



A NEW METHOD FOR SUPER RESOLUTION ALGORITHM BASED ON EXAMPLAR APPROACH INPAINTING

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ABSTRACT

Although tremendous advancement happen in image processing domain, still “filling the missing areas” is area of concern in it. Though lot of progress has been made in the past years, still lot of work should be done. A novel algorithm is presented for exemplar-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. The unique thing of the proposed method is easier to inpaint low resolution than its counter part. To make inpainting image less sensitive to the parameter, it has inpainted several times by different configurations. Results are combined using the lopyy belief propagation and by using the super resolution details are recovered. The proposed algorithm results are compared with the different existing methods; results shown performance and efficiency are more accurate and reliable.

INTRODUCTION

In image processing “Filling the Missing Areas (holes)” is a problem in many image processing applications [1]. Although lot of research done still it’s an area of concern in many image processing applications. Image inpainting is the procedure of reconstructing lost or deteriorated parts of images. Existing methods are broadly classified into two sections a) Diffusion based approach b) Exemplar based approach. These two

existing methods are inspired from the texture synthesis techniques [2]. Diffusion based approach generates the isophotes via diffusion based on variational structure or variational method [3], the main drawback of diffusion based approach is have a tendency to introduce some blur when the filling the missing area is very large. Latter method of approach is Exemplar based approach which is quite simple and innovative, in this method copy the best sample from known image neighborhood. Initially exemplar method approach is implemented on object removal as chronicled in [4], searching the alike patches is done by using the priori rough estimate method of the inpainted image values utilizing the multi-scale approach.

The two varieties of methods (diffusion based approach and Exemplar based approach) are then combined, for example by utilizing the structure tensor to calculate the priority of the patches to be filled in [5]. Latter the exemplar approach is combined with the super resolution algorithm as shown in [6], it’s a two steps approach, firstly rough (coarse) version of the input image is inpainted then in second step originating the high clarity image from the inpainted image. Although lot of advancement done in the past decade on exemplar based inpainting still lot problems to be addressed in all the main area of concern is patch size and filling the holes related to settings configuration. This problem is here addressed by several input

inpainting versions to yield the final inpainting image after combining the all input inpainting versions.

Note that Inpainting is applied on the rough (coarse) version of the input image when the filling area (hole) is very large which reduces the impact of computational complexity and robust behavior against noise entities. In this type of scenario final full resolution image is retrieved from the super resolution algorithm [6].

PROPOSED ALGORITHM

The proposed inpainting algorithm presents the novel inpainting algorithm and also the process of combining the different inpainting images.

NOVEL INPAINTING METHOD BASED ON EXAMPLAR APPROACH

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 P_x . In order to know the data term in a detailed way tensor based [7] and Sparsity-based [8] have been used.

THE PROPOSED ALGORITHM FRAMEWORK

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

$$J$$

in above equation represents the sum of scalar structure tensors of the image $I_i(\mathbf{R})$

G B). The smoothing of the tensor is done without cancelling effects: $J_\sigma = J * G_\sigma$, where $G_\sigma = 1/2\pi\sigma^2 \exp(-(x^2+y^2/2\sigma^2))$, 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.

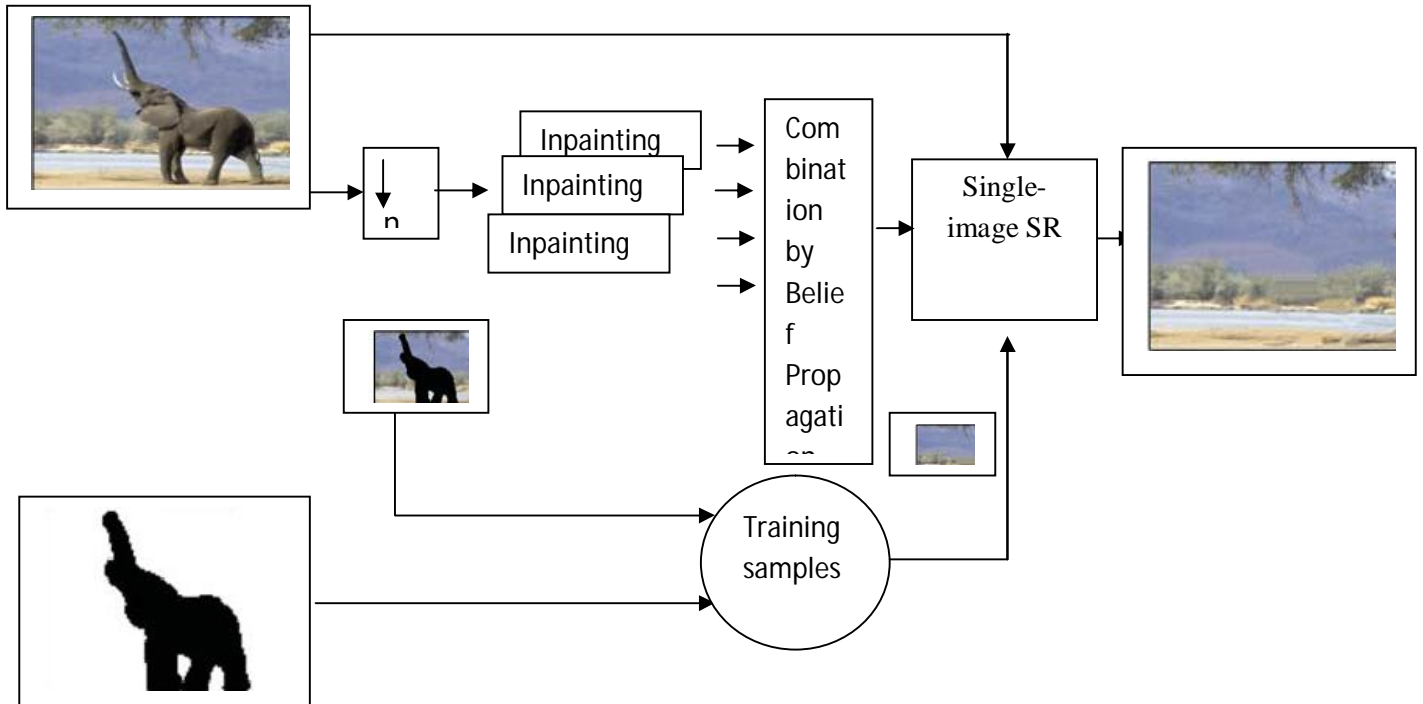
The structure tensor J_σ is computed by using the structure tensor, here the Eigen vectors $V_1 V_2$ represent oriented orthogonal basis and Eigen values represent the structure variation. Then Eigen vector V_1 represents the highest fluctuations and V_2 is the local orientation. The data term

$$D$$

Where α is a positive value i.e. $\alpha = 8$
 $\alpha = 0.8$; lies between 0 and 1

The sparsity based priority 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

Where N_s and N stands for the number of valid patches and the α is high then prediction of candidates is low, if α is low then the predication of candidates is high.



B) *Texture Synthesis* is 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 .

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

The above equations show two initial processes. Initially first equation indicates the argument, based on that argument in our proposed Algorithm by using d_{ssd} (sum of the square differences) the coherence similarity check indicates the degree of

Where K is the number of candidates and the similarity of chosen neighbors lies within $i9n$ a range and d_{min} 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.

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

Setting	parameters
1 (default)	Patch's size 5 5 Decimation factor n=3 Search window 80 80 Sparsity-based filtering 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

The above shown settings play a vital role to obtain the final inpainting picture; in order to get the final inpainting picture at least three of above settings combination should be considered. The first two of three combinations are very simple since it is obtained by using the median or average as shown below

The main advantage of the median and average operator is that its simplicity though its simple in approach still it suffers from the two

cons, in that mainly the average as well as median operator does not consider the neighbors of the pixel to take the final decision. The latter con is that median operator tends to introduce some blur which affects the performance. In order to solve the problems like blur etc we tends to minimize the objective function in the combination .By analyzing the results obtained in the previous algorithms ,in our proposed method we tends to introduce the LOPPY BELIEF PROPAGATION which works efficiently and yields good results in practice.

LOPPY BELIEF PROPAGATION

As described in [9], assigning the label to every pixel P_x of the unknown regions T of the picture $\tilde{\mathbf{I}}^{(*)}$. The major disadvantage of the belief propagation is that when the number of labels is high it's processing is quite slow. As described in [9] the priority belief propagation is merely have high complexity levels during processing. Note here number of labels is equals to the number of patches as described in [9].Here in lopyy belief propagation the approach is simpler the label is small, the label here described is index of the inpainted picture from which the necessary patch is extracted. A finite set of labels L is composed of different M values as (1 to 13).Over the target region the problem of labels is resolved by MRF model. Instead of M values here M lattices is taken of the pixels T . The total energy of MRF model is minimized as shown below

= the label cost or the data cost.

Where 'v' is the squared neighborhood centered on the centre pixel. Then the quadratic cost function of the pair wise potential is as follows

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.

The flow diagram of super resolution is as follows

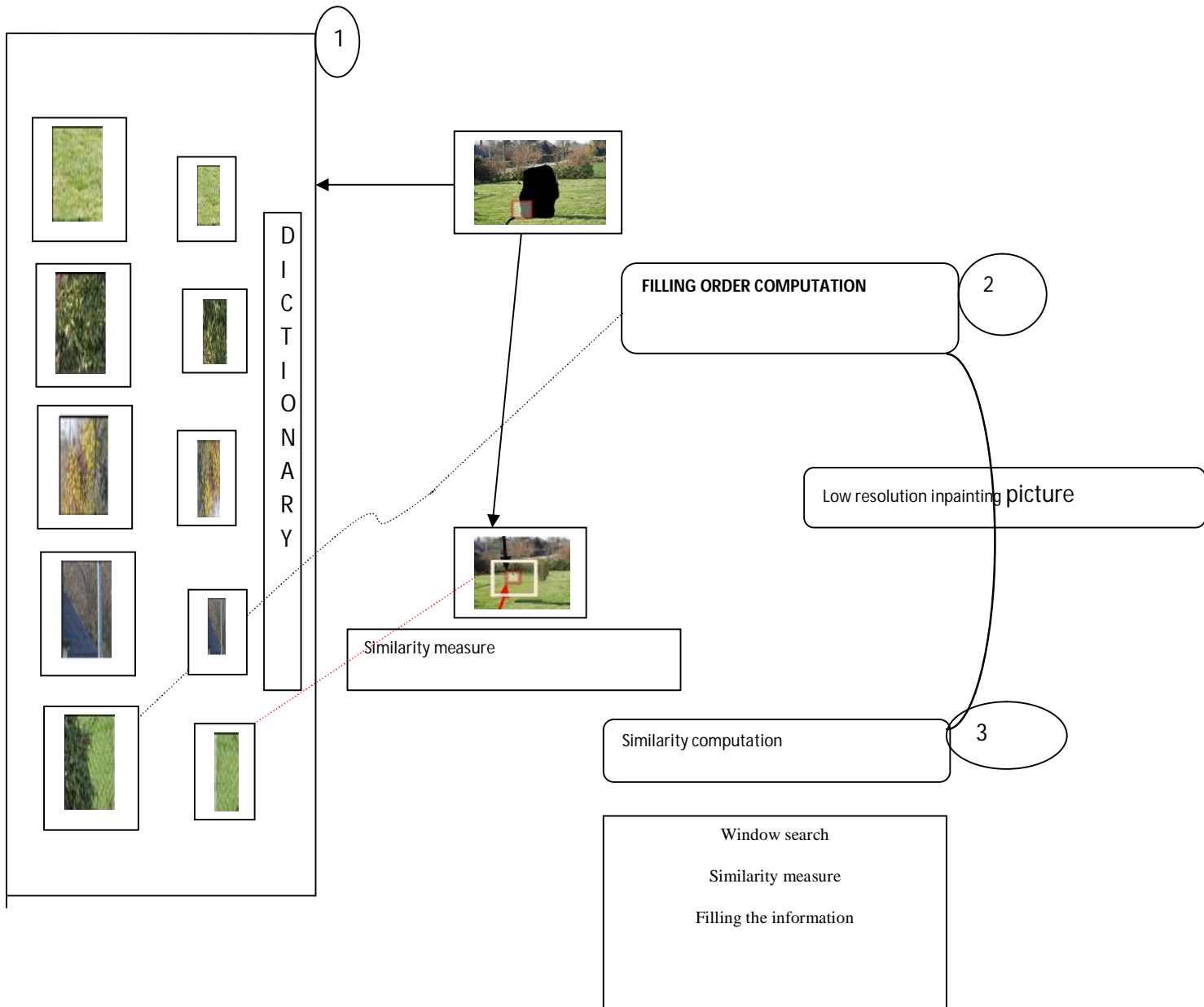
A) Dictionary Building: Dictionary building mainly consists of high resolution and low resolution patches. Note that the high resolution patches must be valid and it is strictly takes from the known parts of the image. The size of the dictionary is a user parameter which has capability of influence the 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.

B) 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.

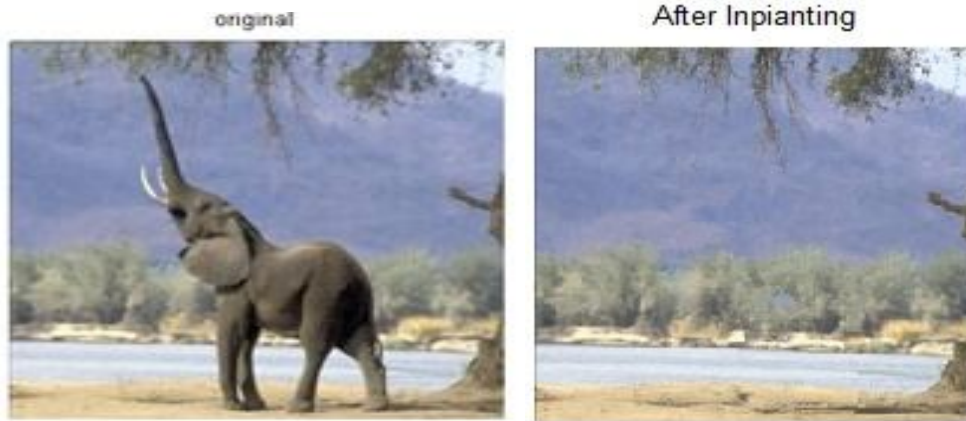
C) The LR patch corresponding to the HR patch having the highest priority, in this type of scenario its best neighbor is sought from the low resolution inpainting images.

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.

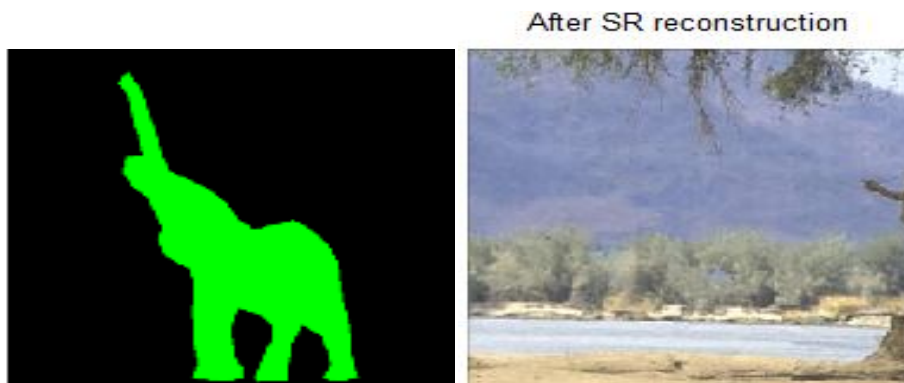
Its pixel values are then copie4d into the unknown parts of the HR patch.



RESULTS:



Mask image



Extension

In Hierarchical inpainting based on super resolution, super resolution plays a vital role, so extension to our proposed method is a advance super resolution algorithm than in proposed algorithm. In literature, Multiscale morphological operators are studied in a huge way for feature extraction and image processing persistence. In extension, a novel super resolution reconstruction

is modeled on non linear regularization model based on Multiscale morphological mechanism. By Bergman's iteration we solve the inverse problem which we get in super resolution reconstruction algorithm, here in our proposed model extension super resolution reconstruction is considered as a deburring problem. The main novelty of the extension is it suppress the inherent noise generated during SR image estimation as a

well as low resolution image formation in an efficient way.

CONCLUSION

The unique thing of the proposed method is easier to inpaint low resolution than its counter part. To make inpainting image less sensitive to the parameter, it has inpainted several times by different configurations. Results are combined using the lopyy belief propagation and by using the super resolution details are recovered.

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 exemplar-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.

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