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Non Blinded Image Inpainting With Low Rank Non-Negative Matrix Factorization

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Abstract: In digital image processing object removal from a digital image is termed as inpainting. Image recuperation especially with high curvature are inpainting challenges. Due to both colour and texture preservation non blinded exemplar based approaches are famous among other inpainting algorithms. In general these algorithm possess greedy approach in the selection of a target patch, the selection is based upon dedicated priority defined on every patch at contour of the target region, this may jeopardize searching and selection of a good exemplar in global space. The whole process is time consuming and computationally expensive. To tackle said problems a novel algorithm is proposed which reduces the dimension of global search space using neighbour patches information of target region throughNon-Negative Matrix Factorization (NMF). Due to NMF nature of lower dimension approximation, improvised efficiency is observed in an experiment without compromising the quality of inpainted image. The inpainted result of the proposed algorithm is comparable with other inpaintingtechniques.

Keywords: Non-negative matrix factorization, exemplar

1. INTRODUCTION

Digital image inpainting aims to recuperate an image in such a way an unsuspicious viewer would not be able to detect the indication of object removal and reconstruction.

Image anomalies in digital images lead to extensive research. Existing inpainting methods are bifurcate as variational and exemplar approaches. Many of variational approaches have utilized Bertalmio et al(Bertalmio 2000) algorithm.Approaches (Chen and Shen, 2001) (Chen, 2001) (Tele, 2004) mainly deal with structural properties and work at pixel level on input mask image. These approachestreat image as three separate channels. For each channel these approaches interpolate information outside the mask along edge isophote(the direction and intensity of pixels on target edge) while preserving boundaries.Variation in color is approximated locally using partial differential equations(PDE) in smooth fashion across the mask region of image. Despite of computational demand PDEs are widely used among research communities as PDE's satisfies arbitrary values on the boundary of domain when propagates small structure.

For large object recovery these approaches are unsuccessful. Non parametric patch based exemplar approaches are ideal while dealing with large objects as they are supported by texture synthesis. In two dimensional textural pattern the most compatible texture fragment of the source region to the texture fragment of the target region is searched globally and partially replicated to the corresponding target region (Ashkmin, 2001) (Crimnsie, 2003) (Bonet, 1997) (Hezy *et al.*,2003) (Leung, 1999) (Freeman, 2001) (Harrison, 2001) (Tang, 2003) (Xu *et al.,* 2001) while dealing with natural textured image, these approaches find difficulties for filling missing piece.With the fusion of both approaches (M.Bertalmio, 2003) proposed a method which used both texture and structure propagation but the resultant inpainted image produces a blur and this method is capable to inpaint only small target. Synthesis by exemplar was first utilized by Harrison (Harrison, 2001) for large object removal, this technique considers the texture of the neighborhood pixel along the level lines(isophotes) but may suffer as a strong linear structure sometimes revoked by the neighbour noise. Freeman (Pasztor, 2000) has proposed non-hierarchical procedure for re-re-synthesize an image by considering close neighbour pixels locally with the help of a user defined 2D mask having same texture.(Morel, 1998) has proposed parallel hierarchical procedure in two levels first by labeling texture map and second by segmenting

Fig.1: An original image, Mask and Inpainted image

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the composite texture into sub texture. Criminsi extended(Harrison, 2001) the combination of both textural and structural approaches in one model and define priority to each block centralized at the contour of the target region, priority is defined on the basis of confidence and data terms. Wong (Wong, 2008)uses global information obtained from several weighted similarity samples within the image, and these sample aggregate to fill the missing part but produces blurring effects. Sangeetha *et al,* Muthu *et al.*(Sangeetha, 2011) (Vallilka, 2013) extended (Criminisi, 2003) they introduced additive weights to the priority term instead of multiplication based priority. (Pirtika. 2014) have extended (Chen and Shen, 2001) by introducing similarity metric based on an image gradient on the assumption that linear structure propagation to target region on color basis is not sufficient. (Zhang, 2012) has extended method by defining priorities on contour on the basis of color distribution. Xu and Sun (Sun, 2010) adopted a sparse representation theory to fix the partial informative patch. Wangand Zhang (Wang, 2011) have given an idea of Weighted Sparse Non-Negative matrix factorization,first by defining the weight matrix in which 1 and 0 belongs to the source and target respectively,second by estimating similar patch using expectation maximization(EM) algorithm in which the corresponding missing values are replaced at E-step and unweighted nmf is applied in M-step. Mao and Saulgive an addition of unweighted sparse constraint for predicting the missing part as (Choi, 2009).This paper proposed a novel approach to improvise efficiency by utilizing the information of neighbor patches having all pixels ON (no missing information)in praxis of Non negative matrix factorization(NMF), refer section2. Assuming that the most reliable information can be obtained through neighbors to the target. These neighbor patches have full structural and textural information, this will revoke the need of weight matrix and sparse representation like previous technique (Sun, 2010). Fundamentals of proposed algorithm are in section 0, result and comparisons on both synthetic and natural inpainted images are under section 3.

2. METHOD FOR LOW RANK NON-NEGATIVE MATRIXFACTORIZATION

Non-Negative Matrix Factorization has widely used Low rank approximation (LRA) technique for the dimension reduction of non-negative data matrix(all elements of matrix are positive) was firstly introduced by Lee (D.Lee, 2000), Formally given non-negative data matrix is $V = [V_{x,y}] \in \Re_{r\times c}$, where x in matrix $V_{x,y}$ represents the dimension of the data and y is the number of sample. Indata matrix $\Re_{r\times c}$ .r *and* $c$represents the rows and columns of a given matrix. The matrices of two non-negative factors obtained by NMF are $W \in \Re_{r\times d}$ and $H \in \Re_{d\times c}$ as

$$\boldsymbol{V_{m\times n}} \approx \boldsymbol{W_{r\times d}} \boldsymbol{H_{d\times c}} (1)$$

Where, d is the decomposition factor. The factors W and H are obtained by minimizing the following objective function.

$$D(W,H) = \frac{1}{2}\sum_{x=1}^{r}\sum_{y=1}^{c}\left(V_{x,y} - (WH)_{x,y}\right)^2 (1)$$

3. PROPOSED INPAINTING USING NON-NEGATIVE MATRIX FACTORIZATION.

In an image I, the observed known source region is Ψ, the unknown area target of an image I is represented by Ω and target edge is Φ. The algorithm initiate from a patch ϕ_p localized at the target boundary having both known and unknown observation, on the assumption that the most reliable information can be determined through neighbors of the target patch of an image, the neighbor region N is defined and searched in global space. In search of good exemplar there is a chance that the patch $n_i \in N$ selects itself, for avoiding this confusion N and Φ are removed from source region. Now source becomes

$$\Psi = \overline{\left(\Psi \cap \left(\Phi \cup N\right)\right)} (3)$$

Four connected neighbors patches $n_i, i = 1,2,3,4$ are introduced to the selected target patch ϕ_p in clock wise direction with their position z preserved refer **(Fig.2)**.

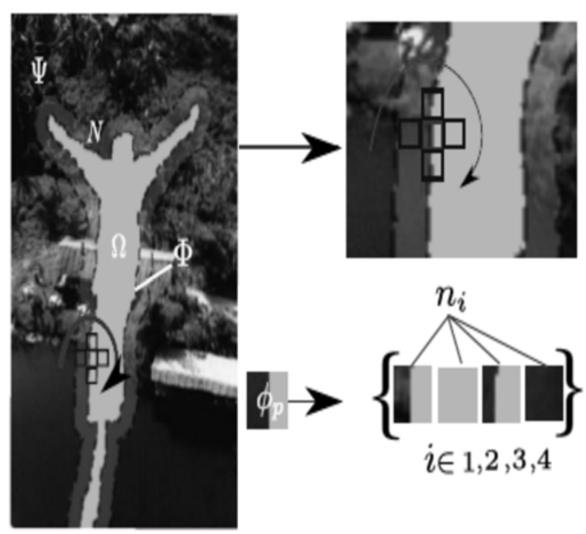


Fig.2: The Selected Target Edge Patch And Its Associated Neighbor Patches.

The first patch n_i having all pixel ON or $n_i \in N$ is used to search the almost identical patch ψ_{qn} in the source region, from ψ_{qn} the patch ψ_q is selected which is at the compliment position $\bar{z}$ of ψ_{qn}. The partial part of the selected patch ψ_q is utilized for filling the missing portion of the target patch ϕ_p and updates the target region. The algorithm continues till all patches in the target region Ω get updated. The algorithm procedure is time consuming as the source region is searched globally to find the similar patch. The time issue the dimension of search space is reduced as defined in next subsection.

A. Dimension Reduction Using NMF

A collection of non-negative patches localized at each pixel in search space Ψ is formally define by $V^{S}_{R\times C,}$ refer**(Fig. 3)**

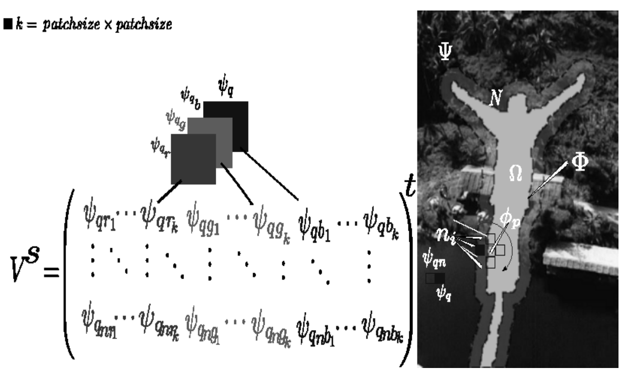


Fig.3: The search space is created by the collection of all source patches with RGB channels.

Patches of size a x b localized at all the pixels in the source region Ψ is defined as S. Those patches having partial information localized at Φ and their associated neighbor patches n are removed from S as these patches are required for fill-front. Each patch in S form column of two dimensional matrix $V^{S}_{R\times C,}$ for RGB color image $R = 3\times a\times b$ and C is the number of observation in the space S .The search space is reduced by Non-negative matrix factorization using an equation 2 as

$$D(W^{S}, H^{S}) = \frac{1}{2}\sum_{x=1}^{r}\sum_{y=1}^{c}\left(V_{x,y} - (W^{S}H^{S})_{x,y}\right)^{2} \quad (2)$$

The obtained factor $W^{S}_{R\times d}$ is a basis matrix while $H^{S}_{d\times C}$ is a coefficient matrix. To find the most relevant patch to ϕ_p in the source region, the first full neighbor patch n_i to ϕ_p is selected and its position z is preserved for future utilization the patch n_i is also converted to column matrix V^{T} . To find the objective coefficient H^{T} , factorize V^{T} with basis matrix $W^{S}_{R\times d}$, Where the dimension of H^{T} is d x1. To find the most relevant patch in source space S , the coefficient of source space H^{S} and coefficient H^{T} contain d feature of patch n_i are searched using L_2 -norm.

$$\mathbf{q} = \mathbf{argmin}|\mathbf{H^{s}}, \mathbf{H^{T}}|_{2} \quad (5)$$

The patch ψ_{qn} is localized at pixel q_n is almost identical to patch n_i and assuming that patch ψ_q is almost identical to ϕ_p which is at position $\bar{z}$ to ψ_{qn}, the corresponding pixels of ψ_q are propagated(filled in) and update the target region Ω . This routine continues till the whole target of the image is completely filled in.

3. COMPARATIVE RESULTS

The proposed algorithm is tested on multiple synthetic and real images having complex textures and high curvatures. The visual and quantitative comparison with othertechniques shows that the proposed algorithm is capable to handle large object recovery more acurately and efficiently. All testsare performed on 2.50 GHZ machine.

A. Time comparison

Due to the dimension reduction nature of NMF . The proposed algorithm performs faster than other traditional techniques.Refer **(Fig.4)**for time comparison.

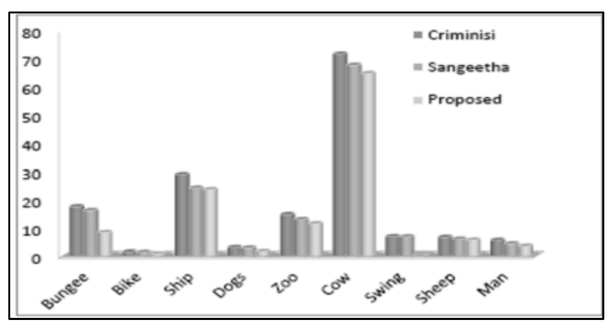
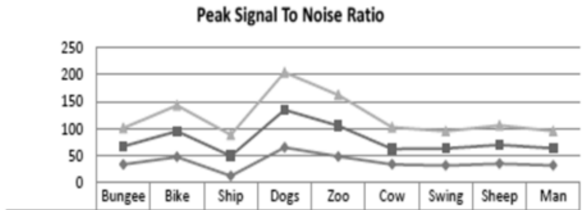


Fig. 4: The above figureshows that the time taken by the proposed algorithm for the recovery of both synthetic and natural images is less than the other techniques.

B. Quality comparison

Peak Signal to noise ratio is used for estimating an image qualitybetween reference and inpaintedimage using equation(3).**(Fig. 5)** shows that the proposed algorithm produces better quality by alleviating the noise effect using NMF.



	Bungee	Bike	Ship	Dogs	Zoo	Cow	Swing	Sheep	Man
Proposed	33.873	47.836	39.012	69.686	57.043	40.33	32.099	36.113	31.971
Sangeetha	33.627	47.683	37.05	69.537	57.036	28.629	31.583	35.011	31.721
Criminisi	33.492	47.469	12.321	65.127	48.254	33.627	31.539	34.981	31.665

Fig.5: The above chart shows that the quality of recovered images by the proposed algorithm is higher than other especially where there is complex texture.

$$\mathbf{PSNR} = \mathbf{10log_{10}}\left[\frac{\mathbf{d^2}}{\mathbf{MSE}}\right] \quad (4)$$

$$Where, \mathbf{d} = \mathbf{max(I_1, I_2)} \quad (8)$$

and MSE is the mean squared error calculated using formula.

$$\mathbf{MSE} = \sum_{\mathbf{R,C}} \frac{[\mathbf{I_{1(r,c),}} \mathbf{I_{2(r,c)}}]^2}{\mathbf{RXC}} \quad (9)$$

C. Visual Comparison

Proposed algorithm is tested on various images,the result shows that proposed algorithm recover images in more acceptable view to unsuspicious eye while comparing to other techniques.See **(Fig.6)** for visual comparison.

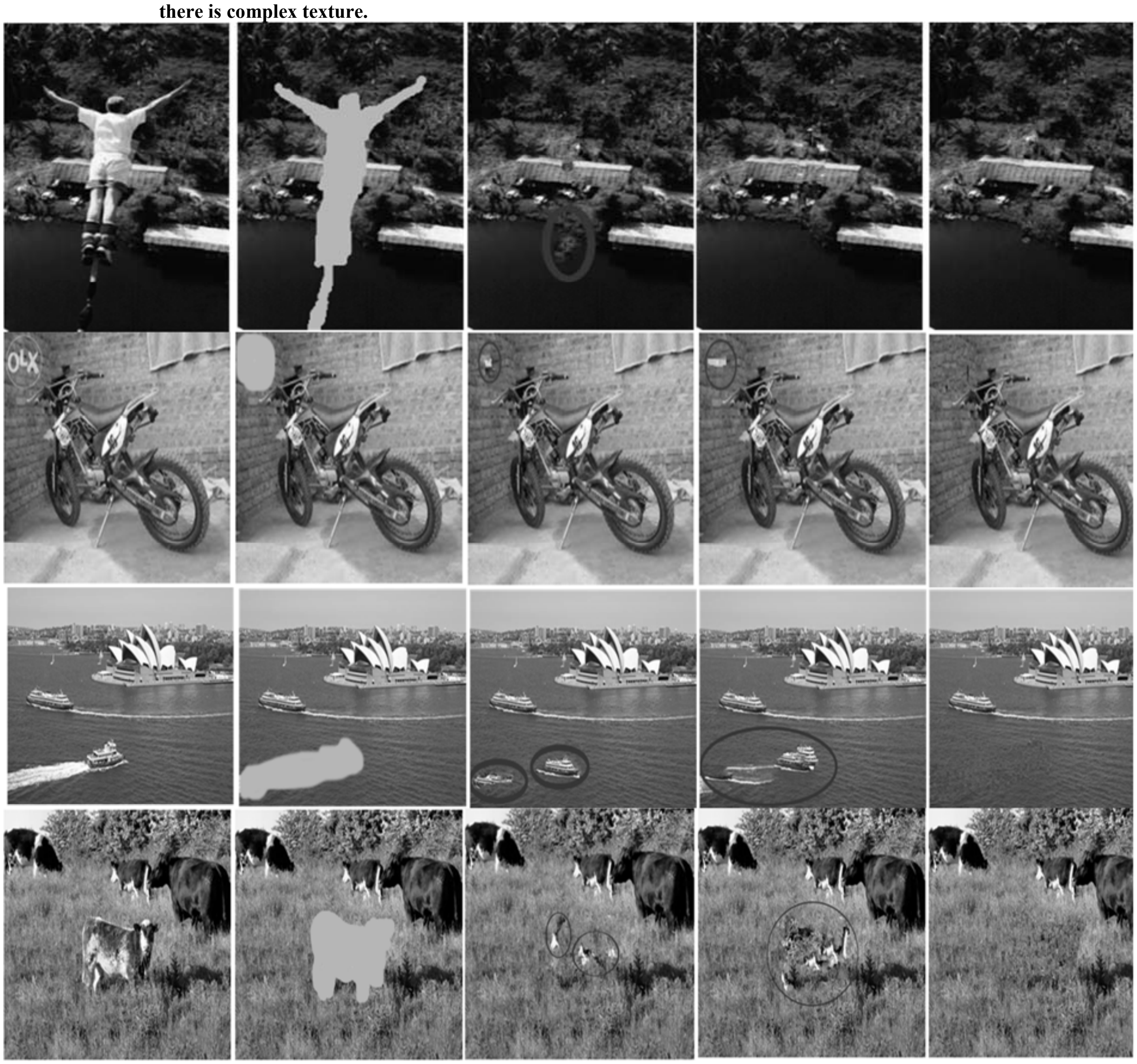


Fig. 6: Visual comparison of different approaches and the proposed technique.

4. CONCLUSION

Removal of large objects and curved structures efficiently is the main emphasis of this paper.An object removal without leaving an evidence of background construction is a challenge, which proposed algorithm has attained through the neighborhood of the target region in application of NMF. Our approach is based on an exemplar and is capable to propagate both texture and structure.The proposed method performs well in contrast to previous restoration and object removing techniques because of dimension reduction it performs faster than earlier algorithm. Currently proposed algorithm is extending to multi images with the dimension reduction technique which will recover the target region by searching multiple images as the source.

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