A Robust technique for Pre-Processing Liver CT images using Double Stage Guassian Filtering with Texture and Contrast Enhancement

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Abstract

Liver is the greatest and largest glandular organ in human body by weight. It is absolutely fundamental to human life as it performs some vital functions such as digestion, metabolism and filtering of possibly harmful bio-chemicals from blood. Due to changing lifestyle and excess consumption of packaged food, liver diseases such as liver cancer are becoming very common. Liver cancer is one of the cancers having very low survival rates. Early detection and proper medication is the key to survival from liver cancer. Many imaging techniques are used to detect liver cancer, with Computed Tomography (CT) images being the most widely used technique. Computer Aided Diagnosis (CAD) involves studying CT scan images to detect liver cancer. Due to noises present in CT images, sometimes the effectiveness of algorithm gets affected. It is therefore important to pre-process CT images before being used as input for cancer detection algorithms. This Paper presents a robust technique for pre-processing CT images to remove any possible noise present in CT images. The evaluation metrics used for this technique are Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR) and Structural Similarity Index Metrics(SSIM). Results obtained are SSIM is .85, PSNR is 57.56 dB, and MSE is 0.13.

Keywords: Computed Tomography; Liver Cancer; Computer Aided Diagnosis; Image Pre-Processing; Medical Imaging;

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1 Introduction

Liver is a very vital organ of human body which performs digestion and other important functions such as filter out risky bio chemicals from human body [1]. Due to rapidly changing lifestyle, various diseases related to liver are becoming more common nowadays. One such disease is liver cancer. Liver cancer is the sixth most diagnosed and Second Most Cause of death Globally due to cancer related deaths [2]. It is estimated that approximately 7,88,000 people died from liver cancer in the year 2018 and this number will rise to 2.5 million by 2030[3]. Liver cancer has very low survival rates [4]. If liver cancer is diagnosed at an early stage than 93% of patients have chances of surviving five years from the date of detection [5]. Traditionally liver cancer was detected manually by examining medical images [6]. This traditional method has several drawbacks such as lack of expert knowledge, it is time consuming and often result in late detection [7]. Now a day's Computer Aided Diagnosis (CAD) is becoming very popular because it is able to remove these drawbacks. CAD involves analyzing medical images detection of cancer [8]. Most common modality of medical imaging is CT scan images which are used very widely all over the world [9]. CT images are usually DIACOM images which are converted into jpg or png images before being used for cancer detection [10-13]. Also, original DIACOM images are of high resolution and coloured. These images are converted into gray scale images and their size is also reduced to 512*512 or 256*256[14]. These changes can result in information loss from original images. Also, it may happen that due to some technical or human errors there might be noises present in medical images. Therefore, it becomes very important to pre-process input images to remove noises in order to achieve better efficiency from cancer detection algorithms.

This paper presents a robust technique for effective pre-processing of CT images. This technique involves use of double stage Gaussian filtering in order to smooth out the edges, which helps in separating multiple objects from each other and clearly identifying the boundaries of each object. Median filter is used to remove salt and pepper noise, Contrast Limited Adaptive Histogram (CLAH) is used to enhance the contrast of image. The images obtained from double stage Gaussian filtering, median filtering and CLAH filtering are combined using image fusion technique in order to obtain final pre-processed image. Different parameters such as Mean Square Error, Peak Signal to Noise Ratio and Structural Similarity index Metrics are used for performance evaluation of proposed approach.

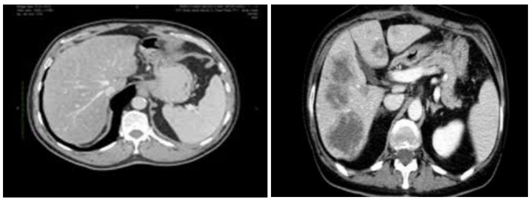
The remaining section of this research is structured as follows: firstly, we have described the materials and dataset used in section II. We have presented and discussed proposed pre-processing approach in detail in section III. Section IV describes various parameters that were tuned in order to achieve best results. Section V describes various performance evaluation parameters that are chosen to measure the quality of proposed approach. Section VI gives comparison of performance of proposed approach with other state-of the-art approaches. Finally results and future scope is discussed in section VI.

2 Materials Used

This section presents the proposed method for image pre-processing on liver CT images. To carry out experimentation Liver images from LiTs Dataset were used. The detailed description of data set and proposed method is described in the following sections.

2.1 Dataset Used

This work made use of the CT dataset of a public database called LiTs[15]. This data set consist of Liver CT images of 200 persons. These images are divided into two parts, 130 CT images for training dataset and 70 images for test dataset. Image size is 512*512.



(a) (b)

Figure. 1.(a)Normal CT image (b) CT image having Cancer Tissue

Fig. 1[16] shows two CT images, first image is liver CT image of a normal person. Second image is liver CT image having cancer cells. It is clearly visible that there seems to be absolutely no difference in above two images, and it requires very expert vision to identify cancer cell from medical images.

3 Proposed Method

This section describes the proposed method in detail. Fig. 2 represents the flow diagram of proposed pre-processing approach. Original liver CT image is converted into gray scale image and then various filters shown in fig.2 are applied on this image to obtain final pre-processes image.

In this research we have used three different filters namely (a) Double stage Gaussian filter, (b) CLAH and (c) Median Filter. These filters are discussed in detail in following section.

3.1 Double Stage Gaussian Filtering

In Image Processing filters are used to smooth out edges so that boundaries between objects or various parts of objects in a image can be separated from each other. Filters basically change the pixel value under consideration depending upon the values of neighbouring pixels and mathematical formulas used. In Liver CT image various organs are captured along with liver. For proper segmentation it is important that liver must be separated from other organs such as pancreas and kidneys. For this we need to smooth out the edges of various organs present in liver CT image so that each organ can be identified separately. Gaussian filter has proved to be the most effective filter that can smooth out the edges of various objects in a image without causing any significant information loss. Gaussian filter has this advantage because the Fourier transform of Gaussian distribution is centred around zero frequency. Gaussian filter is a low pass filter used for reducing noise and is implemented as an odd sized kernel. Equation 1. specifies how Gaussian filter is applied on original image.

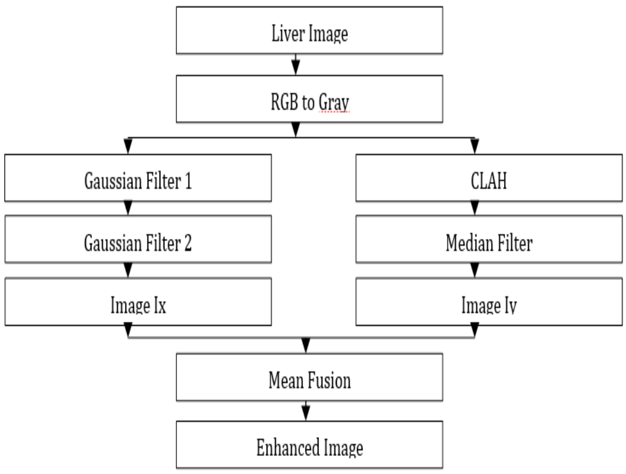
$$I_{guass}(x,y) = (Im(x,y) * G(x,y)) * G(x,y) \quad (1)$$

Where Im is original image and G(x,y) is Gaussian filter.

$$G(x,y) = \frac{1}{2\Pi\sigma^2} e^{\frac{x^2+y^2}{2\sigma^2}} \quad (2)$$

Equation 2. gives the formula for Gaussian filter. Where, σ stands for standard deviation of the Gaussian distribution (σ =0.5), and represents the position of pixels in Gaussian window.

In proposed method Gaussian filter is applied two times in series over original image to obtain image Ix as shown in Fig. 2.



3.2 CLAH(Contrast Limited Adaptive Histogram Equalization)

Histogram equalization is used in image processing in order to smoothen the contrast of entire image [17]. If the image is too white or too dark, histogram equalization is applied to normalize the contrast of image to make it look smooth. In our method we have chosen CLAH, in which the entire image is divided into small tiles and adaptive histogram is applied over each tile. A tile is small portion of an image.

3.3 Median Filter

Median Filter is used to remove salt and pepper noise present in the image. Median filter is also a non-linear filter used to remove noise from a image. It works by moving through the image, pixel by pixel, replacing each value with the median values of neighbouring pixels. It is also very effective in remove majority of irregularities from the input image. Equation 3. specifies median filter.

$$I_{med}(u,v) = median(I(u+i, v+j) \mid (i,j) \in R) \quad (3)$$

Here, u and v indicate the pixel position in image, i and j is pixel position in median filter window, and R is radius of median filtering window. The proposed method gives better performance for R=1 i.e. 3x3 window.

CLAH is applied on original image, then median filtering is applied on the image generated after applying CLAH. This image is referred as Image Iy.

3.4 Mean Fusion

The mean fusion techniques combine the edge smoothen image and contrast and texture enhanced image to provide final enhanced image as shown in fig. 2. Equation 4. specifies mean fusion technique used to obtain enhanced image.

$$I_{enhance} = \left(\frac{I_{gauss} + I_{med}}{2} \right) \quad (4)$$

4 Parameter Tuning

For obtaining the best results from above mentioned filters, following parameters were selected and results were verified for different values of below mentioned parameters. Upon conducting rigorous testing, best results were obtained for following parameters.

4.1 Gaussian Filtering

- Window size= 3x3 pixel (test were conducted on 3x3, 5x5, 7x7)
- б=0.5 (standard deviation)
- Stages of Gaussian filtering=2

4.2 Median Filtering

- Window size= 3x3 pixel (test were conducted on 3x3, 5x5, 7x7)

4.3 Contrast Limited Adaptive Histogram Equalization

- Tile size= 8x8 pixel (It is used while the image is divided into tiles for applying CLAHE.)
- Clip Limit – 40 (This parameter sets the threshold for contrast limiting)

5 Performance Evaluation Parameters

For evaluating the performance of proposed method, following evaluation parameters were selected

5.1 Mean Square Error(MSE)

Mean square error calculates the error between each pixel for the two images that are being compared. One of the images is the original image and the second one is the pre-processed. Low Value of MSR indicates better image quality. Equation 5. MSE is calculated as specified in equation in Equation 5.

$$\mathrm{MSE} = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - k(i,j)]2 \quad (5)$$

Where m, n, i and j are pixel positions for image I and K. Image I is original image and K is image under observation. Achieved value of MSE for proposed approach is 0.13.

5.2 Peak Signal to Noise Ratio(PSNR)

PSNR is commonly used to quantify the reconstruction quality for images. It is a logarithmic value defined in decibel(dB) [18].PSNR is an expression for the ration between the maximum possible value of signal and the power of distorting noise that affects the quality of its representations. Different applications have different range for desired PSNR value. For our application the desired range lies between 40 to 60 dB. Higher value of PSNR within range indicates better quality of picture. PSNR is calculated as specified in Equation 6.

$$\mathrm{PSNR} = 10\log10\left(\frac{2^b-1}{\mathrm{MSE}}\right) \quad (6)$$

Where MSE stands for Mean Square Error. Achieved value of PSNR for proposed approach is 57.56dB.

5.3 Structural Similarity Index Matrix(SSIM)

SSIM is for measuring the similarity between two images. SSIM is opposite of MSE, as it tries to find out the similarity between the pixels of two images we are comparing. Higher value of SSIM indicates better image quality. SSIM is calculated as specified in Equation 7.

$$\mathrm{SSIM}(x,y) = \frac{(2\mu x\mu y + c1)(2\sigma xy + c2)}{(\mu x^2 + \mu y^2 + c1)(\sigma x^2 + \sigma y^2 + c2)} \quad (7)$$

Where, μx and μy are average of x and y. σx2 and σy2 are variance of x and y and σxy is co variance of x and y. c1 and c2 are two variables to stabilize the division with weak denominator. Achieved value of SSIM for proposed approach is 0.85.

6 Comparison of Performance with State-of-art

We compare the performance of proposed method with other state-of-the-art methods. In the following table we have mentioned the work of author's who have used Gaussian, median and CLAHE filter for pre-processing images. These filters and used in wide range of applications and different evaluation parameters are used to validate results. Table 1. presents our findings.

Table 1. Comparison of Performance with other state-of-the-art approaches

Author	Application	MSE	PSNR	SSIM
Sreejith &Nayak(2020)	Digital Image Processing	NA	19.89	NA
Gedraite & Hadad(2020)	Blur image pre-processing	NA	54.63	NA
Pawar et al. (2017)	De-noising MRI and CT Images	NA	30.86	.81
Proposed Method	De-noising liver CT images	0.13	57.56	.85

7 CONCLUSION

Medical images are prone to noise. Noise can be added at the time of image acquisition due to technical error or environmental error or human error. Whatever may be the cause, it is important to remove noise from the medical images before they can be used for computer aided diagnostics. A pre-processed image increases the accuracy of classification and segmentation. Proposed method of Liver CT image pre-processing has shown promising results as the method achieved MSE= 0.13, PSNR = 57.56 dB and SSIM = 0.85. Image obtained from the pre-processing step can be given as input to either segmentation algorithm or classification algorithm. Proposed technique can be developed in future for use on other modalities of medical imaging such as Magnetic resonance imaging and Positron emission tomography images.

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