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# Audiovisual Speech Inversion by Switching Dynamical Modeling governed by a Hidden Markov Process

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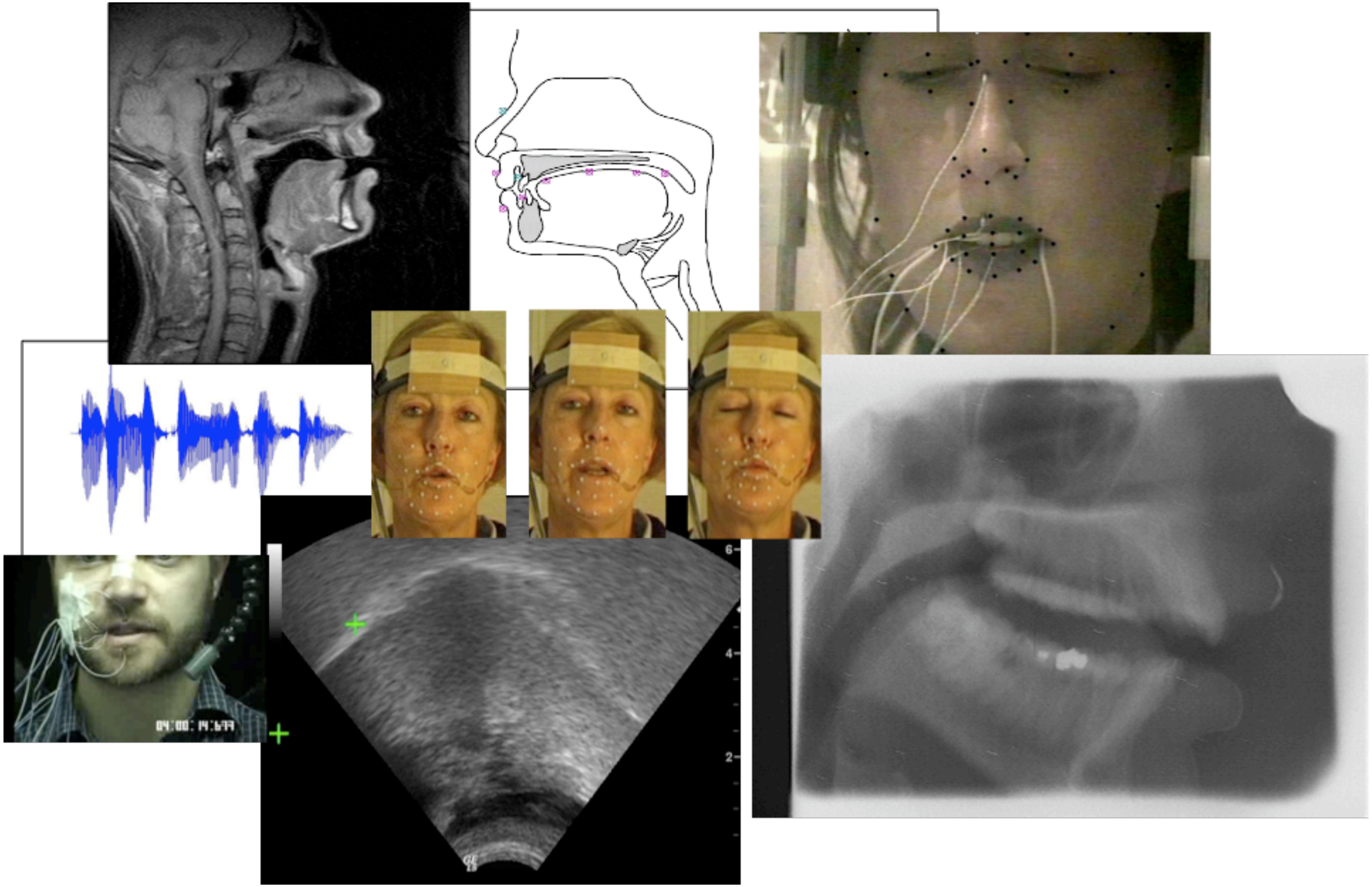
# Speech Inversion

- The Goal
  - Identify the speech production system given observed speech
- The Motives
  - Understanding speech production
  - Applications in speech synthesis, recognition, coding, language tutoring
- The Framework
  - Consider speech to be an audiovisual process
- The Method
  - Switching linear dynamical modeling driven by a hidden Markov process

# Speech production system identification

- Describe Geometry
  - Area function, tube models
  - Articulatory models
    - Geometrical (Mermelstein 1973, Birkholz 2006)
    - Data-driven (Maeda 1979, Engwall 2003)
  - Coordinates of important articulators
    - Tongue tip, lower incisor etc.
- Determine sound sources
  - Location/Spectrum/Intensity

# Data



# Approaches

- From Audio only
  - Codebook (Ouni 2005), Neural networks (Richmond 2003)
  - Gaussian Mixture Model (Toda 2007), Extended Kalman Filtering (Dusan 2000), Hidden Markov Models (Hiroya 2004)

- Exploiting speaker's facial information
  - Significant correlation between speaker's face and vocal tract (Yehia 1998, Jiang 2002)
  - Independent component analysis of the face and relevant vector machines or neural networks to invert (Kjellstrom 2006, 2008)
  - Active appearance model for the face, canonical correlation analysis and late fusion of HMMs (Katsamanis 2007, 2008)

# Contributions

- The inversion problem is one-to-many. Visual and dynamic constraints can alleviate ill-posedness. Nonlinearities can be handled efficiently in a piecewise linear manner.
- Introduction of a switching linear dynamical mechanism to model the audiovisual-to-articulatory mapping.

- Typical quantitative evaluation (RMS error) does not account for the relative importance of the errors.
- Weighted evaluation scheme based on a support vector machine classifier to determine importance of errors.

# Linear Acoustic-Articulatory Mapping

- Observations y, vocal tract parameters x

$$p(\mathbf{x}|\mathbf{y}) = p(\mathbf{y}|\mathbf{x})p(\mathbf{x})/p(\mathbf{y})$$

- Approximate observation model

$$\mathbf{y} = C\mathbf{x} + \epsilon$$

- Assumptions

$$p(\mathbf{x}) \sim N(\mathbf{x}; \bar{\mathbf{x}}, \sigma_x) \qquad\qquad p(\epsilon) \sim N(\epsilon; \mathbf{0}, Q)$$

- Maximum A Posteriori

$$\hat{\mathbf{x}} = (\sigma_x^{-1} + C^T Q^{-1} C)^{-1}(\sigma_x^{-1}\bar{\mathbf{x}} + C^T Q^{-1}\mathbf{y})$$

- Training (Mean Square Error Minimization)

# Linear Dynamic Articulatory Modeling I

- Given the observations up to moment t, $\mathbf{Y}_t = \{\mathbf{y}_1, \ldots, \mathbf{y}_t\}$

$$p(\mathbf{x}_t|\mathbf{Y}_t) = \frac{p(\mathbf{y}_t|\mathbf{x}_t)p(\mathbf{x}_t|\mathbf{Y}_{t-1})}{p(\mathbf{y}_t|\mathbf{Y}_{t-1})}$$

- Analysis

$$p(\mathbf{x}_t|\mathbf{Y}_{t-1}) = \int p(\mathbf{x}_t|\mathbf{x}_{t-1})p(\mathbf{x}_{t-1}|\mathbf{Y}_{t-1})d\mathbf{x}_{t-1}$$

- Model

$$\mathbf{x}_t = A\mathbf{x}_{t-1} + \mathbf{w}_t$$ Articulatory Dynamics

$$\mathbf{y}_t = C\mathbf{x}_t + \mathbf{v}_t$$ Audiovisual Observation

$$\mathbf{w} \sim N(0, Q), \mathbf{v} \sim N(0, R), \mathbf{x}_0 \sim N(\boldsymbol{\mu}_0, V_0)$$

# Linear Dynamic Articulatory Modeling II

- Inference
  - Kalman filter (MAP solution)

$$\hat{\mathbf{x}}_{t|t} = \hat{\mathbf{x}}_{t|t-1} + K_t(\mathbf{y}_t - C\hat{\mathbf{x}}_{t|t-1})$$

- Training/Identification
  - State Model (Articulatory Dynamics)
    - Autoregressive (AR) state modeling
    - Maximum likelihood (MMSE)
  - Observation Model (Audiovisual-Articulatory Mapping)
    - Canonical Correlation Analysis

# Switching Linear Dynamic Modeling I

- For a phoneme/part of a phoneme

$$\mathbf{x}_t = A_{1,c}\mathbf{x}_{t-1} + A_{2,c}\mathbf{x}_{t-2} + B_c\mathbf{u}_c + \mathbf{w}_t$$
$$\mathbf{y}_t = C_c\mathbf{x}_t + \mathbf{v}_t$$

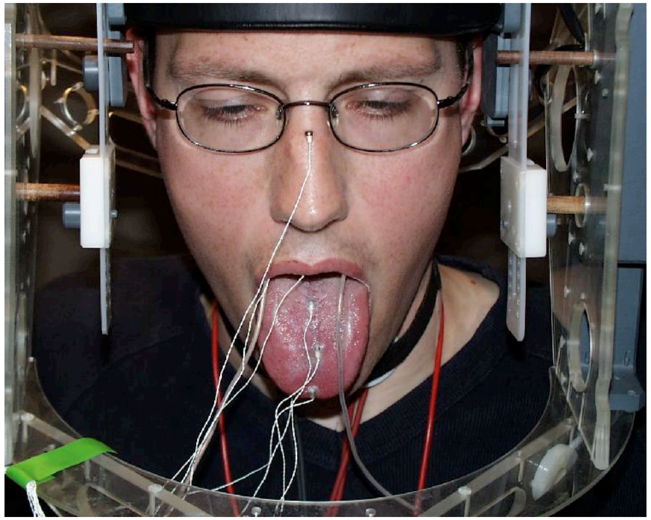
$$B_c = I - (A_{1,c} + A_{2,c})$$

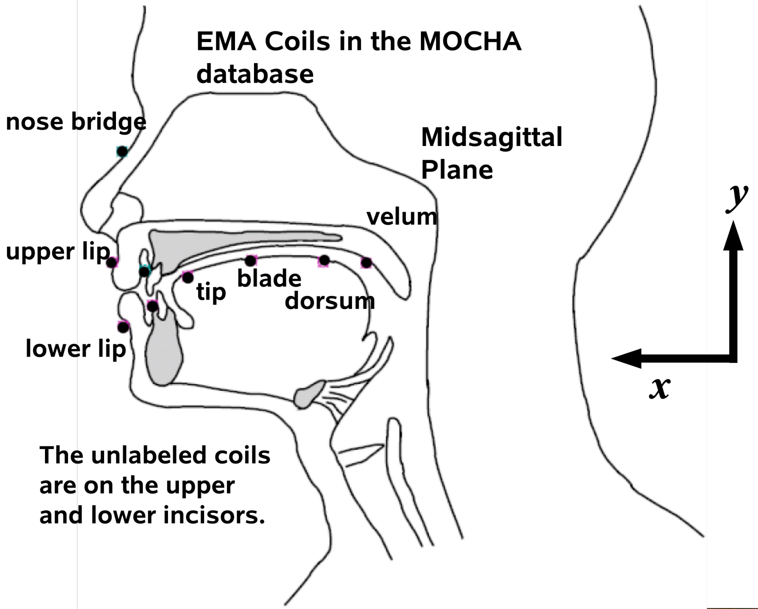
- Previous work (Dusan and Deng, 2000)
  - Separate model for each transition between any two phonemes
  - For each model: SOM clustering to identify piecewise linear mapping
  - Extended Kalman Filtering and Maximum likelihood to choose model and then Extended Kalman Smoothing
- Our Assumption
  - Model switching can be considered to be a Markovian process
  - One model per phonemic HMM state

# Switching Linear Dynamic Modeling II

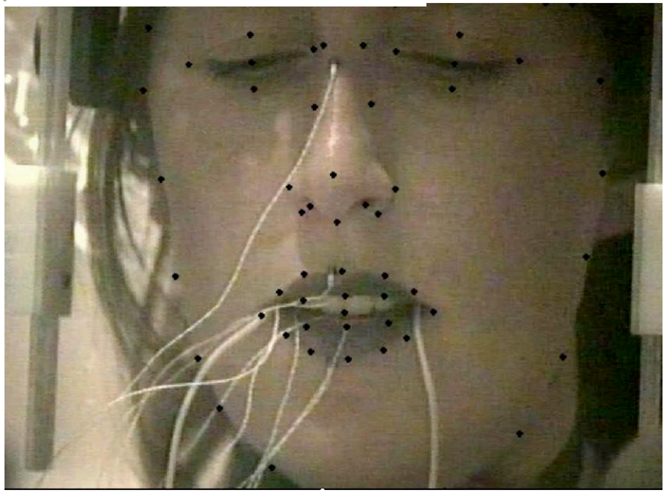
- Switching Process
  - Audiovisual Hidden Markov Models
    - Multistream, Asynchronous
- Training
  - Likelihood Maximization for training (conventionally)
  - Estimate responsibilities
  - Train one separate Linear Dynamic System per state
- Optimal State Sequence
  - Phonetic Information is given
  - Viterbi forced alignment

# Audiovisual Speech Inversion: MOCHA

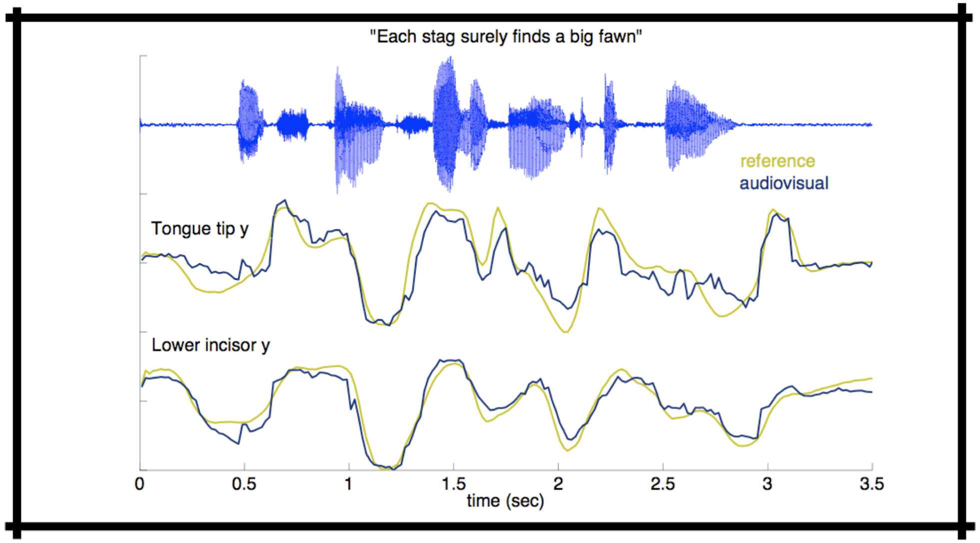




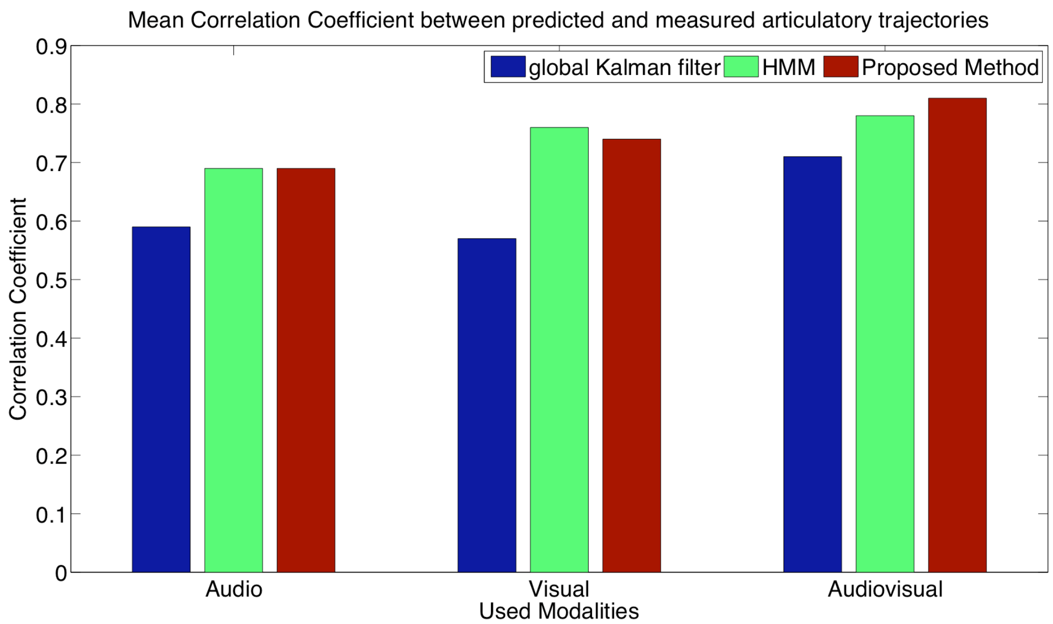

- Provided by CSTR, Univ. Edinburgh
- Two subjects (one male, one female), 460 British TIMIT Utterances each
- Articulation (2-D coords of 9 EMA coils)
- Video of the female speaker's face
- 30 minutes of usable data
- Needed Preprocessing-labeling Video



# Results

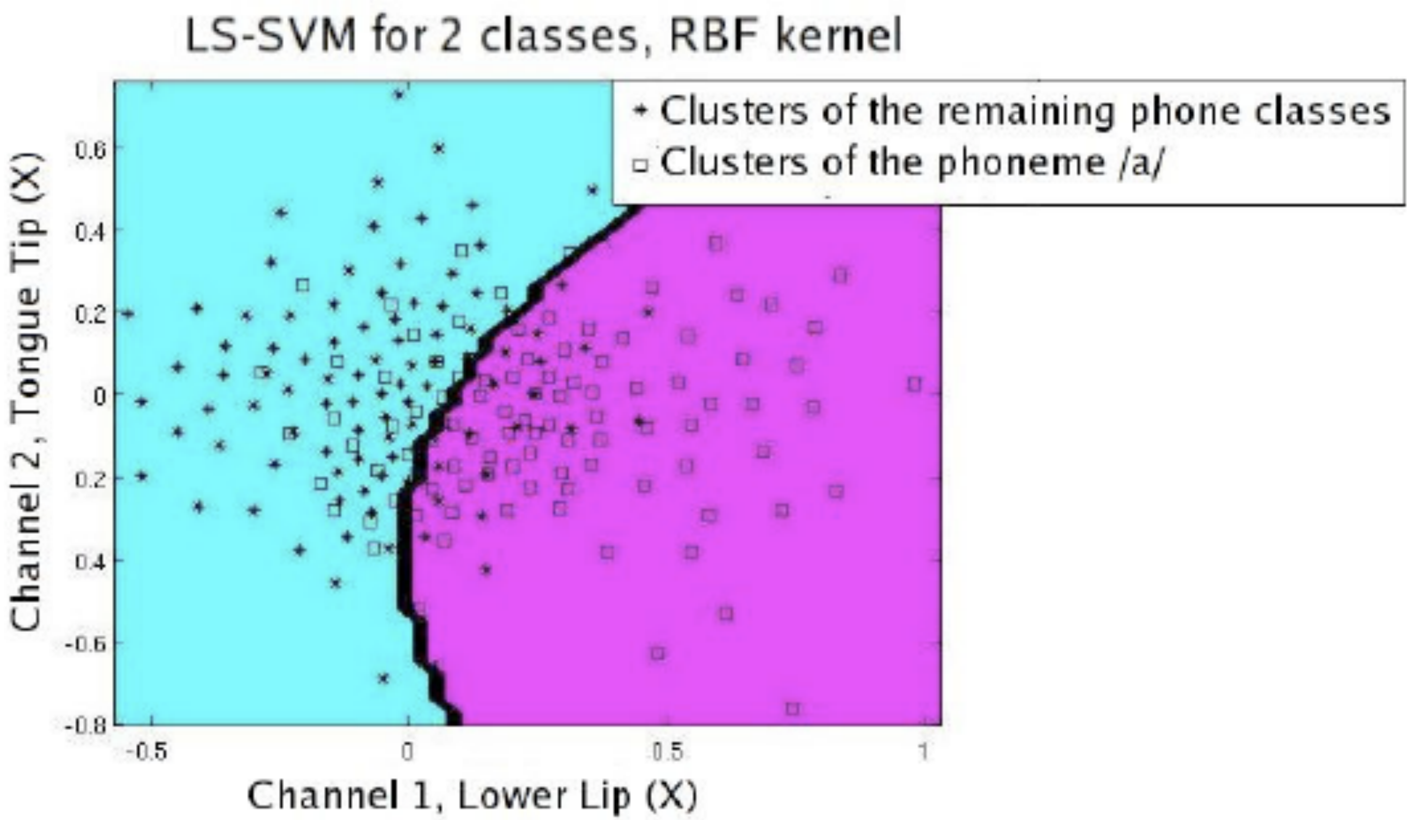


"Each stag surely finds a big fawn"
reference
audiovisual
Tongue tip y
Lower incisor y
0 0.5 1 1.5 2 2.5 3 3.5
time (sec)

Mean Correlation Coefficient between predicted and measured articulatory trajectories
global Kalman filter
HMM
Proposed Method
Correlation Coefficient
0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9
Audio
Visual
Audiovisual
Used Modalities

# Weighted Evaluation



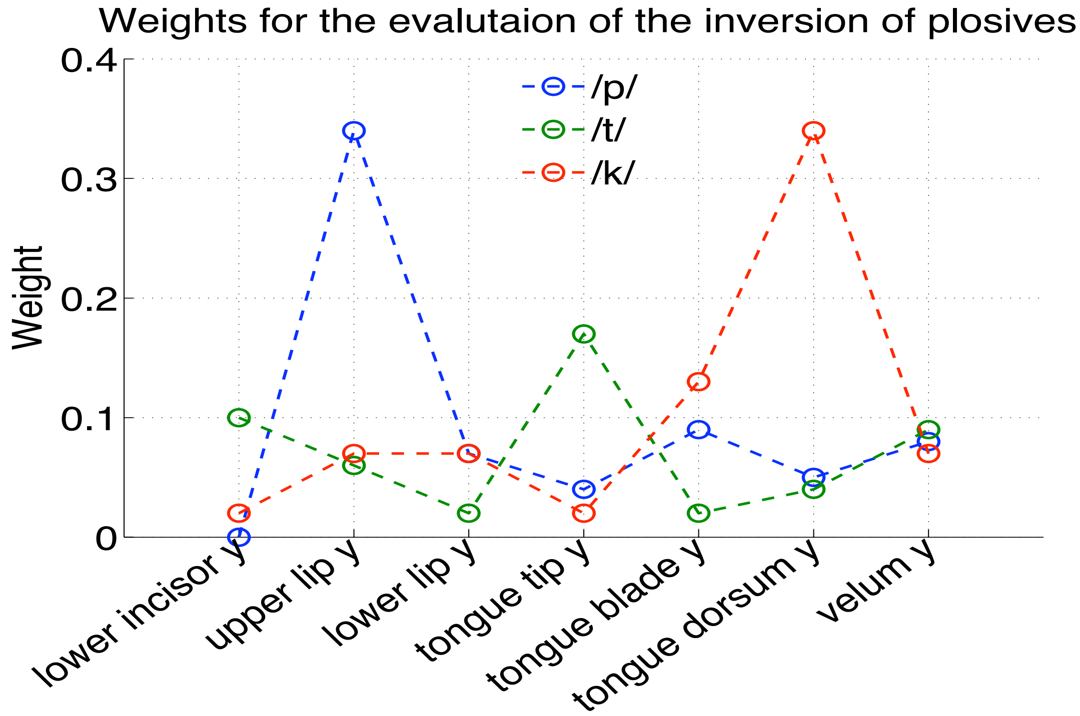
# Weighted Evaluation

- Weighted Root Mean Squared (RMS) Error

$$E_{wrms} = \frac{\sum_{k=1}^{P} \sqrt{\sum_{i \in k} (Y_i - \widehat{Y_i})^T D_k (Y_i - \widehat{Y_i})}}{N}$$

- Weighting matrix for each phoneme
  - Classification using SVMs
  - Sensitivity analysis to estimate weights for each articulatory parameter

# Weighted Evaluation Results




LDS: Global Kalman Filter    HMM: Switching Linear Modeling

Proposed Method: Switching Linear Dynamic System (SLDS)

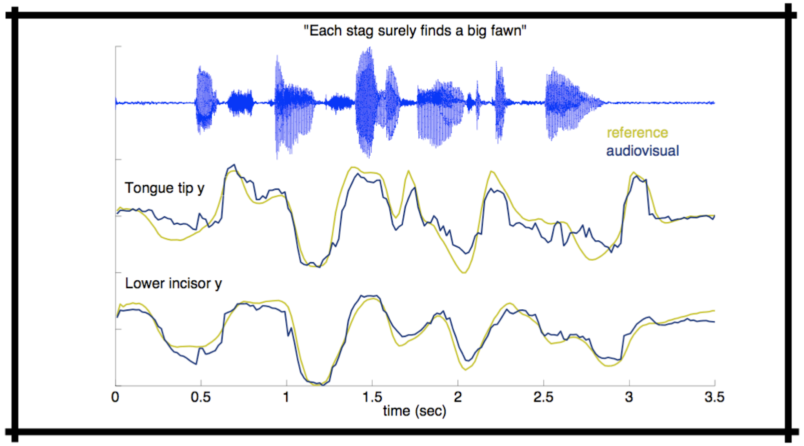
| | **Root Mean Square Error** | | | | | |
|---|---|---|---|---|---|---|
| | Unweighted | | | Weighted | | |
| | LDS | HMM | SLDS | LDS | HMM | SLDS |
| Audio | 2.15 | 1.76 | 1.78 | 2.17 | 1.66 | 1.66 |
| Visual | 2.29 | 1.56 | 1.62 | 2.32 | 1.49 | 1.54 |
| Audiovisual | 1.89 | 1.53 | 1.43 | 1.88 | 1.47 | 1.36 |

# Conclusions

- Audiovisual speech inversion framework
  - Switching linear dynamical model
  - Weighted evaluation scheme to better account for important errors

For the future

- Cope with limited data, over-fitting problems
  - Clustering
    - Tree-based (Hiroya and Honda, 2004), Data-driven
  - Adaptation
    - Adapt global regression model to local data
    - MLLR (King and Frankel, 2005) or Bayesian (Bishop, 2007) adaptation
- Invert to articulatory model parameters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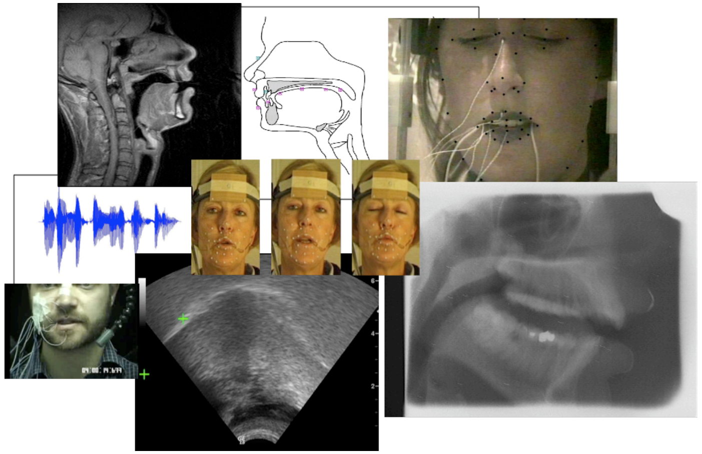
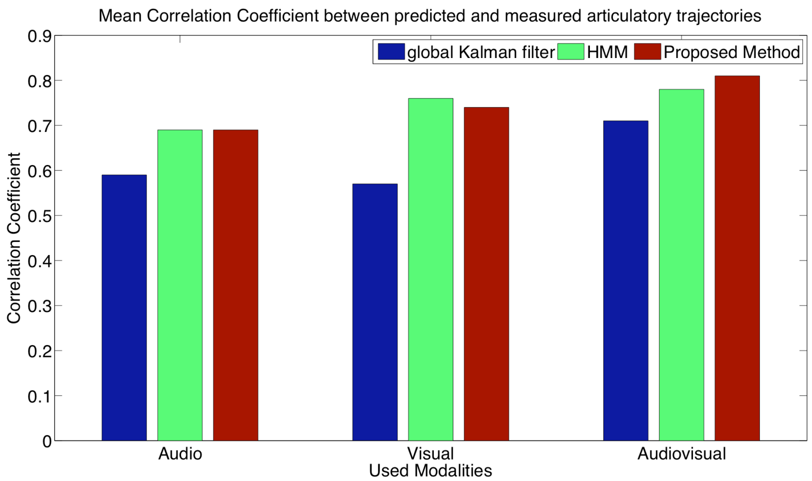


# Thank you !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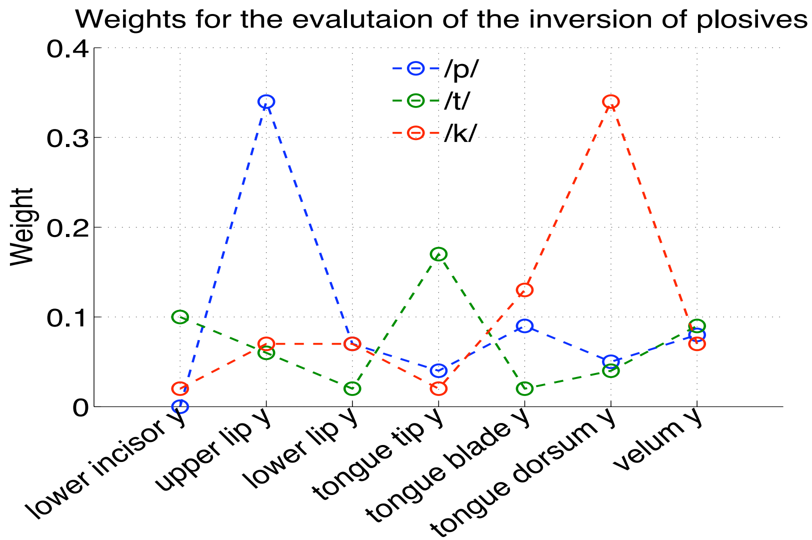
Weights for the evalutaion of the inversion of plosives
/p/
/t/
/k/
Weight
lower incisor y
upper lip y
lower lip y
tongue tip y
tongue blade y
tongue dorsum y
velum y