Image Inpainting and Enhancement using Fractional Order Variational Model

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ABSTRACT

The intention of image inpainting is to complete or fill the corrupted or missing zones of an image by considering the knowledge from the source region. A novel fractional order variational image inpainting model in reference to Caputo definition is introduced in this article. First, the fractional differential, and its numerical methods are represented according to Caputo definition. Then, a fractional differential mask is represented in 8-directions. The complex diffusivity function is also defined to preserve the edges. Finally, the missing regions are filled by using variational model with fractional differentials of 8-directions. The simulation results and analysis display that the new model not only inpaints the missing regions, but also heightens the contrast of the image. The inpainted images have better visual quality than other fractional differential filters.

Keywords: Fractional calculus; Image inpainting; PDE models; Variational model

1. INTRODUCTION

Digital image completion, or inpainting, is used to complete or replace the corrupted or missing zones of an image by using the knowledge from the known regions, such that a neutral observer would not notice any changes. There are diverse important applications of the digital image inpainting techniques, such as: damaged painting reconstruction, photo restoration, superimposed text removal, object removal, image compression and coding.

The image inpainting approaches are branched into the three groups: exemplar-based inpainting1,2, diffusion-based inpainting3-13, and hybrid inpainting14. Exemplar-based inpainting technique repeatedly synthesises the unknown area by a most identical patch in the known area. An influential exemplar-based inpainting approach was developed by Antonio1, et al. Many other innovations improving the speed and efficacy of the Antonio’s proposal have been amplified2.

Diffusion-based image inpainting refers to the technique of completing, which employs the information around the damaged region to estimate isophotes, and propagates information from outside region to inside region by propagation. It utilises the partial differential equation (PDE) based and variational based restoration methods. The PDE techniques follow isophote directions in the image to perform the restoration process. The first PDE-based image completion method was introduced by Bertalmio15, et al.. The first variational method to the image completion was introduced by Nitzberg and Mumford16, and the second variational model to image completion was proposed by Masnou and Morel17, based on interpreting the level lines with minimal curvature. A famous variational model for image inpainting was introduced by Chan and Shen17. Their variational framework completes the damaged areas by minimising the total variation (TV), while retaining approximately the ground truth image in the source regions. This method adopts an Euler–Lagrange (E-L) equation and anisotropic (non-linear) diffusion which depends on the isophotes strength. It fails to connect broken edges. The same authors extended the TV model in curvature driven diffusion (CDD) model. It is based on the geometric information of the isophotes. It modifies the coefficient of conductivity to be stronger when the isophotes have large curvature. Quick curvature driven diffusion is proposed by Xu18, et al. to reduce the computational complexity of the CDD model. Biradar and Kohir19 applied a simple method based on a nonlinear median filter to diffuse median value from exterior to interior regions. Barbu20 proposed a fast converging second order nonlinear diffusion to image inpainting.

Recently, fractional order PDEs have been studied in computer vision. The fractional derivative15,16 finds a major role in digital image processing16-23. It is the generalised form of integer order derivative. Fractional derivative is defined by many mathematicians like Riemann-Liouville, Grunwald-Letnikov, and Caputo. It exhibits the non-local property, as the fractional derivative at a pixel depends on the whole image and not just the neighbourhood pixel values. It is very useful for edge preservation and enhancement of the image. Zhang17,18, et al. proposed $p$-Laplace fractional order variational image inpainting based on Grunwald-Letnikov and Riemann-Liouville definitions. The inpainting process of these models is based on the fractional differential filter in four directions and the diffusion process is controlled by the $p$-Laplacian fractional
order gradient. The total of the coefficients in the fractional
differential filter mask derived from these two definitions
are not equal to zero, whereas for the Caputo definition, it is
close to zero, which is very much required for the contrast
enhancement. The following changes are proposed in this
article. The diffusion process is controlled by the complex
diffusion coefficient\(^{24,25}\), which is more generalised and efficient
to preserve the edges and the Caputo fractional differential
filter is considered in 8-directions because it possesses anti-
rotational capability\(^{22}\).

2. PRELIMINARIES

Given an image, \( u_0 \in L_2(\Omega) \) with \( \Omega \subset \mathbb{R}^2 \) an inpainting
or missing domain having boundary \( \partial \Omega \), and \( E \) as surrounding
domain nearby \( \partial \Omega \). The problem is to recover the ground truth
image \( u \) from the degraded image \( u_0 \). The diffusion models
are propagating local information with smoothness constraints
from exterior to the interior of the missing regions.

2.1. PDE based Inpainting Models

The simplest PDE based inpainting formulation concerns
isotropic diffusion which arises from heat flow equation.

\[
\begin{align*}
\frac{\partial u}{\partial t} &= \Delta u \\
\left. \frac{\partial u}{\partial t} \right|_{t=0} &= u_0 
\end{align*}
\]  

(1)

where \( \Delta u \) denotes image Laplacian. The PDE progression
is parameterised with a time variable \( t \), which describes the
continuous evolution of the function \( u \). It minimises these
changes in all inclinations (directions) and performs as a low
pass filter. Thus, this model gets blurred in the neighbourhood
of contours and edges. Non-linear (anisotropic) diffusion
models are useful to retain prominent edges and sharpness. The
heat flow Eqn. (1) can be rewritten as

\[
\frac{\partial u}{\partial t} = \text{div}(\nabla u) = \nabla \cdot (\nabla u)
\]  

(2)

where \( \text{div}(\cdot) \) represents divergence operator. This led to Perona
and Malik\(^{4}\) to suggest a non-linear expansion of the heat flow
equation by introducing a diffusion coefficient.

\[
\frac{\partial u}{\partial t} = \text{div} \left( c(\|\nabla u\|)\nabla u \right)
\]  

(3)

The propagation (diffusion) mechanism is diluted close to
the edges and is forceful in homogeneous regions.

2.2 Variational Image Inpainting Models

Variational formulation is another image regularisation
 technique, where the image is identified as a function of
bounded variation (BV). Variational models aim at minimising
energy functional. In total variation (TV) model\(^{7}\), the energy
function comes from the TV - norm and it minimizes TV energy
of the image in the missing region under some constraints of
fidelity to image observations.

\[
\min_{u \in BV(\Omega)} \left\{ J(u) = \int_{\mathcal{E} \subseteq \Omega} \nabla u \cdot \text{d}x \text{d}y + \frac{\lambda_{\Omega}}{2} \left( u - u_0 \right)^2 \text{d}x \text{d}y \right\}
\]  

(4)

First part of the equation denotes the regularisation,
the second part of the equation denotes the fidelity, and \( \lambda_{\Omega} \)
denotes the regularisation parameter defined as

\[
\lambda_{\Omega} = \begin{cases} 
\lambda_s(x,y) & \in E \cup \Omega \\
0, (x,y) \notin E \cup \Omega 
\end{cases}
\]

The E-L energy minimisation equation with Neumann
boundary condition associated to Eqn. (4) is

\[
\frac{\partial u}{\partial t} = -\nabla \cdot \left( \frac{\nabla u}{\|\nabla u\|^2} \right) + \lambda_{\Omega} (u - u_0)
\]  

(5)

Even though TV model is stable and provide exclusive
solution, the textures and prominent information are rigorously
smoothed out. The performance of the inpainting can be
improved by combining fractional calculus to the integer order
TV model. The fractional order variational image inpainting
model is proposed by Zhang\(^{17,18}\), et al.. The energy minimisation
equation of that model is

\[
\frac{\partial u}{\partial t} = (-1)^p \text{div}^\alpha \left( \frac{\nabla^\alpha u}{(\|\nabla^\alpha u\|)^{2-p}} \right) + \lambda_{\Omega} (u - u_0), \quad p \in [1,2]
\]  

(6)

where \( \nabla^\alpha \) is a fractional order derivative. Zhang\(^{17,18}\), et al.
considered Grunwald-Letnikov, Riemann-Liouville fractional
derivative definitions in their work. The total of filter coefficients
based on Grunwald-Letnikov and Riemann-
Liouville definitions are not equal to zero. Thereby, the contrast
of the image is reduced.

3. PROPOSED MODEL

The performance of inpainting process and contrast
enhancement can be upgraded by introducing the following
modifications in the fractional order variational model given
in the Eqn. (6).

- The fractional derivative according to Caputo definition.
- The 8-directional fractional differential filter.
- The complex edge stopping or diffusivity function.

The major advantage of Caputo fractional differential filter
over other fractional differential filters is that the total of the
filter coefficients is close to zero and the fractional differential
masks have anti-rotation capability\(^{22}\). Since there are only eight
neighbouring points for each pixel, the fractional mask in the
eight directions has well anti-rotative and it can enhance the
texture well and inpaint the curvy missing regions of the image.

Eight fractional differential masks which are respectively on the
directions of positive \( x \)-direction (\( +x \)), negative \( x \)-direction
(\( -x \)), positive \( y \)-direction (\( +y \)), negative \( y \)-direction (\( -y \)),
right upward diagonal (\( rad \)), left downward diagonal (\( lud \)),
right downward diagonal (\( rdd \)), and left upward diagonal (\( lud \)).

The diffusion process is controlled by complex diffusion
coefficient\(^{24,25}\), which is more generalised and efficient to
preserve the edges in the process of restoration. Hence, the
diffusion strength, \( (\|\nabla u\|)^2 \) in Eqn. (6) is replaced by the
influence of complex diffusion coefficient in the proposed
model. The E-L energy minimisation equation of the proposed
model is represented as

\[
\frac{\partial u}{\partial t} = (-1)^p \text{div}^\alpha \left( c(\text{Imag}(u)) \right) \nabla^\alpha u + \lambda_{\Omega} (u - u_0)
\]  

(7)

where \( c(.) \) is complex edge stopping function, defined as
c(s) = \frac{e^{s}}{1 + \left(\frac{s}{k_{s}}\right)^{2}} \tag{8}

where \( k_{s} \) is edge stopping specification and the value ranges from 1 to 1.5. A subjective property of edge information is described by the small value of \( \theta \). For big values of \( \theta \) the imaginary part feeds back to the real part creating ringing effect, which is unacceptable effect. Here for testing the inpainting performance the value of \( \theta \) is chosen as \( \pi/30 \).

The discrete representation of the first term of Eqn. (7) in 8-directions is

\[
div^{\alpha} \left( c(\text{Imag}(u))\nabla^{\alpha} u \right) = \nabla_{x} \left( c(\text{Imag}(\nabla_{x}^{\alpha} u))\nabla_{x}^{\alpha} u \right) + \nabla_{y} \left( c(\text{Imag}(\nabla_{y}^{\alpha} u))\nabla_{y}^{\alpha} u \right) + \nabla_{ldd} \left( c(\text{Imag}(\nabla_{ldd}^{\alpha} u))\nabla_{ldd}^{\alpha} u \right) + \nabla_{rdd} \left( c(\text{Imag}(\nabla_{rdd}^{\alpha} u))\nabla_{rdd}^{\alpha} u \right) \tag{9}
\]

The computation of this model is based on the gradient descent technique.

### 3.1 Construction of Caputo Fractional Differential Filter

The definition of fractional derivative\(^{15}\) in the Caputo sense of a 1D signal \( u(x) \) existing in the duration \([0, x]\) and for any real number \( \alpha \) is

\[
\nabla^{\alpha} u(x) = \frac{1}{\Gamma(m-\alpha)} \int_{0}^{x} u^{(m)}(\xi) (x - \xi)^{m-\alpha-1} d\xi, (m-1) \leq \alpha \leq m \tag{10}
\]

where \( \Gamma \) is a Gamma function. For processing, one may transform the continuous sum (integral) to the discrete sum of products. Split the integral period\(^{22}\) \([0, x]\) into \( N \) equal segments. The \( N + 1 \) causal points are

\[
\begin{align*}
    u_{0} & = u(0) \\
    u_{x-1} & = u\left(\frac{x}{N}\right) \\
    \vdots \\
    u_{k} & = u\left(x - k\frac{x}{N}\right) \\
    \vdots \\
    u_{N} & = u(x)
\end{align*}
\]

The Eqn. (10) is approximated for \( m = 2 \) as

\[
\nabla^{\alpha} u(x) \approx \frac{1}{\Gamma(2-\alpha)} \sum_{k=0}^{N-1} \int_{k/N}^{(k+1)/N} u^{(2)}(\xi) (x - \xi)^{1-\alpha} d\xi, 1 \leq \alpha < 2 \tag{12}
\]

By referring to the difference expression of second order differentiation\(^{22}\), one has

\[
\begin{align*}
    \int_{k/N}^{(k+1)/N} (x - \xi)^{1-\alpha} d\xi & = \left\{ \begin{array}{ll}
    \frac{x + x - k}{N} - 2u\left(\frac{x - k}{N}\right) + u\left(\frac{x}{N}\right) & \text{if } 0 < \alpha < 1 \\
    \frac{N}{x} & \text{if } \alpha = 1 \\
    \end{array} \right. \\
    \int_{k/N}^{(k+1)/N} (u_{\xi})^{(2)} d\xi & = \frac{N}{x} \left( u_{\xi} - 2u_{\xi-1} + u_{\xi+1} \right) \\
    \end{align*}
\]

Substituting Eqn. (13) in Eqn. (12), one get

\[
\nabla^{\alpha} u(x) \approx \frac{x^{\alpha} N^{\alpha}}{\Gamma(3-\alpha)} \sum_{k=0}^{N-1} (u_{\xi-1} - 2u_{\xi} + u_{\xi+1}) \left( (k+1)^{2-\alpha} - k^{2-\alpha} \right), 1 \leq \alpha < 2 \tag{14}
\]

By substituting the values of \( k \) and \( k = n \leq N-1 \) \( n \) (is odd number) in the Eqn. (14), the filter coefficients, \( C_{n}^{\alpha} \) can be constructed as given below

\[
\begin{align*}
    C_{n+1}^{\alpha} & = \frac{1}{\Gamma(3-\alpha)} \\
    C_{n}^{\alpha} & = \frac{2^{2-\alpha} - 3}{\Gamma(3-\alpha)} \\
    C_{n-1}^{\alpha} & = \frac{3 - 3(2)^{2-\alpha} - 3^{2-\alpha}}{\Gamma(3-\alpha)} \\
    \vdots \\
    C_{n+2}^{\alpha} & = \frac{-(n-3)^{2-\alpha} - 3(n-2)^{2-\alpha} - 3(n-1)^{2-\alpha} - n^{2-\alpha}}{\Gamma(3-\alpha)} \\
    C_{n+1}^{\alpha} & = \frac{-2n^{2-\alpha} + 3(n-1)^{2-\alpha} - (n-2)^{2-\alpha}}{\Gamma(3-\alpha)} \\
    C_{n}^{\alpha} & = \frac{n^{2-\alpha} - (n-1)^{2-\alpha}}{\Gamma(3-\alpha)} \\
\end{align*}
\]

Therefore, the anterior \( n+2 \) approximate backward difference of fractional partial differential can be represented in \( x \)-direction and \( y \)-direction respectively as

\[
\begin{align*}
    \frac{\partial^{\alpha} u(x,y)}{\partial x^{\alpha}} & = C_{n+1}^{\alpha} u(x+1,y) + C_{n}^{\alpha} u(x,y) + C_{n-1}^{\alpha} u(x-1,y) + \cdots \\
    & + C_{0}^{\alpha} u(x-k,y) + \cdots + C_{n-2}^{\alpha} u(x-n+2,y) \\
    & + C_{n-1}^{\alpha} u(x-n+1,y) + C_{n}^{\alpha} u(x-n,y) \\
    C_{n+1}^{\alpha} u(x,y+1) + C_{n}^{\alpha} u(x,y) + C_{n-1}^{\alpha} u(x,y-1) + \cdots \\
    & + C_{0}^{\alpha} u(x,y-k) + \cdots + C_{n-2}^{\alpha} u(x,y-n+2) \\
    & + C_{n-1}^{\alpha} u(x,y-n+1) + C_{n}^{\alpha} u(x,y-n) \\
\end{align*}
\]

Similarly, the fractional differential for the given fractional order subsequently on the symmetric eight directions can be executed and represented in Fig. 1. These are positive \( x \)-direction, negative \( x \)-direction, positive \( y \)-direction, negative \( y \)-direction, right upward diagonal, left down diagonal, right down diagonal and left upward diagonal correspondingly denoted by \( F_{n+1}^{\alpha} u(x,y), F_{n}^{\alpha} u(x,y), F_{n-1}^{\alpha} u(x,y), F_{n-2}^{\alpha} u(x,y), F_{n-3}^{\alpha} u(x,y), F_{n-4}^{\alpha} u(x,y), F_{n-5}^{\alpha} u(x,y) \). One may recognise that, \( C_{n}^{\alpha} \) is the weight of the fractional differential filter for the given \( \alpha \) on non-causal pixel \( u_{\xi} \) and \( C_{n}^{\alpha} \) is the weight of the fractional differential filter of interest pixel. In general, \( C_{n}^{\alpha} \) is the weight of the fractional differential filter for given value of \( k \). If the image is to be processed with a nonlinear filter, the values of its pixels are calculated with a \( n \times n \) size mask using
\[ \nabla_{\alpha} u(x, y) = \sum_{i=0}^{(n-1)} \sum_{j=0}^{(n-1)} F_{\alpha}^{(i,j)} u(x+i, y+j) \]  

(18)

where \( \text{dir} = x^+, x^-, y^+, y^-, ldd, udd, lud, rud \).

4. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed technique has been exercised on large collections of images affected by missing regions. The USC-SIPI\textsuperscript{26} image 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, and reduces the undesirable effects, such as image blurring, stair-casing 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 empirical observation. In this work, \( \alpha = 1.6 \) is considered for optimal reconstruction result. The performance of this model has been quantified by using the well-known metrics, such as peak signal to noise ratio\textsuperscript{27} (PSNR), mean structural similarity\textsuperscript{28} (MSSIM), mutual information\textsuperscript{29} (MI), and normalised cross-correlation\textsuperscript{27} (NCC). All models are implemented under 64-bit Windows 8 and MATLAB R2013b running on a laptop with Intel Core i3, 1.40 GHz and 4 GB of memory.
A text removing example, using the proposed technique is described in Fig. 2, where some method comparison results are displayed. The images of that figure depict the inpainting results achieved by various inpainting techniques on the cameraman image. The text is superimposed on the image and the different inpainting techniques are applied.

To understand the inpainting capacity and loss in contrast, the residual images $u^* = u + 256$ are considered. One can observe that, the inpainting is not done properly in the heterogeneous regions by the state of the art models, such as Chan & Shen model, and two Zhang\textsuperscript{17,18}, \textit{et al.} models. These models do not preserve edges effectively and produce loss in contrast. The inpainting regions after applying the proposed model are filled effectively than the other models. The performance metrics of these models are registered 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 has partially textured regions, but the other fractional order variational models are not. The logic is that, Zhang\textsuperscript{17,18}, \textit{et al.} models ($\alpha = 1.8$) are close to fourth order PDE, whereas the proposed model ($\alpha = 1.6$) is close to third order PDE. The performance of the proposed model based on the fractional differential filter in 4 directions which is used by Zhang\textsuperscript{18}, \textit{et al.} is also applied. The diffusion process of the pixel intensity in the missing regions depends upon only 4-neighbourhood pixels. Hence, the propagation of the pixels from the known pixels into the missing regions in the diagonal direction is less.

The proposed technique is also applied to remove the handwritten text from the image. It is compared with isotropic diffusion, Bertalmio, PM diffusion, You and Kaveh, Zhang models with respect to residual images as shown in Fig. 3. It is found that, the proposed reconstruction technique produces the result without any loss of contrast and blur. This technique is also applied for the removal of text and scratches in the presence of Gaussian noise, $\sigma = 10\%$ and $\sigma = 15\%$ on Peppers and House images. The proposed model inpaints well, even the known regions are affected by the noise and it can also denoise the non-inpainting regions without introducing any unintended effects i.e., edge blur, staircasing effect, and loss in contrast.

The simulation results are listed in Tables 1-4. It is observed that the proposed model is associated with higher PSNR, MI, MSSIM, and NCC values in comparison to other techniques for all four sample images in consideration. The values of MSSIM and NCC associated with the proposed model, which are very close to one, indicate that the proposed scheme is well capable of structures and high MI value indicates that the edge preservation of testing images. One could examine that,

<table>
<thead>
<tr>
<th>Model</th>
<th>PSNR</th>
<th>MSSIM</th>
<th>MI</th>
<th>NCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chan and Shen\textsuperscript{7}</td>
<td>26.48</td>
<td>0.7039</td>
<td>2.6809</td>
<td>0.9816</td>
</tr>
<tr>
<td>Zhang\textsuperscript{17, et al.}</td>
<td>31.53</td>
<td>0.9453</td>
<td>3.8743</td>
<td>0.9941</td>
</tr>
<tr>
<td>Zhang\textsuperscript{18, et al.}</td>
<td>32.15</td>
<td>0.9620</td>
<td>4.2673</td>
<td>0.9949</td>
</tr>
<tr>
<td>Proposed model</td>
<td>33.03</td>
<td>0.9736</td>
<td>5.5312</td>
<td>0.9958</td>
</tr>
</tbody>
</table>

Figure 2. Comparison of various variational inpainting models for superimposed text removal (Residual of inpainted images with ground truth image).
Table 2. Comparison of various image inpainting models for hand-written text removal (Damaged Lena Image, PSNR = 19.38 dB)

<table>
<thead>
<tr>
<th>Model</th>
<th>PSNR</th>
<th>MSSIM</th>
<th>MI</th>
<th>NCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Isotropic diffusion</td>
<td>29.23</td>
<td>0.7805</td>
<td>2.8031</td>
<td>0.9838</td>
</tr>
<tr>
<td>Bertalmio</td>
<td>26.14</td>
<td>0.6088</td>
<td>2.4475</td>
<td>0.9644</td>
</tr>
<tr>
<td>PM diffusion</td>
<td>37.01</td>
<td>0.9602</td>
<td>4.3553</td>
<td>0.9971</td>
</tr>
<tr>
<td>You and Kaveh</td>
<td>34.74</td>
<td>0.9257</td>
<td>3.6613</td>
<td>0.9951</td>
</tr>
<tr>
<td>Zhang, et al.</td>
<td>34.80</td>
<td>0.9352</td>
<td>3.6702</td>
<td>0.9952</td>
</tr>
<tr>
<td>Proposed model</td>
<td>35.86</td>
<td>0.9481</td>
<td>3.9062</td>
<td>0.9962</td>
</tr>
</tbody>
</table>

Table 3. Comparison of various image inpainting models for scratch removal in the presence of Gaussian noise ($\sigma = 15\%$)(damaged house image, PSNR = 16.11 dB)

<table>
<thead>
<tr>
<th>Model</th>
<th>PSNR</th>
<th>MSSIM</th>
<th>MI</th>
<th>NCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chan and Shen</td>
<td>27.01</td>
<td>0.6173</td>
<td>2.0553</td>
<td>0.9771</td>
</tr>
<tr>
<td>You and Kaveh</td>
<td>28.77</td>
<td>0.6318</td>
<td>2.1281</td>
<td>0.9823</td>
</tr>
<tr>
<td>Zhang, et al.</td>
<td>29.45</td>
<td>0.6377</td>
<td>2.0738</td>
<td>0.9848</td>
</tr>
<tr>
<td>Proposed model</td>
<td>30.99</td>
<td>0.6494</td>
<td>2.2456</td>
<td>0.9878</td>
</tr>
</tbody>
</table>

Table 4. Comparison of various image inpainting models for text removal in the presence of Gaussian noise ($\sigma = 10\%$)(damaged peppers image, PSNR = 15.89 dB)

<table>
<thead>
<tr>
<th>Model</th>
<th>PSNR</th>
<th>MSSIM</th>
<th>MI</th>
<th>NCC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chan and Shen</td>
<td>25.20</td>
<td>0.6022</td>
<td>2.2091</td>
<td>0.9523</td>
</tr>
<tr>
<td>You and Kaveh</td>
<td>25.32</td>
<td>0.6122</td>
<td>2.4134</td>
<td>0.9768</td>
</tr>
<tr>
<td>Zhang, et al.</td>
<td>27.65</td>
<td>0.6297</td>
<td>2.4793</td>
<td>0.9805</td>
</tr>
<tr>
<td>Proposed model</td>
<td>27.84</td>
<td>0.6311</td>
<td>2.4927</td>
<td>0.9814</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS

In this paper, Caputo fractional differential filter is proposed and it is applied to inpaint the missing regions. The edge-stopping function is also applied to preserve the edges of the image, which depends on the fractional order gradient. The proposed inpainting technique obtains the better objective quality and visual quality.
sum of the Caputo fractional differential filter coefficients is zero. Thereby, the loss of contrast of the image is minimised, while effectively inpainting the missing regions. The idea of inpainting the missing regions using the proposed model performs the better visual quality and objective quality.

The proposed fractional order variational method may be applied for denoising problems of the astronomical and microscopic images. The proposed framework may be implemented in future work to the problem of completing the damaged or missing wavelet coefficients in view of lossy image transmission.

REFERENCES
CONTRIBUTORS

Ms G. Sridevi received her BTech from Nagarjuna University and MTech from JNT University, Kakinada. Presently she is pursuing her PhD in JNT University, Kakinada. Currently working as an Associate Professor in the Department of ECE, Aditya Engineering College, Surampalem, AP. Her areas of interest include: Image restoration, enhancement, and fractional calculus.

In the current study, she is responsible for the proposal of the technique used in the paper, software implementation and testing the results.

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In the current study, he has provided guidance for implementing the proposed technique.