Maximal Contrast Adaptive Region Growing for CT Airway Tree Segmentation

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Contribution

We introduce a self-assessed region growing technique capable of producing airway segmentations with reasonable quality. The main advantages of our technique are its robustness against leakage, and the absence of any training stages. Our method can not be considered fully automatic as it requires manual seeding of the trachea region, although there exists a variety of techniques to circumvent this requirement.

Preprocessing

Let N be a cubic neighborhood of radius R around the seed, $\vec{x}$ a voxel position, $f(\vec{x})$ the intensity for voxel at $\vec{x}$, and $|N|$ the cardinality of N. Then, provided the intensities can be modeled as Gaussian, $\bar{f}_N$ is the mean intensity Maximum Likelihood (ML) estimate in N, and σ_{f_N} is the ML-estimated standard deviation for intensities in N:

$$\bar{f}_N = \frac{1}{|N|} \sum_{\vec{x}_k \in N} f(\vec{x}_k) \quad , \tag{1}$$

$$\sigma_{f_N} = \sqrt{\frac{1}{|N|} \sum_{\vec{x}_k \in N} \left(f(\vec{x}_k) - \bar{f}_N \right)^2} \quad . \tag{2}$$

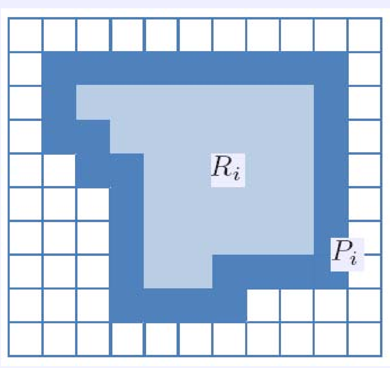
After this estimates have been computed we apply the following non-linear mapping, where $f(\vec{x})$, $f'(\vec{x})$ are the input and output intensities for the transformation, and K is a constant parameter adjusting the mapping window width.

$$f'(\vec{x}) = \left(1 + \exp\left(- \frac{f(\vec{x}) - \bar{f}_N}{\left(\frac{K\sigma_{f_N}}{3} \right)} \right) \right)^{-1} \quad . \tag{3}$$

Finally, we perform non-linear denoising using an in-slice bidimensional median filter with kernel radius Γ.

Contrast

In our method we propose an assessment function based on a simple measure of the evolving contrast for the region growing sequence. The success of the assessment is founded on the assumption that maximal contrast occurs on region boundaries. To make this approach computationally feasible in 3D, we produce only evenly-spaced samples of this function, along the values of the assessed parameter defined on the normalized dynamic range of the image. This sampling strategy dramatically reduces computational complexity while preserving most critical values. The sufficiency of the fixed sampling rate is guaranteed thanks to the normalization stage.



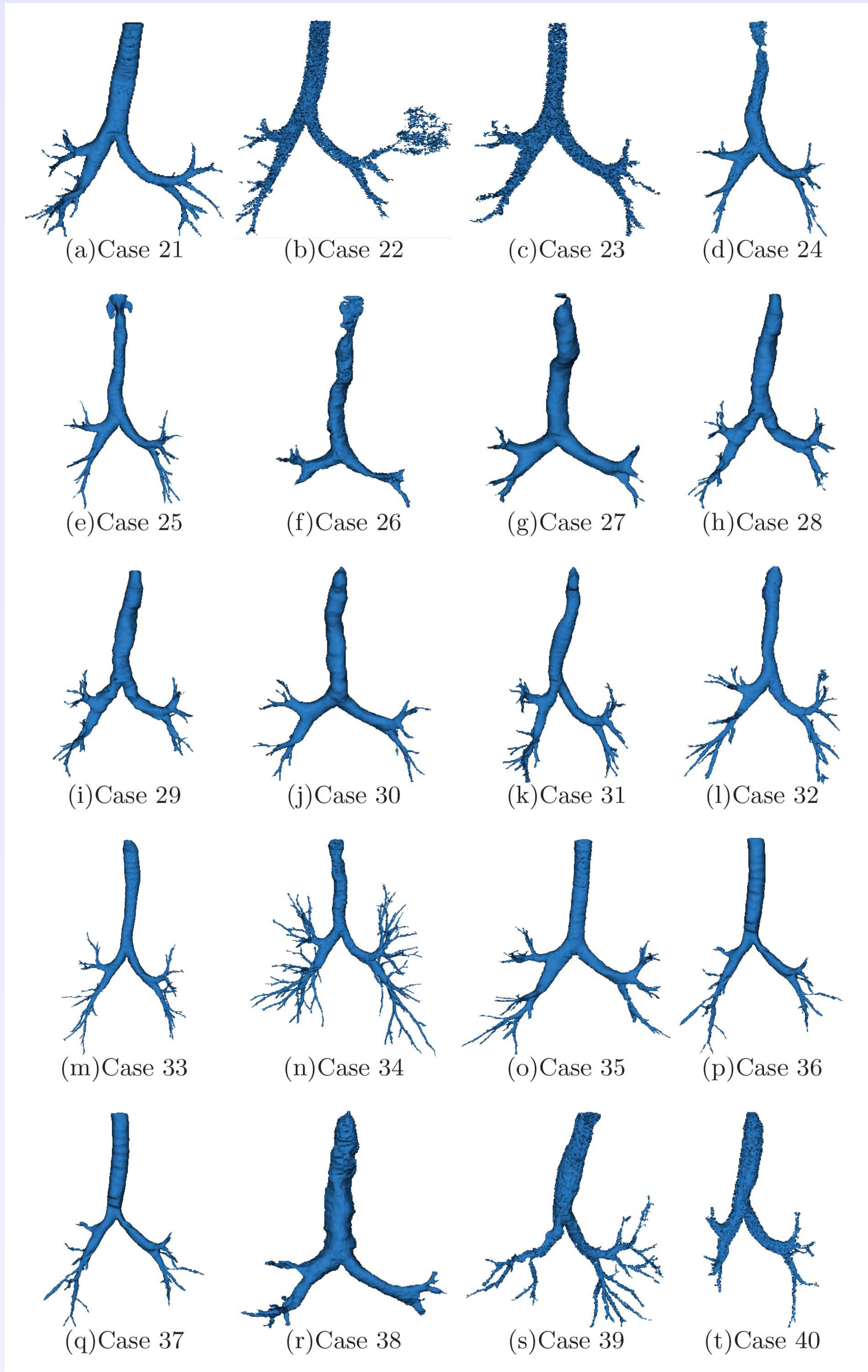
$$O_i\left(\bar{f'}_{R_i}, \bar{f'}_{P_i}\right) = \left| \frac{\bar{f'}_{P_i} - \bar{f'}_{R_i}}{\bar{f'}_{P_i} + \bar{f'}_{R_i}} \right|$$

Self-Assessed Region Growing

Considering an initial region R_0 defined by several seeds along the upper trachea, the i-th iteration of the algorithm is:

1. Update multiplier $k_i = k_0 + i\Delta k$
2. Compute, in last iteration grown region R_{i-1}, ML estimates for the mean (available from last iteration) and standard deviation $(\bar{f'}_{R_{i-1}}, \sigma_{f'_{R_{i-1}}})$
3. For every candidate voxel $\vec{x}_{c_{i-1}}$ being 26-connected to R_{i-1}, $\vec{x}_{c_{i-1}} \in R_i$ if
$$f'\left(\vec{x}_{c_{i-1}}\right) \in \left[\bar{f'}_{R_{i-1}} \pm k_i \sigma_{f'_{R_{i-1}}} \right] \tag{4}$$
4. Compute the assessment function $O_i\left(\bar{f'}_{R_i}, \bar{f'}_{P_i}\right)$ using the intensity average $\bar{f'}_{R_i}$ in R_i and the intensity average $\bar{f'}_{P_i}$ in the external perimeter P_i of R_i according to (1) and the following eqs.:
$$P_i = \{x_{c_i}\} \cap R_i{}^C \quad , \tag{5}$$
$$O_i\left(\bar{f'}_{R_i}, \bar{f'}_{P_i}\right) = \left| \frac{\bar{f'}_{P_i} - \bar{f'}_{R_i}}{\bar{f'}_{P_i} + \bar{f'}_{R_i}} \right| \tag{6}$$
5. If O_{i-1} was a local maximum, when compared to O_{i-2} and O_i (only when $i \geq 2$), then the algorithm stops and the output is R_{i-1}. Otherwise go to step 1.

Segmentation Results



The algorithm run in a 2 GHz Intel Core 2 Duo Windows PC, in an average time of 129 ± 27 s.

EXACT Evaluation

	Branch count	Branch detected (%)	Tree length (cm)	Tree length detected (%)	Leakage count	Leakage volume (mm^3)	False positive rate (%)
CASE21	89	44.7	46.0	41.6	0	0.0	0.00
CASE22	54	14.0	37.0	11.2	8	2085.7	30.67
CASE23	33	11.6	27.3	10.5	0	0.0	0.00
CASE24	49	26.3	43.2	26.6	0	0.0	0.00
CASE25	83	35.5	63.5	25.2	0	0.0	0.00
CASE26	22	27.5	15.8	24.0	0	0.0	0.00
CASE27	35	34.7	26.0	32.1	0	0.0	0.00
CASE28	56	45.5	40.5	37.0	0	0.0	0.00
CASE29	74	40.2	44.4	32.2	0	0.0	0.00
CASE30	44	22.6	30.2	19.8	0	0.0	0.00
CASE31	77	36.0	53.7	30.6	3	31.1	0.35
CASE32	80	34.3	62.4	28.6	2	314.3	2.81
CASE33	83	49.4	56.9	38.7	0	0.0	0.00
CASE34	266	58.1	189.8	53.1	2	39.3	0.18
CASE35	112	32.6	78.4	25.3	0	0.0	0.00
CASE36	59	16.2	54.1	13.1	0	0.0	0.00
CASE37	46	24.9	39.2	22.0	0	0.0	0.00
CASE38	35	35.7	26.9	40.5	0	0.0	0.00
CASE39	93	17.9	73.8	18.0	4	65.8	0.95
CASE40	40	10.3	30.9	8.0	0	0.0	0.00
Mean	71.5	30.9	52.0	26.9	0.9	126.8	1.75
Std. dev.	51.7	13.1	36.5	11.8	2.0	466.5	6.84
Min	22	10.3	15.8	8.0	0	0.0	0.00
1st quartile	40	17.9	30.2	18.0	0	0.0	0.00
Median	58	33.4	43.8	25.9	0	0.0	0.00
3rd quartile	89	44.7	63.5	38.7	2	39.3	0.35
Max	266	58.1	189.8	53.1	8	2085.7	30.67

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