A Comparative Analysis of Exemplar Based and Wavelet Based Inpainting Technique

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Abstract—Image inpainting is the process of filling in of missing region so as to preserve its overall continuity. Image inpainting is manipulation and modification of an image in a form that is not easily detected. Digital image inpainting is a relatively new area of research, but numerous and different approaches to tackle the inpainting problem have been proposed since the concept was first introduced. This paper compares two separate techniques viz, Exemplar based inpainting technique and Wavelet based inpainting technique, each portraying a different set of characteristics. The algorithms analyzed under exemplar technique are large object removal by exemplar based inpainting technique (Criminisi’s) and modified exemplar (Cheng). The algorithm analyzed under wavelet is Chen’s visual image inpainting method. A number of examples on real and synthetic images are demonstrated to compare the results of different algorithms using both qualitative and quantitative parameters.

Keywords- Image Inpainting, Image manipulation, Texture Synthesis, Patch Propagation, color analysis.

I. INTRODUCTION

The Image Inpainting is the art of modifying an image or video in a form that is not easily detectable by an ordinary observer. Image Inpainting is to try and fill a hole in an image with some meaningful data based on information in rest of the image. The inpainting can be described as “the introduction of new paint into and limited areas of loss in the original paint layer in order to restore design continuity.”[3] Ideally we would like to create what was there originally but this is completely unfeasible without the prior knowledge about the image. In case of digital images we only have the image we are working on available to us and thus we are filling in a hole that encompasses an entire object it is impossible to replace that entire item based on the information present. With this in mind, the aim of algorithms presented in this paper is not exactly reconstruct what used to be in that hole but instead to create a visually pleasing continuation of data around the hole in such a way that it is not detectable.

This paper compares exemplar based and wavelet based inpainting technique. Fig. 1 shows an example of inpainting task where the foreground person (manually selected as target region) is automatically replaced by the data samples from the background. In process of inpainting the input image determines target region (what is to be
A Comparative Analysis of Exemplar Based and Wavelet Based Inpainting Technique

Inpainting. One of the papers is referred in the context of this comparative analysis [5]. This paper proposes a simple algorithm where filling in the missing region is carried out by the property of Isophotes (lines of equal gray value). Also soon after this Chan, Shen and coworkers [12] proposed a variation model for filling in gray level and color images. Later Mumford-Shah model [11] has been adopted for good obtaining good approximations from mathematically neat image modeling. These proposed algorithms were structure oriented. These algorithms were able to keep good continuation smoothly however, broken edge estimation with large gap could fail and detail texture surface is not easily reproducible. One of the first attempts to use exemplar-based synthesis specifically for object removal was by Harrison [6]. There, the order in which a pixel in the target region is filled was dictated by the level of “texturedness” of the pixel’s neighborhood.

However, since most ordinary images are not composed of pure texture or pure structure, better performance is expected for those taking advantages of both schemes. Bertalimo [5] propose to decompose each original image into two separate component images of different characteristics. One of them is processed by texture-oriented scheme and the other by structure-oriented one. The two processed components are added back to reconstruct the missing regions. Criminisi’s [6] exploit a path based algorithm, in which the filling order is decided by a predefined priority function to ensure that linear structures will propagate before texture filling to preserve the connectivity of object boundaries. The performance is compatible to previous techniques and better speed efficiency is obtained. In 2005 Cheng and coworkers [10] generalized the priority function proposed by Criminisi to provide more robust performance. In 2006 Wu proposed a cross-Isophotes exemplar based Inpainting technique, in which a cross isotope patch priority term was designed based on analysis of anisotropic diffusion. In 2007 Wu proposed an algorithm using wavelet. This algorithm could be applied to highly lose image. Also in 2008 Wong proposed nonlocal means approach for exemplar based Inpainting algorithm. The image patch is inferred by nonlocal means of a single best match patch. Also simultaneously Dongwook Cho, and Tien D. Bui [13] showed the Use of advantages of wavelets to Image Inpainting. Chan, L/Shen, Cai and Z. Shen [14] showed the advantages of inpainting algorithm applied in transform domain. Recent work on exemplar based approach is by Zongben and Sun [2]. There structure sparsity is used which enables better discrimination of structure and texture. The rest of this paper is organized as follows. Section 2 represents key notation used in image inpainting. Section 3 describes three inpainting techniques used in this paper for comparison namely criminisi’s algorithm, cheng’s algorithm and wavelet based technique. Experimental results and conclusion are given in section 4 and 5 respectively followed by references in section 6.

II-Notations Used in Image Manipulation Techniques

Image inpainting could also be called as manipulation and modification of an image. Adopting notations similar to that used in Criminisi’s inpainting algorithm [1], the region to be filled i.e. the target region or masked region is indicated by Ω and its contour is denoted by δΩ. As shown in fig.2 the contour evolves inward as the algorithm
progresses and so it is also called as “fill front”. The source region $\Omega$ which remains fixed throughout the algorithm, provides samples used in the filling process. Formally we could express the inpainting problem in this way: Given an image $I$ with a target region $\Omega$, fill in each pixel inside $\Omega$ with a pixel value taken from $\Omega$. Suppose that the square template $\Psi_p \in \Omega$ centered at point $p$ (fig 2b) is to be filled. The best match sample comes from source region $\Psi_{\tilde{q}} \in \Omega$. In the e.g. in fig3b, we see that if $\Psi_p$ lies on the continuation of an image edge, the most likely best matches will lie along the same edge (fig.2c). All that is required to propagate the isophote inward is a simple transfer of the pattern from the best match source patch (fig 2d). The quality of the output image is highly influenced by the order in which the filling process proceeds. A better filling algorithm would be one that gives higher priority of synthesis to those lie on the continuation of image structures. Fig 2e specifies all the notations used in Inpainting where $\perp$ denotes the orthogonal operator.

Figure 2 Structure propagation by exemplar-based texture synthesis. (a) Original Image. (b) the patch $\Psi_p$ centered on point $p \in \delta \Omega$. (c) the most likely candidate matches for $\Psi_p$. (d) the best matching patch in the candidates set has been copied into the position occupied by $\Psi_p$. (e) for patch $\Psi_p$, $n_p$ is normal to the contour $\delta \Omega$ of the target region $\Omega$ and $\nabla I_p \perp$ is the isophote at point $p$.

III-IMAGE MANIPULATION TECHNIQUES

Generally, an exemplar-based Inpainting technique includes the following four main steps:
1) Initializing the Target Region, in which the initial missing areas are extracted.
2) Computing Filling Priorities, in which a predefined priority function is used to compute the filling order for all unfilled pixels $p \in \delta \Omega$.
3) Searching Exemplar patch and Copying, in which the most similar example is searched from the source region $\Phi$ to compose the given patch $\Psi_p$ that centered on given pixel $p$.
4) Updating Image Information, in which the boundary $\delta \Omega$ of the target region $\Omega$ and the required information for computing filling priorities are updated.

A. Criminisi’s Exemplar Based Inpainting Technique:
A Comparative Analysis of Exemplar Based and Wavelet Based Inpainting Technique

Given a patch \( \Psi_p \) centered at the point \( p \) for some \( p \in \delta \Omega \), the priority \( P(p) \) is defined as the product of two terms:

\[
P(p) = C(p) \times D(p) \tag{1}
\]

Where \( C(p) \) is the confidence term and \( D(p) \) is the data term and they defined as follows:

\[
C(p) = \sum_{q \in \Psi_p \cap \Theta} C(q) \tag{2}
\]

\[
D(p) = \left| \nabla I_p \cdot n_p \right| / \alpha \tag{3}
\]

Algorithm Steps:
1. Extract the target region
2. Initialize \( C(p) = 0 \) for \( p \) in target region
   \( C(p) = 1 \) for \( p \) in source region
3. Repeat until done
   a) Identify \( p \in \delta \Omega \), if \( \Omega = \emptyset \) then exit.
   b) Compute \( P(p) \) for \( \Psi_p \in \Omega \) where \( P(p) = C(p) \times D(p) \)
   c) Find exemplar patch \( \Psi_q \in \psi \) such that minimizes \( d(\Psi_p, \Psi_q) \)
   d) Copy image data from \( \Psi_q \) to \( \Psi_p \)
   e) Update \( C(p) \) for \( p \in \Psi_p \cap \Omega \)

B. Cheng’s Robust Exemplar-based Inpainting Technique:

It is found that the confidence value of Criminisi’s technique drops rapidly to zero as the filling process proceeds, which makes the computed priority values undistinguishable, and in turn, results in incorrect filling orders. This is called as dropping effect. The numerical multiplication is sensitive to extreme values. The response of additive function is linearly proportional to its input and is more stable to unexpected noise. Therefore modified the priority function is as follows:

\[
P(p) = C(p) + D(p) \tag{4}
\]

Direct combination of \( C(p) \) and \( D(p) \) is still unreasonable.

\[
\text{Figure 3. Illustration of the Curve regularization for } C(p) \quad [10]
\]

\[
Rc(p) = (1- \omega) \times C(p) + \omega \tag{5}
\]

Where \( \omega \) is the regularizing factor for controlling the curve smoothness.

Cheng’s robust priority function is given by

\[
RP(p) = \alpha \times Rc(p) + \beta \times D(p) \quad (6)
\]

Where \( \alpha \) and \( \beta \) are component weights of confidence and data terms respectively. Also \( \alpha + \beta = 1 \).

There are strong connections between the component weights and the resulting image. The resulting images have stronger structures with higher component data weight.

C. Wavelet Based Inpainting Technique:

The primary feature of this technique is to initially separate the given image into two principal components which encompass color composition and texture composition (luminance), respectively. Then, according to the distinctive qualities of the given image, various image inpainting methods are adopted to perform image manipulation. By taking advantage of wavelet transform, this technique processes texture composition of the image sequentially from...
the lower frequency layers of an image to the higher frequency layers. In addition, the color components of the image (Ch and Cr) serve as a supplementary reference to support the linear interpolation method applied during damaged data prediction. In the image in order to separate the texture composition and color composition, we have to use the color conversion formula to the process. The color conversion formula is as follows:

\[
Y = 0.299*R + 0.587*G + 0.114*B \\
Cb = -0.169*R - 0.331*G + 0.555*B \\
Cr = 0.500*R - 0.419*G - 0.081*B
\]

Algorithm Steps:

1. Convert the given RGB images (original image and its mask image) to YCbCr.
2. Apply 2-Level discrete wavelet transform to Y component of the given images.
3. Analyze the LL2 wavelet coefficients.
4. Use directional decision texture law to fill the target region.
5. Apply 1-Level inverse discrete wavelet transform.
6. Again use directional decision texture law to fill the target region.
7. Again apply 1-Level inverse discrete wavelet transform. This provides Y component of the inpainted image.
8. Use bilinear interpolation technique to the color components of the given images. This provides color components of the inpainted image.
9. Now we have inpainted image in YCbCr. Convert the inpainted image into RGB form.

The texture composition part follows same procedure as that of the Exemplar based algorithm once a 2-level DWT is taken. In this texture synthesis also, we compute the patch priority by considering confidence value and the energy term. The priority function does not have data term in it. The priority function having energy term is as follows:

\[
P(p) = \frac{\text{eng}(\Psi p) * C(p)}{\text{Total energy}}
\]

where eng(\(\Psi p\)) is the energy of the patch centered at point \(p\) and total energy is the energy in that respective level wavelet bands of original image. The proposed bilinear interpolation method defines different weighting values that consider the relating distance from the repair target \(P\), as shown in the following figure.
A Comparative Analysis of Exemplar Based and Wavelet Based Inpainting Technique

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Figure 5. The related weighting value of the different distance

\[
W_{\text{total}} = \sum \sum W_{ij}, \quad \text{if } p(i,j) \text{ is valid} \quad (11)
\]

\[
C_{\text{new}} = \frac{\sum \sum W_{ij} * C_{ij}}{W_{\text{total}}}
\]

Where \( p(i, j) \) is the valid pixel value of the image, \( W_{ij} \) is the weighting value on \((i, j)\), \( W_{\text{total}} \) is the total weighting value of valid pixel value, \( C_{ij} \) is the valid pixel value and \( C_{\text{new}} \) is repair value.

IV RESULTS AND COMPARISON

The techniques are applied to different images. All the experiments are performed on a 2.5GHZ Pentium IV with 1GB of RAM. The performance of the above mentioned manipulation techniques can be evaluated by considering the parameters like PSNR and the time required to Inpaint the image. We first evaluate the performance of the criminisi’s algorithm by considering simple images shown below. The figures 6to8 and tables 1 to 3 below show the same. Also by looking at the figure and the respective table one can decide the required palette size.

![Chinese.png](image1)

(a) Chinese.png

![Chinese_mask.png](image2)

(b) Chinese_mask.png

![intermediate image](image3)

(c) intermediate image

![Chinese_inpainted.png](image4)

(d) Chinese_inpainted.png

Figure 6. Chinese image

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<th>Palette Size</th>
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TABLE I

CRIMINI’S ALGORITHM PERFORMANCE EVALUATION FOR IMAGE chinese.png
TABLE II
CHENG’S ALGORITHM PERFORMANCE EVALUATION FOR IMAGE lonavala.png

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TABLE III
WAVELET BASED ALGORITHM PERFORMANCE EVALUATION FOR IMAGE sujit.png

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A Comparative Analysis of Exemplar Based and Wavelet Based Inpainting Technique

![Images of sourabh.png, sourabh_mask.png, intermediate image, inpainted by Criminisi's, inpainted by Cheng's, inpainted by wavelet]

Fig. 9. sourabh image

**TABLE IV**
CRIMINI’S ALGORITHM RESULTS FOR IMAGE sourabh.png

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**TABLE V**
CHENG’S ALGORITHM RESULTS FOR IMAGE sourabh.png

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TABLE VI
WAVELET BASED ALGORITHM RESULTS FOR IMAGE sourabh.png

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Fig.10. Performance evaluation graph for PSNR

Fig.11. Performance evaluation graph for time
A Comparative Analysis of Exemplar Based and Wavelet Based Inpainting Technique

V. CONCLUSION

This paper presents comparison of Criminisi’s exemplar based approach, Cheng’s exemplar based approach and wavelet based approaches. They can be used removing large objects from digital photographs. These techniques are capable of propagating both linear structure and two-dimensional texture into the target region with a single, simple algorithm. A simple selection of the fill order is necessary and sufficient to handle robustness changes in shape and topology. The other advantages of the algorithm are: (i) preservation of edge sharpness, (ii) no dependency on image segmentation and (iii) balanced region filling to avoid over-shooting artifacts. Furthermore we have investigated use of wavelet transform in Inpainting process. The future algorithm based on wavelet transform will combine the advantages of the above proposed exemplar based algorithm with total variation based algorithm. Compared with other kinds of approaches, exemplar based approach is very effective in reducing the undesired blurring artifacts and applicable to both the small and large image gaps. Wavelet based inpainting produces blur effect as well as color interpolation process creates some problem.

VI. REFERENCES