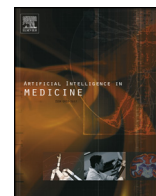




Contents lists available at ScienceDirect

## Artificial Intelligence In Medicine

journal homepage: [www.elsevier.com/locate/artmed](http://www.elsevier.com/locate/artmed)

## Abdominal, multi-organ, auto-contouring method for online adaptive magnetic resonance guided radiotherapy: An intelligent, multi-level fusion approach<sup>☆</sup>

Fan Liang<sup>a,b,c</sup>, Pengjiang Qian<sup>d</sup>, Kuan-Hao Su<sup>a,b</sup>, Atallah Baydoun<sup>e,f,g</sup>, Asha Leisser<sup>a,b,h</sup>, Steven Van Hedent<sup>a,b,i</sup>, Jung-Wen Kuo<sup>a,b</sup>, Kaifa Zhao<sup>d</sup>, Parag Parikh<sup>j</sup>, Yonggang Lu<sup>j</sup>, Bryan J. Traughber<sup>b,k,l</sup>, Raymond F. Muzic Jr<sup>a,b,g,m,\*</sup>

<sup>a</sup> Department of Radiology, Case Western Reserve University School of Medicine, Cleveland, OH, USA

<sup>b</sup> Case Center for Imaging Research, University Hospitals Case Medical Center, Case Western Reserve University, Cleveland, OH, USA

<sup>c</sup> Tianjin Key Laboratory of Information Sensing & Intelligent Control, Tianjin University of Technology and Education, Tianjin, China

<sup>d</sup> School of Digital Media, Jiangnan University, Wuxi, Jiangsu, China

<sup>e</sup> Department of Internal Medicine, Case Western Reserve University School of Medicine, Cleveland, OH, USA

<sup>f</sup> Department of Internal Medicine, Louis Stokes VA Medical Center, Cleveland, OH, USA

<sup>g</sup> Department of Biomedical Engineering, Case Western Reserve University, Cleveland, OH, USA

<sup>h</sup> Department of Biomedical Imaging and Image-guided Therapy, Medical University of Vienna, Vienna, Austria

<sup>i</sup> Department of Radiology, UZ Brussel (VUB), Brussels, Belgium

<sup>j</sup> Department of Radiation Oncology, Washington University School of Medicine, St. Louis, MO, USA

<sup>k</sup> Department of Radiation Oncology, Case Western Reserve University School of Medicine, Cleveland, OH, USA

<sup>l</sup> Department of Radiation Oncology, University Hospitals Seidman Cancer Center, Cleveland, OH, USA

<sup>m</sup> Department of Radiology, University Hospitals Cleveland Medical Center, Cleveland, OH, USA

## ARTICLE INFO

## Keywords:

Auto-Contouring  
Machine learning  
Adaptive radiotherapy  
Image-guided  
Radiotherapy

## ABSTRACT

**Background:** Manual contouring remains the most laborious task in radiation therapy planning and is a major barrier to implementing routine Magnetic Resonance Imaging (MRI) Guided Adaptive Radiation Therapy (MR-ART). To address this, we propose a new artificial intelligence-based, auto-contouring method for abdominal MR-ART modeled after human brain cognition for manual contouring.

**Methods/Materials:** Our algorithm is based on two types of information flow, i.e. top-down and bottom-up. Top-down information is derived from simulation MR images. It grossly delineates the object based on its high-level information class by transferring the initial planning contours onto daily images. Bottom-up information is derived from pixel data by a supervised, self-adaptive, active learning based support vector machine. It uses low-level pixel features, such as intensity and location, to distinguish each target boundary from the background. The final result is obtained by fusing top-down and bottom-up outputs in a unified framework through artificial intelligence fusion. For evaluation, we used a dataset of four patients with locally advanced pancreatic cancer treated with MR-ART using a clinical system (MRIdian, Viewray, Oakwood Village, OH, USA). Each set included the simulation MRI and onboard T1 MRI corresponding to a randomly selected treatment session. Each MRI had 144 axial slices of  $266 \times 266$  pixels. Using the Dice Similarity Index (DSI) and the Hausdorff Distance Index (HDI), we compared the manual and automated contours for the liver, left and right kidneys, and the spinal cord. **Results:** The average auto-segmentation time was two minutes per set. Visually, the automatic and manual contours were similar. Fused results achieved better accuracy than either the bottom-up or top-down method alone. The DSI values were above 0.86. The spinal canal contours yielded a low HDI value.

**Conclusion:** With a DSI significantly higher than the usually reported 0.7, our novel algorithm yields a high

<sup>☆</sup> Meeting presentation: A preliminary report of this research was submitted as an oral presentation for the Radiological Society of North America (RSNA) 2017 annual meeting.

\* Corresponding author at: Radiology, Mail Stop: BSH: 5056, University Hospitals Cleveland Medical Center, 11100 Euclid Avenue, Cleveland, OH, 44106, USA.

E-mail addresses: [bachelormd10@163.com](mailto:bachelormd10@163.com) (F. Liang), [qianpengjiang@jiangnan.edu.cn](mailto:qianpengjiang@jiangnan.edu.cn) (P. Qian), [kuan-hao.su@case.edu](mailto:kuan-hao.su@case.edu) (K.-H. Su), [atallah.baydoun@case.edu](mailto:atallah.baydoun@case.edu) (A. Baydoun), [asha.leisser@meduniwien.ac.at](mailto:asha.leisser@meduniwien.ac.at) (A. Leisser), [steven.vanhedent@case.edu](mailto:steven.vanhedent@case.edu) (S. Van Hedent), [jung-wen.kuo@case.edu](mailto:jung-wen.kuo@case.edu) (J.-W. Kuo), [zhaokaifa@qq.com](mailto:zhaokaifa@qq.com) (K. Zhao), [pparikh@radonc.wustl.edu](mailto:pparikh@radonc.wustl.edu) (P. Parikh), [yonggang.lu@wustl.edu](mailto:yonggang.lu@wustl.edu) (Y. Lu), [bryan.traughber@case.edu](mailto:bryan.traughber@case.edu) (B.J. Traughber), [raymond.muzic@case.edu](mailto:raymond.muzic@case.edu) (R.F. Muzic).

<https://doi.org/10.1016/j.artmed.2018.07.001>

Received 16 June 2017; Received in revised form 6 June 2018; Accepted 6 July 2018

0933-3657/ © 2018 Published by Elsevier B.V.

segmentation accuracy. To our knowledge, this is the first fully automated contouring approach using T1 MRI images for adaptive radiotherapy.

## 1. Introduction

Adaptive radiation therapy (ART) is a radiation treatment process that modifies the treatment plan based on patient-specific functional and anatomic changes during the course of radiation therapy. ART accounts for the daily geometric variation in patient's anatomy resulting from patient's setup, physiological changes, and treatment response. ART may enhance the efficacy via enabling high treatment dose to clinical target volumes (CTVs) while minimizing morbidities by sparing organs at risk (OARs) [1]. There are three timescales for ART, i.e. offline between treatments, online immediately prior to a treatment, and in real time during treatment [2]. During online ART, a plan is generated for each radiation therapy session based on the image data acquired immediately prior to the session while the patient is on the treatment table. On-board imaging is thus required for online ART and with advanced technology, online, MRI-guided, adaptive radiation therapy (MR-ART) has been implemented in clinical and research settings [3,4]. Compared to computed tomography-guided ART (CT-ART), MR-ART provides two, main advantages, i.e. better soft tissue contrast leading to more accurate anatomical delineation [5,6] and further sparing of OARs.

Manual contouring, the delineation of CTVs and OARs, remains the most laborious and time-consuming task in traditional radiation therapy and is a significant hindrance to ART. Moreover, manual contouring is subject to intra- and inter-operator variation. These two features of manual contouring make it impractical for routine clinical use in online MR-ART and very difficult in the research setting. In addition, the waiting time on a treatment table is usually uncomfortable for many cancer patients who have significant morbidities. Recently published case series reported the successful implementation of MR-ART for different abdominopelvic malignancies, using a manual [1] or interactive segmentation algorithm [7]. Different image registration techniques do not meet the clinical needs for adaptive radiotherapy and thus require further manual adjustment of the contours to account for the daily variations. Therefore, an optimal auto-contouring algorithm for online MR-ART is needed in order to efficiently generate new contours each treatment day, and thus minimizing the time gap between image acquisition and the implementation of the corresponding radiation therapy plan.

Currently available, auto-contouring algorithms can generally be classified into two approaches, i.e. model-free and knowledge-based

methods. Model-free methods are based on the analysis of image content and properties such as voxel intensities or gradient analysis. These methods include graph cuts [8], watershed [9], and adaptive thresholding [10] as well as region growing [11]. Model-free methods may roughly identify the organ boundaries, but are sensitive to image noise and artifacts [12]. Knowledge-based methods address these limitations using prior knowledge of the morphology of anatomical structures or the appearance of organs in different types of imaging modalities in order to improve the robustness and accuracy of the boundary determination. The knowledge-based methods include three sub-categories, i.e. atlas-, model-, and machine learning-based methods [13]. Atlas-based segmentation is defined as the process of performing segmentation on a new dataset using the knowledge of prior segmentation, i.e. a dataset from one or more patients that has the structures of interest already labeled [14]. Many commercially available software such as ABAS (CMS-Elekta, Stockholm, Sweden), MIM (MIMVista corp, Cleveland, OH), and VelocityAI (Velocity Medical Systems, Atlanta, Georgia) use atlas-based segmentation in adaptive radiotherapy when based on one re-planning CT acquired during the radiotherapy course [15]. Disadvantages of this method include the large variation in intensity, contrast medium, and geometry between the atlas and the image to be segmented which is also subject to significant image artifacts and inter-patient differences [16]. Model-based organ delineation includes prior knowledge of the organ shape combined with organ-specific parameters, such as intensity range, gradient magnitude, and direction [17]. However, this method requires two, manual steps, i.e. close initialization to the target anatomy with its corresponding model shape according to a drag-and-drop operation and non-rigid manual deformations [16]. Alternatives to overcoming these undesired properties include machine learning methods using voxel-based features to train, for example, neural networks, boosting trees, the support vector machine (SVM), random forests models or ensembles of classifiers [13] in order to find tissue boundaries in new data based on the inferred function determined from the labeled training data. Unfortunately, these algorithms are generally computationally complex and time-consuming and impractical for online and real time MR-ART [18].

Inspired by the human contouring processing model, we developed a novel methodology for auto-contouring that is designed to support online MR-ART. We couple top-down and bottom-up methods to achieve a multiple-level, hybrid method integrating low-level features to object level models in addition to simulating the human fusion

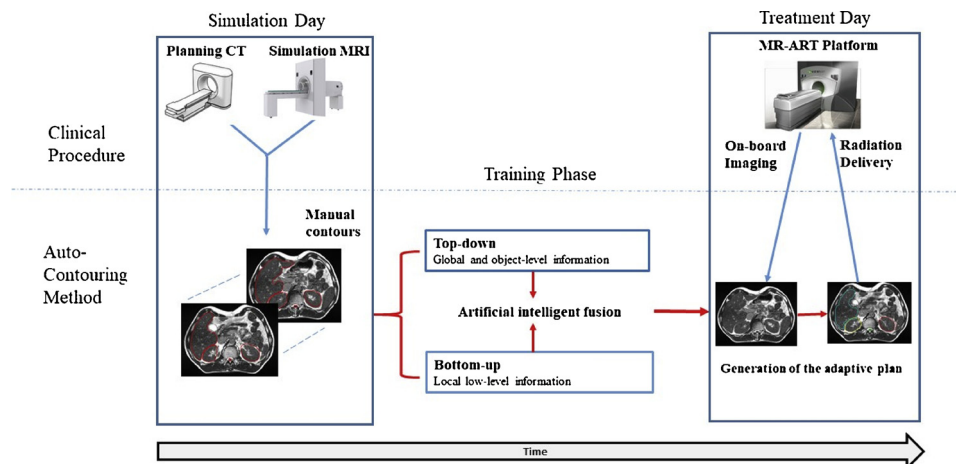


Fig. 1. Schematic representation of the auto-contouring algorithm.

Download English Version:

<https://daneshyari.com/en/article/8947356>

Download Persian Version:

<https://daneshyari.com/article/8947356>

[Daneshyari.com](https://daneshyari.com)