Enhancement of Color Images with its RGB Representation using PDE

Ameena Tabassum, S.Satheesh, Ch.Ganapathy Reddy

Abstract*— Image enhancement is important factor for better visual representation. An extension of scalar diffusion-shock filter coupling model is proposed where noisy and blurred images are denoised and sharpened. The proposed method is based on single vectors of gradient magnitude and second derivatives. In this paper we are presenting proposed method by comparing with previous method. The proposed algorithm is more efficient than previous work without creating false colors. The performance of proposed method with previous method is evaluated with parameters such as Mean Structure Similarity Index Measurement (MSSIM) and Peak Signal to Noise Ratio (PSNR).

Index Terms*— Enhancement, Diffusion, Shock filter, Noise, Blur.

I. INTRODUCTION

Whenever image is captured acquired images are often degraded with blur, noise or blur and noise simultaneously. The processing to be applied on these images depends on the way of extracting wanted information. Particularly, a large number of PDE-based methods have been proposed to tackle the problem of image denoising with a good preservation of edges. In this paper we are interested in PDE-based methods. Hence partial differential equations based on diffusion methods [1,2] and shock filter [6,7,8] have recently dominated image processing research as a very good tool for noise elimination, image enhancement and edge detection [4]. Then many solutions have been proposed in the processing of gray level images by coupling diffusion to shock filter [3,5].

II. BACKGROUND

Originated from a well known physical heat transfer process, the PDE- based approaches consist in evolving in time the filtered image u(t) under a PDE. When coupling diffusion and shock filter the PDE is a combination of three terms:

$$\frac{\partial u}{\partial t} = C_\eta u_{\eta\eta} + C_\xi u_{\xi\xi} - C_{sk} F(\mathrm{u}_{\eta\eta}) |\nabla \mathrm{u}| \quad (1)$$

where *u(t=0) = u0* is the input image, $|\nabla \mathrm{u}|$ is the gradient magnitude, η is the gradient direction, and ξ is the direction perpendicular to the gradient, therefore $u_{\eta\eta}$ and $u_{\xi\xi}$ represent the diffusion terms in gradient and level set directions respectively. C_η and C_ξ are some flow control coefficients. The first kind of diffusion smoothes edges, while the second one smoothes parallel to the edge on both sides. The last term in (1), which is weighted by C_{sk}, represents the contribution of the shock filter in the enhancement of the image. The function *F*(*s*) should satisfy the conditions *F(0)=0* and *F(s)*.s $\geq$ 0. The choice of *F(s)* = *sign(s)* gives the classical shock filter [2]. Hence, by considering adaptive weights C_η, C_ξ and C_{sk}, as functions of the local contrast, we can favor smoothing process under diffusion terms in homogeneous parts of the image or enhancement operation under shock filter at edge locations.

II. PREVIOUS WORK

IIIIIn a more recent work, Bettahar and Stambouli proposed a new reliable and stable scheme, which is a kind of coupling diffusion to a shock filter with a reactive term [5]. This model is based on the following set:

$$\begin{cases} \frac{\partial u}{\partial t} = |\nabla \mathrm{u}| \,\mathrm{div}(g(\nabla \mathrm{u}_\sigma)\frac{\nabla u}{|\nabla \mathrm{u}|}) - \alpha |\nabla(\mathrm{f}(|\nabla \mathrm{u}_\sigma|))|^2 (\mathrm{u}-\mathrm{v}) \\ \frac{\partial v}{\partial t} = \beta(1 - |\nabla(\mathrm{f}(|\nabla \mathrm{u}_\sigma|))|^2)\mathrm{u}_{\eta\eta} - sign(\mathrm{G}_\sigma * \mathrm{u}_{\eta\eta})|\nabla \mathrm{u}| \end{cases} \quad (2)$$

where u_σ is the smoothed image using the Gaussian kernel and $\mathrm{v(t)}$ is the just previous evolution of $\mathrm{u(t)}$. In discrete time, is the last value of $\mathrm{u(t)}$ and $u(0) = \mathrm{u}_o . \mathrm{g}(\nabla \mathrm{u}_\sigma)$ are decreasing functions having the same form with free parameters k_d (for g) and k_c (for f) respectively therefore

$$g(\mathrm{s}) = \frac{1}{1 + \frac{S^2}{k_d^2}} \quad (3)$$

The first function $g(|\nabla \mathrm{u}_\sigma|)$ is used to assure an anisotropic behavior and to select "small edges" to be

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smoothed according to parameter k_d.

However, $f(|\nabla u_\sigma|)$ is introduced to select which "big edges" have to be improved according to k_c. Parameters α and β are positive balance constants. Mentioned models have been developed for enhancement of gray-level images. The natural way to apply them on multivalued images is to process each color component independently of the others in a marginal way.

Gilboa developed a complex diffusion shock filter coupling model that smooths the image with an enhancement of weak edges. This technique is mainly adopted for denoising and enhancement of weaker edges. Complex diffusion process is the combination of diffusion process and shock filter. The complex filter provides an original way to avoid the need for convolving the signal in each iteration and still get smoothed estimations. The time dependency of the process is inherent, without the need to explicitly use the evolution time t. Moreover, the imaginary value receives feedback - it is smoothed by the diffusion and enhanced at sharp transitions by the shock, thus can serve better for controlling the process then a simple second derivative.

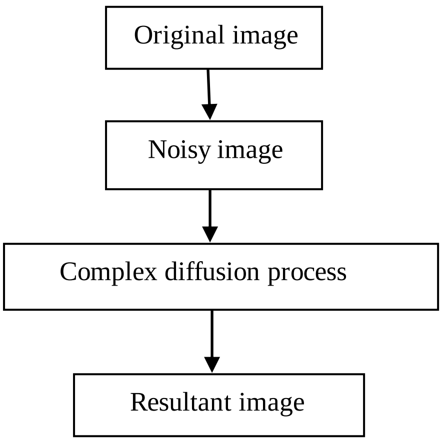


Fig. 1: Flow chart of Gilboa filter

(a) Initially an original image is taken which is processed by noise and noisy image is obtained.
(b) Noisy image is processed by complex shock filter which is given by following set:

$$I_t = -\frac{2}{\pi}\arctan(a\mathrm{Im}(\frac{u}{\theta}))\,u_\eta + \lambda u_{\eta\eta} + \tilde{\lambda} u_{\xi\xi} \quad (4)$$

where first set is for sharpening with a=0.30, $\theta = \pi/100$ second set is representing real parts with $\lambda = 0.1$ and third set is representing imaginary part with $\tilde{\lambda} = 0.5$.

(c) After undergoing complex shock filter process resultant image is obtained.

In Fig. 2 noisy image is obtain by applying Gaussian noise to the original image as shown in fig (b) Noisy signal (sine wave) processed with additive white Gaussian noise (SNR=10dB), left: real values, right: imaginary values, ($|\lambda|$ = 0.5, a = 5). All evolution graphs depict 3 time points along the evolution is 100 times smaller). One can see that the zero crossings are at the inflection points and that the imaginary value energy grows with time - thus enabling good preservation of the shocks.

In Fig (b) a blurred and noisy image is processed. In the two dimensional case only the complex scheme have acceptable results at this levels of noise. Though, the complex process have sharper edges and is closer to the shock process. At the bottom right a plot of one horizontal line of the image shows the denoising achieved by the complex scheme along with sharper large edges.

Fig. (c) and (d) are real values, and imaginary values ($|\lambda|$ = 0.1, $\tilde{\lambda}$ = 0.5, *a* = 0.30), one horizontal line showing the gray level values of the complex evolution (thin line - iteration 1, bold line iteration 200). All evolution results are for 200 iterations, dt=0.1.

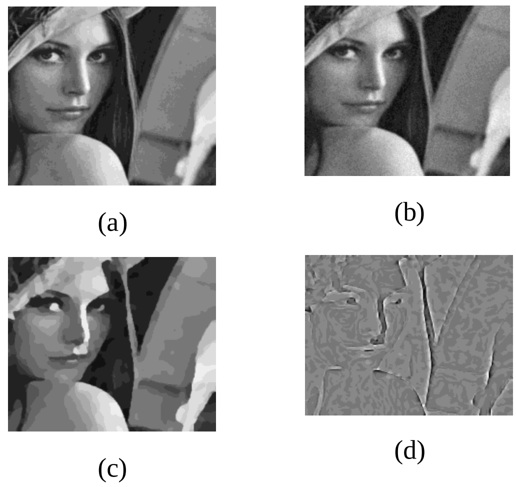


Fig. 2: (a) Original image (b) Noisy image (c) Real part (d) Imaginary part.

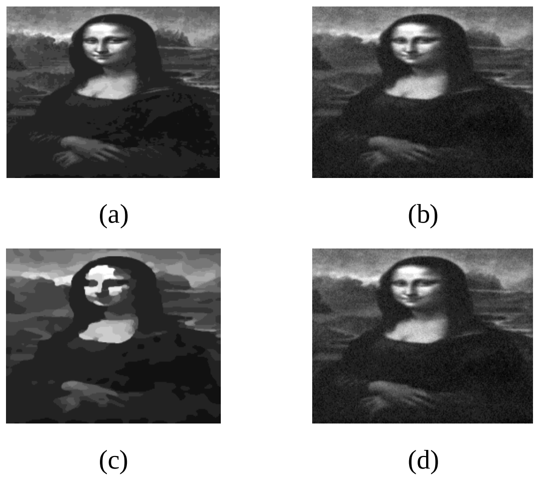


Fig. 3: (a) Original image (b) Noisy image (c) Real part (d) Imaginary part.

IV. PROPOSED METHOD

The proposed method is based on the model (2) as an extension to multivalued images, where each color component of the enhanced image is considered by taking into account the correlation between the three components. This model is given by

$$\begin{cases} \frac{\partial u_p}{\partial t} = |\nabla u| \, \mathrm{div}(g(|\nabla u_\sigma|) \frac{\nabla u_p}{|\nabla u|} - \alpha \\ \frac{|\nabla(\mathrm{f}(|\nabla u_\sigma|))|^2}{1+\beta |\nabla(\mathrm{f}(|\nabla u_\sigma|))|^2 u_{\xi\xi}{}^2} (u_p - v_p) \\ \frac{\partial v_p}{\partial t} = -sign(G_\sigma * u_{\eta\eta}) |\nabla u_p| \end{cases} \quad (5)$$

To understand well the proposed filter behavior, it is necessary to give more details about the reasons that have decided the form of (5). First, the choice of the balance diffusion–shock filter, with the form $\alpha |\nabla(\mathrm{f}(|\nabla u_\sigma|))|^2 / 1+\beta |\nabla(\mathrm{f}(|\nabla u_\sigma|))|^2 u_{\xi\xi}{}^2$ has a critical impact on the behavior of the proposed model at the noncreation of false colors. This choice has been done by considering some practical observations on different cases in order to take the best choice of this balance as follows. Consequently, by using the marginal method, we have computed the balance $\alpha |\nabla \mathrm{f}(|\nabla u_{p\sigma}|)|^2$ of model (2) by processing each image component separately.

The choice of the parameters has a critical impact on the behavior of the proposed filter. Therefore, with reference to the contrast of the image, the value of K_d is chosen to be a threshold of "small edges" to be smoothed under the diffusion process and K_c as "big edges" to be improved according to the shock filter.

One can use the same values for the threshold dedicated to "big" and "small" edges in both Bettahar's filters. In our experiences we saw that in this case, the filters converge to the solution with a considerable number of iterations without good detail preservations compared with the case with $k_c \neq k_d$. Constants α and β contribute in the balance between the diffusion process and the shock filter. If we want to attenuate the effect of the shock filter, we have to take small α and the large value of β.

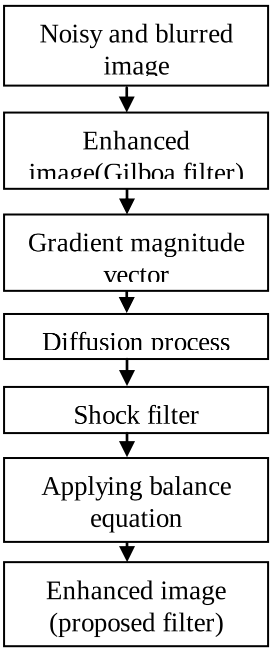
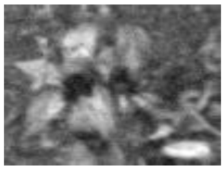


Fig.4: Flow chart of proposed method

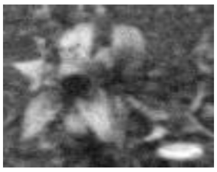
(a)

(b)

R component of (b)



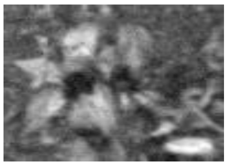
G component of (b)



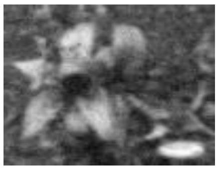
B component of (b)

(c)

R component of (c)



G component of (c)



B component of (c)

Fig. 5: (a) Noisy & blurred image (b) Gilboa filter with its RGB representation (c) Proposed filter with its RGB representation.

(a) The keypoint of gradient magnitude of vector is it avoids false injecting in an image.
(b) Diffusion process helps in smoothening of small edges of an image.
(c) Shock filter is meant for processing bigger edges.
(d) The output of shock filter is processed with balance equation which helps in enhancing equation, which is given by (3) where $g(|\nabla u_\sigma|) = k_d$ and $\mathrm{f}(|\nabla u_\sigma|) = k_c$ are control parameters with σ=1, k_d=5, k_c=28, α=800, β=1 and τ =0.01.
(e) After processing with balance equation resultant image is obtained.

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(a) (b)


R component of (b) G component of (b)


B component of (b) (c)


R component of (c) G component of (c)

B component of (c)

Fig. 6: (a) Noisy & blurred image (b) Gilboa filter with its RGB representation (c) Proposed filter with its RGB representation.

Proposed model is compared by Gilboa filter. These are developed particularly to enhance degraded images in presence of blur and additive noise simultaneously. For this comparison, we choose the parameters that give better results for each filter, except for the number of iterations that must be the same for objective comparison. The number of iterations is chosen in the function of the visual quality of the result. For each test image, we opt for the same number of iterations, and for the step time, we prefer a small value in order to converge to the solution with more precision about the values of the objective criteria while getting more details in the visual aspect of the restored images.

The first criterion used is the color peak signal-to-noise ratio (PSNR), i.e.

$$PSNR = 10\log_{10}\left(\frac{255*255}{\sum_{p=1}^{3}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_p(i,j,p)-u_p(i,j,p))^2}\right) \quad (6)$$

where I_p is the p component of the color image reference I(MxNx3) and u_p is the p component of the restored image u(MxNx3).

For more objective comparison of overall image qualities, we also use the mean image quality assessment index MSSIM which is given by the following expression as for one component p.

$$MSSIM = \frac{(2\mu_{po}\mu_p + C1)(2\sigma_{op} + C2)}{(\mu_{po}^2 + \mu_p^2 + C1)(\sigma_o^2 + \sigma_p^2 + C2)} \quad (7)$$

where σ_0 and σ_p are the standard deviations of the images I_p and u_p, respectively. μ_p is the mean value of the image u_p

$$\sigma_{op} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_p(i,j)-\mu_{po})(u_p(i,j)-\mu_p) \quad (8)$$

and where C_1 and C_2 are small constants that provide stability when the denominator approaches zero. The MSSIM for the color image is the mean value of the MSSIM obtained for each component.

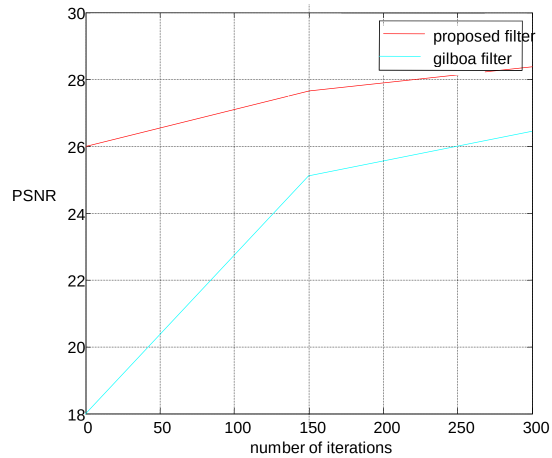


Fig. 7: PSNR representation

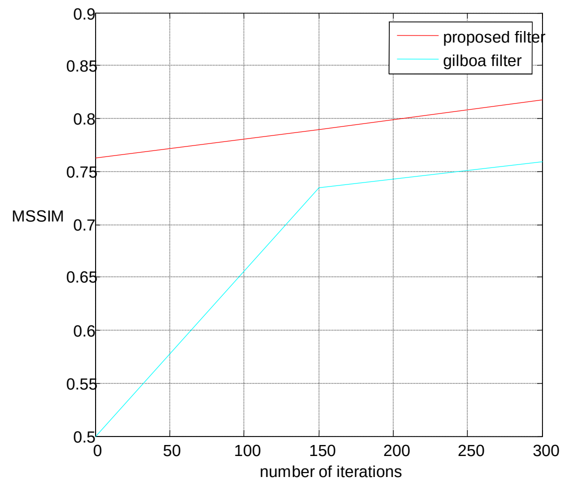
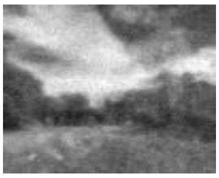


Fig. 8: MSSIM representation

In Fig. 7 we present the PSNR evolution versus the number of iterations for previous method have been compared. It can be noted that, for the same number of iterations, the PSNR of our solution is always bigger than the PSNR of other model. This can be well known by the MSSIM representation (Fig. 8) that confirms the best visual quality of our solution.


(a) **(b)**




R component of (b) **G component of (b)**


B component of (b) **(c)**


R component of (c) **G component of (c)**

B component of (c)

Fig. 9: a) Noisy & blurred image (b) Gilboa filter with its RGB representation (c) Proposed filter with its RGB representation.

All the above experiments has been performed on blurred and noisy image. We use Gilboa filter $|\lambda| = 0.1$, $\bar{\lambda} = 0.5$, $a = 0.30$, $\theta = \pi/1000$ with 200 iterations and for proposed filter $\sigma=1$, $k_d=5$, $k_c=28$, $\alpha=800$, $\beta=1$ and $\tau = 0.01$with 300 iterations.

V. CONCLUSION

From above figures it can be noticed that when compared previous method proposed method is better where it denoises and enhances and produces better visual representation. From the experimental results it can be concluded that proposed method is more efficient than Gilboa at color image restoration in the presence of blur and noise simultaneously and proposed filter does not create false colors that can appear when each component of the image is enhanced separately.

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