Accuracy of an Automatic Patient-Positioning System Based on the Correlation of Two Edge Images in Radiotherapy

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We have clinically evaluated the accuracy of an automatic patient-positioning system based on the image correlation of two edge images in radiotherapy. Ninety-six head & neck images from eight patients undergoing proton therapy were compared with a digitally reconstructed radiograph (DRR) of planning CT. Two edge images, a reference image and a test image, were extracted by applying a Canny edge detector algorithm to a DRR and a 2D X-ray image, respectively, of each patient before positioning. In a simulation using a humanoid phantom, performed to verify the effectiveness of the proposed method, no registration errors were observed for given ranges of rotation, pitch, and translation in the x , y , and z directions. For real patients, however, there were discrepancies between the automatic positioning method and manual positioning by physicians or technicians. Using edged head coronal- and sagittal-view images, the average differences in registration between these two methods for the x , y , and z directions were 0.11 cm, 0.09 cm and 0.11 cm, respectively, whereas the maximum discrepancies were 0.34 cm, 0.38 cm, and 0.50 cm, respectively. For rotation and pitch, the average registration errors were 0.95° and 1.00°, respectively, and the maximum errors were 3.6° and 2.3°, respectively. The proposed automatic patient-positioning system based on edge image comparison was relatively accurate for head and neck patients. However, image deformation during treatment may render the automatic method less accurate, since the test image may differ significantly from the reference image.

KEY WORDS: Automated object detection, radiotherapy, digital image processing

INTRODUCTION

The objective of radiotherapy, to deliver a therapeutic dose to a well-defined target while minimizing the dose to the surrounding normal tissue and critical organs, requires optimization of the conformity of the prescribed dose to the planned target volume (PTV), dose homogeneity within the PTV, and minimal dose to the

surrounding normal tissue and critical organs.¹⁻³ Conformity in radiotherapy is becoming increasingly important in daily clinical practice since the applied target margins are much tighter and the delivered dose is higher. A successful conformal treatment requires precise patient positioning where geometrical precision requirements are higher than for conventional treatments. In general, requirements for patient-positioning accuracy increase when treatment fields are more conformal to the target, as in, for example, intensity modulation radiotherapy (IMRT), heavy ion therapy, and single fraction stereotactic radiosurgery (SRS).⁴⁻⁶

Traditionally, patients are positioned for external beam radiotherapy using optical techniques. Typically, the marks made on the skin of a patient during the simulation process are placed to coincide with the laser lines in the treatment room, with a setup accuracy less than 5 mm.⁷ Although this method is very simple, it is inappropriate for radiographic modalities that require much greater accuracy of patient positioning. In other words, more accurate and reproducible placement of treatment fields is needed in more refined and conformal radiotherapy since optical patient positioning is not highly reproducible. Recent

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improvements in imaging modalities, including computerized tomography (CT) and magnetic resonance imaging (MRI), have initiated a trend toward tighter target volumes, leading to a greater need for accurate and reproducible patient setup and field alignment. Due to recently developed image guidance technology, patient positioning can be automatically verified using on-board images such as an electronic portal imaging device (EPID).

Although automatic patient-positioning algorithms initially utilized edge detectors and ridge detectors to match structures in reference images from the simulation process and test images in the treatment room, the outcomes were not always satisfactory.^{8–10} Another automatic patient-positioning method is based on the correlation of full gray scale information to register two images.^{11–15} Although this approach works well with high-contrast images, it does not always find correct matches if the image quality is poor. Other patient-positioning procedures use a combination of multiscale edge detection with wavelets and Chamfer matching.¹⁶ A similar patient-positioning method, based on normalized binary image correlation using two edge images obtained from kilovolt X-ray imagers, has shown registration errors less than one pixel in the x and y directions and zero degrees in rotation.¹⁷

Although most previous studies resulted in very small registration errors, these methods should be validated before clinical application. Automatic methods can be validated by determining whether the algorithm provides the exact values when a phantom image or an image from a patient is displaced in a given range of rotation, pitch, and translation, in the x , y , and z directions, respectively. Although this method can indicate the effectiveness of a proposed automatic method, it cannot guarantee accuracy during clinical application. Unlike simulations, test images from actual patients can change during treatment, resulting in image deformation, making comparisons with reference images difficult. Therefore, to determine the clinical accuracy of a proposed automatic method, it is essential to compare the test image, obtained from a real patient in the treatment room, with the reference image. Although several previous studies have assessed actual patient data, the number of patient images was too low for determination of accuracy. In addition to this, if possible, a DRR should be used as a reference

image, since the image obtained during the simulation process or during initial treatment may differ from the original reference image acquired during planning CT.

We have developed an automatic patient-positioning method, based on a fast Fourier-transform (FFT)-based image correlation of two edge images in radiation therapy. Compared to pixel-based image registration method, frequency-domain-based methods find the transformation parameters for registration of the images which works well for simple transformations, such as translation, rotation, and scaling. Applying the phase correlation method to a pair of images produces a single peak whose location corresponds to the relative translation between the images. Unlike many spatial-domain algorithms, the phase correlation method is resilient to noise and other defects typical of medical images. Additionally, when the FFT algorithm is used to calculate the correlation distribution, speed is distinctly increased due to the fast transform's efficiency. Using the FFT-based image registration method, we clinically evaluated the accuracy of this automatic patient-positioning system for eight head and neck cancer patients. Unlike previous studies, a reference image was extracted by applying a Canny edge detector algorithm to a DRR of planning CT to more accurately verify the patient position assumed during the planning stage. We validated our automatic positioning system by comparing patient results with the results obtained using a humanoid phantom. We determined its accuracy in positioning real patients in three dimensions by assessing the differences between our automatic method and a manual positioning method.

MATERIALS AND METHODS

We randomly selected eight patients with clinically localized head and neck cancer, who underwent proton radiotherapy at our institution. All the patients were scanned in a supine position, and two images, a reference image and a test image, were obtained for each patient from a DRR through the Eclipse treatment planning system (Eclipse Version 8.0.3; Varian Medical Systems, Salt Lake City, UT, USA) and a 2D X-ray digital image using an on-board digital imaging patient setup (DIPS) system. In this DIPS system, patient

position can be manually adjusted based on two orthogonal X-ray images. The energy of the installed X-ray source ranged from 40 to 150 kV and the tube current ranged from 1 mAs to 500 mAs. The X-ray detector type was amorphous silicon, with an active area of $29.3\text{ cm} \times 40.6\text{ cm}$ and a resolution of $127 \times 127\text{ }\mu\text{m}^2$. A schematic of the setup in the treatment room at our institution shows the DIPS imaging system, a gantry, a couch, and all the geometry we used (Fig. 1). There were two X-ray sources, with detectors installed in the gantry system and 6 *df* in the couch, consisting of the *x*, *y*, *z*, rotation, pitch, and roll directions.

Although a variety of algorithms have been proposed for analyzing image intensity variations, including statistical^{18–20}, difference^{21–23} and curve fitting^{24,25} methods, we used the Canny edge detection method²⁶, mostly because it is considered an optimal edge detector for step edges corrupted by white noise. The Canny edge detection method finds edges by looking for local maxima of the gradient of image. The gradient is calculated using the derivative of a Gaussian filter. The method uses two thresholds to detect strong and weak edges, with the weak edges included in the output only if they are connected to strong edges. Since the Canny edge detector finds a high

Fig 1. The DIPS (Digital Imaging Patient Setup) imaging system for proton therapy. Two X-ray sources and detectors were installed in the gantry. There were three translational directions, along the *x*, *y*, and *z* axes, and three directions, rotation, pitch, and roll, on the couch. The inset shows an actual image of the DIPS system.

Fig 2. A series of edged sagittal X-ray images of the human head obtained with the Canny edge detection methods using threshold values of a 0.8, b 0.4, c 0.2, and d 0.1.

threshold for low-edge sensitivity and a low threshold for high-edge sensitivity, this method is less likely than others to be fooled by noise and is more likely to detect true weak edges.²⁶

Based on the Canny edge detection algorithm, we developed an automatic patient-positioning system using the Matlab program language (Matlab 7.1, Mathworks, Natick, MA, USA). Figure 2 shows a series of edged sagittal images extracted by varying threshold values of the Canny edge detector for a head and neck cancer patient. The number of edged pixels was increased as the threshold value of the Canny edge detector decreased (Fig. 2). Using our automatic patient positioning, we first found the optimal figure for the threshold value, which gives the best results when two images were compared based on edged images. The optimal threshold value was determined manually for each treatment site, which was confirmed by phantom or clinical test. Although the entire positioning system is automatic, it can also be performed manually when there was a failure in the positioning system. Calculation time was less than ~5 s on a PC with a Pentium Dual CPU 1.6 GHz, 2 GB RAM in the automatic mode. In contrast, the manual mode requires greater expertise, skills, and time.

Figure 3 shows a flow chart of the developed program for the manual and automatic options. The first step of the optimization procedure is to obtain DRR and DIPS images from treatment planning system (TPS) and proton patient-positioning system, respectively. Then, the electronic image files obtained from the software were resized at a spacing of 1 mm in the x , y , and z directions for comparison. Next, a common rectangular region of interest (ROI) is defined by a mouse for later comparison of image correlation. Then, Canny edge detection is applied for the reference and the test image. The second step is to apply the optimal

matching algorithm to correct the setup error of the patient positioning. A common approach for verifying the image match involves overlapping the test and reference images, and then evaluating the image correlation index (CI) of two images. While translating and rotating the edged test image, the absolute value of CI between the edged-reference image and the edged test image is iteratively maximized. To obtain a local maximum value for each translation or rotation, a sequential search was conducted within an angle range of $\pm 5^\circ$ with a step of 0.1° and a translation pixel range of 5 cm with a step of 1 mm. This procedure yields the information

Fig 3. Flow chart of the developed automatic patient-positioning program.

how much the test image should be shifted with respect to reference image for optimal patient positioning. An optimization concept that produced a local maximum from a two-dimensional space function was applied to build an optimization algorithm that recognized shifts in the center of the radiation treatment (Fig. 3).

The image correlation index (CI) between the test image and the reference image was decided using a correlation factor, which was supplied as an internal function in the Matlab programming language:

$$CI = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left[\sum_m \sum_n (A_{mn} - \bar{A})^2 \right] \left[\sum_m \sum_n (B_{mn} - \bar{B})^2 \right]}} \quad (1)$$

where $\bar{A}$ and $\bar{B}$ are the mean of the elements of an image matrix A and B , respectively.¹⁴ Although this image correlation factor was very simple, it worked well in most patients. A visual representation of this process is shown in Figure 4, with matching reference, and test images with their corresponding edged images. The FFT-based image correlation

factor between the edged-reference and test images was determined by changing the location of the test relative to the reference images. These results show that when the test image was displaced a certain amount, the correlation factor was maximized, indicating that moving the test image by that amount will align the test and reference images.

RESULTS

Phantom Tests

The effectiveness of proposed method was first evaluated based on a simulation study using a humanoid phantom. No registration errors were observed for a given range of rotation, pitch, and translations in the x , y , and z directions, respectively. When we assessed two sets of orthogonal images of the humanoid phantom (Rando, Alderson Associates, NY, USA) using the DIPS system, we found that the image quality using a kV X-ray source was very good in image analysis when compared with portal images using an MV X-ray source (Fig. 5). Two regions, the head and neck and the

Fig 4. Process of automatic patient positioning, based on image correlation using FFT correlation between the edged test and edged-reference images.

Fig 5. Two sets of orthogonal images of the humanoid phantom using DIPS system. a coronal and b sagittal images of the head and neck. c coronal, and d sagittal images of the pelvis.

pelvis area, were imaged using a humanoid phantom and used for evaluation of the developed image matching system. For verification, the image acquired by the DIPS system was intentionally displaced by given translation and rotation amounts and reassessed after applying the proposed method. Using the humanoid phantom image, we found that the given range of input data, which was artificially made by displacement of the original image, was

Fig 6. DRR (a) of a patient and its edged image (b), and DIPS image (c), and its edged image (d). Each figure was a 512×369 matrix, and the threshold value of each edged image was about 0.18.

perfectly matched after applying the developed method, both in the head and neck and in the pelvis lesions (Table 1). These results indicate that the proposed method can effectively assess the displacement of test images relative to a reference image. In

Table 1. Simulation Data Using a Humanoid Phantom Image

Phantom data		Input					Output				
Image type	Case #	R_x	R_y	R_z	Rotation ($^{\circ}$)	pitch ($^{\circ}$)	R_x	R_y	R_z	Rotation ($^{\circ}$)	Pitch ($^{\circ}$)
Head and neck	Case 1	1	0	0	0	0	1	0	0	0	0
	Case 2	0	3	0	0	0	0	3	0	0	0
	Case 3	0	0	7	0	0	0	0	7	0	0
	Case 4	0	0	0	0.5	0	0	0	0	0.5	0
	Case 5	0	0	0	0	0.5	0	0	0	0	0.5
	Case 6	1	3	7	0.5	0.5	1	3	7	0.5	0.5
	Case 1	2	0	0	0	0	2	0	0	0	0
	Case 2	0	5	0	0	0	0	5	0	0	0
	Case 3	0	0	10	0	0	0	0	10	0	0
	Case 4	0	0	0	0.5	0	0	0	0	0.5	0
Pelvis	Case 5	0	0	0	0	0.5	0	0	0	0	0.5
	Case 6	2	5	10	0.5	0.5	2	5	10	0.5	0.5

Two types of images, head and neck and pelvis, were used to evaluate the effectiveness of the proposed automatic method. The given range of input data, artificially made by the displacement of the original image, was applied to displace the original reference image and then considered a reference image. Input and output data were divided by R_x , R_y , R_z , rotation, and pitch. Output data shows the values for R_x , R_y , R_z , rotation, and pitch for test images matched with original reference images

Table 2. Differences in 3D Displacement Registration Between the Manual and Automatic Methods for 96 Coronal and Sagittal Images

Patient data	Abs (manual-automatic)						Max (ΔR^*) (cm)	Ave (ΔR^*) (cm)
	R_x (cm)	R_y (cm)	R_z (cm)	R_{vector} (cm)	Rotation ($^\circ$)	Pitch ($^\circ$)		
#1	0.098	0.066	0.053	0.174	0.833	0.800	0.221	0.182
#2	0.056	0.053	0.112	0.136	0.667	1.533	0.281	0.158
#3	0.058	0.064	0.043	0.096	0.633	1.267	0.267	0.199
#4	0.100	0.013	0.070	0.122	0.733	0.400	0.247	0.197
#5	0.172	0.198	0.147	0.300	1.800	1.700	0.510	0.351
#6	0.113	0.031	0.018	0.118	0.800	0.867	0.504	0.410
#7	0.106	0.104	0.178	0.232	0.633	0.433	0.281	0.212
#8	0.164	0.178	0.233	0.336	1.533	1.000	0.537	0.393
Aver.	0.108	0.088	0.107	0.189	0.954	1.000	0.356	0.263

R_x , R_y , and R_z are differences in the x -, y -, and z directions, respectively. Rotation and pitch is reflecting a motion angle of the couch from AP images and a motion angle of the human chin from LT images, respectively

$$*\Delta R = \sqrt{(R_x^2 + R_y^2 + R_z^2)} \text{ in cm}$$

Abs absolute value, Max: maximum value, Ave average value

addition to 3D displacement, the proposed method also worked well for pitch and yaw.

Clinical Cases

We compared the results of our automatic system with the results obtained using a manual method performed by physicians or trained technicians. Sagittal head and neck images were obtained from a real patient using the extracted edged images (Fig. 6). Differences in registration between the manual and automatic methods in 3D displacement were determined for 96 coronal and sagittal images, with R_x , R_y , and R_z being the mean differences of each patient in the x -, y -, and z directions, respectively (Table 2). For patient 3, the average and maximum differences for the automatic and manual procedure were each less than 0.3 cm in three dimensions, whereas the maximum difference for patient 8 was almost 0.55 cm in three dimensions. Based on an analysis of 96 images, the average differences in registration between the automatic and manual methods for

the x , y , and z directions were about 0.11, 0.09, and 0.11 cm, respectively, while the maximum discrepancies in registration were about 0.34, 0.38, and 0.50 cm, respectively (not shown in Table 2).

We also assessed registration errors in rotation and pitch, with rotation reflecting the motion angle of the couch from coronal images and pitch reflecting the angle of the human chin from lateral images. We found that the mean registration differences in rotation and pitch between the manual and automatic methods were about 0.95° and 1.00° , respectively, and the maximum differences were 3.6° and 2.3° , respectively (not shown in Table 2). If the tolerance level was 3 mm in the x , y , and z directions, a 2° difference in rotation or pitch, it would result in a failure rate of about 8%.

DISCUSSION

Although the automatic positioning algorithm can be evaluated using a phantom, this method has

Table 3. Summary of Comparisons Between Our Study and Previous Studies for Automatic Patient-positioning System

Investigator	Image material	Reference image	Total number of comparison	Clinical cases		Dimension (2D or 3D)	Rotation and pitch analysis
				Mean registration error			
				x (cm)	y (cm)		
Yoon et al.	Phantom and patient	DRR	96	0.108	0.088	3D	Both
Petrascu et al. ¹⁶	Phantom and patient	Portal image	3	0.095	0.123	2D	Rotation
Sawada et al. ¹⁷	Phantom and patient	Portal image	4	N/A	N/A	2D	Both
Girouard et al. ⁹	Phantom and patient	Potal image	79	0.048	0.141	2D	None
Jones et al. ¹⁴	Phantom only	N/A	N/A	N/A	N/A	3D	Both

Mean registration error are compared based on 2D method (x and y directions), which is common in all studies

limitations. While this method may always provide correct positioning for a phantom, it may provide wrong information when applied to a real patient. In contrast to a phantom, which is a rigid body that always provides the same image contrast, image deformation may occur when dealing with real patients. That is, the original DRR image from a patient may be distorted during acquisition of the test image. Therefore, images should also be evaluated using real patient data.

In contrast to several previous studies, we found that there may be relatively large discrepancies between manual and automatic patient-positioning methods.^{16,17} However, there were several differences between our study and previous studies (Table 3). First, our reference image was a DRR image from TPS, whereas most other studies used a 2D portal image or an image in the simulation room as a reference. Second, we obtained randomly selected test images from the treatment room during the full course of treatment. If the test image only consists of a simple displacement of the original reference image in translation or rotation, it may render wrong information in its accuracy. Although this method can be used to evaluate the effectiveness of the program algorithm and check whether there is a defect or bug in the program or not, it does not provide the clinical accuracy information of the proposed method. To clinically verify the accuracy of our method, it is important to apply this procedure to actual patients. In real situations, there is an unavoidable image deformation, due, for example, to patient weight loss, change in tumor size, and anatomical changes. While our results showed a perfect match in the effectiveness test of our algorithm, we observed several large discrepancies between the manual and automatic methods. Therefore, to assess the accuracy of the proposed automatic patient-positioning method, numerous test images of each patient should be acquired during various treatment stages along the full course of treatment.

In general, application of the automatic method would yield results different from those of the manual method. In the manual method, there is a priority dependent on various regions since the target location or isocenter would be more important than the rest of the anatomy. In the automatic method, however, the edges of the reference and test images will be matched, regardless of their importance. Although auto-registration with appro-

priate ROI may provide better match with the manual results, it possibly results in significant registration error whenever there is image deformation since the planning CT. Therefore, the clinical accuracy of automatic patient-positioning system should be evaluated under these conditions.

CONCLUSION

We have clinically evaluated the accuracy of an automatic patient-positioning system based on the image correlation of two edge images in radiotherapy. While a simulation study using a humanoid phantom showed no registration errors for a given range of rotation, pitch, and translation in the x , y , and z directions, we observed a discrepancy for real patients between our automatic patient-positioning method and manual positioning by physicians or technicians. The relatively large differences between the manual and automatic methods in individual patients may be due to image deformation since the initial CT was taken. Our results suggest the importance of evaluating the accuracy of our automatic patient-positioning system using clinical data acquired throughout the course of treatment, since otherwise it may provide wrong information about the accuracy of our automatic positioning algorithm.

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