Automated Organ Detection in Water-Fat Separated Magnetic Resonance Imaging

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Purpose: To cope with today's healthcare challenges of providing cost-effective care with constant quality, advanced image analysis techniques that automatically extract anatomical information from complex, large image datasets are required [1, 2]. Examples of MRI applications that can benefit from such anatomical intelligence are: operator guidance for planning scans, organ-specific automated motion detection, automated labeling of image volumes, organ-oriented navigation of large datasets, and post-processing applications such as automated organ segmentation. In this work, computer vision techniques based on machine learning and Haar-like features [3] were extended to 3D and applied to automatically detect and localize a number of target organs in 3D water-fat separated, whole-body MR images. Performance and accuracy of the selected classifiers were evaluated in a cross-validation framework. The benefit of using the joint information provided by water and fat separation was investigated.

Methods: A total of 36 (25 males, 18 females) whole-body water-fat separated datasets, acquired with a Dixon dual-echo sequence (TR / TE_1 / TE_2: 3.2 / 1.11 / 2.0 ms, flip angle: 10°) on a 3T MR scanner (Achieva, Philips Healthcare, Best, The Netherlands) and subsampled to an isotropic resolution of 3.0x3.0x3.0 mm^3, were retrospectively analyzed (data courtesy of Prof. Osman Ratib, University Hospital of Geneva, Switzerland). For each dataset, 3D boxes delimiting the target organs (lung, heart, liver) were manually edited based on pre-defined landmarks. These 3D boxes were used as ground-truth to train the classifier and to evaluate the detection accuracy. To characterize the appearance of the target organs, generic 3D image features derived from the Haar-like features [4] were devised: for a given position in the image, features were computed as the difference between the average image intensities of two disjoint cuboids of arbitrary size and position (Fig. 1). For organ detection, an optimal selection and combination of the 3D features computed on the water and fat images was learned from the training data using boosted decision trees [5]. Different classifiers with varying boosting type, tree depth, and with features derived only from water images, only from fat images, or from both water and fat images, were compared in a 6-fold cross-validation experiment. The classifier performance was evaluated by computing the F_2-score [6], which is a widely used measure of test accuracy and ranges from 0 (lowest performance) to 1 (best performance). For each target organ, the configuration yielding the maximum F_2-score was selected to produce the final detection results, again in a 6 fold-cross validation manner. Finally, the distances between the manually edited and the automatically computed boxes were computed.

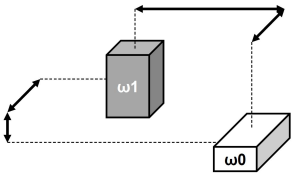
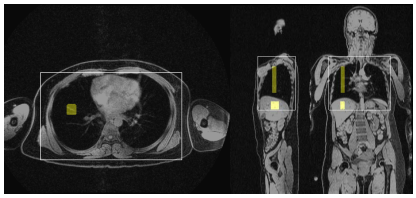


Fig. 1: Design of the 3D image feature family based on disjoint cuboids of arbitrary size and distance (left) and example of 3D image feature (in yellow) automatically selected in the training process for lung detection (right).



Results: For all target organs, the best classifier always consisted of a combination of image features extracted from both water and fat images. The corresponding F_2-scores are listed in Tab. 1. For the large majority of classification configurations, the classifier trained on both water and fat images resulted in a higher F_2-score than the corresponding classifiers trained only on water, respectively fat, images. The mean distances between automatically detected and manually edited organ box centers are summarized in Tab. 1, with an average absolute error below 2 cm in all 3 target organs. Examples of lung, heart, and liver detection obtained with the trained classifiers are shown in Fig. 2. Only in one case the algorithm failed to detect the liver and heart (Fig. 4, left), while in another case the liver was detected at a false position (Fig. 4, right).

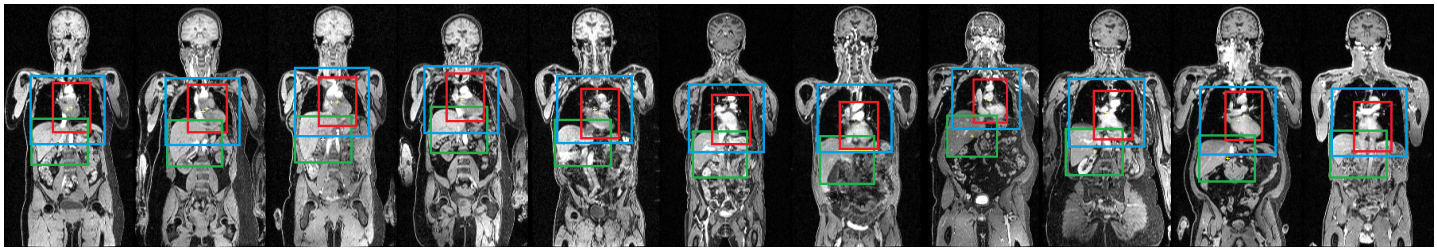


Fig. 2: Examples of detected lung (blue), heart (red), and liver (green) boxes, here super-imposed on the water image from a coronal slice.

Organ	Best F_2-score
Heart	0.9784
Lungs	0.9836
Liver	0.9443

Organ	Mean	Standard deviation
Heart	16.7	7.6
Lungs	16.4	7.8
Liver	19.1	8.4

Tab. 1: Classification (F_2-scores, left) and detection results (in mm, right).

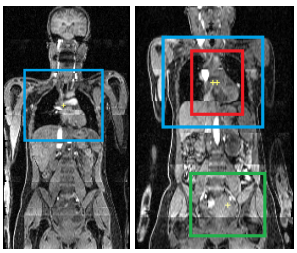


Fig. 3: The two patient data (out of 36) with obvious detection failures: on the left, the algorithm failed to detect the liver and the heart, on the right the liver was detected at a false position. These failures may be due to the imperfect intensity correction applied for the whole-body reconstruction.

Discussion: These preliminary results suggest that the application of simple, yet powerful classification techniques known from the computer vision literature can be applied for the robust and automated extraction of anatomical knowledge from MR images. These techniques allow addressing a plurality of target anatomies in a single framework, which makes them very attractive for large scale applications. In this study, the combination of water and fat images obtained with a Dixon sequence resulted in improved detection accuracy. Further improvements of the detection accuracy may be reached by increasing the number of training datasets and allowing for variable scale factors of the detector window.

References: [1] Ruppertshofen et al, IJCARS 8(4):593-606, 2013 [2] Pauly O et al, MICCAI 2011 [3] Viola P and Jones M, IJCV, 57(2):137-154, 2014 [4] Papageorgiou C et al, ICCV, 555-562, 1998 [5] Friedman et al, Ann Statist, 28(2):337-407, 2000 [6] Hastie T et al, Springer, 2008 [6] Rijsbergen C, Butterworth-Heinemann (1979).