Image deconvolution as an aid to feature identification : a clinical trial

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ABSTRACT

The focus of this paper is to evaluate the clinical performance of the image processing technique which we have developed for computed radiography x-rays. This algorithm, which was presented at the SPIE '99 medical imaging conference, uses iterative deconvolution with a measured point spread function to reduce the effect of scatter. Wavelet denoising is also carried out after each iteration to remove effects due to noise. A random selection of chest x-rays were processed using the algorithm. Both the raw and processed images were presented to the radiologists in a random order. They scored the images with regard to the visibility of anatomical detail and image quality as outlined in the european guidelines on quality criteria for diagnostic radiographic images. The most notable result of the technique is seen in the reduction of noise in the processed image.

Keywords: clinical trial, computed radiography, deconvolution, wavelet denoising

1. INTRODUCTION

Computed Radiography (CR) is a revolutionary development for the entire radiology department. It involves projection x-ray imaging using a photostimulable phosphor plate rather than film as a detector. The photostimulable phosphor plate is placed inside the CR cassette. The x-rays that are incident on the plate form a latent image in the plate. The plate is then placed in a CR scanner; where a laser light stimulates the particles in the plate to luminesce. This light is collected using a light guide and a photomultiplier tube and is converted to a digital signal. This image can then be displayed digitally.

The effectiveness of these digital images is limited in two ways. Spatial resolution is the first limitation. X-rays are used to identify tiny features eg. hairline fractures in bone. In this case the limiting spatial resolution of an x-ray image means that fractures must be of a certain size before being detectable by the digitised image. Secondly, there is little difference in density between normal and tumerous tissue so the contrast range of the image implies that a tumour may only be visible on the image when it exceeds a certain density. Computed Radiography images have an extremely wide exposure latitude (approx. 4000 grey levels) when compared to screen film (approx. 200 grey levels). This is due to the large bit depth of the digitised images ie. 12 bit images. This means that CR can provide diagnostic quality images even when the plate has been underexposed or overexposed. It also allows the creation of single exposures which show both bone and soft tissue. Also, tissues of little density difference (eg. malignant and non malignant tissues) may be identified. On the other hand, the spatial resolution of CR images (at 2-3 line pairs per mm) is very low compared to that of screen film systems (at 10-15 lp/mm). This limitation is due to the finite pixel size on the phosphor plate.

In a previous paper[1] we have proposed an image processing algorithm which could be applied to Computed Radiography images to improve the spatial resolution of these images. The purpose of the work in this paper is to assess the clinical value of this algorithm. An improved quality resultant image should improve clinical acceptance of CR. This is important as the benefits of CR in a hospital are many. One of the greatest benefits of an improved CR image is in the Accident and Emergency department of a hospital. Many radiologists have commented that while emergency medicine specialists are very proficient at reading trauma x-ray images, they lack the necessary training to identify subtle changes.[2] A+E staff also work under very stressful conditions which doesn't allow them to spend much time on diagnosing x-ray images. In this situation a high quality post processed image, in which subtle features are more prominent, would assist greatly in improving the quality of diagnosis.

2. IMAGE PROCESSING ALGORITHM

The image processing algorithm which we use is described in detail in the SPIE '99 paper.[1] Briefly, it corrects the x-ray image for degredation due to screen unsharpness,i.e. the instrumental component of the point spread function, and for noise. Digital radiography systems presently in use are based upon light conversion technology. As with a traditional film/screen system, a phosphor screen is used to convert incident x-ray photons into visible light to create an optical image. This is then recorded using a photo-electric detector such as a CCD or photodiode array. The resolving power of these systems is limited by the scattering of visible light within the phosphor screen, and additionally by the light coupling stage.[3]

The noise in the digitised radiographic images, which we want to correct for, can be associated with three main sources:

- Quantum mottle
- Noise induced when phosphor plate is being scanned
- Noise amplification after the deconvolution algorithm is applied

Quantum mottle is the most significant source of noise and is caused by a statistical fluctuation in the number of photons that exit the patient and is a limiting factor in x-ray imaging. It can be regarded as fluctuations in the brightness of the image. The standard deviation for x-ray photon statistics can be calculated by $SD = \sqrt{N}$, where N is the total number of photons.

The importance of quantum mottle tends to be much greater for small objects than for large ones because larger structures have both inherent subject contrasts and cover larger areas. The signal to noise ratio is directly dependant on the square root of the radiation exposure. Hence increasing the exposure can increase the SNR but this also increases the dose to the patient. The latent charge image on the surface of the phosphor plate is read out by discharging the image pixel by pixel with a pulsed laser beam. A standing charge bias remaining after the x-ray exposure introduces a discharge noise not correlated with the x-ray signal. Commonly, image restoration algorithms suffer from amplification of noise as the number of iterations is increased. In effect, noise present in the original image is mistaken for high frequency features.

In order to estimate the object image, O(x,y), from the observed image, I(x,y), we use a technique known as regularised deconvolution. This involves iteratively deconvolving the observed image with a measured point spread function, P(x,y). A wavelet denoising algorithm is applied to the residual between iterations. The residual is defined as

$$R^{(n)}(x,y) = I(x,y) - P(x,y) * O^{(n)}(x,y) \qquad (1)$$

where $O^{(n)}(x,y)$ is the object estimate at the nth iteration.

Specifically the algorithm performs a hard threshold of the wavelet coefficients of the residual. The threshold level is set by a study of variation of Gaussian noise in this wavelet space. Although the algorithm proposed by Stark et al[4] is effective, it is computationally demanding due to the redundant á trous wavelet transform applied. In addition, the method used to set the denoising threshold is based on the assumption of Gaussian noise. In order to improve upon this, we have developed an algorithm based on a non-redundant transform - the Daubechies wavelet[5] which is more efficient in terms of storage. A wavelet of level 4 was used and hence 4 levels of decomposition were carried out. A constant threshold was applied to all bands. We denoise the residual between iterations by using a soft thresholding (wavelet shrinkage) which is statistically more attractive than hard thresholding.[6] We select the level dependent soft threshold as a fraction k of the wavelet coefficient standard deviation.

This algorithm provides a better estimate of the object image by reducing the effects due to scatter and noise in digitised clinical images.

3. CLINICAL IMAGE ASSESSMENT

Since an x-ray image is a means of visually representing the clinical information captured by the x-ray equipment, at some stage quality must be based on the judgement of a human observer. We approach this by using relative measures of quality. We ask the radiologists to assess different criteria on the image and to assign a scale value to these specific features in the image.

In order to assess the impact of the processing algorithm on clinical images, Guidelines on Quality Criteria for Clinical Radiographs[7]were used. These guidelines have been developed by the Commission of European Communities (CEC). They set out diagnostic requirements for a radiograph of a normal adult for common examinations (CEC, 1996a). Image criteria refer to characteristic features of the normal radiographic image whose degree of visibility is conveyed by the following expressions.[8] *Visualisation*, an atomical feature is detectable but tdetails are not fully reproduced. *Reproduction*, the details of anatomical features are visible but not necessarily clearly defined. *Visually sharp reproduction*, the anatomical details are clearly defined. These criteria account for patient positioning as well as image quality. In our case we only take into account those factors which deal with the quality of the image as shown in Table 1.

Table 1. Diagnostic requirements for a Chest PA projection (CEC, 1996a)

Image criteria
Visually sharp reproduction of the vascular pattern in the whole lung, particularly the peripheral vessels
Visually sharp reproduction of the borders of the heart and the aorta
Visualization of the retrocardiac lung, spine and mediastinum

4. METHOD

4.1. Image Selection

The present work involves assessing CR posteroanterior chest images which were obtained in an x-ray department in one particular day. These chest examinations were performed on adult outpatients (of both sexes) who required radiology for diverse pathologies. Ten of these images were randomly chosen by an independant observer who didn't take part in the experiment.

The chest examinations included in this trial were obtained using x-ray equipment with a high frequency generator and were exposed at 125kVp. All images were processed using the same processor (Agfa). For the purpose of this trial the raw format of the image was obtained i.e. no inherent processing was carried out on the image by the Agfa processor. The reason for doing this is that the PSF is measured for a raw image and in order for the algorithm to perform accurately the conditions in which the PSF is measured must remain constant with the conditions in which the image is taken.

Each of the ten chest images were processed using the regularised deconvolution algorithm. It was found that 15 iterations of the algorithm produced the best supression of noise without affecting the anatomical detail. Hence, each digitised x-ray was processed using 15 iterations. This task was carried out on a DEC Alpha workstation. It was very computationally intensive because image size was 3730 x 3062 pixels and 12 bits deep i.e. 4096 grey levels.

4.2. Image Evaluation

This study was designed to obtain an evaluation of visualised anatomical detail and an overall assessment of image quality in a processed x-ray compared to an unprocessed x-ray. The twenty x-rays[9] (10 unprocessed, 10 processed) were placed in a random order and given code names so that when the image was presented, the radiologist was not told whether it was a processed or an original image. This was done because the more objectively an outcome can be assessed, the less likely observer bias will be.[10]

Three radiologists took part in the trial. All reading sessions were performed under low ambient light conditions. The radiologists were presented with digitized chest x-ray on an "interface" called saoimage. This allowed them to zoom in and out on any part of the image and also allowed them to adjust the contrast settings to give them the best possible visibility. The time spent reading each image was unlimited.

The radiologists were asked to score five criteria for each image on a rating scale of 1 to 5 (1=poor and 5=excellent). Along with the criteria listed in Table 2, two more criteria, namely contrast and noise, were added to the list. If the processed image was given a higher score than the original image then this was termed an improvement. If the situation was reversed, this term was given a negative value.

4.3. Statistical Analysis

For each image criteria and each reader, all improvement scores were calculated, summed and an average improvement score calculated.

5. RESULTS

The results obtained are presented in Table 2. The results are reported as a score out of five. This method is used as because we are depending on human interpretation of image quality, this scale is non linear.

Table 2. Results of the clinical trial

Image criteria	Orig Image (Mean score)	Mean Improvement	Std Error
Vascular lung	2.6	0.5	0.3
Borders of heart and aorta	3.6	0.2	0.3
Retrocardiac lung, spine and mediastinum	2.7	0.2	0.2
Contrast	3.2	0.3	0.2
Noise	3.4	0.6	0.2

The results show that for all the image criteria scored an improvement is seen. Visibility of the vascular lung detail is significantly improved when the x-ray is processed. This is an important factor as many lung diseases are diagnosed in the vascular lung area. In the reproduction of the border of the heart and the aorta there was a slight but insignificant preference for the processed image. The visualisation of the retrocardiac lung, heart and mediastinum were often judged equivalent. Significant improvement in image contrast and noise was noted on the processed x-rays. This shows the accuracy of the noise reduction in the algorithm. In general the algorithm worked very well in balancing noise reduction with improved visibility of anatomical detail in the x-rays.

An example of a section of an unprocessed chest examination and the processed image which was included in the trial is shown in Figure 1 and Figure 2. The vasular lung detail is clearly more prominent in the processed image. The processed image also demonstrated an improvement in the contrast between the rib structure and the vascular lung. The noise structure is notably more smoothed in the processed image.

6. CONCLUSION AND FURTHER WORK

We have demonstrated that the regularised deconvolution algorithm which we have developed is very successful. It enhances the digitised x-ray image to the extent that definite improvements in overall image sharpness and noise quality is noted by radiologists. These effects are achieved without altering the visibility of anatomical detail, a problem which is associated with other deconvolution techniques. This trial is a preliminary trial which demonstrates that the algorithm has achieved a significant improvement in image quality. A larger trial is currently underway, the results of which will be presented at the conference.

The original deconvolution was performed using two 533MHz DEC Alpha processors. Each image took roughly 14,000 seconds to process, however the parallel algorithm employed is readily portable to configurations with more processors. In this way we should be able to deliver processed images within a few minutes of the x-ray being taken. Finally in the future we intend to extend our analysis to include a more appropriate spatially variant PSF - our parallelisation method makes this possible without any increase in execution time.

Figure 1. Left side of an unprocessed chest x-ray

Figure 2. Left side of a chest x-ray processed using regularised deconvolution

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