Image Inpainting Using Coherent Sensitive Hashing

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***ABSTRACT*: In this paper there is comparison of two Inpainting Algorithm Example based inpainting and Coherent Sensitive Hashing Algorithm. First, we use the Example based inpainting Algorithm to the input image which will fill the missing region of the image. Then we compared the results with Coherent Sensitive Hashing Algorithm. Coherency Sensitive Hashing (CSH) extends Locality Sensitivity Hashing (LSH) and Patch-Match is used to quickly find matching patches between two images. The experimental results show the advantage that our technique produces output images with better perceived visual quality.**

***KEYWORDS*: Coherent Sensitive Hashing, Example Based Inpainting, ANNF, Walsh-Hadamard kernels.**

1. INTRODUCTION

Digital image inpainting is an important issue in the image restoration and an international interesting research topic in modern years, and it has different terminology names in distinct areas. For example, it is called error concealment in the signal transmission, and is called art inpainting in art inpainting etc. Now many image inpainting methods introduced, which are mainly two categories. One repairs small-scare damaged digital images and the other repairs large-scale digital image by filling with image information. Those inpainting methods which can repair different damaged image have their advantages, disadvantages and enforced range. The inpainting result will be evaluated by inpainting evaluation method. The result of evaluation can evaluate the advantages and disadvantages of inpainting method.Image inpainting are an important research field. It have very large applications such as digital restoration of ancient paintings, text removal and objects removal in images, film restoration, damaged block recovery of compressed digital image or video, etc. It's essential objective is to fill a missing region of an image with pixels from the other known image regions so that the output image can be visibly plausible. It can be defined as follows: we have an image I with missing region , we need to propagate information from a region named source region so that missing region will get fill . Many techniques have been developed to solve this problem such as exemplar based inpainting approaches. Its main idea is to search the source region to find the best matching sample, then its content is copied directly to missing region [1]. In order to ensure that linear structure will propagate before texture filling, a priority function was defined to control filling order so as to conserve the notable structure. There are much advancement to this technique that is based on enhancing the order of filling and the information propagation. The work in [2] enhanced the efficiency of searching for a similar patch by applying the example based technique. It also enhanced the preference term to ensure that the structure component of the image can be filled first. The search for a matching block was improved in [4] by segmenting the image to obtain separate source regions. Also, the window size has been adjusted flexibly according to the image itself. In this paper, a new inpainting algorithm is introduced that firstly segments the source region Then, it classifies the segments that are contiguous to the missing region based on their confines relative percentage, to be either large segment inpainting problem or no uniform segments inpainting problem and inpaint each of them separately. Since human eye is very perceptive to any produced artifacts in large uniform regions, the algorithm provides more effort to inpaint large uniform regions. On the other hand, it inpaints non-uniform regions differently as human eye is less perceptive to any produced artifacts of non uniform regions. As the essential idea of the proposed technique is that if the algorithm is going to produce an error, then it has to be indistinct by the user. The experimental results show the efficiency of the proposed algorithm to produce more plausible output.

2. LITERATURE REVIEW

So many methods have been proposed for image inpainting so far and we can classify them into several categories as follows:
1. PDE based image inpainting
2. Hierarchical inpainting Technique
3. Texture synthesis based image inpainting

1 .PDE Based Image Inpainting

Partial equation (pde) needs endless iterations before the convergence is also reached. In this method unit of analysis computationally costly. Bertalmio [1] projected degree algorithmic program supported every geometric and live knowledge. It provides border of obstruct area by interactive methodology that propagates linear structures (edges) of the enveloping space conjointly known as isophotes, into the outlet region, employing a diffusion method. Oliver presents 2 completely different in-painting techniques supported second order and third order pde\'s. Tschumperle and derche present general vector worth image regularization approach they used high order pde\'s.

2. Hierarchical Inpainting Technique

The estimated technique consists of 2 main and constant operations. The primary one may be a non-parametric patch sampling method confirmed fill in missing regions. The in painting formula is ideally applied on a coarse version of the input picture. So a low-resolution image is basically diagrammatic by its effective [3] and necessary structures of the scene. It believe that activity the inpainting of such a low-resolution image is distant accessible than activity it on the complete resolution. A low-resolution image is a smaller amount corrupted by noise and consists by the most scene structures. In different words, in this quite image, natural orientation aberration that may have an effect on the filling order computation.. Second, because the image to inpaint is smaller than the first one, the procedure time is appreciably reduced compared to the one necessary to inpaint the complete resolution image. To hand over a lot of strength, we learn to in paint the low-resolution image with completely different settings (patch's size, filling order, etc). By combining these results, a final low-resolution inpainted image is obtained.

3. Texture Synthesis Based Image Inpainting

Texture Synthesis based Image Inpainting algorithms are used to the entire missing regions using identical neighborhoods of the damaged pixels. These algorithms synthesize the new image pixels from an initial seed. And then conflict to protect the local structure of the image. All the earlier Inpainting techniques [3] applied these methods to fill the missing region by sampling and replicating pixels from the adjoining area. For e. g, Markov Random Field (MRF) is used to model the local distribution of the pixel. And new texture is incorporate by querying current texture and finding all similar neighborhoods. Their differences exist mainly in how continuity is maintained between current pixels and Inpainting hole. The essential objective of texture synthesis based inpainting is to generate texture patterns, which is related to a given sample pattern, in such a way that the reproduced texture preserve the statistical properties of its root texture.

4. Wavelet Transform based inpainting.

This technique used with the help of the wavelet transforms. Here the best global structure estimation of damaged regions in addition to shape and texture properties. If we consider the fact of multi-resolution analysis, data separation, compaction along with the statistical properties then we have to consider the wavelet transform due to its good image representation quality. Wavelet transform try to satisfy the human visual system (HVS). The algorithm decomposition of incomplete image is done with the help of wavelet and after that wavelet and scaling coecients is found. The image inpainting process is applied in the wavelet domain by considering both scaling and wavelet coecient from course to _ne scales in the target region. Using this algorithm one bene_t is this utilizes inter and intra scale dependency to maintain image structure and texture quality using Wavelet Transform. But di_culties in this algorithm mask for regions are dened manually.

3. PROBLEM STATEMENT

We can define Inpainting problem in terms of Mathematical point of view. Let us take a simple example to explain it clearly. Suppose there is a sequence {A, B, C,*, E, F} where "*" is the unknown element. If * is derived as D, the whole sequence looks very natural i.e.,{A,B,C,D,E,F} it takes the exact Alphabet as we expected. However, if * is derived as S, i.e. {A, B, C, S, E, F} then the whole sequence does tell us something unexpected .In case of inpainting, the generated plausible regions are commonly looks so natural which indicates that no additional information can be reproduced out of nothing related.

4. OBJECTIVE

Let us first describe the basic terminologies used in inpainting:

1. Image is represented as 'I'.
2. The target region or the region to be inpainted is represented by omega' Ω ' shown in Fig.1.
3. Source region (I-Ω) that is the region which is not to be in-painted and from where the information is extracted to fill the target region is represented by Φ.
4. Boundary of the target region is represented by: δΩ.

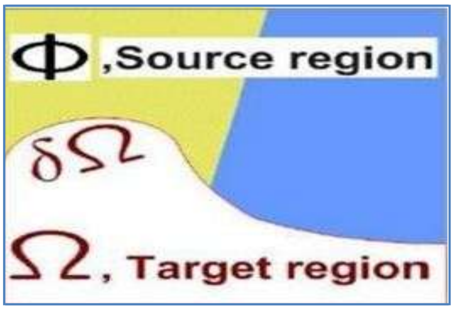

Fig 1.Image Inpainting concept

5. ALGORITHM DETAIL

5.1 Example Based Inpainting

1) For each point p located on the filling front of the missing region δΩ, define a patch Ψ centered at p[5]. This is shown in Figure

2) Compute the priorities of every pixel p by P(p) = C(p)D(p) where C(p) and D(p) are the confidence term and the data term respectively. They are defined as

$$C(p) = \frac{\sum_{q \in \psi_p - \Omega} C(p)}{|\psi_p|}, D(p) = \frac{|\nabla I_p^{\perp}.n_p|}{\propto}$$

5.2 Coherency Sensitive Hashing (CSH)

Input: color images A and B

Output: A dense nearest patch map ANNF

Indexing (of all patches of images A and B) Fig.2

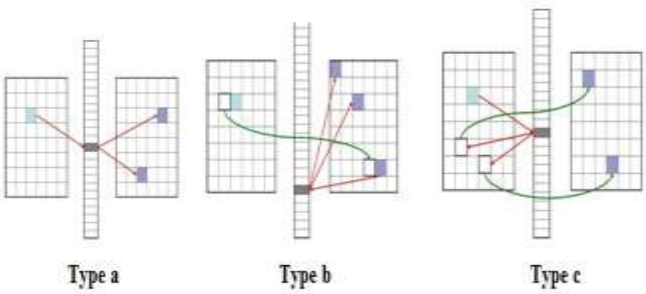

Fig 2. Candidate types for a patch. In each of the sub-figures, Image A is on the left, image B is on the right and the hash table in use is in the center. Arrows relating to a pixel actually relate to the patch whose top left corner is at the pixel. Red arrows represent the hashing (notice their direction), while green arrows point to the patch's current best known representative. The highlighted pixels (patches) in image B on the right are the candidates of the highlighted pixel (patch) in image A on the left. If the width of the hash table is defined to be k (i.e. it stores k representative patches from each of the two images) then the total number of candidates is between 4k and 4k + 2 (types 1 and 3 each contribute k candidates, while type 2 appears both in left/right and top/bottom configurations and contributes k or k+1 in each configuration). In our implementation (and this illustration) we use k = 2.

1. Compute the projection of each of the patches in A and B

on M Walsh-Hadamard kernels $\{WH_j\}_{j=1}^{M}$, using the

Gray Code Kernels technique of [2].

2. Create L hash tables $\{T_i\}_{i=1}^{L}$ Table Ti is constructed as follows:

(a) Define a code $g_i(p) = h_1(p) o \ldots o h_m(p)$ which is a concatenation of M functions $\{h_j\}_{j=1}^{M}$ of the form:

$$h_j(p) = \frac{WH_j.p + b_j}{r}$$

Where r is a predefined value and bj is drawn uniformly at random from the interval [0; r)
(b) Then, each patch p (of both A and B) is stored in the entry

Search

1. Arbitrarily initialize the best candidate map ANNF.

2. Repeat for i = 1, L (for each hash table):

(a) For each patch a in A

i. Create a set of candidate nearest patches PB using the table

Ti and the current mapping

ANNF

ii. Let b be the patch from PB which is most similar to a

iii. If dist (a; b) < dist (a; ANNF (a)) then update: ANNF (a) = b

3. Return ANNF.

6. EXPERIMENTAL RESULTS

To verify the efficiency of the proposed method and the quality of output images, we compared its results to Coherent Sensitive Hashing Algorithm. For input we have given Image & mask image of region to be removed.

Input image

Input mask Image

Fig. 3 Input Image & mask Image

After giving the input images through programming it calculate threshold value & number of iterations. Finally we get the required output image as shown in Fig.4

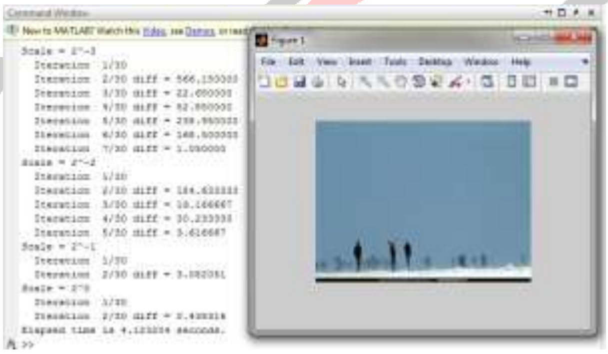

Fig.4 Output Image

A Comparison done between Example Based Inpainting and Coherent Sensitive Hasshing Inpainting. We calculated timing required for execution of different images which shows following results.

Input Data	Example Based Inpainting(EBI)	Coherent Sensitive Hashing (CSH)
Bungee	30sec	11.7sec
Nat	20sec	4.12sec
Cow	34sec	11.09sec
Jump	40sec	12.41sec

Graphically the results are shown in Fig.5

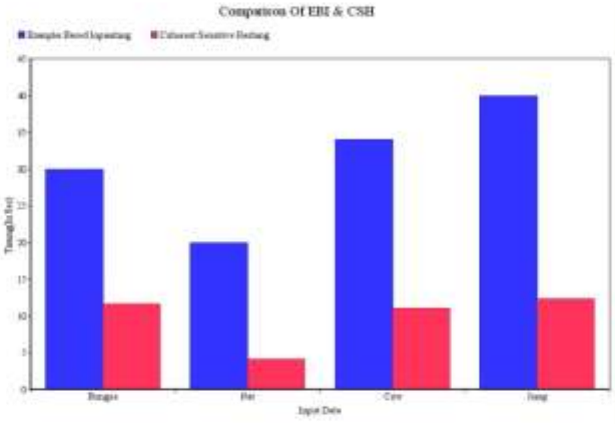

Fig5. Comparison of EBI & CSH

The experimental result shows that CSH gives better results in comparison with other technique.

7. CONCLUSION

In this paper we compare the two techniques of inpainting i.e. Example Based Inpainting and Coherent Sensitive Hashing. The experimental results show that Coherent Sensitive Hashing technique gives better and more efficient results than Example Based Inpainting. Its high incoherence improved reconstruction results and also enhanced the visual quality of the output image.

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