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Colour Image Enhancement Method Combined PCNN and PCA Based on NSCT

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Abstract

A new colour image enhancement method based on NSCT and PCNN is proposed by using HSV model, in order to decrease the influence non-uniform luminance on true colour images. First, a colour image is transformed from RGB colour space to HSV colour space. Second, intensity channel is decomposed by NSCT, and we can obtain the low frequency sub-image and a series high frequency sub-images. Third, PCNN and PCA are applied on the low frequency sub-image, and nonlinear translation is employed on high-frequency sub-images. Then, the intensity component image is obtained by inverse NSCT. Finally, the colour image is obtained by transforming from HSV colour space to RGB colour space. Experiments illustrate that our algorithm can not only corrected non-uniform illumination in images, but also well maintain the colour and local details of images.

Keywords: Non Subsampled Contourlet Transform (NSCT); Pulse Coupled Neural Networks(PCNN); Hue Sataration Value space (HSV); color image enhancement; PCA

1. INTRODUCTION

Colour image contains wealth information. However, the collected colour images are non-uniform in luminance, low contrast and blurring because of the objective factors, which is not conducive to the post-processing of the image. Image enhancement is then used to weaken the useless information and highlight the useful information for the degraded image, which can improve the visual effect of the image and meet the demands of special analysis (Jobson et al., 2004; Rahman et al.,2005).

Colour image enhancement is generally performed in RGB colour space, in which contrast enhancement operations are respectively implemented on the three colour components R, G, B. However, it is difficult to guarantee the same coefficients of linear transformation of the three colour components because the three components are independent. It results in some changes in hue. So, in order to maintain the colour constancy, colour image in RGB space is transformed into HSV space and other colour spaces. Then, some enhancement algorithms, such as histogram equalization, homomorphic filtering(Zhang et al., 2013), wavelet transform(Gorgel et al., 2010), curvelet transform(Tan et al., 2009) and PCNN(Zhang et al., 2008; Zhang et al., 2010)on the grayscale image. Finally, the improved image is re-projected into RGB colour space. This kind of methods produces obvious improvement. This kind of methods based on multi-resolution analysis has been proposed with the development of multi-scale transform technology. Asmare M H, proposed image enhancement based on contourlet transform(Asmare et al., 2014). Zhang enhanced the infrared image in NSCT domain(Zhang et al., 2013; Yuan et al., 2011). Long enhanced colour image in NSCT domain (He et al., 2011; Long et al., 2013; Qiu et al., 2013). These algorithms obtain some improvement in visual effect. But there are also some problems. For example, histogram equalization can effectively improve the dynamic range of the image brightness but it will make the image blurring. Homomorphic filtering and PCNN can enhance the overall brightness of image, but it will produce some blurring effects in edges.

According to the research above, we combines PCNN and PCA to propose a colour image enhancement method in NSCT domain. First, a colour image is transformed from RGB colour space to HSV colour space. Second, intensity channel is decomposed by NSCT, and we can obtain the low frequency sub-image and some high frequency sub-images. In order to maintain the original clean regions of images, then the enhanced low frequencies and original low frequency coefficients are fused to obtain the new low frequency coefficients by using PCA fusion theory. The high frequency sub-bands are enhanced by Tanh Transform, Finally, the colour image is transformed from HSV colour space to RGB colour space. This algorithm can effectively deal with non-uniform luminance, colour deviation and blurring effects.

2. THEORY BASIS

2.1 Nonsubsampled Contourlet Transform(NSCT)

Contourlet transform (CT) is an effective multiscale geometric analysis tool, which can effectively describe straight line and curve singularity in images. CT can accurately capture edge information from different scale and frequency sub-band images. In CT, the advantages of wavelet transform are extended to high dimensional space. CT also can decompose an image in arbitrary directions, which is more suitable for hyperplane singularities of information. But the Gibbs effects are usually introduced in image processing due to the lack of translation invariance of the CT transform. In order to eliminate the spectrum aliasing phenomenon of CT transformation and enhance its shift invariance and directional selectivity, Cunha, Zhou and M. N. Do construct Nonsubsampled Contourlet Transform (NSCT) by combing the undecimated pyramid decomposition and nonsubsampled filter banks(Cunha et al., 2006).

The NSCT is a multi-directional images representation method with translation invariant property. It adopts the Laplacian pyramid transform and filter bank from DFB, to achieve the multi-scale and multi-orientation decomposition of an image. In NSCT, the two-dimensional frequency domains are segmented into some wedged directional sub-bands. NSCT has similar sub-band decomposition with CT transform, but there are no upsampling and downsampling operations in NSCT. Thus, the spectrum aliasing phenomenon cannot be produced in low frequency sub-band, in which the size of all the decomposed sub-bands are the same with that of the source image. Therefore, NSCT transform is applied efficiently in image enhancement and denoising(Cunha et al., 2006).

2.2 PCNN Model

Pulse Coupled Neural Network (Pulse-Coupled neural networks and PCNN) is a new type of Artificial Neural Network (ANN), which can simulate the vision of higher mammals. PCNN model is from research of the visual cortical neurons burst synchronization oscillation of cat. This model employs linear additivity and multiplying nonlinear adjustable coupling characteristics between neurons which overcomes training needs of the traditional neural network and decreases the computation complexity. Subsequently, PCNN model is widely used on many image processing applications(Johnson et al., 1999).

PCNN is a feedback neural network consisting of many interconnected neurons. Single neuron in PCNN model is shown in Figure 1. From Figure 1, we can know that each neuron is composed of three parts: input part, linking part and a pulse generator(Johnson et al., 1999). Receiver domain is constructed by the linear connection input channel L and feedback input channel F. L receives the input information of a local neighborhood of neurons. *F* receives the inputs from local and external information. *U*, name as internal activation element, is a nonlinear neuron connection modulation term, which is formed by the coupling product of *L* and *F*. That is to say U_{ij} is the multiplying modulation of F_{ij} from channel *F* and the positive bias of the transformed signal L_{ij} from input *L* by the connection strength *β*. The bias of model is normalized into 1. In a short period, the internal state signal obtained by multiplying the modulation can be regarded as the superposition result of a fast changing signal and a constant signal, because the change of signal L_{ij} are faster than that of signal F_{ij}. Pulse generating part consists of pulse generator and the comparator with variable threshold. The pulse generation depends on the relationship between internal activation item $U_{ij}$with dynamic threshold Eij. When U_{ij} is larger than the dynamic threshold E_{ij}, neurons are excited and neurons in activated state output a pulse. With the output of a neuron, threshold E_{ij} is improved rapidly through feedback. Pulse generator is closed and stops to transmit pulse and neurons are in non-ignition state until the threshold E_{ij} is exceeded U_{ij}. Then, threshold E_{ij} exponentially decreases. When E_{ij} is lower than U_{ij}, pulse is opened and the neurons are on fire. In PCNN, adjacent neurons with less difference are easier to be synchronously fired.

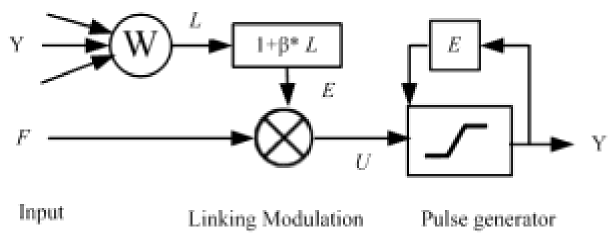

Figure 1. Pulse coupled neural model

The standard PCNN model is described as iteration by the following equations (Johnson et al., 1999):

$$F_{ij}[n] = e^{-\alpha_F} F_{ij}[n-1] + V_F \sum_{kl} W_{ijkl} Y_{kl}[n-1] + S_{ij} \quad (1)$$

$$L_{ij}[n] = e^{-\alpha_L} L_{ij}[n-1] + V_L \sum_{kl} M_{ijkl} Y_{kl}[n-1] \quad (2)$$

$$U_{ij}[n] = F_{ij}[n](1+\beta L_{ij}[n]) \; (3) \; E_{ij}[n] = e^{-\alpha_E} E_{ij}[n-1] + V_E Y_{ij}[n-1] \; (4) \; Y_{ij}[n] = \begin{cases} 1, & U_{ij}[n] > E_{ij}[n] \\ 0, & otherwise \end{cases} \; (5)$$

In equations(1)-(5), $F_{ij}[n]$ and $L_{ij}[n]$ are the feedback input and linking input of the neuron (i, j) in nth iteration, respectively. $S_{ij}$is the external stimulus, which is the value of pixel (i, j) in the input image. *β* is the linking parameter. $U_{ij}[n]$ is the internal state of the neuron. $E_{ij}[n]$ is the dynamic threshold. W_{ijkl} and M_{ijkl} are the synaptic weight coefficients. $Y_{ij}[n]$ depends on the internal state and threshold. αF ,αL, and αE are the attenuation time constants of F_{ij} , L_{ij} and E_{ij}. V_F, V_L, V_E denote the inherent voltage potential of F_{ij} , L_{ij} and E_{ij}, respectively.

2.3Principal Component Analysis(PCA)

Principal component analysis (PCA) is a statistical feature extraction method widely used in image analysis and pattern recognition fields, which is based on K-L decomposition. PCA is usually applied for feature extraction and dimensionality reduction by making full use the second order statistical information of the data. By finding some vectors representing the variance, the original data from the high dimension space is projected into a low dimensional space. The dimension-reduced data maintains the main information of the original data, which makes the data more tractable. The PCA method is widely used in data compression and dimensionality reduction of multidimensional data, in which some relevant indicators are re-combined into a new set of independent comprehensive indexes to replace the original index(Yang et al., 2004).

3. IMAGE ENHANCEMENT OF COLOUR IMAGES BY PCNN AND PCA IN NSCT DOMAIN

The true colour image is converted from RGB space to HSV space, because the human visual system is more sensitive to the change of intensity than those of hue and saturation. In HSV space, NSCT transform is conducted first on the intensity component V, to obtain the low frequency and high frequency sub-band coefficients. And then the low frequency coefficients are enhanced by the PCNN model, which will be fused with the original low frequency coefficients by PCA fusion method to obtain the final low frequency coefficients. Because the adjustment of low frequency will have some influences on the edge and texture information, proper transforms are used on the high frequency coefficients for the preservation of image edges. In this paper, the tangent function is used in the high frequency sub-bands. Then, inverse NSCT transform is implemented to obtain the enhanced component V. Finally, the image is restored into RGB space.

3.1 Low Frequency Enhancement

PCNN can be considered as a single layer of two-dimensional local connection network, when the PCNN is used for image processing. In this model, a neuron corresponds to a pixel in the image, and the adjacent neurons are connected with each other. The pixels with similar grayscale values will be activated simultaneously for the local smoothness. The pixels with lager grayscale differences will be asynchronously activated to enhance the edges and textures.

After NSCT transform of the component V, the main energy of the image is concentrated on the low frequency sub-band that is an approximation of the original image. The improvement of the low frequency sub-band will have a direct impact on the original image. The low frequency coefficients are enhanced by PCNN in this paper. Feedback inputs of neurons are from the low frequency coefficients after NSCT transform. Each neuron is connected with the pixel corresponding to the low frequency sub-image pixel and the neighboring neurons. The pixels activated synchronously have similar grayscale values and different values can be found in the pixels activated asynchronously. In the standard PCNN model, there are only two kinds of states, ignition and non-ignition for its output, due to the hard limiting function, which corresponds to a binary image. In order to make the output mapping function of PCNN more effectively enhance the whole contrast of the image, Eq.(6) is employed as the mapping function, which can map the image intensity to an appropriate visual range.

$$Y_{ij}(n) = \ln I_{\max} - \frac{\Delta t}{\tau_0}(n-1) \tag{6}$$

where Imax is the grayscale maximum in the original image. n is the neuron. N_{ij} denotes ignition time (n=1, 2, 3,……). $\frac{\Delta t}{\tau o}(n-1)$ is the decay step of dynamic threshold function in (n-1) and is the time step of iteration. Δt is the perception output of N_{ij} in nth ignition, which is the intensity of the image.

3.2 Low Frequency Fusion

For the low frequency enhancement, some highlighted regions of the image are over-enhanced by PCNN, which results in the loss of image details. Therefore, the processed low frequency coefficients by PCNN are fused with the original low frequency coefficients by PCA, which can preferably preserve the clear areas in the original image.

There are two categories for traditional PCA fusion methods, principal component substitution fusion method and weighted fusion method. A new fusion rule of PCA is proposed for fusion in this paper. First, normalization is conducted on the original low frequency coefficients and the enhanced low frequency coefficients. Second, the two low frequency bands are divided into small patches with size of N*N which are vectorized to obtain Data1 and Data2. Then, Data2 is connected with Data1 to form a vector Data with length of 2*N. Then, PCA is implemented on Data to obtain the sorted eigenvalues val and eigenvectors vec. Finally, the mean of Data1 and Data2 is used to reconstruct the low frequency coefficients by combining vec. By the experimental comparisons, the proposed PCA fusion method can preserve the useful components of the original low frequency coefficients.

3.3 High Frequency Enhancement

In order to ensure clear image texture and edge, it is necessary to enhance the high frequency sub-bands when the low frequency sub-band is processed. For the high frequency enhancement, there are linear and nonlinear scaling. Linear scaling assigns the same amplification proportion for all the coefficients. However, nonlinear scaling can scale different regions by different ratios, according to the properties of the transform function. Logarithmic transform, exponential transform, tanh transform are widely used, and Figure 2 shows the function of tanh function, logarithmic function and y=x function. From Figure 2, we can see logarithm scaling degree is very small. However, tanh function can amplify the coefficients in middle interval by lager ratios, which is continuous and increasing. Specifically, it can be realized by equations(7)-(10). C is the high frequency sub-band coefficients. a controls the range magnitude of the high frequency, which is set as 0.6 in this paper. The maximum value of the high frequency sub-band coefficients is calculated first by Eq.(7). Second, the coefficients are normalized by Eq.(8). Then, Eq.(9) apply the nonlinear transform on the coefficients. Finally, the enhanced coefficients are transformed into the original range.

$$ma = \max(C(:)) \tag{7}$$

$$C = C./\,ma \tag{8}$$

$$C = \tanh(a.*c) \tag{9}$$

$$C = ma.*C \tag{10}$$

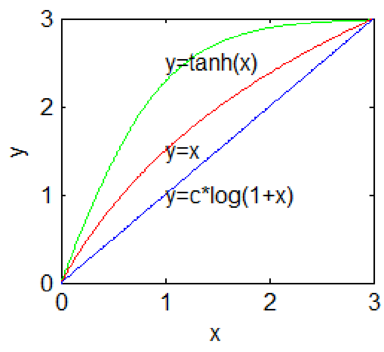

Figure 2. The function curve of transformation function.

4. Experimental Results

In this paper, simulation experiments are conducted on Matlab 2013a. We select two true colour images with non-uniform luminance, low contrast, blurring details for visual and numerical comparisons. Then two methods, spatial PCNN and PCNN in NSCT domain, are compared with our proposed method. Some indexes are employed to objectively evaluate the results, such as information entropy (IE), spatial frequency (SF) and average gradient (AG). According to the visual analysis, our proposed method can provide more natural image with clearer edges and slightest distortions which suggests that the result of the proposed method can well maintain enough information, although the whole luminance of the result from our proposed method is lower than those of compared methods. Besides, we can see that the proposed method performs better than the compared methods with respective of spatial frequency, average gradient from the numerical values in the Table 1. The values of information entropy vary with images. For the 'girl' image with less dark region, information entropy is improved a lot. But the information entropy of the proposed method is lower than that of PCNN in NSCT domain for the 'army' image with more dark regions. Overall, the proposed method can effectively keep the image edges and details with the non-uniform luminance of the image, and provide more natural visual effects.

a b

c d

Figure 3. Visual Comparison of the results from different methods. (a.Original image b.Spatial PCNN c.PCNN in NSCT domain d.Proposed method)

a b

c d

Figure 4. Visual Comparison of the results from different methods.(a.Original image b.Spatial PCNN c.PCNN in NSCT d.Proposed method)

Table 1 Evaluations of Image 'girl'

	IE	SF	AG
Original image	7.3252	23.2145	0.0567
Spatial PCNN	4.8618	26.8329	0.0656
PCNN in NSCT	7.0482	22.1946	0.0542
Proposed method	7.4505	28.9595	0.0707

Table 2 Evaluations of Image 'army'

	IE	SF	AG
Original image	6.3340	17.2505	0.0351
Spatial PCNN	5.0880	18.2073	0.0370
PCNN in NSCT	7.4219	15.4326	0.0314
Proposed method	7.2188	21.8123	0.0444

5. CONCLUSIONS

The method proposed in this paper has the following salient characteristics:

(1) The advantages of PCNN are utilized fully to enhance the overall brightness of the image, which can efficiently reduce the influences of non-uniform luminance in the image.

(2) The enhancement of the low frequency and high frequency are conducted in NSCT domain, which can simultaneously preserve details and improve the contrast of the image.

(3) Due to the use of the fusion of low frequencies, over-enhanced effects are suppressed, which can reduce the impacts of noise on images. Thus, the enhanced results are more similar with the original image in which the proper regions of original image have no over-enhanced effects.

6. ACKNOWLEDGMENTS

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