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Research Article

A Comparative Study of Existing Exemplar based Region Filling Algorithms

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Abstract

In the field of multimedia processing, the image inpainting technology is a hot spot. Inpainting is the process of filling in the missing/unclear regions of an image utilizing spatial information from its neighbouring region so as to preserve its overall continuity in a way that the changes made are not easily detected by an ordinary observer. Digital image inpainting is a new and young research area in image processing with numerous applications including wireless image transmission (recovering lost blocks), red eye removal, multimedia editing (special effects in movies) and image restoration. Eliminating unnecessary portions of an image (removal of objects) is another exceedingly significant area of digital inpainting. Exemplar-based image inpainting is the technique that works well in this area, where the removed/lost information can be filled in by selecting appropriate patches from the neighbouring areas of the same image. This paper presents a brief survey of Exemplar-based inpainting techniques and compares and analysis some recent Exemplar-based inpainting methods. The performance of these methods is compared using both qualitative approach as well as quantitatively in terms of processing speed, Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE).

Keywords: *Inpainting, Exemplar-based, Texture Primitive, PSNR, MSE*

1. Introduction

The term inpainting has been derived from the ancient paper art of restoring images by professional restorers in museums etc. This process was also known as retouching [Alexandra Ioana Oncu Feie], the motive being to bring the medieval pictures close to the original or back to the original state. The purpose of inpainting is to restore the corrupted or deteriorated parts of an image in a way that the restored image looks natural to the casual observer. This inpainting extended gradually from restoring paintings to photography and film, the purpose of all being the same. Digital Inpainting techniques try to imitate this process and are starting to be a common way of performing inpainting automatically, all the way to software tools. The filling of corrupted /lost information with some meaningful data from rest of the image is the basic idea at the back of any inpainting process. Image Inpainting techniques have numerous applications in diverse areas including wireless image transmission (recovering lost blocks), image coding, red eye removal, multimedia editing (special effects in movies), image restoration and object removal.

In order to retain the image data effectively, different researchers have proposed various inpainting methods and these works are classified into two broad categories namely diffusion based methods (non exemplar) and exemplar based methods. Bertalmio et at. [M. Bertalmio *et al*.], were the first to present the notion of diffusion based digital inpainting using the third order Partial Differential Equations (PDE) [Yasmine Nader El-Glaly] to propagate the known image information into the unclear or missing regions of an image along the direction of the lines of equal gray value (isophotes). Various new diffusion based algorithms were also proposed by the image restoration scientists but all these algorithms were effective for small missing regions (cracks or scratches in photographs, dust spots in film) only and none of them was suitable for filling in large missing regions. Natural images are composed of both the structures as well as textures [R.C. Gonzales], where the structures consist of the primitive sketches of an image (corners, edges etc.) and the textures are regular/homogenous patterns. Purely texture synthesis techniques cannot restore the lost region with merged textures and structures in a reasonable manner.

However, the second category of approaches namely Exemplar-based inpainting which stems from texture synthesis has the capability to restore large missing regions in an image in a visually plausible manner as shown in figure 1. Criminisi *et al*. [A.Criminisi *et al*. and Komal Mahajan *et al*.] were the first to introduce the concept of patch based algorithms in which the texture is synthesized by sampling the best-match patch from the known region of the image and a predefined priority function decides the filling order so as to propagate both the structural as well as textural information simultaneously into the large gaps to be filled. When compared with diffusion based inpainting methods, the exemplar based inpainting methods have performed exceptionally well for inpainting the large missing image region [Michael E Taschler].

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(a)

(b)

Fig.1 Object removal from photograph. (a) Original Image (b) Inpainted Image

In this paper, various exemplar-based image inpainting algorithms are analysed and compared, the aim of each being not to exactly reconstruct what used to be in that gap but instead to create a visually pleasing continuation of data around the hole in such a way to maintain its perceptual constancy so that the changes made in the inpainted domain seem undetectable to the human eye.

2. Existing Exemplar-Based Inpainting Algorithms

The exemplar based inpainting approach is an important class of inpainting algorithms and the core of this algorithm is an isophote driven image sampling process which has proved to be very effective. Exemplar based inpainting method inspired by local region growing techniques iteratively synthesizes the target region by sampling the best matching candidate patches from the source region whose similarity is measured by certain metrics, and pastes it at the target patches' position. This method of Image Inpainting has proved to be very effective for reconstructing large target regions and is able to produce reasonably better quality results by combining texture synthesis with isophote driven inpainting methods [Christine Guillemot *et al*. and Nirali Pandya *et al*.]. The concept behind the Exemplar-based inpainting technique is the use of image exemplars/texels that are taken either from the same image or from other representative images. Basically Exemplar-based Inpainting approach consists of two basic steps:

Firstly, priority assignment with the help of some priority function is done. Each pixel p belonging to the target patch Ψp has a patch priority value which is defined as the product of the confidence term $C(p)$ and the data term $D(p)$. The confidence term gives us an idea about the number of existing pixels in this patch and the data term gives us an idea about the strength of the isophote that hits the boundary to maintain the structure of an edge at the target patch and focuses on maintaining the linear structure of the image. Patch priority function is given mathematically as [A.Criminisi *et al* and Nirali Pandya *et .al*]:

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

where,

$$C(p)=\frac{\sum_{q\in\Psi p\cap\Phi} C(q)}{|\Psi p|} \tag{2}$$

and

$$D(p)=\frac{\left|\nabla^{\perp} I_{np}\cdot\vec{np}\right|}{\alpha} \tag{3}$$

where , $|\Psi p|$ is the area of target patch Ψp , np is normal to the boundary $\partial\Omega$, $\nabla^{\perp} I_{np}$ is the isophote at p and α is the normalization factor whose value is 255 for an 8 bit gray scale image. Secondly, this method synthesizes the region to be inpainted iteratively by selecting the best matching patch.

The general idea behind the exemplar based inpainting algorithm is that the texels/patches (P) centred at the boundary $\partial\Omega$ of the target region (Ω) are sorted as per priority which depends on the confidence value $C(p)$ of the previously inpainted pixels (Taking initial value of confidence value as: $C(p)=0 \quad \forall P\varepsilon\,\Omega$ and $C(p)=1 \;\forall P\varepsilon\,\Phi$). The patch with the maximum patch priority is selected and is known as the target patch Ψp . A source patch Ψq of the same size as the target patch, as shown in the notation diagram (figure 2) [A. Criminisi *et al*], having minimum SSD (Sum of Squared Differences) with the patch Ψp centred at p is selected from the source region and this best-match patch is copied to the target patch's position. The confidence value $C(p)$ of the pixel point p in the target patch Ψp is updated and the complete process is repeated until whole target region is completely filled.

A number of algorithms have been proposed for exemplar based image inpainting and here follows a brief introduction about some existing exemplar based algorithms that have been analysed and compared in this piece of work.

2.1 Criminisi et al's Exemplar based Inpainting Algorithm

While discussing the exemplar based inpainting techniques, one of the techniques that is frequently given as a reference is the one introduced by Criminisi *et al* [A.Criminisi *et al*]. Criminisi *et al*. developed a novel and effective algorithm to encourage fill in from the boundaries of target region where the isophote strength of nearby pixels is strong. This algorithm uses SSD i.e Sum of Squared Differences to choose the best matching patch among the candidate patches from the source region and then uses a priority based mechanism to determine the region filling order. In this way, the linear structure is recovered because the target patches which possess high structural information are likely to be filled first. This algorithm is well suited for filling in large missing regions or gaps with visually plausible information from the neighbouring areas [Christine Guillemot *et al*. and Yasmine Nader El-Glaly].

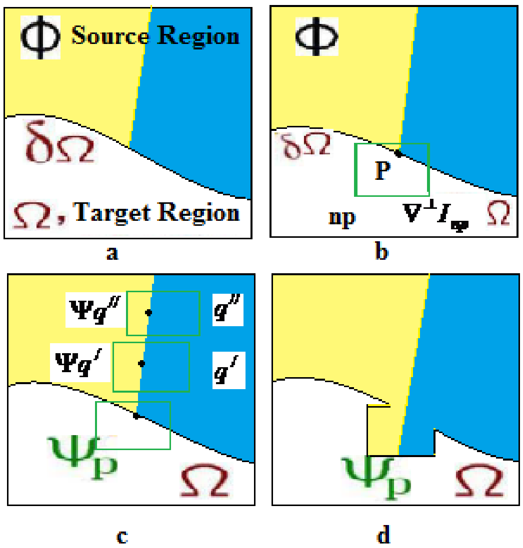


Fig.2 Criminisi *et al* Exemplar based Texture synthesis Algorithm.(a)Original image with target region (Ω) , its source region ϕ and boundary d Ω. (b) Area to be synthesized delimited by the patch ψp centred at point p.(c) Most likely candidate patches (ψq/ ,ψq// lying in the source region ϕ . (d)Best matching patch among candidate patches copied to the position occupied by ψp, thereby achieving partial fill-in in target region Ω.

Figure 2 illustrates Criminisi algorithm in a simpler way. As illustrated by the notation diagram, the information from the top right corner of the patch p is used for finding the candidate patches from the source region of the image. The filling order greatly determines the quality of the restored image and the pixels that lie on the edge path are given high priority than rest of the image pixels. After the search for the high priority pixel ends, this algorithm searches for the best match patch among many candidate patches ($\psi q', \psi q''$) from the source region using SSD function. The best match patch among those candidate patches is thus selected and is used to fill the highest priority patch in the target region. Other important aspects of Criminisi algorithm that determine the quality of the image is the size of the patches and the patch size must be chosen carefully for maintaining the perceptual constancy of the inpainted image.

Figure 3 shows the performance for object removal task using Criminisi's exemplar based method. The PSNR value of the restored sample image (bungee jumping) shown in figure 3(b) obtained from Criminisi's method is 33.16dB with a low MSE value [A.Criminisi *et al*].

(a) (b)

Fig. 3 A Classical Example of Removing large objects from a photograph using Criminisi's Algorithm (a) Original Sample image from [A.Criminisi *et al*], (b) The Inpainted image where the bungee jumper has been completely removed and the occluded region reconstructed by Criminisi at el.'s algorithm

This algorithm however produces impressive results for a wide range of images unlike PDE and texture synthesis based methods that inevitably produce blur in the inpainted region but since it is well known fact that nothing is perfect, this algorithm also has a disadvantage. This algorithm fails to produce visually pleasing results if the patch size is too small or too large as small patches result in noticeable blocky patterns as well as increase the inpainting time while choosing a large patch increases the chances of choosing a bad patch which mostly contains undesirable information [A. Wong *et al*]. So more sophisticated exemplar based inpainting algorithms were proposed to combat the disadvantages of this algorithm.

2.2 Zhaolin Lu et al's Novel Exemplar Based Image Completion Scheme

Zhaolin Lu *et al*.[Zhaolin Lu *et al*] further improved the criminisi's method to produce a reasonably good quality output for larger regions on images by the use of a novel method based on image completion model which combines the characters of both texture synthesis as well as inpainting. Zhaolin used a similar notation (figure 2) for his Image completion model as used by Criminisi in his exemplar based model. The basic building block of the image completion scheme is the patch which contains the texture and structure information of an image. In the criminisi's method, the size of the patch is fixed which leads to some drawbacks i.e if the patch size is too large, tiny texel information will be lost and if the patch size is small, the texture is not thoroughly preserved. However, the size of patch is adaptively determined in Zhaolin Lu *et al*'s work and is based on the gradient domain of image and local texture property of patch [Zhaolin Lu *et al*]. The symbol ∇I represents the information in the gradient domain of an image and gradient value $|\nabla I|$ of each image pixel is calculated to decide the size of patch by determining the variation in gradient values of pixels in the patch. The pixel position is represented by (x, y) coordinate and the number of known pixels in patch ψ_s which is initially fixed at patch size 5x5 is denoted by num.

$$Var(|\nabla I\psi_s|) = \frac{\sqrt{\sum_{x\subset\psi_S}\sum_{y\subset\psi_S}\left(|\nabla I_{x,y}| - |\overline{\nabla I_{x,y}}|\right)^2}}{num-1} \tag{4}$$

$$|\nabla I| = \sqrt{I_x{}^2 + I_y{}^2} \tag{5}$$

The above given equation determines the texture property of the patch. The more the value of (4), more complicated is the texture of patch ψ_s and smaller is the patch size. Thus based on the value of above equation, the patch size ψ_s is reseted to 3x3, 5x5 or 7x7adaptively. After determining the patch size, the patch filling priority $P(p)$ is determined by the product of the confidence term $C(p)$ and the data term , $D(p)$ as:

$$P(p) = C(p)D(p) \tag{6}$$

where, $$C(p) = \frac{\sum_{q\in\Psi p\cap\Phi} C(q)}{|\Psi p|} \tag{7}$$

and

$$D(p) = \frac{\left|\nabla^{\perp} I_{np} \cdot \vec{np}\right|}{\alpha} \tag{8}$$

In order to preserve the geometrical property of image structure, Zhaolin Lu *et al*. applied curvature of isophotes to $D(p)$ in order to calculate the patch priority $P(p)$.

$$D(p) = (\nabla I_p^{\perp} \cdot n) + \nabla \cdot (\nabla I / |\nabla I|) \tag{9}$$

where, $\nabla I / |\nabla I|$ is the to the normal to isophote and $\nabla \cdot (\nabla I / |\nabla I|)$ is the curvature of isophote.

After priority is assigned the search for the best match patch is next and this algorithm introduces a better patch-match scheme that includes both the curvature and the colour of the image. The most similar best-match patch ψ_t is determined by the below given equation as:

$$\psi_t = \text{argmin}(d(\psi_s, \psi_t)) \tag{10}$$

At last, the determined most similar source template is copied to the target template patch and the information of the target patch is updated.

Figure 4(a) shows the sample image (bungee jumping) and the restored image using this method is shown in figure 4(b) where the roof top of the house is completed /restored more efficiently than criminisi's method which has some visible artifacts. The PSNR of the restored image using this method is higher equal to 34.79dB with a very low MSE than Criminisi's method. This method overcomes the disadvantage of Criminisi method by making the patch size variable and this improvement has enhanced the perceptual quality of the image making it more reasonable.

(a) (b)

Fig.4 Removing large objects from photograph using Zhaolin Lu *et al*'s Algorithm. (a) Original Sample image from [Zhaolin Lu *et al*], (b) The Inpainted image where the bungee jumper has been completely removed and the occluded region reconstructed by Zhaolin Lu at el.'s Image Completion algorithm.

2.3 Sarawut Tae-O-Sot's Exemplar-Based Image Inpainting with Patch Shifting Scheme

Most of the exemplar based approaches do not take into account the number of known and unknown pixels in the destination/target patch, so the satisfied results for a meaningful representation of an image cannot be achieved when large unknown region is filled with small number of known pixels.

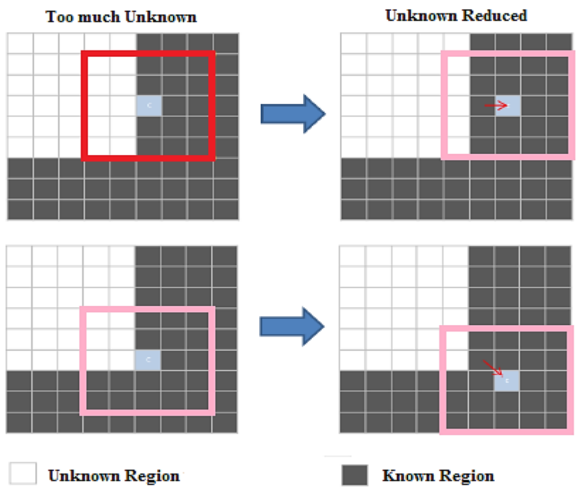


Fig.5 Patch Shifting Scheme

If this situation arises, it can ruin the final result as the number of known pixels is one parameter to determine the patch priority for choosing the target patch. Thus in order to combat this problem Sarawut [Sarawut Tae-o-sot *et al*] introduced a patch shifting technique to make sure that the target patch which contains known pixels less than a predefined threshold value would be shifted in a direction that increases the number of known pixels in the patch. Then the patch that contains enough known pixels is efficiently compared with the candidate patches in the source region. In this way, more reliable and meaningful patch is chosen to fill-in the target/unknown region more naturally. Figure 2 clearly shows the patch shifting process where the target patches in the right column are the one with reduced unknown region and produce better results than those produced by the target patches that lie in the left column.

The horizontal shift S_h and the vertical shift S_v of the patch are determined by the following equations:

$$S_v(p) = \sum_{n=-1}^{1} \sum_{m=-1}^{1} \psi(i+m, j+n) \ \ M_v(m+2, n+2)$$
$$S_h(p) = \sum_{n=-1}^{1} \sum_{m=-1}^{1} \psi(i+m, j+n) \ \ M_h(m+2, n+2) \tag{11}$$

where,

$$M_v = \begin{bmatrix} +1 & +1 & +1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}, \ M_h = \begin{bmatrix} +1 & 0 & -1 \\ +1 & 0 & -1 \\ +1 & 0 & -1 \end{bmatrix} \tag{12}$$

And ψ is a binary image whose pixel is 1 at unknown pixel and 0 at known pixel, and $p=(i, j)$ is the center of the target patch.

(a) (b)

Fig.6 Removing bungee jumping man from photograph using Sarawut Tae-O-Sot's Algorithm. (a) Original Sample image (b) The Inpainted image where the bungee jumper has been completely removed and the occluded region reconstructed by Sarawut Tae-O-Sot's Patch Shifting Scheme [Sarawut Tae-o-sot *et al*].

The target patch is repeatedly shifted till the number of known pixel in the target patch become more than the threshold. If none of the pixels in shifted patch are present in the initially selected maximum priority patch, the next target patch with lower maximum priority is chosen this process is repeated until best target patch is found. After this a best match candidate patch from the source region is searched and filled in at the target patch's position. To maintain the advantages of patch priority, the patch shifting scheme is applied to only a limited number of target patches as the target patches having very less priority cause discontinuity at the edges. On comparing with both criminisi's and Zhaolin Lu's [Zhaolin Lu *et al*] traditional exemplar-based approach, the results of Sarawut's exemplar based patch shifting approach shows significant improvement in both mathematical aspects and visual quality.

In Figure 6, the performance for object removal task using Sarawut's exemplar based patch shifting approach is shown. The object (man) from the bungee jumping image shown in 6 (a) is removed and the missing region is restored by Sarawut's method as can be seen from figure 6 (b). This method reconstructs the structure of the missing part completely unlike criminisi's and Zhaolin Lu's method where some discontinuity can be noticed. Comparing with Criminisi's and Zhaolin Lu's results, visual result and PSNR of this method which is 36.24dB (for same sample image) is higher. The only disadvantage of this method is that it takes 0.5 seconds more than Criminisi's processing time [Sarawut Tae-o-sot *et al*].

2.4 K. Sangeetha et al.'s Extended Exemplar Based Image Inpainting Technique Using Texture Primitive

The main objective of any inpainting technique is to construct an image that appears to be 'normal', means that the changes made in the restored image must seem undetectable to the observer [Mahalingam Vijay Venkatesh]. K. Sangeetha *et al*. [K. Sangeetha *et al*] extended the exemplar-based image inpainting technique by incorporating texture primitives for eliminating large objects from digital images and for effective region filling. The core of this technique is an isophote driven exemplar based image sampling process. But in case a single non repetitive structure is corrupted, there are no patches in the locality that can produce results without observable artifacts and blur. So the variety and number of these available patches can be increased by their geometrical or photometrical transformation in which the source patch can be scaled, rotated, flipped, or its intensity can be adjusted to better match the patch that needs to be reconstructed.

A single iteration of this technique is discussed to show how texture and structure are effectively propagated by the extended exemplar based texture primitive technique. If the square templates $\psi p \in \Omega$ centered at the point p is to be filled, the best-match sample approaches from the patch $\psi q \in \Phi$ in the source region that is nearly comparable to the previously filled parts ψp. All that is essential is to transmit the isophote (lines of equal gray value) inwards and that the isophote orientation is routinely preserved.

Texture Primitive

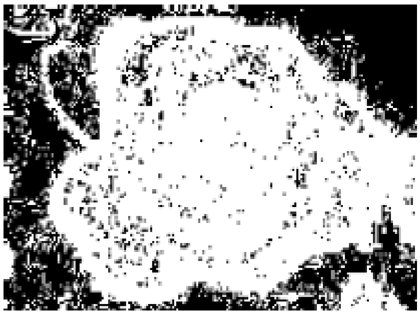
As Different regions possess different characters i.e some regions have a complex gray value difference and others may be regular without a clear contrast [Lixin Yin *et al*]. To be precise, if the gray difference is huge, it is easily distinguishable and as a result it is easy to segment the images into small blocks based on the gray value difference in an image to clearly get the texture information. Consider an image I of size M x N segmented into m x m non-overlapping small blocks and for each of these small blocks, the mean and standard deviation is calculated. After this using the BTC (Block Truncation Code) method [R.C. Gonzales], those pixels (block) whose gray value is larger than mean value are transformed and made equal to '1'otherwise '0'thereby obtaining a series of binary blocks which represent the texture feature of the image blocks and also indicate the shape distribution to certain extent. It is important to note that the similar texture-structure will form the similar binary blocks and these binary blocks are known as texture primitive which can intern use the decimal value of equivalent binary value to represent the texture primitive codes. Figure 7 gives the extraction of texture primitive for m=2. It can be clearly understood from figure 7 that certain different blocks lead to identical texture values. As a result, a threshold is set to avoid the confusion. Thus, image blocks having standard deviation less than the threshold are considered as even blocks and are assigned a primitive value '0' and if the standard deviation is greater than the threshold value, the texture primitive value is computed based on the above method.

Image Blocks		Binary Blocks		Binary Codes	Texture Primitive Codes
20	22	1	1	1100	12
8	7	0	0		
9	19	0	1	0101	5
11	20	0	1		
17	11	1	0	1010	10
18	9	1	0		
20	7	1	0	1001	9
6	23	0	1		
8	7	1	0	1001	9
6	8	0	1		

Fig.7 Image Blocks and their Texture Primitive Codes

Figure 8 [K. Sangeetha *et al*] shows a sample image and its corresponding texture image and it can be clearly seen that the image expressed by the texture primitive expresses the texture information of the original image extremely well to some extent.

(a) Query Image



(b) Image expressed by Texture Primitive

Fig. 8 Query Image and its Corresponding Texture Image

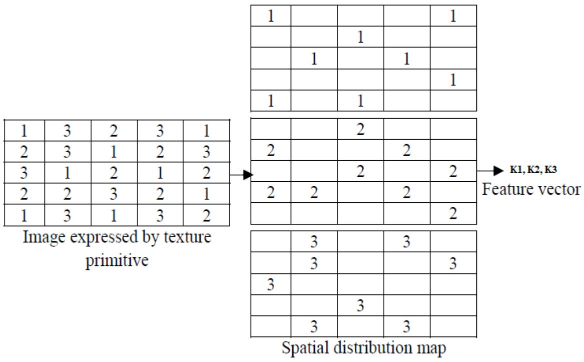


Fig.9 Extraction of feature vector from Texture Primitive

After generating the texture primitive codes, a spatial distribution map of texture primitive is built according to which the spatial feature is constructed. This newly synthesized patch is then placed at the target patch's position to give visually pleasing results. Figure 10 shows the output of the exemplar based image inpainting technique using texture primitive.

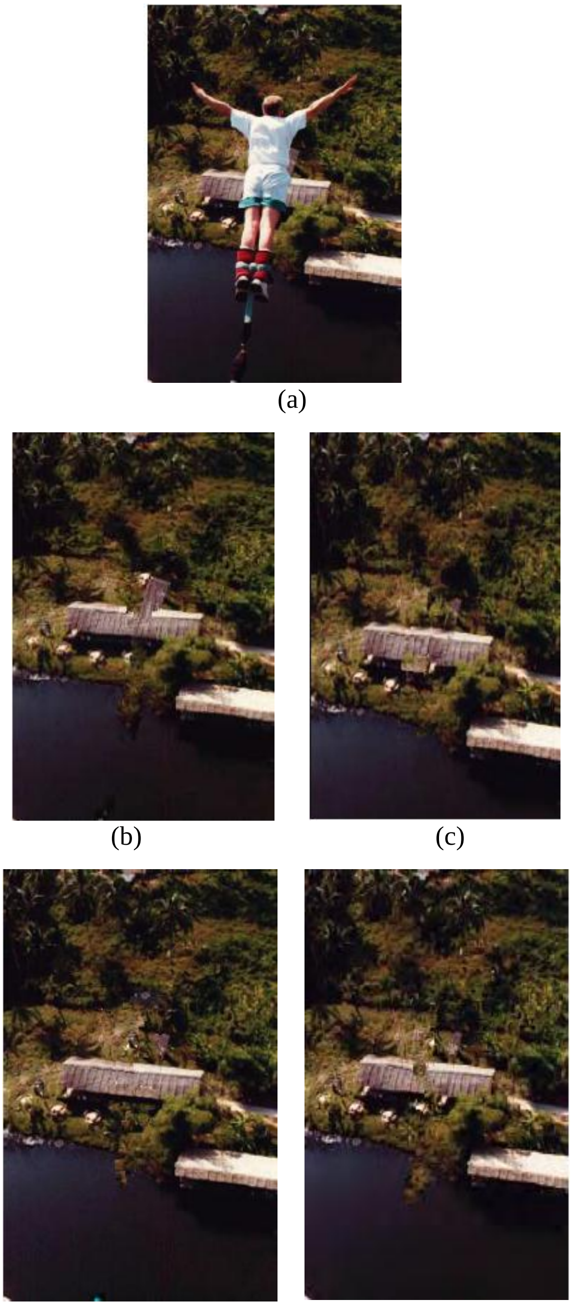
(a) (b)

Fig.10 Output of the Exemplar based Image Inpainting Technique using Texture Primitive [K. Sangeetha *et al*].

It is observed that exemplar-based image inpainting technique using texture primitive is capable of effective region filling and gives very high PSNR value with very low MSE value. The PSNR value for restored sample image in figure 10 is equal to 62 dB [K. Sangeetha *et al*] which is very high than that obtained in the previously described exemplar based image inpainting techniques to eliminate the undesired objects (in this case bungee jumping man) from the image.

3. Comparison and Analysis

The above described methods include basic as well as improved and more recent methods to fill in the missing regions in a visually plausible manner so that the inpainted target region mimics the source region in appearance. The below given figure (Figure 11) is a classical image [A.Criminisi *et al.*] used in many papers so we have used it to compare various exemplar based inpainting methods.



(a)

(b) (c)

(d) (e)

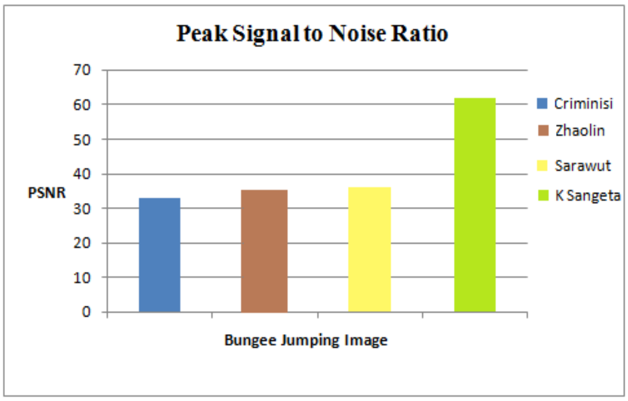
Fig.11 Results of Various Exemplar based Inpainting methods.

The bungee jumping man in the sample image (Figure 11(a)) is the object which is removed in each case. Figure11(b), Figure 11(c), Figure 11(d) and Figure 11(e) show the restored results by Criminisi's method, Zhaolin Lu *et al*'s method, Sarawut Tae-O-Sot's method and K. Sangeetha *et al.*'s method respectively. Each successive method has some advantage over its predeceaser. The PSNR values of the restored sample images (bungee jumping) from Criminisi's method, Zhaolin Lu *et al*'s method, Sarawut Tae-O-Sot's method and K. Sangeetha *et al.*'s method are 33.16dB, 34.79dB ,36.24Db and 62dB respectively as depicted in Table I.

Table 1 PSNR Values and Processing Speed of some Existing Exemplar Based Inpainting Algorithms (for sample Image).

Image	Methods	PSNR (dB)	Time (sec)
Bungee Jumping Man	Criminisi *et al*'s Method	33.16	83
	Zhaolin Lu *et al*'s Method	34.79	64
	Sarawut Tae-O-Sot's Method	36.24	83.5
	K. Sangeetha *et al.*'s Method	62	61

As can be seen from figure 11(b) which is a Criminisi result, the roof top of the house is not fully completed /restored and has some visible artifacts. Figure 11(c) shows Zhaolin Lu *et al*'s result which are reasonable than criminisi's result but still have some blur and blocking artifacts. Sarawut Tae-O-Sot's results as can be seen from figure 11(d) are more pleasing than previously discussed exemplar based inpainting methods. It is observed that K. Sangeetha *et al.*'s exemplar-based image inpainting technique using texture primitive is capable of effective region filling and gives pleasing results with a high PSNR value and low MSE value.



Graph 1 PSNR Performance Analysis Chart

4. Limitations

Each of the algorithms described here is not perfect and have a number of limitations. Based on the comparisons and analysis it is observed that Criminisi *et al*.'s method [A.Criminisi *et al*] is not designed to handle curved structures [Yongbo Qin *et al*]. This method also produces undesirable results if the patch size is too small or too large as small patches result in noticeable blocky patterns as well as increase the inpainting time while choosing a large patch increases the chances of choosing a bad patch which mostly contains undesirable information. However, Zhaolin Lu *et al* and Sarawut Tae-O-Sot's algorithms produce better results than criminisi's algorithm, yet they still have a problem that they work well only if the missing region consists of simple structure and texture. If there are not enough sample texels/exemplars in the image, it is impossible to synthesize the desired image that looks reasonable to the human eye. In addition to these shortcomings, Sarawut Tae-O-Sot's method takes 0.5 seconds [Sarawut Tae-o-sot *et al*] more than Criminisi's processing time and is a little slower than criminisi's inpainting method. Although K. Sangeetha *et al*.'s [K. Sangeetha *et al*] algorithm has a high PSNR value and produces surprisingly better results in case a single non repetitive structure is corrupted ; there are certain cases where this algorithm fails to successfully reconstruct the image.

Conclusion

This study provides estimable contextual information about four different types of exemplar based inpainting techniques with an aim to remove elements from an image in a visually plausible manner. The success of any inpainting techniques is estimated in a precise way by the quality assessment of how well the geometric structure, photometric information and texture is propagated into the target region. In this paper, we have performed both a qualitative as well as quantitative analysis of these algorithms on the basis of which a number of advantages and shortcomings were highlighted in relation to the type and amount of information each algorithm can restore. Despite extensive research carried out in the field of image inpainting, the inpainting problem is still far from being completely solved. Although a large number of algorithms exist that are capable of producing amazing results, yet many challenges lay ahead in making inpainting robust and practical in day to day applications. These algorithms are usually limited to images that portray certain features so in order to make the inpainting methods applicable to almost all types of images more research still needs to be done. It is hoped that this piece of work can provide a good framework for additional research that might be undertaken to further improve the methods that have been discussed here.

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