AUTOMATED DETECTION OF SUPPORTING DEVICE POSITIONING IN RADIOGRAPHY

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Abstract: Portable X-ray radiographs are heavily used in the ICU for detecting significant or unexpected conditions requiring immediate changes in patient management. One concern for effective patient management relates to the ability to detect the proper positioning of tubes that have been inserted into the patient. These include, for example, endo-tracheal tubes (ET), feeding tubes (FT), naso-gastric tubes (NT), and other tubes. Proper tube positioning can help to ensure delivery or disposal of liquids and air/gases to and from the patient during a treatment procedure. Improper tube positioning can cause patient discomfort, render a treatment ineffective, or can even be life-threatening. However, because the poor image quality in portable AP X-ray images due to the variability in patients, apparatus positioning, and X-ray exposure, it is often difficult for clinicians to visually detect the position of tube tips. Thus, there is a need for detecting and identifying tube position and type to assist clinicians. The purpose of this paper is to present a computer-aided method for automated detection of tubes and identification of tube types. Use of this method may allow clinicians to detect the tube tips more easily and accurately, thus improving the quality of patient management in the ICU.

1 INTRODUCTION

Computer-aided diagnosis is designed to help physicians improve the diagnostic accuracy of radiological images and for detection of the disease, and to explain the consistency, reduce the rate of misdiagnosis, and cause less opportunity for eye fatigue. The chest CAD system (Brem and Baum, 2003) and the Mammography CAD system (Bram and Bart, 2001) are both used in clinics. Clinical results show two aspects: Medical diagnostic radiology consults the CAD output and it is thus easier to find more features, such as micro-calcifications and the changes that have taken place in the tiny structures, greatly improving the efficiency and accuracy of diagnosis. We research the method of tube automatic detection for improving the quality of patient management in the Intensive Care Unit (ICU) (Doi and MacMahon, 1999).

ICU patients, particularly those with heart and lung diseases, rely on the existence of tubes to live and be treated. In the intensive care setting, catheters, tubes, and monitoring devices play an important role. Proper placement of these devices is crucial to their function Personnel are well aware of the need for timely medical ICU care for patients, correct placement of tubes, and the changes that need to be made around these tubes' positions. If the computer can automatically identify the location of tubes and their tips, and enhance medical images around tubes to provide diagnosis, it is a clear and very important improvement to their procedures.

ICU patients' chest X-ray images can be fuzzy, exhibit low contrast and noise, and contain many different types of tube connections on the image, such as the endo-tracheal tube, feeding tube, naso-gastric tube, pulmonary artery, central venous catheter, and other catheters required for the treatment of a variety of medical conditions. These bring a significant challenge to accurately detect tubes and their tips. Figure 1 shows a general original ICU chest image.

2 METHODS AND MATERIALS

We collected a database consisting of 107 portable X-ray images from 20 patients using Kodak's computed radiography (CR) system. An experienced

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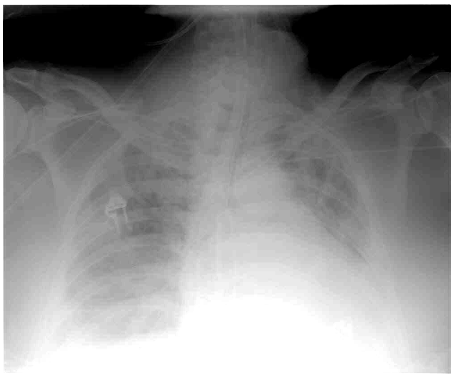

Figure 1: Original ICU chest X-ray image.

chest radiologist reviewed all the images from the 20 patients and provided a diagnosis for each image including the types of tubes and locations of their tips. The technique we developed here was evaluated for the detection of the three commonly used tubes in the ICU, the endo-tracheal tube, the feeding tube, and the naso-gastric tube. In this database, 33 images were identified to have endo-tracheal tubes, 54 with feeding tubes, and 22 with naso-gastric tubes. This technique will be used and evaluated for the detection of other tubes/lines in the future.

Figure 2 lists the steps used in the automated detection method. In the image-processing step, the contrast-limited adaptive histogram equalization (CLAHE) (Pizer and Amburn, 1987) (Zuiderveld) is used to enhance the contrast, and the anisotropic filtering is used to remove the noise prior to the generation of a gradient image. CLAHE can enhance the contrast details of the regions and avoid noise amplification as a result of histogram equalization in a similar region. As with the general histogram equalization, which can change the grey scale of the image to enhance the contrast, its distinction is that the operation region is a small region from which the whole image is divided, and then merged together again as the whole image and using bilinear interpolation between two neighbourhood intercropping to eliminate false results of the border reduced by histogram equalization. The combination of a canny filter (Parker, 1997 and Canny, 1986) and Hough transform (Kamat and Ganesan, 1998) is then applied to detect edges and lines on the tiles of an enhanced gradient image. A whole gradient image is divided into many tiles for performing Hough transform. The tube in a small tile can be considered a straight tube. The double-line/edge criteria are applied to identify potential tube candidates by paring a detected "left" edge with a "right" edge (See Fig.3). Theoretically, the paired left and right edges should have a fixed distance between them and each should have a gradient with an opposite direction (i.e., G, -G). Therefore, tubes' edges should be basically parallel so it can be determined which tube is the valid one (See Fig. 4). Further, we apply bilateral Hough transform to detect the missing lines between potential tube candidates.

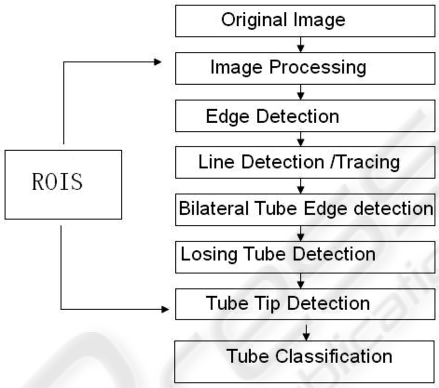

Figure 2: Tubes' automatic detection flowchart.

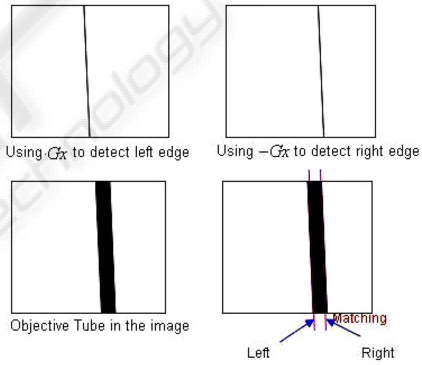

Figure 3: Tube matching.

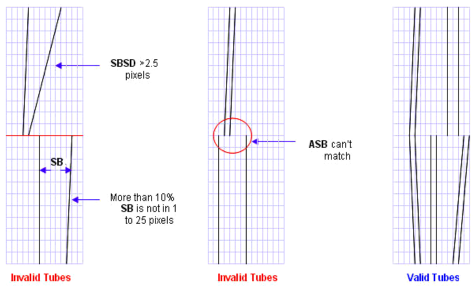

Figure 4: Determine the valid tube.

Note: SB is the abbreviation of Space Between. SBSD is the abbreviation of Space Between Standard Deviation. ABS is the average of SB.

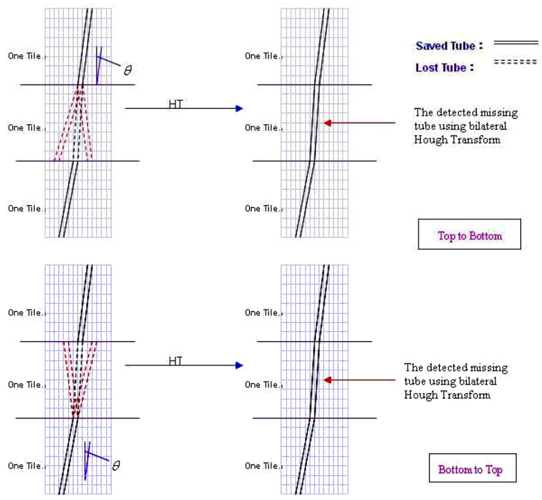

Figure 5: Bilateral Hough transform.

Figure 5 shows the detected missing/lost lines between the two potential tubes identified in the previous step. Bilateral HT: Using the tube's grey gradient (left is Gx and right is –Gx) to do bilateral Hough Transform. The paired left and right edges should have a fixed distance between the two edges and each should have a gradient with an opposite direction. The detected tube's size is assumed as the distance. Basing the detected tube's position, we do the bilateral Hough Transform to gradient image from top to bottom, then from bottom to top. After doing the bilateral Hough transform, we can locate the missing tubes.

In a small tile each to be linked with at least the boundary line is another small tile. In other words, the starting point of the boundary line and the end point of another boundary line must be in one pair of neighbouring tiles. The connective tubes' directive angle difference should be in pi/24. The tubes on the images are consistent. When detecting ET, only the isolated tube in the region of interest (ROI) upper part is valid. If a tube can connect with more than two tubes, we will choose the tube that bears a closer directive angle. See Fig. 6.

Tip detection is an important element of our work. Combining the region's information and anatomic structure, we use our algorithm (See Fig. 7). The tubes' edges should be crossing or the tube size should be less than the defined size (i.e., ET, NT: 3-10 pixels , FT: 15-25 pixels). (See Fig. 7: Case 1-2). We use the proper bilateral Hough Transform to stretch or shrink the tube for getting an accurate tip (See Fig. 7: Case 3).

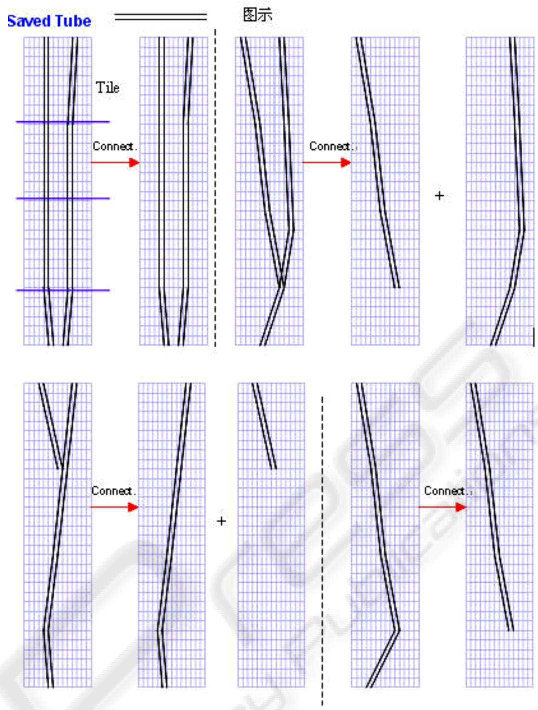

Figure 6: Tubes' connection.

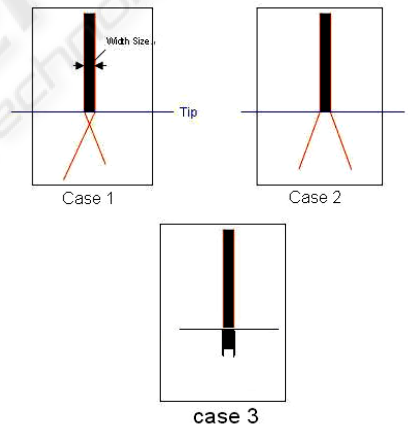

Figure 7: Tip detection.

After determining the tip, a classification step is executed to provide a decision on apparent tube type for the matched pairs of left and right edges. Information such as the length of the line, the location of the tube, and/or the tip relative to anatomic structures is used for classifying the tube types. The ROIs containing relevant anatomic structures, such as lung, mediastinum, and stomach, are identified and used to determine the relative position of tubes in the image. These ROIs serve as landmarks for tube detection and classification.

3 RESULTS

The detection result can be illuminated. See Fig.8-12. We evaluated the performance of the technique for ET, FT, and NT. Our preliminary results showed that use of the presented technique correctly detected the location for 94% of the 33 ET tubes, 82% of the 54 FT tubes, and 82% of the 22 NT tubes with no false positive detection (See Table 1). The performance is expected to improve when detection results from the same patient are used.

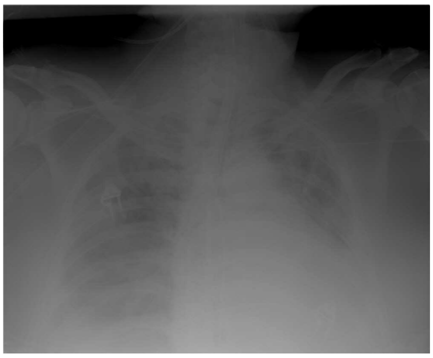

Figure 8: The original X-ray chest image.

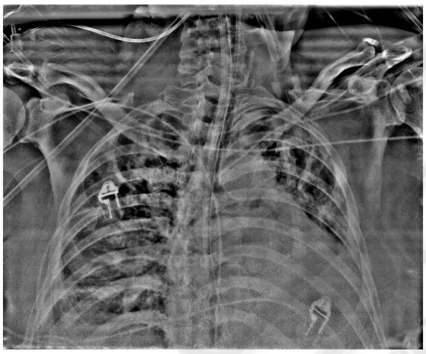

Figure 9: Image pre-processing (CLAHE)

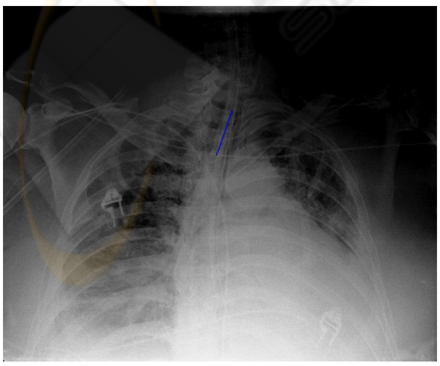

Figure 10: ET detection

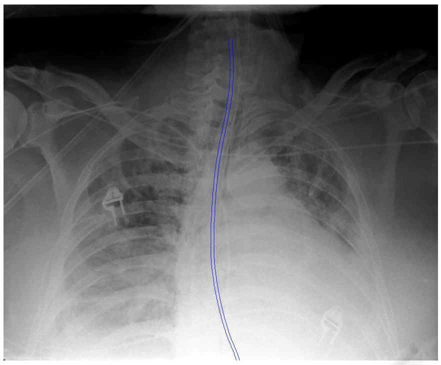

Figure 11: FT detection.

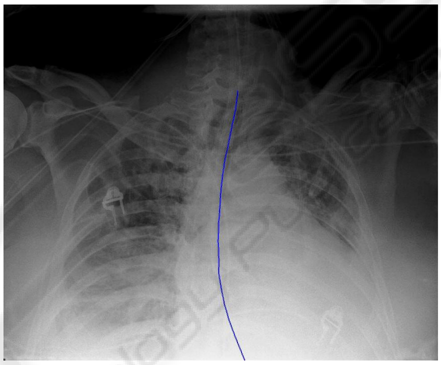

Figure 12: NT detection

Table 1: The result table.

107 images of 20 ICU patients, and the images were captured by portable CR system of Kodak			
	ET	FT	NT
Tube amount	33	54	22
Detection rate	94%	82%	82%

4 CONCLUSIONS

Our novel detection technique can accurately detect the tubes in ICU images at a high sensitivity level. A function of automated detection of tube placement can potentially improve the overall workflow and patient management in the ICU.

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