Automatic Segmentation of Laryngeal Cartilages using Support Vector Machines

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Introduction: MR is critical in the staging of laryngeal cancer. However, the presence and extent of cartilage invasion is difficult to assess. Image segmentation could enhance the ability to determine tumor volume and extent. While fully automated segmentation of the laryngeal cartilages remains unexplored, the use of a multi-contrast and multi-dimensional approach has proven useful for segmenting articular cartilage [1]. One of the shortcomings of this approach is the lack of automatic intensity correction to compensate for the coil sensitivity profile when a dedicated array is used. In this work, we propose an intensity correction algorithm, and we explore the use of support vector machines (SVMs) to automatically segment the cartilages from high-resolution MR images of the larynx.

Table 1. Imaging Parameters

Sequence	TR (ms)	TE (ms)
PD	2000	20
SE	800	32
FSE-IDEAL	3500	101
FSE-XL	800	8

Methods: A larynx-dedicated 3-channel array coil [2] was used to image a healthy volunteer on a GE 1.5 T scanner. Four 3D sequences, proton-density-weighted SE (PD), SE, FSE-IDEAL, and FSE-XL, were run to acquire four sets of images. The following imaging parameters were used for all scans: bandwidth = ±32 kHz, FOV = 10 cm, in-plane resolution = 0.781 x 0.391 mm^2, slice thickness = 2 mm, # of averages = 2, # of slices = 17, acquisition matrix = 256 x 128. The timing parameters specific to each sequence are listed in Table 1.

Four slices covering the thyroid and cricoid laryngeal cartilages were chosen for processing; three were used for SVM training and one for SVM testing. The following procedure was carried out to prepare the data sets, train an SVM model, and test the performance of the SVM model. 1) Registration was done in Matlab using mrVista [3]. Registration is essential prior to segmentation as the larynx is vulnerable to motion between scans. 2) Intensity correction was done to correct for the coil sensitivity profile that makes regions near the array undesirably bright. We implemented an intensity correction method that fits a low-order polynomial to the PD image in each slice [4]. Amplitude thresholding is used to mask background and low-SNR regions of the image, and polynomial coefficients are computed by solving the following convex optimization problem [5]: $min._a \ \|W(Xa-y)\|^2 \ s.t. \ Xa > 0$. W is the diagonal matrix of binary mask weights, X is the matrix containing powers and cross terms of x and y coordinates up to the desired fitting order, y is the vector of original image values, and a is the vector of polynomial coefficients. 3) Manual segmentation was done using 3DSlicer, an ITK-VTK based software [6]. Pixels were labeled as cartilage and fat, muscle, and background. For training, only regions that could be labeled with high confidence were used. For testing, all pixels were labeled, as the manual segmentation is used as a gold standard to measure accuracy. Cartilage and fat were given the same label due to their similar contrasts in all images. 4) LibSVM was used for implementing and solving the multi-class SVM [7]. 5) The SVM performance was assessed by automatically segmenting the test image using the SVM model and comparing the results with the gold standard.

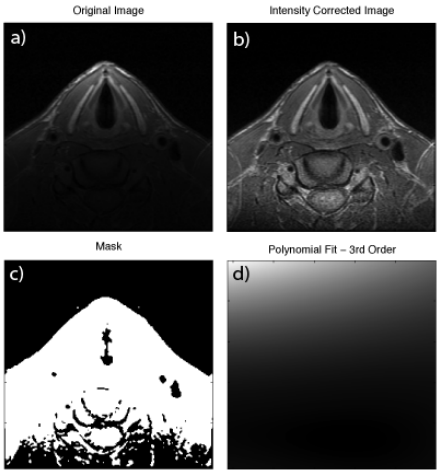

Figure 1. Intensity correction on one slice of the proton-density-weighted dataset: original (a), corrected (b), mask (c), and resulting third-order polynomial fit (d).

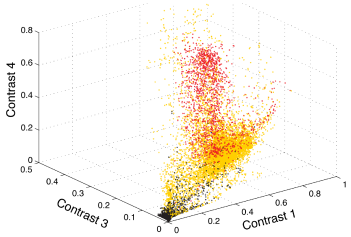

Figure 2. Scatter plot showing contrast levels of the testing image for contrast 1 (PD), contrast 3 (FSE-IDEAL), and contrast 4 (FSE-XL), after manual segmentation. Cartilage and fat (red), muscle (yellow), and background (black) form well-localized clusters suggesting that automatic segmentation will yield good accuracy.

Results & Discussion: Figure 1 shows one slice of the PD dataset before and after intensity correction. The 3rd order polynomial fit to the original image resulted in good intensity correction in reasonable computation times. Figure 2 shows the scatter plot of the test image based on three of the four contrasts, after manual segmentation (gold standard). Each species forms a fairly well-localized cluster, suggesting that automatic segmentation will yield good accuracy. Figure 3 shows the manual segmentation of the training image (a), testing image (b), and the result of the SVM segmentation (c). An accuracy of 86% relative to the manually-segmented gold standard was obtained. The automatic segmentation algorithm produces good overall segmentation, accurately labelling the ossified portions of thyroid cartilage. Non-ossified cartilage has a contrast very similar to muscle in all sequences, and the same holds for subcutaneous fat and ossified cartilage (fatty marrow). Future work is required to investigate additional sequences that distinguish between non-ossified cartilage and muscle. Additional features for SVM training, such as spatial position or connectedness of pixels, will be necessary to correctly classify subcutaneous fat and ossified cartilage.

Conclusion: We have successfully implemented an SVM algorithm with automatic intensity correction to segment the cartilages from MR images of the larynx. The algorithm will now be adapted for multiple-subject testing.

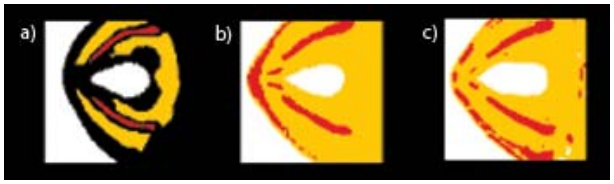

Figure 3. Training labels (a), desired testing labels (b), SVM labels for test data (c). Training and desired testing labels were obtained via manual segmentation. Results of automatic segmentation (c) demonstrate classification of cartilage and fat (red), muscle (yellow), and background (white) with 86% accuracy.

References:

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