Morphology Based Inpainting For Removal Of Markers In Medical Images

Deepthy Mary Alex, D. Abraham Chandy, S. E. Vinodh Ewards, Arvinder Singh, Pushkaran M.

Abstract: The art of restoring the missing pixels or eliminating the unwanted pixels in an image using an appropriate algorithm is called Inpainting. Inpainting is used in wide range of image processing applications. Processing of medical images requires inpainting to remove markers made by the radiologists. The paper proposes a fast and efficient technique to solve Dirichlet boundary value problem using discrete Laplacian and morphological operations in order to remove the unwanted marking present on the medical images that can complicate further processing. Experimentations were done on 165 medical images and the performance is evaluated. The results enhance a simple and promising way for automatic disease diagnosis interpretation.

Index Terms: Medical image, Restoration, Inpainting, morphological operation, interpolation, discrete Laplacian, Dirichlet boundary value problem.

1. INTRODUCTION

Images are one of the important mode of representation in the present world. A single Image can express a huge number of information. Images are of different types based on formats such as png, jpg, tiff etc. and considering the circumstances such personal, medical etc... Personal images are those images one take of themselves or others as an act of remembrance or pleasure whereas medical images such as ultrasound (US), Computed Tomography (CT), Magnetic Resonance Imaging (MRI) etc. are taken by doctors or radiologists to detect or diagnose certain diseases in a human being. Medical images have Digital Imaging and Communications in Medicine (DICOM) format. This work is confined to only medical images. Medical images are one of the top medical tools that helps the doctors and radiologists to detect and diagnose certain problems and disease within the human body. Few examples of medical imaging are detection of fractures in bones using X-rays, detection of stones in kidneys using US, identification of tumors using MRI etc... Medical images display several datas to the viewers. Medical images consist of information such as model and details of the machine used in imaging, date and time of scanning, part of the body scanned etc. An US image of the kidney displaying various information is shown in Fig1. As seen in Fig. 1., many markers are present on the image. Image markers are present on the image for easy and reliable identification of the images.

Image markers serves many purposes. The image markers are used to get the length, area, size etc. of the organs and other masses present in the body. The radiologists make the markings while scanning so that these markings can act as reference for the present and future diagnosis by the doctor. Markings also provides as a base for investigations by any other doctors thereby enabling them to come into a conclusion about the diagnosis. Ultimately, markings lead to the improvement in patient care. However, markings on medical images causes several problems in medical image processing. Some of the problems faced are absence of the originality required for image processing, missing of several important features required for further processing, false results and as a result expected final accuracy and efficiency cannot be met etc. The challenge of eliminating the markings or restoring the originality of the image is done using a method called inpainting. Inpainting can be defined as an art of restoring an image consisting of undesirable or missing parts [1], [2] and restoration is the processing of bringing back the originality of the image. Some of the image restorations are noise removal, image enhancement, inpainting etc. Several inpainting techniques have been proposed and implemented over the past [3]. Some of the techniques surveyed are mentioned. The author A video inpainting technique was proposed in [4] using a filter with annihilation property and a low rank structured matrix but this technique limits the movement of the camera with respect to various background geometries. Inpainting technique using low gradient regularization was done in [5], but this technique is computationally complex. In [6], the main limitation of inpainting using fast marching algorithm is the blurring caused when inpainting objects thicker than 10-15 pixels. Xie et al. [7] have proposed an inpainting technique using neural networks. The technique involves supervised learning and as a result only objects like that in the training set can be removed. In [8], the author uses Markov random field

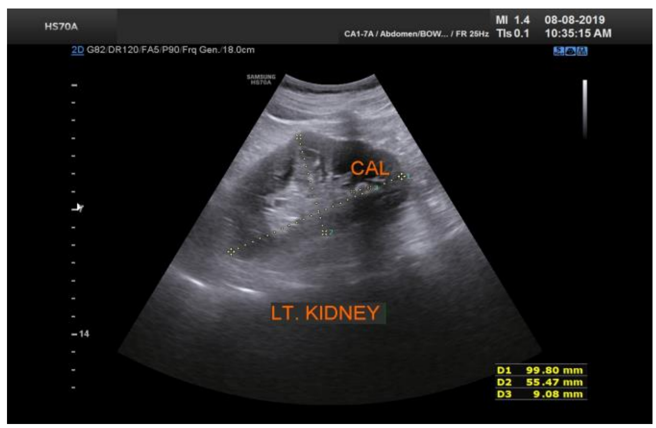


Fig. 1. *An US image displaying image markers*

- *Dr. D. Abraham Chandy is currently working as Associate professor in Electronics and Communication Engineering Department in Karunya Institute of Technology and Sciences, Tamil Nadu, India, PH:+919944686808. E-mail: abrahamdchandy@gmail.com*
- *Deepthy Mary Alex is currently pursuing Ph.D. in Electronics and Communication Engineering Department in Karunya Institute of Technology and Sciences, Tamil Nadu, India. E-mail: deepthymalex@gmail.com*
- *S. E. Vinodh Ewards is currently working as Head - Computer Technology Centre in Karunya Institute of Technology and Sciences, Tamil Nadu, India.*
- *Dr Arvinder Singh is currently working as Radiologist in Radiodiagnosis Department, Government Medical College, Punjab, India*
- *Dr. Pushkaran M. is currently working as Radiologist in Radiology Division, Kovai Diagnostic Centre, Tamil Nadu, India.*

modelling to inpaint but the patch size need to be tuned for every image that is to be inpainted. An exemplar-based method using sum of squared differences and image rotation invariance for inpainting on grayscale images is explained in [9]. Ding et al. in [10] proposed a method based on gaussian-weighted nonlocal texture similarity measure to inpaint unwanted objects in an image. The algorithm doesn't perform well when there is lack of information to describe various textures in an image. Fractional-order nonlinear diffusion based inpainting is mentioned in [11]. It eliminates limitations caused by second order and fourth order diffusion models, but the type of images used is grayscale. In [12], the author briefs an algorithm to detect gaps and inpaint lines using convolutional neural network (CNN). The model provides satisfactory results but fails to perform on complex and thick structures. The author in [13] proposed a CNN network that used Shift-Net instead of context encoder to inpaint the missing areas. The computation time increases when the layer size is small and on increasing the layer size, the information about the fine details is lost. The objective of this paper is to develop a fast, easy and efficient novel technique to remove image markers from medical images that causes noises using morphological operation and discrete Laplacian to solve Dirichlet boundary value problem. The remaining of the paper is organized as follows: Section 2 explains in detail the methodology involved in the proposed technique followed by results and discussions in the Section 3 and finally the conclusion in Section 4.

2 METHODOLOGY

The novel inpainting technique proposed consist of a mask based on thresholding and morphological operation dilation. The schematic representation of the proposed method is shown in Fig. 2. The red dashed rectangle in Fig. 2 shows the mask generation. The obtained mask is then used to remove unwanted objects from the medical image using inward interpolation. The method used for the same is discrete Laplacian to solve Dirichlet boundary value problem. The mask generation and removal of objects using the mask obtained is briefed below.

2.1 Mask Generation

The automatic mask generation is the main step in this novel technique. Better the mask generated then better the results expected. The medical images are color images and as a result they have three channels/components of color, i.e. red, green and blue. Each step in mask generation is explained below:

1. Channel separation: Color images consists of three channels of color each having a unique pixel value that contribute in providing the respective overall expected color, for e.g., the pixel intensity value of different shades of orange color lies somewhere between 135-255 in red plane, 30-180 in green plane and 0-100 in the blue plane [14]. The intensity value for a color might change from image to image as the image might be having a slight change in the color which is difficult for the human eye to perceive and understand. The first step in this technique is to separate the color image into three color components.
2. Thresholding: Thresholding can be defined as a process of separating an image into foreground and background with respect to a particular threshold value [15]. Once the image is separated into red, green and blue plane, each plane is separated into foreground and background based on a range of thresholding values. The thresholding value is selected such that most of the image markers intensity values lies within the thresholding range. Thresholding in each plane is done individual with respective threshold values since the pixel value of a color in each plane varies.
3. Dilation: This is a morphological operation that requires a structuring element to move over a grayscale image or a color component. The structuring element or kernel determines the effect of dilation on the image plane.

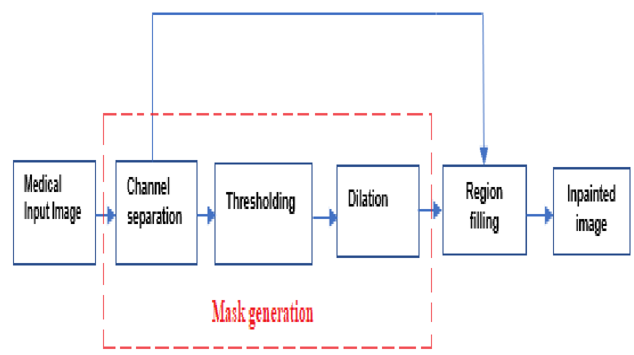


***Fig. 2**. Schematic representation of the proposed technique*

Dilation can be defined as a morphological operation that increases the sizes of objects in the image by adding pixels to the object boundary [16], [17] and dilation can be represented by (1).

$$A \oplus B = \left\{ z \mid (\hat{B}_z) \cap A \neq \varnothing \right\} \tag{1}$$

where, A is the color component and B is the structuring element. Assuming that B is reflected by its origin, then A dilation B is the set of all components if and only if A and B have at least one pixel in common when displaced or shifted by z.

4. Mask: After dilation in each color plane, the color plane is combined back into a color image to obtain a mask. The mask will contain only the image markers, rest of the image pixels are turned black.

2.2 Region Filling

The generated mask is used to remove the unwanted pixels from the image and fill those areas with pixel intensities similar to the surrounding pixel intensities. The location to replace the pixel intensities is identified from the mask. Replacing of the intensities is done using inward interpolation. Interpolation can be defined as method to identify unknown pixels [18]. Discrete Laplacian equation used to solve the Dirichlet boundary value problem [19] is given in (2).

$$\begin{aligned} \nabla^2 f = [& f(x+1,y) + f(x-1,y) + f(x,y+1) \\ & + f(x,y-1)] - 4f(x,y) = 0 \end{aligned} \tag{2}$$

where, f(x,y) is the intensity at locations (x,y); x and y are coordinates values in x and y plane, respectively.

3 RESULTS AND DISCUSSIONS

The proposed technique was experimented on a dataset of 165 medical images. The dataset comprises of US, CT, X-ray and MRI images. The dataset comprises of 2D US, MRI, X-ray and CT images obtained from online and various scan centres in India. The images from the said modalities are shown in Fig. 3. Several markers can be seen in the images. Some are generated automatically by the modality while others are marked by the radiologists for diagnosis.

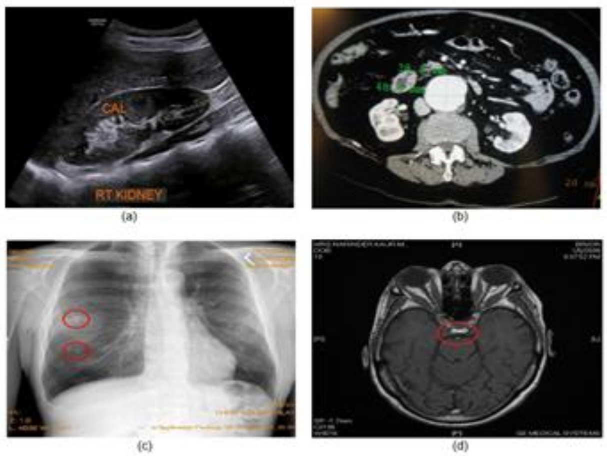


***Fig. 3**. Images from different modalities (a) US, (b) CT, (c) X-ray, (d) MRI*

3.1 Performance Metrics

The performance metrics used in the evaluation of the proposed method is mentioned below. In metrics evaluation two parameters are considered: the inpainted output image (Y) and the ground truth image (X1) which was obtained by manual inpainting. The ground truth images for images shown in Fig. 3 is given in Fig. 4.

1. Mean square error (MSE): MSE can be calculated by evaluating the average of the square difference between inpainted output image and the ground truth image [20]. MSE can be given by (3).

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(X1-Y)^2 \quad (3)$$

2. Peak signal to noise ratio (PSNR): This metric can be calculated using (4) by taking the ratio of maximum possible power of the signal to the noisy content [21]. Generally, the value of PSNR of a despeckled image lies in the range 30-50dB. The image quality increases as PSNR increases.

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right) \quad (4)$$

3. Structural similarity (SSIM) index: SSIM is a metric used to determine the similarity between two given images [22] and it is represented using (5).

$$SSIM = \frac{(2\mu_{X1}\mu_Y + C_1)(2\sigma_{X1Y} + C_2)}{(\mu_{X1}^2 + \mu_Y^2 + C_1)(\sigma_{X1}^2 + \sigma_Y^2 + C_2)} \quad (5)$$

where, μ_{X1}, μ_Y, σ_{X1}, σ_Y and σ_{X1Y} are the means, standard deviation and cross-covariance of X1 and Y resp... C_1 and C_2 are constants.

4. Inpainting accuracy: The accuracy of the proposed method can be determined based on the accuracy calculated using removal score value of image object (S_{OI}). This value can be determined based on the percentage of removal of each marking in the image, e.g. if a text has three letters and only 25% of one letter is inpainted then S_{OI} of that particular letter is 0.25. Inpainting accuracy can be calculated using (6).

$$Accuracy = \frac{\sum_{i=1}^{n} S_{OI}(i)}{n}\times 100 \quad (6)$$

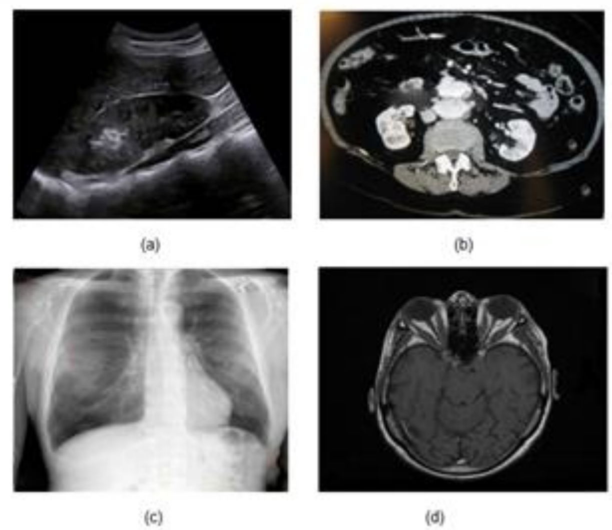
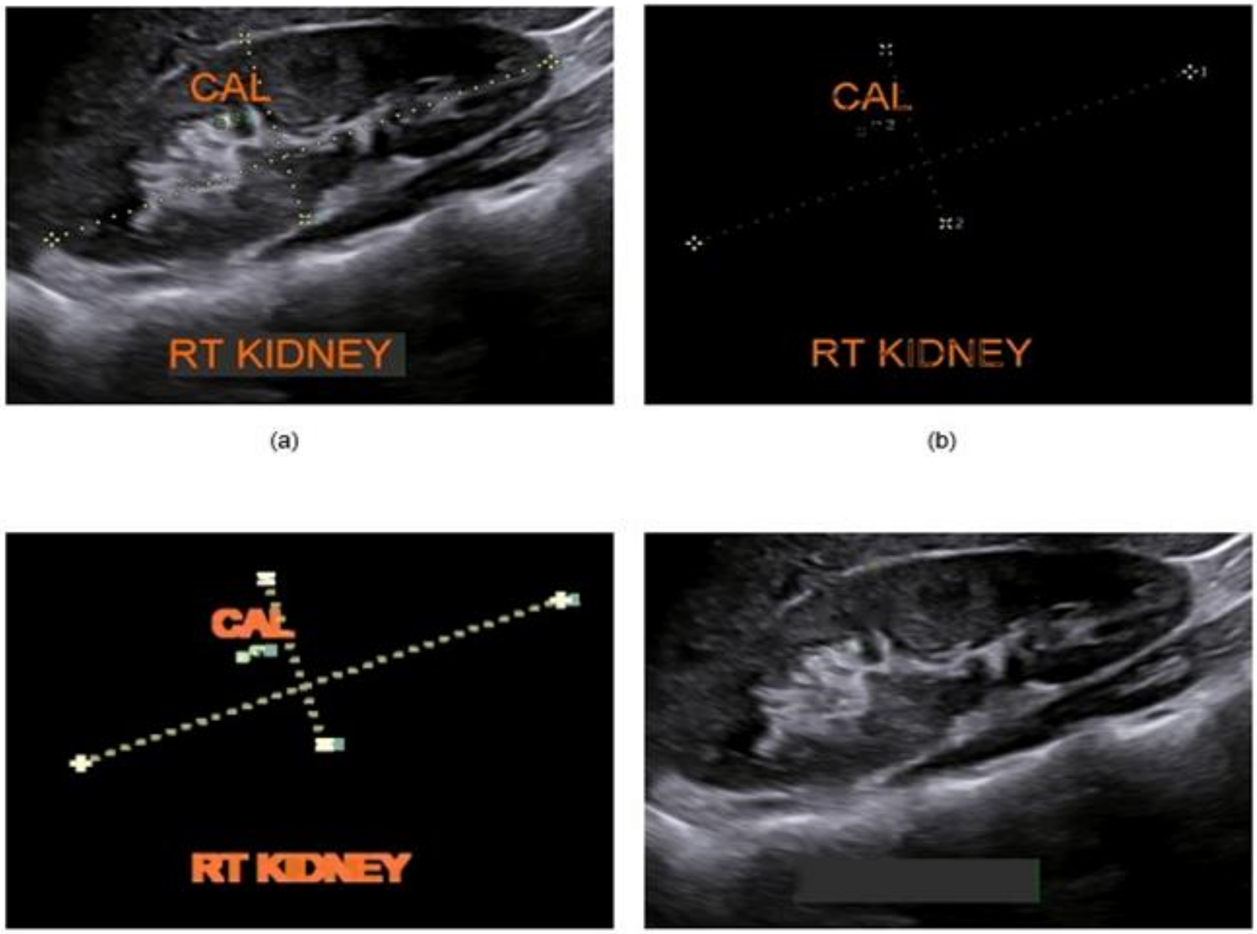


***Fig. 4**. Ground truth images from various modalities (without markers).*

where, n is the total number of markers present that need to be removed.

5. Elapsed time: The time needed to obtain an inpainted image from the original image is called elapsed time.

The proposed algorithm was implemented using MATLAB2018 and the evaluated results of various performance metrics are shown in Table 1. The inpainted image results of Fig. 3(a) are shown in Fig. 5, for better visual analysis only the area where inpainting is required is shown. It is seen from the table that the proposed algorithm on an image from US scanner has produced a maximum PSNR of 43.357 dB and least MSE of 2.796 while the least performance was from CT scan image with PSNR 36.271 dB and MSE 15.342. The average PSNR and MSE obtained from images of all modalities are 39.927 dB and 8.454, respectively. The average SSIM from all the images is 0.851 which indicates that the similarity between the manually inpainted and automatically inpainted images is quite high. The average elapsed time for execution of the proposed technique is 1.383s which is very less. The average overall inpainted accuracy of the proposed method make up to 92.915% which indicates that almost all the unwanted objects



(a) (b) (c) (d)

***Fig. 5**. Inpainting results: (a) Input image, (b) Image after thresholding, (c) Mask after dilation, (d) Inpainted output*

or image markers were removed as expected. It is seen that unwanted pixels with similar intensity values as the foreground was not removed during inpainting.

TABLE 1

RESULTS FOR PROPOSED INPAINTING ALGORITHM

Metrics	US	CT	X-Ray	MRI	Average
MSE	2.796	15.342	12.306	3.371	8.454
PSNR	43.357	36.271	37.229	42.852	39.927
SSIM	0.894	0.806	0.830	0.874	0.851
Accuracy	97.37%	88%	90.6%	95.69%	92.915
Elapsed time (s)	0.896	2.984	0.855	0.798	1.383

4 CONCLUSION

Inpainting is one of the research areas in image processing that is gaining interest. Inpainting is a technique of removing unwanted pixels or missing objects in an image. Inpainting in medical image processing is of importance. In medical images, image markers are present which causes some limitations. The originality of the image needed for image processing is absent and some of the features required for further processing is also lost. In this paper a simple, fast and efficient inpainting technique is proposed using a mask generated by thresholding and morphological operation dilation followed by region filling using discrete laplacian. A dataset of 165 images comprising of US, CT, MRI and X-ray images were considered. The proposed method gave an average PSNR of 39.927, MSE of 8.454 and SSIM of 0.851 in just 1.383s. The inpainted accuracy of 92.65% was attained. The proposed method can further be used to evaluate larger datasets and interpretation in automated disease diagnosis. Further work can be done in inpainting the unwanted pixels with similar intensity values as that of the foreground.

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