden layer uses the Sigmoid function as the activation function and the output layer uses the linear function.

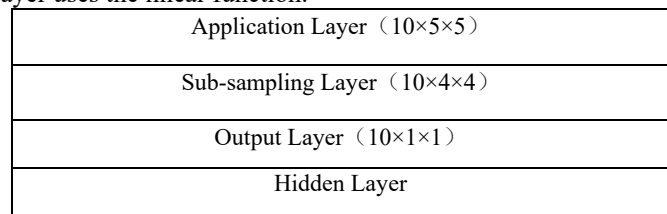


Figure 2. The structure of interactive entertainment Hopfield neural network.

5 Conclusion

In this paper, the application of interactive entertainment Hopfield neural network in image restoration is studied and image restoration is realized step by step. The image restoration effect is carried out from the aspects of network setting structure and the number of iterations. What's more, the

nonlinear mapping relationship between the degraded image and the real image is established through sample training. This method does not need to know the leading data of the degradation process, and does not need to consider the estimated point spread function. It takes the sliding window to select the sample directly, and takes full consideration of the influence of the domain in the degradation process. The restoration effect is better than the existing research method in small scale ambiguity.

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