

Visual Emotion Recognition Using Compact Facial Representations and Viseme Information

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Face during Emotional Speech

emotional gestures + articulation movements

Focus

- Multi-speaker emotional database
- Detailed Motion Capture (MOCAP) facial data
- Low dimensional facial representations
 - Decorrelated markers, PCA, Fisher criterion
- Dynamically model articulation using visemes
- Improvement in recognition performance

IEMOCAP Database

- Dyadic acted emotional database
- Multimodal (audio, video, MOCAP, text)
- Multi-speaker: 10 actors
- Improvisations + scripts
- Annotations
 - Categorical attributes
- Dimensional attributes
- http://sail.usc.edu/data.php

Emotions examined

angry, happy (+excited), neutral, sad



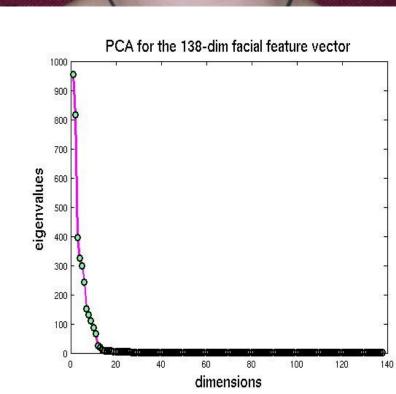
Facial Marker Information

- Motion Capture
- Normalize head rotation/translation
- Nose is the coordinate center
- 46 markers * 3 coordinates
 - 138 dimensions
- Redundant:
- Underlying muscles
- Facial configuration



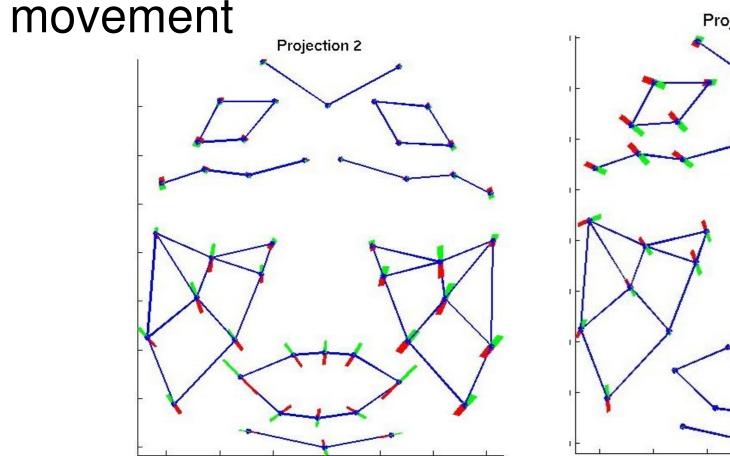
Speaker Face Normalization

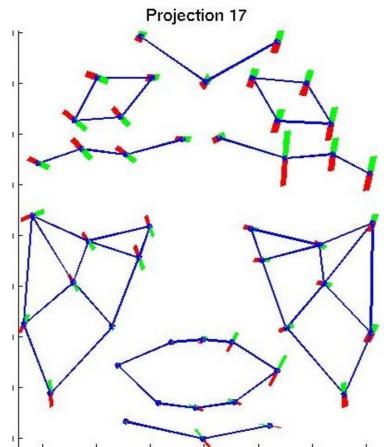
- Shift each marker such that:
- Speaker mean marker positions
- → global mean marker positions



Facial Feature Extraction Principal Component Analysis-PCA

- Linear projection to maximize variance
- 30 first principal components (out of 138)
 - Keep >95% of variance
- Derivatives of projections: 60-dimensions
- Interpretation: principal directions of facial

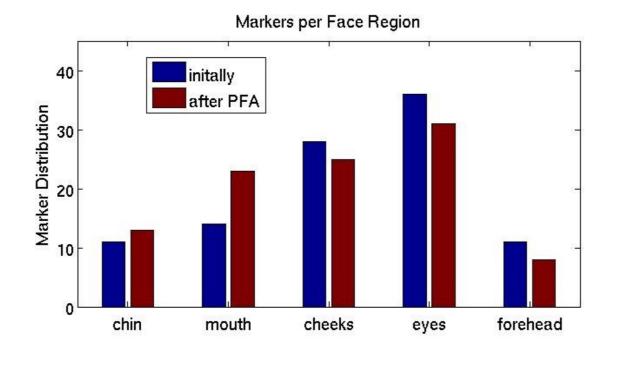




Principal Feature Analysis-PFA

- Decorrelate markers using PCA criteria
- Select a reduced set of decorrelated markers
- Method:
 - Average neighboring markers
 - PFA to select 30 features
 - Normalization
- Plus derivatives →60 dimensions

Lower face bias

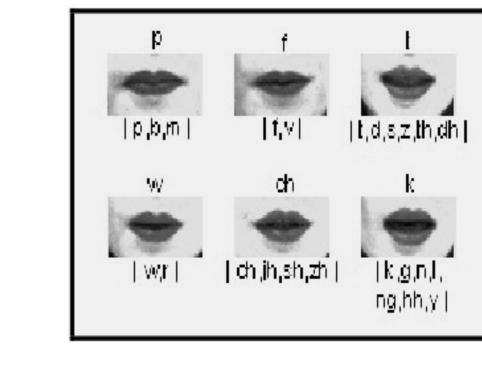


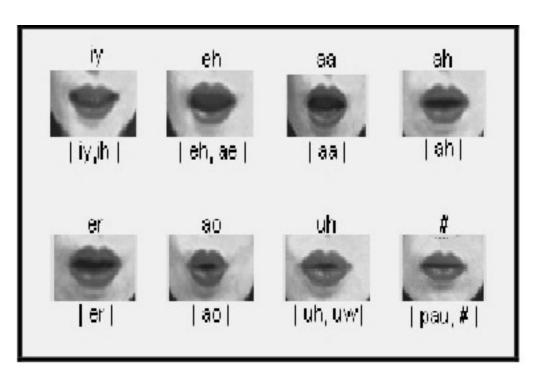
Fisher Feature Selection

- Select features that:
- Maximize between class variability
- Minimize within class variability
- Method:
- Average neighboring markers
- Normalization
- Fisher feature to select 30 features
- Plus derivatives
- →60 dimensions

Viseme Modeling

- Viseme: Lip shape during the voicing of a phoneme
- Modeling emotional visemes:
- Constraint the speech-related variability
- Use available phoneme-level transcriptions
- Dynamic modeling using HMMs





Experiments

PFA	ANG%	HAP%	NEU%	SAD%	UW %
GMM(16)	47.03	73.37	36.55	58.35	53.83±6.09
Viseme-GMM(16)	58.44	71.71	37.22	49.28	54.16±6.24
Viseme-HMM(16)	57.52	76.98	34.79	53.68	55.74±5.26
Fisher	ANG%	HAP%	NEU %	SAD %	UW %
GMM(8)	49.87	72.82	27.35	55.27	51.33±7.23
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Viseme-GMM(8)	62.78	73.76	29.57	42.62	52.18±7.05

- 10-fold leave-one-speaker-out cross validations
- Report the average over the 10 folds
- Decisions are per sentence
- Majority rule used

Discussion and Conclusion

Emotions:

- Happiness is the best recognized emotion
- Neutrality is the lowest recognized state
- Great performance differences between speakers
- PFA and Fisher features have similar performance

Visemes:

- Dynamic articulation modeling is beneficial:
- Total unweighted performance (UW)
- Anger and happiness
- ...but sadness recognition performance decreases Limitations:

Multimodal nature of emotional expression

References

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