SPEEDY RECOVERY OF DAMAGED DIGITAL PHOTOGRAPHS USING MULTI STRUCTURE MORPHOLOGY

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Abstract

A speedy recovery of damaged digitized photographs based on orientation driven multi structure morphology is proposed. The recovery order plays an important factor for human visualization and hence it is guided by the orientation of edges at the surrounding known regions of the missing domain. The image is edge detected by thresholding the image gradient along the eight possible orientations. These eight edge images are represented as eight edge planes. The edge-plane-sliced information is used twice manifold for reconstructing the regions within the missing part, as well as for guiding the integration that follows. The damaged regions are morphologically eroded using the structuring elements of corresponding orientations dictated by the edge-planes. The resultant filled image is obtained using local isotopic driven integration. The novelty of our approach is to explicitly specify the direction of filling herby ensuring ease in convergence in different orientations and then streamlining the process to guarantee complete and natural look. By implementing region-filling through morphological erosion, several pixels instead of one can be restored at every inpainting step, making the method faster than many traditional texture synthesis inpainting algorithms and successfully recovers images with better Peak Signal to Noise ratios even for massive damages.

Keywords:

Image Gradient, Morphological Erosion, Structuring Elements, Texture Synthesis, Inpainting

1. INTRODUCTION

Film and Photography archives nowadays go through an accelerated process of degradation. Since the early days of art and photography, filling-in and inpainting has been done by professional artists. Imitating their performance with semi-automatic digital techniques is currently an active area of research. The basic idea behind the algorithms that have been proposed in the literature is to fill-in these regions with the available information from their surroundings.

1.1 LITERATURE REVIEW

In all image filling methods the known information on the image is used to fill the gaps. However how the information is used defines the methodology of filling. Basically the algorithms discussed in the literature perform best either for pure structure by diffusion [1, 2, 3] or for pure texture by sampling [4, 5, 6]. A Method based on long range correlation is also proposed by David zhang et al [7] recovers by sampling not only the information in local areas, but also in the remote regions in the image. The texture synthesis fails to recover edges and structure methods fails to recover texture and the recovery is a blurred version for massive damages.

Since most image areas are not pure texture or pure structure, simultaneous methods [8, 9] are also proposed either by classifying the lost block based on the nature of the surrounding of the lost region or by decomposing the image into texture and structure parts and duly filling by the respective methods i.e either texture synthesis or inpainting for texture and structure region respectively. Exemplar based filling method is proposed by Antonio Criminsi et al[10] emphasis on the order by which the image synthesis proceeds, usually using a confidence map computed based on heuristics and ad hoc principles, which may again lead to visual inconsistencies. Block based recovery by alternating projection onto convex sets is proposed by Jiho park et al [11] recovers either in horizontal or vertical directions. Inpainting of binary images by solving the cahn-hilliard diffusion equation is proposed by Andrea L. Bertozzi et al [12]. Julia A. Dobrosotskaya et al [13] proposed a method for the recovery of piecewise constant signals and images using a combination of variational methods and wavelet analysis. These methods when applied to images where the missing regions are large usually over smooth the image and introduce blurring artifacts and may take few thousands of iterations.

A method using morphology is proposed by Hao Guo et al [14] which replicate the structure details by sum of square differences (SSD) based matching but fails to recover non repetitive edge features like corners, curves with large curvature, etc. The methods reported in the literature have high complexity due to its iterative nature and exhaustive searching for its matching patch. A Discrete wavelet transform (DWT) based orientation driven morphological inpainting [15] fills the missing region using multi structure morphology in 4 possible directions but fails in integration to provide a complete look.

The technique presented here is inherited from Mathematical Morphology. Mathematical Morphology is a mathematical theory which can be used to process and analyze the images. It provides an alternative approach to image processing based on shape concept stemmed from set theory [16]. In the mathematical morphology theory, images are treated as sets, and morphological transformations which derived from Minkowski addition and subtraction are defined to extract features in images. The proposed algorithm has 3 main building blocks and are discussed briefly in the following sections. Section 2 Edge Plane Slicing initially determines the orientation of surrounding regions by the first order derivative of the image thereby influencing the orientation of the structuring element used to erode the missing regions, Section 3 Morphological sealing leads to erosion of the damaged regions in varied orientations, Section 4 Integration of the filled damage regions with reference to their orientations, Section 5 Experimental Results compares the method with those obtained by state of the art techniques and Section 6 Conclusion. The system can preserve isotope continuity by orientation driven morphological erosion and texture characteristics by local isotopic orientation driven integration that outputs a complete, natural-looking and non-blurred image. As several pixels instead of just one can be restored at every inpainting step, the method is faster than many traditional texture synthesis-inpainting algorithms.

2. EDGE PLANE SLICING

In this section the orientation of the missing domain is predicted. The structure in the missing region is dictated by the orientation of edges in its surrounding region. Information from the environment of masked missing areas is propagated along isophotes by inpainting. Usually the Partial Differential Equation (PDE) that performs inpainting must be accurate in the sense it can ensure continuation of level lines. The continuation ought to be strong and allows the restoration of even thin structures occluded by a wide gap.

The Frei and Chen [17] operator is used to detected edges in an image. The Frei and Chen edge detection technique is less sensitive to noise than other edge operators Compass operators [18, 19] are also used for orientation detection but they are not isotropic .Frei and chen operator an isotropic edge detector detects the orientation of the surrounding region and thereby steering the Morphological inpainting process. The goal of using such operator is the accurate detection, description, and linking of edges, corners, and junctions in natural images. The response of the respective edge masks and line masks along the four possible directions {0°, 45°, 90°, 135° } are laid in layers.

3. MORPHOLOGICAL SEALING

The edge plane information dictates the filling process and it is through morphological erosion. The erosion process of a binary image can be considered as an inpainting process of the binary image. The main advantage of this process is that it explicitly maintains the narrow band that separates the known from the unknown image area, and specifies the next pixel to be inpainted. For gray or color images, the gray or color information of the unknown pixels can be restored based on information from the neighborhood. Inpainting of a damaged area can also be performed using the erosion process and it is done by grayscale morphological erosion of the damaged region.

3.1 MORPHOLOGICAL EROSION

Morphological erosion [20] of a gray-scale image $F(x, y)$ by a gray-scale structuring element (SE) B(s, t) is denoted by ($F\Theta B$) (x, y) and given in Eq.(1),

$$\begin{aligned}&(F\Theta B)(x,y)=\min\{F(x+s,y+t)+B(s+t)\}/(s+x),\\&(t+y)\in D_f;(s,t)\in D_d\end{aligned}\tag{1}$$

where, D_f and D_d are the domains of F and B respectively. $F(x,y)$ denotes a gray-scale two dimensional image, $B(s,t)$ the structuring element (SE) itself a sub image function.

The choice of the structure element is a key factor in morphological image processing. The size and shape of the SE decides the direction of erosion in this manner the recovery trend of the restored damaged regions. The basic theory of multi-structure elements morphology is to construct different structure elements in the same square window. For the square window of size 3X3 the direction angles of the structure elements are 0º,45º, 90º, and 135º and given by Yuqian Zhao et al[21].

3.2 THE RECOVERY

Let Ω be the missing domain of the original damaged image I. The boundary of the missing domainΩ' in the edge images is extracted to propagate the features of the boundary into the missing domain. In general the boundary of any domain A denoted by $\beta(A)$ is obtained by first dilating A by B and performing set difference between the dilated version of A and A as given in Eq.(2),

$$\beta(A) = (A \oplus B) - A \tag{2}$$

where, B is a suitable structuring element and ($A \oplus B$) is binary morphological dilation[19] and is given as in Eq.(3)

$$A \oplus B = \{z/(B)_z \cap A \in A\}. \tag{3}$$

The response of the edge planes alongΩ' determines the structuring elements for eroding the missing region. The structuring elements corresponding to the orientation of the positive response planes are used for eroding the error image (original damaged image) to obtain a degree filled images.

Let N=8 be the number of edge orientation planes ℘ where ℘ = {P_i / 1 ≤ i ≤8} are edge planes obtained using Edge plane slicing and each i corresponds to an orientation. N' ≤ N be the number of positive response planes℘' where ℘'= {P'_j / j ∈ {1..8} }, ℘'⊆ ℘ and each j corresponds to an orientation. Element P'_j of℘' is selected if the element P_i of ℘ satisfy the following condition given in Eq.(4)

$$\int_{x\in\Omega'} P_i\,\partial x \;>\; 0. \tag{4}$$

Let ϑ' ={ $\theta_j^{`}$ / j ∈ {1..8}} represents the set of orientations of ℘'. The error image is eroded with each structuring element corresponding to the orientation of ϑ' to obtain ℜ' images, cardinality (ℜ', ϑ', ℘') = N' and ℜ'={ $R_j^{`}$ /j∈ {1..8} }where $R_j^{`}$ is given as in Eq.(5)

$$R_j^{`} = I \,\Theta\, SE_{\theta_j^{`}} \tag{5}$$

where, $SE_{\theta_j^{`}}$ denotes the structuring element corresponding to the orientation θ_j' .

4. INTEGRATION

At each iteration of recovery the recovered imagesℜ' are integrated to obtain the completely filled image. The integration is by winner-takes-all addition of the pixels in the eroded regions of images Rj ∈ ℜ'.

Let Ω' at edge images℘' be ℘'$_{\Omega'}$ and at I be I $_{\Omega'}$. At any iteration of filling let $\Omega'_t \subseteq \Omega$ be the area to be filled and Ω_{t-1} is its recently filled boundary . During the progress of filling each pixel (m',n') at Ω'_t is filled from $R_j^{`}$ (m', n') and the plane j for pixel (m',n') at iteration t denoted as $j_{(m',n')_t}$ is selected as the closest response edge pixel from ℘' at Ω'_{t-1} in the mean square sense and is given in Eqs (6) and (7),

$$\underset{(m',n')_t}{j} = \arg\min_{i} \left\| (m,n)_{P'_{i\Omega'_{t-1}}} - (m',n')_{\Omega'_t} \right\| \forall i \in N', \tag{6}$$

$$\forall (m,n) \in P'_{i\Omega'_{t-1}} \text{ and } \forall (m',n') \in \Omega'_t$$

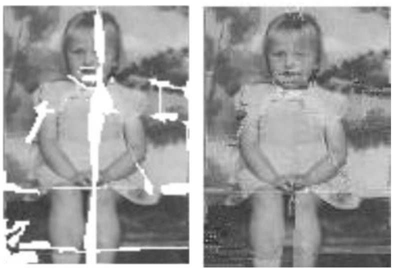
$$I_{\Omega'_t}(m',n') = R_{\underset{(m',n')t}{j}}(m',n') \tag{7}$$

where, (m, n) is an edge pixel of $P'_{i\Omega'_{t-1}}$ and $R_{\underset{(m',n')t}{j}}(m',n') \in \Re'$. j obtained in Eq.(6) represents the local isotopic orientation and the pixel value corresponding to the particular orientation eroded image is the candidate pixel for recovery. Pixel (m', n') of R'_j (m', n') is the winner whose sole value is assigned to the damaged region. The recovery followed by integration is iteratively applied to restore all the discrete pixels of the current boundaryΩ'^{t} (Ω't denotes the boundary at time t, t = 0,1,…T, Ω'^{0} is the initial boundary),and the boundary is advanced inside Ω until the whole region is restored.

5. EXPERIMENTAL RESULTS

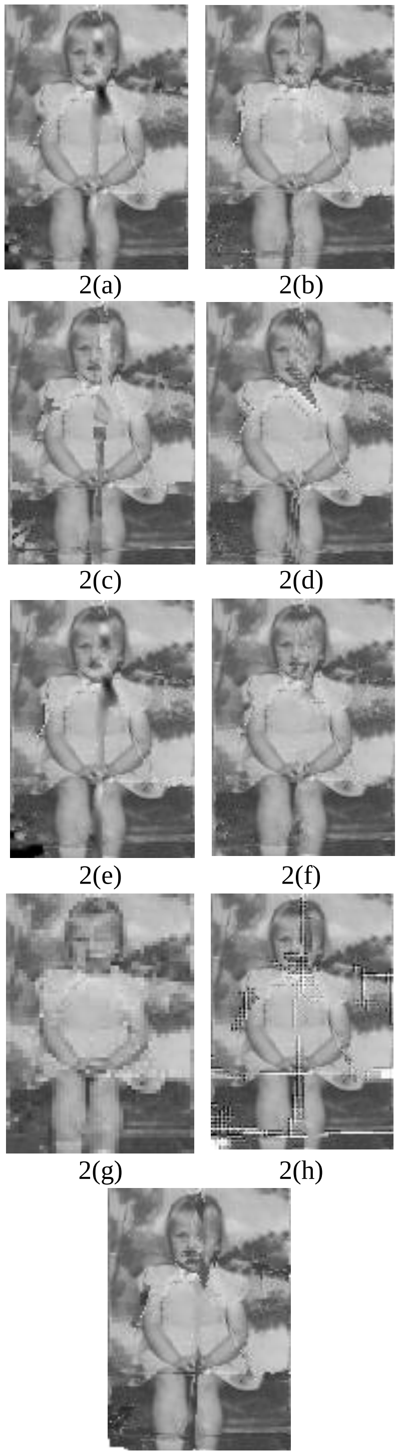
The algorithm is implemented in MATLAB 6 under WINDOWS 2000, Pentium IV- 2.4 GHz processor. The images used are digitized photographs that are damaged due to aging. The quality of an inpainting in recovery of damaged digitized photographs is a subjective issue. Hence Fig.1(a) shows the original damaged image and 1b the recovered image by the proposed method.

Figs.2(a) – 2(i) compares the restoration for same image with the existing methods. To test the algorithm a standard Peak Signal to Noise ratio is also used. Julie.bmp of size 107 X 146 is used to compare the method in terms of PSNR's for various percentages of losses. Fig.3 and Fig.4 shows still more examples of recovery by the proposed method. Fig.5(a) shows the original image Julie.bmp, Fig.5(b) the manually corrupted Julie.bmp, Fig.5(c) the restored image by the proposed and Figs.6(a) – 6(h) shows the recovery for the existing methods. Fig.7 shows the strength of the method the recovery at edge crossings and recovery at curved edges.



1(a) 1(b)

Fig.1(a). Damaged digitized photograph Girl.bmp for recovery, 1(b). Recovery by the proposed method



2(a) 2(b) 2(c) 2(d) 2(e) 2(f) 2(g) 2(h) 2(i)

Fig.2(a). Recovered by inpainting[2], 2(b). Recovery by Texture synthesis[4], 2(c) Recovered by Long Range correlation (0th order)[7], 2(d). Recovered by Long Range correlation (1st order)[7], 2(e). Recovered by the Simultaneous method [8], 2(f). Recovered by Exemplar based inpainting[10], 2(g). Recovered by Foe-inpainting[22], 2(h). Recovered by Morphological Erosion[14], 2(i). Recovered by DWT based Morphological Erosion[15]

3(a)

3(b)

Fig.3(a). Damaged Digitized photo (Boys.bmp)
3(b). The recovered (Boys.bmp) by the proposed method

4(a) 4(b)

Fig.4(a). Damaged Digitized photo (Boy.bmp),
4(b). The recovered (Boy.bmp) by the proposed method

5(a) 5(b) 5(c)

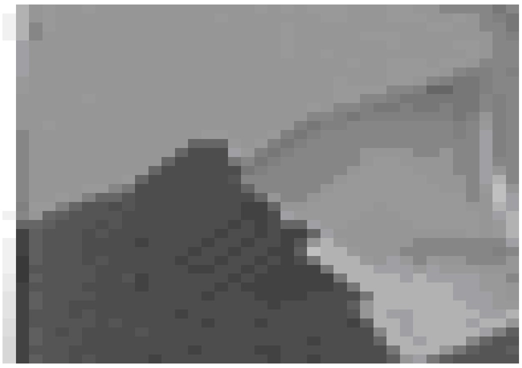
Fig.5(a). Original Julie.bmp 5(b). Manually corrupted Julie.bmp(15 % loss) 5(c). Recovery by the proposed method

6(a) 6(b) 6(c)

6(d) 6(e) 6(f)

6(g) 6(h) 6(i)

Fig.6(a). Recovered by inpainting[2], 6(b). Recovery by Texture synthesis [4], 6(c). Recovered by Long Range correlation (0^{th} order) [7], 6(d). Recovered by Long Range correlation (1^{st} order)[7], 6(e). Recovered by the Simultaneous method [8], 6(f). Recovered by Exemplar based inpainting [10], 6(g). Recovered by Foe-inpainting [22], 6(h). Recovered by Morphological Erosion[14], 6(i). Recovered by DWT based Morphological Erosion[15]



7(a)

7(b)

Fig.7(a). Zoomed recovery at edge crossings, 7(b). Zoomed recovery at curved edges

Table.1 compares the performance of the algorithm in terms of PSNR's for the image Julie.bmp by the proposed method with other methods for various percentages of losses. It can be inferred from the table that the proposed method produces better ratios for all percentage of losses when compared with the methods reported earlier in literatures.

Table.2 compares the time for recovery in seconds by the proposed method with other methods for various percentage of losses for the same image julie.bmp. The proposed method converges easily by steerable morphological erosion followed by isotope driven winner takes all integration for complete and natural look. It can be inferred from Table.3 that the proposed method is faster than the traditional methods like inpainting and texture synthesis but comparable with Morphological erosion [14,15]. However it can be referred from Table.1 that the recovery is more reliable for the proposed method when compared with the time compatible methods.

6. CONCLUSION

The proposed method fills the missing data in damaged regions of digitized photographs/images by interpolating from the vicinity. It fills the damaged regions based on morphological erosion synchronized with image feature replication. Standard image inpainting algorithms are inspired by the partial differential equations of physical heat flow and are ensured by continuation of level lines / Laplacian (a smoothness operator). Their drawback is that the diffusion process introduces some blur, which becomes noticeable when filling larger regions and the convergence for the solution take few thousands of iterations. The main feature of this work is yielding a solution that may have strong continuation of edges even for massive loss in a fast manner. It is motivated by two factors 1) Oriented edge detection help in steerable sealing pays for strong continuation and easy convergence and 2) Pursued by integration (Streaming the filling process to incorporate natural and complete look). The extension of the effort includes filling several pixels at every inpainting step instead of just one. Hence the process is faster than many traditional texture synthesis inpainting algorithms resulting in better and compatible PSNR's with other methods previously reported in literatures.

Table.1. Compares the performance of the algorithm in terms of PSNR's for the image Julie.bmp

Sl. No.	Method	% Loss						
		10	15	20	25	30	35	40
1	Inpainting [2]	27.6440	21.0716	18.6014	15.8120	13.3258	14.5835	13.6660
2	Texture Synthesis [4]	24.6705	19.5296	19.8859	17.6618	15.4805	15.002	14.1168
3	Long range Correlation - 0^{th} order [7]	19.9276	16.8636	16.2392	16.2708	13.5617	13.2236	12.3495
4	Long range Correlation - 1^{st} order [7]	29.3517	21.9038	21.4386	20.7521	17.3702	17.3808	15.7505
5	Exemplar based Inpainting[10]	26.9357	25.6926	22.1001	21.3042	21.7093	19.6107	17.9941
6	Foe-inpainting [22]	30.6237	27.3811	26.1763	24.8823	22.7952	21.7733	20.4155
7	Morphological Erosion[14]	28.001	26.2404	25.6997	22.1387	21.8926	21.3153	19.1929
8	DWT-Based Erosion [15]	18.5106	19.2835	16.7038	15.8604	15.1265	14.4596	13.5615
9	Proposed Method	32.8506	28.4143	27.9083	24.6473	23.7913	22.2590	21.5618

Table.2. Compares the performance of the algorithm in terms of Execution Time (seconds) for the image Julie.bmp

Sl. No.	**Method**	**% Loss**						
		10	15	20	25	30	35	40
1	Inpainting [2]	101.4219	105.2031	159.1875	188.3281	238.8594	240.9375	285.3125
2	Texture Synthesis [4]	834.2969	1799.2	9180.7	14112.0	30905.0	18144.0	23141.0
3	Long range Correlation - 0^{th} order [7]	272.6250	377.3906	393.7344	395.5313	421.788	383.7818	455.2969
4	Long range Correlation - 1^{st} order [7]							
5	Exemplar based Inpainting[10]	7.1563	11.6406	15.5000	20.6250	26.2500	29.8750	40.3125
6	Foe-inpainting [22]	77.0313	78.9063	76.25	82.4531	76.2626	80.5	81.5938
7	Morphological Erosion[14]	1.7344	1.7344	1.8706	1.8750	1.9063	1.9216	1.9375
8	DWT-Based Erosion [15]	1.25	1.25	1.25	1.2188	1.288	1.2656	1.2656
9	Proposed Method	1.3594	1.4219	1.5938	1.7530	2.0625	2.1094	2.3594

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