Denoising And Inpainting Techniques forRestoration of Images

L Praveen Kumar¹, Akku Madhusudan², Anil Kumar Gona³

¹Dept. of ECE, Anurag group of Institutions ²Dept. of ECE, Anurag group of Institutions ³Dept. of ECE, Anurag group of Institutions

Abstract—

Digitalinpaintingisthetechniqueoffillinginthemissingregionsofanimageusinginformationfro mthesurroundingareainavisuallyindistinguishableway.Inthispaper,wetrytoimprovetheExem plarbasedmethod[2]bymanipulating the values of various parameters like patch size, shape and of the mask. We present analysis size an of the impactofvariousgeometricparametersonthequalityofinpaintedimages.Imagedenoisingrefers totheremovalofunwantednoisefromtheimages.Inmostcases,theimageswhichneedto be which inpainted makes are noisv. it necessarv to eliminatenoiseandfillinthemissingregionsfromneighboringpixels. Therefore, fillinginofmissi ngregionsandremovalofnoisearethetwoveryimportanttopicsinimageprocessing. Thispaperals *oaddressestheissueofperformingbothinpaintinganddenoisingsimultaneouslyusingtwodiffer* entapproaches:pipelinedapproachandinterleavedapproach.Theeffectivenessof these approaches is demonstrated with a number of results onvariousimages.

Index Terms—Image inpainting, Denoising, Restoration, Exemplar, Userinteraction, Image completion.

1. INTRODUCTION

The of inpainting introduced concept image was first byBertalmioetal.[1].ThemethodwasbasedontheuseofPDEsand diffusion process. Bertalmio et al. [6] introduced anothermethod using the framework of the Navier-Stokes equations.Masnou and Morel proposed inpainting algorithm [7] an basedonlevellines.ChanandShendescribedimageinpaintingalgorithms[8]basedontheTVmodel. Oliveira[9] inpaints by repeatedly convolving a filter mask with the inpainting domain. Wangetal. [10]describedaninpaintingtechniquethatisbasedon the propagation of isophotes. Later, Bertozzi et al. [11]proposed an inpainting technique based on the Cahn-Hilliardequation.

Exemplar based approach proposed by Criminisi et al. [2]fills in large regions by combining the use of both texturesynthesisandisophotedriveninpainting. Thisapproachisbasedonfirstpropagatingimagestr ucture(regionsboundaries)in the target region and then propagating texture informationfrom surrounding areas constrained by this structure. Structurereconstruction is performed in order to preserve the globalstructure of the image, by creating regions in the hole withwelldefinedboundariessuchthattheymatchthesurroundings.It also gives higher priority of synthesis to those regions oftarget area which lie on the continuation of image structures. While the texture synthesis stage is important, the structure completion aspect is avital complexity of the structure of the structure synthesis and the structure of the structureponentinimproving the perceptual image inpainting quality. There are a number of approaches which are based on the Exemplar based inpaintingalgorithm.Someofthesetechniquesposesomeconstraintson the Exemplar based

algorithm while others have modified few steps of the algorithm. Here, we describe some of the techniques based on Exemplarapproach.

WuandRuan[12]introducedacrossisophotesdataterminexemplarbasedinpainting.Nieetal.[13] proposedanimprovedsimilaritybasedimageinpaintingmethod.Kuoetal.[14]describedanadaptive restoredapproachbasedongradient-

based analysis inspired by the advantages of the color interpolation and the exemplar-

basedinpaintingmethods.Wong and Orchard [15] described the use of nonlocal imageinformationfrommultiplesampleswithintheimage.Hunget al. [16] proposed a novel algorithm based on mean shiftsegmentation and Bezier curves. Qin and Wang [17] tried toaddresstheshortcomingsofExemplarbasedapproach.XuandSun[18]introducedtwonovelconce ptsofsparsityatthepatchlevel for modeling the patch priority and patch representation,whicharetwocrucialstepsforpatchpropagationintheexemplar-basedinpaintingapproach.

this addressed the of In paper. we have drawback Exemplarbasedapproachbymanipulatingsomeofthegeometricparam-eters which play a vital role in the process of inpainting. Wehave analyzed the effect of manipulating the values of variousgeometric parameters like patch size. mask size, mask shape.typeoftheimageonthefinaloutcomeofinpainting.

Also, most of the images comprising of some lost or dete-riorated regions which require fill-in, generally are corrupted with noise. Hence, image inpainting and denoising are quiterelated topics in the field of image processing. This paper presents approaches for simultaneously performing inpaintingand denoising on given noisy degraded images. Inpainting of the images has been performed by following the approach of Exemplar based method [2] and Fields of Experts model [3],[4]. Denoising of images has been performed based on theFields of Experts model [3], [4]. User interaction is extremelyimportant for our system which takes all the above parameters input and performs inpainting and denoising operation on he image. In the next section, we describe the purpose of userinterventionintheprocessofinpaintinganddenoising.

Inthispaper, we have included the images/figures from the original sources required for the explanation of the background work and have cited thereforences where verrequired.

I. PURPOSEOFUSERINTERVENTION

Since like some of geometric parameters patch size, masksizeandshapeandthegivenimagetypeplayavitalrolein the image inpainting process (as would be discussed indetailinthenextsection)andparametertweakingyieldsbetterresultsthanusingthedefaultparamet values ersasmentionedinthe Exemplarapproach, hence,their mustbe altered by the user to obtain nearly accurate in painted results. In this paper, we have dealt with this issue of analyzing the impact of parameter manipulation on the Exemplar based in painting approach. We have compared the results obtained by setting various patchsizes and we observed that a taparticular value of patch size or for a particular range of patchsizes, the results obtained were satisfactory and very poor, otherwise. Hence, user interaction is extremely important forour system to generate praiseworthy results. Also, we have simultaneously performed inpainting and denoising on a givennoisy degraded image. This also requires considerable amountofuserinteractionsinceforinpainting, hehastospecify the abovementioned parameters and t hen, bothinpainting and denoising can be performed in an interleaved manner. Also, user has the freedom to perform inpainting first followedby denoising or vice-versa or both inpainting and denoising simultaneously. Now, this parallel approach requires that thevalues of above mentioned parameters need to be specified, also, the number of iterations of inpainting, denoising and thetotal number of iterations should be mentioned by the user. The number of these iterations depends on the given image, level of noise present in the image, inpainting region to befilled-in. In such parametric centric system, user intervention plays a significant role.

II. EFFECTOFPARAMETERSONINPAINTING

Some of the geometric parameters play a vital role in the process of inpainting. Parameter tweaking results in fairly bet-ter quality inpainting than obtained by applying the Exemplarbased approach.

Factors which have a great impact on the quality of theinpaintedimagesare:(i)PatchSizewhichreferstothesizeof the patch selected for filling in the target region, (ii) Shapeand Size of the mask which means the number of the pixelscoveredbythetargetregionwhichneedstobefilledinusing the inpainting algorithm, shape of the mask implies the polygonal boundary of the target regions elected by the user,

(iii) Type of the given image which refers to the kind of imageto be inpainted, comprising of natural scenes or geometricshapes.

The above 3 factors are not independent of each other. One factor influences the others. Now, we describe the impact of these various parameters on the quality of the inpainted result.

A. Typeoftheimage

Images can be broadly classified into two types: (i) imagescomprising of natural scenes which have a high smoothnessfactor, and (ii) images of geometric objects comprising of various geometric shapes, geo metric objects. The edges of these objects are linear (straight lines).

B. Patchsize

Forimagesofnaturalscenes, generally as maller patch size is selected so that it can closely approximate the curved structures. In case, if a larger patch size is selected, then the staircase artifact will be more pronounced and for images of geometric objects, patch size selected should be generally larger because the geometric objects are composed of linear structures (straightlines gements).



Fig.1:Resultofimageinpainitngofanimagecomprisingof geometric shapes requires a smaller patch size of 9 by 9pixels.

Moreover, in addition to the above facts, appropriate selec-tion of patch size is further dependent on the size of the target region or mask size (or in other words, the ratio of the source region to the target region).

Following results have been obtained by manipulating thevalues of the parameters in the Exemplar based approach. InFigure 2 and Figure 4, various results are obtained by varyingthepatchsize.





 $(d) 41 \times 41 patch \qquad (e) 67 \times 67 patch \qquad (f) 75 \times 75 patch \\ Fig.2: Results of inpainting an image comprising of geometric shapes with different patch sizes.$

C. Shapeandsizeofthemask

Given an image, filling a smaller mask would yield moreappropriate result than filling a larger mask. This is because for a given image, a smaller mask ensu resalarger source region



(a) (b) (c) Fig.3:Resultofimageinpaintingwithpatchsizeof47by47.



(a) 3×3 patch (b) 5×5 patch (c) 9×9 patch(d) 13×13 patch Fig. 4: Result of inpainting an image comprising of naturalscenewith different patch sizes.



Fig.5:Resultoftextremovalwithpatchsizeof9by9.



Fig.6:Resultofimagerestorationwithpatchsizeof9by9.

which implies more information is available to fill in the targetregion, the best matching patch can be found out from a widevariety of patches present in the source region, hence,

yieldingmore accurate result. In contrast, a larger mask would meancomparatively smaller source region i.e. the information usedtofillinthetargetregionisnotadequate.

Shape of the mask determines the kind of polygonal bound-ary selected by the user which
enclosesthetargetregiontobefilledinbythealgorithm.Thisfactorwillultimatelydeterminethesizeofthetargetregion.

Also, in inpainting, few more characteristics of the imagecome into picture i.e. the intensity, and texture. If the imagehas uniform background or foreground with respect to thecolor of all its pixels or it has homogeneous texture, then evenfilling a larger target region would yield a fairly good qualityresult. But, in contrast, if the image has heterogeneous textureandvariedintensities, then selecting as maller maskwould be beneficial as the surrounding pixels will play a major role infiling the area and thus the concepts like locality of reference and the proximity to the specified target region would comeintopicture.

III. SIMULTANEOUS INPAINTING AND DENOISING

In this section, we address this is sue of simultaneous denoising and in painting.

A. InpaintingfollowedbyDenoising

In this approach, the target region is filled in first and thenthenoiseiseliminated from the image.

B. DenoisingfollowedbyInpainting

In this approach, denoising and inpainting are carried out ina pipelined manner one after the other. First, noise removal iscarried out followed by the fill-in of the missing region. Themajor disadvantage of following this approach is that carryingout denoising first blurs the image. Because of the application of several filters to remove noise, blurring is introduced in the image. But, the mask has bee nconstructed with respect to the original image. Mask has not been modified by the application of filters, so, it has not undergone any blurring. Hence, inpainting of the blurred image would be

performed with the same original image based mask. Therefore, the output obtained is not of supremeq uality.

- *C. InpaintingandDenoisinginInterleavedmanner* Stepsfollowedinthistechniqueare:
- 1) Inpaint the image inside the inpainting region. M itera-tionsofinpaintingareperformed.
- 2) SmoothingprocessstartsafterthecompletionofMstepsof inpainting. N iterations of denoising are performedusingtheFieldsofExpertsmodel.
- 3) Repeattheabove1)and2)stepsKtimes.

Followingare the advantages and disadvantages of adopting this interleaved approach:

- 1) Advantages: If the values of M and N are small and thevalue of K is quite large, then the results obtained are of goodquality. Values of M, N and K are dependent on the givenimage, the given mask size, the level of noise with which theimageiscorrupted.
- 2) *Disadvantages:*By increasing the value of K and de-creasing the values of M and N, the overhead and the runningcostincreasestremendously.

2. RESULTS

Inthissection, results are obtained by performing inpainting followed by denoising, denoising followed by inpainting and inpainting and denoising in an interleaved manner. In Figure 7(b), (c), inpainting is performed using the Exemplar based approach using 9×9 patch followed by

denoising using FieldsofExpertsmodel.Onthecontrary,inFigure7(d),(e),initiallythe image is denoised using Fields of Experts model and then,itisinpaintedusing13×13patchbyExemplarbasedapproach.InFigure8,interleavedmannerof performinginpainting and denoising is performed, where 10 iterations of inpainting arefollowed by 10 iterations of denoising and this loop repeatstwice.



Fig. 7: (a) Noisy image, (b) Inpainting the noisy image, (c)Denoising (b), (d) Denoising the noisy image, (e) Inpainting(d)





3. CONCLUSION

In this paper, we have analyzed the impact of various ge-ometric parameters on the inpainting process while following the Exemplar based approach. As evident from the results, parameter tweaking greatly improves the quality of the results. Alongwith the given input image which needs to be inpainted, the user also has to specify the mask or the target region to befilled in, the patch size and the fill region color. Hence, userinteraction is extremely important for the system which takes all the above parameters as input and performs inpainting and denoising operation on the image. Also, we have proposed two different methodologies of performance of the image of th mingbothinpaintingand denoising simultaneously on a given degraded image: thepipelinedapproachwhereinpaintingisperformedfollowedby denoising and vice versa and the interleaved approach inwhich few iterations of inpainting are performed followed byfewiterationsofdenoising. In the pipelined approach, we observed from the results that in painting f ollowedbydenoising yields better results than performing denoising first followedby inpainting. But, the interleaved manner of performing bothinpaintinganddenoisingoutperformsthepipelinedapproach.

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