An Improved Air Tissue Boundary Segmentation Technique for Real Time Magnetic Resonance Imaging Video Using SegNet

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Section 1

Introduction

- **Goal**: Segmentation of the Air-Tissue Boundaries (ATBs) with minimum number of training videos

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- **Approach**: Semantic segmentation using Segmentation Network (SegNet).

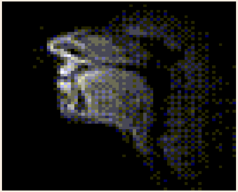
Motivation

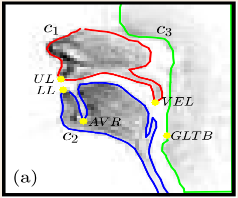
Need for study

Understanding speech production.

Dataset

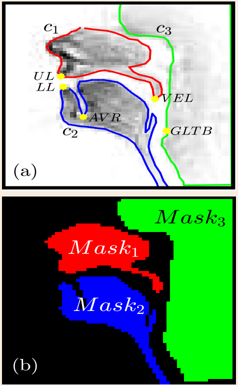
- **USC-TIMIT** corpus
- **2-Female** (F1, F2) and **2-Male** (M1, M2).
- Subset : 16 Videos from each subject.
- Video : 23.18 fps
- Spacial resolution of 68×68.





Dataset

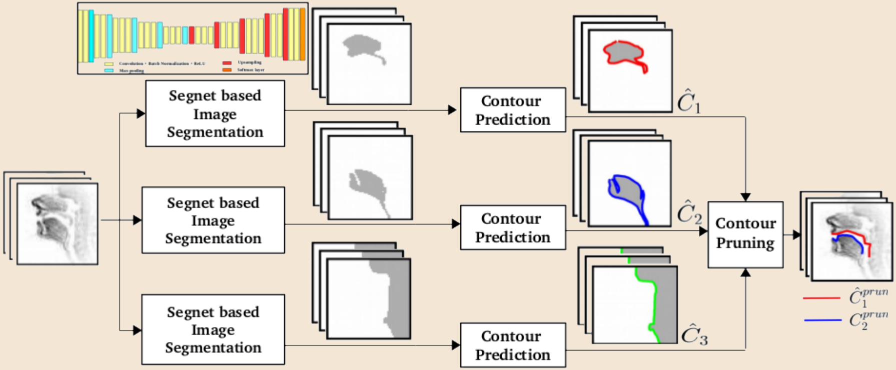
- **Manual annotation:**
  1. Complete ATBs
  2. Upper lip (UL)
  3. Lower lip (LL)
  4. Tongue base (AVR)
  5. Velum tip (VEL)
  6. Glottis begin (GLTB)
- Number of frames: 1462, 1270, 1642, 1399 for subjects F_1, F_2, M_1, M_2 respectively.
- Division of tissue regions into **3 masks**.



Section 2

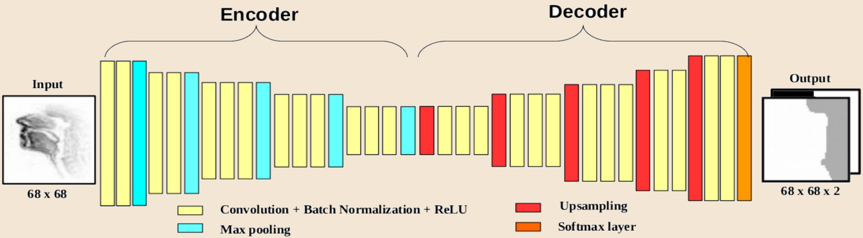
Proposed SegNet based Approach

Illustration of the steps in the proposed SegNet based approach



Proposed SegNet based segmentation

SegNet architecture[1]



1. Symmetric encoder-decoder.

[1] Karen et. al, "Very Deep Convolutional Networks for Large-Scale Image Recognition," CoRR, 2014.

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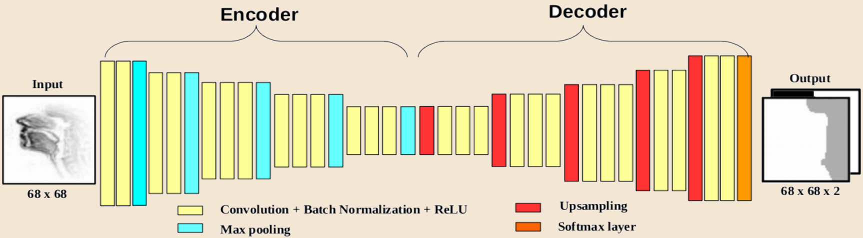

1. Symmetric encoder-decoder.
2. **Three Segnets:** One SegNet for each mask.

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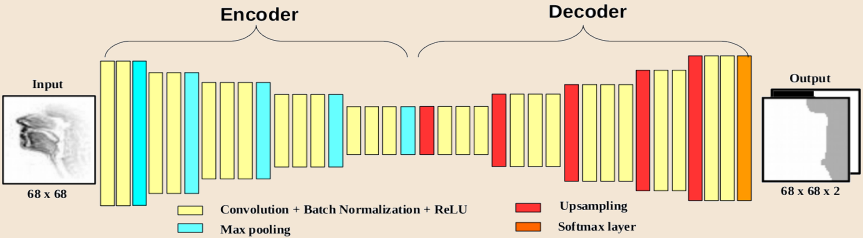

1. Symmetric encoder-decoder.
2. **Three Segnets:** One SegNet for each mask.
3. SegNet_i : Does a given pixel belong to mask_i or air cavity region?

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Contour Prediction

- **Stage 1:** Canny edge detection
- **Stage 2:** Connecting edges via concave hull algorithm [1]

[1] J.-S. Park et. al "A new concave hull algorithm and concaveness measure for n-dimensional datasets", 2018

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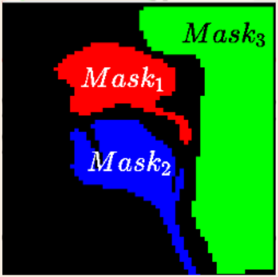

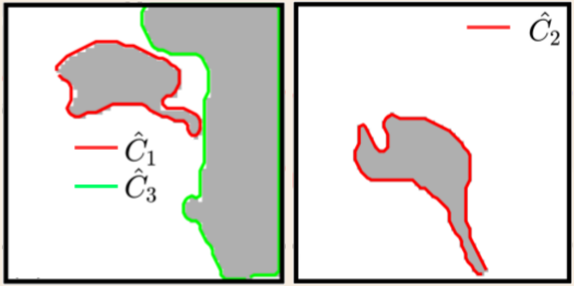

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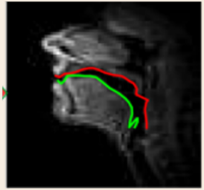
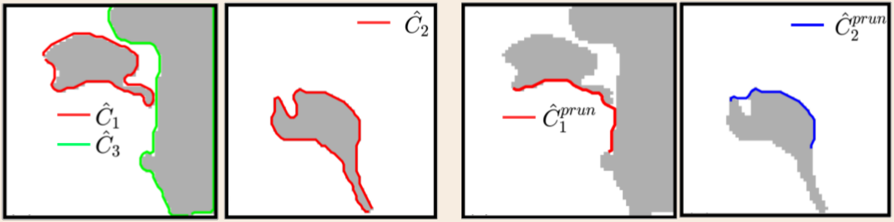
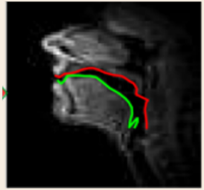
Contour Pruning

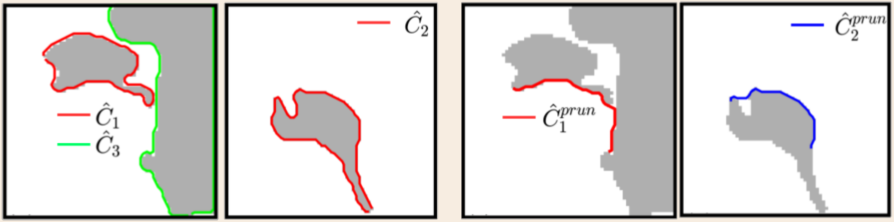




Contour Pruning

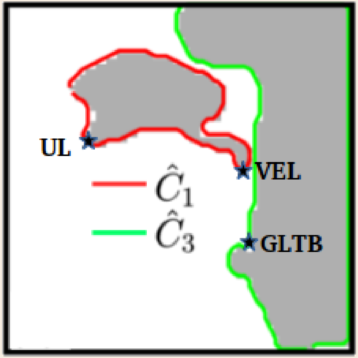
Obtain **upper** and **lower** contours within the vocal tract





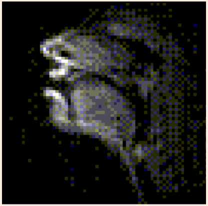
Contour Pruning

Obtain upper contour within vocal tract:



Contour Pruning

Obtain lower contour within vocal tract:



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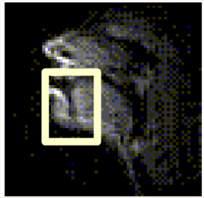
Obtain lower contour within vocal tract:



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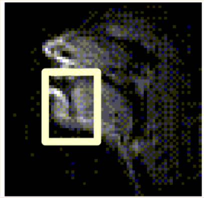
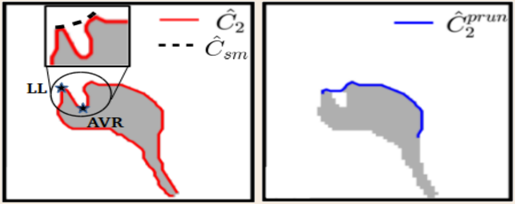
Obtain lower contour within vocal tract:





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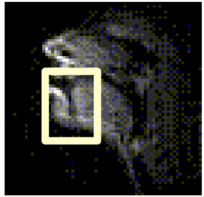

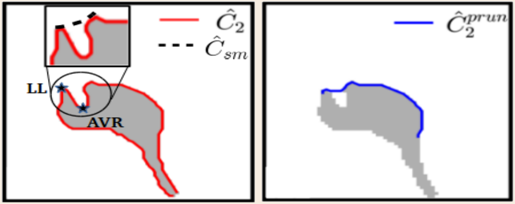

2^{nd} order polynomial fit

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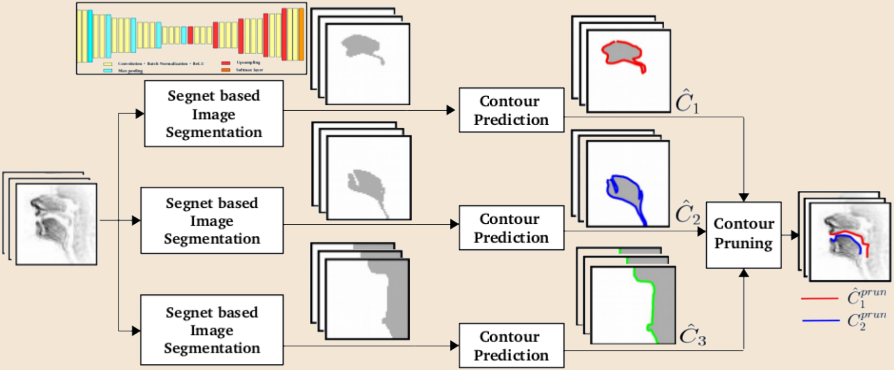

Section 3

Experimental Setup

Baselines:

- Maeda grid-line[1] (MG).

[1] Kim et.al, "Enhanced airway-tissue boundary segmentation for real-time magnetic resonance imaging data," ISSP, 2014.

Experimental Setup

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- Maeda grid-line[1] (MG).
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Experimental Setup

Baselines:

- Maeda grid-line[1] (MG).
- Fisher-discrimination measure based segmentation[2] (FDM)
- fully convolutional networks based segmentation[3] (FCN)

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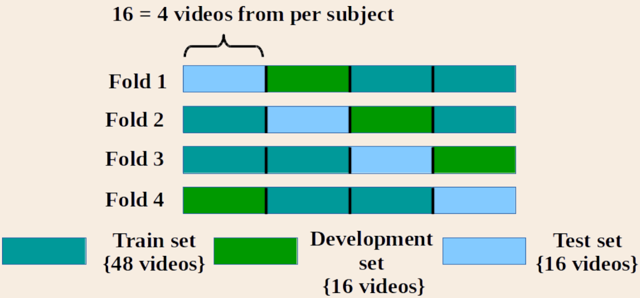
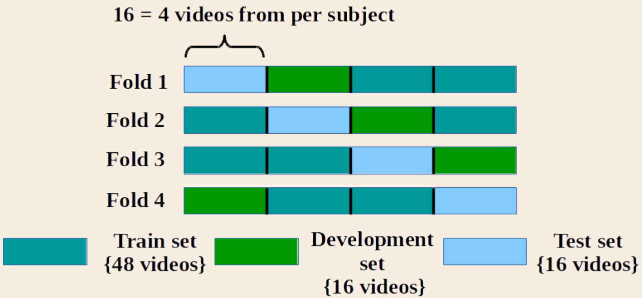
[3] Valliappan CA et. al, Air-tissue boundary segmentation in real-time magnetic resonance imaging video using semantic segmentation with fully convolutional networks," Interspeech, 2018

Experimental Setup-1 for ATB Estimation



- **4-fold** setup

Experimental Setup-1 for ATB Estimation



- **4-fold** setup
- Training set : ~ 2900.
- Development & Test set : ~ 1443

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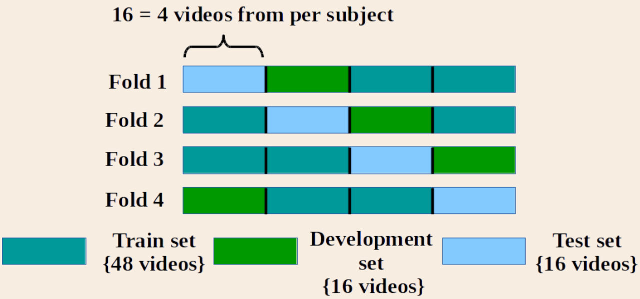

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- **30 epochs**, early stopping condition.

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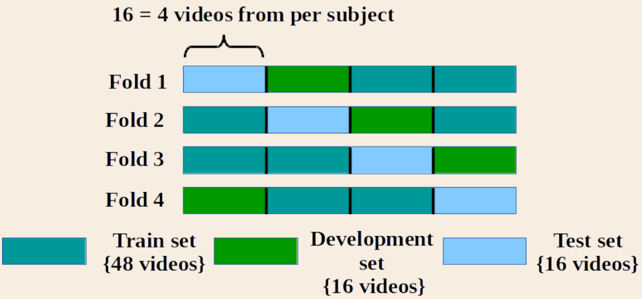

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- Estimating the minimum number of rtMRI videos required for training for FCN and SegNet.

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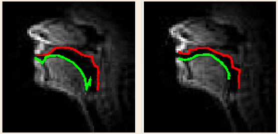
- 8 Models of **FCN and SegNet**
- The i^{th} model - i training videos from four subjects, where $i \in \{1, 2, ...8\}$.

Experimental Setup-2

- Estimating the minimum number of rtMRI videos required for training for FCN and SegNet.
- 8 Models of **FCN and SegNet**
- The i^{th} model - i training videos from four subjects, where $i \in \{1, 2, ...8\}$.
- Each video - ∼90 frames
- Fixed Development & Test set : ~ 1443
- **30 epochs**, early stopping condition.

Evaluation metrics

- **DTW distance**[1]: Measures the closeness of the estimated contour to the ground truth contour (unit:pixel).



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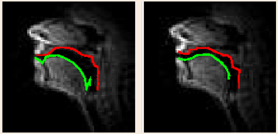
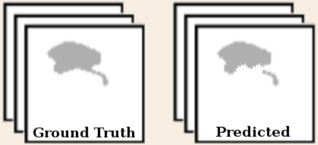


- **Pixel accuracy**[2]: To evaluate the performance of FCN and SegNet.



1 Berndt et. al, "Using dynamic time warping to find patterns in time series," KDD, 1994.

2 J. Long et. al, "Fully convolutional networks for semantic segmentation", 2015.

Section 4

DTW distances (Upper ATB)

	Upper ATB			
SUB	MG	FCN	SegNet	FDM
F_1	1.02 ± 0.19	0.91 ± 0.21	**0.83±0.11**	0.94 ± 0.17
F_2	1.24 ± 0.29	1.08 ± 0.19	**0.96±0.15**	1.16 ± 0.19
M_1	1.10 ± 0.20	**1.02±0.20**	1.15 ± 0.16	1.11 ± 0.20
M_2	1.19 ± 0.24	**1.09±0.21**	1.10 ± 0.19	1.10 ± 0.23
AVG:	1.13 ± 0.22	1.02 ± 0.20	**1.02±0.15**	1.08 ± 0.19

Average ($\pm$ standard deviation) DTW distance of the predicted upper ATBs within the vocal tract

DTW distances (Upper ATB)

	Upper ATB			
SUB	MG	FCN	SegNet	FDM
F_1	1.02 ± 0.19	0.91 ± 0.21	$\mathbf{0.83 \pm 0.11}$	0.94 ± 0.17
F_2	1.24 ± 0.29	1.08 ± 0.19	$\mathbf{0.96 \pm 0.15}$	1.16 ± 0.19
M_1	1.10 ± 0.20	$\mathbf{1.02 \pm 0.20}$	1.15 ± 0.16	1.11 ± 0.20
M_2	1.19 ± 0.24	$\mathbf{1.09 \pm 0.21}$	1.10 ± 0.19	1.10 ± 0.23
AVG:	1.13 ± 0.22	1.02 ± 0.20	$\mathbf{1.02 \pm 0.15}$	1.08 ± 0.19

Average ($\pm$ standard deviation) DTW distance of the predicted upper ATBs within the vocal tract

- SegNet yields better or comparable performance relative to baselines.

DTW distances (Lower ATB)

	Lower ATB			
SUB	MG	FCN	SegNet	FDM
F_1	1.21 ± 0.21	1.00 ± 0.25	**0.92 ± 0.17**	0.99 ± 0.23
F_2	1.28 ± 0.27	1.13 ± 0.31	**1.12 ± 0.29**	1.24 ± 0.25
M_1	1.26 ± 0.60	1.17 ± 0.25	**1.16 ± 0.26**	1.17 ± 0.26
M_2	1.35 ± 0.30	1.21 ± 0.23	1.18 ± 0.24	**1.16 ± 0.41**
AVG:	1.27 ± 0.35	1.13 ± 0.26	**1.09 ± 0.23**	1.14 ± 0.29

Average ($\pm$ standard deviation) DTW distance of the predicted lower ATBs within the vocal tract

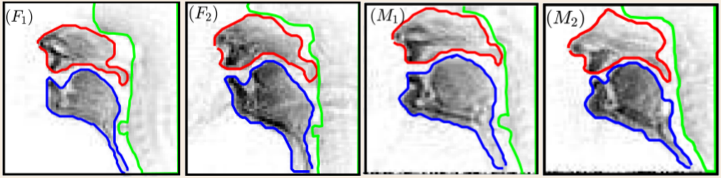
DTW distances (Lower ATB)

	Lower ATB			
SUB	MG	FCN	SegNet	FDM
F_1	1.21 ± 0.21	1.00 ± 0.25	**0.92 ± 0.17**	0.99 ± 0.23
F_2	1.28 ± 0.27	1.13 ± 0.31	**1.12 ± 0.29**	1.24 ± 0.25
M_1	1.26 ± 0.60	1.17 ± 0.25	**1.16 ± 0.26**	1.17 ± 0.26
M_2	1.35 ± 0.30	1.21 ± 0.23	1.18 ± 0.24	**1.16 ± 0.41**
AVG:	1.27 ± 0.35	1.13 ± 0.26	**1.09 ± 0.23**	1.14 ± 0.29

Average ($\pm$ standard deviation) DTW distance of the predicted lower ATBs within the vocal tract

- SegNet yields better or comparable performance relative to baselines.

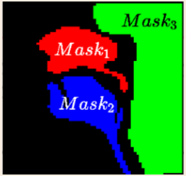
Complete ATBs



	C_1		C_2		C_3	
SUB	SegNet	FCN	SegNet	FCN	SegNet	FCN
F_1	**0.88**	0.89	**0.85**	1.05	**0.80**	0.83
F_2	**0.98**	1.02	1.15	**1.12**	0.81	**0.80**
M_1	1.03	1.03	**0.94**	1.37	**0.79**	0.80
M_2	1.03	**0.89**	1.03	**1.01**	**0.83**	0.85

Average DTW distance of the predicted complete ATBs for all the subjects

Pixel Accuracy For the SegNet and FCN models



SUB	$Model_1$	$Model_2$	$Model_3$	$Model_4$	$Model_5$	$Model_6$	$Model_7$	$Model_8$
$Mask_1^{seg}$	88.70	**99.54**	99.53	99.57	99.54	99.54	99.55	99.57
$Mask_2^{seg}$	85.89	**98.64**	98.65	98.61	98.65	98.60	98.64	98.68
$Mask_3^{seg}$	90.30	**99.78**	99.77	99.77	99.76	99.76	99.78	99.77
$Mask_1^{fcn}$	85.68	90.89	94.47	96.09	98.14	**99.17**	99.24	99.28
$Mask_2^{fcn}$	84.12	88.14	93.88	95.51	97.77	**98.09**	98.08	98.14
$Mask_3^{fcn}$	89.45	93.45	95.80	98.80	**99.60**	99.71	99.73	99.72

Pixel classification accuracy averaged across all subjects (on test set) for each mask vs number of training videos for SegNet, FCN. (**Bold** indicating the saturation point)

Section 5

Discussion

1. On an average $\sim \mathbf{0.70\%}$ **pixels** are being **misclassified** (unlike 1% for FCN).
2. Misclassified pixels – **boundary** region : due to **low resolution** of the image.
3. Precision of annotation : 1 **decimal** place
4. Proposed method : **Pixel** level

Section 6

Conclusions

- Proposed method yields better performance than the baseline – DTW distance
- SegNet requires only two training videos per subject.

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- SegNet requires only two training videos per subject.

Future Directions

Data augmentation to further reduce the minimum number of training videos required for better pixel accuracy.

Section 7

The authors thank Pratiksha Trust for their support

Questions?