HIERARCHICAL BE IN CHARGE RESOLUTION BASED INPAINTING

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ABSTRACT

In digital image processing “filling the missing areas” is still area of concern. Although so many algorithms proposed in the literature to tackle this issue of “filling the missing areas”. A new framework is presented in this paper for examplar-based inpainting. In the proposed literature, algorithms are mainly classified into two stages. Firstly 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 and creating a mask based on the priority of missing information. To make inpainting image less sensitive to the parameter, it has inpainted several times by different configurations. The output from the inpainting phase is efficiently combined using the novel loppy belief propagation and finally by using the super resolution algorithm details are recovered based on the dictionary building approach. The proposed literature results are compared with the different conventional methods, to prove that the proposed literature results more reliable and yield high performance in all concern areas.

INTRODUCTION

In 60 years of advance image processing domain, important researches are done to make image processing domain more flexible and easy to use. Although after lots of advancements still there are many unresolved issues in the image processing such as saliency detection, filling the missing areas etc. Even in 21st century after lot of advancements and researches still inpainting is unresolved one. Here in our proposed framework we use two different things one is low resolution inpainting images and single image super resolution algorithm. 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

The proposed framework includes mainly two important aspects .Firstly, introducing the non parametric sampling method to filling the missing area. Inpainting algorithm is preferably applied on the rough (or coarse) version of the input image. Here low resolution image is mainly presented dominant and most vital information of the structure of the scene in the digital image. Note most important thing here we get by applying the inpainting on the image is, applying on the low resolution image is easier than the applying the inpainting on high resolution images. A low resolution image is less affected by irregularities like noise and it has vital information of the structure of the scene. The second aspect is the image to be inpaint is smaller than original image it is done by performing the low sampling. To give more strong nature and visual quality to the inpainting image we perform it in the many configurations with different settings by using the default settings we used in the proposed framework. By combining the results we got from different configurations inpainting images we finally got a low resolution inpainting image which is of good quality when viewed by the human visual system. The output of first step that is inpainting the low resolution image with different in built settings and different configurations are directly or indirectly to the second step that is final inpainting image ,we perform this two tasks in order to give the subjective approach quality to the images and to enhance the resolution of the image of inpainting. Then giving the low resolution we got the final high resolution HR by using the super resolution algorithm. The super resolution image we got should have good quality to view

In the world of image processing“Filling the Missing Areas (holes)” is a problem in several image processing applications . Even though so much research has done in this area, still it's an area of concern in many digital image processing applications. Image inpainting is the approach of reconstructing lost or manipulated parts of images. Existing methods are broadly classified into two sections a) Diffusion based approach b) Examplar based approach. These two existing methods are inspired from the texture synthesis techniques.Diffusion based approach generates the isophotes via diffusion based on variational structure or variational method, 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 Examplar based approach which is quite simple and innovative, in this method copy the best sample from known image neighborhood. Initially examplar method approach is implemented on object removal as chronicled in , searching the alike patches is done by using the priori rough estimate method of the inpainted image values utilizing the multi-scale approach.

In order to yield the better result, both diffusion based approach and Examplar based approach are then efficiently combined. For example by utilizing the structure tensor to calculate the priority of the patches to be filled, based on this priority filling is done as explained in. Latter the examplar approach is combined with the super resolution algorithm as shown in , 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 examplar 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.

EXISTING METHOD:

DIFFUSIONBASED APPROACH:

Existing methodscanbeclassifiedintotwomaincategories.

Thefirstcategoryconcernsdiffusion-basedapproacheswhichpropagatelinearstructuresorlevel lines(so-calledisophotes)viadiffusionbasedonpartialdifferentialequations,andvariationmethods.Thediffusion-basedmethodstendtointroducesomeblur hole is to be large.**EXEMPLER BASED APPROACH:**

Thesecondfamilyofapproachesconcernsexemplar-basedmethodswhichsampleandcopybestmatch-intexturepatchesfromtheknownimageneighbourhood.Thesemethodshavebeeninspiredfromtexturesynthesistechniquesareknowntoworkwellincasesofregularorrepeatabletextures.Thefirstattempttouseexemplar-basedtechniquesforobjectremovalhasbeenreportedin. Theauthorsinimprovethesearchforsimilarpatchesbyintroducinganaprioriroughestimateoftheinpaintedvaluesusingamulti-scaleapproachwhichthenresultsinaniterativeapproximationofthemissingregionsfromcoarse-to-findlevels.

Thetwotypesofmethods(diffusion-andexemplar-based)canbeefficientlycombined,e.g.byusingstructuretensorstocomputethepriorityof thepatchestobefilledinasin.

Bregman iteration was successfully used by Osher in the field of computer vision for finding the optimal value of energy functions in the form of a constrained convex functional. Since then, a class of efficient solvers has been proposed for constrained and unconstrained problems .Among them, the "fixed point continuation" (FPC) method was proposed to solve the unconstrained problem by performing gradient descent steps iteratively. The linearized Bregman algorithm is derived by combining the FPC and Bregman iteration to solve the constrained problem in a more efficient way. Those methods are successfully used in sparse reconstruction problem, i.e., compressed sensing and sparse coding ,due to their simplicity, efficiency, and stability. Later, Goldstein developed the "split Bregman method" for more structured regularization in variational problems of image processing.Marquina and Osher formulated a model for SR based on a constrained variational model that uses the total variation of the signal as a regularizing functional.In this section, an algorithm based on Bregman iteration and the proposed morphologic regularization for the SR image reconstruction problem is developed.

Bregman Iteration

Consider the following minimization problem:

$$\min_{X}\{\Upsilon(X) : T(X) = 0\} \quad (13)$$

where Υ and Tare both convex functionals defined over $R^n \rightarrow R^+$. Now the Bregman iterations [11], [15] that solve the above constrained minimization problem are as follows:

Initialize $X^0 = p^0 = 0$

$$X^{(n+1)} = \arg \min_{X}\{\mu B_{\gamma}^{p^{(n)}}(X, X^{(n)}) + T(X)\}$$

$$p^{(n+1)} = p^{(n)} - \nabla T(X^{(n+1)})$$

where $B_{\gamma}^{p^{(n)}}$ is the Bregman distance corresponding to the convex functional Υ(.)and is defined from point **X** to point **V** as $B_{\gamma}^{p}(\mathbf{X},\mathbf{V}) = \Upsilon(\mathbf{X}) - \Upsilon(\mathbf{V}) - (p, X - V)$.

Bregman iterations can be reduced to a more simplified form [50] with l_2 norm, as

$$X^{(n+1)} = \arg \min_{X}\{\mu\gamma(X) + 1/2||RHX - Y^{(n)}||2\_2\}$$

$$Y^{(n+1)} = Y^{(n)} + (\hat{Y} - RHX^{(n+1)})$$

Note that the first equation solves the unconstrained minimization problem (6). As, in general, there is no explicit expression for $X^{(n+1)}$to solve the unconstrained optimization subproblem (first equation) (12-a), we go further to solve it explicitly by proximal map.

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 PRIORTY: 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 $\mathbf{J} = \sum_{\mathbf{i=1}}^{\mathbf{m}} \nabla\mathbf{I}_{\boldsymbol{i}}\nabla\mathbf{I}_{\boldsymbol{i}}^{\boldsymbol{T}}$'J'

in above equation represents the sum of scalar structure tensors $\nabla\mathbf{I}_{\boldsymbol{i}}\nabla\mathbf{I}_{\boldsymbol{i}}^{\boldsymbol{T}}$of the image **$\mathbf{I}_i$(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 fromcoherence 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

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

Where η is a positive value i.e. η=8

$\propto$=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

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

Where N_s and N stands for the number of valid patches and the $\left\|W_{\mathrm{p_x}}\right\|_2$ is high then prediction of candidates is low, if $\left\|W_{\mathrm{p_x}}\right\|_2$ 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.

$$\psi^*_{\mathrm{p_x}} = \arg\min_{\psi_{p_j}\epsilon W} d\left(\psi^{\mathrm{k}}_{\mathrm{p_x}}, \psi^{\mathrm{k}}_{\mathrm{p_j}}\right)$$

$$s.t Coh\left(\psi^{\mathrm{uk}}_{\mathrm{p_x}}\right) < \lambda_{coh}$$

$$coh\left(\psi^{\mathrm{uk}}_{\mathrm{p_x}}\right) = \min_{p_j\epsilon S}\left(d_{SSD}\left(\psi^{\mathrm{uk}}_{\mathrm{p_x}}, \psi^{\mathrm{uk}}_{\mathrm{p_j}}\right)\right)$$

The above equations show two initial processes. Initially first equation indicates the argument, based on that argument in our proposed Algorithm by using d_{ssd} (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

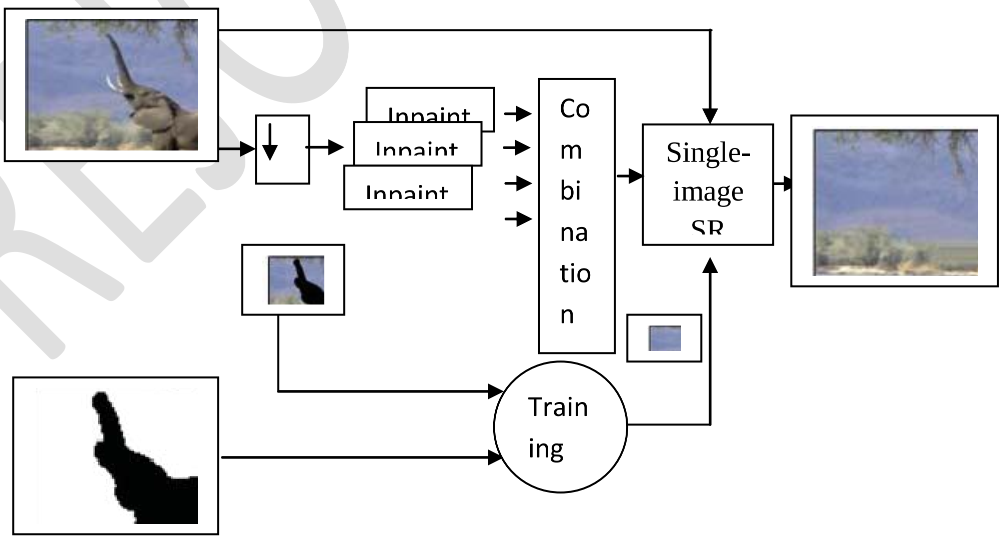

Figure (i) Block Diagram of Proposed Framework

Setting	parameters
1	Patch’s size 5×5 Decimation factor n=3 Search window 80×80 Sparcity-based filtering order
2	Default+rotation by 180 degrees
3	Default+patch’s size 7×7
	Default+rotation by 180 degrees
4	+patch’s size 7×7
	Default+patch’s size 11×11
5	Default +rotation by 180 degrees
	+patch’s size 11× 11
6	Default+patch’s size 9×9
7	Default +rotation by 180 degrees
	+patch’s size 9× 9
8	Default+patch’s size 9×9
	+Tensor-based filling order
9	Default+patch’s size 7 ×7
	+Tensor-based filling order
10	Default+patch’s size 5 ×5
	+Tensor-based filling order
11	Default+patch’s size 11×11
	+Tensor-based filling order
12	Default +rotation by 180 degrees
13	+patch’s size 9×9+Tensor-based filling order

Tabular form: Different Configuration settings for inpainting

$$\psi_{p_x}^{uk} = \sum_{i}^{K} \omega_{p_x,p_i} \times \psi_{p_i}^{k}$$

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

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 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 above.

combinations are very simple since it is obtained by using the median or average as shown below

$$\hat{I}^{(*)}(p_x) = \frac{1}{M}\sum_{i=1}^{M} \hat{I}^{(i)}(p_x)$$

$$\hat{I}^{(*)}(p_x) = MED_{i=1}^{M}\hat{I}^{(i)}(p_x)$$

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, 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 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.Here in loppy 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 to .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

$$E(l) = \sum_{p\epsilon v} V_d(l_p) + \sum_{(n,m)\epsilon N_4} V_s(l_n, l_m)$$

$V_d(l_p)$ = the label cost or the data cost.

$$V_d(l_p) = \sum_{n\epsilon L}\sum_{u\epsilon v}\left\{\hat{I}^{(l)}(x+u) - \hat{I}^{(n)}(x+u)\right\}^2$$

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

$$V_s(l_n, l_m) = \lambda \times (l_n - l_m)^2$$

The image to be inpaint is smaller than original image it is done by performing the low sampling. To give more strong nature and visual quality to the inpainting image we perform it in the many configurations with different settings by using the default settings we used in the proposed framework. By combining the results we got from different configurations inpainting images we finally got a low resolution inpainting image which is of good quality when viewed by the human visual system. The output of first step that is inpainting the low resolution image with different in built settings and different configurations are directly or indirectly to the second step that is final inpainting image ,we perform this two tasks in order to give the subjective approach quality to the images and to enhance the resolution of the image of inpainting.

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. A low resolution image is less affected by irregularities like noise and it has vital information of the structure of the scene. The main aspect is the image to be inpaint is smaller than original image it is done by performing the low sampling. To give more strong nature and visual quality to the inpainting image we perform it in the many configurations with different settings by using the default settings we used in the proposed framework. By combining the results we got from different configurations inpainting images we finally got a low resolution inpainting image which is of good quality when viewed by the human visual system. In order to solve the problems like blur etc we tends to minimize the objective function in the combination

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 with high priority; this composition must be done with unknown parts. Compare to the existing methods like raster scan method 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 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 copied into the unknown parts of the HR patch.

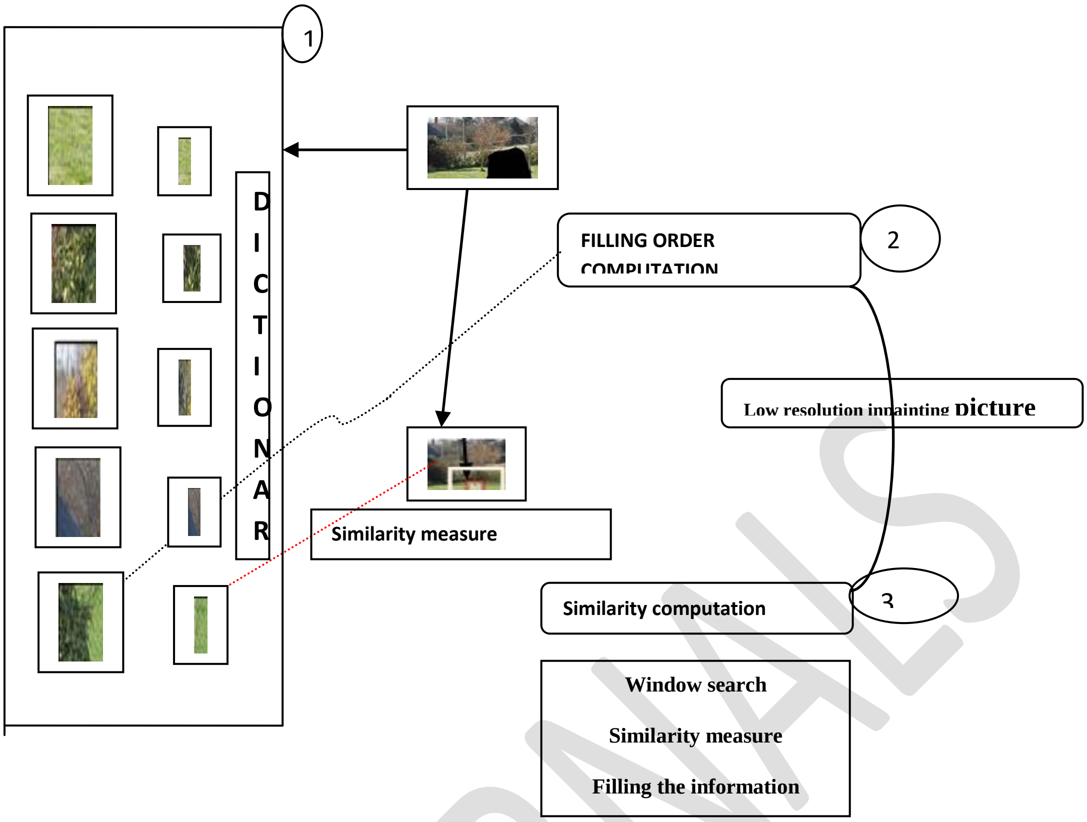

Figure (ii)Flow diagram of super resolution algorithm

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 loppy 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 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.

SIMULATION RESULTS

Inpainting based super resolution approach both for the proposed work and Bregman super resolution approach is shown in following figures and statistics shown in terms of tabular form in terms of psnr values on elephant, bird and bunget images respectively.

Case 1

Figure 1(a) (Proposed Literature) after inpainting 1(b)

Fig:original image,masking of input

Case2

image

fig: After completion of inpainting &sr method of SR reconstruction.

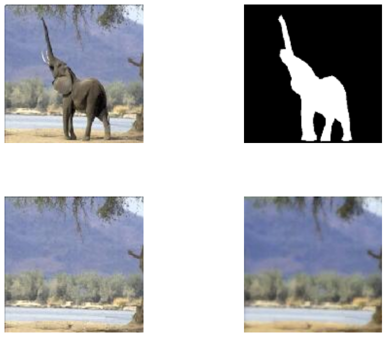

Figure 1 (a) Original image (b) mask of input image (c) after inpainting (d) after superresolution Algorithm

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