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Adaptive Fast Exemplar-Based Image Inpainting For Object Removal using Nelder-Mead simplex Algorithm

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Abstract—Image inpainting is the prime important technique used for removing defect from paintings and photographs. The challenge for the inpainting is to fill in the hole that is left behind in a visually plausible way so that it seems reasonable to the human eye. Image Inpainting refers to the art of restoring lost parts of image and reconstructing them based on the background. There have been several approaches proposed for the same. On the basis of exemplar based inpainting, adaptive image inpainting algorithm was proposed to solve the problem that Criminisi algorithm easily leads to mismatching problems in the process of searching the best match. A algorithm automatically inpaint the selected area by changing values of variables adaptively using Nelder-Mead simplex algorithm.
Keywords—Image inpainting; Object removal; Exemplar match; Priority; Nelder-Mead simplex algorithm

I. INTRODUCTION

Information exchange is very important part of human evolution. In computer all images are presented in digital format. Digital Image inpainting is a process to reconstruct the lost or selected part of image from the background information. Region completion is a method to fill that portion of image from the remaining area of the image. Region filling is a most important role of image processing. It is used for removing unwanted object and medical processing. Figure 1 show an example of this technique where one small child (manually selected as the target region) is replaced by information from the remaining of the image in a visually plausible way. Details that are hidden/ occluded completely by the object to be removed cannot be recovered by any mathematical methods. So that the objective for image inpainting is not to recover the original image, but try to create some image that has a close resemblance with the original image.

The "digital image inpainting" was firstly put forward on the international conference in 2000 in Singapore. There are many typical image inpainting algorithms proposed by researchers during the past decade. The BSCB [1] model was presented by Sapiro, Caselles, Bertalmio and Ballester. The TV (total variation) model [2] was proposed by Chan and his team. The CDD (curvature driven diffusions) model [3] was introduced by Shen J and Chan T. and. An isotropic diffusion of fast image inpainting was proposed by Oliverira. There have been a very few algorithms that utilize the advantages of both the image inpainting methods i.e. the structure recreation and texture synthesis algorithms. One such work was proposed in the paper by Criminisi et al. [4]. Exemplar based image inpainting is a very simpler and faster method compare to other which is not suffer from any blurry effect. First the object is removing and then it is filled by some special

(a) (b)

Fig: 1: Removing objects using Image Inpainting.

(a) The original image, (b) Image with the small child removed. Notice how the contour of mountain and the textures have both been corrected.

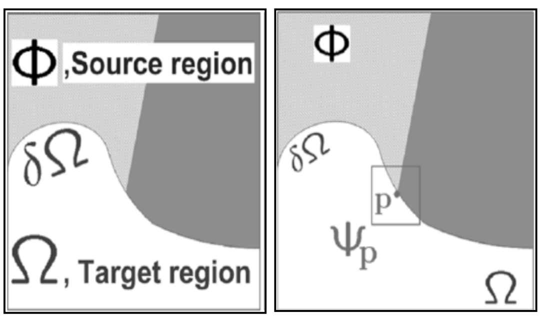
First the boundary of region is filled and identified after boundary is done first and then find the best priority, priority given to those patch which are continuous of strong edge or surrounded by the high confidence value is filled in a non- linear format using Exemplar based technique.
In this paper, we propose an extension to earlier inpainting algorithms with a focus on improving the efficiency and qualitative performance of existing methods by finding minimum of unconstrained multivariable function using derivative-free method

II. OVERVIEW OF EXEMPLAR BASED IMAGE INPAINTING

Exemplar Based image inpainting was introduced by Criminisi [4]. The process of the algorithm starts with marking the region of the image to be inpainted. For the removal of the object, the unwanted regions have to be marked whereas for damaged images, missing regions have to be marked.

We use conventions throughout the paper those are similar to earlier papers that deal with this problem of image inpainting. The missing region or unknown region Ω is filled with patches from source region or known region Φ, Where I is the entire image (Ω = I- Φ), the boundary of the target region is define as δΩ, also we refer to as fill front. An algorithm iterates the following three steps until all pixels have been filled:

A. Computing patch priorities
B. Structure and Texture synthesis and Filling order
C. Updating Confidence Values



(a) (b)
Fig: 2: Structure Propagation by Exemplar Based Texture Synthesis.

A. Computing Patch Priorities

An algorithm performs the synthesis task through a best first filling strategy that depends entirely on the priority values that are assigned to each patch on the fill front. The priority computation is biased toward patches which: (1) are on the continuation of strong edges and (2) are surrounded by high confidence pixels. Given a patch p centred at the point p for some p Є δn, we define its priority P(p) as the product of two terms:

$$P(p) = C(p) \times D(p) \qquad (1)$$

Where, C(p) is the confidence term and D(p) is the data term:

$$C(p) = \frac{\sum q \in \psi_p \cap \emptyset \; C(q)}{|\psi_p|} \qquad (2)$$

$$D(p) = \frac{|\nabla I_{p}^{\perp} . \, n_p|}{\gamma} \qquad (3)$$

Where |ψp| is the area of the patch ψp and np is a unit vector orthogonal to the front δΩ at the point p, γ is the normalization factor (equal to 255 for a normal grey level image) and $\nabla I_p^{\perp}$ represents the perpendicular isophote at point p. The confidence term C (p) may be thought of as a measure of the amount of reliable information surrounding the pixel p. The confidence value for all pixels in the source region is to be 1 and the confidence value for all the pixels in target region is to be 0. The confidence value does not change once the pixel has been filled.

B. Structure and Texture synthesis and Filling Order

Once all priorities on the fill front have been computed, the patch with highest priority is found and then filled it with data extracted from the source region. Image texture is propagated by direct sampling of the source region by searching in the source region.

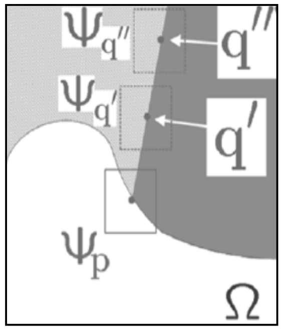


Fig: 3: select the best match patch from the source region

For that patch which is most similar to target patch by simply the sum of squared differences (SSD) of the already filled pixels in the two patches.

C. Updating Confidence Values

After replacing target patch with its exemplar, the confidence value for the patch that is just filled is updated by as follows: C(p) = C(q), where C(q) represents the confidence term for the patch with maximum priority.

The summary of the region filling algorithm [4] is:

Extract the manually selected initial front $\delta\Omega^0$.

Repeat until done :

1a. Indentify the fill front $\delta\Omega^t$. If $\Omega^t = \varphi$, exit.

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

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

2b. Find the exemplar $\psi_{\hat{q}} \in \emptyset$ that minimizes $d(\psi_{\hat{p}}, \psi_{\hat{q}})$.

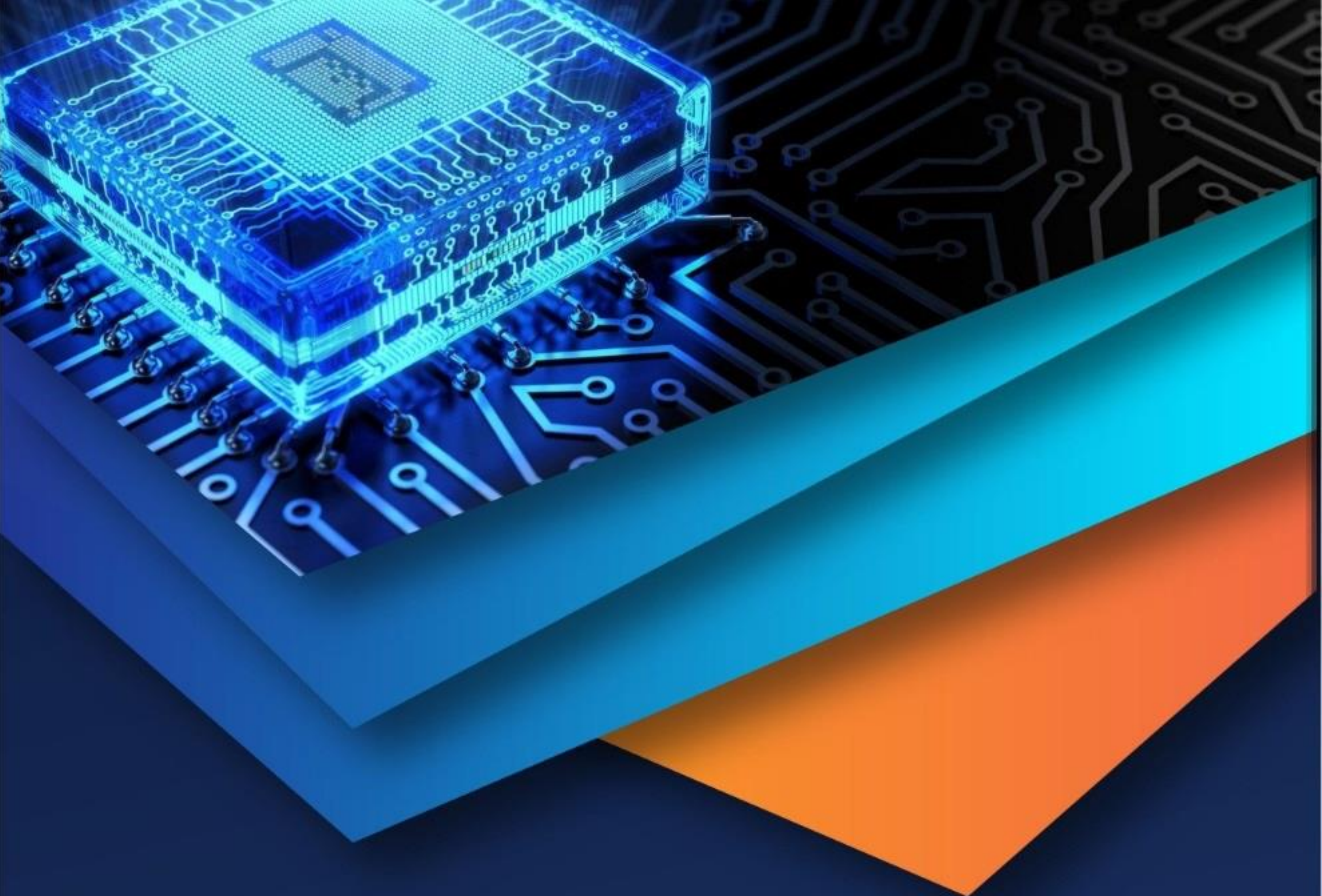
2c. Copy image data from $\psi_{\hat{q}}$ to $\psi_{\hat{p}}$ $\forall_p \in \psi_{\hat{p}} \cap \Omega$.

3. Update C(p) $\forall_p \in \psi_{\hat{p}} \cap \Omega$.

III. ADAPTIVE EXEMPLAR BASED IMAGE INPAINTING

The procedure of Adaptive Exemplar Based image inpainting is as shown in (4).

A. Modified priority term



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