Improving Exemplar-based Image Completion Methods using Selecting the Optimal Patch

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Abstract

Image completion is one of the subjects in image and video processing which deals with restoration of and filling in damaged regions of images using correct regions. Exemplar-based image completion methods give more pleasant results than pixel-based approaches. In this paper, a new algorithm is proposed to find the most suitable patch in order to fill in the damaged parts. This patch selection method is recommended for exemplar-based approaches. The proposed method consists of three modifications: First, the selected patch's size is considered bigger and then different weights are applied to different sections of the patch. Second, harmonic inpainting method is used in order to reduce the error propagation. Third, limiting the search space is done to improve and reduce the executing time. The acquired results depict that this method is effective and there is an improvement for quality of exemplar-based approaches.

Keywords—Exemplar-based, Image Completion, Inpainting, Patch

I. INTRODUCTION

Completion or restoration of damaged images is one of the machine vision's problems. In this subject, missing regions and data (missing pixels) are filled in by safe regions. Missing regions in images may be created because of errors happening while images or video are sent on a wireless network or they may occur because of manipulation of images. Filling in these regions can be useful for many applications such as image coding (damaged blocks retrieval), image restoration (line and scratch removal from an image), object removal and other applications.

Recently, several works have been performed on image completion which are dependent on the amount of missing data and the size of the hole. Partial differential equations (PDE) methods are usually used for small and narrow regions, and Exemplar-based methods (such as texture synthesis) are used for large damaged regions. There is another categorization which defines two classes of methods in this field: pixel-based and patch-based. Generally, since patch-based methods preserve structure of the image, these approaches produce higher quality rather than pixel-based methods.

PDE-based methods fill in the hole in such a way that pixels' values are propagated from surrounding of the hole to inside of it. Based on these approaches, the procedure of propagation is simulated by solving PDEs which are known as nonlinear high order equations.

The problem of inpainting was firstly introduced by Bertalmio et al. [1]. This method used Laplace transform and direction of lines' gradients. In this method, some data around the hole (boundary of the hole ($\partial\Omega$) are propagated towards inside the hole (Ω) for each iteration and inpainting procedure continues until the damaged region is completely filled in. In addition, Bertalmio et al. introduced another method in [2] that preserves continuity edges. In this method, a third order PDE by Theiler sequence has been used. Oliveira [3] introduced a mask-based approach for filling in small holes and scratches of images. In [4] an algorithm has been introduced which uses global statistics of image for missing region completion. In [5] and [6], Markov random field have been used to complete the corrupted image. According to [7], the user helps to determine the structure of the image; the user draws lines which depict how much the surrounding region must be extended. This method finds patches of neighborhoods lines using energy minimization.

Exemplar-based methods complete the holes and unknown regions using portions of image which are safe and are determined as source region. One of the most important and referenced approaches in this field is the one introduced by Criminisi et al. [8].This approach uses a priority for selecting surrounding pixels to fill in at first. Greediness and low speed of the algorithm are two disadvantages of exemplar-based methods. Greediness of the algorithm causes error propagation towards inside the hole, and comparison with all of the existing patches causes speed reduction for this approach. Kwok et al.[9] proposed an algorithm to speed up the exemplar-based method so that patches are translated to frequency domain and used cosine coefficients. Then, they considered some important coefficients for patch comparison.

Sun et al. [11] used an exemplar-based approach

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while patches are defined by moments' attributes. Since in patch selection moment's attributes are considered, it is robust against rotation. There are other papers based on Criminisi method that changed the priority measure for filling in the hole. Anupam et al. [10] proposed a priority for the hole completion which controlled the smoothness of curve changes.

Bertalmio et al. [12] separated an image into two components; texture and structure (non-texture). They used PDE-based and texture-synthesis methods for structure and texture sections, respectively. One of the disadvantages of PDE-based methods is that they are used for narrow and directional holes. Also, these approaches suppose that the corrupted region is flat and non-textured.

The paper has been organized as follows: a fast review of exemplar-based methods is presented in section 2. Section 3 introduces the proposed method for image completion. Section 3 presents experimental results and finally section 4 concludes the paper with a discussion to future work.

II. Exemplar-based method

Exemplar-based approach has been introduced by Criminisi [8] for object removal. This approach restores the hole (Ω) using the correct region (Φ). To fill in the hole, a square patch is considered for each point P on the boundary of the corrupted region ($\partial\Omega$). The damaged portions of this patch are completed by most similar patch from correct region. A value named priority *P(p)* is defined to preserve the structure of image on pixels of the hole boundary. The patch around the highest priority pixel is the first patch that will be completed. The priority of each pixel *P(p)* is calculated by production of two factors; confidence term *C(p)* and data term *D(p)*.

The confidence term, *C(p)*, is the ratio of the number of undamaged pixels to all of patch. Data term *D(p)* determines how much the gradient of the pixel and orthogonal to boundary of the pixel are same directional;. These two terms are explained as follows:

$$C(p) = \frac{\sum_{q \in \psi_p \cap (I-\Omega)} C(q)}{|\Psi_p|} \quad (1)$$

$$D(p) = \frac{|\nabla I_p^{\perp} \cdot n_p|}{\alpha} \quad (2)$$

$$P(p) = D(p).C(p) \quad (3)$$

where Ψ_p is a patch centered at p, $|\Psi_p|$ is the area of Ψ_p, α is a normalization factor (e.g. $\alpha = 255$ for gray-scale images), n_p is a normal to the boundary of the target region and $\nabla I_p^{\perp}$ is the isophote in location p. The target region, source region and the original image are depicted on Fig.1 by Ω, Φ and I, respectively.

Anupam et al. [10] used Eq. 4 to define the priority of the best patch that is appropriate for filling in hole.

$$P(p) = \alpha \times R_c(p) + \beta \times D(p), \quad 0 \le \alpha, \beta \le 1 \quad (4)$$

where $\alpha + \beta = 1$ and the confidence term $R_c(p)$ is changed as follows:

$$R_c(p) = (1-w) \times C(p) + w, \quad 0 \le w \le 1 \quad (5)$$

The patch Ψ_p with the highest priority (i.e. $\Psi_{\hat{p}} \mid \hat{p} = \arg\max_{p \in \partial\Omega} P(p)$) is found and it is completed using the best matching patch from the source region. Sum of squared differences of pixels of two patches $d(\Psi_{\hat{p}}, \Psi_{\hat{q}})$ is used to calculate the most similarity. When Ψ_p was found, the value of each pixel P', $(P' \in \Psi_{\hat{p} \cap \Omega})$ is copied from similar coordinates of $\Psi_{\hat{p}}$. At the end, the confidence terms for all pixels intersecting with the target region are updated as below:

$$C(p) = C(\hat{p}) \quad \forall p \in \Psi_{\hat{p}} \cap \Omega \quad (6)$$

This algorithm is run iteratively until the missing region fades away. Initial confidence values for the hole and source region are zero and one, respectively.

III. The proposed method

In this algorithm, some issues in Exemplar-based method such as error propagation and computational speed are considered. Three different modifications are considered to improve the exemplar-based method. The first modification review to find the best matching patch. The second modification introduces an algorithm to prevent error propagation inside the hole. In the third modification, the speed of the algorithm that was reduced during the first and second modifications gets better.

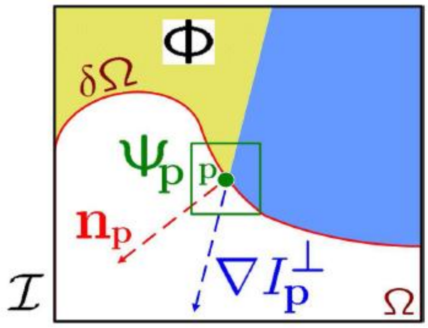


Fig. 1. Exemplar-based inpainting (borrowed from Criminisi [8]).

A. Considering bigger patch and Linear Weighting

After finding the target patch (the patch which is going to be filled in) with the highest priority, the most similar patch to this patch must be found. In this step, we consider the patch size bigger than initial patch's size and search for the best patch with the new size. After finding the best patch, only the inner values of the source patch (the most suitable patch) are copied into the target patch. This algorithm considers the structure of the area around the initial patch to find the best patch through better patch selection mechanism.

To do this, a scale coefficient named PatchScale is defined. This value is multiplied by the size of the target patch and the obtained number is rounded and considered as the new patch size. Then, to find the best match, target patch with the new size is searched in the source region. For example, if *PatchScale*=1.5 and the initial patch's size is 9×9 ($\Psi_{\hat{p}}$), then the patch which is used for searching will be 13×13 ($\Psi_{\hat{p}L} = round(PatchScale \times \Psi_{\hat{p}})$); because $round(PatchScale \times 9) = 13$.

After obtaining a new size for the patch, a linear weighting is used to find the best patch. To do linear weighting, inner section (that has the size of initial patch) is multiplied with greater weight than outer section. If minimum squared error is used as a criterion of patch similarity, the similarity by patch weighting will be calculated as follows:

$$d = \alpha \times d(\Psi_{\hat{p}}, \Psi_{\hat{q}}) + \beta \times d(\Psi_{\hat{p}L} - \Psi_{\hat{p}}, \Psi_{\hat{q}L} - \Psi_{\hat{q}}) \qquad (7)$$

where coefficients α and β are the factors of weighting for inner region and outer region of the patch with new size, respectively.

B. Harmonic Inpainting

After finding the most suitable patch, there is possibility of error propagation. It is because of existence of differences in color, structure and etc. between the correct portion of the target patch and the part of the selected patch from source region that is going to be copied to the hole of the target region. This error is propagated into the next steps inside the hole and causes unpleasant results.

To solve this problem, variational methods can be used in which an energy function is considered for the hole and by propagation of data from correct region to corrupted region, the energy function is minimized [13]. Two simple variational methods are total and harmonic model which are used for inpainting. These two models use absolute and square of the image's gradient as the minimum energy value, respectively. Both of them are suitable for non-textured images. Inpainting using total variational method preserves the sharpness of edges. But, sharp edges changes smoothly by harmonic model. Since harmonic model is very fast and the target patches are small, it will be used in the proposed method.

As mentioned above, harmonic inpainting model causes correct region propagates to hole region and patch with high priority $\Psi_{\hat{p}}$ being completed. Harmonic inpainting model minimizes the squared gradient value of image [14] as follows:

$$u = \min_{u} \int_{\Omega} |\nabla u|^2 dx \qquad (8)$$

where u is the region around Ω. It should be noticed that one side of target patch is always empty (and when inpainting is running, the area around the hole is not filled in). Therefore, before inpainting of target patch, the mean value of the correct part of the target patch is replaced in the hole part. Then, inpainting model is applied on the patch. This makes the background of the hole to be closer to the correct part of the target patch.

Finally, to find the best patch, a comparison is done between the completed target patch, which inpainted from harmonic model, and patches from source region. This comparison is added with previous similarity measure using a coefficient. As a result, similarity measure is calculated as follows:

$$\begin{aligned} d = {} & \alpha \times d(\Psi_{\hat{p}}, \Psi_{\hat{q}}) + \\ & \beta \times d(\Psi_{\hat{p}L} - \Psi_{\hat{p}}, \Psi_{\hat{q}L} - \Psi_{\hat{q}}) + \\ & \lambda \times d(\Psi_{\hat{p}H} \cap \Omega, \Psi_{\hat{q}}) \end{aligned} \qquad (9)$$

where λ is the similarity coefficient between the filled part of the target patch obtained from harmonic inpainting method and patches from source region. $\Psi_{\hat{p}H}$ is the patch $\Psi_{\hat{p}}$ with its hole completed using harmonic inpainting method.

C. Limiting the Search Space

Due to added changes in modifications one and two, the speed of finding the best patch and consequently, the speed of the algorithm has been reduced. In this section, to speed up and improve the operation of the algorithm, search space for finding an appropriate patch is restricted. Usually, the best and most suitable patch for filling in the hole can exist around the hole and using these patches for natural images has a good impact. Therefore, the search space

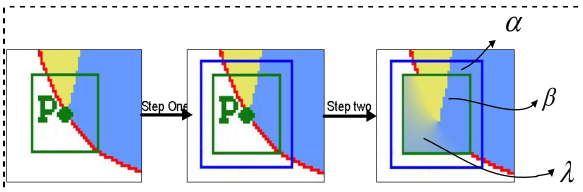


Fig. 2. Applying modifications one and two of the algorithm on patches.

is limited for finding the best patch for Ψ_p (centered at pixel p = (p_x ,p_y) and it is considered as the following rectangle:

$$Rect\_Search = [\max(0, p_x - w/4), \max(0, p_y - h/4), \min(w, p_x + w/4), \min(h, p_y + h/4)] \quad (10)$$

where w and h are width and length of the original image, respectively.

IV. Experimental Results

The proposed method for image completion has been implemented using Windows 7 operating system and MATLAB R2011a software. To run the algorithm, the input image and the mask (which determines the hole) are inputs for the system. According to the algorithm, first of all, the patch with highest priority, based on the boundary points between source and target regions, is calculated. The algorithm iterates until the mask region is completed. Patch size and *PatchScale* are considered 9×9 and 1.3, respectively.

Fig. 3 illustrates *Bungee*image with the size of 206×308 that has 8794 damaged pixels. Input image and mask of the image are shown on (a) and (b) panels, respectively. Results of Criminisi method [8] and the proposed algorithm are shown in (c) and (d) panels, respectively.

As shown in Fig. 3-d, the best patch selection method preserves the structure of the image better and produces more pleasant results.

Fig. 4 shows an image with the size of 256×170 pixels. The specified object by red mask in part (b) is going to be removed. 6472 pixels of this image are damaged. Panels (c) and (d) illustrate the result of criminisi method [8] and the proposed algorithm, respectively.

As shown in Fig. 4, the proposed algorithm by Criminisi*et al.* selects the patches in a way that makes error propagation in the hole and a part of other objects of the scene has been appeared in the hole.

Applying the optimal patch selection to Anupam et al. algorithm [10] is another experiment. The priority calculation is different in Anupam algorithm [10] from Criminisi algorithm [8]. Fig. (5) and (6) show the results of Anupam et al. algorithm [10] on (a) panels and the results of the proposed algorithm for patch selection on (b) panels, respectively. It must be mentioned that our patch selection method has been applied to Anupam priority calculation method.

As can be seen in Fig. 5, optimal patch selection prevents errors from propagating into the hole. Besides, the priority measure defined using Eq. 4 does not produce pleasant results.

(a) (b) (c) (d)

Fig. 3. (a) Bungee image (b) image mask (c) result of the Criminisi algorithm [8] (d) result of our algorithm.

(a) (b) (c) (d)

Fig. 4. (a) Input image (b) image mask (c) result of the Criminisi algorithm [8] (d) result of our algorithm.

(a) (b)

Fig. 5. (a) Result of the algorithm proposed in [10], (b) result of the algorithm proposed in [10] using our optimal patch selection algorithm.

(a) (b)

Fig. 6. (a) Result of the algorithm proposed in [10] for Bungee image (b) result of the algorithm proposed in [10] using our optimal patch selection algorithm.

As shown in Fig. (6), our patch selection algorithm produced more pleasant result compared to Anupam algorithm. Also, image structure has been preserved in our method. The obtained results show that the proposed method with both values for priority P(p) (Criminisi et. al. method and Anupam et. al. method) give good results.

TABLE I
EXECUTING TIME COMPARISON BETWEEN THE EXEMPLAR-BASED ALGORITHMS AND THE PROPOSED ALGORITHM (IN SECONDS)

Image	Criminisi algorithm[8]	Anupam algorithm [10]	The proposed method
Baseball man	156	130	127
Bungee	327	304	282

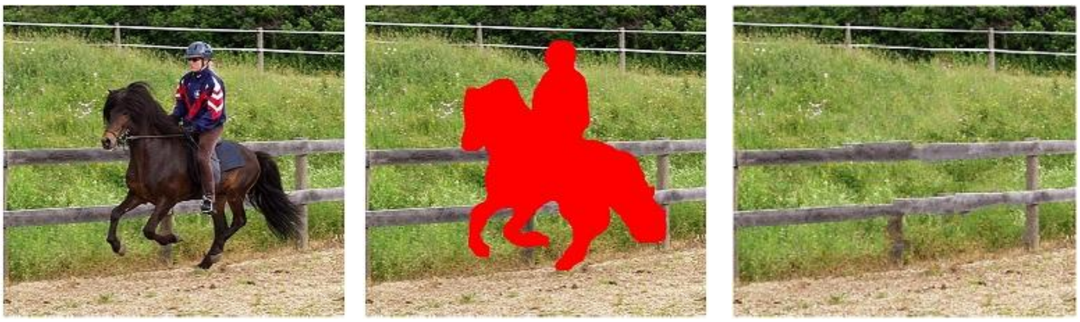
The computational costs are presented in Table (1). As it can be seen, the executing time for the proposed algorithm is less than Criminisi and Anupam algorithm.

Figs. 7, 8 and 9 show more experimental results using the proposed method and Criminisi priority calculation.

Fig. 10 shows pseudo-code of the proposed algorithm. Bold lines are proposed modifications in Criminisi's exemplar-based algorithm. The superscript *t* indicates the current iteration.

V. CONCLUSION

Exemplar-based methods are used for image completion; safe patches are used for filling in and restoration of damaged regions. In this paper, a method for selecting the optimal patch has been proposed so that it can be used in other Exemplar-based approaches. The proposed method finds the best patch using three modifications. The algorithm is independent of how to calculate the highest priority for completion. The proposed method prevents error propagation in the hole and preserves the structure of the image. Also, the proposed method runs faster than other compared methods. This approach can be used for most exemplar-based methods and also for other applications which search the best matching patch.

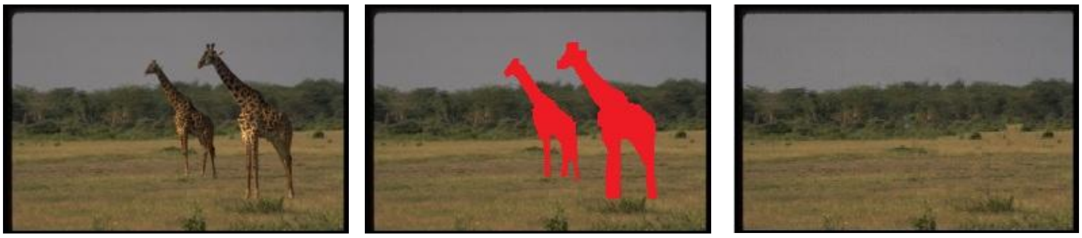


(a) (b) (c)

Fig. 7. (a) Input image (b) image's mask (c) output of the proposed algorithm.

(a) (b) (c)

Fig. 8. (a) Input image (b) image's mask (c) output of the proposed algorithm.



(a) (b) (c)

Fig. 9. (a) Input image (b) image's mask (c) output of the proposed algorithm.

- Extract the manually selected initial front $\delta\Omega^{\circ}$
- Repeat until done:

1a. Identify the fill front $\delta\Omega^t$. If $\Omega^t = 0$;, exit.

1b. Compute priorities $P(p)\ \forall p \in \delta\Omega^t$

2a. Find the patch $\psi_{\hat{p}}$ with the maximum priority, i.e. $\hat{p} = argmax_{p \in \delta\Omega^t} P(p)$.

2.a.1. Consider a larger patch $\psi_{\hat{p}L}$ with $round(Scalepatch \times size(\psi_{\hat{p}}))$ size

2.a.2. Obtain the patch $\psi_{\hat{p}H}$ by harmonic inpainting of patch $\psi_{\hat{p}}$

2.a.3 Find the exemplar $\psi_{\hat{q}} \in \Phi$ that minimizes d in a bounded region from image

$d = \alpha \times d(\Psi_{\hat{p}}, \Psi_{\hat{q}}) + \beta \times d(\Psi_{\hat{p}L} - \Psi_{\hat{p}}, \Psi_{\hat{q}L} - \Psi_{\hat{q}}) + \lambda \times d(\Psi_{\hat{p}H} \cap \Omega, \Psi_{\hat{q}})$

2b. Copy image data from $\psi_{\hat{q}}$(inner section of $\psi_{\hat{q}L}$ (to $\psi_{\hat{p}}$; $\forall p \in \psi_{\hat{p}} \bigcap \Omega$

3. Update $C(p)\ \forall p \in \psi_{\hat{p}} \bigcap \Omega$

Fig. 10. Pseudo code of the proposed algorithm.

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