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● *Original Contribution*

AUTOMATED COMPUTED TOMOGRAPHY–ULTRASOUND CROSS-MODALITY 3-D CONTOURING ALGORITHM FOR PROSTATE

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Abstract—A novel fully automated algorithm is introduced for 3-D cross-modality image segmentation of the prostate, based on the simultaneous use of co-registered computed tomography (CT) and 3-D ultrasound (US) images. By use of a Gabor feature detector, the algorithm can outline in three dimensions and in cross-modality the prostate, and it can be trained and optimized on specific patient populations. We applied it to 16 prostate cancer patients and evaluated the conformity between the automatically segmented prostate contours and the contours manually outlined by an experienced physician, on the CT–US fusion, using the mean distance to conformity (MDC) index. When only the CT scans were used, the average MDC value was 4.5 ± 1.7 mm (maximum value = 9.0 mm). When the US scans also were considered, the mean ± standard deviation was reduced to 3.9 ± 0.7 mm (maximum value = 5.5 mm). The cross-modality approach acted on all the largest distance values, reducing them to acceptable discrepancies. (E-mail: davide.fontanarosa@maastro.nl) © 2015 World Federation for Ultrasound in Medicine & Biology.

Key Words: **Ultrasound imaging, Computed tomography imaging, Automated image segmentation, Cross-modality, Radiotherapy, Image-guided radiation therapy.**

INTRODUCTION

Cancer Research UK (http://www.cancerresearchuk.org) estimated that about 900,000 men worldwide were diagnosed with prostate cancer in 2008, accounting for almost one in seven (14%) cancers diagnosed in men. Radiotherapy (RT) is one of the primary treatment modalities for prostate cancer patients. The definition of the regions to be treated (regions of interest) and of the organs at risk to be spared is increasingly becoming a crucial step of the RT workflow. Segmentation (or contouring) is involved not only at the planning stage, at which reliable contours can make the difference between positive and negative treatment outcomes, but also during treatment, for example, for image guided radiation therapy (IGRT) (Davis et al. 2005; Xing et al. 2006) or for outcome evaluation, based on comparisons between target contours before and after the treatment.

Segmentation can be very time demanding. In particular, for prostate, manual segmentation is a tedious task. Computed tomography (CT) is the most widely used imaging modality for segmentation in RT because it is required for dose calculation and, therefore, is always available prior to treatment planning. But integration of imaging information from different modalities may help improve segmentation of structures. This is why fused multimodality data sets are frequently used for contouring. Several imaging methods can be used in combination with CT for better localization and definition of the prostate: the most common are cone-beam computed tomography (Oldham et al. 2005; Zeng et al. 2008), magnetic resonance imaging (MRI) (Raaymakers et al. 2009) and ultrasound (US) imaging (Fraser et al. 2010; Fung et al. 2006; Lattanzi et al.1999; Mayyas et al. 2013; Morr et al. 2002; Robinson et al. 2012; Wein et al. 2007). US is currently mostly used for segmentation and IGRT (Molloy et al. 2004; Smith et al. 2007) because it

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provides a quantitative and cost-effective imaging technique that avoids unwanted radiation dose to the patient.

To combine the required accuracy with an efficient workflow, semi-automated and automated segmentation strategies were introduced (*e.g.*, Pekar et al. 2004). Recently, 2-D and 3-D state-of-the-art-prostate automatic segmentation methodologies have been reviewed (Ghose et al. 2012). In this work, the most common methods were classified into the following categories: contour- and shape-based methods; region-based methods; supervised and unsupervised classification methods; and hybrid methods. For CT images, several automatic segmentation algorithms have been proposed (Costa et al. 2007; Davis et al. 2005; Lu et al. 2011; Tang et al. 2004; Siqi and Radke 2009), but this imaging modality typically exhibits poor soft tissue contrast, which leads in most cases to an intrinsic limitation of the features that can be used for a correct automated segmentation procedure. For the pelvic area, for example, the key features are the boundaries between bladder, prostate and seminal vesicles, which are often very difficult to identify.

For prostate segmentation based on US scans, most of the algorithms previously developed segment structures only in two dimensions (Betrouni et al. 2005; Jendoubi et al. 2004; Shen et al. 2003). For 3-D image data sets, contours are created on each slice separately. This leads to a partial use of the information provided by the whole volume and is likely to produce errors. In fact, even when the boundary curve obtained as the result of a single-slice 2-D segmentation is used as the starting configuration to propagate and adapt to nearby slices (*e.g.,* Ding et al. 2007), the error introduced at each step could propagate to the following steps and compromise the entire result. Three-dimensional prostate segmentation methodologies based on active shape and appearance models were introduced by Cootes et al. (1994). Ghose et al. (2013) merged this basic shape-driven process with feature learning support. This approach adapts well to the characteristics of different types of imaging modalities, but it was limited to a single modality (US).

To our knowledge, no automated cross-modality segmentation algorithm is available for CT–US combined data sets. Chowdhury et al. (2012) proposed a framework to build a statistical shape model for a structure of interest using multiple imaging modalities. Contextually, they derived an algorithm for prostate segmentation based on magnetic resonance (MR)–CT images. Although, in principle, this general approach for the definition of the shape model could also be applied to US images (instead of MR images), its application is less effective for imaging modalities such as US, in which the signal derives mainly from the region boundaries and it has differential sensitivity to different boundaries (*e.g.*, parallel or perpendicular to the US beam propagation direction).

A common basis of many techniques in medical image segmentation is the active contour model framework (Kass et al. 1988). In this work, an initial contour (snake or 2-D spline) is positioned inside the image; then an energy function is defined in terms of internal components (*i.e.*, contour shape, continuity, smoothness) and external components (*i.e.*, image features such as the intensity or the gradient of the intensity); finally, the contour is iteratively deformed to the desired shape and position by minimizing the energy function. A well-known problem associated with this approach is that the information provided locally by low-quality images may not be sufficient to characterize the border in every control point of the contour spline. Then most of the state-of-the-art segmentation methods tried to enforce the internal energy evaluating the target shape as a whole (level sets) (Osher and Sethian 1988; Tsai et al. 2003) or to enforce the constraints on the target shape (active shapes) (Cootes et al. 1995); in both cases, the possibility of locally characterizing the border of the target is lost.

In our work we propose a new representation of the target region shape that preserves the local description, as in the original active contour model, but can also efficiently take into account all the additional information present in advanced multimodality imaging (and exploits the improved computational capabilities available today): the polar defined convex volume (PDCV). The PDCV is a meshlike data structure defined in a polar coordinate system, with its origin representing the floating center of mass of the region. Its intrinsically 3-D definition allows analysis of the features extracted from image data directly in 3-D space. Moreover, we introduce surface classes, which are a partition of the target border allowing the use of different trained feature models on different surface areas independently. We also introduce the concept of topologic multiplicity, which allows for a more accurate representation of such surface areas, retrieving information not only from structures found on the border, but also in its neighborhood.

The prostate segmentation process consists of approximating an initial position for the PDCV, then iteratively extracting features along the local normal directions to the PDCV surface. This procedure simultaneously takes into account the information from all the modalities (multimodality approach) and also in the neighboring locations along the normal directions to the contour (topologic multiplicity). These feature vectors are evaluated with respect to a model previously trained for the specific local surface region (class); on the basis of this evaluation, the best new candidate position for the surface points is chosen and the PDCV is updated