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# Body-wide hierarchical fuzzy modeling, recognition, and delineation of anatomy in medical images

Jayaram K. Udupa [a,*], Dewey Odhner [a], Liming Zhao [a], Yubing Tong [a], Monica M.S. Matsumoto [a], Krzysztof C. Ciesielski [a,b], Alexandre X. Falcao [d], Pavithra Vaideeswaran [a], Victoria Ciesielski [a], Babak Saboury [a], Syedmehrdad Mohammadianrasanani [a], Sanghun Sin [e], Raanan Arens [e], Drew A. Torigian [c]

[a] Medical Image Processing Group, Department of Radiology, University of Pennsylvania, 423 Guardian Drive, Blockley Hall, 4th Floor, Philadelphia, PA 19104, United States
[b] Department of Mathematics, West Virginia University, Morgantown, WV 26506-6310, United States
[c] Department of Radiology, Hospital of the University of Pennsylvania, Philadelphia, PA 19104-4283, United States
[d] LIV, Institute of Computing, University of Campinas, Av. Albert Einstein 1251, 13084-851 Campinas, SP, Brazil
[e] Division of Respiratory and Sleep Medicine, Children's Hospital at Montefiore, 3415 Bainbridge Avenue, Bronx, NY 10467, United States

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ABSTRACT

To make Quantitative Radiology (QR) a reality in radiological practice, computerized body-wide Automatic Anatomy Recognition (AAR) becomes essential. With the goal of building a general AAR system that is not tied to any specific organ system, body region, or image modality, this paper presents an AAR methodology for localizing and delineating all major organs in different body regions based on fuzzy modeling ideas and a tight integration of fuzzy models with an Iterative Relative Fuzzy Connectedness (IRFC) delineation algorithm. The methodology consists of five main steps: (a) gathering image data for both building models and testing the AAR algorithms from patient image sets existing in our health system; (b) formulating precise definitions of each body region and organ and delineating them following these definitions; (c) building hierarchical fuzzy anatomy models of organs for each body region; (d) recognizing and locating organs in given images by employing the hierarchical models; and (e) delineating the organs following the hierarchy. In Step (c), we explicitly encode object size and positional relationships into the hierarchy and subsequently exploit this information in object recognition in Step (d) and delineation in Step (e). Modality-independent and dependent aspects are carefully separated in model encoding. At the model building stage, a learning process is carried out for rehearsing an optimal threshold-based object recognition method. The recognition process in Step (d) starts from large, well-defined objects and proceeds down the hierarchy in a global to local manner. A fuzzy model-based version of the IRFC algorithm is created by naturally integrating the fuzzy model constraints into the delineation algorithm.

The AAR system is tested on three body regions – thorax (on CT), abdomen (on CT and MRI), and neck (on MRI and CT) – involving a total of over 35 organs and 130 data sets (the total used for model building and testing). The training and testing data sets are divided into equal size in all cases except for the neck. Overall the AAR method achieves a mean accuracy of about 2 voxels in localizing non-sparse blob-like objects and most sparse tubular objects. The delineation accuracy in terms of mean false positive and negative volume fractions is 2% and 8%, respectively, for non-sparse objects, and 5% and 15%, respectively, for sparse objects. The two object groups achieve mean boundary distance relative to ground truth of 0.9 and 1.5 voxels, respectively. Some sparse objects – venous system (in the thorax on CT), inferior vena cava (in the abdomen on CT), and mandible and naso-pharynx (in neck on MRI, but not on CT) – pose challenges at all levels, leading to poor recognition and/or delineation results. The AAR method fares quite favorably when compared with methods from the recent literature for liver, kidneys, and spleen on CT images. We conclude that separation of modality-independent from dependent aspects, organization of objects in a hierarchy, encoding of object relationship information explicitly into the hierarchy, optimal threshold-based recognition learning, and fuzzy model-based IRFC are effective concepts which allowed us to demonstrate the feasibility of a general AAR system that works in different body regions on a variety of organs and on different modalities.



* Corresponding author. Tel.: +1 215 662 6783.
*E-mail address:* jay@mail.med.upenn.edu (J.K. Udupa).

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# 1. Introduction

## 1.1. Background

Since the birth of radiology in 1895, the emphasis in clinical radiology has been on *human visualization* of internal structures. Although various tomographic image modalities evolved subsequently for deriving anatomic, functional, and molecular information about internal structures, the emphasis on human visualization continued and the practice of *clinical radiology* has remained mostly *descriptive* and *subjective*. Quantification is amply employed in radiology in clinical research. However, in clinical radiological practice, this is not common. In the qualitative mode, quantifiable and/or subtle image information is underutilized, interpretations remain subjective, and subtle changes at early disease stages or due to therapeutic intervention may be underestimated or missed (Torigian and Alavi, 2007). It is generally believed now that if Quantitative Radiology (QR) can be brought to routine clinical practice, numerous advances can be made including: improved sensitivity, specificity, accuracy, and precision of early disease diagnosis; more objective and *standardized* response assessment of disease to treatment; improved understanding of what is "normal"; increased ease of disease measurement and reporting; and discovery of new disease biomarkers.

To make QR a reality, we believe that computerized *Automatic Anatomy Recognition* (AAR) during radiological image interpretation becomes essential. To facilitate AAR, and hence eventually QR, and focusing only on the anatomic aspects of shape, geography, and architecture of organs, while keeping the larger goal in mind, we present in this paper a novel fuzzy strategy for building body-wide anatomic models, and for utilizing these models for automatically recognizing and delineating body-wide anatomy in given patient images.

## 1.2. Related work

Image segmentation – the process of recognizing and delineating objects in images – has a rich literature spanning over five decades. From the perspective of the direction in which this field is headed, it is useful to classify the methods developed to date into three groups: (a) Purely image-based, or pI approaches (Beucher, 1992; Boykov et al., 2001; Kass et al., 1987; Malladi et al., 1995; Mumford and Shah, 1989; Udupa and Samarasekera, 1996), wherein segmentation decisions are made based entirely on information derived from the given image; (b) object model-based, or OM approaches (Ashburner and Friston, 2009; Cootes et al., 2001; Heimann and Meinzer, 2009; Pizer et al., 2003; Shattuck et al., 2008; Staib and Duncan, 1992), wherein known object shape and image appearance information over a population are first codified in a model and then utilized on a given image to bring constraints into the segmentation process; and (c) hybrid approaches (Chen and Bagci, 2011; Hansegard et al., 2007; Horsfield et al., 2007; Liu and Udupa, 2009; Rousson and Paragios, 2008; Shen et al., 2011; van der Lijn et al., 2012; Zhou and Bai, 2007), wherein the delineation strengths of the pI methods are combined synergistically with the global object recognition capabilities of the OM strategies. pI algorithms predate other approaches, and they still continue to seek new frontiers. OM approaches go by various names such as statistical models and probabilistic atlases, and continue to be pursued aggressively. Particularly, atlas-based techniques have gained popularity in brain MR image segmentation and analysis (Cabezas et al., 2011). Hybrid approaches hold much promise for AAR and QR and are currently very actively investigated. Since our focus in this paper is the body torso, and since the nature of the images and of the objects and challenges encountered are different for these regions (from, for example, for the brain), our review below will focus mainly on methods developed for the torso.

Since the simultaneous consideration of multiple objects offers better constraints, in recent years, multi-object strategies have been studied under all three groups of approaches to improve segmentation. Under pI approaches, the strategy sets up a competition among objects for delineating their regions/boundaries (e.g.; Bogovic et al., 2013; Saha and Udupa, 2001). In OM approaches, the strategy allows including inter-relationships among objects in the model to influence their localization and delineation (e.g.; Cerrolaza et al., 2012; Duta and Sonka, 1998). In hybrid approaches, multi-object strategies try to strengthen segmentability by incorporating relevant information in model building, object recognition/localization, and subsequently also in delineation via the pI counterpart of the synergistic approach (Chen et al., 2012; Chu et al., 2013; Linguraru et al., 2012; Lu et al., 2012; Meyer et al., 2011; Okada et al., 2008; Shen et al., 2011; Tsechpenakis and Chatzis, 2011). Motivated by applications (such as semantic navigation) where the focus is just locating objects in image volumes and not delineating them, a separate group of methods has been emerging (Criminisi et al., 2013; Zhou and Rajapakse, 2005; Zhou et al., 2013). They use features characterizing the presence of whole organs or specific anatomic aspects of organs (such as the femoral neck and head) combined with machine learning techniques to locate objects in image volumes by finding the size, location, and orientation of rectangular bounding boxes that just enclose the anatomic entities.

The state-of-the-art in image segmentation seems to leave several gaps that hinder the development of a body-wide AAR system. First, while multi-object strategies have clearly shown superior performance for all approaches, in all published works they have been confined to only a few (three to five) selected objects and have not taken into account an entire body region or all of its major organs, the only exception being (Baiker et al., 2010), whose focus was whole body segmentation of mice on micro CT images. Second, and as a result, there is no demonstrated single method that operates on different body regions, on all major organs in each body region, and at different modalities. Third, all reported modeling strategies have a statistical framework, either as statistical models of shape and intensity pattern of appearance of objects in the image or as atlases, and none taking a fuzzy approach, except (Zhou and Rajapakse, 2005) and our previous work (Miranda et al., 2008, 2009), both in the brain only. Fuzzy set concepts have been used extensively otherwise in image processing and 3D visualization. Fuzzy modeling approaches allow bringing anatomic information in an all-digital form into graph theoretic frameworks designed for object recognition and delineation, obviating the need for (continuous) assumptions made otherwise in statistical approaches about shapes, random variables, their independence, functional form of density distributions, etc. They also allow capturing information about uncertainties at the patient level (e.g., blur, partial volume effects) and population level, and codification of this information within the model. Fourth, objects have complex inter-relationships in terms of their geographic layout. Learning this information over a population and encoding this explicitly in an object hierarchy can facilitate object localization considerably. Although several multi-object methods have accounted for this relationship indirectly, its direct incorporation into modeling, object recognition, and delineation in an anatomic hierarchical order has not been attempted. The AAR approach presented in this paper is designed to help overcome these gaps.

## 1.3. Outline of paper and approach

We start off by describing a novel hierarchical fuzzy modeling framework for codifying prior population information about object