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# Image Texture Enhancement Method based on Convolutional Neural Network

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**Abstract:** The existing image texture enhancement methods have the problem of imperfect image structure and texture layer decomposition process, resulting in low definition. A novel image texture enhancement method based on convolutional neural network is designed. The local gray changes of the image are measured to obtain the texture mapping index of the image. The convolutional neural network decomparts the image structure and texture layer to remove the information that does not conform to the given scale. By introducing the histogram matching constraint, the deblurring model is constructed to increase the gradient value of the image detail area and improve the image texture enhancement mode. Experimental results: The average sharpness of the image texture enhancement method in this paper and the other two image texture enhancement methods are 63.952, 53.340 and 54.952 respectively, indicating that the image texture enhancement method integrated with convolutional neural network has higher application value.

**Keywords:** Convolutional neural network; Image texture; Feature fusion; The texture layer; Image edge; Brightness

## 1. Introduction

Images are often an important way for people to understand information. Therefore, image plays an important role in information acquisition. Noise exists in any imaging system, which greatly affects the image quality under low light conditions. Image texture enhancement can be regarded as a general term for a class of image processing problems [1-2]. As a typical local texture descriptor, local binary pattern is widely used in machine vision and pattern recognition. Image deblurring and texture enhancement are used to enhance image quality and lay a foundation for image recognition. The research on low illumination image processing is one of the hot topics in today's society. In medicine, for example, the quality of b-ultrasound images will directly affect doctors' diagnosis and treatment. In military, the quality of military reconnaissance images is judged by image reconnaissance. Image texture enhancement technology has been widely applied in various fields, such as medical imaging, monitoring system and other fields. In terms of monitoring, the image quality obtained by the monitoring system under the condition of low illumination is usually fuzzy, so it is necessary to process the image obtained under this condition to achieve the purpose of observation. At the same time, image texture, as an important visual underlying feature, directly reflects the inherent properties of the object surface, and plays an important role in the field of image analysis and understanding. In addition, image fusion has been widely used in the field of image texture enhancement. Its algorithm principle is to carry out information complementation and feature fusion of images with different sensors, different phases and different resolutions in the same scene, so as to obtain pleasant and clearly visible images. Image texture enhancement can improve the interpretability of images or produce results more suitable for visual perception, thus providing more suitable input data for subsequent tasks. However, some of the existing algorithms are still sensitive to illumination diversity and texture rotation changes, and lack the ability to express the features of texture images containing noise. In general, the main purpose of image texture enhancement is to process the image so as to make it more suitable for a specific task or produce a specific effect [3-4]. Image texture enhancement involves a lot of image processing problems, and this paper will focus on image texture enhancement, texture smoothing and image blur and blur. There are many existing methods for image texture enhancement, but how to get different source images and how to set appropriate fusion strategies still need to be studied in depth.

## 2. Image Texture Enhancement Method based on Convolutional Neural Network

### 2.1. Obtaining the image texture mapping index

Image texture enhancement is an important research content in image processing as well as the most basic underlying operation, mainly through improving the visual effect of images [5]. Highlight some key points in the image to make the image more suitable for human observation or machine recognition and analysis. The main principle of image texture enhancement is to use Fourier transform to process the image, then use filtering function to process the operation, and finally use inverse Fourier transform to get the enhanced image after processing [6]. It is equivalent to judging from a point of view of human vision. Then the image brightness calculation formula is:

$$L = \frac{1}{E}\sum_{p=1,q=1}^{E} D_{pq} \tag{1}$$

In formula (1), $E$ represents the local gray value in the image, $D$ represents the pixel point vector, and $p,q$ represents the information entropy of the image smooth area and texture area. Image contrast calculation formula is as follows:

$$G = \left(\frac{1}{W-1}\sum_{p=1,q=1}^{E}\left(D_{pq}-1\right)^2\right) \tag{2}$$

In formula (2), $W$ represents image gradient, and other variables have the same meanings as formula (1). The greater the brightness and contrast of the image, the more likely that area of the image is to be an edge. Edge is the high-frequency information of the image, which basically includes all the details of the video image, so it is necessary to extract the edge of the filtered image. The smaller the brightness and contrast values, the more likely it is to be textured and smooth. Mean is used to estimate brightness and standard deviation is used to estimate contrast. However, because the extracted edge image does not provide the trend of image details to be corrected, it is not easy to directly map the calculated edges to the original image to enhance the details in the original image. Image brightness and contrast, can measure the local gray changes in the image, equivalent to judging from a perspective of human vision. Once the low threshold is set too high, edge detection will occur, while if the low threshold is set too low, it will still face the phenomenon of too much noise. Whether the threshold value is reasonable or not directly affects the final result of the algorithm. The greater the brightness and contrast of the image, the more likely that area of the image is to be an edge. The smaller the brightness and contrast values, the more likely it is to be textured and smooth. The image texture mapping algorithm firstly uses the filtering algorithm in this paper to deblur the input low-illuminance video image, that is, to smooth the video image and remove the influence of false details. Then the mean value is used to estimate brightness and standard deviation is used to estimate contrast for the details of the enhanced filtered video image. Spatial image texture enhancement method is to use convolution operation to operate the image pixels, and use the mask operator to move and operate each pixel in the image to enhance the image. Based on the above description, the steps of obtaining the image texture mapping index are completed.

### 2.2. Convolutional neural networks decompose image structure and texture layers

Convolutional neural network is inspired by biological natural visual cognition mechanism. The function of the convolution layer is to use the convolution kernel as a window to slide on the input image, so as to iterate over all pixels of the image, that is, to extract the characteristic information of the input image through the convolution operation [7-9]. Up to now, many classical network models have appeared in the fields of image recognition, target detection, image segmentation and image super-resolution reconstruction. A complete convolutional neural network consists of convolutional layer, activation layer, pooling layer, full connection layer, loss function, optimizer and other basic units, forming a large number of operational layers stacked on the input layer. In the case of full convolution, noise is eliminated step by step. After passing through each convolution layer, the noise level decreases and the details of the image content may be lost accordingly. In convolutional neural networks, feature dimensions extracted by convolutional operations are deep and large, which tends to increase the time complexity of the network [10, 11]. The convolutional layer retains the main image content, while the deconvolution layer is used to compensate details and improve brightness, which can achieve good de-blurring effect and improve image contrast and brightness. Different from the convolutional layer, the core of the pooling layer refers to the size of the local area, and there is no parameter to learn [12-13]. On the other hand, the convolutional layer gradually reduces the size of the feature graph, while the deconvolution layer gradually increases the size of the feature graph, ultimately ensuring the consistency of the input and output sizes, and also ensuring the test efficiency under the condition of limited computing capacity of the mobile terminal. In the process of scene segmentation, the forward formula of three-dimensional convolution and deconvolution is simplified to obtain:

$$H = \left[\frac{\phi}{S}\right]^{\frac{1}{2}} \times \frac{1}{9} \tag{3}$$

In formula (3), $\phi$ represents the number of convolution layers, and $S$ represents the convolution step length. Generally speaking, the image is composed of different components. In the frequency domain, the image is regarded as a set of high frequency signals and low frequency signals. The obtained image is the result of the environmental light hitting the object and then entering the lens of the human eye or camera through the reflection of the object. Therefore, the factors affecting the final imaging include two parts: the external light and the reflection of the object to the light. For different computer vision problems, researchers often regard images as the combination of different image layers. Therefore, image decomposition has been concerned in the field of image processing and is an important and challenging reverse problem. In fact, the scale of defining structure and texture is not clear. Usually different parameters are given according to the specific problem, and the information layer in the input image that does not conform to the given scale is removed as the content of another layer. In digital signal processing, noise model is generally divided into additive model and multiplicative model. Considering that consumer depth camera can provide depth image and its corresponding intensity image at the same time, many depth image deconfuzzification algorithms introduce intensity image as the guidance information of image decomposition. In addition, the color information of the intensity image actually has no direct relationship with the depth value, which means that the area with the same pixel value of the intensity image does not correspond to the same depth value. Based on the above description, the steps of image structure and texture layer decomposition are completed.

### 2.3. Building a defuzz model

The purpose of image deblurring is to retrieve texture details that are weakened or hidden due to image blurring. Image deblurring is a classic inverse image problem. Although it has a long history of research, it is still very active up to now. With the increasing popularity of mobile phones and other camera devices, this problem has more practical significance. Regularization model plays an important role in image deblurring. Although many regularization models are used to deblur images, some texture areas are still too smooth, making it difficult to restore texture details [14]. By introducing histogram matching constraints, natural textures can be produced in areas that are too smooth. Firstly, an image deblurring model based on histogram matching is proposed and its solution is given in detail. According to whether there is intensity image as the guidance information of image deblurring, there are generally two kinds of deblurring ideas as follows: one is single image deblurring algorithm, the other is image deblurring algorithm based on intensity image guidance. As seen in the previous chapter, in order to introduce the histogram matching model, an important problem is the estimation of the reference gradient histogram. Considering the complex relationship between histogram of fuzzy process and pixel image, bayesian nonparametric method is used to estimate the reference histogram. However, intensity images usually have too much redundant information while providing structural information, leading to some side effects. Define single image deblur, and decompose the input image into structure layer and texture containing noise. The expression formula is as follows:

$$Q = \max \sum \left\| \frac{1}{V_t - V_{t-1}} \right\| \tag{4}$$

In formula (4), $V$ represents the gradient of the structural layer, and $t$ represents the parameter controlling the smoothness of the structural layer. Rich texture information in images of different intensiities may introduce false edge information, resulting in texture overload phenomenon in the results obtained by depth deblurring algorithm. Compared with clean depth images, it is found that the deblurring results are obvious. When the average brightness of the input image is low, global brightness adjustment can effectively improve the visibility of the structure layer. The global distribution of image brightness is expressed as follows:

$$R_g = \frac{\log\left(Y + \frac{1}{g}\right)}{\log\left(Y_{\min} - \eta\right)} \tag{5}$$

In formula (5), $Y$ represents the number of guiding filters, $g$ represents the initial image brightness diagram, and $\eta$ represents adjustment parameters. Before the image texture enhancement, the difference between the noise points in the image and the surrounding pixels is not large, and the threshold value cannot be reached during the denoising process, leading to the unsatisfactory denoising effect. The noise is suppressed after the image texture is enhanced, because the noise has been amplified, and the image details and textures are mixed together, resulting in poor denoising effect and loss of some details. Combined with noise suppression and image decomposition, the main information of the image can be separated from the texture and noise, and the main information of the image can be better preserved without blurring the edges of objects in the image when suppressing noise. A single global illumination cannot reflect the local brightness distribution of the image, and the local illumination map cannot improve the overall brightness of the image. Therefore, the brightness enhancement amplitude of the input image is calculated by combining the two methods, and the brightness adjustment model layout is calculated by using the following formula:

$$\mu = \frac{T - T_d}{U} \tag{6}$$

In formula (6), $T$ represents the filter core scale, $U$ represents the threshold value of the control parameter value, and $d$ represents the difference between the global illumination map and the local illumination map. Image defuzzing research is divided into deep image sequence defuzzing research and single depth image defuzzing research, image defuzzing research mainly focuses on single image. Through detailed analysis and comparison, we can see the reliability of the estimation method proposed in this chapter and the effect of histogram matching constraint on improving image texture details. But when the input night image contains high brightness area, adjust its calculation method. It cannot reflect the brightness distribution of the local area, so it cannot effectively improve the brightness value of the dark image area. Based on this, the steps of constructing the defuzzification model are completed.

### 2.4. Improving image texture enhancement mode

The details of the image are mainly the edge texture part of the image. The gradient value of the edge texture part of the well-exposed video image is usually high, but once the texture gradient value of the image is reduced, the details of the whole image will become blurred [14, 15]. For example, some details are white, while the neighborhood is black, and the corresponding edge tends to increase the pixel value. Some details are black, but the neighboring pixels are white, and the corresponding edges tend to decrease the pixel value. The uniform mapping direction is adopted for all corresponding edges without considering the neighborhood distribution of details. Image brightness and contrast, you can measure the local gray changes in the image. The expression formula for texture extraction of a given image is:

$$f = \frac{1}{\gamma}\left(\frac{1}{\sum w + l}\right) \tag{7}$$

In formula (7), $\gamma$ represents the average vector of feature vectors of all texture images in the database, $w$ represents fuzzy kernel, and $l$ represents additive white Gaussian noise. The high-dimensional original feature vectors extracted from the image are projected into the low-dimensional feature vector space by linear transformation, so that most of the feature information in the original feature space can be retained to the maximum extent while reducing data redundancy. In the process of image detail enhancement, it is necessary to find the texture position in the image through edge extraction algorithm, that is, the detail part of the image, and then increase the gradient value of the detail area of the image, so that the details are highlighted. In order to construct an adaptive differential order mathematical model, it is necessary to automatically calculate the optimal order of each pixel in the image according to the local feature information of the image. If a video image is sharpened in a traditional way, the details will be highlighted, but the texture will be so sharp that the gradient transition will be unnatural. Firstly, an appropriate edge extraction algorithm is selected, and then an image texture mapping method is proposed to enhance the details of the image. The image gradient can be expressed as the rate of change of image gray scale, and the gray scale change is obvious when the gradient is large. Where the gradient change is small, the image gray level changes gently. If the gray level is the same, the gradient is zero. In the actual operation, special attention should be paid to the selection of the threshold value of the image. Because there is double threshold detection in the algorithm process, if the high threshold value is set too high, too few edges will be detected, and the real edge will miss detection. If the setting is too low, there will be a lot of image noise, which will affect the subsequent enhancement. The image gradient is actually a quantitative reflection of the texture. The image information entropy reflects the richness of the image texture information. In other words, in order to represent the original data with as little information as possible, the feature vectors after linear mapping must be linearly independent or orthogonal. Based on the above description, the steps of improving the image texture enhancement mode are completed.

## 3. Experimental Test

### 3.1. Building an experimental environment

The software environment of this chapter is Windows operating system. The CPU is Intel Core I7-37708 processor, the memory is 48GB, the video card is NVIDIA GeForce GTX 1080, and the video memory is 8GB. Framework: Tensor flow, compiler: Pycharm and the size of convolution kernel of each part of the network were set to 4*4. Parameters were initialized by Xavier method. Adam optimizer was used to perform gradient optimization algorithm to improve the stability of parameter update. A total of 100 epochs were iterated. When the return value of the loss function tends to be stable, the parameters completed by training are saved. In the above experimental environment, experimental tests are carried out.

### 3.2. Analysis of experimental results

The image texture enhancement method based on machine learning and the image texture enhancement method based on LBP Operator are selected to compare their performance with the image texture enhancement method in this paper. As we all know, sharpness is one of the most important standards to measure image quality. If the sharpness of the image is high, the figure outline in the image is relatively clear. If the definition is low, the figure outline in the image is very blurred. It can be used to measure the clarity of local details and their boundaries on the image. Clarity is defined as:

$$P = \frac{1}{\varphi}\left[\frac{1}{\sum_{x=1}^{x}\sum_{y=1}^{x}\sqrt{m_i(x,y)^2 + m_j(x,y)^2}}\right] \tag{8}$$

In formula (8), $\varphi$ represents the size of the image, $x, y$ represents the gray value of image pixels, $i, j$ represents the derivative of the image in the $i$ and $j$ directions, and $m$ represents the image gradient. Test the clarity of the three image texture enhancement methods under different learning rates, as shown in Figure 1-2:

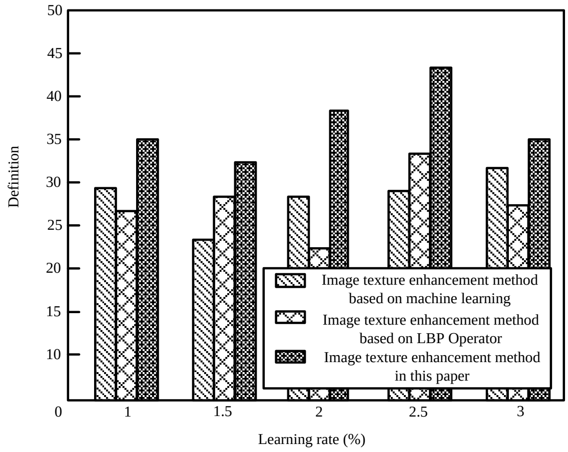



**Figure 1. Sharpness of the learning rate 3% image texture enhancement method**

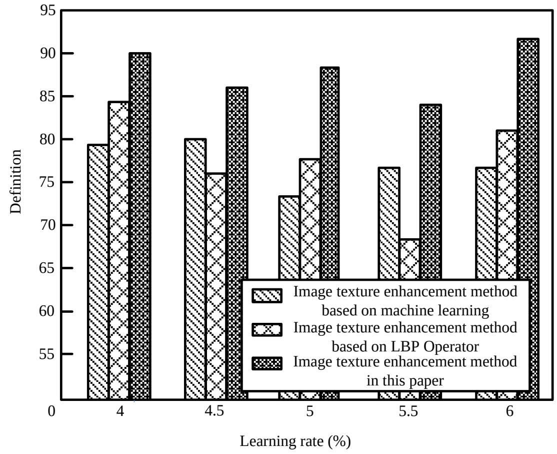
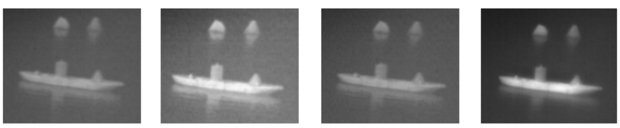



**Figure 2. Sharpness of the learning rate 6% image texture enhancement method**

According to fig. 1 and fig. 2, the mean sharpness of the three image texture enhancement methods can be obtained, as shown in Table 1 and Figure 3:

**Table 1. Average sharpness of image texture enhancement methods**

| Vector (%) | Image texture enhancement method based on machine learning | Image texture enhancement method based on LBP operator | Image texture enhancement method in this paper |
|---|---|---|---|
| 1 | 29.313 | 26.115 | 35.102 |
| 3 | 32.004 | 26.152 | 34.966 |
| 6 | 77.458 | 81.205 | 91.223 |
| 9 | 74.586 | 86.334 | 94.516 |



(a) Original image (b) Image texture enhancement method based on machine learning (c) Image texture enhancement method based on LBP Operator (d) mage texture enhancement method in this paper

**Figure 3. Comparison of the effects of different methods of image enhancement**

It can be seen from table 1 that the average clarity of the image texture enhancement method in this paper and the other two image texture enhancement methods are 63.952, 53.340 and 54.952 respectively, and the image texture enhancement method in the expository text has higher clarity.

## 4. Conclusion

According to the local statistical characteristics of the image, the image deblurring model is constructed, and the image structure and texture layer are decomposed by the convolutional neural network, and the optimal fractional order of each pixel in the image is automatically calculated. This method can adaptively adjust the operator mask coefficient according to the local feature information of each pixel in the image. Then, the gray value in the local neighborhood patch of the pixel is used to replace the gray value of the central pixel. Finally, the correlation information between image scale features is described by the symbiotic features of gray symbols, amplitudes and gray values of central pixels between different scale images, so as to enhance the performance of texture classification. Due to my limited ability, this paper also lacks the correlation test between feature tags, and will focus on related topics in the future.

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