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IMAGE COMPLETION BY SPATIAL-CONTEXTUAL CORRELATION FRAMEWORK USING AUTOMATIC AND SEMI-AUTOMATIC SELECTION OF HOLE REGION

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Abstract

An image inpainting scheme has been proposed that utilizes the spatial contextual information approach for image completion. The domain to be inpainted is smooth for texture images. It can be inpainted using exemplar and variational methods. In proposed method, the regions to be removed from the image are segmented and pull out of the image where it is tenure as hole. As the hole in the image to be inpainted is an unsupervised approach, we are computing the pixel in the holes using spatial contextual correlations. The method's efficacy is embodied by real images.

Keywords:

Inpainting, Segmentation, Spatial Contextual Correlation, Dissolve

1. INTRODUCTION

Image inpainting algorithms intend to pack the omitted information of an image in a visually credible manner, so that the editing cannot be easily visible by the viewers. It was originally used for restoring old and scratched pictures [1]. Due to the development of technology in the mobile world, cell phones are equipped with cameras and the increase in consumer-level computational power, digital image manipulation is becoming omnipresent [3], [4]. Therefore we can remove the unknown objects present in the scene, and pack the omitted region with its background as if the unknown object was never there. This leads to the development of new technologies like image editing and adaptive resizing [5], [3].

The given image A and a omitted region B that is an unknown area, the purpose of image inpainting is to pack B to produce the visually credible C. The existing methods can be classified as exemplar-based or variational schemes.

The Variational scheme [5]–[10] performs inpainting as the variational function that instructs the constraints for spatial smoothness. Thus results in linear or nonlinear heat equations. So the inpainted images obtain by this method contain smooth spatial regions. An exemplar-based scheme [11]–[15] performs operation by inpainting omitted region B by repeating the patches given in a reference set image A. This proves to provide good solutions, but not having the best possible solution of the variational approaches. Therefore the combination of Exemplar and variational approach were also proposed that has both global geometric completion and texture synthesis [15], [18]-[19].

Another approach for image inpainting is done by performing the image completion algorithm using diffusion map feature space [1], [20]. Each and every pixel of A other than the B region can be represented as patch of size 5×5 or 7×7 to form the reference set. The diffusion maps are used for analyzing the high dimensional large data set for dimensionality reduction [1], which was patent by local association [21]. When proceeding with texture images, the holes in the given image can be inpainted using simple interpolation methods [1]. The omitted region can be inpainted using embedding inversion scheme that assigns an image patch to each inpainted point. This is applicable for both textured and textureless images.

In this work we proposed a method based on Spatial-contextual correlation framework for image completion. The core of our approach is to utilize association of a pixel with its neighborhood to tempt appliance precise smoothness over the inpainted image. The region to be inpainted can be chosen initially by performing the segmentation approach. The region growing method is applied thus segmenting the regions. The multiple and single region selection is also applicable. Now the region to be inpainted is termed as hole in the given image which is removed from the image. The omitted region can be packed using the correlation made by the information supplied by the neighbors and its information. This is initially applied in the borders of the omitted region which is forwarded towards the centre pixel of the omitted region. Multiple regions can also be removed from the image and they are collected together using Dissolve algorithm. The framework we present can also be applied to various data sources of interest. This paper is organized as follows: the previous work on image inpainting in Section II. The proposed image in painting framework is introduced in Section III. It is experimentally verified in Section IV. Concluding remarks are discussed in Section V.

2. BACKGROUND

Exemplar based techniques proved to be successful in many image completion tasks. Such methods pack the omitted region pixels by copying source patches from the known parts of the image to construct reasonable visual results.

Shai Gepshtein and Yosi Keller [1] proposed a Diffusion based framework for image completion that utilizes the Diffusion embedding that relates to both variational and sparse reconstruction based approaches. The induced smoothness is manifested by the smoothness of the embedding eigenvectors and LBP texture features used as affinity measures. For approximating inverse-diffusion mapping, an approach based on discrete optimization for spectral relaxation is done.

Texture synthesis by nonparametric sampling was introduced by Efros and Leung [11] that proposed a greedy scheme that operates on the boundary pixels and then proceeds towards its center. The most similar patch of given image is copied as the predicted new value. Such schemes are susceptible to the packing order, and might promulgate errors of wrongly selected pixels, leads to visual contradiction.

Igehy and Pereira [15] proposed to inpaint the texture synthesis by packing the unidentified image region with texture synthesized from a second image by computing the histogram of the resultant image. Criminisi et al. [12] proposed a scheme by initiating the priority of the pixels to be inpainted.

Barnes et al. [4] proposed an efficient approach to search image patches, denoted as Patchmatch where the random initiation of the patch match followed by the propagation of patches in the neighborhood of well matched patches.

Wexler et al. [13] suggested a best formulation of exemplar based inpainting where the omitted pixels have to be consistent with the surrounding patches. The inpainting is iterated until the best solution appears. This allows improved global consistency and speed. He introduced spatial and temporal constraints for video inpainting.

Drori et al. [14] proposed an iterative exemplar based scheme where the omitted region can be inpainted by classifying the pixels with high confidence regions of the image. It is iterated until the methods of operation converge. The main disadvantage of the exemplar-based schemes is the searching of a most similar patch for the omitted region which is repeated for many iterations.

The variational schemes is formulated using the calculus of variations [6], where the pixels on the boundary are used as conditions and using such conditions the image completion can be propagated towards the hole. Shen proposed variational image inpainting schemes [10] based on a Bayesian formulation.

Pérez et al. [5] proposed an image inpainting variational scheme using Poisson Distribution and Laplacian equation based on the boundary condition.

Masnou et al. [24] uses the propagation approach and the edges developed by this approach are smooth and continuous at the boundary of the omitted region, and it shows good results for inpainting thin holes.

Bertalmio [18] proposed a method which contains the combination of variational and exemplar based methods which concentrate on texture synthesis and geometric methods for image inpainting through structure texture decomposition.

Tschumperle and Deriche [23] proposed a framework that derives local filters applicable for image processing tasks. Le Meur et al. [25] proposed a combinational image inpainting scheme to determine the packing order and the best image patch used to inpaint the hole using template matching.

3. IMAGE COMPLETION BY SPATIAL-CONTEXTUAL CORRELATION

Image inpainting algorithms intend to pack the omitted information of an image in a visually credible manner, so that the editing cannot be easily visible by the viewers. It was originally used for restoring old and scratched pictures [1].

A novel approach is proposed by automatically selecting the regions to be inpainted and then it is being removed from the image. The region to be inpainted is packed using the information supplied by its neighbors and its own information. The method proves its efficacy by providing best results than the methods available in the literatures.

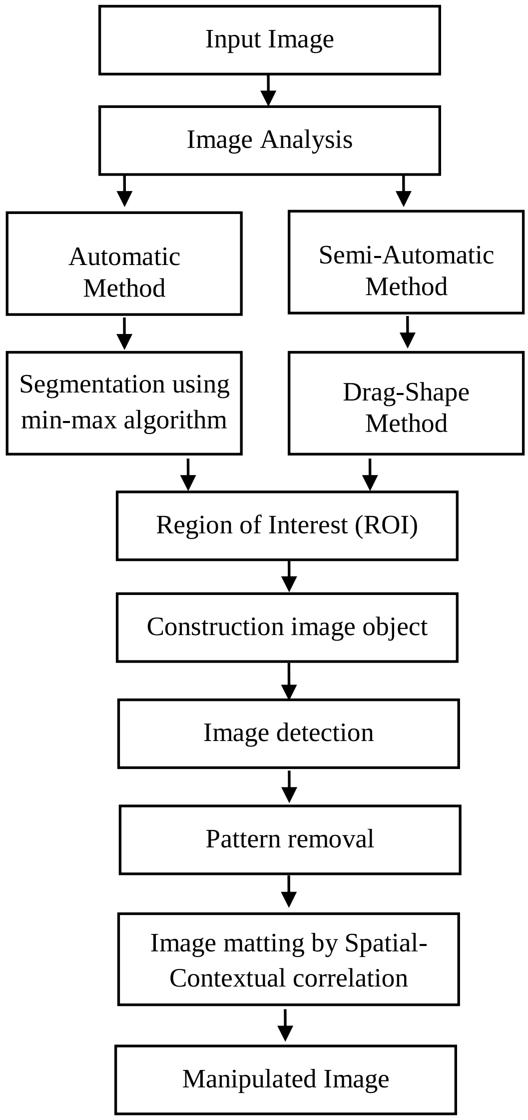


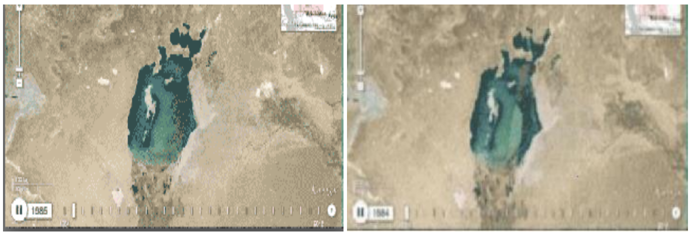
Fig.1. Proposed Methodology of Image Completion by Spatial-Contextual Correlation

3.1 AUTOMATIC METHOD OF REGION SELECTION

The automatic selection of region by the proposed method to perform inpainting includes the following steps to be performed.

3.1.1 Preprocessing of images:

In practice, a pixel may display anomalous values corresponding to small-scale cloud cover, shading, or other short-lived events. When the results are obtained from the image without removing such discrepancies may result in inaccuracy. Therefore in-order to increase the efficiency in the resultant image the input images should be preprocessed. Gaussian filter is used to remove the noise and distortion present in the image. The image gets smoothed as a result of preprocessing.



(a) (b)

Fig.2. (a) Image before Preprocessing (b) Image after preprocessing

3.1.2 Segmentation algorithm using min-max region growing:

Image segmentation is one of the most important and difficult problems in many applications. There are many segmentation methodologies present in the literature and each methodology has unique features to be considered for specific applications. Fuzzy C-means (FCM) algorithm is one such methodology that is known for best results and also retains more information of the original image. The segmentation is mostly based on the local properties of the pixel.

Image segmentation can be related to perceptual grouping and organization in vision and the key factors such as similarity, proximity and good continuation that lead to visual grouping [2]. The visual grouping can also be formed as a graph that contains set of points or nodes. An edge is created between every pair of pixels and the weight function between each pair gives the similarity between the pixels. The weight function reflects the likelihood of to pixels belonging to same object. When the neighborhood gray level difference value decreases, then the weight function has to be increased.

Region growing algorithms separate the regions in the image with similar properties correctly. It also produces clear edges of the original image. The segmentation should be done efficiently such that each and every pixel in the image should belong to only one region. The image can be segmented into regions, if it is well defined. Merge-split routine with min-max difference region growing algorithm is a prime method. This creates the split in blocks near the edges of the image. The threshold selection is an important step in this method. This becomes tedious job because if this value is low which creates very small regions and if it is high then a large region is created. The region growing is done along with merge-split to get the efficient result else this generates the blurred edges in the regions.

The merge-split algorithm needs threshold as input that determines what blocks that can be merged or which blocks can be divided. Usually the single blocks are taken with the standard size of 2×2. The blocks can be sub divided based on the difference between the minimum and maximum intensities of each block. If this difference is close to max-min difference of its neighboring blocks then it can be merged to form a single block. If this difference exceeds the threshold, then the block is divided into halves. This process is repeated until no blocks satisfy the criteria (i.e) the block exceeds, then the block can be splitter until the subsequent blocks min-max value within threshold. The min-max strategy is chosen for presenting the region edges and to handle the texture of the image. This is applied for the image taken from [26].

(a)

(b)

Fig.3. (a) Input Image (b) Segmented image

3.1.3 Selection of Region of Interest:

After segmenting the regions using region growing algorithms, the region of interests are determined. The regions can also be selected for performing further operation can be opted region after region. There are two different possibilities available for selecting the region of interest:

3.1.3.1 Single region selection method:

In this selection procedure, one of the regions from the segmented image is chosen where those regions can be filled up with the values of the neighbors.

3.1.3.2 Multiple region selection method:

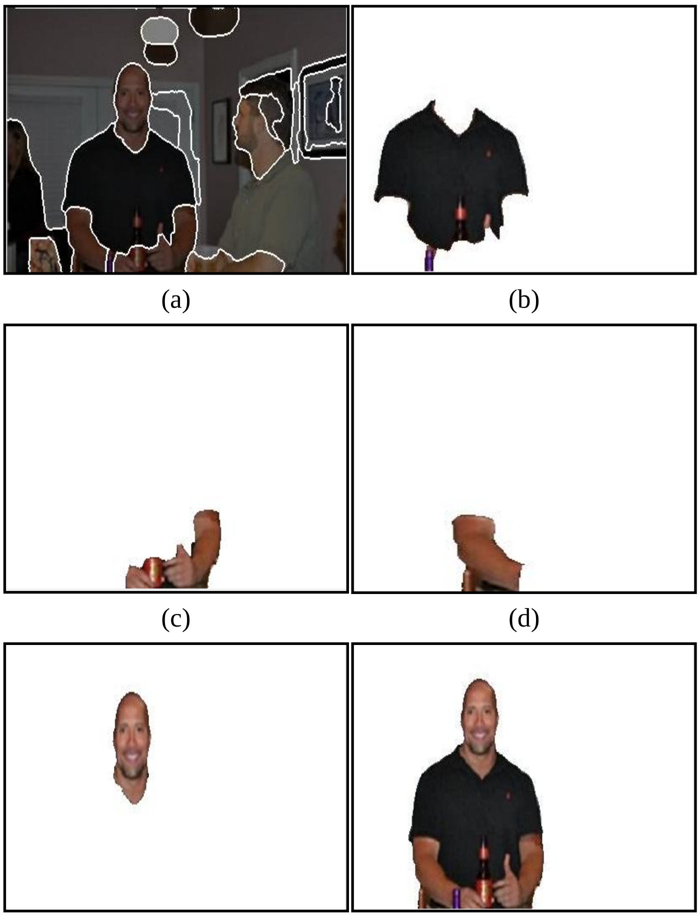
In this, two or more regions can be selected from the segmented image to perform the operation of inpainting. The multiple regions get merged to form the single region using the Dissolve algorithm. The regions got merged in order to perform the matching operation in the future step.

(a)

(b)

Fig.4. (a) Segmented image (b) Single region selection

The dissolve algorithm merges the region by calculating the mean value. When the mean value of the region has an equivalent value with the neighbors then those regions can be dissolved to form a single region. This helps in getting an efficient segmented image and to reduce the complexity of having number of regions. This is done for [27].



(a) (b) (c) (d) (e) (f)

Fig.5 (a) Segmented image (b)-(e) Selected Regions in the segmented image (f) Merging of Selected regions

3.1.4 Image detection with pattern matching:

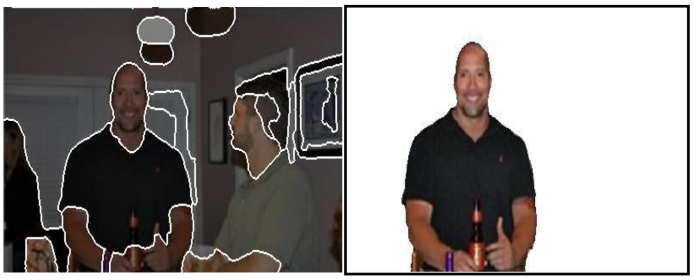
The template chosen as an object in the image is retrieved and compared with the input image to detect the exact location of the region.

The selected region should match exactly with the already selected pattern object. The resultant region is checked in the input image and the image differencing can be done.

The image differencing is the method that compares pixel by pixel with the single resultant region and the input image. The mean value of each and every pixel of the selected region is added as a feature vector to determine the pattern matching.

The features carry enough information about the image and should not require any domain specific knowledge for their extraction. They should be easy to compute in order for the approach to be feasible for a large image collection and rapid retrieval.

Along with this the shape, color, texture and size of the region can also be used as features in order to increase the efficacy of the method.



(a) (b)

Fig.6. (a) Segmented image (b) Selected region

3.1.5 Removal of detected pattern:

(a) (b)

Fig.7. (a) Input image (b) Removal of selected region

The region selected in the previous step is being removed from the segmented image and thus it should be highlighted. The pattern matched region is differentiated from all other regions by displaying them in different color. The highlighted or the differentiated area has to be filled up with the information supplied by its neighbors.

3.1.6 Image matting using spatial contextual correlation and self data information:

Each and every pixel is dependent on the characteristics of the neighborhood pixels. The 8-adjacency explains the impact of the selected pixel with its neighbors. In the literatures, the spatial contextual information is given great priority as it gives more featured information. But self data information is exploited in the calculation of the pixel value. But in this, both self data and spatial contextual information carries equal importance and that are included for finding the pixel value for the selected region which has to be filled up with the help of its neighbors.

(a) (b)

Fig.8. (a) Image to be inpainted (b) Patch matching from spatial contextual information

The existing inpainting schemes concentrate on the already chosen patches from the different parts of the input image. Instead of selecting the exact matched patch from the other region of the image for the hole to be filled up, the patch matcher had a great contribution over the pixel by considering its spatial contextual neighborhood and self data information.

Thus the full connectivity of the pixels is taken into consideration by filling the values starting from the edges that proceed towards the central pixel of the region in form of concentric circles. Thus self data information is also influenced along with the spatial contextual information to determine the strength of a pixel with its neighborhood. Thus the overall connectivity provides a better strength in the relationships of the pixel.

3.2 SEMI-AUTOMATIC METHOD FOR INPAINTING: DRAG & SHAPE METHOD

The inpainting can also be done semi automatically. For implementing this, drag and shape method is followed. The region that has to be inpainted can be selected by the user.

The box- bounding approach is implemented in this method where the region to be selected have to be clicked around by the user manually. The box is formed from the starting position of the region and proceeds towards the whole edge of the selected region. The procedure gets repeated until the bounding box approach end up with the same starting point. This method is also useful for selecting single and multiple regions.

3.2.1 Single region selection method:

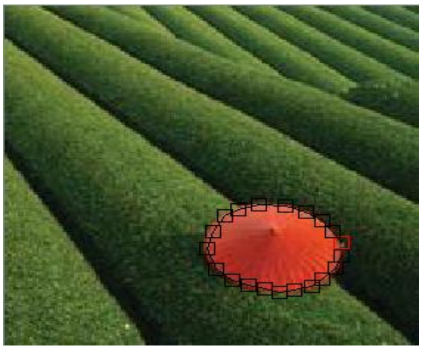
In this selection procedure, one of the region from the input image is dragged using bounding-box approach.

3.2.1.1 Selection of region:

The region in the image gets segmented manually by the user to retrieve the segmented image.

The segmented region is removed from the input image where it can be filled up by the patch matcher getting information from the neighbors.

(a)

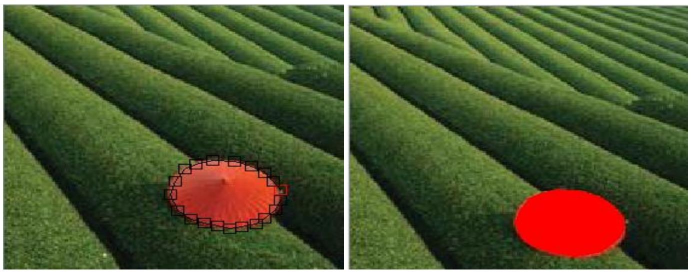


(b)

Fig.9. (a) Input image (b) Manual Segmentation of region using Drag and Shape method

3.2.1.2 Removal of detected pattern:

The region selected in the previous step is being removed from the input image and thus it should be highlighted. The selected region is differentiated from all other regions by displaying them in different color. The highlighted or the differentiated area has to be filled up with the information supplied by its neighbors.



(a) (b)

Fig.10. (a) Manual selection of Segmented Image (b) Region to be inpainted

3.2.1.3 Image matting using spatial contextual and self information:

Each and every pixel is dependent on the characteristics of the neighborhood pixels. The 8-adjacency explains the impact of the selected pixel with its neighbors. In the literatures, the spatial contextual information is given great priority as it gives more featured information. But self data information is exploited in the calculation of the pixel value. But in this, both self data and spatial contextual information carries equal importance and that are included for finding the pixel value for the selected region which has to be filled up with the help of its neighbors.

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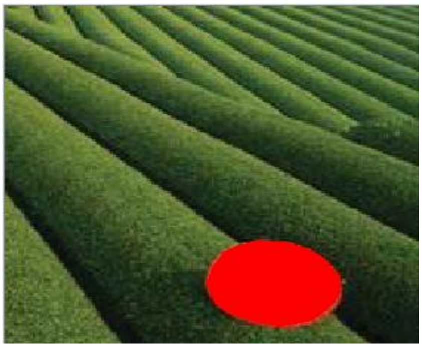
Thus the full connectivity of the pixels is taken into consideration by filling the values starting from the edges that proceed towards the central pixel of the region in form of concentric circles. Thus self data information is also influenced along with the spatial contextual information to determine the strength of a pixel with its neighborhood. Thus the overall connectivity provides a better strength in the relationships of the pixel.



(a)

(b)

Fig.11. (a) Region to be inpainted (b) Inpainted image using Semi-automatic method

3.2.1.4 Multiple region selection method:

In this, two or more regions can be selected from the input image to perform the operation of inpainting. The multiple regions can be segmented manually by the user. This is also implemented using drag and shape method. In this a box is bounded around the necessary regions. The multiple selection method can be done both in vertical and horizontal direction or both.

3.2.1.5 Multiple region selection in vertical direction:

The multiple regions in the image can be selected in vertical pattern. The user has the rights to opt the region with their own wish as this is an semi automatic approach.

The region growing is done using drag and shape segmentation method. The vertical multiple regions collectively have to be removed from the input image, where the holes formed in the image can be filled using the patch matching done by the neighboring pixels around those selected regions.

3.2.1.6 Multiple region selection both in vertical and horizontal direction:

The multiple regions in the image can be selected both in vertical and horizontal patterns. The user can select the regions to be removed from the image in both the directions. The same drag and shape segmentation method is applied here. The vertical and the horizontal multiple regions removed from the input image, where those regions can be completed to get the result.

The experiment is tested with many set of data. It is done for both single region and multiple regions selection and removal method. Those selected regions get inpainted from the information supplied by its neighbors.

4. EXPERIMENTAL RESULTS

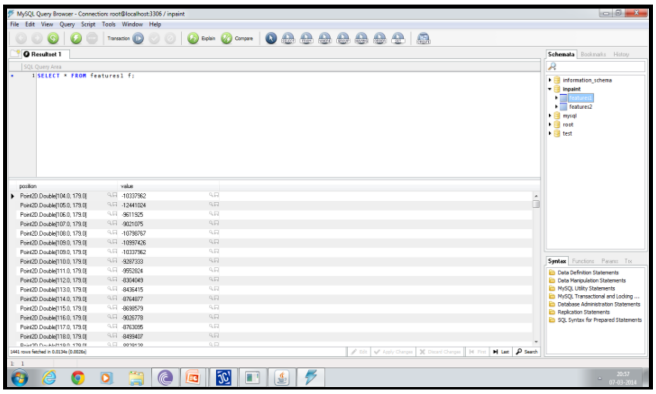
The experiment is implemented in matlab and tested with many set of data. Some of the images tested in this experiment were taken from the internet sources. And others are taken from our own source. It is done for both single region and multiple regions selection and removal method. Those selected regions get inpainted from the information supplied by its neighbors.

4.1 AUTOMATIC SINGLE REGION SELECTION

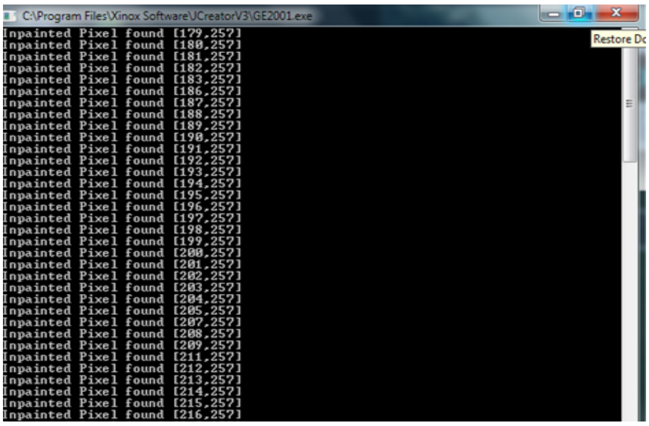
(a) (b)

(c) (d)

(e)



(f)

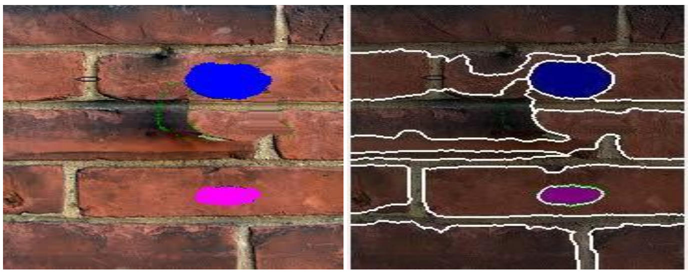


(g)

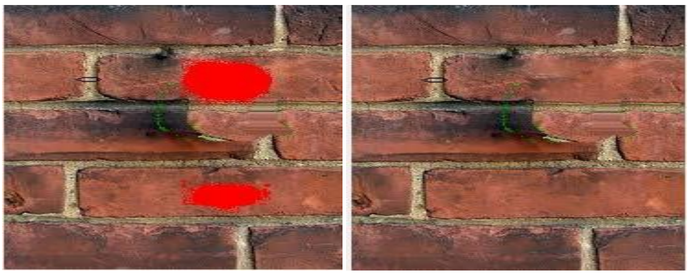
(h) (i)

Fig.12. (a) Input image (b) segmented image by region growing algorithm (c) selected region 1 (d) selected region2 (e) object selection (f) features from the selected region (g) pixels to be inpainted (h) object detection in input image (i) Image Completion Using Matting

4.2 AUTOMATIC MULTIPLE REGION SELECTION



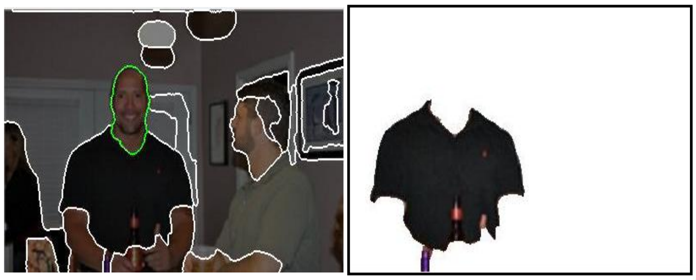
(a) (b)



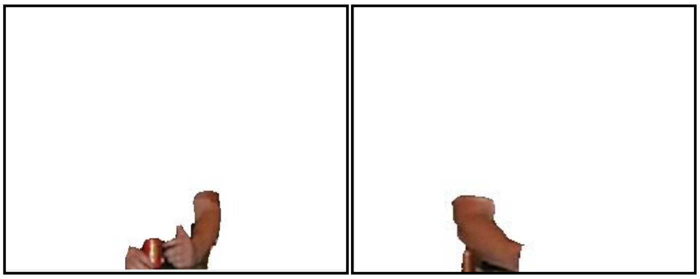
(c) (d)

Fig.13. [28] (a) Input image (b) segmented image by region growing algorithm (c) regions to be inpainted (d) Image Completion Using Matting

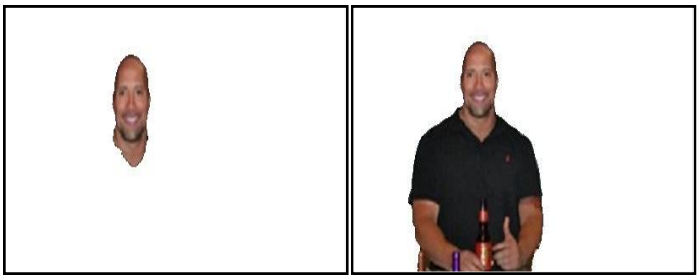
(a) (b)



(c) (d)



(e) (f)

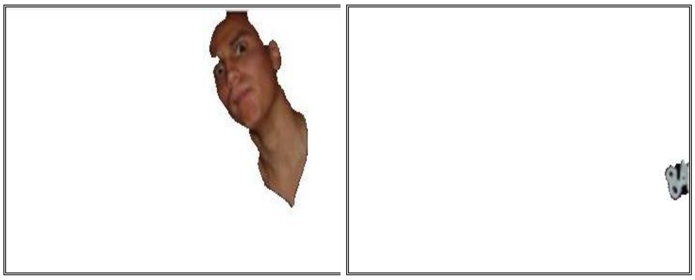


(g) (h)

(i) (j)

Fig.14. (a) Input image (b) segmented image by region growing algorithm (c) selection of regions (d) – (g) selected region (h) object to be removed (i) object detection in input image (j) Image Completion Using Matting

(a) (b)



(c) (d)

(e) (f)

(g)

Fig.15. (a) Input image (b) segmented image by region growing algorithm (c) – (d) selected region (e) object to be removed (f) object detection in input image (g) Image completion by Matting

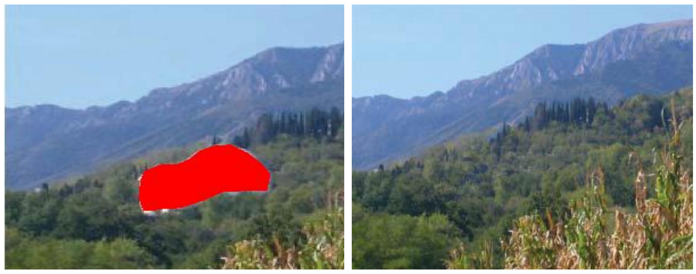
4.3 SEMI- AUTOMATIC SINGLE REGION SELECTION

(a) (b)

(c) (d)

Fig.16. [30] (a) Input image (b) Manual selection for Segmented Image (b) Region to be inpainted (d) Inpainted image using Image Matting

(a) (b)



(c) (d)

Fig.17. [29] (a) Input image (b) Manual selection for Segmented Image (b) Region to be inpainted (d) Inpainted image using Image Matting

4.4 SEMI-AUTOMATIC MULTIPLE REGION SELECTION METHOD - ONLY IN VERTICAL DIRECTION

(a)

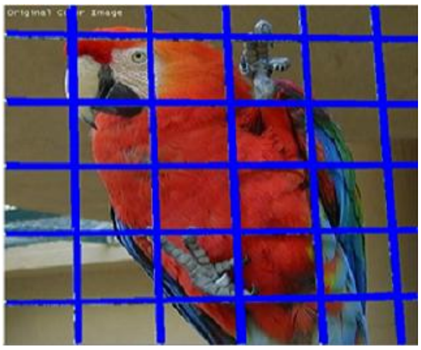
(b)

(c)

Fig.18. [32] (a) Input image (b) Region to be inpainted (c) Resultant Inpainted image using Image Matting

4.5 SEMI-AUTOMATIC MULTIPLE REGION SELECTION METHOD BOTH IN HORIZONTAL AND VERTICAL DIRECTION

(a)



(b)

(c)

Fig.19. [31] (a) Input image (b) Region to be inpainted (c) Resultant Inpainted image

5. CONCLUSION

In this work we proposed a method based on Spatial-contextual correlation framework for image completion. The core of our approach is to utilize association of a pixel with its neighborhood to tempt appliance precise smoothness over the inpainted image. The region to be inpainted can be chosen initially by performing the region growing segmentation approach. The automatic and semi-automatic selection of region is performed. The automatic selection of regions can extend its way to select both multiple and single regions which is applicable to semi-automatic method also. The omitted region can be packed using the correlation made by the information supplied by the neighbors and its information that is applied in the borders eventually proceeded towards the centre. Multiple regions can also be removed from the image and they are collected together using Dissolve algorithm. The image matting can also be done for multiple region selection. The framework we present can also be applied to various data sources of interest. The proposed inpainting scheme proves to provide better results than previous state-of-the-art methods.

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