# An improved detail enhancement algorithm based on difference curvature and contrast field

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**Abstract**: The gradient image is always sensitive to noise in image detail enhancement. To overcome this shortage, an improved detail enhancement algorithm based on difference curvature and contrast field is proposed. Firstly, the difference curvature is utilized to determine the amplification coefficient instead of the gradient. This new amplification function of the difference curvature takes more neighboring points into account, it is therefore not sensitive to noise. Secondly, the contrast field is nonlinearly amplified according to the new amplification coefficient. And then, with the enhanced contrast field, we construct the energy functional. Finally, the enhanced image is reconstructed by the variational method. Experimental results of standard testing image and industrial X-ray image show that the proposed algorithm can perform well on increasing contrast and sharpening edges of images while suppressing noise at the same time.

**Key words**: image enhancement; contrast field; difference curvature; variational enhancement scheme

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## 0 Introduction

Images often have the shortcomings of low contrast and blurred texture details in the process of acquisition, quantization and transmission, such as X-ray images. This usually degrades the visual quality of images, for example, industrial X-ray images have blurred textures at the position of weld joint[1]. It is necessary to enhance the faint details to give qualified image information in practical situations. Image enhancement therefore is often used as a pre-processing stage for pattern recognition and registration.

Many algorithms have been proposed for image enhancement, including contrast enhancement[2-3] and detail enhancement[4-5]. The common algorithms for image contrast enhancement include histogram equalization[6-7] and its improved algorithms[8-11]. They redistribute image gray level in the histogram with equivalent probability, thus extending the dynamic range of the histogram. In addition, many researchers used the unsharp mask technique to enhance low contrast image, i.e., the model of symmetric logarithmic image processing (SLIP)[12] and the modified contrast-stretching method[13-14]. Furthermore, the approaches based on mathematical morphology[15-17] and human visual property[18-20] were proposed to process low contrast images.

At present, variational partial differential equation (PDE) based algorithms have been efficiently used. Although these algorithms are mainly focus on image denoising, it has been proved that variational PDE is useful for image enhancement. WANG, et al.[21] presented an approach for gray-level image enhancement, in which the amplifying contrast field of the image was constructed and the enhanced image was obtained via the variational approach. Then he pro-

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posed a variational enhancement method for infrared images based on total variation (TV) and contrast for infrared images[22]. ZHAO, et al. proposed a method of Gaussian mixture model-based gradient field reconstruction, which enhances image edge details well[23]. However, most gradient field-based studies only use image gradient, which is sensitive to noise and sometimes cannot distinguish between noise and edges.

In order to effectively enhance the details and features of an image and to address the problem of noise, in this study, we propose an improved contrast field enhancement algorithm based on difference curvature. Firstly, the difference curvature involving more pixels in neighbors is used to determine the amplification coefficient instead of the gradient, and then the contrast field is amplified according to the new amplification coefficient. Secondly, we construct the energy minimization scheme by using enhanced contrast field. Finally, the enhanced image is reconstructed by the variational method. Compared with bi-histogram equalization with adaptive sigmoid functions in Ref. [24], Laplacian sharpening in Ref. [25] and multiscale top-hat transform in Ref. [15], the proposed algorithm shows better performance in increasing low contrast and sharpening edges of images while suppressing noise at the same time.

# 1 Methods and materials

## 1.1 Simple contrast field amplification

Supposing $I(i,j),((i,j)\in\Omega=\{0\leqslant i\leqslant N-1,\ 0\leqslant j\leqslant M-1\}$, is a gray image, in which $M$ and $N$ represent the width and height separately, the definition of contrast at point $p\in\Omega$ is[26]

$$T_I(p)=\left(\frac{\partial I}{\partial i}(p),\frac{\partial I}{\partial j}(p)\right),\ p\in\Omega. \qquad (1)$$

Obviously, the contrast at $p$ is the gradient at $p$, i.e. $\nabla I(p)$, which describes the speed of gray-level change and its directions, the 2D contrast field (or gradient field) is therefore constructed by the contrast at every point in the image.

There is no doubt that an enhanced image should have big contrast values at edges and details, especially at weak edges and details. Thus, the contrast field should be amplified through a stretch of contrast values, keeping the direction unchanged. In other words, to enhance an image $I$ is to find an image $I'$ that has an amplified contrast field, namely

$$T_{I'}=kT_I=\begin{cases}k\nabla I, & |\nabla I|>\varepsilon,\\ 0, & |\nabla I|\leqslant\varepsilon,\end{cases} \qquad (2)$$

where $T_{I'}$ is the contrast field of enhanced image; $\varepsilon$ is the threshold, which is based on the thought that only edges need to be processed and flat regions need not; $k$ is the amplification coefficient indicating the stretch degree, traditionally $k$ is a constant, $k>1$. But a constant $k$ will have equal intensity either at strong edges or weak edges, resulting in an over-amplification at strong edges or under-amplification at weak edges. Therefore, we should strongly increase the contrast values at weak edges (always have small gradient values), while appropriately increasing the contrast values at strong edges (always have big gradient values). Thus, the selection of $k$ should be changed with the gradient value.

## 1.2 Improved contrast field amplification

According to the analysis above, the selection of $k$ plays an important role in the contrast field based enhancement algorithm. Some previous studies selected $k$ as a function of the gradient value, such as the study in Ref. [27]. A typical form of $k$ is

$$k(\nabla I)=1+\frac{\lambda}{(1+(\nabla I/C)^2}, \qquad (3)$$

where $\lambda$ is the amplification factor, $\lambda>0$, and $C$ is a constant and controls the attenuation speed of amplification coefficient with the gradient. Although the form of $k$ has been demonstrated to be able to achieve good enhanced edges and details, it is based on the image gradient, which is very sensitive to noise. In order to overcome this shortcoming, in this paper we use the edge indicator proposed by CHEN[28] to avoid noise. The edge indicator $E$ is called difference curvature, namely

$$E=\|\,I_{\eta\eta}|-|I_{\xi\xi}\,\|, \qquad (4)$$

where $\eta$ and $\xi$ are the direction of the gradient and the direction perpendicular to $\nabla I$, respectively; $I_{\eta\eta}$ and $I_{\xi\xi}$ represent the second derivatives in the directions of $\eta$ and $\xi$, respectively; and operator $|\cdot|$ denotes the absolute value. $I_{\eta\eta}$ and $I_{\xi\xi}$ can be calculated by

$$I_{\eta\eta}=\frac{I_x^2 I_{xx}+2I_xI_yI_{xy}+I_y^2I_{yy}}{I_x^2+I_y^2}, \tag{5}$$

$$I_{\xi\xi}=\frac{I_y^2 I_{xx}-2I_xI_yI_{xy}+I_x^2I_{yy}}{I_x^2+I_y^2}. \tag{6}$$

$I_x$, $I_y$, $I_{xx}$, $I_{yy}$ and $I_{xy}$ are discretizedly got by

$$\begin{cases} I_x=I(x+1,y)-I(x,y), \\ I_y=I(x,y+1)-I(x,y), \\ I_{xx}=I(x+1,y)+I(x-1,y)-2I(x,y), \\ I_{yy}=I(x,y+1)+I(x,y-1)-2I(x,y), \\ I_{xy}=\dfrac{I(x+1,y+1)+I(x-1,y-1)-I(x+1,y-1)-I(x-1,y+1)}{4}. \end{cases} \tag{7}$$

The new amplification coefficient $k$ is rewritten as

$$k(E(I))=1+\frac{\lambda}{1+(E(I)/C)^2}. \tag{8}$$

The amplification coefficient $k$ is a monotonous decreasing function of the difference curvature. According to Eq. (7), we take more neighboring points around $p$ into account when calculating $k_p$. In detail, this new amplification function not only involves the gradient components of four directions, but also involves other four pixels in neighbors. Fig. 1 shows how the amplification coefficient changes with the difference curvature.

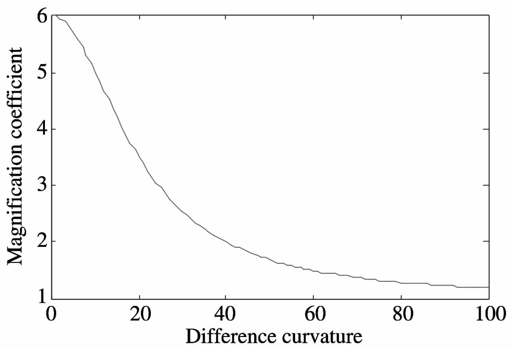



**Fig. 1 Relationship between curvature and amplification coefficient**

In addition, the parameter in our study is adaptive, which can be set to the value at 90% of the histogram of the gradient magnitude of the image and then to be processed according to the study in Ref. [29].

## 1.3 Improved contrast enhancement algorithm

According to the analysis above, the magnified contrast field in Eq. (2) can be rewritten as

$$G=T_{I'}=k(g(I))T_I=\begin{cases} k(g(I))\nabla I, & |E|>\varepsilon, \\ 0, & |E|\leqslant\varepsilon. \end{cases} \tag{9}$$

The difference curvature is used as the limiting condition for contrast amplification. The behavioral analysis of the edge indicator is as follows:

1) For edges, $I_{\eta\eta}$ is large and $I_{\xi\xi}$ is small, so $\|E\|$ is large;

2) For flat and regions, $I_{\eta\eta}$ and $I_{\xi\xi}$ are both small, so $\|E\|$ is small;

3) For isolated noise, $I_{\eta\eta}$ and $I_{\xi\xi}$ are both large and almost the same, so $\|E\|$ is small.

Therefore, the difference curvature $\|E\|$ is very useful to distinguish edges, plat regions and isolated noises.

To find the enhanced image $I'$, a common method is adopted to find an image $f$ in $L^2$ norm. Using a mathematical formula, it can minimize the following function

$$F(f)=\iint_\Omega |\nabla f-G|^2\mathrm{d}x\mathrm{d}y. \tag{10}$$

Using the variational method, the Euler-Lagrange in Eq. (10) is

$$\Delta f=\mathrm{div}G, \tag{11}$$

where $\Delta$ is the Laplacian operator, and div is the divergence operator. Several methods can solve the Poisson equation in Eq. (11). In this study, we adopt a simple iteration method according to Ref. [30] as

$$f^{n+1}=f^n-\frac{1}{4}(\Delta f^n-\mathrm{div}G), \tag{12}$$

where $n$ represents the number of iterations and $G=(G_x, G_y)$. The Laplacian operator and divergence operator must be discretized appropriately to avoid image displacement. For the Laplacian operator, we reconstruct the new image using forward difference derivatives while the divergence operator is computed using backward difference derivatives, which are expressed by

$$\Delta f(i,j)=f(i-1,j)+f(i+1,j)+f(i,j-1)+f(i,j+1)-4f(i,j), \tag{13}$$

$$\mathrm{div}G=G_x(i,j)-G_x(i-1,j)+G_y(i,j)-G_y(i,j-1). \tag{14}$$

Combining Eqs. (12)−(14), this integration is done intuitively as follows

$$f^{n+1}(i,j)=f^{n+1}(i,j)-\frac{1}{4}[(f(i-1,j)+f(i+1,j)+f(i,j-1)+ \\ f(i,j+1)-4f(i,j))-(G_x(i,j)-G_x(i-1,j)+G_y(i,j)-G_y(i,j-1))]. \tag{15}$$

We should notice that for a gray image, the range of values must set between [0,255]. Therefore, each iteration should be a restrained iterative form as

$$\begin{cases} f_{\text{temp}}=f^n-\dfrac{1}{4}(\Delta f^n-\mathrm{div}G), \\ f^{n+1}=\max\{0,\min(255,f_{\text{temp}})\}. \end{cases} \tag{16}$$

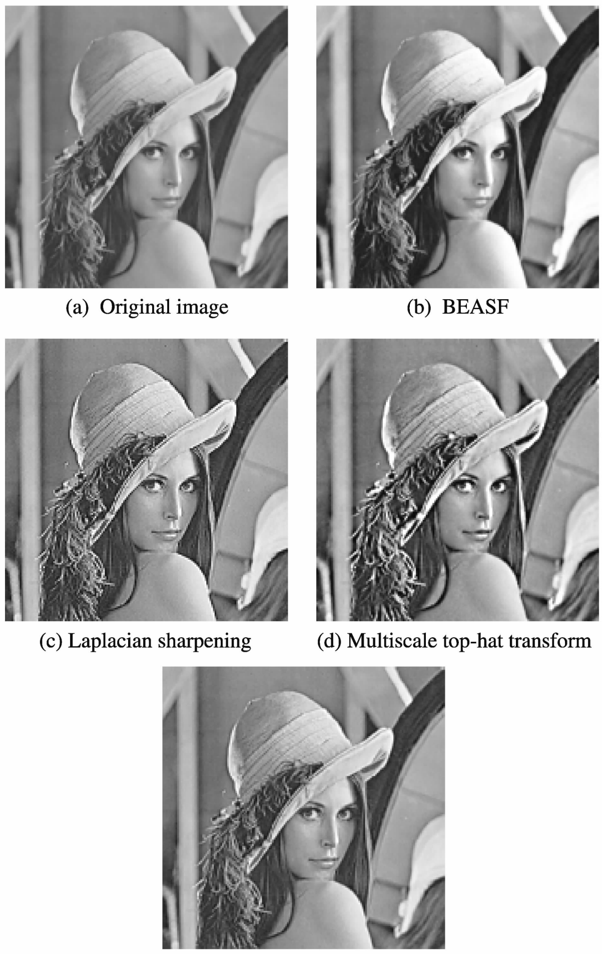
Thus the enhanced image can be obtained from any initial value $f^0$ by using Eq. (16).

## 2 Experimental results

In this section, we present experimental results to evaluate the proposed method. Test samples include Lena image and industrial X-ray image. The proposed method is compared with bi-histogram equalization in Ref. [24], Laplacian sharpening in Ref. [25] and multiscale top-hat transform in Ref. [15]. All the sharpening results obtained by different sharpening algorithms are based on individual parameter settings that give the best visual performance. The algorithms were performed using Matlab R2010 under the environment that OS: 32-bit; Windows 7; CPU: Intel Core(TM) 2 Duo, 4G RAM, NVIDIA GeForce GT 730M+Intel GMA HD 4600.

### 2.1 Visual compassion experiment

Fig. 2 shows the comparison results of different enhancement methods mentioned above on Lena image. The image size is 256×256. Fig. 2(a) is the original image. Figs. 2(b)−(e) show the results enhanced by bi-histogram equalization with adaptive sigmoid functions (BEASF), Laplacian sharpening, multiscale top-hat transform and the proposed algorithm, respectively. It can be observed from Fig. 2(b) that the image contrast is slightly improved, however, the details are not well enhanced, for example, the details on her hat. Laplacian sharpening approach performs well on the sharpening of image details, but it cannot avoid noise effectively, as shown in Fig. 2(c).



(a) Original image (b) BEASF

(c) Laplacian sharpening (d) Multiscale top-hat transform

(e) Proposed algorithm

**Fig. 2 Example of Lena image**

By comparison, the multiscale top-hat transform has better performance on the enhancement of details, however, noise still exists in the background region. In our algorithm, the processed image is obtained after 20 iterations with the thresholds of 1 and of 2.5. It can be seen that the edges and tiny details are well sharpened while less noise exists in the image compared with that of multiscale top-hat transform. This indicates that, among the mentioned algorithms above, the proposed algorithm has the best performance on enhancing details and edges without increasing noise.

Fig. 3 is an example of comparison results on an industrial X-ray image.

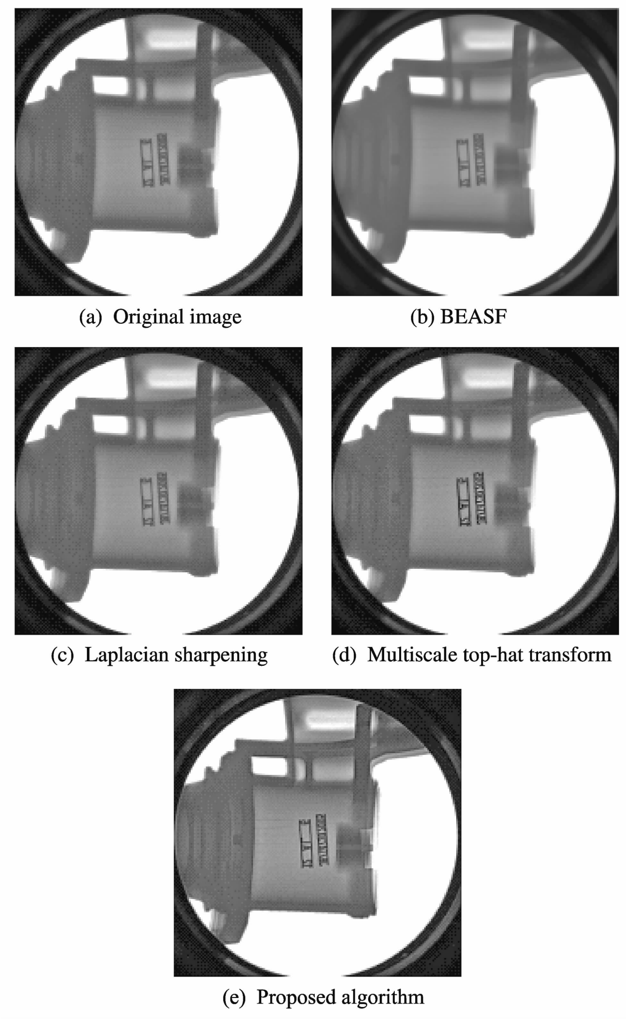



**Fig. 3 Example of X-ray image**

Fig. 3(a) shows an X-ray image of penetrameter, with size of 1 024×1 024. Figs. 3(b)−(e) show the enhanced results by bi-histogram equalization with adaptive sigmoid functions, Laplacian sharpening, multiscale top-hat transform and our algorithm, respectively. It is quite clear that BEASF shows little effect on the image. Laplacian sharpening enhances the letters in the image, but the details of lines are still obscure, moreover it introduces noise. The top-hat transformation enhances the lines better compared with Laplacian sharpening, however, some white points appear in the region of letters. In our algorithm, the threshold is set to 0, $\lambda$ is 4.5, and the number of iterations is 30. Obviously, the enhanced image by our method is clearer than by the other algorithms in terms of visual effect. In addition, it does not introduce much noise.

In addition, we show the zoomed images of a region of interest (ROI) from different algorithms, as shown in Fig. 4.

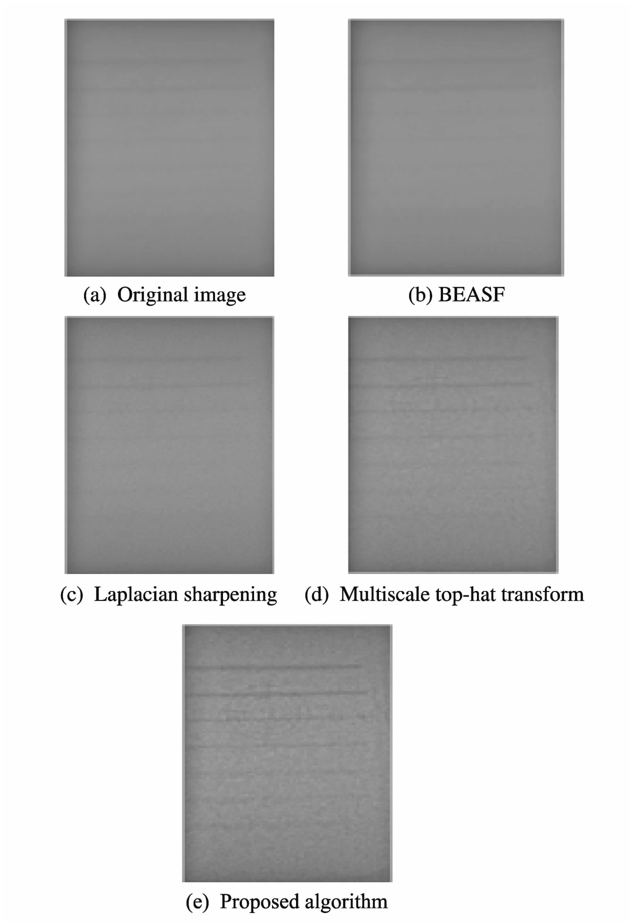



**Fig. 4 Comparison of zoomed images of a ROI from different algorithms**

From Fig. 4 it can be obviously seen that the proposed algorithm performs best on detail enhancement, meanwhile, noise that yielded in the procedure of enhancing is dramatically suppressed.

## 2.2 Quantitative comparison

In this paper, the effectiveness and quality of enhanced imagesare evaluated by signal-to-noise ratio (SNR) and information entropy (IE) that are widely used for measuring image quality. The $SNR$ is generally defined as

$$SNR = 10\lg\left[\frac{\sum_{i=1}^{MN}(f_i - m_i)^2}{\sum_{i=1}^{MN}(f_i - g_i)^2}\right], \tag{17}$$

where $f_i$ and $g_i$ denote the pixel gray-values of the processed image and the original image separately; $m_i$ is mean value of the processed image; $M$ and $N$ represent the height and width of the image, respectively. A larger value of $SNR$ indicates a better suppression of noise.

The definition of $IE$ is[31]

$$IE = -\sum_{i=1}^{L} p_i \ln p_i, \tag{18}$$

where $i$ denotes the $i$-th gray level of the image, $L$ is the total number of gray levels and $p_i$ represents the probability that gray level shows in the image. The information entropy of an image is a statistical form of image features and reflects the average information that the image holds and of peculiarity of gray level's distribution. A larger value of $IE$ implies more details and less noise in the enhanced image.

We calculate $SNR$s and $IE$s of Figs. 2—3 for objective comparison of image enhancement effect by different algorithms, as listed in Table 1. Whether the standard testing image Lena or the X-ray image, the values of $IE$ by different algorithms are much close, while the values of $SNR$ by the proposed algorithm are larger than that by other methods at the matched $IE$, which verifies the effectiveness of our method.

**Table 1 Comparison of proposed algorithm with other methods in terms of SNR and IE**

| Image | Method | SNR | IE |
|---|---|---|---|
| Lena | BEASF | 11.339 | 4.947 |
| | Laplacian sharpening | 7.873 | 5.314 |
| | Multiscale top-hat transform | 7.455 | 5.327 |
| | Proposed method | 11.825 | 5.329 |
| X-ray image | BEASF | 28.047 | 3.185 |
| | Laplacian sharpening | 27.207 | 3.956 |
| | Multiscale top-hat transform | 25.555 | 3.972 |
| | Proposed method | 28.449 | 3.981 |

# 3 Conclusion

The standard testing image and X-ray image have been applied in the experiments and the image details and edges are well enhanced. The results show that our algorithm can not only effectively enhance standard testing images, but also enhance other types of images.

In this paper, an improved detail enhancement algorithm based on difference curvature and gradient field is proposed. In the proposed algorithm, the difference curvature is used to determine the amplification coefficient instead of the gradient. Its advantage is mainly embodied in the fact that it can avoid noise when enhancing edges and details. Experimental comparison also illustrates that the image enhanced by the proposed algorithm has outstanding edges as well as clearer texture and less noise introduced, furthermore, it shows better performance on maintaining image information effectively.

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# 一种改进的基于差分曲率和对比度场的细节增强算法

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**摘　要：** 针对图像细节增强过程中梯度对噪声敏感的缺点，本文提出了一种改进的基于差分曲率和对比度场的细节增强算法。首先，该算法利用差分曲率代替梯度值决定系数的放大倍数，以差分曲率作为自变量的放大系数函数考虑了更多的邻域像素，从而克服了图像梯度对噪声敏感的缺点；然后，利用该放大系数非线性地放大对比度场，并构造能量泛函；最后，通过变分方法得到增强后的图像。标准测试图像和工业 X 射线图像的实验结果表明，本文提出的算法在有效增强图像对比度的同时，能够较好地抑制噪声。

**关键词：** 图像增强；对比度场；差分曲率；变分增强方法

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