Definition and Automatic Anatomy Recognition of Lymph Node Zones in the Pelvis on CT Images

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ABSTRACT

Currently, unlike IALSC-defined thoracic lymph node zones, no explicitly provided definitions for lymph nodes in other body regions are available. Yet, definitions are critical for standardizing the recognition, delineation, quantification, and reporting of lymphadenopathy in other body regions. Continuing from our previous work in the thorax, this paper proposes a standardized definition of the grouping of pelvic lymph nodes into 10 zones. We subsequently employ our earlier Automatic Anatomy Recognition (AAR) framework designed for body-wide organ modeling, recognition, and delineation to actually implement these zonal definitions where the zones are treated as anatomic objects. First, all 10 zones and key anatomic organs used as anchors are manually delineated under expert supervision for constructing fuzzy anatomy models of the assembly of organs together with the zones. Then, optimal hierarchical arrangement of these objects is constructed for the purpose of achieving the best zonal recognition. For actual localization of the objects, two strategies are used – optimal thresholded search for organs and one-shot method for the zones where the known relationship of the zones to key organs is exploited. Based on 50 computed tomography (CT) image data sets for the pelvic body region and an equal division into training and test subsets, automatic zonal localization within 1-3 voxels is achieved.

Keywords: Pelvic lymph node zones, automatic anatomy recognition, fuzzy models, object recognition.

1. INTRODUCTION

In clinical practice, no practical solution is currently available for radiologists, nuclear medicine physicians, and others to automatically and reliably define and recognize lymph node zones in the pelvis. This is, in part, related to the lack of available standardized definitions to classify pelvic lymph nodes into different zonal locations. Quantification of lymphadenopathy in the pelvis is important for the management of patients with various neoplastic and non-neoplastic disorders. Unlike the lymph node stations and zones defined by International Association for the Study of Lung Cancer (IASLC)[1] in the chest, there is no comparable standardized definition of the various lymph node zones in other body regions, in particular, the pelvis. Standardized lymph node zone definition will greatly facilitate meaningful and standardized reporting, staging, management, and quantification of lymph node disease conditions.

Firstly, it is necessary to develop standardized definitions of pelvic lymph node zones in a manner that is analogous to those the IASLC standard provides for the thorax. If standardized definitions are developed and implemented to localize zones automatically, one can obtain information about specific lymph nodes quickly and distinctly through the localized zones. Second, it is important to separate lymph nodes into different anatomic zones, as the spatial extent of lymph nodes by pathology affects disease stage, patient prognosis, pretreatment planning, and therapeutic approaches implemented[2]. Lastly, automatic recognition and quantification of the lymph nodes in each zone can then be utilized for more in-depth analytic assessment of patients with cancer and other disease conditions for purposes of disease staging, prognostication of treatment outcome, response assessment, etc[3-4].

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With these greater goals in mind, we created new definitions of the pelvic lymph node zones. In this paper, we present these definitions and an automatic anatomy recognition (AAR)[5] method to localize/recognize these lymph node zones in pelvic computed tomography (CT) images using fuzzy models.

2. METHODS

2.1 Definition of pelvic lymph node zones

We use the term *zones* broadly for lymph node stations or groups of lymph node stations, and define each of them as roughly a rectangular parallelepiped 3D region for the purpose of geographically localizing the anatomic space containing the nodes. These are defined with respect to anatomic landmarks so that it makes sense to model their shape and geographic layout over a population of subjects.

In the pelvis, we broadly define five lymph node zones and call them Zone 1: common iliac zone; Zone 2: external iliac zone; Zone 3: internal iliac zone; Zone 4: inguinal zone; and Zone 5: pelvic mesenteric zone. For each of these 5 zones, we identify left (L) and right (R) sub-zones as depicted in Figure 1.

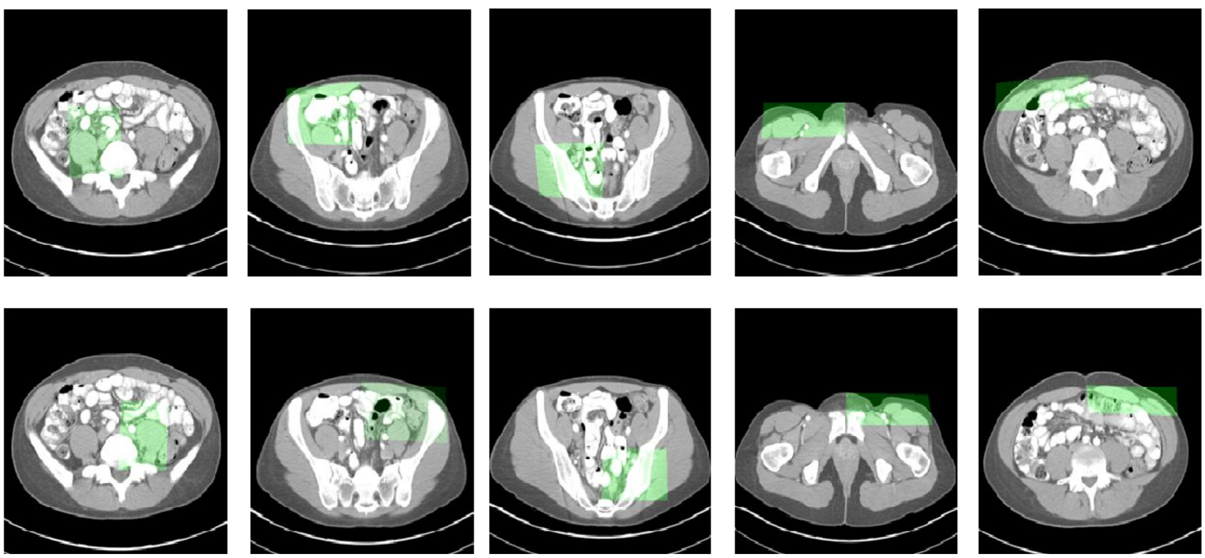


Figure 1. Illustrations of definition and delineation of pelvic lymph node zones. From top to bottom, left to right: Zones 1R, 1L, 2R, 2L, 3R, 3L, 4R, 4L, 5R, and 5L.

Our proposed method to automatically localize or recognize lymph node zones is based on the framework of automatic anatomy recognition (AAR)[5]. It consists of two steps: building anatomic models of the zones, and automatically localizing the zones by employing the models.

2.2 AAR model building

Gathering image database: This retrospective study was conducted following approval from the Institutional Review Board at the Hospital of the University of Pennsylvania along with a Health Insurance Portability and Accountability Act waiver. For the pelvis, contrast-enhanced CT images of 50 near normal (radiologically normal with exception of minimal incidental focal abnormalities) female subjects are utilized. Image data sets from 25 of these subjects are used for model building and the remaining sets are used for testing the AAR recognition performance of the 10 zones. In these data sets, image size = 512 x 512 x 37-49, and voxel size = 0.9 x 0.9 x 5.00 mm^3.

Delineating organs and lymph node zones in images: The idea behind the AAR approach to localize lymph node zones is to make use of the information about the natural geographical layout of lymph node zones, their relationship to key anatomic organs, and their interrelationships by encoding this information in the model. Thus, about 6 anatomic organs and 10 lymph node zones in the 50 pelvic image data sets were all manually delineated under expert supervision and verification. Figure 1 shows some examples of delineations of the 10 zones. The pelvic organs or objects that were included and their abbreviations are as follows: Outer skin boundary of the pelvis (PSkn), urinary bladder (Bldr), pelvic muscles (PMsl), pelvic skeleton (PSk), uterus (Ut), and pelvic visceral region (PVr).

Constructing fuzzy anatomy model: The fuzzy anatomy model FAM(B) for the lymph node zones of body region B (pelvis) is defined to be a quintuple: (H, M, ρ, λ, η)[6]. H is a hierarchy, represented as a tree, of the objects considered in B for inclusion in the model. The objects considered are the anatomic organs and the zones. M is a collection of fuzzy models, one fuzzy model for each object in B. ρ describes the parent-to-offspring object relationship in H. λ is a set of scale factor ranges indicating the size variation of each object in B. η represents a set of measurements pertaining to the objects in B.

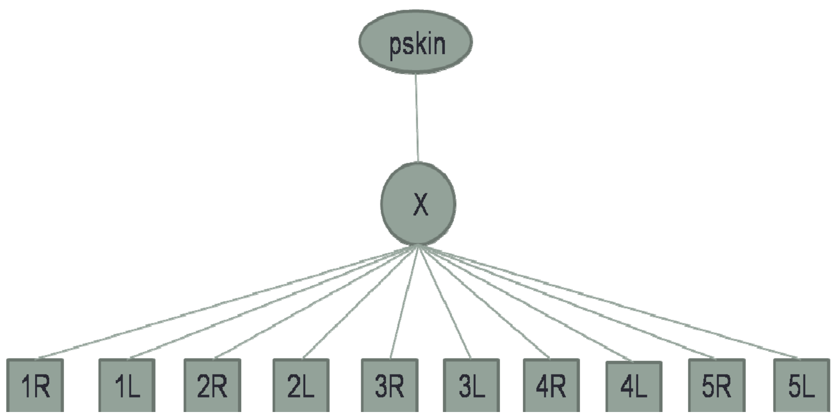


Figure 2. Testing the suitability of different organs (denoted by X) as parent for each zone for pelvis.

2.3 AAR object recognition

Object recognition in the AAR approach[5] proceeds hierarchically in H. The hierarchy chosen influences object localization accuracy considerably. Finding the best hierarchy is crucial for obtaining good object localization results. The variabilities observed in ρ and λ are used to make informed decisions about the choice of appropriate parent organs for different zones. To this end, we have used skin (PSkn) as the root object, and each of the other organs as the root's offspring to test which organ yields the best recognition result for each zone in a simple hierarchy illustrated in Figure 2. This allows us to determine with which organ each zone should be associated from the perspective of accurate zone localization. For each zone, that organ X is chosen which yields the smallest localization error for the zone.

For the actual recognition of objects in a given image I, we have combined two different strategies[7]: *thresholded optimal search* and *one-shot* method. In the one-shot method, an object is localized in I based on its already localized parent and the known prior parent-to-offspring relationship information encoded in ρ. In the thresholded optimal search approach, the one-shot method is first applied and the result is refined by optimally matching the model to I by using the known best threshold for each object. For the organs, the optimal threshold approach is used. For the zones, since they do not have any specific intensity characteristics, the one-shot method is used. This is the reason that finding the best organ to use as the anchor object (parent) for each zone becomes important.

3. RESULTS

The best hierarchy found for the pelvis is shown in Figure 3.

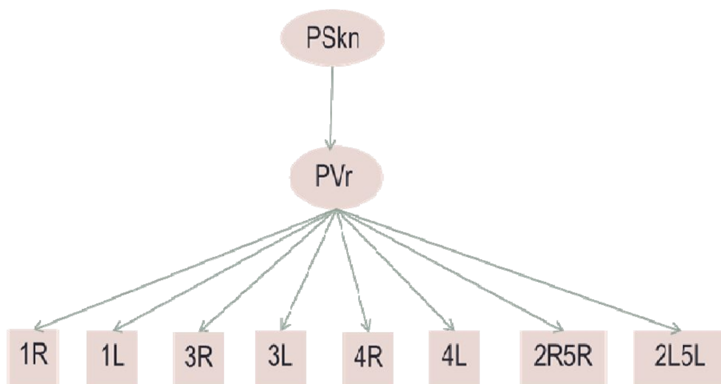
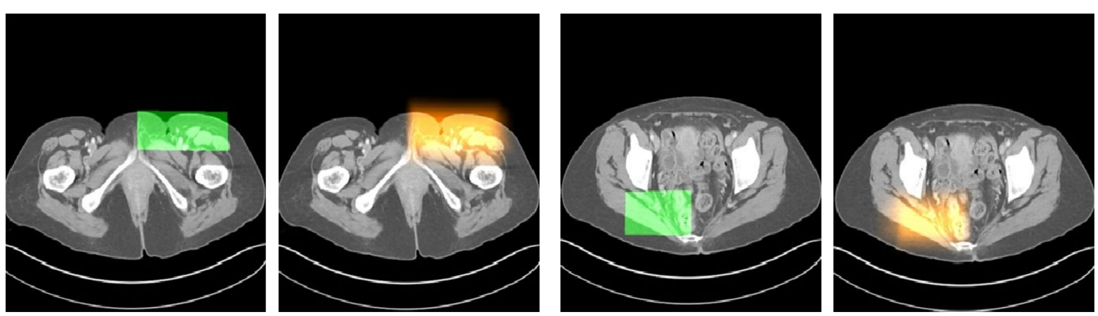


Figure 3. The best hierarchy obtained for pelvic zones. In the figure, 2R5R= 2R+5R, 2L5L=2L+5L. These are composite zones resulting from performing a union of basic zones.

Figure 4 displays sample recognition results for some pelvic zones where fuzzy model cross sections are overlaid on test image slice displays.



(a) (b) (c) (d)

Figure 4. Sample displays of recognition results. (a) true delineation of 4L; (b) recognition result of 4L; (c) true delineation of 3R; (d) recognition result of 3R.

We express recognition performance of the proposed methods in terms of position error and scale error as in our prior work[5]. The position error describes (in mm) the distance between the true and found locations of the object. Scale error expresses the ratio of the estimated to the true object size. Note that the ideal values for the two measures are 0 and 1, respectively. Mean and standard deviation over the tested data sets are shown in Table 1.

Table1. Error in recognizing pelvic lymph node zones.

	PSkn	PVr	1R	1L	3R	3L	4R	4L	2R5R	2L5L
Position error (mm)	1.48	3.46	12.92	14.98	9.14	12.93	13.03	10.78	11.02	12.67
	0.64	2.38	5.16	5.05	5.09	6.43	8.98	4.88	6.40	7.05
Scale error	1.00	1.00	1.02	1.02	1.00	1.01	0.96	0.99	0.98	1.01
	0.00	0.01	0.06	0.08	0.04	0.05	0.09	0.03	0.05	0.05

From Table 1, it can be seen that, as in our earlier work[5], organ localization accuracy is excellent with a location error close to one voxel. Lymph node zones can be localized within 2-3 voxels of their true locations overall. Some zones yield better accuracy when they are combined, such as combined zones 2L5L and 2R5R. Note that scale estimation is excellent, as has been observed for organ localization in the past[5]. It remains to be seen if the achieved localization accuracy is sufficient to accurately quantify diseases within the detected zones. There is also the possibility of further improving localization accuracy by building composite zones and objects as suggested by zones 2R5R and 2L5L.

4. CONCLUSIONS

It is important to formulate standardized zonal definitions for lymph nodes in body regions other than the thorax which, to our knowledge, do not exist[8-9]. This paper constitutes the first such effort to do so by taking the pelvis as an example. Through extensive adaptations of our AAR framework, we were able to arrive at lymph node zonal localizations within 2-3 voxels of the true locations. Compared to other efforts in the literature related to object feature localization on whole-body images developed for the purpose of image navigation, these results are comparable or better. Additional research will be required to further improve the performance of AAR for automatic lymph node zone recognition in the pelvis, particularly from the viewpoint of disease quantification.

5. REFERENCES

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