Automated Multidetector Row CT Dataset Segmentation with an Interactive Watershed Transform (IWT) Algorithm: Part 1. Understanding the IWT Technique

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Segmentation of volumetric computed tomography (CT) datasets facilitates evaluation of 3D CT angiography renderings, particularly with maximum intensity projection displays. This manuscript describes a novel automated bone editing program that uses an interactive watershed transform (IWT) technique to rapidly extract the skeletal structures from the volume. Advantages of this tool include efficient segmentation of large datasets with minimal need for correction. In the first of this two-part series, the principles of the IWT technique are reviewed, followed by a discussion of clinical utility based on our experience.

KEY WORDS: 3D segmentation, computed tomography, body imaging

BACKGROUND

Three-dimensional (3D) rendering of computed tomography (CT) datasets has become an integral component of various applications, particularly vascular and orthopedic imaging. Current multidetector row CT (MDCT) technology yields isotropic datasets amenable to high resolution rendering in any orientation. However, a MDCT volume dataset contains such an abundance of information; segmentation is necessary to remove extraneous structures that could hinder evaluation during 3D rendering. Coupled with improvements in data acquisition and rendering, volume editing tools have been developed using a variety of algorithms.¹⁻¹² Clinical implementation of segmentation methods requires techniques to process quickly and edit accurately.

The purpose of this manuscript is to describe a promising automated segmentation tool, which uses and extends an interactive watershed trans-

form (IWT) technique to remove selected portions of the anatomy.¹³⁻¹⁸ This tool rapidly segments the osseous structures from a CT dataset with minimal interactivity to enhance evaluation of the vascular structures with CT angiography (CTA) or to improve visualization of bone surfaces. In part 1 of this two-part series, a description of the IWT is presented. This is followed by a demonstration of its utility for 3D CTA and skeletal imaging in the subsequent Experience Report.

METHODS

The automated bone removal technique described is a novel editing tool based on the IWT.¹³⁻¹⁵ Unlike many other segmentation tech-

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niques, the watershed transform makes very few assumptions about the objects being segmented. In fact, the only assumption made is that an object is connected (that is, contiguous in space) and that there is a similarity in specific image properties over the object. The IWT is an extension of the standard watershed transform designed for efficient processing (no more than a minute of processing even on large datasets) and fast, simple user correction.

The watershed transform gets its name through analogy with the process of rain falling on mountainous regions. When rain falls onto a mountainous region with many basins, the rain that falls on the soil will flow downhill until it reaches a basin, where it collects. That part of the terrain that contributes water to a given basin is the basin's *watershed*. Note that the definition of a basin is dynamic, in that, if rain were to be very heavy and the water level collecting in basins were to rise, adjacent basins could merge together. If rain were to lessen, a single basin could separate into two or more.

With the watershed transform, the source data is treated as a topological map, where image characteristics are mapped to height of a terrain (in our case Hounsfield units are mapped to depth). Basins are connected regions around local minima in depth. Specifically, in our case, a basin surrounds a local maximum in Hounsfield units and may represent a bone, a piece of bone, or the union of a bone with another structure (perhaps adjacent bone). Basins are labeled automatically in real-time based on the Hounsfield unit characteristics,

namely, mean and maximum intensity and Hounsfield unit variance, besides the basin size measured in cubic millimeters.¹⁶ In analogy to our “heavy rain” scenario, a single threshold called preflooding height¹⁷ can be adjusted to cause adjacent basins (high density regions of the CT) to merge. Whereas the system estimates the proper preflooding height automatically, the user has the option to adjust it to make global corrections to the segmented result.

RESULTS

The preliminary step performed by the IWT technique (Syngo Inspace4D visualization platform, Siemens Medical Solutions, Malvern, PA) is an automated segmentation, whereby a preflooding height is applied to select the osseous structures. The segmentation result can be adjusted globally through an optional master parameter called *segmentation aggressiveness*, and locally. For both types of interaction, full undo and redo functionality are available. Following the initial automated segmentation, 2D reformations and a 3D-rendered image are presented with the segmented anatomy marked in blue (Fig. 1), allowing the user to assess and override the segmentation if necessary. If the segmentation is acceptable, the selected osseous structures are removed (Fig. 1).

Local refinement of the segmentation is accomplished through the placement of bone markers (Fig. 2) or non-bone markers (Fig. 3) on the 2D or 3D image to include or exclude objects. Markers

Fig 1. Coronal MIP renderings from an intravenous (IV) contrast-enhanced MDCT dataset (a–c). Automated segmentation removes the skeletal structures (marked blue in b), facilitating visualization of the renal arteries and aorta, and revealing an accessory renal artery on the right side (arrow in c).

Fig 2. Posterior coronal volume renderings of the hand from an MDCT dataset. Interactive application of multiple bone markers (+ in a) can result in either display of the selected carpal, metacarpal, and phalangeal bones (b) or a rendering that displays the remaining osseous structures (c).

have the advantage of being a simple form of interaction, no more complex to use in 3D than in 2D, a distinct advantage over contours. If two bone markers are placed in adjacent basins, the IWT will join the two tissues into one object, permitting the user to extend a portion of the skeletal anatomy that was only partly segmented. If the preflooding parameter causes some non-bone tissue to be identified as bone, a non-bone marker can be placed

in the non-bone basin (Fig. 3). This will cause the IWT to separate the tissues. In all cases (adjustment of the preflooding height, marker placement, or undo/redo), the result can be recalculated and redisplayed in approximately one second, allowing for fast human interaction. Real-time feedback, as well as fast undo and redo, are facilitated using a hierarchical organization of all emerging basins during the initial watershed transform.¹⁸

Fig 3. Posterior coronal volume renderings of a normal popliteal artery (a–c). Automated segmentation was performed in b. Note that two small vessels (arrows in b) adjacent to the bone were incorrectly segmented. This can be overridden by placing non-bone markers, resulting in image c.

DISCUSSION

The variety of segmentation algorithms investigated in the literature^{1–12} reveals the challenge inherent in developing a reliable and practical editing tool. A successful program must be both accurate and fast to be accepted and used in practice. This includes requirements for (1) the ability to handle large data sets at full resolution (currently accepted minimum for CTA studies: $512 \times 512 \times 1,600$ voxels), (2) highly automated segmentation, (3) rapid execution, in the order of less than 1-min computation time for as many as 1,600 slices, and (4) simple interface to allow the user to easily and quickly correct the results, including full undo/redo capability.¹⁸ Advantages of the IWT algorithm include efficient interaction as a result of the hierarchical organization of all bright image regions.¹³ With respect to speed, tested datasets up to a size of 1,750 slices can be processed at full resolution within less than 1 min on standard single-processor hardware.¹⁸ In addition, real-time, interactive correction of any inappropriately segmented or unsegmented anatomy can be performed.

The bone removal technique based on the IWT presented in this paper differs from state-of-the-art in a combination of the following four points:¹⁸

1. The algorithm is split into an unsupervised (automatic) and an interactive part. The first takes the bulk of computation time before any user interaction is required.
2. Through a sparse volume representation, data sets of, e.g., $512 \times 512 \times 2,000$ voxels at 12 bit, equivalent to 1 GB of input data, are processed at full resolution with only 500 MB of working memory.^{16,18}
3. The marker-based interaction scheme provides equally intuitive segmentation control in 2D and 3D, with close to real-time feedback (approximately 1 s for a full 3D update).
4. Because few assumptions are made about bone shape or other characteristics, the system is robust under a wide range of acquisition protocols and clinical variations.

Similar to the work by Moore et al.,¹ our system provides a specific operating mode for segmenting head CTA images with the specific problems of extensive vessel-bone interfaces. In addition to Moore's work, based on the bone removal technique

described above, full efficient interactive control is offered.

CONCLUSION

This manuscript describes the principles behind segmentation with the IWT technique and provides an understanding of how to use the tool for editing MDCT datasets. Clinical utility for both CT angiography and 3D orthopedic imaging is broad, as illustrated in the subsequent Experience Report.

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