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A Versatile Medical Image Enhancement Algorithm Based on Wavelet Transform

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Abstract

This paper proposed a versatile algorithm based on a dual-tree complex wavelet transform for intensifying the visual aspect of medical images. First, the decomposition of the input image into a high sub-band and low-sub-band image is done. Further, to improve the resolution of the resulting image, the high sub-band image is interpolated using Lanczos interpolation. Also, contrast enhancement is performed by singular value decomposition (SVD). Finally, the image reconstruction is achieved by using an inverse wavelet transform. Then, the Gaussian filter will improve the visual quality of the image. We have collected images from the hospital and the internet for quantitative and qualitative analysis. These images act as a reference image for comparing the effectiveness of the proposed algorithm with the existing state-of-the-art. We have divided the proposed algorithm into several stages: preprocessing, contrast enhancement, resolution enhancement, and visual quality enhancement. Both analyses show the proposed algorithm's effectiveness compared to existing methods.

Keywords

Contrast Enhancement, Dual Tree Complex Wavelet Transform, Resolution Enhancement, Singular Value Decomposition

1. Introduction

Image enhancement is one of the essential preprocessing techniques in image processing technology that leads to the improvement of contrast and visual appearance of an image to make the original image more appropriate for the specific application. For example, enhancing medical images plays a vital role in providing effective medication to the patient. For this, we have improved the resolution, and the contrast of the input image. In medical science, there are various requirements for image analysis. Some of the requirements include improving resolution and contrast, denoising, etc. Radiographic images considered for enhancement include magnetic resonance imaging (MRI), computed tomography (CT) scan, X-ray, ultrasound, etc. The image enhancement domain comes under the image processing technique, which deals explicitly with improving the quality of the input image. In addition, there are other domains, such as image restoration [1], image denoising [2], image forensics [3], etc., that also cover image processing. For image enhancement, various researchers have proposed different algorithms based on transforms like wavelet, curvelet, and contourlet [4-6]. The wavelet transform is most popular

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because it provides localization in the time and frequency domain. In literature, several variations of wavelet transform proposed like discrete wavelet transform (DWT), stationary wavelet transform (SWT), decimated DWT [7], etc. DWT generates an improved image with a higher resolution than the input image.

Certain disadvantages related to the decimated DWT is that it is not shift-invariant. Therefore, it will allow artifacts to appear in the resulting image. To overcome the problem encountered by DWT, we have used a dual-tree complex wavelet transform (DTCWT) for improving the resolution of the image. Due to the shift-invariant property of DTCWT, it is helpful for image enhancement purposes. To obtain the scaling and wavelet coefficients, we have used DTCWT. A high sub-band image needs to be processed to obtain a high-resolution image. The estimation of wavelet coefficients accomplishes this. We used two methods to improve the image's contrast: contrast limited adaptive histogram equalization (CLAHE) and singular value decomposition (SVD). We have organized the paper such that Section 2 explains the literature reviewed. Section 3 describes the proposed work, whereas Section 4 presents the simulated results and comparison with existing methods. Finally, Section 5 provides the conclusion.

2. Literature Review

Some of the relevant previous work includes algorithms based on a fast filtering process [4], histogram equalization [1,5], wavelet transform [1,6], computer-aided flow analysis [2], and top-hat transform [8]. Fast filtering algorithm [4] was used to filter the noise present in the input image. The filtered image is a weighted approximation of the four sub-band images. It reduces the noise in an image and enhances the edges of the resulting image. Image enhancement also emphasizes intensifying the contrast of the picture. This contrast improvement can be disease-specific also. Stetson et al. [5] have demonstrated a contrast improvement of the lesion. The authors emphasized the ultrasound images for improving the contrast-to-noise ratio (CNR). The major problem related to the ultrasound image is speckle noise [5].

Eklund et al. [9] have used a graphical processing unit (GPU) for image segmentation, image registration, and image denoising techniques. They have also emphasized ultrasound images that can be transmitted using hand-held transducers, which are cost-effective and flexible. Humied et al. [6] have used the histogram equalization (HE) technique and fast gray-level grouping to increase the image's contrast. This algorithm is suitable for low contrast images. Fan et al. [2] have proposed an adaptive algorithm for enhancing electric pictures. Kumar et al. [10] have used a quaternion wavelet transform (QWT) algorithm for medical image enhancement. It is well known that edge preservation plays a crucial role in medical image improvement [5,9], so QWT proved promising results. Different types of filters are used for transforming the image, such as wiener, Gaussian, and infinite impulse response (IIR) [11]. Image enhancement deals with enhancing the quality of the input image subjectively and objectively. In addition, it deals with improving the intensity level of the picture by providing values to newly added pixels.

3. Proposed Work

This paper presented a technique for medical image enhancement. For enhancing the images, preprocessing is performed, followed by post-processing. First, resizing the image is done during preprocessing by converting high resolution (HR) to low resolution (LR). Here, we have taken α as a resizing factor whose value lies between one-fourth and half. The second block of this process is an image enhancement algorithm. First, to preprocess, the image resolution and contract-related algorithm are applied. Then, it requires the transformation of the images in the frequency domain. In the next step, we have filtered the noise using Gaussian and median filters. Then, the inverse transformation is processed.

Further, post-processing of the output image improves the visual quality. We have considered MRI, X-ray, and ultrasound images to visualize the algorithm's effectiveness [5,12]. Evaluation of specific parameters for visualizing the effectiveness of the algorithm is done. Some of those parameters are structural similarity index measure (SSIM), mean square error (MSE), peak signal to noise ratio (PSNR), contrast ratio (CR), and naturalness image quality evaluator (NIQE) index.

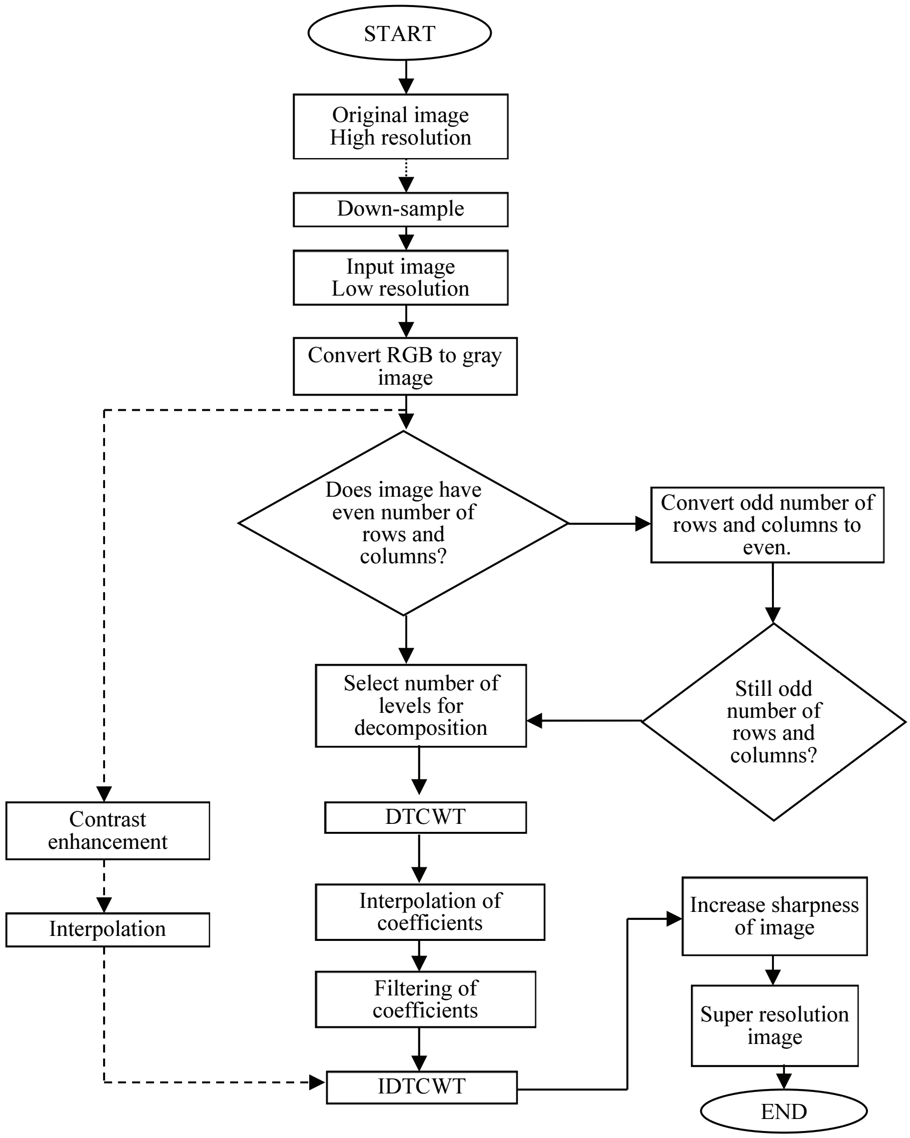


Fig. 1. Flowchart of the proposed algorithm.

Factors that may degrade the visual quality of the medical image are as follows:

- The environment constituting the radiographic image.
- The patient's motion while an examination is going on.
- Low light illumination in radiographic imaging like MRI, X-ray, etc.
- The patient's critical condition while the image capturing process continues.

These are the reasons which motivate us to develop a new algorithm that will enhance the quality of the medical image. Doctors and radiologists require a good quality image to provide effective and better medication to the patient. This paper emphasizes medical image enhancement, including radiographic images such as MRI, X-ray, ultrasound, etc. The proposed work is to process medical images to improve their visual quality. Fig. 1 shows the flow chart. Fig. 2 shows the detailed description of the same. We have done the software processing on MATLAB (version 2017).

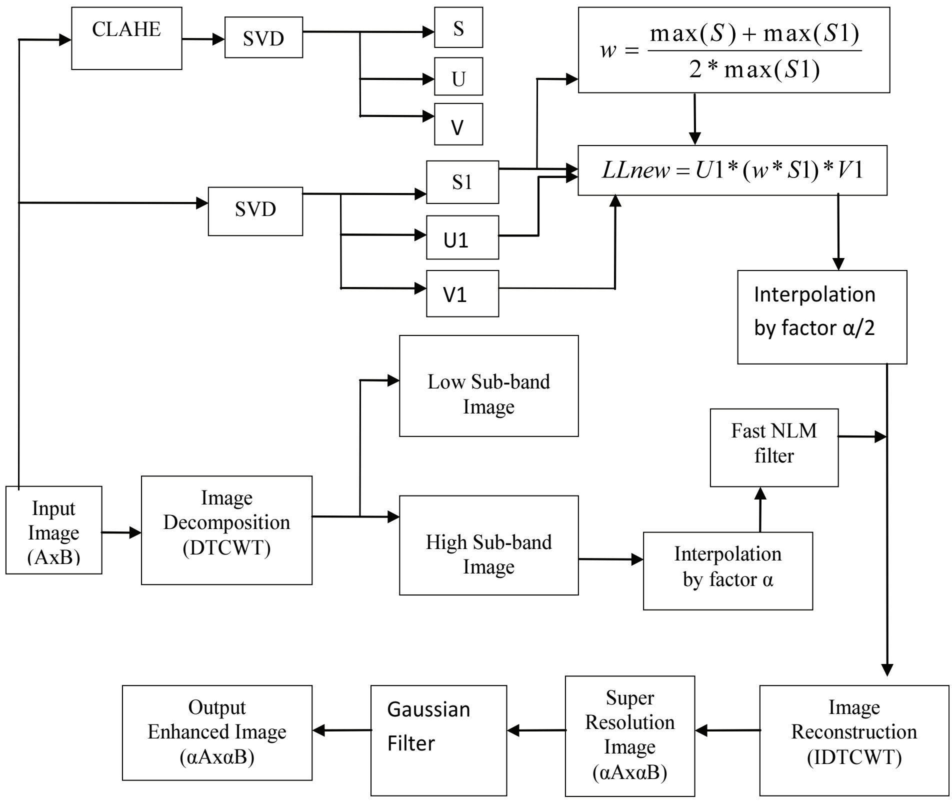


Fig. 2. A detailed description of the proposed algorithm.

The proposed algorithm comprises four stages: preprocessing, contrast enhancement, resolution enhancement, and visual quality enhancement. Fig. 3 shows the various simulation images. In Stage 1, preprocessing is performed. First, the input image "x" acts as an input, and then DTCWT is performed on this image, as mentioned below in Fig. 3(a). For contrast enhancement, we have used the SVD algorithm. Here, three matrices, namely S1, U1, and V1, are generated as described below in Fig. 3(b).

Stage 1: Pre-processing
a. Read image = x
b. Convert colored image to grayscale image using "rgb2gray" command.
c. Convert HR image to LR image using "imresize" command.
d. Generate even rows and even column image.

```
If (row= =even no. && column= = even no.)
x= read image
else
        if (row~ =even no. && column~ = even no.)
        x= read image by reducing size of the image by row-1 and column-1
                                        end
                                        end
```

(a)

Stage 2: Contrast Enhancement

a. Compute singular value decomposition of input image = x.
b. Generate U1, S1 and V1 images.
c. Compute adaptive histogram equalization of input image = x.
d. Generate U2, S2 and V2 image.
e. Evaluate weighting function as $w = \frac{\max(S) + \max(S1)}{2 * \max(S1)}$
f. Calculate final output as LL= (U1*(w*S1)*V1')

(b)

Stage 3: Resolution Enhancement

a. Select number of stages as L=1.
b. Apply DTCWT on input image = x.
c. Separate wavelet and scaling coefficients.
d. Interpolate wavelet coefficient using Lanczos interpolation.
e. Filter the coefficients using fast non local mean filter.
f. Take IDTCWT.

(c)

Stage 4: Visual quality enhancement

a. Pass resulting image from Median filter = filt.
b. Filter 'filt' with Gaussian filter and generate 'gau'.
c. Again pass this by Gaussian filter and generate 'smooth'.
d. Subtract = filt – smooth.
e. Add = filt + output.
f. Apply adaptive histogram equalization to the above generated image.
g. Show resulting image and histogram of the output image.
h. Compute PSNR, MSE, SSIM, contrast ratio (CR) and NIQE index.

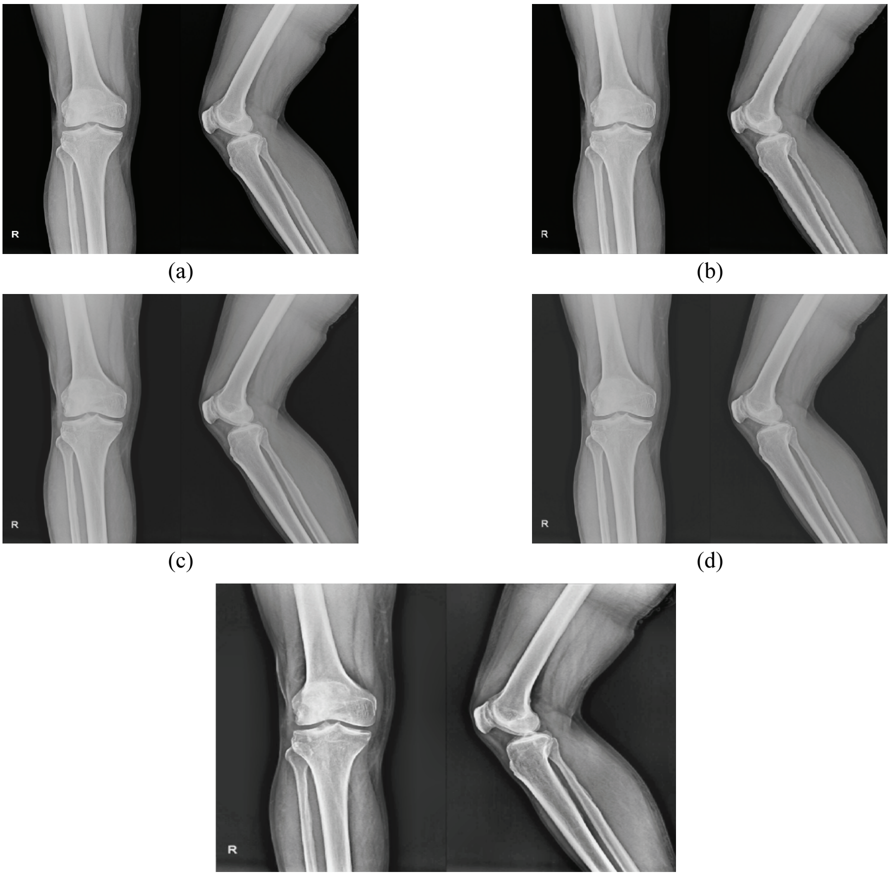
(d)

Fig. 3. Simulation stages of the proposed algorithm: (a) pre-processing stage, (b) contrast enhancement stage, (c) resolution enhancement stage, and (d) visual quality enhancement stage.

In the decomposition stage, DTCWT will generate wavelet and scaling coefficients. Interpolation of these coefficients is using Lanczos interpolation [13]. Further, these are filtered using a fast non-local mean filter (NLM) [13]. Finally, Fig. 3(c) shows the output of the inverse DTCWT algorithm as a final step. For visual quality improvement, various filters namely Median filter "filt," Gaussian filter "gau," and fast NLM filter are used as shown in Fig. 3(d).

4. Simulated Results and Comparison with Existing Methods

The proposed system has been tested and verified on various medical images to show the superiority of the proposed system in terms of visual and numerical results over the existing system. Several test images from the hospital and the Internet [14] are collected. These images are radiographic images such as ultrasound, MRI, and X-ray images. For this face X-ray and ribs X-ray image of size 512×512, knee X-ray of size 1954×2256, stomach X-ray of size 350×448, and stomach ultrasound [20] of size 634×437 is considered. We have compared the proposed algorithm with the DTCWT-NLM-SVD-RE [13] and DTCWT-Gaussian-CLAHE [15]. Fig. 4 shows the simulated result for the knee X-ray image. Fig. 4(a) shows the original image of size 1954×2256, Fig. 4(b) shows the input image of size 977×1128, Fig. 4(c) shows the DTCWT-NLM-SVD-RE [13] method based image. Fig. 4(d) shows the DTCWT-Gaussian-CLAHE [15] method based image, and Fig. 4(e) shows the DTCWT-Fast NLM-CLAHE method based image. Tables 1 and 2 show the quantitative analysis of the proposed algorithm with an existing algorithm [13,15-18].



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

Fig. 4. Simulated result for 1954×2256 knee X-ray image, (a) original image of size 1954×2256, (b) input image of size 977×1128, (c) DTCWT-NLM-SVD-RE image [13], (d) DTCWT-Gaussian-CLAHE image [15], and (e) DTCWT-Fast NLM-CLAHE image.

Table 1. Quantitative analysis of the proposed algorithm with the existing algorithms for face and ribs X-ray

Image	Parameter	Methods		
		DTCWT-NLM-SVD-RE [13]	DTCWT-Gaussian-CLAHE [15]	DTCWT-Fast NLM-CLAHE (proposed)
Face X-ray	PSNR	33.0000	34.0000	34.9880
	MSE	0.00050	0.00040	0.00030
	SSIM-Index [16]	0.90000	0.91000	0.90680
	NIQE	4.04100	4.00000	4.91540
Ribs X-ray	PSNR	36.1111	36.5000	37.1539
	MSE	0.00020	0.00010	0.00019
	SSIM-Index [16]	0.91000	0.91200	0.91100
	NIQE	3.62300	3.50000	4.65100

Table 2. Quantitative analysis of the proposed algorithm with the existing algorithms for knee x-ray, stomach X-ray and stomach ultrasound

Image	Parameter	Methods		
		DTCWT-NLM-SVD-RE [13]	DTCWT-Gaussian-CLAHE [15]	DTCWT-Fast NLM-CLAHE (proposed)
Knee X-ray	PSNR	26.7534	26.5138	32.5136
	MSE	0.00210	0.00220	0.00050
	SSIM	0.77370	0.72000	0.70450
	SSIM-Index [17]	0.95250	0.92230	0.89970
	CR	0.49950	0.46740	0.68960
	NIQE Index [18]	4.48270	4.27980	3.74530
Stomach X-ray	PSNR	24.0860	24.1160	31.1000
	MSE	0.00390	0.00390	0.00070
	SSIM	0.96020	0.96990	0.87920
	SSIM-Index [17]	0.97610	0.97880	0.60160
	CR	0.41770	0.42020	0.76610
	NIQE Index [18]	4.29780	4.04900	3.85930
Stomach ultrasound	PSNR	25.3902	25.3145	39.4680
	MSE	0.00290	0.00290	0.00013
	SSIM	0.83680	0.54580	0.72290
	SSIM-Index [17]	0.89930	0.81370	0.69630
	CR	0.71640	0.87770	0.87470
	NIQE Index [18]	3.12830	2.60630	2.83220

It is verified from the qualitative and quantitative analysis that the proposed algorithm outperforms other existing algorithms. The proposed algorithm has various advantages over existing methods. DTCWT produces fewer artifacts than DWT and SWT; due to the shift-invariance property of the DTCWT, the output will not change due to a slight shift in the input signal or image. Therefore, it will provide the perfect reconstruction of the picture. From Tables 1 and 2, we can visualize that achieved PSNR (in dB) is high for the images considered compared to other existing methods. It also provides smoothness to the generated image.

5. Conclusion

The proposed algorithm is a hybrid approach using DTCWT, NLM filter, and SVD and tested on a set of medical images. The efficiency calculation by examining various X-ray and ultrasound test images. The quantitative analysis evaluates PSNR, MSE, SSIM, CR, and NIQE index parameters. In the proposed algorithm, a fast NLM filter reduces the computational time, while SVD is used to improve the intensity distribution of the image. From both the analysis (quantitative and qualitative), it is clear that the proposed algorithm outperforms the other existing algorithms.

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