Adaptive image enhancement using nonsubsampled contourlet transform domain histogram matching

Yan Zhou (周 妍)[1,2], Qingwu Li (李庆武)[1,2*], and Guanying Huo (霍冠英)[1,2]

[1]*College of IOT Engineering, Hohai University, Changzhou 213022, China*
[2]*Changzhou Key Laboratory of Sensor Networks and Environmental Sensing, Changzhou 213022, China*
[*]*Corresponding author: li_qingwu@163.com*

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In this letter, we propose a novel adaptive image enhancement algorithm based on nonsubsampled contourlet transform (NSCT) coefficient histogram matching. Firstly, the original image is decomposed in the NSCT domain. Secondly, the NSCT coefficient histograms of the original image in corresponding subbands are adaptively mapped to those of the reference image via histogram matching after threshold denoising. Finally, the enhanced image is reconstructed from the modified coefficients via inverse NSCT. Experimental results demonstrate that the proposed adaptive algorithm effectively improves subtle features while suppressing noise compared with existing algorithms.

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Image enhancement is to improve the interpretability or perception of information in images for human viewers and providing "better" input for other automated image processing techniques. As a preprocessing technique, image enhancement is necessary for many important fields, for example, computer vision, remote sensing, and biomedical image analysis. Various techniques have been developed to improve the contrast of an image. These approaches can be broadly divided into two categories: spatial domain methods and transform domain methods.

Spatial domain enhancement methods deal with the image pixels. The pixel values are manipulated to achieve desired enhancement. Commonly used spatial techniques are linear stretch, histogram equalization (HE)[1], convolution mask enhancement, adaptive HE, etc. These conventional spatial techniques are usually simple and fast, but they often amplify noise and blur subtle edges when enhancing structures.

Transform domain enhancement methods involve transforming the image intensity data into a specific domain by using methods such as the discrete cosine transform (DCT), Fourier transform, and wavelet transform. Commonly used two-dimensional wavelet transform is a separable extension of one-dimensional (1-D) wavelet transform, which does not work well in capturing the image's geometric edges because of its isotropy. Multiscale geometric analysis[2] is developed to overcome the weakness of the separable wavelet transform in sparsely representing lines, curves, and edges. As one of representative multiscale geometric transforms, the contourlet transform[3,4] possesses very high directional sensitivity and anisotropy. Accordingly, contourlet-based image enhancement methods have been proposed owing to the attractive properties of contourlet transform[5]. However, the contourlet-based enhancement schemes often have two problems: one is that some artifacts may be introduced, partially because the contourlet transform is not shift invariant and the other is that the contourlet-based methods often need to adjust parameters manually according to the input test images.

The nonsubsampled contourlet transform (NSCT) is proposed to offer a shift-invariant version of the contourlet transform[6,7]. Owing to the properties of directionality, anisotropy, and shift invariance, NSCT has been well applied to image enhancement, segmentation, and edge detection[8–11]. In Ref. [12] an automatic image enhancement method based on NSCT was proposed to enhance the image contrast by modifying the NSCT coefficients using a nonlinear mapping function in each directional subband. Owing to its nonlinear mapping function, this method does not always inhibit noise and improve the image contrast very well.

In this letter, we propose a new image enhancement method based on NSCT coefficient histogram matching. The NSCT coefficient histograms of an original image are adaptively adjusted to the desired histograms of a good reference image via histogram matching without any parameters tuning, and threshold denoising is also adopted to remove noise. Some exciting experimental results show that the proposed method can effectively enhance the contrast while suppressing noise and preserving edges and produce better enhanced images than existing methods.

In the following paragraphs, we first discuss the NSCT and histogram processing technologies in detail.

Considering the limitation of separable wavelet transform in capturing directional information, researchers have recently considered multiscale and directional representations, for example, contourlet transform, that can capture the intrinsic geometrical structures such as smooth contours in natural images[3].

Due to downsampling and upsampling, a drawback of contourlet transform is its shift variant[4]. In 2006, Cunha *et al.*[7] constructed the NSCT, which was a shift-invariant version of the contourlet transform. In NSCT, the nonsubsampled laplacian pyramid is first used to capture the point discontinuities, then it is followed by a nonsubsampled directional filter bank to link point discontinuities into linear structures. The analysis part of this type of filter bank is shown in Fig. 1.

The NSCT not only has the multiscale and time–frequency localization properties of wavelets but also offers a high degree of directionality, anisotropy, and shift invariance. Therefore, it can effectively capture geometry and directional information of images.

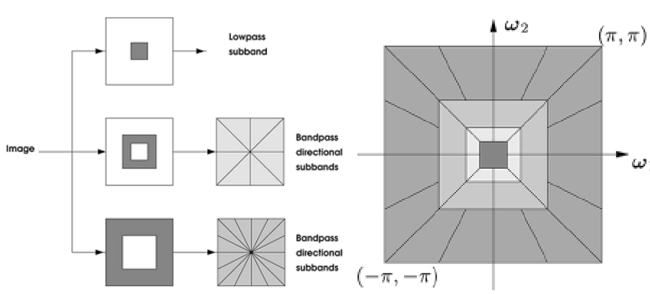
HE is one of the most conventional methods to perform contrast enhancement owing to its simplicity, automation, and effectiveness. HE attempts to alter the spatial histogram of an image to closely match a uniform distribution automatically[1]. Because of its global treatment of the image, HE results in an undesired loss of local detail. It is also common that HE tends to over enhance the image contrast if there are high peaks in the histogram, often resulting in noise amplification and other artifacts in the output image. Histogram matching, a more generalized version of HE, allows us to specify the shape of the histogram that we wish the processed image to have. This is also known as histogram specification. In our case, we promote it to NSCT domain, effectively mapping the NSCT coefficient histograms to match our desired histograms.

Since the NSCT can distinguish edges from noise and histogram matching can adaptively adjust image contrast, we present an adaptive image enhancement method based on NSCT domain histogram matching which combines histogram matching and NSCT domain enhancement. A block diagram of the proposed method is shown in Fig. 2.

To be specific, the method is executed as follows:

Input: Original image and reference image, for example, standard image *Lena*.

Step 1: Both the original image and reference image are transferred into NSCT domain. The NSCT coefficient histograms of the reference image are regarded as the desired histograms.



(a) (b)

Fig. 1. (a) NSCT filter bank structure. (b) NSCT frequency domain partitioning.

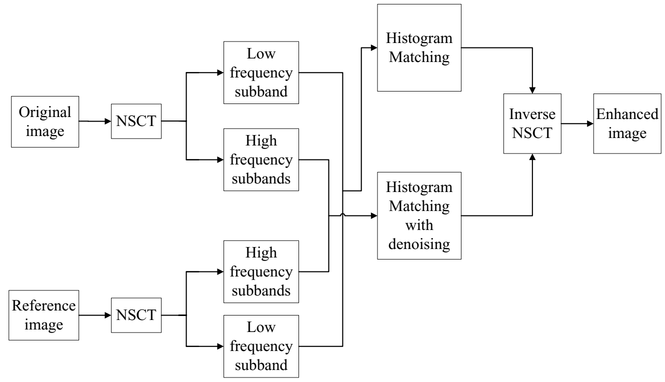


Fig. 2. Block diagram of proposed method using NSCT domain histogram matching.

Step 2: Since there is little noise in low-frequency subband, the low-frequency subband histogram of the original image is directly mapped to that of the reference image without denoising.

Step 3: Taking noise into account, histograms matching in high-frequency subbands are accomplished with adaptive denoising. The hard-thresholding rule is used for estimating the unknown NSCT coefficients. The threshold for each subband is chosen according to

$$T_{j,k} = k\sigma\sqrt{\sigma_{j,k}}. \tag{1}$$

This has been termed K-sigma thresholding. We set $k = 4$ for the finest scale and $k = 3$ for the remaining ones. The noise standard deviation σ of the original image is estimated using the robust median operator[13], that is, $\sigma = \mathrm{median}(abs(C))/0.6745$, where C refers to the NSCT coefficients in the finest subband. An approximate value $\sigma_{j,k}^2$ of the individual variances in the kth directional subband of the jth scale is calculated using Monte-Carlo simulations[14].

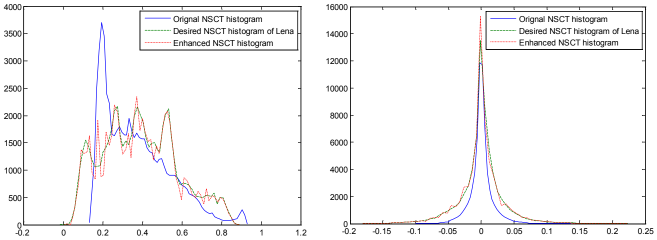
Each high-frequency subband histogram of the original image is mapped to that of the reference image after denoising.

Step 4: The enhanced image is reconstructed from the modified NSCT coefficients of the original image by inverse NSCT.

Output: Enhanced image.

Through mapping the data to our desired histogram, we can expand the dynamic range of the image and enhance the contrast. As an example, the NSCT histograms of image *Babies* mapped to those of image *Lena* can be seen in Fig. 3.

To demonstrate the effectiveness of our method, we compare it with two image enhancement methods: HE and the method in Ref. [12]. For our method, the NSCT decomposition level is selected to be 3. From low-resolution scale to high-resolution scale, the direction numbers of decomposition are 4, 8, and 16. The 1-D prototype filter used in multiscale decomposition is “maxflat” filter, and the 1-D prototype filter used in multidirection decomposition is “dmaxflat7” filter. The standard image *Lena* is chosen as a



(a) (b)

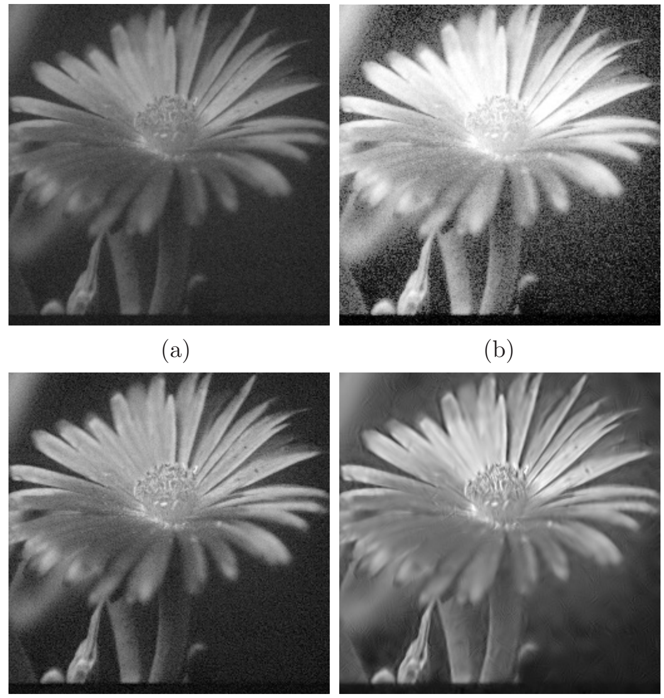
Fig. 3. NSCT histogram matching of image *Babies*: (a) low-frequency histogram matching and (b) high-frequency histogram matching in the first directional subband of the first scale.

Fig. 4. Standard image *Lena*.

reference image of good contrast and three typical low contrast images are chosen as test images, which are shown in Figs. 5(a), 6(a), and 7(a). Enhancement results on the test images are shown in Figs. 5(b)–(d), 6(b)–(d), and 7(b)–(d), respectively.

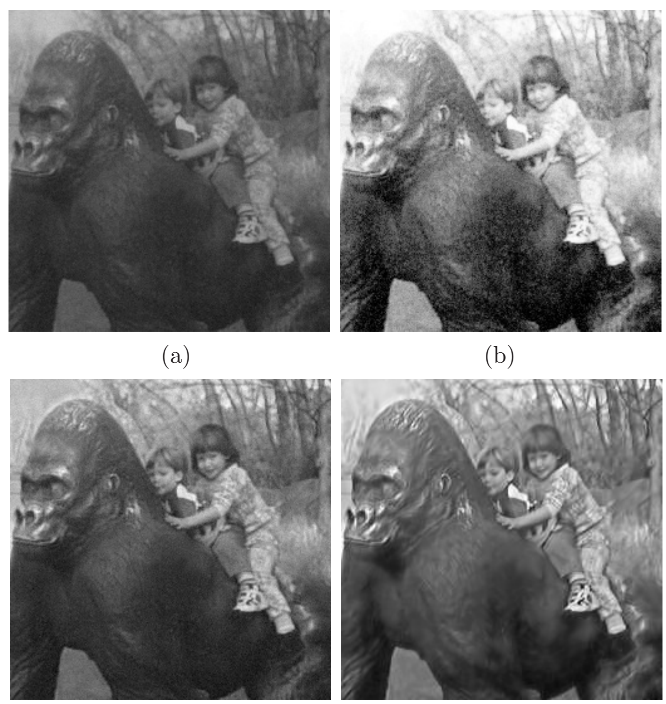
Qualitatively, the images in Figs. 5(b), 6(b), and 7(b) show that HE makes a considerable change in intensity distribution of test images, but it over-enhances the image contrast and hides some important subtle features (e.g., the flower's center in Fig. 5(b), the babies' clothes and shoes texture in Fig. 6(b), and the girl's button in Fig. 7(b)). In addition, the noise is amplified and thus the weak edges are blurred. Compared with HE, the method in Ref. [12] can preserve more fine edges and remove more noise, but the subtle features mentioned above are still faint accompanied with residual noise as shown in Figs. 5(c), 6(c), and 7(c). Moreover, the enhanced image *Girl* in Fig. 7(c) produces brightness distortion. However, our method offers some faint features in Figs. 5(d), 6(d), and 7(d), which are almost invisible in Figs. 5(c), 6(c), and 7(c). The subtle features (e.g., the flower's center in Fig. 5(d), the clothes and shoes details in Fig. 6(d), and the button and hair details in Fig. 7(d)) are emphasized wonderfully by the proposed method, while the overall contrast is well improved and noise is efficiently suppressed.

To allow quantitative evaluation of enhancement results, the no-reference image quality assessment factor Q was proposed[15]. The evaluation factor Q is based on



(a) (b) (c) (d)

Fig. 5. Enhancement results for image *Flower*: (a) original image, (b) enhanced image by HE, (c) enhanced image by Soyel and Mcowan[12], and (d) enhanced image by proposed algorithm.



(a) (b) (c) (d)

Fig. 6. Enhancement results for image *Babies*: (a) original image, (b) enhanced image by HE, (c) enhanced image by Soyel and Mcowan[12], and (d) enhanced image by proposed algorithm.

the singular value decomposition of the local structure tensor of an image and can measure both noise and blur level in an image[15]. The value of Q should increase

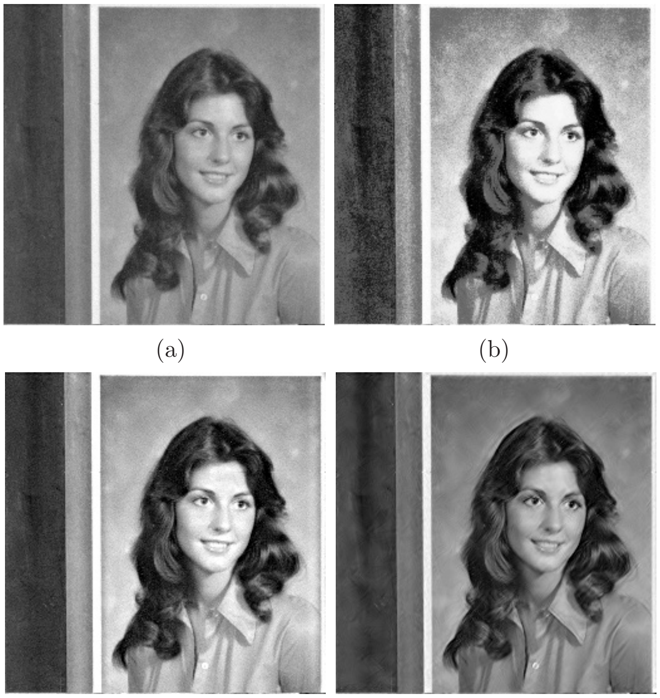


Fig. 7. Enhancement results for image *Girl*: (a) original image, (b) enhanced image by HE, (c) enhanced image by Soyel and Mcowan[12], and (d) enhanced image by proposed algorithm.

when an image becomes clearer with less noise. We use the evaluation factor Q to compare the enhancement performance of various methods listed in Table 1. We observe that the proposed method offers larger values of Q and outperforms other methods in enhancing image contrast, improving edge sharpness, and suppressing noise. Both subjective and quantitative assessments have shown that the proposed method is superior to the existing methods.

In the conclusion, we propose an adaptive image enhancement algorithm based on the NSCT coefficient histogram matching. The proposed algorithm maps the NSCT coefficient histograms of an image to those of a reference image adaptively without any parameter tuning. Experimental results show that the proposed algorithm can effectively enhance the contrast and subtle features in an image while simultaneously suppressing noise compared with the existing techniques.

Table 1. Factor Q Values Comparison of Different Enhancement Methods

Image	Original	HE	Soyel and Mcowan[12]	Proposed
Flower	0.0125	0.0868	0.0790	0.1493
Babies	0.0136	0.0744	0.0934	0.1239
Girl	0.0945	0.3108	0.4013	0.4935

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References

1. C. G. Rafael and E. W. Richard, *Digital Image Processing,* 2nd ed. (Publishing House of Electronics Industry, Beijing, 2002).
2. L. C. Jiao and S. Tan, Acta Electron. Sin. (in Chinese) **31,** 1975 (2003).
3. M. N. Do and M. Vetterli, Stud. Comput. Math. **10,** 83 (2003).
4. M. N. Do and M. Vetterli, IEEE Trans. Signal Process. **14,** 2091 (2005).
5. A. Swaminathan, S. S. K. Ramapackiam, T. Thiraviam, and J. Selvaraj, Biomed. Tech. Biomed. Eng. **58,** 87 (2013).
6. J. P. Zhou, A. L. Cunha, and M. N. Do, in *Proceedings of* IEEE *International Conference on Image Processing* I-469 (2005).
7. A. L. Cunha, J. P. Zhou, and M. N. Do, IEEE Trans. Image Process. **10,** 3089 (2006).
8. S. Li, L. Fang, and H. Yin, IEEE Geosci. Remote Sensing Lett. **9,** 836 (2012).
9. H. J. Li, Z. M. Zhao, and X. L. Yu, IET Image Process. **6,** 264 (2012).
10. Q. W. Li, G. Y. Huo, H. Li, G. C. Ma, and A. Y. Shi, IET Radar Sonar Nav. **6,** 526 (2012).
11. C. C. Lee, C. Y. Shih, S. K. Lee, and W. T. Hong, Multidimen. Syst. Sign. Process. **23,** 423 (2012).
12. H. Soyel and P. W. Mcowan, Electron. Lett. **48,** 917 (2012).
13. D. L. Donoho and I. Johnstone, Biometrika **81,** 425 (1994).
14. D. D. Y. Po and M. N. Do, IEEE Trans. Image Process. **15,** 1610 (2006).
15. Y. Shao, F. C. Sun, and Y. Liu, J Electron Inform. Technol. (in Chinese) **34,** 1779 (2012).