Filtering Combined Dynamic Stochastic Resonance for Enhancement of Dark and Low-contrast Images

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***Abstract*—Dynamic stochastic resonance (DSR) based dark and low-contrast image enhancement has attracted more and more attention in recent years. For DSR based image enhancement, noise is essential and will be enhanced simultaneously with the contrast of the image, which is undesirable for improvement of perceptual quality. Nonlinear anisotropic diffusion (NAD) is one of the most widely used denoising methods due to good performance of edge preservation, but often fails for contaminated images with high level of noise. In this paper, we propose a novel partial differential equation method for image enhancement by introducing filtering into the stochastic resonance equation, and we consider two kinds of NAD filters. Numerical results demonstrate that the improved methods can not only increase brightness and contrast of the dark and low-contrast images efficiently by optimum iterations, but also remove the noise while preserving edges well, and therefore can achieve good perceptual quality.**

***Keywords*— dynamic stochastic resonance, anisotropic diffusion, image enhancement, image denoising**

I. Introduction

Enhancement of dark and low-contrast image is urgent and extensive demand in many fields including medical imaging, night-vision monitoring, remote sensing and so on. The literature survey of image enhancement techniques reveals many well-known and interesting techniques such as histogram equalization (HE) [1], gamma correction [2], single-scale retinex (SSR) [3], multi-scale retinex (MSR) [4], dynamic stochastic resonance (DSR) [5]–[8] and so on. In this paper, we focus on the DSR based method which has attracted more and more attention in recent years.

Conventionally, noise is undesirable in image processing. However, DSR is a counter-intuitive phenomenon where the presence of noise in a non-linear system is essential for optimal system performance. According to this property, various DSR based methods have been proposed for dark and low-contrast image enhancement in spatial domain [5], in discrete wavelet transform (DWT) domain [6], [7], in discrete cosine transform (DCT) domain [8] and in Fourier Transform domain [9]. These DSR based methods can improve contrast and brightness of the image efficiently, but the noise will be enhanced simultaneously which is obviously undesirable for the improvement of visual quality of the image. Nonlinear anisotropic diffusion (NAD) is one of the most widely used methods for image denoising [10], [11]. NAD holds good edge-preserving characteristics, but also fails for contaminated images with high level of noise. It implies that if we enhance the dark and low-contrast image using DSR firstly, and then remove the noise using NAD, it is difficult to preserve edges well due to the enhanced high level of noise.

In this paper, we propose a novel method for dark and low-contrast image enhancement by leading two kinds of diffusion filtering into the stochastic resonance equation in the spatial domain. In our method, processes of enhancement and denoising are simultaneous. In traditional DSR based methods, the noise level is increasing in the process of enhancement, while driven by the NAD, the noise level is decreasing in our method. On one hand, we can avoid over-enhancement because the phenomenon of resonance cause by noise is vanishing gradually with the decreasing of the noise; on the other hand, the decreasing of noise level is also beneficial for edge preservation.

The rest of this paper is organized as follows. In Section 2, we briefly discuss DSR. In Section 3, we introduce our improved methods and the iterative algorithms for solving the proposed models. Experimental results with quality analysis are given in Section 4 to demonstrate the efficiency of our method. Finally, the discussion and conclusion are provided Section 5.

II. Dynamic Stochastic Resonance

The concept of DSR was invented in 1981−1982 in the context of the evolution of the Earths climate. Recent studies have convincingly shown that in non-linear systems, noise can induce more ordered regimes that cause amplification of weak signals and increase the signal-to-noise ratio. In the context of image processing, DSR refers to the transition of pixel values while varying the intensity from low to high and vice versa. Benzi's double-well theory [12] suggests two states of image contrast, i.e., low and high, where the particles are analogous to the state of coefficient magnitude. The transition of a particle placed in a double-well potential system is based on Brownian motion. The equation of motion of particle in the double well is described by Langevin's equation stated as follows [12]

$$\frac{dx\left(t\right)}{dt} = -\frac{dU\left(x\right)}{dx} + \sqrt{D}\xi\left(t\right) \ . \tag{1}$$

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where ξ is the friction (i.e. noise) under which a particle of mass is moving within well. Additive stochastic force is applied with the intensity D. $U(x)$is the bistable potential function defined as

$$U(x) = \frac{bx^4}{4} - \frac{ax^2}{2} \ . \quad (2)$$

where a and b are positive bistable double-well parameters. The double-well system (2) is stable at $x_m = \pm\sqrt{a/b}$ and separated by a barrier of height $\Delta U{=}a^2/4b$ when $\xi = 0$. Adding a periodic input signal $B\sin(\omega t)$ into bistable system, one can obtain

$$\frac{dx(t)}{dt} = -\frac{dU(x)}{dx} + B\sin(\omega t) + \sqrt{D}\xi(t) \ . \quad (3)$$

where B and ω are amplitude and frequency of the periodic signal, respectively. When the signal amplitude is small, the resonance caused by the stochastic noise can force a particle to move from one well to another, which will lead to the enhancement of the weak signal. The stochastic differential equation (3) can be solved by using the stochastic version of Euler-Maruyamas iterative method as follows:

$$x_{n+1} = x_n + \Delta t \cdot \left(ax_n - bx_n^3 + Input\right) \ . \quad (4)$$

where Δt is the step size and $Input = B\sin(\omega t) + \sqrt{D}\xi(t)$ denotes the input signal with noise. For the DSR based method in spatial domain [5], the $Input$ is the observed noisy low-contrast image; for the DSR based method in wavelet transform domain [6], the $Input$ in the equation (4) is the wavelet coefficients; for the DSR based method in DCT domain [8], $Input$ is the DCT coefficients. In this paper, we focus on the DSR based image enhancement method in spatial domain, namely, $Input$ is the observed noisy low-contrast image.

III. Improved Methods

Introducing diffusion filtering into the stochastic resonance equation in the spatial domain, we proposed a new model for dark and low-contrast image enhancement as follows

$$\frac{\partial u}{\partial t} = -\frac{dU(u)}{du} + f + \lambda F(u) \ . \quad (5)$$

where f is the observed noisy image with low contrast, $F(u)$ is a diffusion term and $\lambda > 0$ is a parameter used to adjust the strength of filtering.

Nonlinear anisotropic diffusion (NAD) filtering has been widely used for image denoising. Perona and Malik have proposed a NAD model called P-M equation [10] for image denoising as follows

$$\frac{\partial u}{\partial t} = div\left[c(|\nabla u|)\nabla u\right] \ . \quad (6)$$

where u represent a gray-scale image, $c(\cdot)$ is a non-negative single reduction function, which can be chosen as

$$c(x) = \frac{1}{1+(x/K)^2} \ . \quad (7)$$

with K a positive threshold. The value of $c(|\nabla u|)$ is small at edge which is beneficial for edge preservation; the value of $c(|\nabla u|)$ is large in the flat region which can improve the performance of denoising.

The anisotropic P-M equation (6) can preserve edges well while removing noise, but it often causes staircase effect. To eliminate the staircase effect, high-order NAD models have been proposed. One of the most widely used fourth-order NAD models for image denoising is as follows [11]

$$\frac{\partial u}{\partial t} = -\nabla^2\left[c\left(\left|\nabla^2 u\right|\right)\nabla^2 u\right] \ . \quad (8)$$

Obviously, the performance of NAD model has strong dependence on first-order or high-order derivative of the image. However, high level of noise leads to great difficulties in the accurate computation of derivative, and therefore the directions of diffusion will be wrong and cause blurring at the edges. Therefore, instead of removing high level of noise after the image enhancement process is complete, we propose to introduce the diffusion terms of (6) and (8) into our model (5),and consider two improved models as follows

(i) DSR_{NAD^2}:

$$\frac{\partial u}{\partial t} = (au - bu^3 + f) + \lambda\, div\left[c(|\nabla u|)\nabla u\right] \ . \quad (9)$$

(ii) DSR_{NAD^4}:

$$\frac{\partial u}{\partial t} = (au - bu^3 + f) - \lambda\,\nabla^2\left[c\left(\left|\nabla^2 u\right|\right)\nabla^2 u\right] \ . \quad (10)$$

The parameters a and b in our models are inherited from the DSR system, which have been discussed in detail for maximizing contrast enhancement, where $a = 2\sigma^2$ and $b < 4a^3/27$ with σ^2 the variance of noise. However, the level of noise is unknown in practice. In this paper, we utilize the relationship $b < 4a^3/27$ while choosing $a = 2\sigma^2/10^3$. Similar to (4), the DSR_{NAD^2} model can be solved iteratively according to the following scheme

$$u_{n+1} = u_n + \Delta t\left\{au_n - b{u_n}^3 + f + \lambda\, div\left[c(|\nabla u_n|)\nabla u_n\right]\right\} \ . \quad (11)$$

and the DSR_{NAD^4} model can be solved iteratively according to the following scheme

$$u_{n+1} = u_n + \Delta t\left\{au_n - b{u_n}^3 + f - \lambda\,\nabla^2\left[c\left(\left|\nabla^2 u_n\right|\right)\nabla^2 u_n\right]\right\} \ . \quad (12)$$

The threshold K in the function $c(x)$ plays an important role in noise removal and edge preservation. For the enhancement of dark and low-contrast image, the gray scale of image changes greatly. In this paper, we propose to choose the threshold K adaptively according the current image. Here, we define $K = mean(|\nabla u|)$ in the DSR_{NAD^2} model (9) and $K = mean(|\nabla^2 u|)$ in the DSR_{NAD^4} model (10), where $mean(\cdot)$ is the mean operator.

IV. Numerical Experiments

To demonstrate the efficiency of our method, we compare the proposed models DSR_{NAD^2} and DSR_{NAD^4} with some widely used and related methods for image enhancement as follows:

(a) **HE**: histogram equalization proposed in [1]

(b) **SSR**: single-scale retinex method proposed in [3]

(c) **MSR**: multi-scale retinex method proposed in [4]

(d) **DSR**: DSR based method proposed in [5] in spatial domain.

(e) $\boldsymbol{DSR_{DWT}}$: DSR based method in discrete wavelet transform domain proposed in [6]

All experiments are performed in a system having Intel Core i5-5200U Processor with 2.20 GHz speed and 4 GB RAM with windows operating system. The platform used is MATLAB v.7.14 on Windows 8. In our method, $b = 4a^3/(27 \times 255^2)$ and the parameters λ is adjusted manually.

The proposed technique is tested on various types of dark and low-contrast noisy images. In this paper, we just show the results obtained for three representative images. The low-contrast "CP image" in Figure 1 is a real color image obtained by cell phone (CP) at night. The low-contrast MR image in Figure 2 is a real magnetic resonance image with weak signals.The low-contrast noisy "VS image" in Figure 3 is a video surveillance (VS) image with weak signals.

For the quantitative and statistical performance analysis, three quantitative measures are used: the perceptual quality measurement (PQM), the relative contrast enhancement factor (RCEF) and the distribution separation measure (DSM).

To simplify, let f and $\tilde{u}$ be the input image and the enhanced output image of size $M \times N$, respectively. For evaluation of perceptual quality, we have used a no-reference metric for judging the image quality taking into account visible blocking and blurring artifacts, which we shall refer to as PQM [14]

$$PQM = \alpha + \beta B^{\gamma_1} A^{\gamma_2} Z^{\gamma_3} . \tag{13}$$

where $\alpha, \beta, \gamma_1, \gamma_2$ and γ_3 are model parameters that were estimated with the subjective test data as described by [14] ($\alpha = -245.9, \beta = 261.9, \gamma_1 = -0.0240, \gamma_2 = 0.0160$ and $\gamma_3 = 0.0064$). B is the average blockiness, estimated as the average differences across block boundaries for horizontally and vertically. A and Z constitute the activity of the signal. Although blurring is difficult to be evaluated without the reference image, it causes the reduction of signal activity. A is the average absolute difference between in-block image samples and Z is the zero-crossing rate. According to Mukherjee and Mitra [15] , the PQM value should be close to 10 for best perceptual quality.

Metric of contrast enhancement factor is based on global variance and mean of original and enhanced images. It can be stated that when an image is enhanced and clearer heterogeneity in its structure is obtained, the value of enhancement can be characterised by variation of Michelson contrast index (which is given by the ratio of spread and mean image intensity). We have therefore used the relative contrast enhancement factor (RCEF) defined as follows [13]

$$RCEF = \frac{\sigma_{\tilde{u}}^2}{\mu_{\tilde{u}}} \cdot \frac{\mu_f}{\sigma_f^2} . \tag{14}$$

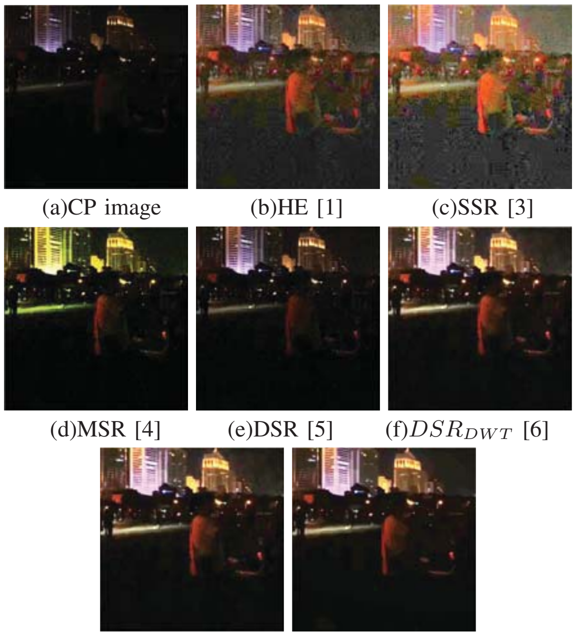
where $\sigma_{\tilde{u}}^2$ and $\mu_{\tilde{u}}$ are the variance and mean of the enhanced output image $\tilde{u}$, σ_f^2 and μ_f are the variance and mean of the input low-contrast image f, respectively. The DSM measures the difference of enhancement between the output image and the observed images. This measures how much the target area is enhanced with respect to its background area. Mathematically,

$$DSM = \left(\left|\mu_{\tilde{u}}^T - \mu_{\tilde{u}}^B\right|\right) - \left(\left|\mu_f^T - \mu_f^B\right|\right) . \tag{15}$$

where T and B denote target and background area in image which are divided by the method of Otsu.

In Figures 1-3, we show the comparison of enhanced images obtained by using our method and the compared methods mentioned above. In Table 1, we show the comparison of the objective indexes.

The results in Figure 1 show that the HE can enhance the dark image efficiently. However, the HE cannot distinguish the signal and noise, and therefore the noise is significantly enhanced too. Moreover, the HE is a global transformation, which often leads to over-enhancement. The MSR can increase the contrast efficiently, but the perceptual quality is not good. The SSR, DSR and DSR_{DWT} can enhance illumination and contrast efficiently, but the noise is enhanced too. Our method DSR_{NAD^2} and DSR_{NAD^4} can enhance illumination and remove the noise efficiently, which is the reason that the PQM of the images obtained by using our method is closest to 10. It implies that the required and useful information is at a maximum and, simultaneously, the noise amount is at a minimum. The results in Figures 2-3 show that the HE and MSR will enhance the noise significantly and cause over-enhancement. The DSR_{DWT} method cannot enhance the weak structures because the wavelet transform cannot detect these weak structures efficiently. Our method can enhance the image efficiently with good perceptual quality.



(a)CP image (b)HE [1] (c)SSR [3]
(d)MSR [4] (e)DSR [5] (f)DSR_{DWT} [6]
(g)DSR_{NAD^2} (h)DSR_{NAD^4}

Fig. 1. Comparison of the enhanced image for the low-contrast color image obtained by cell phone at night.

TABLE I
COMPARISON OF THE OBJECTIVE INDEXES

	Techniques	HE [1]	SSR [3]	MSR [4]	DSR [5]	DSR_{DWT} [6]	DSR_{NAD^2}	DSR_{NAD^4}
CP image	PQM	8.07	7.54	9.33	9.53	9.73	**9.81**	**9.95**
	RCEF	11.26	2.96	12.89	4.10	4.38	**4.55**	**4.65**
	DSM	52.27	36.01	43.57	33.84	39.63	**45.60**	**48.31**
MR image	PQM	8.41	8.88	9.47	9.37	9.57	**9.65**	**9.88**
	RCEF	2.27	2.30	4.37	2.40	1.48	**3.56**	**3.67**
	DSM	39.03	37.59	109.84	26.85	32.50	**49.89**	**51.32**
VS image	PQM	8.41	8.68	9.35	9.65	9.67	**9.78**	**9.86**
	RCEF	2.57	1.82	7.37	3.42	4.34	**4.41**	**4.43**
	DSM	38.53	7.59	48.91	8.06	8.13	**9.96**	**11.05**

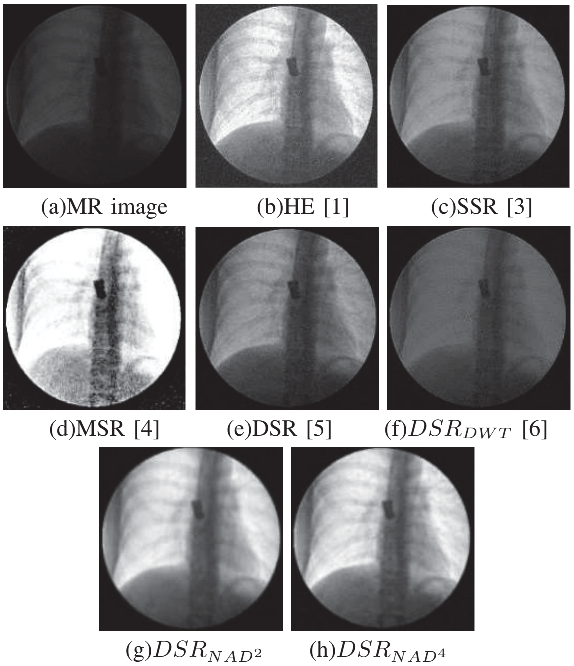


Fig. 2. Comparison of the enhanced image for the MR image.

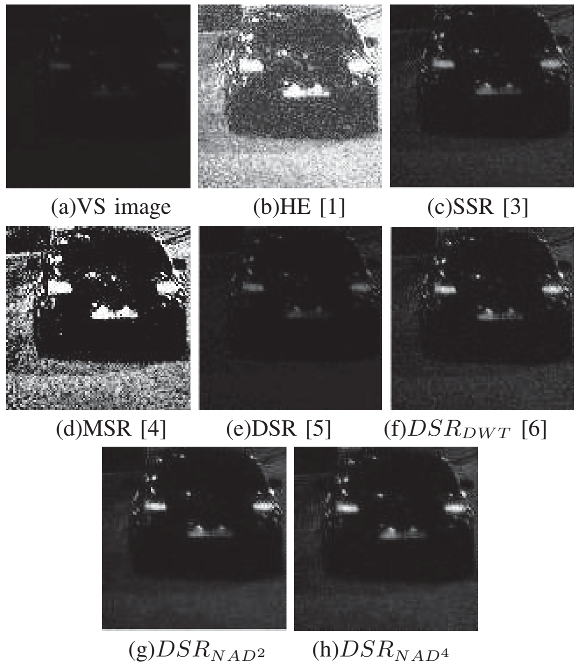


Fig. 3. Comparison of the enhanced image for the video surveillance image.

V. CONCLUSION

In this paper, we propose a novel method for dark and low-contrast image enhancement by leading NAD into DSR. In our method, processes of enhancement and denoising are simultaneous. Numerical experiments demonstrate that the proposed method has a remarkable performance in terms of illumination and contrast enhancement while ascertaining good perceptual quality. In fact, the NAD terms in our model can perform well in edge preservation, but are not suitable for texture preservation. In our future work, we will focus on introducing some new diffusion terms which are beneficial for texture preservation in our model to improve the performance of detail preservation. Moreover, the parameters are chosen adaptively in this paper to obtain the PQM closest to 10 or better perceptual quality. However, the original images are unknown in practice. Thus, how to choose the parameters adaptively and propose a proper objective index to evaluate the performance of enhancement needs further research in future.

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