International Journal of Electrical and Computer Engineering (IJECE)
Vol. 7, No. 2, April 2017, pp. 850 – 857
ISSN: 2088-8708, DOI: 10.11591/ijece.v7i2.pp850-857

p-Laplace Variational Image Inpainting Model Using Riesz Fractional Differential Filter

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Article Info

Article history:
Received May 25, 2016
Revised Mar 14, 2017
Accepted Mar 29, 2017

Keyword:
Fractional calculus
Image inpainting
Partial Differential Equations
Riesz fractional derivative
Variational models

ABSTRACT

In this paper, p-Laplace variational image inpainting model with symmetric Riesz fractional differential filter is proposed. Variational inpainting models are very useful to restore many smaller damaged regions of an image. Integer order variational image inpainting models (especially second and fourth order) work well to complete the unknown regions. However, in the process of inpainting with these models, any of the unindented visual effects such as staircasing, speckle noise, edge blurring, or loss in contrast are introduced. Recently, fractional derivative operators were applied by researchers to restore the damaged regions of the image. Experimentation with these operators for variational image inpainting led to the conclusion that second order symmetric Riesz fractional differential operator not only completes the damaged regions effectively, but also reducing unintended effects. In this article, The filling process of damaged regions is based on the fractional central curvature term. The proposed model is compared with integer order variational models and also Grunwald-Letnikov fractional derivative based variational inpainting in terms of peak signal to noise ratio, structural similarity and mutual information.

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1. INTRODUCTION

Image inpainting, is an art of implementing untraceable modifications on images. It is used to restore the damaged regions of an image based on the pixel information from the known regions. It is not only used to recover the damaged parts but also used to discard the overlaid text and undesired objects. Inpainting is most useful in recovering the old photographs and images in fine art museums. It can be used as a pre-processing step for other image processing problems like image segmentation, pattern recognition and image registration. In this work, image inpainting model for text removal and scratch removal are demonstrated.

The image inpainting techniques are mainly classified into three categories: textural inpainting, structural inapinting and hybrid inpainting (combination of two approaches). Textural inpainting is mainly connected with the texture synthesis. Many texture inpainting methods have been proposed since a famous texture synthesis algorithm was developed by Efros and Leung [1]. Many other texture synthesis algorithms are proposed with the improvement in speed and effectiveness of the Efros-Leung method.

Structure inpainting is the process of introducing smoothness priors to diffuse (propagate) local structured information from source regions to unknown regions along the isophote direction. It uses partial differential equations (PDE) and variational reconstructions methods. Marcelo et al. [2] introduced first PDE based digital image inpainting. These models produce good results in restoring the non-textured or relatively smaller unknown regions. Navier-stokes equations of fluid dynamics were used by the same authors, to inpaint the unknown regions by considering the image intensity as a stream and isophote lines as flow of streamlines. However, these are slow iterative processes. In order to minimize the computational time a fast marching technique is described in [3], which fills the unknown region in single iteration using weighted means.

First variational approach to image completion was proposed by Masnou and Morel [4]. A famous variational work was introduced by Chan and Shen [5] in 2001. Their method completes the missing regions by minimizing the total variation (TV) norm. They retain the sharp edges for non-textured parts using curvature term in the corresponding Euler-Lagrange equation. TV-norm converts smooth (flat) regions into piecewise constant levels (staircase effect). Meanwhile, small details and textured regions are smoothed out. The TV inpainting model has been extended and considerably improved in subsequent works, such as curvature driven diffusion [5], Euler's elastica equation [6], Gauss curvature driven diffusion [7], fractional curvature driven diffusion [8], fractional TV inpainting in spatial and wavelet domain [9], and fractional order anisotropic diffusion [10].

Fractional differentiation[11], [12] finds an important role in the area of signal and image processing. Fractional differentiation can be viewed as the generalization of integer differentiation. The definition of fractional differentiation is not united. The commonly used definitions are proposed by the authors Grünwald-Letnikov (G-L), Riemann-Liouville (R-L), Caputo and Riesz. Many researchers have applied these definitions to many image processing applications. Yi et al. [8] proposed G-L fractional derivative based curvature driven diffusion for the minimization of metal artifacts in computerized X-ray images. Benoît et al. [13] implemented fractional derivative for the detection of edges. Yi-Fei et al. [14] constructed the fractional differential masks to enhance the texture elements in the images. Yi et al. [15] proposed two new non-linear PDE image inpainting models using R-L fractional order derivative with 4-directional masks. Stanislas and Roberto [16] proposed fractional order diffusion for image reconstruction inspired by the work of [17]. Qiang et al. [18] applied symmetric Riesz fractional derivative for enhancing the textured images. Yi et al. [9] applied fractional order derivative defined by the second definition of Yi-Fei et al. [14] and filling process is achieved by the fractional curvature term.

In this article, fractional derivative is combined with integer order variational inpainting model. The second order symmetric Riesz fractional differential operator is considered in this work, because it possesses non-local and anti-roational characteristics. The proposed model gives good visual effects and superior objective performance metrics viz., PSNR, SSIM, and MI with respect to integer order variational image inpainting models.

This article is organized in five sections. In section 2, fractional order variational inpainting model is presented and fractional central curvature term is also represented. In section 3, construction of symmetric Riesz fractional differential filter is presented. Simulation results are explained in section 4. Conclusions are given in section 5.

2. PROPOSED MODEL

Given an image, $f \in L^2(\Omega)$, with $\Omega \subset R^2$ an inpainting or missing domain having boundary $\partial\Omega$, and E an surrounding domain nearby $\partial\Omega$. The problem is to reconstruct the original image u from the observed image f.

A fractional order variational model is proposed in this article, which provides not only an effective image inpainting, but also visible reduction of unintended effects. The proposed variational model mnimizes an energy cost functional J, containing a mask that specify known and unknown regions of the image. Therefore, the completed and enhanced image is determined as a result of the next minimization

$$J_\alpha(u(x,y)) = \frac{1}{p}\sum_{x=1}^{M}\sum_{y=1}^{M}|\nabla^\alpha u(x,y)|^p + \frac{\lambda_\Omega}{2}\sum_{x=1}^{M}\sum_{y=1}^{M}|u(x,y)-f(x,y)|^2 \tag{1}$$

where α is any real number and $p \in [1,2]$, the mask is based on the characteristic function of the inpainting region, which is represented as

$$\lambda_\Omega = \begin{cases}\lambda, & (x,y) \in \Omega \\ 0, & otherwise\end{cases}$$

and the Neumann boundary condition $\partial u/\partial n = 0$ is applied. Where n is an unit vector outward perpendicular to $\partial\Omega$.

The first term of (1) is the fractional regularization term, which is used to inpaint the damaged parts based on the non-local characteristics of the image. The second term of (1) is fidelity term, which is used to preserve the important features like edges and λ_Ω is a scaling parameter in the inpainting region Ω, which is used to tune the weight of two terms in the inpainting region only. According to the fractional calculus of variations, the Euler-Lagrange equation is

$$\overline{(-1)^\alpha} div^\alpha\left(\frac{\nabla^\alpha u(x,y)}{|\nabla^\alpha u(x,y)|^{(2-p)}}\right) + \lambda_\Omega(u(x,y)-f(x,y)) = 0 \tag{2}$$

The computation of numerical algorithm is based on the gradient descent approach. and the following fractional variatinal model is obtained.

$$\frac{\partial u(x,y)}{\partial t} = \overline{(-1)^{\alpha}} curv^{\alpha} u(x,y) + \lambda_{\Omega}(u(x,y) - f(x,y)) \tag{3}$$

The result of minimization (1), representing the restored image, will be determined by solving (3). The fractional central curvature is introduced to increase the performance of image reconstruction. The discrete representation of the fractional central curvature term $curv^{\alpha}u(x,y)$ is represented as

$$\begin{aligned} curv^{\alpha}u(x,y) = div^{\alpha}\left(\frac{\nabla^{\alpha}u(x,y)}{|\nabla^{\alpha}u(x,y)|^{(2-p)}}\right) =& \nabla^{\alpha}_{x-}\left(\frac{\nabla^{\alpha}_{x+}u(x,y)}{\left(|\nabla^{\alpha}_{x+}u(x,y)|^2 + 0.5 * |\nabla^{\alpha}_{yc}u(x,y)|^2 + \epsilon\right)^{\frac{2-p}{2}}}\right) + \\ & \nabla^{\alpha}_{y-}\left(\frac{\nabla^{\alpha}_{y+}u(x,y)}{\left(|\nabla^{\alpha}_{y+}u(x,y)|^2 + 0.5 * |\nabla^{\alpha}_{xc}u(x,y)|^2 + \epsilon\right)^{\frac{2-p}{2}}}\right) \end{aligned} \tag{4}$$

where, ϵ is a small constant to stay away divide by zero. The proposed symmetric Riesz fractional differential filter coefficients are used to diffuse the pixel information in the inpainting region based on fractional central curvature term. The construction of the Riesz fractional differential coefficients will be explained in the next section.

3. CONSTRUCTION OF RIESZ FRACTIONAL DIFFERENTIAL FILTER

The second order symmetric fractional order derivative of $u(x)$ for the infinite interval $(-\infty < x < \infty)$ based on the Riesz definition is represented as a combination of the right and left sided R-L fractional derivatives

$$\frac{\partial^{\alpha}}{\partial |x|^{\alpha}}u(x) = -c_v\left(\frac{\partial^{\alpha}}{\partial(-x)^{\alpha}} + \frac{\partial^{\alpha}}{\partial x^{\alpha}}\right)u(x) \tag{5}$$

where $c_v = \left(2cos\left(\frac{\pi\alpha}{2}\right)\right)^{-1}$ with $\alpha \neq 1, (m-1) < \alpha < m < 2$ for $m \in N$

$$\frac{\partial^{\alpha}}{\partial(-x)^{\alpha}}u(x) = \frac{1}{\Gamma(m-\alpha)}\left(-\frac{\partial}{\partial x}\right)^{m}\int_{x}^{\infty}\frac{u^{(m)}(\zeta)}{(\zeta - x)^{\alpha-m+1}}d\zeta \tag{6}$$

$$\frac{\partial^{\alpha}}{\partial x^{\alpha}}u(x) = \frac{1}{\Gamma(m-\alpha)}\frac{\partial^{m}}{\partial x^{m}}\int_{-\infty}^{x}\frac{u(\zeta)}{(x-\zeta)^{\alpha-m+1}}d\zeta \tag{7}$$

The symmetric Riesz fractional order derivative is represented based on second order fractional centered difference method [19] with step h,

$$\frac{\partial^{\alpha}u(x)}{\partial |x|^{\alpha}} = -\frac{1}{h^{\alpha}}\sum_{k=-\infty}^{\infty}\frac{(-1)^k\Gamma(\alpha+1)}{\Gamma\left(\frac{\alpha}{2}-k+1\right)\Gamma\left(\frac{\alpha}{2}+k+1\right)}u(x-kh) \tag{8}$$

By noting Euler's reflection formula for Gamma function, $\Gamma\left(\frac{\alpha}{2}\right)\Gamma\left(1-\frac{\alpha}{2}\right) = \frac{\pi}{sin\left(\frac{\pi\alpha}{2}\right)}$ and
$\Gamma(\alpha)\Gamma(1-\alpha) = \frac{\pi}{sin(\pi\alpha)} = \frac{\pi}{2sin\left(\frac{\pi\alpha}{2}\right)cos\left(\frac{\pi\alpha}{2}\right)}$ gives

$$\frac{\Gamma(\alpha)\Gamma(1-\alpha)}{\Gamma\left(\frac{\alpha}{2}\right)\Gamma\left(1-\frac{\alpha}{2}\right)} = \frac{1}{2cos\left(\frac{\pi\alpha}{2}\right)} \tag{9}$$

By substituting equ. (9) in equ.(8), one can has

$$\frac{\partial^{\alpha}u(x)}{\partial |x|^{\alpha}} = -\frac{1}{2cos\left(\frac{\pi\alpha}{2}\right)h^{\alpha}}\left[\sum_{k=0}^{\infty}w_k^{\alpha}u(k-xh) + \sum_{k=-\infty}^{0}w_k^{\alpha}u(k-xh)\right] \tag{10}$$

where

$$w_0^{\alpha} = \frac{\Gamma\left(1-\frac{\alpha}{2}\right)}{\alpha\Gamma\left(1+\frac{\alpha}{2}\right)\Gamma(-\alpha)} \tag{11}$$

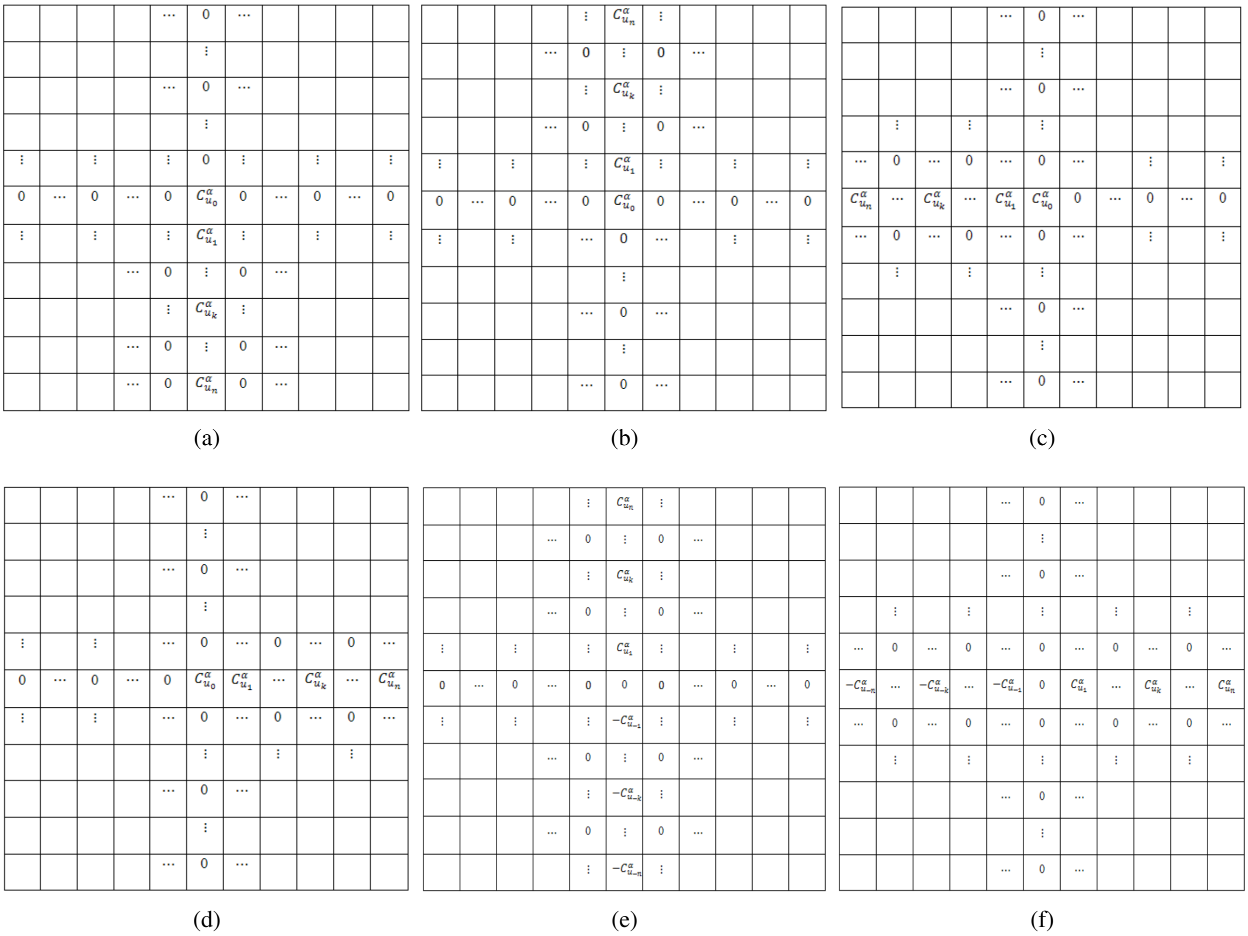

Figure 1. Fractional differential filters $(a)W^{\alpha}_{x-}$ $(b)W^{\alpha}_{x+}$ $(c)W^{\alpha}_{y-}$ $(d)W^{\alpha}_{y+}$ $(e)W^{\alpha}_{xc}$ $(f)W^{\alpha}_{yc}$

$$w_k^{\alpha} = \frac{(-1)^{k+1}\Gamma\left(\frac{\alpha}{2}\right)\Gamma\left(1-\frac{\alpha}{2}\right)}{\Gamma\left(\frac{\alpha}{2}-k+1\right)\Gamma\left(\frac{\alpha}{2}+k+1\right)\Gamma(-\alpha)}, k = \pm1, \pm2, ... \tag{12}$$

In the perspective of images, the smallest distance between the two pixels in x-direction and y-direction is one. For a 2-D image, $u(x, y)$ at a pixel (x_1, y_1), in the positive x-direction $N + 1$ pixels are considered. Therefore, $u_k(x_1, y_1) = u(x_1 - kh, y_1)$, where $h = x_1/N, 0 \leqslant k \leqslant N$, and N is the number of divisions. Similar procedure is considered in other directions, like positive y-direction, negative x-direction, negative y-direction. Consider $h = 1$ and the anterior forward $N + 1$ equivalent fractional order difference of the fractional partial differentiation in the positive x-direction is

$$\frac{\partial^{\alpha}u(x)}{\partial|x|^{\alpha}} \cong -\frac{1}{2cos\left(\frac{\pi\alpha}{2}\right)h^{\alpha}}\sum_{k=0}^{N} w_k^{\alpha}u(k-xh), 0 < \alpha \leqslant 2, \alpha \neq 1 \tag{13}$$

For the central difference in x-direction of the image $u(x, y)$ at a pixel (x_1, y_1), $N + 1$ pixels are considered in the positive x-direction and N pixels are considered in the negative x-direction. Therefore, $u_k(x_1, y_1) = u(x_1-kh, y_1)-u(x_1 + kh, y_1)$. Similar procedure is considered for central y-direction. So, the anterior $2N + 1$ equivalent fractional order centeral difference of the fractional partial differentiation in the central x-direction is

$$\frac{\partial^{\alpha}u(x)}{\partial|x|^{\alpha}} \cong -\frac{1}{2cos\left(\frac{\pi\alpha}{2}\right)h^{\alpha}}\sum_{k=-N}^{N} w_k^{\alpha}u(k-xh), 0 < \alpha \leqslant 2, \alpha \neq 1 \tag{14}$$

The fractional differential filters along symmetric directions, the positive x-axis (W^{α}_{x+}), negative x-axis (W^{α}_{x-}), positive y-axis (W^{α}_{y+}), negative y-axis (W^{α}_{y-}), central x-axis (W^{α}_{xc}), central y-axis (W^{α}_{yc}) are constructed

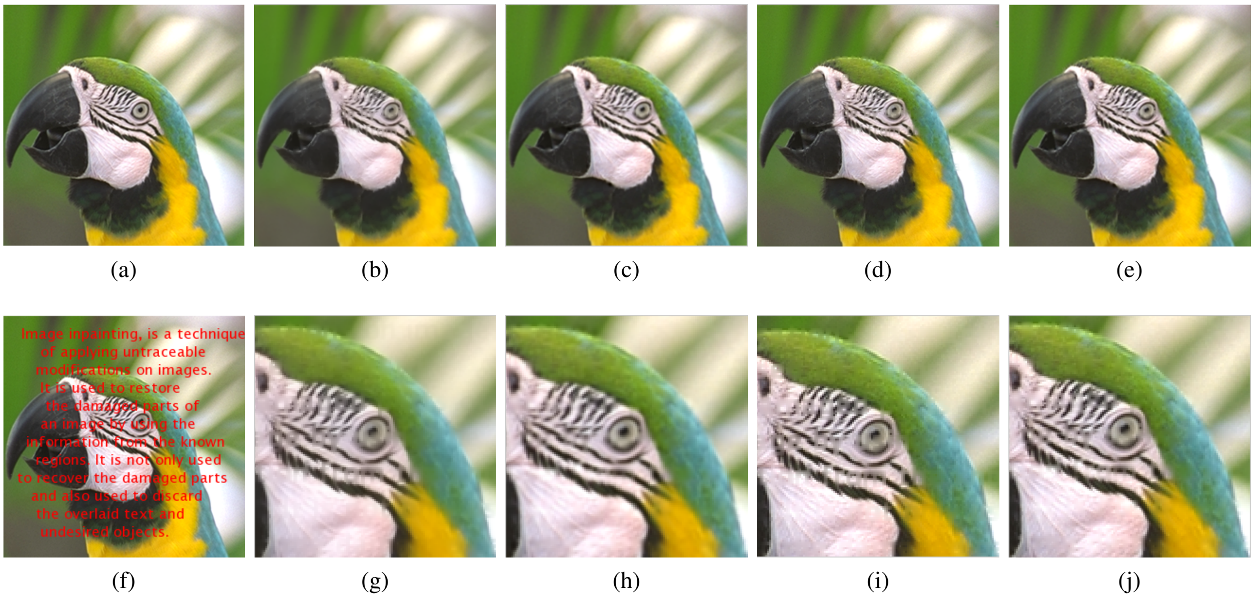

Figure 2. Comparison of variational inpainting models for text removal (a) Ground truth image, (f) Image with overlaid text (PSNR = 17.75 dB), (b) Inpainted image using TV model [20] (PSNR = 30.45 dB), (c) Inpainted image using fourth order PDE model [21] (PSNR=31.6 dB), (d) Inpainted image using Yi et al. model [9] (PSNR = 31.6 dB), (e) Inpainted image using proposed model (PSNR = 32.8 dB), (g) Enlargement of parrot's face of (b), (h) Enlargement of parrot's face of (c), (i) Enlargement of parrot's face of (d), (j) Enlargement of parrot's face of (e)

and shown in Figure 1. These fractional differential filters possess non-local and anti-rotational properties. In Figure 1, $C^{\alpha}_{u_0}$ is the filter coefficient corresponding with the interested pixel. The size of the filter is $2N+1$, where N is any positive integer and, one implements $(2N+1)\times(2N+1)$ fractional differential filter. Airspace filtering technique is performed on the symmetric directions with $(2N+1)\times(2N+1)$ fractional differential filter. The usage of the airspace filter is to move the window pixel by pixel and these are computed using

$$\nabla^{\alpha}_{l} u(x,y) = \sum_{i=-N}^{N}\sum_{j=-N}^{N} W^{\alpha}_{l}(i,j)u(x+i,y+j) \tag{15}$$

where $l = x+, x-, y+, y-, xc, yc$
The fractional differential filter coefficients are

$$C^{\alpha}_{u_0} = \frac{1}{2cos\left(\frac{\pi\alpha}{2}\right)}\frac{(\alpha-1)\Gamma\left(1-\frac{\alpha}{2}\right)}{\Gamma\left(1+\frac{\alpha}{2}\right)\Gamma(2-\alpha)} \tag{16}$$

$$C^{\alpha}_{u_k} = \frac{1}{2cos\left(\frac{\pi\alpha}{2}\right)}\frac{(-1)^k\alpha(\alpha-1)\Gamma\left(\frac{\alpha}{2}\right)\Gamma\left(1-\frac{\alpha}{2}\right)}{\Gamma\left(\frac{\alpha}{2}-k+1\right)\Gamma\left(\frac{\alpha}{2}+k+1\right)\Gamma(2-\alpha)}, k=\pm1,\pm2,... \tag{17}$$

4. RESULTS AND DISCUSSION

The proposed technique described here has been tested on large collections of images affected by missing regions. The USC-SIPI database is used in our experiments. The proposed technique provides an effective restoration of the degraded image, completing successfully the missing zones. It also preserves the image details, like edges, and reduces the unintended effects, such as image blurring, staircasing and speckle effects. The optimal image reconstruction results are achieved by the proper selection of fractional order. This value is detected by trial and error, through emprical observation. In this work, when $\alpha = 1.4$ the proposed model produces optimal reconstruction result.

The performance of this fractional order vartional model has been quantified by using well-known measures, such as peak Signal to Noise Ratio (PSNR), Structural Similarity (SSIM) [22], and Mutual Information (MI)[23]. This approach outperforms numereous state of the art inpainting methods. This fractional order variational image inpainting technique is able to restore multiple missing regions. For this reason, it can be successfully used for some important tasks, such as removing the superimposed text, removing the scratches, or removing the watermarks from the digital images.

A text removing example using proposed technique described in Figure 2, wheresome method comparison results are displayed. The images of that figure depict the inpainting results achieved by various inpainting techniques on the parrots color image collected from LIVE image database and cropped to [256 X 256] . The text is superimposed on the image and the inpainting techiniques are are applied. These inpainting techniques are carried out in YCbCr color space. The text is almost removed by all the models. However, one can observe that, the texture part near the parrot's eye is not restored well by state of the art methods, such as TV inpainting b), fourth order PDE model c), and Yi et al. model d) [9]. These models do not preserve edges and produce loss in contrast. The zoomed version of these techniques are shown in Figure 2(g)-(j). The inpainting regions after applying the proposed model are filled effectively than the other three models. Inpainting models for text removal with the same damaged mask are applied on different images and registerd in Table 1. As one could observe in that table, the performance measures of proposed inpainting technique achieve the highest values. One more observation is that, the proposed model works well even if the image having partially textured regions, but the other three models are not. The logic is that, the total variation model is second order PDE, Yi et al. model (α=1.8) is closed to fourth order PDE, where as the proposed model (α=1.4) is closed to third order PDE.

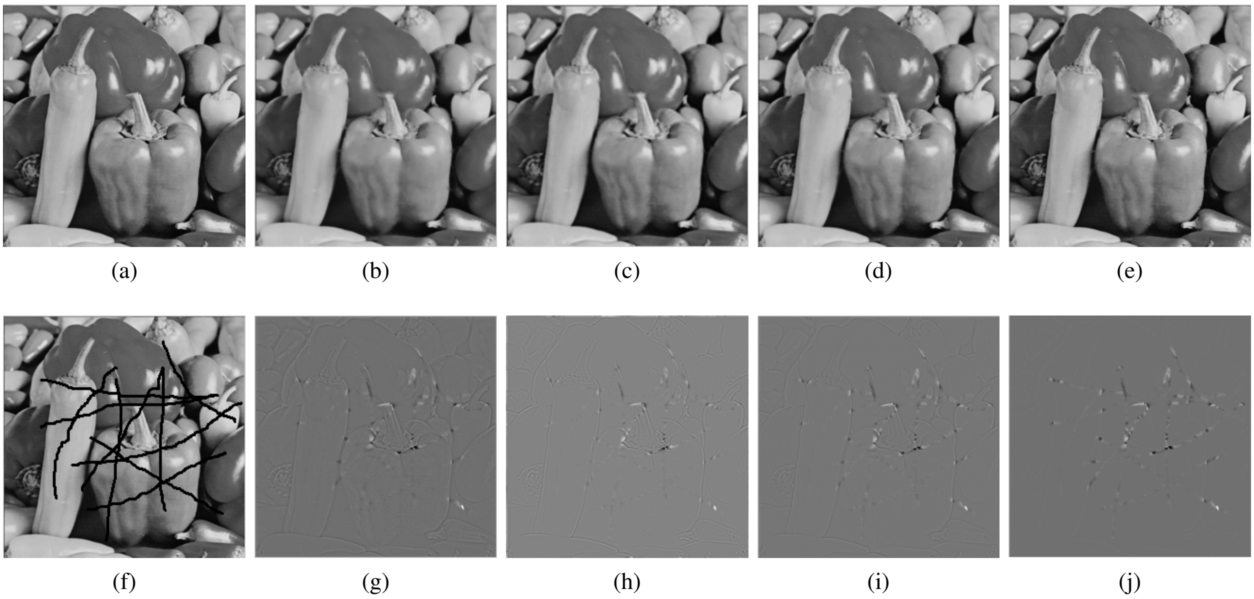

Figure 3. Inpainting of artificial lines on pepper's image (a) Ground truth image, (f) Damaged image (PSNR=16.60dB) (b) Inpainted image using TV model [20] (PSNR = 33.97 dB, SSIM = 0.9001, MI = 3.6850), (c) Inpainted image using fourth order PDE model [21] (PSNR = 33.89 dB, SSIM = 0.9312, MI = 3.8402), (d) Inpainted image using Yi et al. model [9] (PSNR = 35.9 dB, SSIM = 0.9497, MI = 4.3149) (e) Inpainted image using proposed model (PSNR = 36.16 dB, SSIM = 0.9712, MI = 5.4789), (g) Residual image of (b), (h) Residual image of (c), (i) Residual image of (d), (j) Residual image of (e)

Table 1. Comparison of inpainting models for text removal on different images

Image	I/P	TV [20]			Fourth order PDE [21]			Yi et al. [9]			Proposed model		
	PSNR	*PSNR*	*SSIM*	*MI*	*PSNR*	*SSIM*	*MI*	*PSNR*	*SSIM*	*MI*	*PSNR*	*SSIM*	*MI*
Cameraman	16.16	30.38	0.9374	3.74	30.58	0.9379	3.75	31.05	0.9396	3.79	32.94	0.9473	5.23
Elaine	18.69	38.16	0.9420	4.89	38.56	0.9478	4.92	38.72	0.9587	4.94	39.60	0.9694	5.95
Lena	19.60	34.21	0.9288	4.51	34.32	0.9327	4.57	34.52	0.9369	4.64	35.02	0.9532	5.75
Mandrill	19.53	31.18	0.8275	3.03	31.20	0.8349	3.04	31.23	0.8455	3.06	33.53	0.9516	4.80

The proposed model is also applied to remove the unwanted scratches from the image. The simulation results on pepper's image are shown in Figure 3. This inpainting technique outperforms the TV inpainting, fourth order PDE model, Yi et al. model. The experiment shows the loss of contrast after applying the inpainting techniques. In order

Table 2. Comparison of inpainting models for scratch removal on different images

Image	I/P PSNR	TV [20]			Fourth order PDE [21]			Yi et al. [9]			Proposed model		
		PSNR	*SSIM*	*MI*	*PSNR*	*SSIM*	*MI*	*PSNR*	*SSIM*	*MI*	*PSNR*	*SSIM*	*MI*
Cameraman	17.47	26.68	0.8020	3.05	26.55	0.8532	3.22	27.64	0.9290	3.82	29.20	0.9234	5.28
Man	18.24	32.21	0.9050	3.48	31.76	0.9145	3.42	32.10	0.9277	3.64	33.52	0.9493	5.11
Lena	16.64	31.84	0.8762	3.94	32.42	0.9124	3.60	32.68	0.9381	3.96	33.26	0.9590	5.15
House	16.97	34.74	0.8522	3.08	34.94	0.8865	3.22	34.87	0.9043	3.42	35.91	0.9211	4.93

to understand the loss of contrast, the residual images $(f - u + 100)$ are shown in Figure 3(g)-(j). Figure 3(g), shows the result of total variation inpainting. It produces loss in contrast and edges are also blurred. Fourth order PDE model fills the damaged regions effectively than TV model. However, edges are smoothed. Yi et al. model preserves the contrast to some extent only because the fractional curvature term is applied, which is based on forward and backward fractional differences. The proposed model uses fractional central differences. Hence, there is no loss in contrast and edges are also not blurred by the proposed model. When the fractional order is 1.4, the proposed model gives higher results than other models in terms of PSNR, SSIM, and MI also in visual quality. The inpainting techniques on different images with the same mask are applied and the simulation results are registered in Table 2. One could observe that, the performance measures of proposed inpainting technique achieve the highest values.

5. CONCLUSIONS

In this article, symmetric Riesz fractional differential filter is applied to *p*-Laplace variational image inpainting. Fractional order variational inpainting models restored superior to integer order variational models. The symmetric Riesz filter possesses non-local property, anti-rotational property, and inpainting region is filled based on the fractional central curvature term. It uses forward, backward, and fractional central differences. Therefore, this model provides the effective image inpainting and overcomes the unintended visual effects. The simulation results display that the performance of the proposed model is exceeding integer order variational models and Yi et al. model [9].

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