Artifact Removal and Image Inpainting Using Fuzzy Confidence Term

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Abstract

The inpainting of image is a process in which the damaged region or region which is missing is completed by diffusing information taken from the known region. Inpainting using exemplar method is in general used for filling large damaged or unknown areas left after object removal. The main components of exemplar based inpainting are to compute the filling order through priority term and finding the best match patch by iterative algorithm. Though the exemplar based approach is proved to be simple and efficient , its main drawback is rapidly dropping priority value. A novel approach is introduced in exemplar based image inpainting by extending the fuzzy sets theory to cover uncertainty in digital images. A modified fuzzy confidence term is proposed to control the rapidly dropping priority value. Experiments are performed on images varying in amount of texture and structure content. The results are compared with the standard inpainting algorithm and qualitative analysis is done on the basis of more visibly plausible output.

Keywords: *Exemplar, fuzziness, image inpainting, image reconstruction, self similarity priors.*

1. Introduction

Image inpainting is method of image reconstruction where the damaged part of image or missing region of an image is filled using the information present in the known part. The inpainting procedure was originally used for artwork restoration to repair the damage of paintings [1]. The damaged portion is conventionally restored manually by a professional artist such that the reconstructed area is not detectable or is most acceptable to human eye. Image inpainting has found importance in areas such as visual reconstruction of heritage sites, adding special effects in films, editing, medical image processing, image compression etc. With the advent of digitization of images and consequently digital image processing the concept of inpainting is further extended to digital images where image priors are introduced . An assumption is made about the known region and unknown region that they share the same structural and statistical properties. This assumption is used to broadly categorize inpainting methods in two categories. The first category is of diffusion based inpainting [1,2] which introduces the use of smoothness priors where partial differential equations (PDEs) are used for propagating structures present locally from the outside to the inside of the image to be inpainted. The mathematically computational digital image inpainting which is pioneered by Bertalmio [2] uses Partial Differential Equations, where, the area to be inpainted is filled by propagating structures along the isophotes. In diffusion based inpainting the local image geometry is first retrieved and after that PDEs or variational methods are used to describe evaluation of the inpainted region in a continuous manner. The damaged region to be inpainted is denoted by 'Ω' and '$\partial\Omega$' denotes the boundary . The concept is to diffuse the information around 'Ω' smoothly in the direction of propagation of isophotes

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that enter '$\partial\Omega$' .The gray values as well as direction of isophotes both are propagated inside the region. This method suits best for completing structures such as curves , lines and for inpainting of small regions. But , for large textured regions this method creates a blur. The image inpainting can also be categorized into exemplar based inpainting which uses statistical priors of image and self similar priors. The exemplar based image inpainting is proposed in the seminal work on texture synthesis [3]. In texture synthesis, the texture produced is larger than the sample at source and has visual coherence. This is referred as sample-based texture synthesis. The texture synthesis is done by, using local region growing techniques or by using global optimization. Exemplar based inpainting is, inspired by local region growing techniques where the texture of the region is grown pixel by pixel or patch by patch, and at the same time maintaining coherence with neighborhood pixels. Since most of the images cannot be called as pure structure or pure texture images a simultaneous texture and structure inpainting approach is used in[4,5]. The Criminisi method [5] has received vast acceptance because of its simplicity and effectiveness through computation of priority value. In this method onion peel approach is used to fill the patches centered around pixels on boundary region. For every iteration boundary of region to be inpainted is updated till all unknown pixels are filled. As the algorithm progresses towards the patches with more number of unknown pixels the overall confidence of the patch drops significantly , thus dropping the priority value . In [6] a regularization term is used which smoothens the dropping confidence term.

2. Exemplar Based Inpainting

Let 'I' be image to be inpainted then, according to Criminisi et al.[5] the image 'I' is divided in two parts. The target region is denoted as 'Ω', the source region i.e. the known region is given as 'ϕ'. The target region boundary is given by '$\delta\Omega$' as shown in figure.1(a). The task is to fill a patch Ψ_p, of given window size where $p \in \delta\Omega$, with the best matched patch from the source region as given in figure.1(a) . The inpainting algorithm based on exemplar approach includes the following four main steps:

a) Initialization of the target Region , Ω:

The damaged region is selected. A mask is created by extracting the target region and representing it with proper data structure.

b) Identifying the fill front '$\delta\Omega$' and computing filling priority:

The boundary of target region is identified as initial fill front. For every pixel 'p' on boundary patch Ψ_p of given window size is considered and a priority value is computed using predefined priority function given as ,

$$P(p)=C(p)*D(p) \tag{1}$$

Where the confidence term is given as C(p) and the data term is given as D(p). The confidence of pixel, p, is computed as,$|\Psi_p|$, which is area of the patch surrounding pixel p. Data term is given as,

$$D(p)=\frac{\left|\nabla I_p^{\perp}.n_p\right|}{\alpha} \tag{2}$$

$\nabla I_p^{\perp}$ - direction perpendicular to the gradient

n_p- unit vector perpendicular to each pixel on boundary.

α is used for normalization and for grayscale images its value is 255. The confidence of a patch is given as,

$$C(p)=\frac{\sum_{q\in\Psi p\cap(I-\Omega)}C(q)}{\left|\Psi_p\right|} \tag{3}$$

During initialization, C(p) has value 0 when p∈ Ω (unknown region) and C(p) is 1 when p∈ ϕ i.e. source region. A search for matching exemplar is conducted using different similarity priors and the most similar is copied in the damaged region according to the priority value assigned.

c) Finding the best exemplar:

The algorithm is used to search for the most matching patch, $\Psi_{q'}$, for the patch, Ψ_p, in the source region. The distance metric, d, computes the similarity between the patches in source region and target region as given in Figure.1(b). The best matching patch is found by,

$$\Psi_{q'} = \arg\min d(\Psi_p, \Psi_q) \tag{4}$$

The metric 'd' of distance provides a quantitative measure of the degree of similarity between two image patches, A and B. The similarity measures using distance metrics is broadly classified in two categories i.e. pixel based similarity measures and statistical based similarity measures. The distance function refers to difference between samples that are regarded as points in high dimensional space. The measure of similarity between two images IA and IB can be given mathematically as,

$$S(I_A, I_B) = D[T(I_A), T(I_B)] \tag{5}$$

Where, T, is the transformation used to extract the characteristics of the input image and represent it as multidimensional feature vector. In earlier work of exemplar based image inpainting [5], sum of squared difference (SSD) is used for similarity measurement. This similarity measure is based on pixel to pixel difference intensities between two images. The match can be determined by considering the location of minimum value in the image matrices. The sum of squared difference between two patches Ψ_p and Ψ_q can be given as ,

$$d_{SSD}(\psi_p, \psi_q) = \Sigma[(R_{\psi_p} - R_{\psi_q})^2 + (G_{\psi_p} - G_{\psi_q})^2 + (B_{\psi_p} - B_{\psi_q})^2] \tag{6}$$

The minimum value of difference will give the best match patch. However in some cases it may occur that multiple patches may have numerically very close SSD and the patch with the lowest value of SSD may not necessarily be the most visually plausible one. A possible solution for this problem is given in [6] where mean SSD distance is proposed which better reflects the average of similarity between the two patches. The mean SSD is given as,

$$\overline{d_{SSD}}(\psi_p, \psi_q) = \Sigma[(\overline{R_{\psi_p}} - \overline{R_{\psi_q}})^2 + (\overline{G_{\psi_p}} - \overline{G_{\psi_q}})^2 + \overline{B_{\psi_p}} - \overline{B_{\psi q}})^2] \tag{7}$$

Where, mean of image intensity of individual color channel is denoted by $\overline{R}$, $\overline{G}$ and $\overline{B}$ respectively . In [7] a computationally less complex sum of squared absolute difference (SSAD) of the two feature vectors is calculated for finding matching patches. The Sum of Squared Difference distance favors uniform region and this drawback is overcome using weighted Bhattacharya distance in [8,9]. Other distance metrics use geometric transformations where the patches are transformed for matching[10,11].

d) Updating the fill front:

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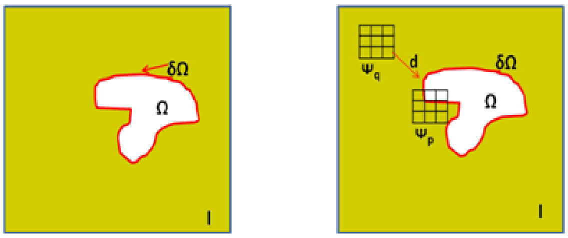
The fill front is updated for every iteration after copying the patches which are most matching into the unknown region. The confidence value of the new fill front is computed.



(a) (b)

Figure 1(a) Target Region Ω , Source Region Φ And Fill Front δΩ in Image ‘I’. (b) Distance ‘D’ between The Patch, ψ p, in Target Region and a Patch ψq , in The Source Region.

3. Proposed Modified Confidence Term

The Criminisi’s algorithm is successful because of its simplicity and effective priority function which considers the pixel confidence as well as structure information. However as the algorithm progresses the confidence drops drastically as given in figure. 2(a). This affects the priority value as shown in figure. 2(b) and hence reduces the performance of inpainting. A regularized confidence term is used in [6] to control the dropping rate of confidence term. The priority function P(p) is crucial to the end result of inpainting . The confidence term is calculated from eq. (3) which is average data present in the patch. These values are obtained from confidence map. The confidence map of the area to be inpainted is obtained by complementing the binary mask image. Hence, this confidence map is also binary in nature. As we move to the core of region to be inpainted , more and more pixel values are unknown and hence overall confidence of the patch decreases drastically . In this paper this crisp nature of confidence values is converted into vagueness using the concept of fuzzy logic [12].

The proposed fuzzy confidence term is given as,

$$C(p)_{fuzzy} = \exp\left\{-\frac{(C(p)-m)^2}{\sigma^2}\right\} \tag{8}$$

Where,

C(p) - is confidence term given in eq. (3).

m – is the mean value of confidence term.

The standard deviation ‘σ’ is considered as 0.7 for experimental results. The priority is calculated from eq.(1), while the distance metric used for similarity measure is given by eq. (6). Figure.3 shows improvement in dropping priority value and confidence value as proposed in this paper. As observed in Figure.3(a) as the confidence drops drastically, there is sudden drop in priority value respectively. Figure. 3(b) shows an offset where the confidence term is boosted rather than reaching null value.

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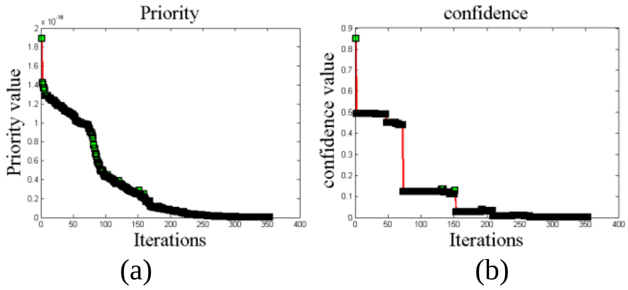

Figure 2 (a) Dropping Effect of Priority (b) Dropping Confidence Term.

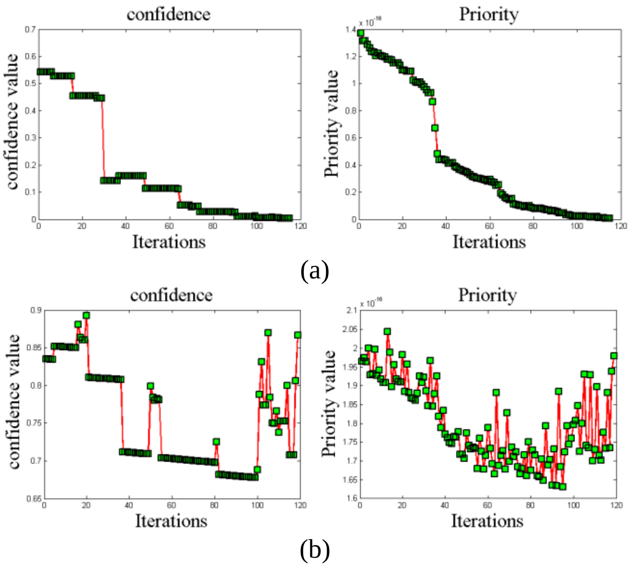

Figure 3 (a) Priority and Confidence Term for Using Criminisi's Algorithm (b) Priority and Confidence Term Using Proposed Fuzzy Confidence Term

4. Experimental results and discussion

The improved inpainting algorithm with fuzzy priority term is introduced and the results are compared with two most popular algorithms for image inpainting [5,6] as given in figure.4 Column (a) shows original image, column (b) shows object removal, column (c) shows implementation of original; inpainting algorithm by Criminisi [5], column (d) shows implementation of modified priority as given in [6] and column (e) shows results of the proposed approach. An image database is formed where images of different texture and structure content are considered. A patch size of 9 X 9 pixels is considered for experimental setup. In general the patch size should be greater than the size of texel. In the image of 'Bungee' from figure.4, the object to be removed is occluding texture part of the image at the same time structure of the house. The result in column (c) shows failure in reconstruction in both structure as well as texture in a visibly plausible manner. Whereas , column (d) and column (e) shows visibly acceptable reconstruction. In the images of 'Tiger', 'Two bird' and 'Shyamrai', the standard algorithm [5] as shown in column (c) is biased towards reconstruction of uniform background rather than texture A good tradeoff is obtained by the proposed algorithm as shown in column(e). The image of 'Rowboat' shows total reconstruction by all three methods but the quality assessment of reconstruction can be different as per the perception of observer. It is observed from all the results that from column (c) that Criminisi's algorithm[5] is biased towards propagation of uniform texture but fails in propagating structure. Whereas this problem is partially solved in [6] as given in column (d). Our proposed algorithm with modified priority term propagates structure as well texture while maintaining the homogeneity of the image as shown in column (e). The quality assessment methods for inpainting are basically classified as subjective and objective as shown in figure. (5) [13,14] . The Objective methods can further be classified as full reference [15,16,17] , reduced reference [18] and no reference[15] . But it is observed that the best quality assessment is through subjective analysis. The subjective analysis is done by allowing the observer to rate the inpainting result on different criteria as given in Table-1. For the quality assessment of our proposed method , the results were shown to 10 different observers. The observers were selected from different backgrounds ranging from naive observers to experts in the subject. The average observer score is used to determine the effectiveness of the proposed method as shown in Table-2. Whereas, the comparison of [5], [6] with the proposed method is as shown in Table-2.

Table-1: Observer's Survey For Inpainted Result

Sr.no.	Questionnaire for observer survey	Observer score (1- poorest, 2-poor, 3-satisfactory, 4-very good, 5-best)
1	How is quality of inpainted region?	
2	How is the continuity of structure in inpainted region maintained properly?	
3	How is the texture of inpainted region in accordance with global coherence?	

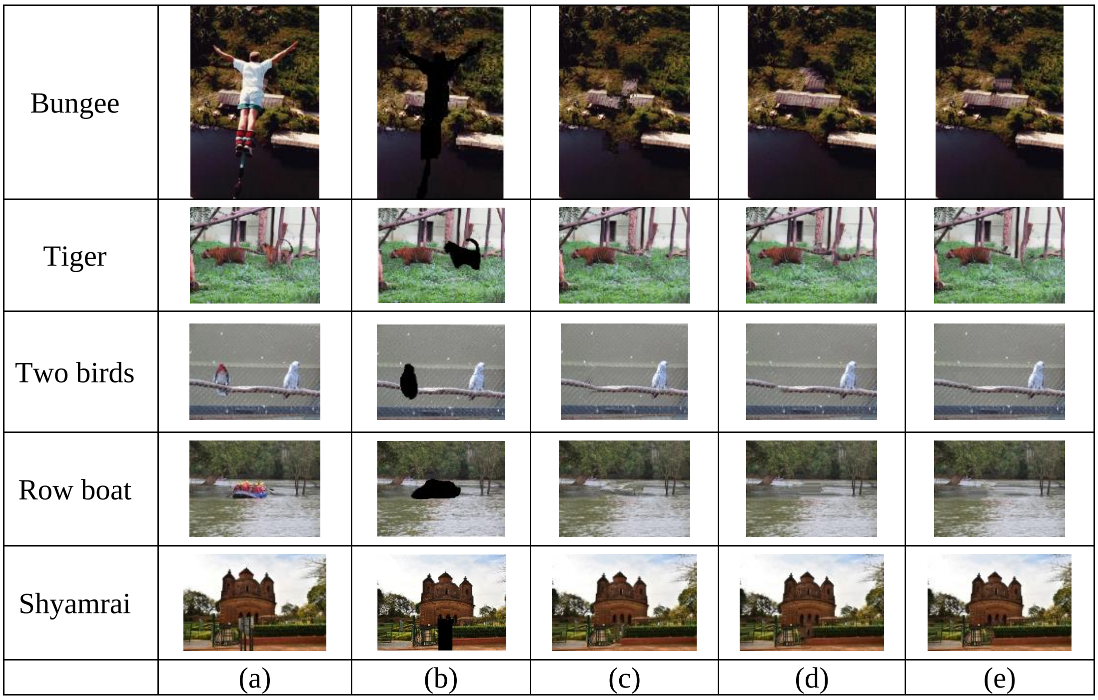

Figure 4. Implementation of Artifact Removal and Image Inpainting. (a) Original image, column (b) Object removal (c) Criminisi et al. [5] (d) Jing Wang et. al [6] (e) Proposed approach.

Table-2: Subjective Quality Assessment Of Inpainting Algorithms

Sr.no.	Image	Method used	Percentage of object removal	Average observer score
1	Bungee	[5]	12.6	2.33
		[6]		3.66
		Proposed		4
2	Tiger	[5]	5.6	2.998
		[6]		3
		Proposed		3.66
3	Two birds	[5]	3.64	2.33
		[6]		3
		Proposed		4.33
4	Row boat	[5]	5.94	1.33
		[6]		1.66
		Proposed		2.66
5	Shyamrai	[5]	3.38	2.66
		[6]		2
		Proposed		3

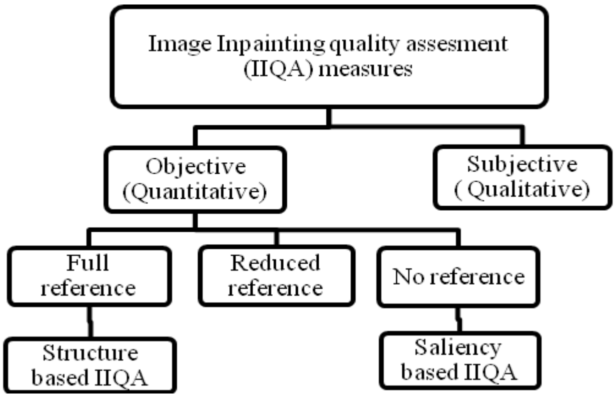

Figure 5. Classification of Image inpainting quality assessment (IIQA) measures.

5. Conclusion

The image inpainting algorithm based on exemplar approach is implemented for reconstructing image after object removal. It is observed that the inpainting result mainly depend on the filling priority which in turn is decided by the priority term. Since the exemplar based inpainting fills the unknown area through onion peel approach, the confidence of the patch is dropped drastically thus affecting the quality of inpainting. An effective fuzzy priority term is proposed in this paper which allows the confidence to reduce at some offset value instead of null . Thereby boosting the priority. The proposed method propagates structure and fill the texture so as to maintain global coherence. The final result of inpainting also depends on the initial mask of the object removal. We have selected the initial mask manually. But various segmentation techniques can be used for obtaining the mask automatically, thus , reducing human error. Further work can be done on the mask optimization so as to get optimal result.

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