Energy and F0 contour modeling with Functional Data Analysis for Emotional Speech Detection

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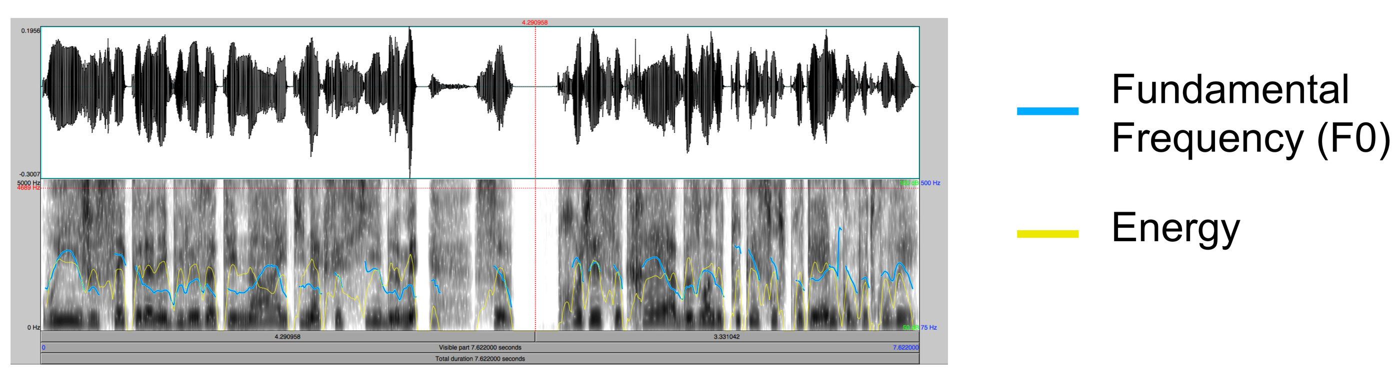
Introduction

- State-of-the-art: extract global statistics from acoustic features
- Do we capture all the emotional cues with global statistics?
  - Rising and falling F0 movements within accents [Paeschke & Sendlmeier, 2000]
  - Concavity and convexity of the F0 contour [Yang & Campbell, 2001]
  - Pitch accents and boundary tones [Liscombe et al., 2003]



- Goal: modeling the **shape** of the energy and F0 contours
  - Emotional prominence using shape-based neutral models

Modeling Approach with Functional Data Analysis (FDA)

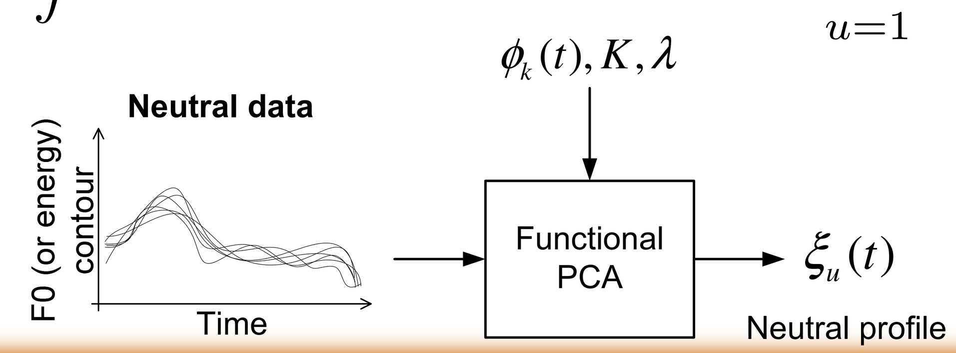
- FDA represents the structure of signals as functions
  - *x(t)* : signal *y(t)*: sampled value $\phi_k(t)$: basis functions

$$y_j = x(t_j) + \epsilon_j \qquad x(t) = \sum_{k=1}^{K} c_k \phi_k(t)$$

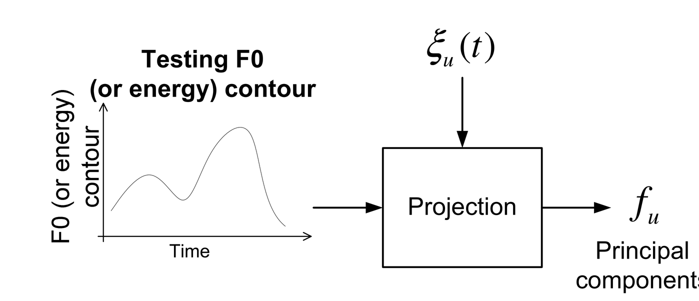
$$\hat{c_k} = argmin_{c_k} \sum_{j=1}^{n} [y_j - x(t_j)]^2 + \lambda \int [D^m x(s)]^2 ds$$

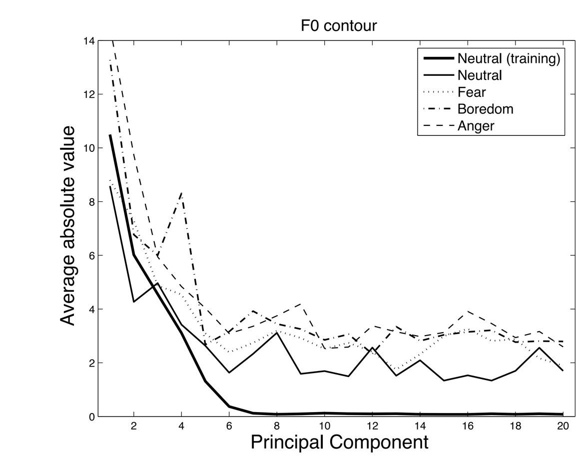
- Functional Principal Component Analysis (fPCA)
  - $x_v(t)$: set of functions $\xi_u(t)$: orthonormal basis

$$f_{u,v} = \int \xi_u(t) x_v(t) dt \qquad \hat{x}_v(t) = \sum_{u=1}^{U} f_{u,v} \xi_u(t)$$

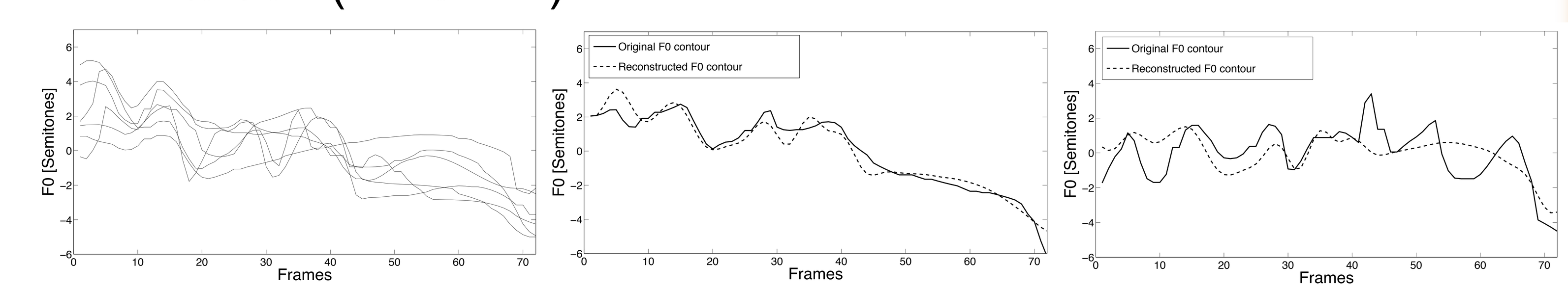


- We use fPCA to train neutral reference models
  - Projections $\{f_1, \ldots, f_U\}$ are used as features





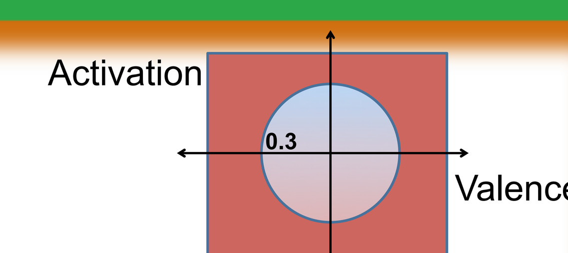
- Intuition (EMO-DB):



F0 contours of six neutral sentences | Reconstruction of F0 contour for **neutral** sentence (*U*=5) | Reconstruction of F0 contour for **happy** sentence (*U*=5)

- Implementation: ϕ_k ➔6th order B-spline with *K*=40 and *U*=20

Discriminant Analysis



- Emotional detection (neutral vs. emotional)
- Quadratic discriminant classifier (QDC)
  - SVM achieves similar performance
- We evaluate lexicon-independent models
  - Neutral speech with different lexical content
- Benchmark classifiers (QDC)
  - Trained with statistics from F0 and energy
  - Subset from IS challenge 2010 [Schuller et. Al, 2010]
  - Forward feature selection
    - 20 for (F0) or (E)
    - 40 for (F0+E)

EMO-DB corpus [Burkhardt et al. 2005]:

- Sentences' durations are linearly warped
- Speaker-independent cross-validation
  - Development, training, testing sets
- Emotional classes grouped into 1 class
  - Trained with under sampling (100 times)

EMO-DB	Accuracy	Average Precision	Average Recall	F-score
FDA (F0)	71.3 (3.6)	75.6	64.1	0.691
FDA (E)	75.9 (1.6)	80.0	69.2	0.742
FDA (E+F0)	80.4 (1.8)	88.3	70.3	0.782
Ben. (F0)	69.0 (9.7)	88.9	45.8	0.555
Ben. (E)	65.9 (7.3)	67.3	67.5	0.666
Ben. (E+F0)	62.8 (9.1)	95.9	27.2	0.390

SEMAINE corpus [McKeown et al., 2010]

- FDA neutral models trained with WSJ1
- Time based segmentation (1 sec)
- Neutral and emotional classes based on averaged activation-valence scores
- Two-fold cross-validation (5 train, 5 test)

SEMAINE	Accuracy	Average Precision	Average Recall	F-score
FDA (F0)	63.6	63.6	63.6	0.636
FDA (E)	57.6	57.1	59.0	0.570
FDA (E+F0)	64.2	64.3	64.2	0.642
Ben. (F0)	58.4	57.8	57.7	0.577
Ben. (E)	56.3	54.9	54.8	0.548
Ben. (E+F0)	57.4	56.5	56.3	0.563

Results & Conclusions

- EMO-DB:
  - fPCA projections increase performance up to 17.6%
  - The fPCA classifiers are more consistent (lower std)
- SEMAINE
  - Classifiers with fPCA projections are 6.9% better than benchmark
  - Performance is not affected by shorter segments (results on paper)
- Global statistics do not capture all emotional cues

Future Directions:

- Evaluation of the approach with prosodic & spectral features
- Detect localized emotional information in dialogs

References

① Juan Pablo Arias, Carlos Busso, and Nestor Becerra Yoma, "Shape-based modeling of the fundamental frequency contour for emotion detection in speech," Computer Speech and Language, vol. In Press, 2013.

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