A Novel Color Microscope Image Enhancement Method Based on HSV Color Space and Curvelet Transform

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Abstract

A new method which is suitable for enhancing the color microscopic image quality based on HSV color space and curvelet transform is presented in this paper. The color microscopic image is firstly divided into hue, saturation and value components from RGB color space to HSV color space through the color space conversion. The value component is decomposed by the curvelet transform. A modulus square function and a linear gain operator are applied to the high frequency curvelet coefficients to reduce noise and weight the detail. Then, the processed curvelet coefficients are reconstructed in order to obtain the enhanced value component by inverse wavelet transform. The saturation component is enhanced by adaptive histogram equalization. The enhanced value and saturation components together with unchanged hue component are finally converted back RGB color space. The experimental results show that the proposed method effectively enhances the color microscopic image which is better to reduce noise and render the clarity and colorfulness of the original image.

Keywords: *Color Microscopic Image, Color Image Enhancement, HSV Color Space, Curvelet Transform, Modulus Square Function, Denoise.*

1. Introduction

In mining industry, digital microscope has become a valuable tool for observing very small copper sulfide concentrate particles (CSCP) in stage froth flotation, which provides a wealth of information, i.e. particle number count, particle size, shape and color, to control and improve the flotation process recovery. Unfortunately, the limited capacity of digital imaging microscope often produces badly illuminated images. The gangue minerals, such as quartz and feldspar that show bright color, have a great effect on the quality of microscopic image, while the intensity of light falling on a concentrate specimen is too much higher. Hence, microscopic image requires to be enhanced for improving the quality of color microscopic image for the further image processing such as edge detection, segmentation, feature extraction etc. Moreover, particle edge in pre-processing needs to be enhanced for particle number count and particle size characterization.

Color image enhancement is a necessary stage of image pre-processing technique which is used to improve the quality of color microscopic image for the better contrast or the visibility of specific features [1,2]. A few methods have been proposed to enhance color microscopic image in general. A very simple Phong model of illumination approaches a hue preserving enhancement problem between two objects in [3]. It is based on the assumption that ferrogram images are taken from a microscope looked at a three-dimensional microstructure with a parallel beam of reflected light. In order to enhance the interest regions of the digital color microscopic image, Ming Gao et al. [4] introduced two enhancement schemes, nuclei enhancement and cytoplasm enhancement, for enhancing the details pertaining to cell regions. To improve the quality of confocal microscopy fluorescent images, Edisson Alban [5]extended grey-level enhancement method to RGB color system image, balancing the overall contrast of the image at both ends, and preserving the edges of the micro particles for further detection, localization and analysis. By comparing performance between RGB and HSI linear stretching, Osman et al. [6] suggested that linear stretching in HSI color space was more suitable for enhancing the tuberculosis bacilli in Zieh1-Neelsen tissue slide image.

Most of enhancement methods discussed above treats the color microscopic image by extending grey-level contrast stretching enhancement. However, the main problem of such methods is that the noise may be amplified simultaneously and the edges of microscopic image cannot be enhanced. In this paper, we propose a novel color microscopic image enhancement method, based on HSV color space. This method for color microscopic image enhancement consists of curvelet transform [7-11], luminance processing and color preserving in the HSV. Firstly, the captured microscopic image is converted from RGB color space into HSV color space, in which Value (V) and Saturation (S) components are used to the

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enhancement process respectively, and Hue (H) component is kept intact. Secondly, the curvelet transform is applied to decompose the V component, and then new simple enhancement and denoising function are applied to the high frequency coefficients in curvelet domain. Finally, the S component is stretched for getting rich color display, and the S and V components together with the H component that is kept unaltered are converted back to RGB color image.

This paper is organized as follows. Section 2 briefly introduces HSV color space and the curvelet transform. Section 3 briefly presents the color microscopic image enhancement method in HSV color space. Experimental results are provided in section 4 and the conclusion is shown in section 5.

2. A Review of HSV and Curvelet Transform

2.1 HSV Color Space

In all of the color spaces, the HSV color space was been chosen in this paper duce to the three advantages as follows: firstly, it is closer to human perception, secondly it is user-oriented and thirdly, it gives better color conversion accuracy [12].

The HSV model consists of three components: hue, saturation and value. The hue component H, of which the range is from 0 to 360 degree, denotes the spectral composition of color, such as the green primary at 120 degree. The saturation component S defines the relative purity of the color, which ranges from 0 to 1.0. it indicates how much white light dilutes a pure color. The larger the S value is, the purer the color is. The value component V refers the luminance value of the color, which also varies from 0 to 1, namely, from black to white. Larger V value means brighter color.

The precise transformation between RGB and HSV color space is reference in [12].

2.2 The Curvelet Transform

The idea of the first curvelet transform [11] was first introduced by Candes and Donoho in 1999. The second generation curvelet transform [9] reconstructed by Candes and Donoho in 2004, Then a fast discrete algorithm [8] was added to the second generation transform by Candes et al. in 2005. This curvelet transform is not only a kind of nultiscale geometric transform with frame element indexed by scale, location and strong direction parameters in the frequency domain, but also much simpler structure, easier

manipulation, and less redundancy than its first generation version. There are two digital implementations of the second generation curvelet transform. The first one is fast discrete curvelet transform (FDCT) via unequally spaced fast Fourier transform (USFFT), and the other one is FDCT via wrapping. Both the implementations are linear and taken as inputting a Cartesian array to obtain an output of curvelet coefficients.

In this paper, we focus on FDCT via wrapping for image denoising [10]. The algorithm for the FDCT via wrapping can be summarized as follows[7,8,10]:

Step 1: Using the two dimensional (2D) fast Fourier transform (FFT) for the image and generate Fourier samples $\hat{f}[n_1, n_2]$, $-n/2 \leq n_1, n_2 \leq n/2$ in the frequency domain. The second generation curvelet transform form of the image $f(x_1, x_2)$ is:

$$\hat{f}(n_1, n_2) = \sum_{x_1, x_2 = 0}^{N_1-1, N_2-1} f(x_1, x_2) \cdot e^{-i2\pi(\frac{x_1 n_1}{N_1} + \frac{x_2 n_2}{N_2})}$$

Step 2: For each scale j and angel l, form the product $\tilde{U}_{j,l}(n_1, n_2)\hat{f}(n_1, n_2)$, $\tilde{U}_{j,l}(n_1, n_2)$ is the localized waveform window.

Step 3: Wrap the product around the origin and obtain the wedge $\tilde{f}_{j,l}[n_1, n_2] = W(\tilde{U}_{j,l}\hat{f})[n_1, n_2]$, where $0 \leq n_1 < L_{1j}$ and $0 \leq n_2 < L_{2j}$.

Step 4: Apply the inverse 2D FFT to each wedge $\tilde{f}_{j,l}$ and compute the discrete curvelet coefficients $c_{j,l,k} = \left\langle \tilde{f}(n_1, n_2), \hat{\varphi}_{j,l,k} \right\rangle$.

The inverse curvelet transform is computed by reversing the above steps.

2.3 A Characteristic of Curvelet Coefficients

By applying the FDCT via wrapping for nultiscale analysis, the image is decomposed into a series of disjoint sub bands, which are composed of the curvelet coefficients. It can be seen from Fig. 1. The sub bands are mainly classified as three groups, namely, the coarse scale, the detail scale and fine scale. The innermost scale is the coarse scale composed of the low frequency curvelet coefficients, which reflects the general information and key energy of the image. The outermost scale is the fine scale containing the high frequency curvelet coefficients, which reflects the detail information and edge feature of the image. The

remaining scales are classified as the detail scales containing the middle high frequency curvelet coefficients, which also shows the edge feature information of the image.

3 Our Method for Color Microscopic Image Denoising and Enhancement

The color microscopic image enhancement is an image preprocessing that reduces noise and preserves details in order to render it better quality than the original one for the later analysis. In general, the color microscopic image is represented by the RGB color space. Through the conversion the HSV color space from RGB color space, the image is divided into H, S and V components. All these enhancements are mainly achieved by changing the values of the V and S components.
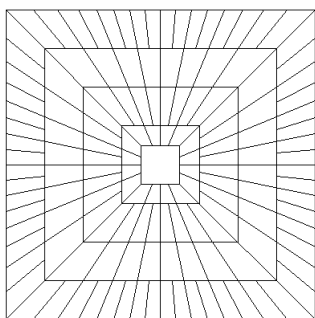

Fig. 1 Discrete curvelet tiling of space and frequency

3.1 V Component Enhancement

In our method, the V component can be seen as a 2D signal, and the FDCT via wrapping is applied to decompose the V component into different sub bands. The low frequency coefficients of the coarse scale are remained intact. The detail and fine scales for the high frequency curvelet coefficients of the various directions contain both the detailed information and the unwanted noise. The noise can be also magnified while we deal with these scales in order to enhance the detailed information. Therefore, we use a novel soft threshold function to solve this problem, and the function is called a modulus square function.

Let c_{jlmn} denotes the matrix of the high frequency curvelet coefficients in the curvelet transform decomposition, which dependent on scale index j, direction index l and spatial coordinate index m,n. The modulus square function is expressed as follows:

$$\hat{c}_{jlmn} = \begin{cases} c_{jlmn} - \frac{1}{2} \times (\sqrt{c_{jlmn}^2 - \lambda_{jl}^2} - \sqrt{c_{jlmn}^2 + \lambda_{jl}^2}) & c_{jlmn} \geq \lambda_{jl} \\ 0 & |c_{jlmn}| < \lambda_{jl} \\ c_{jlmn} + \frac{1}{2} \times (\sqrt{c_{jlmn}^2 - \lambda_{jl}^2} - \sqrt{c_{jlmn}^2 + \lambda_{jl}^2}) & c_{jlmn} \leq -\lambda_{jl} \end{cases} \quad (1)$$

Where λ_{jl} is a local soft threshold at scale index j and direction index l, and $\hat{c}_{jlmn}$ denotes the denoised curvelet coefficients. Obviously, the λ_{jl} varies with different scales in the curvelet transform, and it is defined as [13]

$$\lambda_{jl} = 2\sqrt{2}\, \sigma^2 / \sigma_{jl} \quad (2)$$

Where σ_{jl} represents the noise variance of the j-th scale and l-th direction sub band, and it is defined as

$$\sigma_{jl} = \sqrt{\frac{1}{N_{jl}} \sum_{k=1}^{N_{jl}} (c(j,l,m,n) - \overline{c}(j,l,m,n))^2} \quad (3)$$

In equation (3), N_{jl} represents the sub band length, and $\overline{c}_{jlmn}$ denotes the mean value of the sub band.

In equation (2), the parameter σ stands for the noise variance, which it is impossible to directly estimate in a single image. Let us assume that the noise variance is σ, and the fine scale coefficients are C_J. The noise variance is estimated from the parameter C_J by the robust median estimator [14]. It can be obtained by Eq. (4):

$$\sigma = median(|C_J|)/0.6745 \quad (4)$$

After the new shrinkage thresholding the high frequency curvelet coefficients, the detailed information of the V component is enhanced by the gain coefficients. Different high frequency curvelet coefficients contain different detailed information, so we can enhance different sub bands through different gain coefficients. Its mathematical model is defined as:

$$W_j = \frac{J - j}{J - 1} p + 1 \quad (5)$$

Where p denotes a gain factor, $p \in [0,1]$, J stands for the maximum number of the curvelet decomposition scale.

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We enhance all the high frequency curvelet coefficients with the follow equation:

$$H_{jl} = W_j \hat{c}_{jl} \qquad (6)$$

In equation (6), H_{jl} is the enhanced curvelet coefficient.

3.2 S Component Enhancement

Besides of the V component enhancement, we also appropriately improve the whole values of the saturation component in order to avoid color shifting or distorting. In this paper, we enhance the saturation component by implementing adaptive histogram equalization on the saturation distribution, and then obtain the better visual effect.

3.3 A Routine for the Proposed Method

The above curvelet transform enhancement method and saturation component improvement method are applied to the color microscopic CSCP image, and the proposed method is represented by the following routines:

Step 1: Convert the observed color microscopic CSCP image into HSV color space from RGB color space.

Step 2: Carry on the curvelet transform to decompose the V component, and obtain the low and the high frequency curvelet coefficients of each sub band.

Step 3: Estimate the noise variance σ Eq. (4) by using the fine scale coefficients.

Step 4: Obtain the threshold value using Eq. (3) on each sub band.

Step 5: Use the modulus square function (1) to denoise the high frequency coefficients, and obtain the weighted high frequency coefficients using Eq. (6), while the low frequency curvelet coefficients remain unchanged.

Step 6: Reconstruct the V component via the inverse curvelet transform and get the enhanced V component.

Step 7: Enhance the S component by histogram equalization.

Step 8: Convert HSV space to RGB space, and obtain the enhanced color microscopic CSCP image.

4 Experimental Results

In order to verify the effectiveness of the proposed method, the experiments are conducted on a set of color microscopic CSCP images of size 1200×1200 (already shown in Fig. 5 (a)) in MATLAB platform.

In these experiments, we focus on the color images us our analysis. In the preliminary validation phase, denoising and enhancement are performed on the V component with the curvelet transform and the novel soft thresholding of the curvelet coefficients prior to reconstruction.

The qualitative denoising abilities of the proposed method is analyzed and compared with the hard thresholding based on curvelet transform method (Hard_CT), soft thresholding based on curvelet transform method (Soft_CT). Simultaneously, the comparison of noise shrinkage has been investigated. In this paper, the V component of the color microscopic CSCP image in the HSV color space is used. The V component has been contaminated by additive Random noise, white Gaussian noise, Speckle noise, and Poisson noise, respectively. The noise parameters are set as follows: the standard deviation of 10, 20 and 30 for Random noise, a mean of 0 and a variance of 0.01 for Gaussian white noise, a variance of 0.04 for Speckle noise, and the default value for Poisson.

The denoising results on the V component are shown in Fig. 2 and Fig. 3, respectively. Fig. 2 shows denoised the V component denoised and Gaussian noise reduced by different methods. Further, according to the PSNR curve in Fig. 3, the proposed method has the better performance than the Soft_CT. The Hard_CT has the best performance for the above-mentioned noise, but this method can't generally yields more visually pleasing results. The Hard_CT method has almost the different performance for these noise. It means that the Hard_CT has the different ability for reducing different types of noise, also the Soft_CT and our method do. In summary, our method has a competitive performance for reducing these noise.

After denoising and enhancing the high frequency curvelet coefficients of the V component, we adjust the saturation component of color image to void the color-shifting in the second stage. The results are shown in Fig. 4. Fig. 4(a) is the saturation histogram of the original image, which has a 'bad' histogram peak. Fig. 4(b) is the result after adaptive histogram equalization processing, and the histogram curve is bell-shaped.
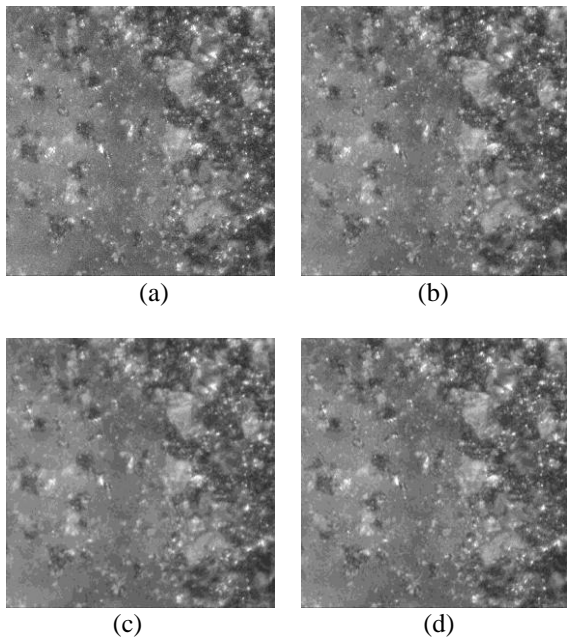
(a)   (b)

(c)   (d)

Figure 2 The V component denoised by different method: (a) The V component distorted by Gaussian noise, (b) Hard_CT (PNSR= 21.5077), (c) Soft_CT (PNSR= 19.9147), (d) our proposed method (PNSR= 20.3521).
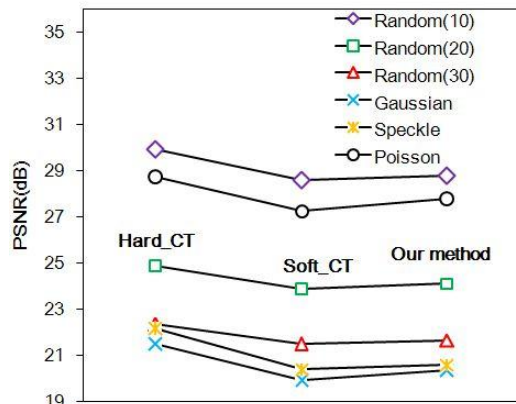

Fig. 3 Evolution of PSNR (dB) for V component

Lastly, we tested our proposed method on the color microscopic CSCP image as shown in Fig. 5. Fig. 5(a) is the original color image. This image quality is not good in colorfulness and lacks in clarity. Fig. 5(b) is the enhanced color microscopic image through modifying the V component values using the proposed algorithm, from which we can see that the particles and other objects become clearer than in Fig. 5(a). Fig. 5(c) is the result of colorfulness processing using adaptive histogram equalization processing for saturation component, which is improved greatly. We can see that the colorfulness is better

than that of Fig. 5(a), and the clarity effect is the same as Fig. 5(b).
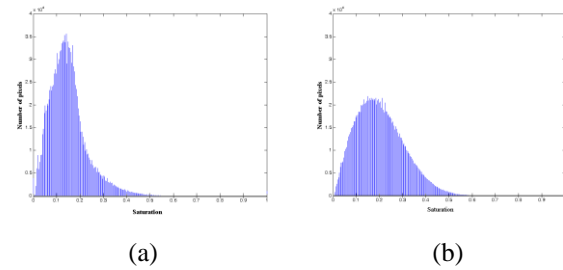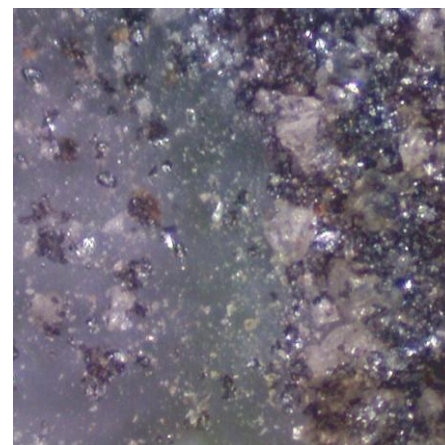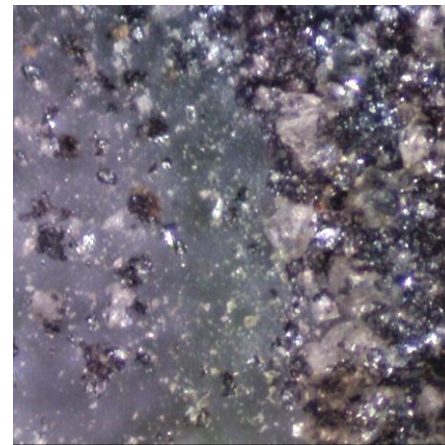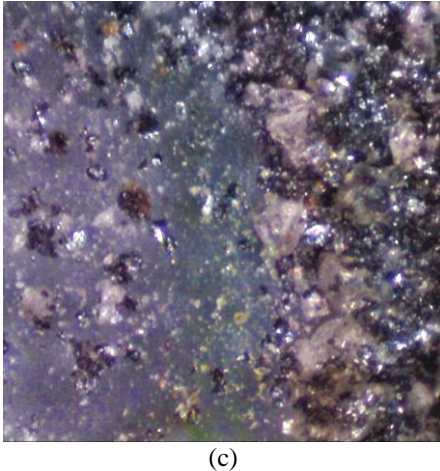

(a)   (b)

Fig. 4 The S component histogram: (a) Original S-histogram, (b) S-histogram after adaptive histogram equalization.

(a)

(b)

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(c)

Fig. 5 Enhancing results for the color microscopic CSCP image: (a) original color image, (b) enhanced color image after altering the V component values, (c) color image after adjusting the saturation.

5 Conclusions

In this paper, a new method for color microscopic image enhancement is presented, which consists of the color space conversion, the detail enhancement operation based on curvelet transform via soft shrinkage and the saturation adjustment. More specifically, we present a new curvelet soft thresholding method called modulus square function, which modifies the high frequency curvelet coefficients of the V component. The experimental results show that the method consistently produce the satisfactory result for the V component degraded by Random noise, Gaussian noise, Speckle noise, and Poisson noise, and the S component is adjusted to render the microscopic image colorfulness by adaptive histogram equalization. Hence, the proposed method is an efficient and reliable method for hue preserving and color microscopic image enhancement. To obtain satisfactory enhancement results, our future research will focus on optimizing the proposed method.

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