Tongue Tracking in Ultrasound Images with Active Appearance Models

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1. Outline

- Ultrasound (US) imaging of speakers' tongues
  - Widely used for human speech production analysis and modeling
  - Captures the shape & dynamics of tongue during speech
  - Simple to use, no radiation, high frame rates
- Automatic tongue tracking
  - Extremely helpful for large datasets of acquired US videos
  - Difficulties: high speckle noise, non-visible tongue parts

Contributions

- We propose a novel tracking method
  - Built on a variant of Active Appearance Models
  - Incorporates prior about tongue shape variation
  - Bayesian formulation of the tracking
- Properties of the method
  - Robust even in cases of bad tongue visibility
  - Also extrapolates the contour in the non-visible parts
  - Improved performance compared to other, previously proposed techniques

2. Preliminaries

- Acquired speech articulation data of the same speaker:
  - Ultrasound imaging @ 66 Hz
  - Electro-Magnetic sensors on US probe & head @ 40 Hz
  - Magnetic Resonance Imaging (static)
  - X-ray videos @ 25 Hz
- Exploitation of the X-rays to model the tongue shape
  - The entire tongue contour is visible, in contrast to US images
  - Usage of a Vocal Tract (VT) grid to represent the tongue shape
    - fixed pose w.r.t. the speaker's palate
    - it bypasses the point correspondence problem
- Estimation of the VT grid's pose at every US frame, using EM sensors data & the head's MRI

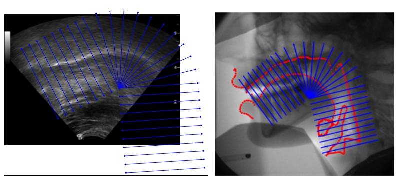


Fig. 1. Ultrasound and X-ray images of the speaker, with the registered Vocal Tract grid superimposed.

- Preprocessing of the US frames using our method of [2]

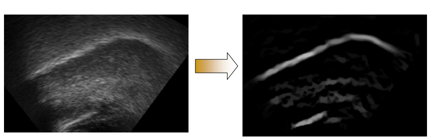
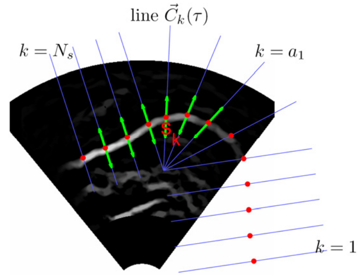


Fig. 2. Original and filtered US frame, using the method of [2]

3. Tongue Appearance Representation



- Tongue appearance
  - Shape

$$\boldsymbol{s} = [s_1, .., s_{N_s}]^T$$

  - s_k : scalar that determines the intersection of the tongue contour with the grid line k
  - Texture

$$\boldsymbol{g}(\boldsymbol{s}) = \Big[\underbrace{[u_{a_1}(s_{a_1}+t)]^T_{t\in W}}_{1\times N_W} \cdots \underbrace{[u_{a_{N_a}}(s_{a_{N_a}}+t)]^T_{t\in W}}_{1\times N_W}\Big]^T$$

  - Only the texture-active grid lines G_{act} are used for texture, since some parts of the tongue contour are never or rarely visible
  - $W = \{-d, -d+1, .., d\} \cdot \delta\ell$: sampling window
  - $u_k(\tau) = u(\vec{C}_k(\tau))$: restriction of the image to grid line k
- Differences from classic AAMs
  - Various modifications to exploit application-specific properties
  - Reduced complexity of the appearance representation & model
  - Lighter optimization problem for the model fitting

4. Modeling Appearance Variation

- Shape model

$$\boldsymbol{s} \approx \boldsymbol{s}_0 + \mathrm{Q_s}\boldsymbol{b}$$

- $\boldsymbol{b}$: normalized shape parameters vector with $\mathrm{p}(\boldsymbol{b}) = \mathcal{N}(\boldsymbol{b}|\boldsymbol{0}, \mathrm{I}_{N_b})$
- Principal Component Analysis (PCA) to learn $\boldsymbol{s}_0$ and $\mathrm{Q_s}$
  - Training vectors from manually annotated tongue contours on 700 X-ray frames
- Texture model

$$\boldsymbol{g} = \boldsymbol{g}_0 + \mathrm{Q_g}\boldsymbol{\lambda} + \boldsymbol{\varepsilon}$$

- $\boldsymbol{\lambda}$: texture parameters with $\mathrm{p}(\boldsymbol{\lambda}) = \mathcal{N}(\boldsymbol{\lambda}|\boldsymbol{0}, \mathrm{I}_{N_\lambda})$
- $\boldsymbol{\varepsilon}$: texture reconstruction error with:

$$\mathrm{p}(\boldsymbol{\varepsilon}) = \mathcal{N}(\boldsymbol{\varepsilon}|\boldsymbol{0}, \Sigma_{\boldsymbol{\varepsilon}}), \quad \Sigma_{\boldsymbol{\varepsilon}} = \widetilde{\mathrm{Q}}_{\mathrm{g}} \mathrm{diag}(\rho_1, .., \rho_{N_g}) \widetilde{\mathrm{Q}}_{\mathrm{g}}^T$$

- Training of the model
  - Manual annotations at 400 US frames. This training set is divided into 2 subsets T_1 and T_2
  - Subset T_1 is used to learn $\boldsymbol{g}_0$ and $\mathrm{Q_g}$ using PCA
  - Subset T_2 is used to learn the optimum parameters $\rho_1, .., \rho_{N_g}$

5. Tongue Tracking

- Tracking via fitting of the appearance model in every US frame
- MAP estimation of shape & texture parameters $\boldsymbol{b}$ and $\boldsymbol{\lambda}$ by maximizing:

$$\mathrm{p}(\boldsymbol{b}, \boldsymbol{\lambda}|\underbrace{u(x,y)}_{\textit{filtered US frame}}) \propto \mathrm{p}(u|\boldsymbol{b}, \boldsymbol{\lambda})\,\mathrm{p}(\boldsymbol{b}, \boldsymbol{\lambda}) = \mathrm{p}(\boldsymbol{\varepsilon})\,\mathrm{p}(\boldsymbol{b})\,\mathrm{p}(\boldsymbol{\lambda})$$

$$\boldsymbol{\varepsilon} = \boldsymbol{g}(\boldsymbol{s}(\boldsymbol{b})) - \boldsymbol{g}_0 - \mathrm{Q_g}\boldsymbol{\lambda}$$

- Equivalently: minimization of the energy:

$$E(\boldsymbol{b}, \boldsymbol{\lambda}) = -\ln \mathrm{p}(\boldsymbol{b}, \boldsymbol{\lambda}|u) = C + \tfrac{1}{2}\left\{\|\boldsymbol{b}\|^2 + \|\boldsymbol{\lambda}\|^2 + \boldsymbol{\varepsilon}^T \Sigma_{\boldsymbol{\varepsilon}}^{-1} \boldsymbol{\varepsilon}\right\}$$

- Gradients of the energy:

$$\nabla_{\boldsymbol{b}} E = \boldsymbol{b} + \mathrm{Q_s}^T (\partial \boldsymbol{g}/\partial \boldsymbol{s})^T \Sigma_{\boldsymbol{\varepsilon}}^{-1} \boldsymbol{\varepsilon}$$

$$\nabla_{\boldsymbol{\lambda}} E = \boldsymbol{\lambda} - \mathrm{Q_g}^T \Sigma_{\boldsymbol{\varepsilon}}^{-1} \boldsymbol{\varepsilon}$$

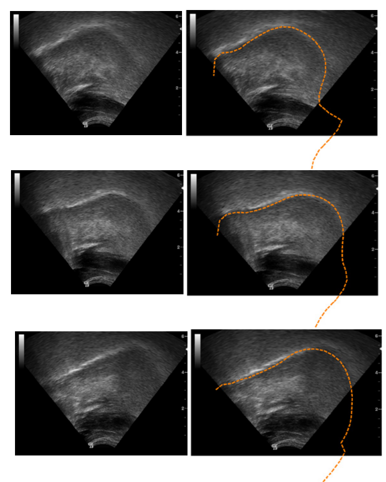
where:

$$\frac{\partial \boldsymbol{g}}{\partial s_k} = \begin{cases} [0 \cdots\cdots 0]^T, & \text{if } k \notin G_{act} \\ \big[\underbrace{0 \cdots 0}_{(k-1)N_W}\ [u'_k(s_k+t)]^T_{t\in W}\ \underbrace{0 \cdots 0}_{(N_s-k)N_W}\big]^T, & \text{if } k \in G_{act} \end{cases}$$

- Optimization algorithm
  - Gradient descent
  - Initialization of parameters:
    - $\boldsymbol{b}_0$: from previous frame result
    - $\boldsymbol{\lambda}_0$: maximization of the posterior $\mathrm{p}(\boldsymbol{\lambda}|\boldsymbol{g}(\boldsymbol{s}(\boldsymbol{b}_0)))$

6. Experimental Results

I. Results of the proposed method



Original US frames *Same frames + extracted contour*

Fig. 3. Tongue tracking & extrapolation in a US image sequence, using the proposed method.

- Parameters of the method:

	Dimensionality of original vector	Number of model parameters	Variance explained (% of the total)
Shape	30	6	96%
Texture	1215	35	93%

II. Comparisons with other tracking methods

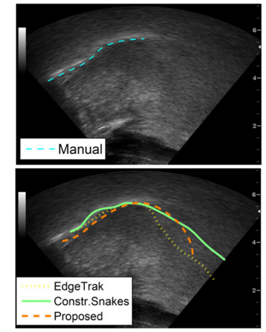
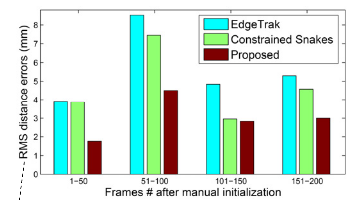


Fig. 4. Frame from a sequence where the tongue tracking methods have been applied. *Top*: manually annotated contour. *Bottom*: comparison of the methods' results.

- Quantitative evaluation



$$e_d = \sqrt{(d_{om}^2 + d_{mo}^2)/2}$$

where d_{om} (d_{mo}) is the RMS distance of the points of the output (manual) contour from the manual (output) contour.

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