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IMPLEMENTATION OF SUPER RESOLUTION ALGORITHM FOR IMAGE INPAINTING

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ABSTRACT

Inpainting is the ability of modifying an image in an unnoticeable form, it is a very old fine painting itself. The goals and applications of Inpainting are regular from the re-establishment of damaged paintings and image photographs to the removal or alternative of particular objects. Image Inpainting is the ability of filling in absent data in an image. The principle of inpainting is to restructure missing regions in a visually reasonable way so that it seems realistic to the human eye. There have been numerous approaches proposed for the equivalent. In this paper, we present an algorithm that improves and extends a previously proposed algorithm and provides faster inpainting. Using our approach, one can inpaint huge regions i.e. remove an object as well as recover minute portions. The inpainting is based on the exemplar based approach. The fundamental idea behind this approach is to find examples, i.e. patches, from the image and replace the missing data with it.

KEYWORDS: Image-restoration, Image-inpainting, Object removal, Examplar-based Inpainting, Super resolution.

INTRODUCTION

Inpainting is the process of reconstructing lost or deteriorated parts of an images and videos. In the museum world, in the case of a painting, this task would be carried out by a trained art conservator or art restorer. In the digital world, inpainting also called as Image Interpolation or Video Interpolation refers to the application of sophisticated algorithms to replace lost or corrupted parts of the image, generally to remove small regions or small defects. Image inpainting refers to the technique of reconstructing the original image which has been scratched due to factors such as ageing, wear and tear and occlusion.

The challenge lies in the fact that the viewer seeing the inpainted image should not be able to estimate that the image had been tampered among. Around lots of inpainting techniques available in literature. Some performance are based on Partial Differential Equations (PDE), some are Statistical-based techniques and some are Exemplar-based techniques. Due to the better correctness of inpainting, the modern period has seen an increasing focus on exemplar-based method for image inpainting by researchers.

(1)　　　　　　　　　　　　　　　　(2)

Fig: (1) Input original image, (2) Output inpainted image

The term inpainting is also called retouching. The need to retouch the image in an unremarkable way extended logically from paintings to photography and film. The purposes remained the same, to lapse deterioration (e.g. scratches and dust spots), or to add or remove objects. In the digital domain, the in-painting problem primary appeared under the name 'Error concealment' in Tele-communication, where the need was to fill-in image blocks that had been lost during data transmission. Popular requirements used to denote inpainting algorithms are also 'Picture Completion' and 'Image Fill-in'.

Inpainting refers to methods which consist in filling missing regions or holes in an image [1]. Existing methods can be classified into two most important categories. The first category concerns diffusion-based approaches which propagate linear structures or level lines so called Isophotes, using diffusion based on PDE [2][4] and variation methods [4]. The diffusion-based method tends to initiate some blur when the hole to be filled in is large. The consequent relations of approache concerns examplar-based methods which sample and copy finest matching texture patches from the recognized image region [4]. These methods have been stimulated from texture synthesis techniques [8] and are known to work well in the case of expected or repeatable textures. A modern approach [10] combines an examplar-based approach with super-resolution. It is a two-steps algorithm. First a coarse version of the input picture is inpainted and the second step consists creating an improved resolution picture from the coarse inpainted image. Even though remarkable improvement has been made in the past years on examplar-based inpainting, there still exists a number of problems. We believe that the most significant one is associated to the parameter settings such as the filling order and the patch size.

RELATED WORK
This section describes the various existing schemes which are compared in this paper:
M. Bertalmio and Guillermo Sapiro [2] introduced image inpainting for digital image handing out. Their representation is based on nonlinear partial differential equation, and imitates the techniques of museum artist who specialize in restoration. They focused on the principle that better inpainting algorithms should propagate sharp edges into the scratched parts that need to be filled in. This can be ended, by involving contours of constant gray scale image strength, called isophotes to each one across the inpainting region so that gray levels at the periphery of the scratched region enlarge constantly into the interior. They also impress the direction of the isophotes as a edging line condition at the edge of the inpainting domain.

A. Criminisi, P. P´erez and K. Toyama [7] decomposes the original image into two mechanism; each of which is processed by inpainting and the other by quality synthesis. The output picture is the sum of the two processed mechanism. This approach still remains inadequate to the elimination of small image gaps, nevertheless, as the dispersion process continues to blur the filled region. One of the first attempts to utilize exemplar-based synthesis exclusively for object deletion. There, the order in which a pixel in the objective area is filled was dictated by the level of 'texturedness' of the pixel's neighborhood. Although the insight is sound, strong linear structures are often overruled by close to noise, minimizing the value of the additional computation. A associated technique group the fill order by the general form of the target area, but did not search for to explicitly propagate linear formation.

Manuel M. Oliveira [5] uses a diffusion kernel to convolve the inpainting domain try to reduce the complex of PDE. However this method doesn't preserve the isophotes directions very well, some high-gradient image area must be manually select before inpainting to prevent blur. But, among numerous inpainting techniques, exemplar-based inpainting [9] is most frequently used to complete scratched area or remove objects in an image. The algorithm proposed in [9] deal with the topology of inpainting by using a priority value for each patch. The priority value P is evaluated by function P = C * D. The confidence value C value is computed according to the percentage of "real" information which is used in the filling process. The data term D is computed by the inner product of an orthogonal-gradient and a unit vector orthogonal to the front damaged area. The work of this inpainting procedure starts with robust algorithm of colour segmentation: mean shift segmentation. After we separate out structure information form image, the missing contour could be repaired by using Bézier90 curve. Finally, the exemplar-based image inpaintng method would be applied to recover all information of damaged area from other source area.

Le Meur and C. Guillemot [10] combines an examplar-based approach with super-resolution. It is a two steps algorithm. First a coarse portion of the input picture is inpainted. Another step consists in creating an improved resolution image from the coarse inpainted image. Even though remarkable movement has been made in the past years on examplar-based inpainting, there still exists a number of problems. We believe that the most important one

is related to the parameter settings such as the filling order and the patch size. This problem is here addressed by considering multiple inpainted versions of the input image. To generate this set of inpainted pictures, different settings are used. Notice that the inpainting algorithm is preferably applied on a coarse portion of the put in image; this is particularly interesting when the gap to be filled in is large. This provides the advantage to be less demanding in terms of computational resources and less sensitive to noise and local singularities. Super Resolution (SR) methods refer to the process of creating one enhanced resolution image from one or several input low declaration images. These problems are subsequently referred to as distinct or multiple images SR in that order. In both cases, the trouble is of estimating high frequency facts which are misplaced in the input image(s)

Rosner et. al. [9] have presented efficient algorithms for image warping and image inpainting for frame interpolation and their implementation on the GPU. For each pixel on the edge of the fill region, they disseminate its intensity to the fill region and calculate its distance to the boundary of the fill region. Depending on the distance as well as the intensity values, the pixel is inpainted. Kwok et al. [14] have proposed an proficient algorithm for exemplar based inpainting, in which they isolate the exemplars into the frequency coefficients and select only the relevant coefficients. Investigation for best exemplar is prepared by the use of a search array data structure, which can simply be ported to the GPU. Hamilton Chong [8] has followed a texture-synthesis approach to image inpainting. He assigns weights to every single one pixel in the undamaged portion of the image and based on these weights, he determines the pixel on the way to replaced as the injured pixel that is most constrained by its neighbours. He then replaces the preferred damaged pixel by the pixel with the best district region match. The determination of the replaced pixel and its replacement is carried out on GPU

Olivier Le Meur, Mounira Ebdelli [1] proposed method builds upon the super-resolution based inpainting method which is base on examplar-based inpainting and single-image examplar-based super-resolution [10]. The main innovation of the algorithm is the combination of multiple inpainted versions of the input picture. The underlying principle behind this approach is to cope with the sensitivity of examplar-based algorithms to parameters such as the patch size and the filling array. Unusual combinations have been experienced and compared. The proposed method improves on the state-of-the-art examplar-based inpainting methods by proposing a new framework involving a combination of multiple inpainting versions of the input picture followed by a single-image examplar based SR method. Note that the SR method is used only when the inpainting method is applied on a low resolution of the input picture.

PROPOSED SYSTEM
Image completion of huge missing portion is a challenging job. There are a number of solutions to deal with the inpainting problem. In this paper, we propose a latest inpainting framework relying on both the combination of low-resolution inpainting images method and a single-image super-resolution algorithm. In this section, we briefly present the main ideas of this paper and the reasons why the proposed system is latest and innovative. The proposed method is composed of two major and sequential operations.
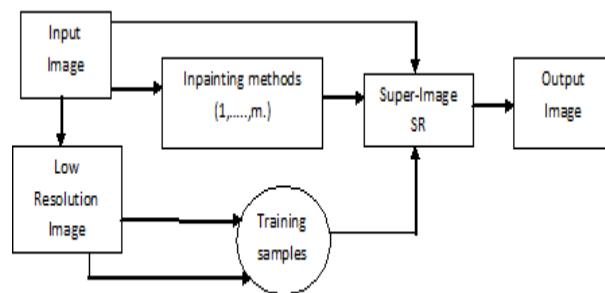

Fig :(3) Proposed Methodology

In proposed system two main components are the inpainting and the super-resolution algorithms. More specifically, the following steps are performed:
- A low-resolution image is first built from the original picture;
- An in-painting algorithm is applied to fill-in the holes of the low-resolution picture;
- The quality of the in-painted regions is improved By using a single-image SR method

Novel Inpainting Method Based On Examplar Approach
The proposed inpainting algorithm presents the novel inpainting algorithm and also the process of combining the different inpainting images. As described in the literature, filling the missing information or filling order computation and texture synthesis are the two classical steps. Based on these classical steps the proposed examplar based approach is presented. These two steps are discussed in latter section.

A. Patch Priority : This section describes the first classical step i.e. filling order computation. The patch priority mainly focuses on two ideas; firstly differentiate the structures from the coarse version latter knowing the priority is salient step if the priority is high it indicates the presence of structure. By using the data term and the confidence term the priority of patch can be centered on Px. In order to know the data term in a detailed way tensor based [7] and Sparsity-based [8] have been used.

The priority term which is based on tensor approach is defined by a Di zenzo matrix or structure tensor is as follows:

$$\mathbf{J} = \sum_{i=1}^{m} \nabla I_i \nabla I_i^T$$

In above equation **J** represents the sum of scalar structure tensors $\nabla I_i \nabla I_i'$ of the image *Ii (R G B).* The smoothing of the tensor is done without cancelling effects:

$$\mathbf{J}_\sigma = \mathbf{J} * \mathbf{G}_\sigma ,$$

Where Gσ =1/2πσ2 exp (-(x2+y2/2σ2)), with standard deviation σ. The main advantage of the structure tensor is that structure Eigen values is deduced from coherence indicator. Based on the accuracy that we are getting from the Eigen values we locate the anisotropic of the local region can be evaluated. The structure tensor Jσ is computed by using the structure tensor, here the Eigen vectors V1 V2 represent oriented orthogonal basis and Eigen values represent the structure variation. Then Eigen vector V1 represents the highest fluctuations and V2 is the local orientation. The data term D

$$D(\mathrm{p_x}) = \propto + (1-\propto)\exp\left(\frac{\eta}{(\lambda_1-\lambda_2)^2}\right)$$

Where η is positive value and
$\alpha \in [0,1]$ $(\eta = 8$ and $\alpha = 0.01)$

The sparsity based priority inpainting is another method recently proposed by the professor Xu at el in [8].In this template matching is performed between the current patch and neighboring patch of the known pixel. By using the non local means of approach similarity weight is computed between the each pair of the patch as shown below,

$$D(\mathrm{p_x}) = \|W_{\mathrm{P_x}}\|_2 \times \sqrt{\frac{|N_s(\mathrm{p_x})|}{|N(\mathrm{p_x})|}}$$

Where Ns and N stands for the number of valid patches and the $\|W_{\mathrm{P_x}}\|_2$ is high then prediction of candidates is low, if $\|W_{\mathrm{P_x}}\|_2$ is low then the predication of candidates is high.

B.Texture Synthesis : This a method opts for the filling process starts with the patch having the highest priority. To fill in the unknown part of the current patch, similar patch in the local neighborhood on the current patch is sought .Then the similarity measure is done between the current patch and co- located pixel of the patches that belongs to W.

$$\psi_{\mathrm{P_x}}^* = \arg\min_{\psi_{p_j \in W}} d\left(\psi_{\mathrm{P_x}}^{\mathrm{k}}, \psi_{\mathrm{P_j}}^{\mathrm{k}}\right)$$
$$s.t\ Coh\left(\psi_{\mathrm{P_x}}^{\mathrm{uk}}\right) < \lambda_{coh}$$

$$coh\left(\psi_{\mathrm{P_x}}^{\mathrm{uk}}\right) = \min_{p_j \in S}\left(d_{SSD}\left(\psi_{\mathrm{P_x}}^{\mathrm{uk}}, \psi_{\mathrm{P_j}}^{\mathrm{uk}}\right)\right)$$

The above equations show two initial processes. Initially first equation indicates the argument, based on that argument in our proposed Algorithm by using dssd (sum of the square differences) the coherence similarity check indicates the degree of similarity between the current patch and synthesize patch. In the argument equation the texture results which we sought is far from the original textures. If none of the patches is sought then the process restarts by seeking the highest priority. Then the estimated patch is done by

$$\psi_{Px}^{*} = \sum_{i}^{K} \omega_{Px,Pi} \times \psi_{Pi}^{k}$$

Where K is the number of candidates and the similarity of chosen neighbors lies within i9n a range and dmin shown the current patch and its closest neighbors. Combining the several candidates increases the blur though it increases the algorithm robustness. In our proposed algorithm we opts a solution for this problem, instead of several candidates we opts for best one and pasted in the missing areas. It gives the more robustness by locally arranging the results based on the different settings we sought for the inpainted picture.

*C. Combining several inpainting images :*The combination of several M inpainting pictures is done in order to yield the final inpainting picture. Before going into the detailed analysis, following figure shows the different inpainting results for the respective setting as shown below:

Table I
Thirteen Configurations Used To Fill In The Unknown Parts Ofthe Pictures

Setting	Parameters
1 (default)	Patch's size 5×5 Decimation factor $n = 3$ Search window 80×80 Sparsity-based filling order
2	default + rotation by 180 degrees
3	default + patch's size 7×7
4	default + rotation by 180 degrees + patch's size 7×7
5	default + patch's size 11×11
6	default + rotation by 180 degrees + patch's size 11×11
7	default + patch's size 9×9
8	default + rotation by 180 degrees + patch's size 9×9
9	default + patch's size 9×9 + Tensor-based filling order
10	default + patch's size 7×7 + Tensor-based filling order
11	default + patch's size 5×5 + Tensor-based filling order
12	default + patch's size 11×11 + Tensor-based filling order
13	default + rotation by 180 degrees + patch's size 9×9 + Tensor-based filling order

Super Resolution Framework
A hierarchical single image super resolution Framework is used to reconstruct the high resolution image based on high resolution image details, super resolution framework is implemented after the completion of combination low resolution inpainted images. Note super resolution algorithm is applied when the original image is down sampled for the inpainting process. Otherwise super resolution algorithm is not necessary.
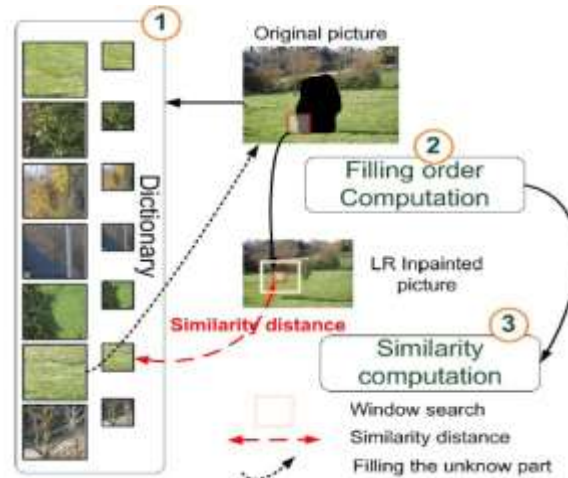
Fig:(4) Flowchart of Super Resolution Algorithm

The flow diagram of super resolution is as follows:

- Dictionary Building: Dictionary building mainly consists of high resolution and low resolution patches. Note that the high resolution patches must be valid and it is strictly takes from the known parts of the image. The size of the dictionary is a user parameter which has capability of influence the overall speed/quality trade off. The spatial coordinates of high resolution HR patches is stored by using an array then by the usage of decimation factor equals to 2 lo resolution patches LR patches is deduced.
- Filling order of the HR picture: The filling order of the HR image is done by Sparsity based method. The process of filling is done with unknown HR patches allows to create the structure and simultaneously then preserve it.
- The LR patch corresponding to the HR patch having the highest priority, in this type of scenario its best neighbor is sought from the low resolution inpainting images.This with high priority; this composition must be done with unknown parts. Compare to the existing methods like raster scan method it. search is done in the dictionary part and in the local area neighborhood, then once the best candidate is get for LR candidate its corresponding HR patch is simply deduced. Its pixel values are then copie4d into the unknown parts of the HR patch.

After the filling of the current patch, the priority value is propagated and the aforementioned steps are iterated while there exist unknown areas. A Poisson and alpha-blending are again used to hide seams between known and unknown parts and to improve robustness.

EXPERIMENTAL RESULTS
Following are the experimental results expected from the proposed system:
- ➤ *Sparsity Based Inpainting*

Fig:(5) Sparsity based filling order, patch size=9, 180 degree rotation

➢ *Tenser Based Inpainting*

Fig:(6)Tensor based filling order, patch size=5, 180 degree rotation

➢ *Super Resolution Inpainting*

Fig:(7) Super resolution Inpainting

➢ *Final SRA Output*

Fig:(8) Final SRA Output

CONCLUSION

The proposed algorithm is intended for filling in locally small areas. For larger inpainting domains, a scale-space approach can be used to preserve the algorithms speed at the expense of reconstruction quality. The proposed algorithm results are compared with the different existing methods; results shown performance and efficiency are more accurate and reliable. A novel algorithm is presented for examplar-based inpainting. In the proposed algorithm initially inpainting is applied on the coarse version of the input image, latter hierarchical based super resolution algorithm is used to find the information on the missing areas.Here we included a new method i.e, Bergmen Iteration to get better PSNR peak signal to noise ratio. These PSNR values are shown below table.

Table 2
PSNR comparison with Sparsity and Tensor Inpainting

Input Image	Inpaint Rotation by	Sparsity Based Inpainting PSNR	Tensor Based Inpainting PSNR
Man	0 Degree	18.8989	18.8745
	180 Degree	18.9957	19.0257
Cow	0 Degree	17.7529	18.6109
	180 Degree	18.9428	18.7578
Bungee	0 Degree	23.0009	22.9512
	180 Degree	23.0104	22.9333
Bridge	0 Degree	20.6309	21.1880
	180 Degree	20.9763	21.2211
Elephant	0 Degree	18.7341	19.5857
	180 Degree	19.4530	19.2634

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