Enhancement Contrast and Denoising of Low Illumination Image of Underground Mine Tunnel

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Abstract—**For enhancing low lumination image of underground mine tunnel, a hybrid local histogram equalization with partial differential equation is proposed to combine a local histogram equalization and total variation method with edge-stopping function via partial differential equation. The local histogram equalization is to enhance contrast of image with keeping shape and edge, while total variation method with edge-stopping function is to smooth image by gradient diffusion for lowing noise. In the presented hybrid method, a parallel trade-off scheme is utilized for simultaneous denoising and contrast enhancement. Experiments are carried out to validate the hybrid method using a standard image and a real image of underground mine tunnel. The results prove that it is an alternative processing method for low luminous image of underground mine tunnel.**

Index Terms—**Histogram Equalization, Denoising, Contrast Enhancement, Image Processing, Total Variation Method**

I. INTRODUCTION

The environment in underground coal mine is very complex, especially after an accident [1]. Robots have a great potential to assist in the underground operation, searching ahead of rescue teams and reporting conditions that may be hazardous to the teams by providing video and atmospheric monitoring information at several emergency and recovery sites [2, 3]. As one of the key technologies image processing technology has been paying attention in visual sensation with low illumination of autonomous mine rescue robot. Underground coal mine environment is low illumination and more dust, making the camera lens covered with a layer of dust, thus affecting the quality of image. The acquired image often have low contrast and more noise, blurring the details of the original characteristics of the image and making human visual resolution or machine identification more difficult. Therefore, it is necessary to preprocess image for further control of coal mine rescue robot, mainly consisting of denoising and contrast enhancement of these images.

Image enhancement is one of image process technologies, not considered the reasons of low quality of image, only highlighting interested features in image and attenuating unwanted characteristics. The improved image is not necessarily close to the original image, by projecting object contour, denoising, and strengthening contrast. From the viewpoint of the image quality evaluation, the image enhancement technology is to make image more suitable than the original image for human visual or machine recognition. Many image enhancement methods were proposed to enhance images degraded by low illumination: linear contrast stretching, global histogram equalization and local histogram equalization etc. [4]. They are simple transformations for contrast enhancement, but they do not always produce good results. Particularly for images with large spatial variation in contrast, they causes over enhancement contrast in some portion of the image and undesired effect of more noise in the input image, along with the image features, further weakening minutia part. To improve the process of denoising, researchers developed frequency-based filters [5-7], average within neighborhood region [8-10], and partial differential equation [11, 12], etc.. A low pass filter or average filtering can smooth the noise image, but blurring its details, because both noise and edge in image are within high frequency domain [13]. Discrete cosine and wavelet transform methods are used to alter the frequency content of an image to improve desired traits for low complexity of computations and conveniently manipulating the frequency composition of the image.[5] However, they still have some basic limitations, for example, introducing block artifacts. Partial differential equations (PDE)-based filters are modeling an image restoration or enhancement process through a partial differential equation that regards a degraded image as the initial state of a diffusion process and relates the image's spatial derivatives with its time derivative. A large number of PDE-based methods have been proposed to tackle the problem of image denoising. The regularized P-M method [11] smoothed the edges of the image slowly and the edges are kept, but some details still lost. Basing on the above analysis, we can find that enhancing edges in image will simultaneously increasing noise in the image, in turn, reacting on the edge to be fuzzy to a certain extent. Therefore, in the paper, we propose a compromise method to for both denoising and contrast enhancement of image.

The paper presents an integrated enhancement method of PDE-based filter and local histogram equalization. The local histogram equalization is to enhance contrast of

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connected component in image for preserving detail shape, while regularized diffusion function along the tangent direction of the edge serves as a filter. In addition, it is important reason that one of the advantages of the use of PDE for image processing is the more possibility to combine algorithms. In general, there are two combination schemes. One is to reduce noise before stretching contrast of image, the other is to stretch contrast in first, and then denoise of image. However, we adopt a parallel trade-off scheme for the proposed hybrid local equalization with PDE (HLEPDE) for simultaneous denoising and contrast enhancement.

This paper is organized as follows. Section 2 presents the proposed PDE-based histogram equalization for image enhancement. In section 3, simulations are carried out to validate the proposed method by processing a test image and an underground image in coal mine. Finally, a conclusion is drawn in section 4.

II. PDE BASED HYBRID ENHANCEMENT METHOD OF IMAGE

A. Global Histogram Equalization based on PDE

Global histogram equalization (GHE) [4] is one of the basic and most useful operations in image processing, improving image quality by extending dynamic range of intensity using the histogram of the whole image.

Let I be an image defined in N×M size with grey values in the range [a, b], where a and b are respectively minimal and maximal value of image grey. For continual image, we can first define an area function

$$A(D) := Area\{(x, y) : I(x, y) \geq D\} \tag{1}$$

It displays overall area of image $I(x,y)$ not less than the given threshold D. When D increasing to $D+\triangle D$,

$$A(D+\Delta D) \approx A(D) + \frac{\mathrm{d}A(D)}{\mathrm{d}D}\Delta D \tag{2}$$

and then the difference between $A(D+\triangle D)$ and $A(D)$ is area of image in range $[D, D+\triangle D]$. So we can get the following form

$$-\frac{\mathrm{d}A(D)}{\mathrm{d}D} \approx \frac{Area\{(x, y), D \leq I(x, y) \leq D+\Delta D\}}{\Delta D} \tag{3}$$

When considering $\triangle D$=1 in a digital image, the right of Eq. (3) is sum of pixel of grey level equal to D in image. While for continual image, the left of Eq. (3) must divide the overall image A_Ω, corresponding to histogram definition of digital image. Hence, the histogram of continual image can be expressed as

$$h(D) = -\frac{\mathrm{d}A(D)}{A_\Omega \mathrm{d}D} \tag{4}$$

As Eq. (4) is showed, $A(D)$ is decreasing, leading to $\mathrm{d}A(D)/\mathrm{d}(D)<0$. It can derive that the histogram $h(D)$ of continual image must be positive. The cumulative distribution function of continual image is

$$H(D) = \int_0^D h(\xi)\mathrm{d}\xi \tag{5}$$

subject to $H(a) = 0$ and $H(b) = 1$

The histogram equalization corresponds to selecting $h(\bullet)$ to be the distribution function $H(\bullet)$ of I. Basing on Eq.(1)-Eq.(5), $H(\bullet)$ is given by

$$H(D) = \frac{A_\Omega - A(D)}{A_\Omega} = \frac{Area\{(x, y) : I(x, y) \geq D\}}{A_\Omega} \tag{6}$$

Obviously, $H(\bullet)$ is strictly increasing. The transformation function for histogram equalization image is

$$f(D) = (b-a)H(D) + a \tag{7}$$

and it is a monotonic increasing function. Hence, for every grey value of pixel in input image I_A, there is a corresponding output using the relation

$$I_B(x, y) = f(I_A(x, y)) \tag{8}$$

In addition, it follows that the basic information of an original image is contained in the family of level sets

$$\chi_{D_A}[I_A] = \{(x, y) \in \Omega : I_A(x, y) \geq D_A\} \tag{9}$$

for all values of D_A in the range of I_A. Observe that, under fairly general conditions, an image can be reconstructed form its level sets by the formula

$$I_A(x, y) = \sup\{D_A : (x, y) \in \chi_{D_A}[I_A]\} \tag{10}$$

Since $H(\bullet)$ is an increasing function, the linear transformation of Eq.(8) does not modify the family of level-sets of I_A. We can get

$$\chi_{D_B}[I_B] = \chi_{D_A}[I_A] = \{(x, y) \in \Omega : I_A(x, y) \geq D_A\} \tag{11}$$

Therefore, the global histogram equalization of image basing on Eq.(8) is a homeomorphic transformation.

Further, a resulting image by histogram equalization can be expressed $I(x,y,t)$ as the following equation developing

$$\frac{\partial I(x, y, t)}{\partial t} = [1 - \frac{I(x, y, t) - a}{b-a}]A_\Omega - A(I(x, y, t)) \tag{12}$$

subject to $I(x, y, 0) = I_0(x, y)$

It was shown in [14] that the equalization of an image was to minimize the function

$$\begin{aligned} E(I) = &\frac{\Omega}{2(b-a)}\int_\Omega (I(x, y) - \frac{b-a}{2})^2 dxdy \\ &-\frac{1}{4}\int_\Omega\int_\Omega \left|I(x, y) - I(u, v)\right| dxdydudv \end{aligned} \tag{13}$$

where the first term tries to keep the grey values of I near as near as possible to the mean $(b-a)/2$ and the second term is a measure of the contrast of the whole image. Obviously, Eq. (12) is gradient descent flow of Eq.(13) and it has only stable resolution when is equal to zero.

$$\frac{\partial I(x,y,t)}{\partial t}=0\Rightarrow$$
$$I(x,y,\infty)=\frac{A_\Omega-A(D)}{A_\Omega}(b-a)+a=(b-a)H(D)+a \tag{14}$$

The resolution is same with Eq. (13). When Eq. (14) is up to be stable, the image I has finished the global equalization. So Eq. (12) for histogram equalization is feasible and stably convergent and is rewritten using Eq. (7) and Eq. (14).

$$\begin{aligned}\frac{\partial I(x,y,t)}{\partial t}&=(\frac{A_\Omega}{b-a})(\frac{A_\Omega-A(I(x,y,t))}{A_\Omega}(b-a)+a-I(x,y,t))\\&=(\frac{A_\Omega}{b-a})(f(I(x,y,t))-I(x,y,t))\end{aligned} \tag{15}$$

In order to restrict change of grey value within the range [-255 255], the above equation is rescaled by multiplying constant coefficient $(b-a)/A_\Omega$. Hence, the general expression of histogram equalization based on PDE is shown by

$$\frac{\partial I(x,y,t)}{\partial t}=f(I(x,y,t))-I(x,y,t) \tag{16}$$

B. Shape Preserving Local Histogram Equalization

A considerable large amount of the research in image processing is based on assuming that regions with almost equal grey values, which are topologically connected, belong to the same physical object in the word. Following this it is natural to assume then that the shapes in a given image are represented by its level sets. If the relation between the original and resulting image is not homeomorphic using some local contrast enhancement methods, these methods may be undesirable for extracting and recognizing feature. This paper introduces a local histogram equalization, called shape preserving local histogram equalization (SPLHE) [12], to modify the transformation function $f(\bullet)$ in Eq.(11) for enhancing contrast and preserving the shape of image.

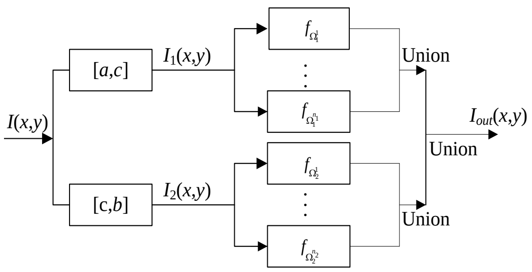


Figure 1. Local histogram equalization scheme

Suppose pixels of I in the domain $\mathbf{\Omega}$ have grey value in range $[a, b]$. Now divide I into two subdomains and get two sets.

$$\left.\begin{aligned}\Omega_1&:=\{(x,y),a\le I(x,y)\le c\}\\\Omega_2&:=\{(x,y),c\le I(x,y)\le b\}\end{aligned}\right\} \tag{17}$$

subject to

$$\Omega_1\cap\Omega_2=\varnothing \text{ and } \Omega_1\cup\Omega_2=\Omega \tag{18}$$

The edge of subdomain is a closed curve of part of level set $I(x,y)=c$. There are existing two subimages in these two subdomains, taking the following form:

$$I_1(x,y)=\begin{cases}I(x,y), \ \forall(x,y)\in\Omega_1\\0 \quad\quad \text{others}\end{cases} \tag{19}$$

$$I_2(x,y)=\begin{cases}I(x,y), \ \forall(x,y)\in\Omega_2\\0 \quad\quad \text{others}\end{cases} \tag{21}$$

In a similar way, if continuously dividing subimage into two sections, we get much more subdomains.

$$\Omega_1=\cup\Omega_1^i,\quad \Omega_2=\cup\Omega_2^i \quad \left(i=1,2,\ldots,k;\ N\approx 2^{k+1}\right) \tag{21}$$

Here, $\Omega^i{}_1$ and $\Omega^i{}_2$ is respectively called a connected component of Ω_1 and Ω_2. A local image processing is to enhance connected component of image. The transformation function can be rewritten basing Eq.(7) for equalizing connected component of image because the global histogram equalizing is a homeomorphic transformation.

$$f_\Omega(I(x,y))=\sum_i^k f_{\Omega_1^i}(I_{\Omega_1^i}(x,y))+\sum_i^k f_{\Omega_2^i}(I_{\Omega_2^i}(x,y)) \tag{22}$$

where

$$\left.\begin{aligned}f_{\Omega_1^i}(I_{\Omega_1^i}(x,y))&=(c_i-a_i)H_{\Omega_1^i}(I_{\Omega_1^i}(x,y))+a_i\\f_{\Omega_2^i}(I_{\Omega_2^i}(x,y))&=(b_i-c_i)H_{\Omega_2^i}(I_{\Omega_2^i}(x,y))+c_i\end{aligned}\right\} \tag{23}$$

Therefore, Eq.(22) and Eq.(23) constitute a local equalization method basing on PDE, whose structure [15] shows in Fig. 1. The advantage of local histogram equalization is better contrast enhancement with preserving local shape, while the use of PDE for the local image process makes it possible to combination of different methods for better quality image. We will later see how to simultaneously reduce noise and enhance contrast of image.

C. Hybrid Enhancement Method via PDE

Local histogram equalization allows a better contrast enhancement with preserving local shape of image. The use of PDE method makes it possible to combine different methods for better quality image. A flow for simultaneous denoising and histogram modification is presented in this section.

A smooth operator can be achieved by minimizing the total variation of the image [12], given by

$$\min\int_\Omega |\nabla I(x,y)|\,dxdy \tag{24}$$

The Euler-Lagrange of this functional is given by the curvature of level-sets of image, which leads to the gradient descent flow

$$\frac{\partial I(x,y,t)}{\partial t}=\mathrm{div}(\frac{\nabla I(x,y,t)}{|\nabla I(x,y,t)|}) \tag{25}$$

This flow smoothes the image in the parallel direction to the edges for preserving anisotropic diffusion. Using this smoothing operator, together with the histogram modification part, gives very similar results as those obtained with the affine based flow. If this smoothing operator is combined with the histogram flow, the total flow

$$\frac{\partial I(x,y,t)}{\partial t} = \lambda \mathrm{div}\left(\frac{\nabla I(x,y,t)}{|\nabla I(x,y,t)|}\right) + f(I(x,y,t)) - I(x,y,t) \tag{26}$$

will therefore be such that it minimizes

$$\lambda \int_{\Omega} |\nabla I(x,y)|\, dxdy + E(I) \tag{27}$$

where λ is a positive parameter controlling the trade-off between smoothing and histogram modification, called balance factor, $E(I)$ is shown by Eq.(13). In order to reduce diffusion rate of near edge, Eq.(26) is modified using an edge-stopping function. Hence, the proposed HLEPDE is shown by

$$\frac{\partial I(x,y,t)}{\partial t} = \lambda g(|\nabla I(x,y,t)|)\mathrm{div}\left(\frac{\nabla I(x,y,t)}{|\nabla I(x,y,t)|}\right) + f(I(x,y,t)) - I(x,y,t) \tag{28}$$

where

$$g(r) = \frac{1}{1+(r/K)^2} \tag{29}$$

The function g(•) becomes gradually larger with the diffusion from a local plane region to edge, and hence the first term in Eq. (28) gradually increases and the denoising and smooth effect will strengthen. The Eq. (28) via PDE function permits to consider simultaneous denoising and local histogram modification, and the edge-stopping function makes it to adaptively adjust diffusion rate for image processing. However, the *I* image must be preprocessed by Gaussian regularization because the noise in *I* image may provide false gradient information, leading to a unstable solution for Eq. (28).

For a digital image, the main strategy of the HLEPDE is that its PDE in a discrete form is performed iteratively, based on the implements of SPLHE to enhance contrast of edge and diffusion flow of total variation of the image to smooth edge, and then balance these two functions by a trade-off factor. Fig. 2 shows the outline procedure of the hybrid algorithm, and the detailed procedure involved in HLEPDE is described as follows.

Step 1: Initialize the parameters, set iteration number n=1.

Step 2: Gaussian regularization of the input image to prevent false edge occurring.

Step 3: Compute divergence information of the input image and then local histogram equalization of SPLHE is carried on the input image.

Step 4: The output image is gotten by using a discrete form of Eq. (28).

$$I_{n+1} = \lambda g(|\nabla I_n|)\mathrm{div}(\nabla I_n) + f(I_n) - I_n \tag{30}$$

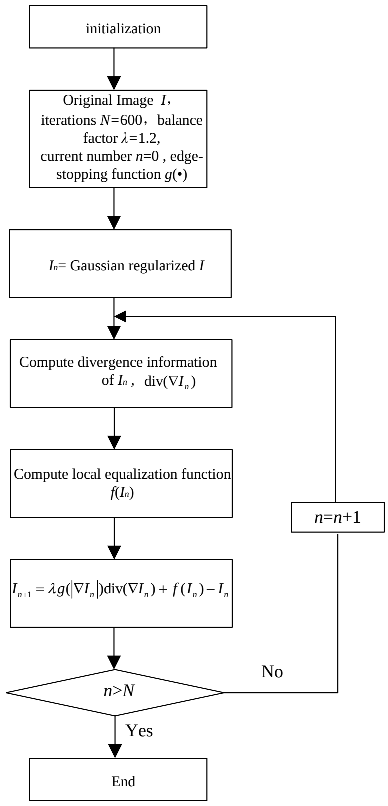


Figure 2. Flow diagram of HLEPDE

Step 5: Termination judgment. The loop terminates if the number of current iteration n reaches the maximumiteration N. Otherwise, the program goes back to the step 3, n= n +1, and repeats executing the remaining steps.

Step 6: The program completes and obtains processed image with better quality.

III. EXPERIMENTS

In this section, the proposed HLEPDE based on Fig. 2 is compared with other image processing methods to validate its effect by enhancing a standard image and practical image of underground mine tunnel.

A noised image is produced by adding random Gaussian noise to a 512×512 pixel standard test image, called Lenna. An original image added into gauss noise, shown in Fig. 3(a), is enhanced using different methods. Since Fig. 3(b) is resulted by only using SPLHE for contrast enhancement, there remains a lot of noise and even more.

However, only using TV [15] method for denoising has also bad effect, as shown by Fig. 3(c). So we incorporate the diffusion flow of TV method and local enhancement of SPLHE for complementary image processing. There are three ways to combine these two methods for making full of use of their advantages. One is to first stretch contrast using SPLHE method and then denoise with TV, by which we enhance Fig. 3(a) and get Fig. 3(d). On the contrary, the other way is to first utilize TV method then SPLHE, by which Fig. 3(e) is attained.

(a) Original image (b) Image using SPLHE (c) Image using TV

(d) Image using SPLHE before TV (e) Image using SPLHE after TV (f) Image using HLEPDE

Figure 3. Image processing using different methods

TABLE I. INDEX DATA OF TEST IMAGE USING DIFFERENT METHODS

	Mean intensity	Entropy	RMSE	PSNR	Average gradient
SPLHE	132.1163	7.4011	36.2310	16.9492	17.2582
TV	118.2512	7.5464	11.0485	27.2647	5.9030
SPLHE then TV	132.1324	7.8790	38.3591	16.4534	11.0172
TV then SPLHE	133.6356	7.3353	36.0948	16.9819	9.3244
HLEPDE	130.5254	7.9395	30.3357	18.4917	12.0784

as Fig. 3(d) and Fig. 3(e), they are still obvious block effect and lower contrast. In addition, the third way is the proposed method that is a parallel scheme for simultaneous denoising and contrast enhancement. Comparing Fig. 3(d), Fig. 3(e) and Fig. 3(f), we achieve that Fig. 3(f) has higher contrast, less noise, and more distinct.

In order to further evaluate the performance of the proposed, we introduce some characteristic indices. That is mean intensity (MI), standard deviation (SD), entropy, RMSE (root mean square error), peak signal-to-noise ratio (PSNR), average gradient (AG) of image, as defined as the following equations.

$$MI = \frac{1}{N*M}\sum_{x=1}^{N}\sum_{y=1}^{M} I(x,y) \tag{31}$$

$$Entropy = -\sum_{g=0}^{255} P_g \log_2 P_g \tag{32}$$

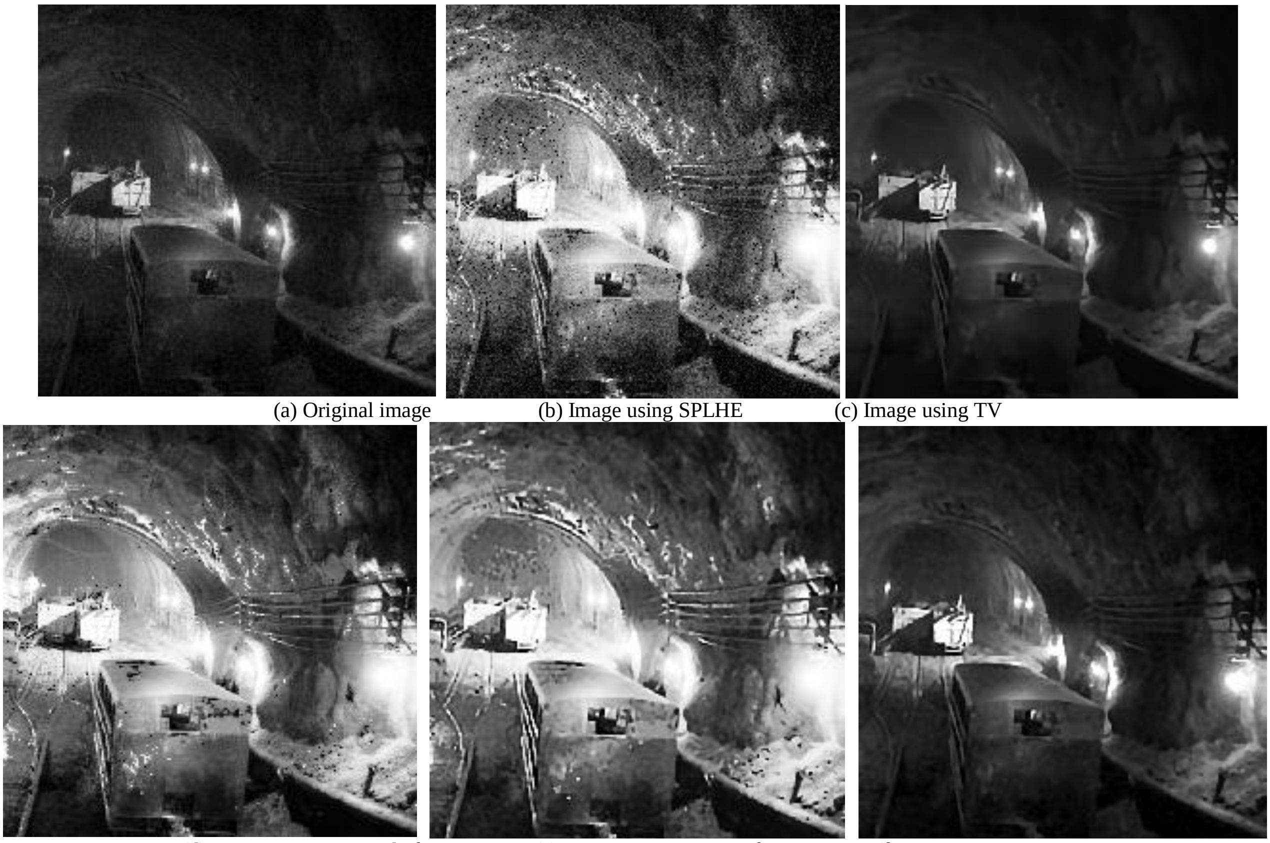
$$RMSE = \sqrt{\frac{1}{M*N}\sum_{x=1}^{N}\sum_{y=1}^{M}(I_A(x,y)-I_B(x,y))^2} \tag{33}$$

$$PSNR = 10\log_{10}(\frac{R}{RMSE})^2 \tag{34}$$

$$\mathrm{AG} = \frac{1}{(M-1)*(N-1)} \times \sum_{i=1}^{N-1}\sum_{j=1}^{M-1}\sqrt{\frac{(I(i+1,j)-I(i,j))^2+(I(i,j+1)-I(i,j))^2}{2}} \tag{35}$$

where P_g is the probability of grey value g in the image, R is the maximum difference in the original image data type, $I_A(x,y)$ and $I_B(x,y)$ is respectively the enhanced and original gray pixel at position (x,y). MI is mean intensity value of I image. RMSE and PSNR are two error metrics used to compare the quality of original image and enhanced image. AG is average gradient reflecting the clarity of the resulted image.

Furthermore, we analyze different index data of images in Fi.1 using different methods, as data shown in Table 1. The entropy of image sing HLEPDE is greatest among five methods. Commonly, the greater the entropy



(a) Original image (b) Image using SPLHE (c) Image using TV

(d) Image using SPLHE before TV (e) Image using SPLHE after TV (f) Image using HLEPDE

Figure 4. Underground mine tunnel image processing using different methods

TABLE II. INDEX DATA OF UNDERGROUND MINE TUNNEL IMAGE USING DIFFERENT METHODS

	Mean intensity	Entropy	RMSE	PSNR	Average gradient
SPLHE	107.8075	6.6002	79.6146	10.1109	20.4215
TV	41.1985	6.6444	10.9632	27.3384	2.1029
SPLHE then TV	106.7225	7.8183	79.1620	10.1605	7.1535
TV then SPLHE	105.9427	6.5563	78.4404	10.2400	5.6608
HLEPDE	48.4188	6.9060	15.1575	24.5183	10.7511

of image is, the more abundant information included in it, and the greater the quality of image is. In addition, RMSE represents the cumulative squared error between two images, whereas PSNR represents the measure of the peak error. A larger average gradient means a higher contrast. HLEPDE has worse denoising effect for Fig. 3(f) from HLEPDE has lower PSNR, but PSNR of Fig. 3(f) is greater than those of Fig. 3(b), Fig. 3(d) Fig. 3(e). Furthermore, HLEPDE can enhance higher contrast of image by comparing data in the sixth column of Table 1, but it has lower average gradient value than SPLHE. Although HLEPDE has worse contrast enhancement ability than SPLHE and worse denoising effect than TV, it has better contrast enhancement and denoising than other two methods. Therefore, HLEPDE can allow for simultaneous denoising and contrast enhancement using a trade-off scheme.

Finally, HLEPDE is applied to process image of mine tunnel (see Fig. 4(a)) with low illumination, low contrast , and some noise. Fig. 4(f) using HLEPDE has better quality than Fig. 4(a)-Fig. (e). Since illumination of Fig. 4(a) is not uniform, Fig. 4(f) cant enhance too much illumination for keeping detailed shape, otherwise it is excessively exposed as shown in Fig. 4(b), Fig. 4(d), and Fig. (e). Fig. 4(f) has lower noise polluted and higher contrast than Fig. 4(a), but its contrast and denoising are respectively not enhanced much more than Fig. 4(b) and Fig. 4(c) in case local shape or detail is lost. Data in Table 2 also illustrates that HLEPDE enhancing image is better than other methods. In a word, HLEPDE can process image of mine tunnel for simultaneous denoising and contrast enhancement using a trade-off scheme.

IV. CONCLUSIONS

A hybrid process method, called HLEPDE, is presented that integrated SPLHE into TV method with edge-stopping function via PDE for simultaneous denoising and contrast enhancement. The SPLHE is to enhance local contrast and preserve shape of image, while TV method with edge-stopping function is to denoise and keep edge information of image. With closing to edge of image, the smooth operation of TV is weakening. The HLEPDE is validate by processing a standard image, and further applied to a real image of mine tunnel. The results prove that HLEPDE is effective for simultaneous denoising and contrast enhancement.

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