Automatic Patient Table Removal in CT Images

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Abstract In many medical imaging applications, it is desirable and important to localize and remove the patient table from CT images. However, existing methods often require user interactions to define the table and sometimes make inaccurate assumptions about the table shape. Due to different patient table designs, shapes, and characteristics, these methods are not robust in identifying and removing the patient table. This paper proposes a new automatic approach which first identifies and locates the patient table in the sagittal planes and then removes it from the axial planes. The method has been tested successfully against different tables in different products from multiple vendors, showing it is both a versatile and robust technique for patient table removal.

Keywords Computed tomography · Patient table · Hough transform

Introduction

Computed tomography (CT) is a procedure that uses a scanner to acquire and reconstruct cross-sectional pictures of the body [1]. In many medical imaging applications, it is

desirable and sometimes important to localize and subsequently remove the patient table from CT images.

- For 3D visualization such as digitally reconstructed radiographs or maximum intensity projections (CT or CT fused with another dataset such as positron emission tomography (PET)), the table can obscure potentially vital data [2].
- In radiation treatment planning, the presence of the patient table in images can impact the dose modeling since the table used during imaging often has different attenuation properties than the table used during treatment [3]. In these cases, you want to modify the image and replace the imaging table with the treatment table to obtain more accurate planning.
- In PET/CT systems, the CT is used for attenuation and scatter correction in PET reconstruction [4]. The scatter correction is patient specific and the patient boundary has to be estimated accurately. Removal of the table facilitates accurate estimation of this boundary.
- In image registration, it is preferable that the two images to be registered have similar image content. Since the patient table is not visible in PET, MR (magnetic resonance), or SPECT (single photon emission computed tomography) modalities, the presence of a table in a CT image can adversely impact the registration when CT is registered with these other modalities. Even for CT–CT registration, the table design, shape, and location (supine versus prone) can be different and adversely affect the registration process.

Literature on table removal is scarce. Some methods have been reported only recently [2, 5] and researchers and vendors alike have included them in software applications [6]. These methods can be broadly classified as manual or automatic. In a manual method, the user draws a contour or plane to localize the table [7], which is time consuming and lacks reproducibility. Automatic algorithms can be

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template based [2] or connected component analysis based [5, 8]. The template method requires a pre-acquired template, which limits its applicability. The connected component analysis methods sometime fail to isolate the table, particularly when the patient body touches the table edges. In addition, they may also remove clothes and sheets and potentially remove internal body structures, particularly in low-density regions such as lung.

The development of a robust, automated, table identification and removal method which is independent of table characteristics is certainly challenging. Many methods are sensitive to the shape of the patient table. Figure 1 shows patient tables from Philips, General Electric, and Siemens PET/CT as well as CT products. Considering the availability of other products and vendors, the variation is even higher. Another factor that complicates table removal is a change in relative position/location of the table from image to image. This often occurs if the table is not leveled well with respect to the scanner. For example, a tilt of 0.5° can shift the table in the vertical direction by as much as 18 mm from the first slice to last slice for a scan with 2 m of coverage which is not atypical in total-body studies.

This paper reports on an automatic table identification and removal method which has been shown to be independent of table characteristics. It is based on a simple observation that, in sagittal planes, the top of the table essentially forms a vertical line. We describe the details of this method in “Methods”. “Results” provides a few examples to illustrate its effectiveness and “Concluding Remarks” concludes the paper with a discussion and summary.

Methods

It is hard to localize the table in transverse images without resorting to heuristics and assumptions such as its shape, size, and possible location. However, in sagittal planes, the table top forms a straight line, as shown in Fig. 2. As the image indicates, the portion of the table forms two straight lines. We observe that this is due to the fact that the table cross-section is almost invariant axially and use this characteristic as the basis for our method. We note that if the table is not perpendicular to the scanner, the axial-invariant assumption is broken, which seems to be rare in practice. In the case of table sag, the top of the table will not form a straight line on sagittal plane. We ignore the table sag beyond a certain threshold in this study as it is well under control, at least for radiation treatment tables.

Our automatic method includes the following steps: (1) reformat the data to get a sagittal image, starting with the mid-sagittal plane; (2) use a threshold to binarize the sagittal image; (3) detect vertical edges in the binary image; (4) perform a Hough transform with angle and intercept as parameters, choose the angle that gives the largest bin count, followed by the intercept determination that corresponds to the table top; (5) repeat steps 1–4 to the left side of the mid-sagittal planes until no further table top is identified, and repeat steps 1–4 to the right side of the mid-sagittal planes until no further table top is identified; (6) smooth the table top profile (all intercepts); and (7) with the angle and table top profile on the first transverse slice, calculate the table top

Fig. 1 CT acquired on Philips, General Electric, and Siemens PET/CT products (*top row*) and their CT products (*bottom row*)

Fig. 2 A typical mid-sagittal CT image (data acquired on a Philips PET/CT scanner)

profiles for all other transverse slices and replace all pixel data under the table with a CT value equivalent to “air” if table removal is desired.

When binarizing sagittal images, a threshold of -500 Hounsfield units is empirically chosen (halfway between the density of air and water) to ensure the table is shown on the binarized image. To generate the binary image, each pixel is set to 1 if the corresponding pixel value in the sagittal image is above or equal to the threshold; otherwise the pixel is set to 0. Edges on the binary image are then

detected using a Sobel operator. As we are interested in vertical lines, the following mask is used:

$$\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}.$$

A typical vertical-edge-detected image is shown in Fig. 3 (top). The width of the image is the same as the number of pixels from patient front to back in the original CT image and the height is the same as the number of CT slices. The image is scaled vertically to reflect the actual physical dimension as voxel dimensions typically vary in different directions. A Hough transform is then applied to the edge-detected image. The Hough transform is a classical method to detect shapes expressed in parametric forms [9]. The table top in the sagittal plane is almost vertically arranged and it can be expressed as

$$x = ky + b,$$

where k is the tangent of the angle and b is the intercept (x goes from left to right and y runs from top to bottom). Assume the vertical lines are within -1° and $+1^\circ$ from the vertical direction. Using a step size of 0.1° (thus 21 values of k) and the original number of image columns (typically 512), one has the graphical representation of the Hough transform as shown in

Fig. 3 (Top) Vertical-edge-detected sagittal image. (Bottom) Hough transform of the sagittal image, with the vertical axis represents slopes and horizontal axis represents intercepts

Fig. 3 (bottom). The optimum number of angles to be used can be determined by the performance of the implementation and the desired range of angular deviation from the vertical direction. In the histogram image shown in Fig. 3 (bottom), the row with the highest accumulation is chosen, which yields the slope of the table (-0.6° in this example). Along that row (same slope, but different intercepts), one has a list of potential line intercepts. For the bottom image in Fig. 3, there are three aggregated intercept candidates, corresponding to the three parallel lines seen on the top image of Fig. 3 (cushion, table top, and table bottom).

The positions of the intercept candidates are determined automatically. This is accomplished by scanning the histogram row from left to right and identifying the center of a line segment on which all points have a value greater than a chosen threshold. The threshold is set equal to half of the number of transverse slices. The rationale is that a structure can be considered part of the table if it appears on at least half of the slices. Once the peaks are identified, they are further merged if they are close to each other. The largest distance between two peaks to be merged is set to 5 pixels in our experiment (~ 5 mm). After the processing, the table top is one of the so-identified peaks.

Depending on the actual table design, there can be multiple peaks identified. One has to determine which one is the table top. The cushion sometimes forms a line long enough to be detected, but sometimes it is too short and not detected. So the table top can be either the first or second peak. Two criteria can be used to decide where the table top is located: (a) distance between first two peaks and (b) the length of the line (counts in the histogram bin). If the distance is small (e.g., about the thickness of the cushion), the second peak is the table top; otherwise the first peak is the table top. The table top also tends to be longer than the cushion as the latter is not always a straight line. The above description is applicable to both supine (patient lies on back) and prone (patient lies on stomach) cases.

When the table profile is searched on other sagittal planes towards patient left and right sides, the previous table top is used as reference and the candidate closest to the previously

Fig. 4 Deviation angles from vertical lines determined from individual sagittal images

Fig. 5 Table top profiles determined using the same slope as in the mid-sagittal plane (*top*) or individual slope determined from each sagittal plane (*bottom*)

identified point is used for the current sagittal plane. To avoid searching beyond the table boundaries, the search is aborted as soon as no vertical lines are detected. During the searching, the slope of the vertical lines on each sagittal plane has to be determined. It can be determined for each slice using the same method as discussed above or the slope for the mid-sagittal plane is used for all sagittal planes. These two approaches give comparable results, as will be shown in the “Results” section. In the rest of the paper, the slope determined on the mid-sagittal plane is used for all sagittal planes unless stated otherwise. This approach gives a slight improvement in speed and error reduction.

Once the table top positions in all sagittal planes are localized, those positions are connected to form the table

Fig. 6 Philips PET/CT: *top row* shows the original CT and *bottom row* shows the CT with the table removed

Fig. 7 GE PET/CT: *top row* shows the original CT and bottom row shows the CT with the table removed

top profile. Those points are smoothed using a median filter, where a sliding window of width 5 pixels is employed (~ 5 mm). The so-determined table profile is for the most superior slice (closest to head). The table profile is then extended to the inferior slices linearly by considering the slope determined earlier. Since the table profile is estimated collectively from all slices and extrapolated over the table long axis, the problem associated with the connected component analysis approach (difficulty in isolating the table from the patient when the body touches the table edges) is avoided.

To remove the table, one works in the transverse images. The pixel intensities below the table top (inclusive) are set to the same value as air. Since the position information of the table is available, one can also insert an alternate digital table if needed.

Fig. 8 Siemens PET/CT: *top row* shows the original CT and bottom row shows the CT with the table removed

Fig. 9 Philips CT: the *top row* shows the original CT and bottom row shows the CT with the table removed

Results

The automatic table identification and removal algorithm has been applied to various table designs from different vendors. The method has been employed in a commercial product (Fusion Viewer from EBW-NM Workstation, Philips Healthcare) which has passed rigorous verification and is in undergoing clinical validation at the time of this writing. Many datasets from major vendors (with a focus on Philips data) have been used to test the algorithm with overall clinically acceptable results. The exact number of test cases is not available to the authors, however. We have tested the algorithm independently on a few dozen datasets with success. The datasets include total body scans (typically 300–400

Fig. 10 GE CT: the *top row* shows the original CT and bottom row shows the CT with the table removed

slices), whole body scans (typically 200 slices), and other short body scans (typically around 100 slices). A few examples are illustrated here with an emphasis on data from different vendors (Philips, General Electric, and Siemens). With an optimized implementation, the time to identify and localize the table top in a whole body scan is typically less than 1 s as measured on a Dell Precision M90 laptop.

Figure 4 shows the table top deviations from the vertical line determined on individual sagittal planes, where the same patient data as in Fig. 3 is used. It can be seen that for most sagittal planes, the angles are stable, changing between -0.5° to -0.6° . Toward the table boundary the angle fluctuates due to error or noise. To improve the speed and reduce the error towards the sides of the table, the angle determined from the mid-sagittal plane is assumed for all sagittal planes.

Figure 5 compares the table top profiles determined using the single slope (top) and using individual slopes determined on each sagittal plane (bottom), where the top profile is shifted by 100 pixels and both are flipped for display purposes. As can be seen, the detected table tops are virtually the same.

The table removal results for some of the data in Fig. 1 are further illustrated in Figs. 6–8 as screen captures. This is a subset of the data we have tested. By visual inspection, all table removal results are acceptable.

Figure 6 shows the results on the Philips CT data acquired on its Gemini PET/CT product (176 slices with a voxel size of $1.17^2 \times 5 \text{ mm}^3$, each with 512^2 pixels). The top row shows the images before the table is removed. To the left is the volume surface rendering, where the impact of the table is clearly seen. The bottom row shows the images after the table is removed. The table is not visible on the surface rendering, which is presented in the same viewing orientation as the rendering with table. The table structure is also clearly removed from the transverse and sagittal displays.

Figure 7 shows similar results on GE CT data acquired on a Discovery LS PET/CT scanner (205 slices with a voxel size of $0.977^2 \times 4.25 \text{ mm}^3$, each with 512^2 pixels). The volume rendering is chosen to show the patient's skeleton. Since the table is not axially uniform, the portion of the table under the patient's head is not removed.

Figure 8 shows similar results on a Siemens CT data acquired on its Emotion 6 PET/CT scanner (488 slices with a voxel size $0.977^2 \times 2 \text{ mm}^3$, each with 512^2 pixels). Some residual cushion is visible on the axial view, which is expected as it was not targeted for removal.

Figures 9 and 10 further show the algorithm performance when a table with a flat surface is encountered. In Fig. 9, the data was acquired on a Philips Brilliance CT (113 slices with a voxel size of $1.17^2 \times 3 \text{ mm}^3$, each with 512^2 pixels),

while in Fig. 10, the data was acquired on a GE Discovery ST CT (56 slices with a voxel size $0.977^2 \times 3 \text{ mm}^3$, each with 512^2 pixels). As the results indicate, the algorithm works equally well.

Concluding Remarks

We have proposed an automatic CT table identification and removal method based on a simple observation that the table top forms a vertical line on the sagittal image planes. This method has been tested on variety of CT images acquired on different products made by different vendors. In all cases tested, the algorithm performed well. We expect that it will find its application in various medical imaging tasks.

The proposed method has its limitation, however. As it is based on a simple observation, it will fail when the assumption does not hold, i.e., when the table cross-section varies axially. Some axial variation can be handled by modifying the algorithm and others cannot. When the table in the sagittal planes forms piece-wise line segments, the algorithm can be extended to localize those piece-wise line segments by searching large deviations from the vertical line, with increased computation burden, however. When there is a special object such as a patient head support as seen in Fig. 7, the algorithm will have to work with other approaches. We intend to further pursue the research to improve its robustness.

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