A IMAGE PROCESSING METHOD FOR COMPARISON OF MULTIPLE RADIOGRAPHS

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Abstract: Portable chest radiography is the most commonly ordered radiographic test in the intensive care unit (ICU). In the ICU, a succession of portable images is usually taken over a period of time to monitor the progress of a patient's condition. A prompt diagnosis of any changes in the conditions of these ICU patients allows clinicians to provide immediate attention and treatments that are required to prevent the conditions from worsening and which could result in a treat to the patient's life. However, because of differences in X-ray exposure setting, patient and apparatus positioning, scattering, and grid application, for example, differences in image quality from on image to the next taken at different times can be significant. The differences in image quality make it difficult for clinicians to compare images to detect subtle changes. This paper presents an image-rendering method that reduces the variability in image appearance and enhances the diagnostic quality of these images. Use of the presented method allows clinicians to detect subtle pathological changes from one image to the next, thus improving the quality of patient management in the ICU.

1 INTRODUCTION

In the ICU, clinical evaluation can rely heavily on diagnostic images such as portable chest radiographic images. The successive diagnostic images taken by a portable computed radiography (CR) system are helpful for indicating significant pathological changes of the patient, such as a collapsed lung or and improper tube placement within the patient.

However, image differences owing to different exposure settings, or patient and apparatus positioning, limit the accuracy of image comparison in the ICU, even for those images obtained from the same patient over a short treatment interval. Obviously it constrains the ability of the clinician to subtle changes that can be highly significant. An important problem is allocating the output dynamic ranges to display the clinically important part of the input code values. The process of selecting the relevant sub-range of input code values and constructing the proper mapping function from the input code values to the output display media is termed a tone-scale adjustment. Using a tone-scale method in CR images provides an optimal rendering result (Lee and Barski, 1997). There are also other methods (Barski and Metter, 1998) that provide improvements in contract enhancement for diagnostic imaging.

However, these methods do not address the problem of consistent rendering between images of the same patient taken at different times. Application of such tone-scale techniques is not likely to provide consistent rendering results, which makes accurate changes assessment by the ICU clinician difficult.

In this paper, we present a region of interest (ROI)-based lookup table (LUT) mapping method for diagnostic images that provides a consistent rendering result for images taken of the same patient at different times. This will help the clinicians compare images and track patient progress. First is a background segmentation step when the background of all the images (that may have different amounts of background content or no background content) are segmented. In the ROI selection step, the ROI region is located. These are the images of the tissue parts that are critical for clinicians to make a correct diagnosis. Next, an LUT constructed for the pixel values in the ROI. Then a toe-shoulder construction step is taken, constructing a LUT for very dark and very light regions. In the LUT mapping step, the pixel values in the input images are mapped to the corresponding pixel values in the output image.

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The structure of this presentation is organized as follows: in section2, we introduce why and how the ROI is selected. In section3, the ROI-based LUT construction method is presented. Section4 reports the performance comparison result of the current method and of baseline method. Finally, the conclusion is drawn in Section 5.

2 AUTOMATED ROI SELECTION

After doing a background segmentation based on ICU's image histogram and difference histogram (Kuhn, 1999), we get an appropriate threshold for removing the background. A region-labeling operation can be done to prevent over-segmentation. Then we perform the automated ROI selection.

In ICU images, the position of the parts necessary for the clinicians' diagnosis varies. In some cased, they will only take up a little part of the image. The basic principle of automated ROI selection is to identify the RIO in each image automatically and adjust the image contrast values within the ROI to a suitable range for each image, so that comparison of one image to another is feasible.

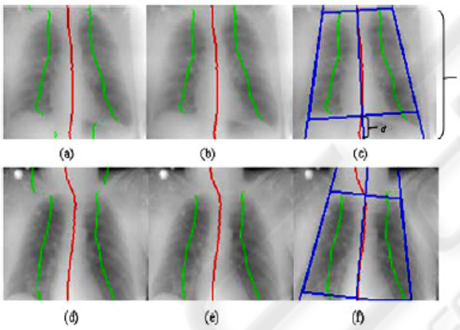

Figure 1: Automated region of interest selection; this is an example of selecting similar regions of interest for two images of the same patient.

ROI identification located key features (lung line, spine line) in an image and allows the correlation of two or more images accordingly. Figures1(c) and (f) show two chest X-ray images of the same patient with two automated regions of interest (ROI) selected.

First we use a median filter to resize the image, then a Gaussian filter for noise removal. Next, the locations of the spine line and lung line are detected (Amit and Mark, 2005). Fig.1 (a) and (d) show the spine and lung line detection. We search for the highest/lowest mean column value row by row. Connecting these points, we validate the lung line step (Fig.1 (b) and (e)), and combine and validate similar lung line parts based on gray-level and position.

With the approximate lung line and spine line determined, a spine-line-fitting step can be executed. This is performed by doing an iterative of the spine-line-fitting step. We search all the rows between the top and bottom of the lung lines. We then choose the fitting result that has the lower mean residual form these two. We then can get a trapezoid ROI for all the images of the same patient based on the spine line and the distance of the spine line to the lung line.

3 ROI-BASED LUT CONSTRUCTION

Once one or more ROIs have been identified, we can do the ROI-based LUT construction step.

First we identify the primary area o the image from the histogram data that is related only to the ROI. Points lp and rp represent left and right points, respectively, of the histogram data that is from the main range (2.5%-95%) in the ROI. After that, for each image, left points lp1 and lp2, and right points rp1 and rp2, are obtained. The goal of next few steps is to remap left points lp1 and lp2, and right points rp1 and rp2, to the corresponding points A1 and A2, in order to form consistent images in the output images.

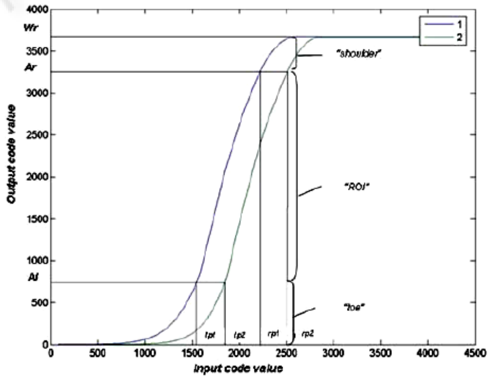

Figure 2: Lookup table construction.

Figure 2 shows how various portions of the image are remapped for consistent rendering. We can map the right point rp, obtained from the ROI of each input image, to the same value Ar in the output image that has been determined for the same patient. However, to accommodate the difference in patient position between two images of same patient, we proposed to use Ar for each image. Here, the diaphragm in Fig.1 (a) is higher that that in Fig.1 (d). This difference can be best expressed by means of a proportion of distance d to column length Lc for each image as illustrated in Fig.1.

Given these considerations, Ar can be calculated using the following calculations to adjust the difference in patient position:

$$Ar_1 = p_1 \cdot \left(\frac{d}{L_c}\right) + p_2; Ar_2 = p_1 \cdot \left(\frac{d}{L_c}\right) + p_2; \qquad (1)$$
$$Ar = (Ar_1 \cdot t) + Ar_2 \cdot (1-t) 0 \le t \le 1$$

Where d and column length L_c are illustrated in Figure 1. p_1, p_2 and t are empirical parameters.

In out method, features used to determine the value Al include the difference $rp - lp$, and the value of $rp - lp/(spinedifference)$:

$$x = \overline{rp - lp}; Al' = ax^2 + bx + c$$
$$pdark = \frac{\overline{rp - lp}}{spdv - spuv} \qquad (2)$$
$$Al = Al' + \max(a_1, \min(a_2 \cdot (pdark - a_0), a_4))$$
$$Al = \max(\min Al, \min(\max Al, Al))$$

$a, b, c, a_1, a_2, a_0, a_4, \min Al, \max Al$ are empirical parameters and $spdv, spuv$ (spine down-part value and spine up-part value) are the main gray-level range in the spinal region (10%-80%), which can be detected automatically. Note that the A1 can be justified differently by the ratio of $pdark$ for each image. Here we choose the same Al for all the images from the same patient.

After we get lp, rp, Al, Ar for each image, the LUT construction between lp and rp to Al and Ar can be applied. The mapping from $[lp, rp]$ to $[Al, Ar]$ is established based on the active rate (Lee, 2004) calculated in equation (3).

$$Activity[k] = \frac{\sum_{(i,j)\in ROI, img(i,j)=k} \sum_{u=i-3}^{i+3} \sum_{v=j-3}^{j+3} H(u,v,i,j)}{h(k)}$$

$$ActNor[i] = \frac{\ln\left(\frac{\sum_{i=-t}^{t} Activity[i+t]\cdot h[i+t]}{\sum_{i=lp}^{rp-1} h[i]} + 1\right) + 1}{\sum_{i=lp}^{rp-1} \left(\ln\left(\frac{\sum_{i=-t}^{t} Act[i+t]\cdot h[i+t]}{\sum_{i=lp}^{rp-1} h[i]} + 1\right) + 1\right)} \qquad (3)$$

$$when hl \le |img(i,j) - img(u,v)| \le hr, H(u,v,i,j) = 1$$

$activity[k]$ is the activity of intensity k and h(i) is the number of the pixel at that intensity.

Figure 3 shows an ICU image's active rate and example of LUT construction using equation(4) considering the active rate.

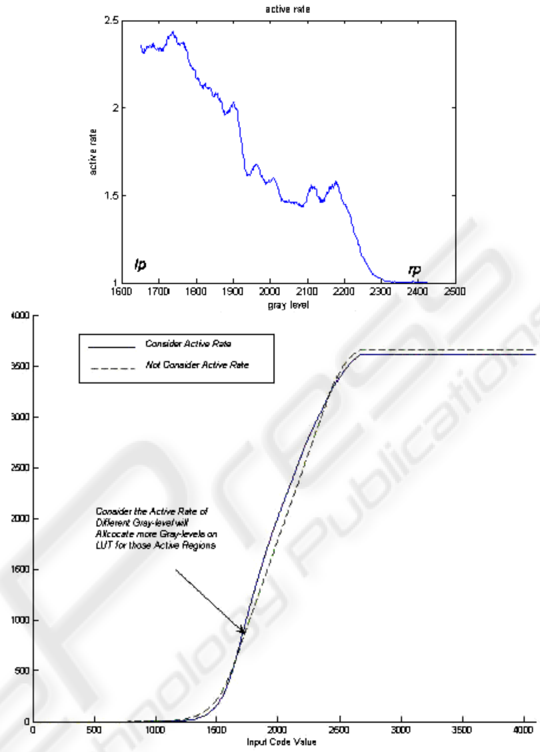

Figure 3: Active-rate in LUT construction.

$$LUT(lp) = Al$$
$$LUT(i+1) = LUT(i) + ActNor(i)(Ar - Al)ratio$$
$$+\left(\frac{(Ar - Al)(1 - ratio)}{rp - lp}\right) \qquad (4)$$
$$Here, 0 \le ratio \le 1, when ratio = 0$$

In addition to mapping the ROI of the image, for darker or brighter regions, a toe-shoulder LUT construction step was performed for additional mapping, such as the toe region and the shoulder region in the LUT curve in Fig.3. The toe region was constructed for mapping the dark area in the image and the shoulder region was constructed for the bright area in the image.

4 PERFORMANCE

We collected 83 portable X-ray images from 19 patients. There were two to nine images of each patient. An experienced chest radiologist reviewed all the images from the 19 patients and provided a diagnosis that included the types of diseases detected and any change in a patient's condition (improved/worsened). We compare the presented method with a baseline image enhancement technique that is an image optimization technique based on single image (Barski and Metter, 1998). An evaluation of the images from the 19 patients was performed in order to compare the overall consistency in the image and the lung areas as well as the ability to detect changes in patients' conditions against the radiologist's diagnosis.

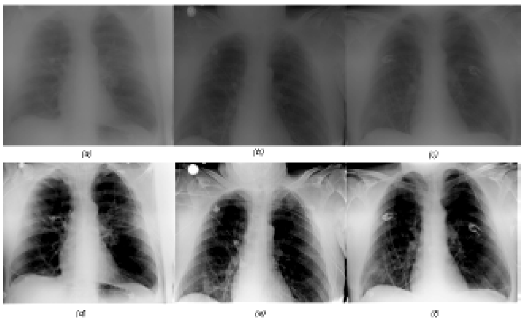

Figure 4: Processed image of the same patient. (a), (b), and (c) are raw images of the same patient, and (d), (e) and (f) are the processed result using the current method.

Figure 4 shows the processing result examples of a patient's ICU chest X-ray images. In the evaluation, all of the processed images form each patient were presented to a radiologist in the order of the processed images form the baseline method first and next the processed images from the presented method. The radiologist gave a rating on a 5-point acceptability scale where 1 is not acceptable and 5 is outstanding in terms of the consistency rendering effect demonstrated among the images presented for diagnostic purposes. Table 1 is the evaluation result. A t-test is also done to compare the baseline and current methods.

5 ROI-BASED LUT CONSTRUCTION

Our image-rendering technique reduces the variability in the image appearance caused by the differences in patient or apparatus positioning and image acquisition parameters. The improved consistency over the baseline image enhancement technique can potentially improve the overall workflow and patient management.

Thus, it is a method for enhancing diagnostic images taken at different time in order to provide consistent rendering for regions of interest.

Table 1: The evaluation result.

	Patient Number	Score					Average	T-test
		5	4	3	2	1		
Current Method	19	9	8	1	1	0	4.32	Accept P-Value =0.039
Baseline Method	19	2	9	5	3	0	3.52	
	Image Number	Score					Average	T-test
		5	4	3	2	1		
Current Method	83	42	30	9	2	0	4.35	Accept P-Value =0.0034
Baseline Method	83	27	34	17	4	1	3.99	

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