ROBUST OBJECT REMOVAL BY MODIFIED EXEMPLAR-BASED IMAGE INPAINTING

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ABSTRACT

Image inpainting is the reconstruction and restoration of damaged images by filling in the damaged parts in a visually plausible manner. Exemplar based image inpaining uses sample patches from the rest of the image for restoration and object removal. In this project, we build upon Criminisi's [1] approach, first proposed in 2004. We use variance [2] on top of the SSD criterion for the best patch selection. A regulariser is incorporated in the confidence term [3] to control the dipping confidence values. Finally, the data term is computed using the edge map technique [4] instead of isophototes. We implement these in MATLAB and C and report the results obtained on various images.

***Index Terms*—** Image inpainting, object removal, regulariser, confidence value.

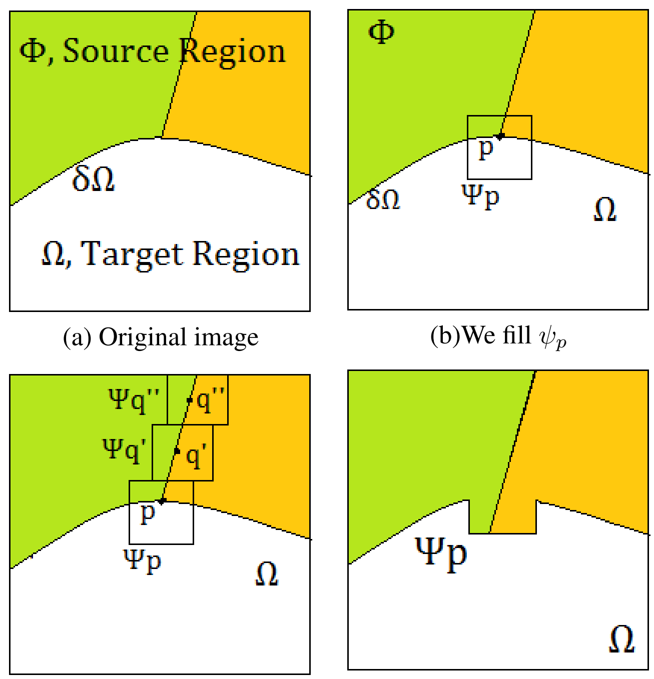
1. INTRODUCTION

Historical photos get damaged over time. Creases and spots are formed on old photos and need to be removed via some digital means. In the modern photo-frenzied youth, there is also a demand to remove unwanted objects from personal photos. All these issues can be addressed by image inpainting. Image inpainting refers to the restoration of damaged images in a visually plausible way. The techniques work by identifying the damaged region and then filling up those regions using instances from the rest of the image. Criminisi proposed an exemplar based approach for object removal. We build upon it by incorporating modifications proposed by [2], [3], [4] and implementing the same.

2. CRIMINISI'S APPROACH

Criminisi's approach [1] combines Texture synthesis as well as Image inpainting techniques for object removal and region filling. The filling process is based on texture synthesis algorithms which generate textures using stochastic models. The order on which the damaged regions are filled is based on techniques that rely on linear structures. The large amount of redundant information present in photographs is utilised in the search of a similar patch.

The image is divided into 2 regions - Source region and Target region. The source region ϕ, contains all the pixels whose values are known and form the undamaged part which has to be utilised for selecting the patch with which the damages are filled. The target region Ω, consists of all the damaged pixels which have to be replaced. The Target region Ω is filled from the boundary to inwards. The pixels in Ω forming the boundary to be filled at any given instant are denoted by $\delta\Omega$. The algorithm works in three stages.



(a) Original image (b)We fill ψ_p

(c) The best matched patch is found (d) ψ_p is filled by ψ'_q

Fig. 1. Structure propagation by exemplar-based texture synthesis: Criminisi's approach.

2.1. Deciding the order of filling

In the first stage, the filling priority of all the pixels $p \in \delta\Omega$ is computed. The pixel with the highest priority is selected and patch ψ_p around it is filled first. The priority of pixel p, $P(p)$, consists of 2 terms: the Data term $D(p)$ and the Confidence term $C(p)$ and is given by:

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

The terms $C(p)$ and $D(p)$ are calculated as:

$$C(p) = \frac{\sum_{q \in \psi_p \cap (I-\Omega)} C(q)}{|\psi_p|} \tag{2}$$

$$D(p) = \frac{|\nabla I_p^{\perp} . n_p|}{\alpha} \tag{3}$$

I refers to the entire image, $|\psi_p|$ refers to the area of patch ψ_p, $\nabla I_p^{\perp}$ represents the linear structure or edge: its magnitude and direction at p and n_p represents the direction orthogonal to $\delta\Omega$ at p; α is a normalization constant. Initially $C(p) = 0 \forall p \in \Omega$ and $C(p) = 1 \forall p \in (I - \Omega)$. The confidence values for pixels in Ω re updated later.

The confidence of a pixel $C(p)$ reflects the confidence or surety with which the value of pixel p is known. It favours those pixels for filling priority which have large number of neighbours with known pixel values. Th data term identifies the pixels which are close to linear structures and edges and gives high priority to them. The inner product of $\nabla I_p^{\perp}$ and n_p is high when these vectors have similar direction and hence enables to determine pixels lying close to linear structures.

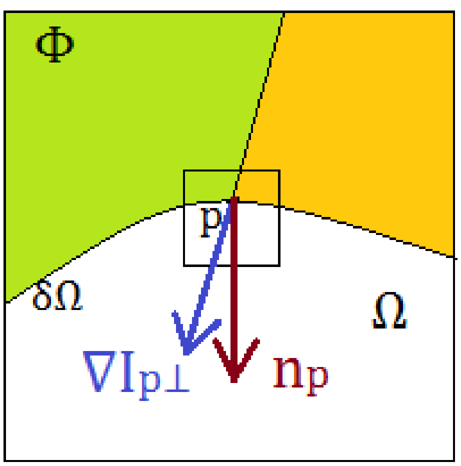


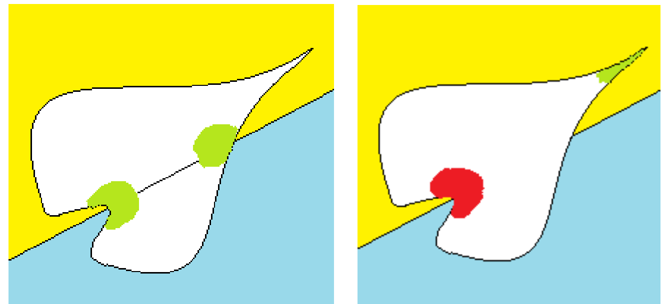
Fig. 2. Notation diagram for computing the data term

2.2. Deciding the best matched patch

After the pixel $p \in \Omega$ with highest priority $P(p)$ is determined, the patch ψ_p is filled by finding a corresponding best match ψ_q from the image part $I - \Omega$. The sum of square distances criterion is minimised to determine the closest patch.

$$\psi_{\hat{q}} = \arg min_{\psi_q \in \phi} d(\psi_p, \psi_q) \tag{4}$$

where d is the SSD distance between ψ_p and ψ_q.



(a) Data term influence (b) Confidence term influence

Fig. 3. Effects of data and confidence terms. In (a), the green regions are preferred by the data term. In (b), the green regions are preferred by the confidence term whereas the red regions are not.

2.3. Updating Confidence values

After the patch ψ_p is completed with the help of the best matched patch ψ_q, the confidence values of pixels lying in $\psi_p \cap \Omega$ are updated as:

$$C(\hat{p}) = C(p) \;\; \forall \;\; \hat{p} \in \psi_p \cap \Omega \tag{5}$$

By the combined effect of Data and Confidence, filling proceeds in a boundary to inwards manner, with the confidence values falling as filling proceeds.

3. MODIFICATIONS

The algorithm proposed by Criminisi was a pioneering work in Image inpainting and solved the problem of object removal to a large extent. However, several issues and details were still unresolved for which we accommodate the following modifications in our implementation.

3.1. Regularizer

It is observed that confidence values decreased rapidly as filling proceeded. As the interior parts of the Target region are approached for filling, the extremely low values of confidence term lead to significantly small priority values $P(p)$. As a result a random selection of the patch ψ_p takes place for filling. To avoid this problem, the incorporation of a regularizer [3] was proposed in the Confidence term as follows:

$$R_C(p) = (1 - \omega)C(p) + \omega \tag{6}$$

$$P(p) = R_C(p)D(p) \tag{7}$$

ω denotes the regularizer and controls the fall. We have taken $omega = 0.7$ for our implementation. However, an adaptive regularizer can also be used depending on the Target patch size.

3.2. Variance for best patch selection

The criterion for deciding the best match patch(4) computed the SSD distances but considered only those pixels whose values are known. For textures regions this might lead to unexpected results as patches with only a small part matching with the target patch but the rest of the part different might get selected. To resolve this problem, variance [2] is used as an indicator of the stability of image patch. We add the variance criterion on top of the SSD criterion to determine the best match patch as follows:

$$\psi_q = \arg min_{\psi_q \in \phi} d(\psi_p, \psi_q) + \delta \times (v(\psi_p) - v(\psi_q))^2 \quad (8)$$

δ is a weighing constant and has been taken as 0.005 in our implementation. $(v(\psi_p) - v(\psi_q))^2$ is computed as the sum over Red, Green and Blue channel.

$$(v(\psi_p) - v(\psi_q))^2 = \sum_{i \in R,G,B} (v_i(\psi_p) - v_i(\psi_q))^2 \quad (9)$$

3.3. Data term

The data term in Criminisi's approach has been calculated through isophotes i.e. the computing the inner product between the perpendicar to $\delta\Omega$ at p and the edge represened by $\nabla I_p^{\perp}$. Another alternative to represent the data term is by using the edge map of the image.

$$D(p) = max\Big(1, (\sum_{q \in (\psi_p \cap \psi_\epsilon)} c)\Big) * \frac{var(\psi_p)}{|\psi_p|} \qquad (10)$$

The constant c is taken as 0.1 in the implementation. The pixels near edges will have higher variance n pixel values, also $\psi_p \cap \psi_\epsilon$ will include a larger region for pixels p lying near edges.

4. RESULTS

4.1. Criminisi's algorithm

The results in figure 4 are obtained by Criminisi's algorithm. An undesirable out-of-place dent is visible in the shed by the water body.

4.2. With Regularizer

A regularizer (ω = 0.7) is added in the confidence term and the corresponding results illustrated in figure 5. The dent is gone and the reconstructed image is visually appealing.

Another particularly striking example is that of a wind mill being inpainted as in figure 6. Without regularizer, the criminsi's algorithm inpaints a new building in place of the mill, which is undesirable. The addition of a regularizer prevents this from happening.

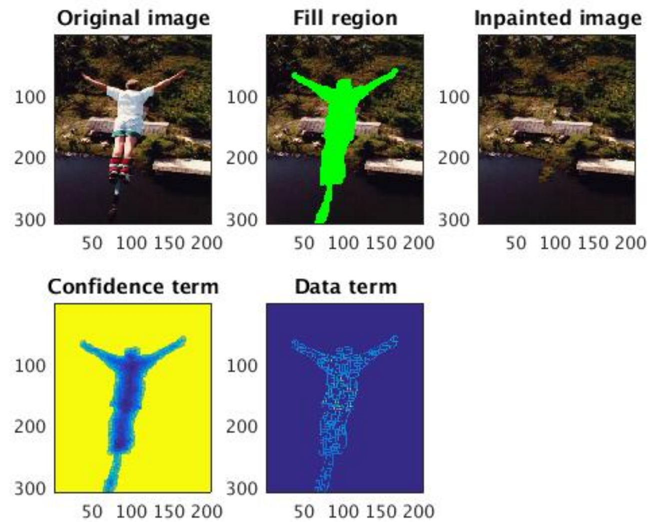
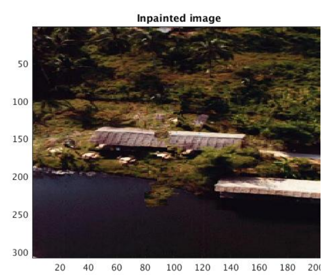
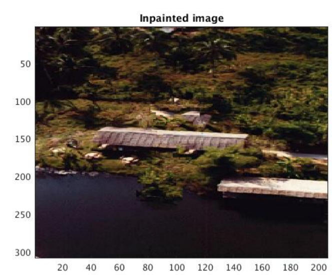


Fig. 4. Results by Criminisi's algorithm



(a) Without regularizer



(b) With regularizer

Fig. 5. Effect of adding regularizer

4.3. With Regularizer and Variance+SSD Criteria

On top of the regularizer, a measure of variance for patch similarity is appended. This makes a better (stabler) patch selection. An example is illustrated in figure 7 where a few rogue patches in place of the wind mill are also removed by the Variance+SSD criteria.

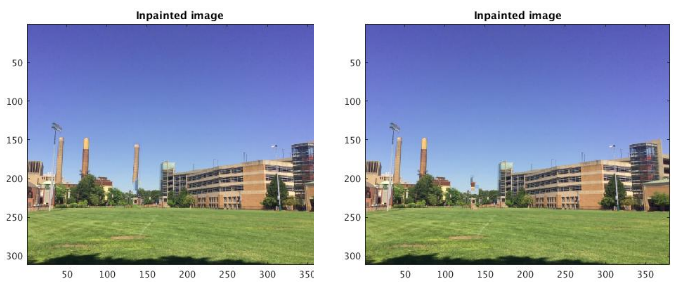
4.4. With Regularizer and Edge-based Data Term

The gradient-based data term is also swapped for one based on the edge-mapping technique. The results are reported in figures 8, 9 and 10.

4.5. With all three modifications

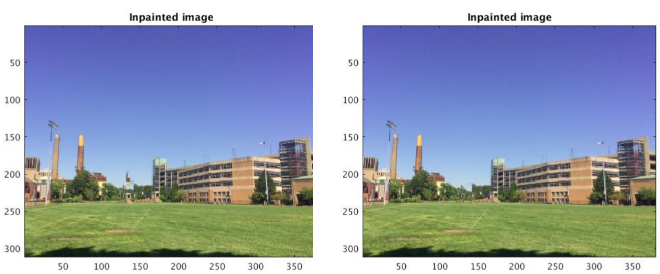
Finally, all three modifications were appended on top of Criminisi's algorithm and the results are displayed in figures 11 and 12 with visible improvements.

(a) Original Image (b) Masked image



(c) Without regularizer (d) With regularizer

Fig. 6. Effect of adding regularizer



With SSD criteria With Variance+SSD criteria

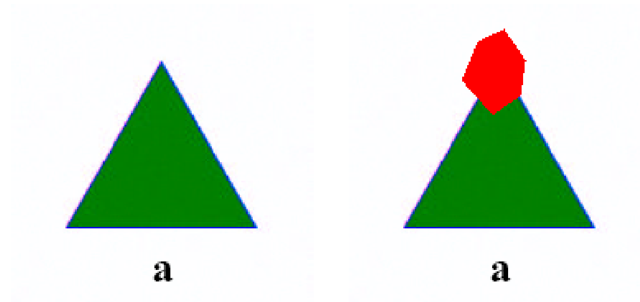
Fig. 7. Effect of adding Variance for patch similarity

5. CONCLUSION

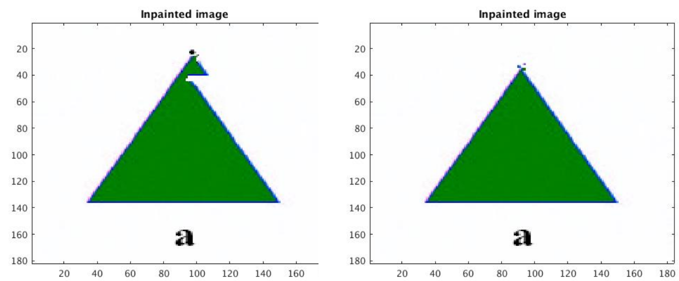
Thus, we demonstrate with examples that the addition of a regularizer, the usage of variance on top of the SSD criterion for a stabler patch selection and the use of an edge-map based data term serve to improve the visual appeal of inpainted images, separately and as a whole.

6. FUTURE WORK

We propose to improve the algorithm by incorporating an adaptive regularizer. The regularizer is proposed to be directly proportional to the size of the original Target region Ω, and inversely dependent on its boundary length $\delta\Omega$. Also, the regulariser tends to dip sharply as filling proceeds, hence to control this dip, it should also be proportional to the number



(a) Original image (b) Masked Image



(c) With the gradient-based D(p) (d) With the edge-based D(p)

Fig. 8. Effect of using an edge-map based data term

of the round of filling n i.e.

$$\omega = \frac{k|\Omega| * n}{|\delta\Omega|} \tag{11}$$

where k is the proportionality constant, $|\Omega|$ is the size of the Target region and $\delta\Omega|$ is thelength of the boundary of target region.

7. DATASET AND CODE

Some part of the code was taken from [5] for the implementation of Criminisi's algorithm. The code was debugged and modified to fit our needs. All the modifications proposed were then implemented in MATLAB and C++. Results were computed on images taken from the dataset [6].

8. REFERENCES

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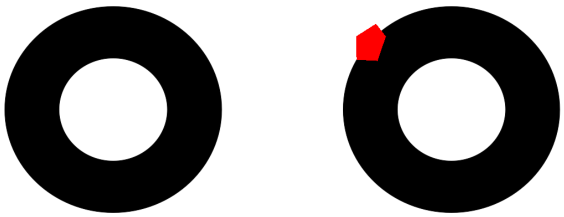
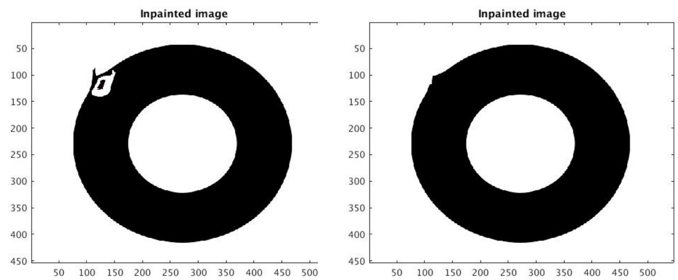


(a) Original image (b) Masked image



(c) With the gradient-based D(p) (d) With the edge-based D(p)

Fig. 9. Effect of using an edge-map based data term

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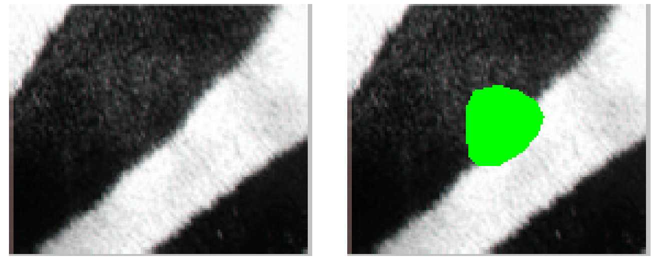
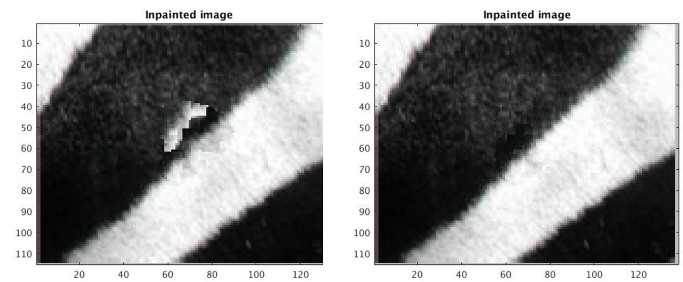


(a) Original image (b) Masked image

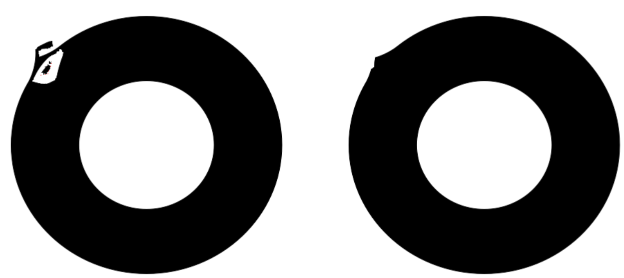


(c) With the gradient-based D(p) (d) With the edge-based D(p)

Fig. 10. Effect of using an edge-map based data term

(a) By Criminisi's algorithm (b) By our integrated approach

Fig. 11. Comparison with Criminisi's algorithm



(a) By Criminisi's algorithm (b) By our integrated approach

Fig. 12. Comparison with Criminisi's algorithm