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3D CT spine data segmentation and analysis of vertebrae bone lesions *

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***Abstract*— A method is presented aiming at detecting and classifying bone lesions in 3D CT data of human spine, via Bayesian approach utilizing Markov random fields. A developed algorithm for necessary segmentation of individual possibly heavily distorted vertebrae based on 3D intensity modeling of vertebra types is presented as well.**

I. Introduction

Metastatic bone tumor in the spine is currently a widespread problem; the spine is the third most common site for cancer cells to form metastases, following the lung and liver. Spine tumors are usually detected by CT or MRI examination; the early detection is substantial to set up a respective treatment. The knowledge of position and volume of tumors and even risk areas is important in the diagnosis of the patient and also as an input to scoring systems for prospective surgical planning. Then, evaluation of tumor temporal changes is important, requiring time series of scans, ideally with the same scanning parameters. To support decisions on optimal treatment strategy, various prognostic score systems were introduced [1]–[5], defining several parameters influencing also the patient's prognosis. Thus, segmentation of individual vertebrae in the image data and detection of their pathologic changes is needed for evaluation of patient's health status, and for decisions on possible treatment. However, manual segmentation and analysis require extensive and time-consuming involvement of a clinical expert; therefore automated processing is highly desirable.

This problem consists basically of two components: segmenting the spine and individual vertebrae in the image data, and subsequently detecting and evaluating the lesions in the vertebrae. Several approaches to identification and segmentation of individual vertebrae in CT data have been published, based either on manually placed landmarks [6] [7], on affine and flexible registration of their atlases [8], [9], on application of level sets [8], [10], or on constrained adaptation of triangulated vertebra surface models [11]. Among these, the automated framework proposed by Klinder et al. [11] may be considered the current state of the art; however still not fully compatible with the peculiarities of shape deformations of vertebrae due to illness. The subsequent detection and classification of metastases in bones still belongs among generally unsolved problems, although several published papers deal with these problems, e.g. [12], [8], [14]. The problem is in low specificity of textural features in the bone lesion areas of different types.

In this paper we are describing the results of a running project aiming first at a more reliable spine segmentation even in difficult cases of heavily distorted vertebrae, and second at the subsequent lesion detection, classification and measurement in the vertebrae that would reasonably correspond to the (rather uncertain) visual evaluation by medical experts. The presented approach of spine segmentation is based on twenty two differing spatial models of human vertebrae (six cervical, twelve thoracic and four lumbar) capable of being flexibly deformed by locally defined refinement respecting the actual distortion and position of a concrete vertebra. Moreover, the thoracic models were complemented with models of their adjacent ribs, enabling more accurate local refinement of the vertebra segmentation. The method for the following detection, segmentation and classification of osteolytic (hypo-dense) and osteoblastic (hyper-dense) metastases within individual vertebrae is proposed, which utilizes the intensity distribution dissimilarities in different kinds of metastases to classify the lesions. The method uses a Markov Random Fields model in the Bayesian classification framework. The results of both processing phases were visually and numerically compared with the medical expert evaluations and the results statistically evaluated.

II. Experimental Data

Total of 17 image CT spinal scans were acquired using Philips Brilliance iCT scanner with 256-channel multi-detector row at the Osteo-Oncology Center, Istituto Scientifico Romagnolo per lo Studio e la Cura dei Tumori (I.R.S.T.) S.r.l., Meldola, Italy. The setup as in Table I was used for the image acquisitions. Contrast agent was present in seven image scans, while the remaining scans were provided without application of contrast agent. The inconsistency between contrasted and non-contrasted images was not an important obstacle in segmenting and analyzing individual scans; however a comparison of scans from these two different groups in time series of scans (separated by several weeks or months) was precluded due to differing lesion image parameters.

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TABLE I. CT DATA ACQUISITION PARAMETERS

Parameter	Value
Resolution	768 x 768 pixels ~2500 slices
Slice thickness [mm]	0.67
Anode voltage [kV]	140
Spacing between slices [mm]	0.335
X-ray tube current [mA]	232
Pixel spacing [mm]	0.65

Depending on the number of investigated vertebrae, individual 3D CT image scans consisted of some ~ 890 to ~2500 standard 2D DICOM® files containing the slice image data. Three men (65-73 years) and seven women (60-77 years) were identified in the experimental image dataset.

III. METHODOLOGY

A. *Segmentation of spine*

The segmentation of spine utilizes a database of 3D intensity models of the individual types of vertebrae that has been prepared by averaging healthy vertebra image data. Using these models, accordingly modified for each individual vertebra, the concrete patient's spine is segmented into separated vertebrae, subsequently then submitted to the analysis of lesions.

Models of vertebrae

The a-priori formed 22 models of individual types of vertebrae (six cervical, twelve thoracic and four lumbar) derived ahead, are the key concept in the presented segmentation approach. On the difference to [11] where the shape models are formulated as triangulated meshes, our models are 3D intensity data, derived by averaging of a number of normalized and registered healthy cases of the concrete vertebra type. Possible problems, as e.g. that ribs and the transverse processes of the thoracic vertebrae may be mutually connected in the image data, are treated correspondingly by details of the algorithms.

The vertebra database consists of models in the form of 3D intensity data as in the first row of Figure 2. ; each model

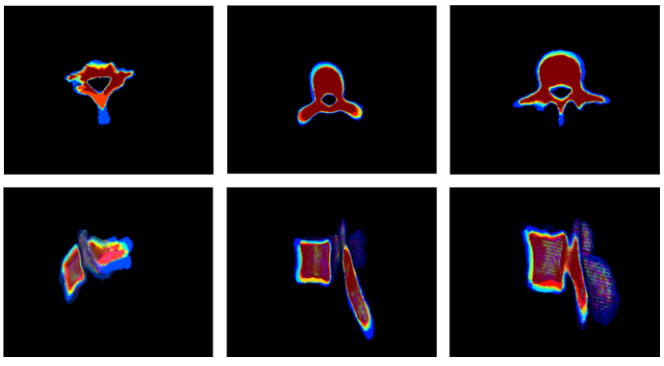


Figure 1. Averaged images of registered selected cervical, thoracic and lumbar vertebrae; from minimum intersection of corresponding vertebrae (bright blue) to maximum intersection (dark red)

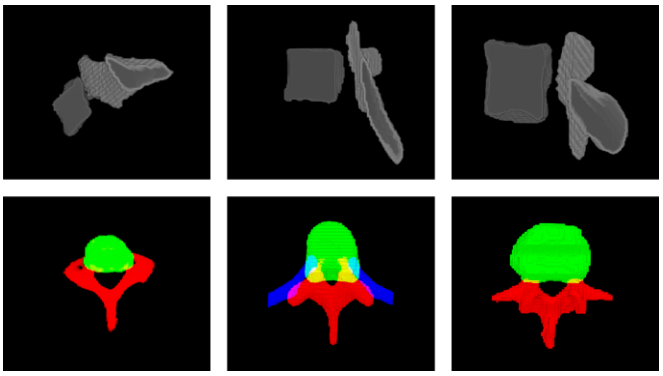


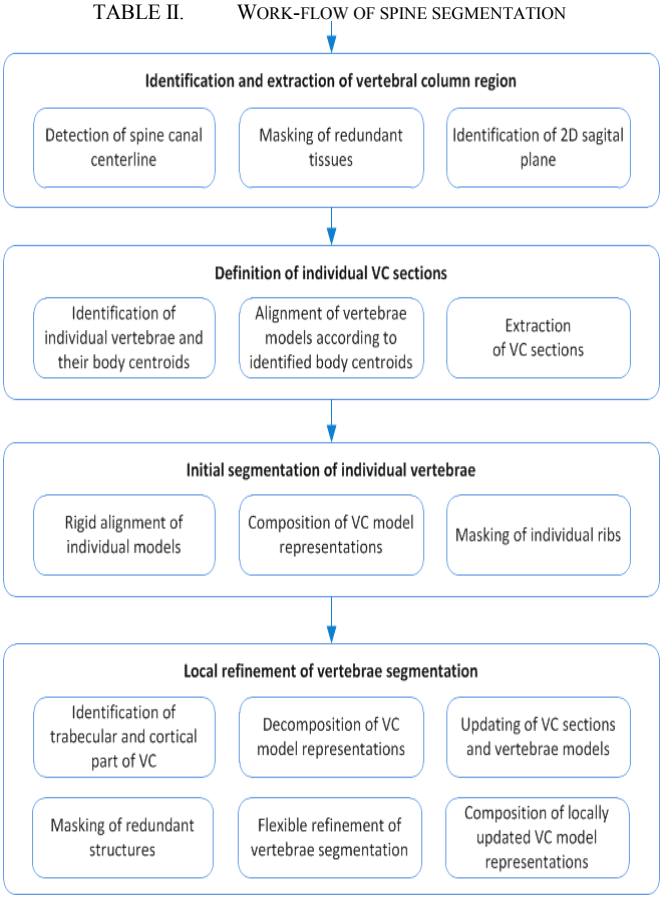
Figure 2. 3D visualization of examples of cervical (i=7), thoracic (i=15) and lumbar (i=22) vertebrae models. First row: intensity models, second row: corresponding masks of parts of vertebrae. Intentionally, different views are presented to provide a better insight.

is complemented by the corresponding binary 3D masks (lower row of the figure) as required by the segmentation algorithm. Each 3D model can be deformed in a large extent by different types of liner or non-linear spatial transforms (possibly based on local 3D disparities) thus capable of matching even substantially distorted shape and possible misplacement of a vertebra, afflicted by the illness.

Segmentation of individual possibly distorted vertebrae

The generic overview of the spine segmentation procedure can be seen on TABLE II. , where the individual successive steps are indicated. First, the vertebral column is

TABLE II. WORK-FLOW OF SPINE SEGMENTATION



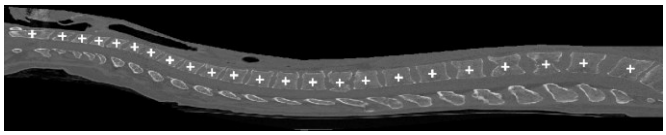


Figure 3. Automatically detected sagittal plane with manually identified centers of individual vertebrae

to be identified via finding its curved axis and indicating simply the individual vertebrae (Figure 3. - this only manual step so far will be automated in future). For each vertebra, the corresponding model according to the spine sequence is then registered initially by rigid and then by sophisticated flexible geometric transforms, in frame of the refinement phase.

This way, the algorithm is capable of dealing with vertebrae affected by various pathologies, where e.g. the trabecular centers of such vertebrae may be visually unrecognizable from their surrounding soft tissues, and/or cortical shells may demonstrate an abnormal growth, deformation and/or necrosis. Moreover, the shape of the vertebra may differ significantly from the standard, due to metastasizing leading to fractures, compressions, etc. The presented segmentation accounts for various deformation scenarios of the pathologic vertebrae via deforming the respective models accordingly based on local disparity analysis. Another uneasy aspect that had to be considered under these circumstances is the necessity of masking the redundant structures. An example of partial results of the segmentation is on Figure 4.

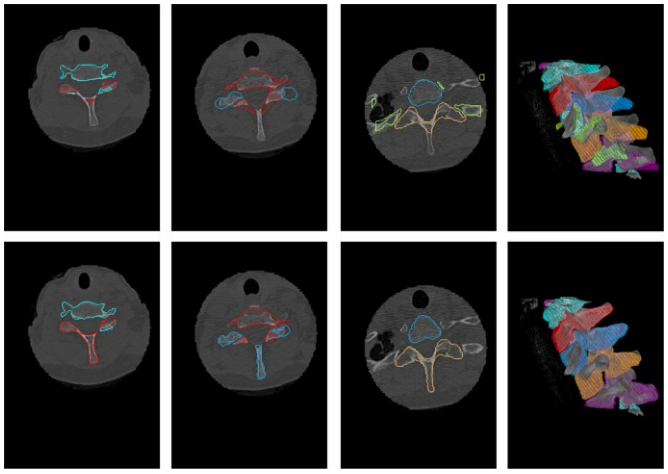


Figure 4. Example of segmentation of three thoracic vertebrae. First row: imprecise initial segmentation of posterior segments, second row: segmentation result with additional registration of the model posterior

B. Detection, segmentation and analysis of lesions

Lack of distinct texture inside lesions in the CT spine data (Figure 5.) makes the process of metastases classification difficult; none of the run-length coding, co-occurrence matrices, local binary patterns or Fourier-based methods has provided relevant features. Therefore, only local mean intensities could have been so far considered. Verified differences of local mean intensity within the metastatic tissues with respect to the surrounding healthy tissue enabled us to use the classification model based on Bayesian distribution combined with Markov random field (MRF) approach [14], [15]. It is advantageous that this model is not sensitive to noise in the image data.

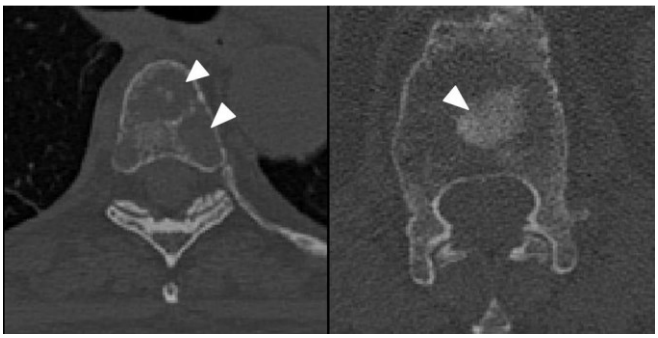


Figure 5. Well visible osteolytic (left) and osteoblastic (right) metastases

The MRF approach requires knowledge of the intensity distribution of the healthy tissue, approximated by Gauss curve. Due to known differences among individual types of vertebrae, their parameters (mean intensities and variances) should be experimentally determined by averaging for each type of vertebra individually (as the mean values in TABLE III. for contrast enhanced CT data).

TABLE III. MEAN INTENSITY (IN SCALE OF 255)OF HEALTHY TISSUE FOR INDIVIDUAL TYPES OF VERTEBRA (CE DATA)

Cervical	1	2	3	4	5	6	7	8				
μ_h	84	84	84	84	83	83	82	82				
Thoracic	9	10	11	12	13	14	15	16	17	18	19	20
μ_h	81	81	80.5	80.5	80.5	80.5	80	80	80	80	79.5	79.5
Lumbar	21	22	23	24	25							
μ_h	79.5	79.5	79	79	79							

This plays a crucial role in tumor detection and classification by the MRF approach optimizing a certain merit function based on the Bayesian approach; the tissue is locally classified into three classes (Figure 6.): osteolytic metastases, osteoblastic metastases and healthy tissue. The parameters of the merit function had to be determined experimentally, similarly as the parameters of the used optimization method (Metropolis dynamic), utilizing the "ground truth" based on classification by medical experts.

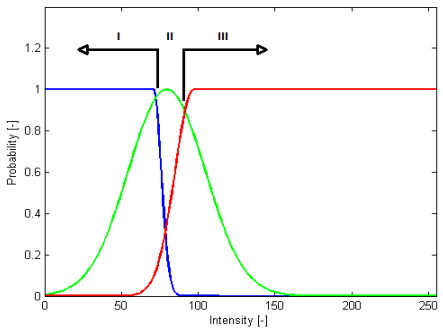


Figure 6. Curves showing the distribution of initial labels (I - osteolytic, II - healthy and III - osteoblastic

Bayesian classification utilizing the MRF approach allows the tissue classification independently on the spatial extent of the metastases, which is important for the tumor detection, particularly in initial phases of the illness.

IV. Results

The final goal of the process is to segment and classify bone lesions in the 3D CT data, as can be seen on a slice in Figure 7.

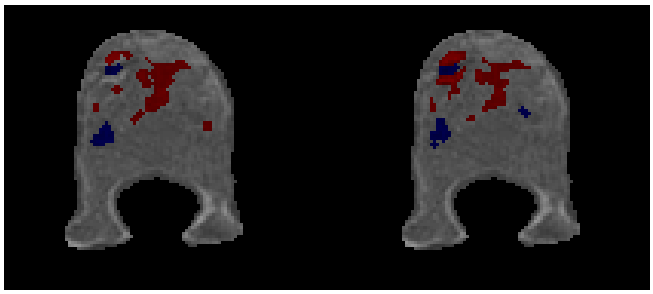


Figure 7. Classification of both types of tumors segmented by MRF based classification method (left: manual expert classification; right: MRF classification). Uncertainty of decission base is obvious.

Each of both parts of the analysis – spine segmentation and lesion classification – has been thoroughly tested in different aspects with rather convincing results. Only very summarizing results can be mentioned here.

For the segmentation phase, 320 vertebral bodies were segmented with rate of accurate results in 82 % with moderately deformed vertebrae and in 53% in heavily distorted ones. Similarly, small local inaccuracies have been found in about 10% (28% in the last group). It seems to surpass the so far reported results.

With respect to the method of lesion analysis, it is positive that the presented algorithm is able to classify metastases of various sizes; from 5 voxels up to many hundreds of voxels. The sensitivity and specificity of the lesion analysis was evaluated separately for hypo-dense metastases with sensitivity 55.7% and specificity 91.4%; similarly for hyper-dense metastases they were 63.5% and 95.1%, respectively.

V. Conclusion

The developed method of spinal lesion detection and classification corresponds to the expectations, considering the generic level of reliability of visual expert evaluation. The method was declared, by medical experts, satisfactory for automatic classification of osteolytic and osteoblastic metastases within the spine. Namely its ability to detect very small lesions might be an important feature possibly enabling diagnosing even the initial phases of the illness.

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