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IMAGE ENHANCING METHOD BASED ON BEMD AND CONTRAST-STRETCHING TRANSFORMATION

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Abstract. *Contrast-stretching transformation (CST) is a basic tool for processing image in dynamic range. For an image, the detailed information is mainly represented by high-frequency components, image background is associated with low-frequency components. Conventional CST does not distinguish well high and low frequency information of image. In this paper, we propose a method combining bidimensional empirical mode decomposition (BEMD) with CST to enhance the discernment of image details. An image is decomposed into different sub-images with different frequency components by BEMD, and then the sub-images with high frequency component are preserved, while the sub-images with low frequency component are removed. The high frequency sub-images are enhanced by CST and finally added for fusion. Experimental results and quantitative analysis show that the proposed method can enhance the image details better than conventional CST and other methods.*
Keywords: Image enhancement, Bidimensional empirical mode decomposition, Contrast-stretching transformation

1. **Introduction.** Image enhancement is important in medical image processing. CST [1] is a basic method of image enhancement, it can better enhance contrast, but CST inspects the details by using both high-frequency and low-frequency components, instead of treating differently, thus resulting in unsatisfied enhancement [2]. In recent years, image enhancement technology mainly includes fuzzy enhancement [3], non-subsampled contourlet transform (NSCT) image enhancement [4], retinex image enhancement [5], unsharp masking image enhancement [6] and optimization-based image reconstruction [7]. Although these methods have been greatly improved, there are still flaws. For example, Negrete and Sanchez-Yanez use a multi-level infrared fuzzy enhancement algorithm to enhance image [8], and the algorithm can highlight the multi-level gray and contour information of image. However, the membership function of the fuzzy set is deterministic and not flexible, and it is difficult to minimize the influence of uncertainty. Li et al. propose an adaptive image enhancement method based on NSCT [9], it can effectively suppress the noise of SAR images, while enhancing the significant features and contrast, but it adds redundant information. Rahman et al. propose Retinex algorithm for automatic image enhancement [10], and although it can reduce artificial artifacts, it will lose data. Liu et al. use adaptive thresholding in NSCT domain combined unsharp masking for medical image enhancement [11], which is simple, but the effect of enhancement is not obvious. Therefore, although the above mentioned methods can enhance the details of image, they also simultaneously introduce some unfavorable factors limiting image analysis. In addition, other image enhancement methods such as wavelet transform [12], guided filtering [13], histogram normalization [14] and filter construction [15] have also been developed; however, they have some limitations such as the wash effect and lose details [6]. In this study, we propose a method of combining BEMD [16] and CST to highlight image details.

BEMD is an adaptive time-domain analysis method suitable for nonlinear and non-stationary signals, and it is to obtain the upper and lower envelope surface by calculating the extremum of image and the mean envelope surface. Its filtering algorithm can be used to obtain a series of natural vibration modes of the two-dimensional image signals [17]. For our method, first, we decompose an image into different frequency sub-images by BEMD, and then filter out high-frequency sub-images, discard low-frequency sub-images which do not express the details, high-frequency sub-images are then manipulated by CST, and finally, sub-images transformed are fused by adding. Comparing conventional related methods, our proposed method has advantages that can process image by different frequency forms, and has local adaptability and multi-scale. Experimental results show that the proposed algorithm can remove the impact of low-frequency information on the details, the effect of enhancing details is better, and its implementation is simple.

The paper is organized as follows. Section 1 presents the background of this research topic. The hybrid algorithm combining BEMD and CST is provided in this section. Section 2 describes BEMD method with the advantages of local adaptability and multi-scale. Section 3 introduces CST algorithm that is a basic method for dynamic range image and good to change the image contrast and highlight the details. Section 4 describes the concrete steps of the proposed algorithm. Experimental results and analysis are shown in Section 5, and we visually and quantitatively compare the effects of the different methods for image enhancement. We conclude and introduce further research work in Section 6.

2. **Bidimensional Empirical Mode Decomposition Algorithm.** BEMD is based on empirical mode decomposition (EMD) [18]. Firstly, a time series is decomposed by EMD, and signals are decomposed into a limited number of intrinsic mode function. For each intrinsic mode function (IMF) component, instantaneous frequency and amplitude are obtained using Hilbert transformation [19,20]. In essence, the result of this method is to separate the fluctuations or trends of different scales in the signals. Since this decomposition is based on the local feature scale, it has good local adaptability and multi-scale advantages. The bidimensional empirical mode of an image $f(x, y)$ is decomposed into a finite two-dimensional IMF and the final residual function (REF). BEMD algorithm's specific implementation is the following steps [20,21].

(1) Initial value, let $i = 1$ and $k = 1$ denote the ith *IMF* and the kth cycle for calculating IMF_i respectively, and the initial value of the remainder is $r_{ik}(x, y) = f(x, y)$.

(2) Calculate the maximal envelope $h_{up}(x, y)$ of $r_{ik}(x, y)$ and its minimal envelope $h_{low}(x, y)$.

(3) Calculate the mean surface of $r_{ik}(x, y) : mean(x, y) = (h_{up}(x, y) + h_{low}(x, y))/2$.

(4) Calculate the difference function according to $r_{ik}(x, y)$ and its mean surface $mean(x, y) : D_{ik}(x, y) = r_{ik}(x, y) - mean(x, y)$.

When the difference function $D_{ik}(x, y)$ satisfies the characteristics of *IMF* function as described above, *IMF* is obtained: $IMF_i(x, y) = D_{ik}(x, y)$; let $r_{(i+1)1}(x, y) = r_{i1}(x, y) - IMF_i(x, y)$, $i = i + 1$ and $k = 1$, repeat steps (2)∼(4) to calculate next *IMF* when the characteristics are not satisfied; let $r_{i(k+1)}(x, y) = D_{ik}(x, y)$, and $k = k+1$, repeat (2)∼(4) until the difference function satisfies *IMF*.

In summary, an image $f(x, y)$ decomposed into n IMF_i and the remaining function $r(x, y)$ by BEMD can be expressed by the following formula:

$$f(x, y) = \sum_{i=1}^{n} IMF_i(x, y) + r(x, y) \tag{1}$$

In the above equation, IMF_i is the details of the image, which corresponds to the edge of the image, noises and other high-frequency information. The smaller value of i indicates the earlier decomposed *IMF*, and it corresponds to the higher-frequency. The remainder function $r(x, y)$ represents the trend information of the image [20].

3. **Contrast-Stretching Transformation (CST).** CST is a basic method for dynamic range manipulation. Its function is [1]

$$s = T(r) = 1/\left(1 + (m/r)^E\right) \tag{2}$$

where r represents gray value of the input image, s is the corresponding gray value of the output image, E controls the slope of the function, and m is average pixel value of the input image. The result is an image of higher contrast.

Since the limiting value of $T(r)$ is 1, output values are scaled to the range $[0, 1]$ when working with this type of transformation. Let $E = 20$, the curved shape of the input and output is shown below [1,22].

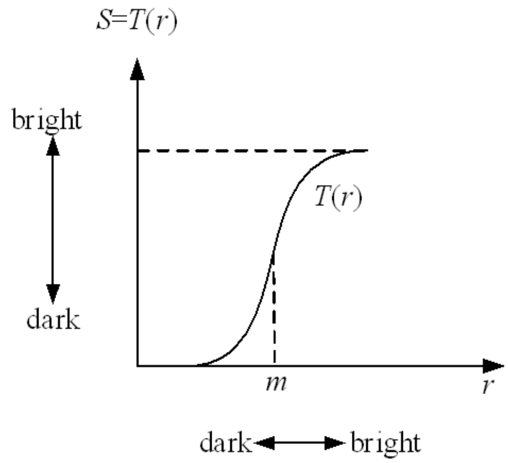


Figure 1. Contrast-stretching transformation

It can be seen from Figure 1, CST can be better to deepen the bright part and highlight the details.

4. **The Combined Algorithm of BEMD and CST.** In general, we are concerning image details in medical imaging rather than paying more attention to trend information. An image is composed of different frequency components. The high-frequency component represents the details of the image and the low-frequency component represents the trend information of the image.

The brief steps of the proposed hybrid method are as follows:

(1) The original image is decomposed using BEMD;

(2) Retained high-frequency components are kept and low-frequency components are removed;

(3) The high-frequency components are transformed by CST;

(4) The transformed high-frequency components are fused by adding;

(5) And then enhanced image is obtained.

In order to remove the impact of the trend information on the details, first using the BEMD algorithm that separates the fluctuations or trends of different scales in the signals, the image is decomposed into four sub-images IMF_1, IMF_2, IMF_3 and REF with different frequencies. IMF_1 represents the high-frequency part of the original image; IMF_2 contains the high-frequency components less than IMF_1, but it still has rich details; IMF_3 contains more low-frequency components; REF represents the low-frequency part of the original image, which represents the trend information.

We remove low-frequency sub-images IMF_3 and REF, keeping the high-frequency sub-images IMF_1 and IMF_2. In fact, that is because details are mainly concentrated on the high frequency part of the image. The value of E can be determined interactively, we let $E = 0.9$ in this paper, and then CST algorithm is used for IMF_1 and IMF_2, which can increase the contrast of IMF_1 and IMF_2, getting more clear and more prominent details. Finally, IMF_1 and IMF_2 are fused by adding, and its formula is as follows:

$$H = T(IMF_1) + T(IMF_2) \tag{3}$$

H represents the image enhanced by this algorithm, $T(IMF_1)$ and $T(IMF_2)$ are obtained using CST. Algorithm flowchart is shown in Figure 2.

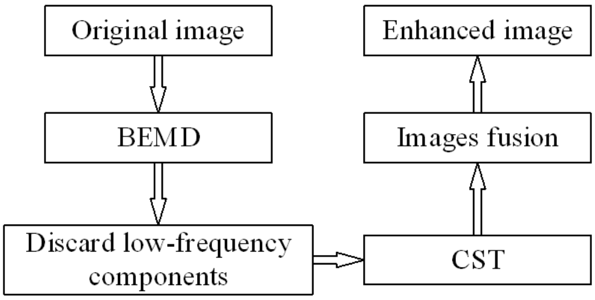
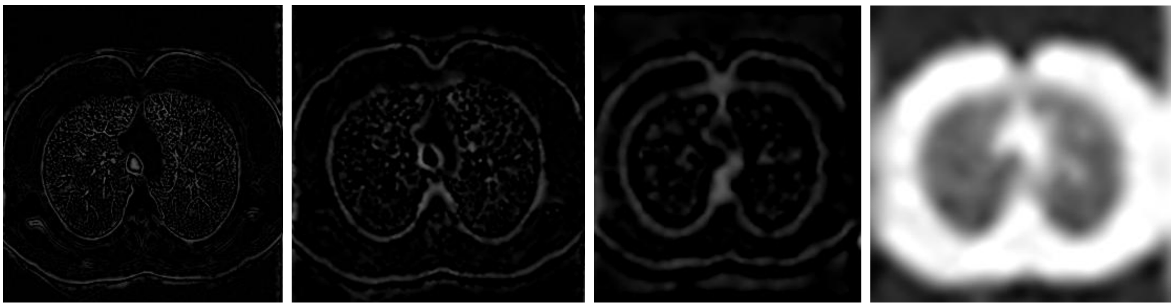


FIGURE 2. Algorithm flowchart

5. **Experimental Results and Analysis.** The two-dimensional gray image of 267×284 is used for experiment and analysis. In the experiment, BEMD method is used to decompose the image into three IMF components (IMF_1, IMF_2, IMF_3) and a residual function REF, and the resulting sub-image is shown in Figure 3. We note that the first component IMF_1 obtained has rich borders and details; the second component IMF_2 contains the high-frequency components less than the component IMF_1, but it still has rich boundary information; the third component IMF_3 contains more low-frequency components; the remaining part of the image REF is more vague, and it mainly contains low-frequency components, which represents the trend information as shown in Figure 3.



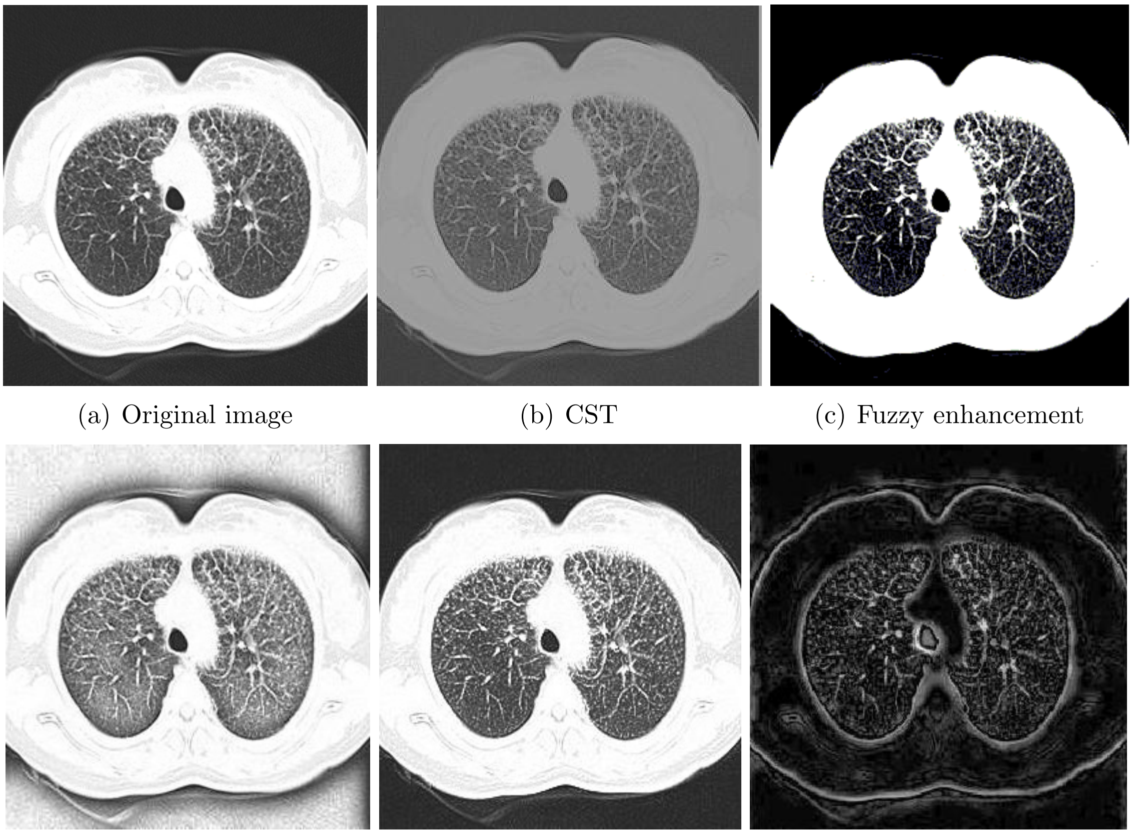
(a) IMF_1 (b) IMF_2 (c) IMF_3 (d) REF

FIGURE 3. Sub-images decomposed using BEMD. (a) and (b) show clear details, and (c) and (d) show unclear details.

The proposed method and other methods in this paper are used to enhance the original image respectively. Figure 4 shows the contrast images enhanced using different methods. As shown in Figure 4(f), the image enhanced by using the proposed method in this paper effectively highlight details, what is more, the boundary contour is clear.

From Figure 4 we can see that the enhanced effect based on the proposed method is better than the enhanced image by other methods, and it has a good enhancement effect on details. Our method can remove the impact of low-frequency information on the image, and the boundary becomes clear, which has some potential practical values in reality.

In addition, the enhancement effect is quantitatively evaluated by two methods calculating mean squared error (MSE) and peak signal to noise rate (PSNR) of the enhanced image as shown in Table 1.



(a) Original image (b) CST (c) Fuzzy enhancement

(d) Retinex enhancement (e) Unsharp masking (f) Our method

Figure 4. The comparison of different algorithmic effects. (a) shows the details unclear, (b) shows the details less and vague, (c), (d) and (e) show some details lost, and (f) shows the clear details and boundary contour.

Table 1. Image enhancement evaluated by MSE and PSNR

Methods/Evaluation index	MSE	PSNR
Original image	84.9933	28.8366
CST	85.0000	28.8366
Fuzzy enhancement	154.5529	26.2400
Retinex enhancement	84.9842	28.8374
Unsharp masking	84.9840	28.8374
Our method	45.1000	31.5890

From the above Table 1, the enhancement effect of our method is better than the CST and other methods. In addition, the image enhanced using the CST and other methods has no obvious enhancement details.

6. **Conclusion.** In this paper, we propose a hybrid method combining BEMD and CST, which mainly focuses on high frequency components to highlight image details. Experimental results evaluated by visual and quantitative assessment show that the proposed method significantly has more effectiveness. In the future research, we are investigating the proposed method on three dimensional model, and in other fields, such as image recognition, image segmentation and image compression.

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