

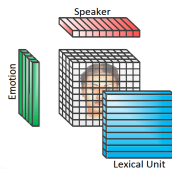


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## Motivation

- Variabilities in Facial Expressions:**
  - Speaker** (i.e., who is speaking)
    - Intrinsic cultural, physiological and idiosyncratic characteristics
  - Lexical Content** (i.e., what is being spoken)
    - Underlying articulatory process
  - Emotional Content** (i.e., how is being spoken)
    - Externalization of emotional cues
- Goals:**
  - Decode the variability in the face
  - Propose solutions for robust emotion recognition systems



## Methodology

### Database (IEMOCAP) [Busso et al. 2008]

- ~12 hours of data, read, scripted and spontaneous
- Speech and motion capture markers (53)
- Speaker**
  - 10 speakers (5 male, 5 female)
- Lexical Content**
  - The 10 most frequent syllables and words

Syllables	AY	Y_UW	AX	N_OW	T_AX	AX_T	L_AY_K	DH_AX	G_OW	AX_N_D
Words	I	YOU	KNOW	A	TO	THE	LIKE	AND	DO	ME

- Emotional Content**
  - The four most frequent emotions (Happiness, sadness, anger and neutral)

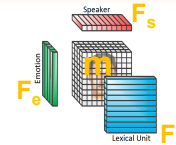
### Trajectory Model (marker $m$ )

- Interpolation-Resampling
- Mean trajectory ( $\mu_m$ )
- Variations ( $\Sigma_m$ )
- Models for word "WELL"



### Factor Analysis

- $m$  = markers
- $F$  = factors
  - speaker, lexical and emotional contents
- Goal:** Measure the contribution of the factors in the variability of the features
- Mutual Information



$$IG(m, F) = H(m) - \sum_{f \in F} P(f)H(m | f)$$

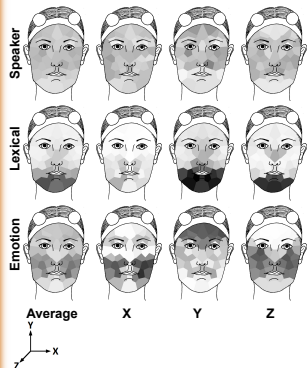
- Proposed Relevance Measure (RM)

$$RM(m, F) = \text{tr}(\Sigma_m) - \sum_{f \in F} P(f)\text{tr}(\Sigma_m | f)$$

- Normalizing to compensate for different initial uncertainties
- $$RM_n(m, F) = \frac{RM(m, F)}{\text{tr}(\Sigma_m)}$$

## Factor Analysis Results

### Distribution of the factors (lexical-independent): $RM_n(m, F)$



Div#	Syllable Level			Word Level		
	Speaker	Syllable	Emotion	Speaker	Word	Emotion
F1	0.068	0.014	<b>0.069</b>	0.070	0.016	<b>0.071</b>
F2	<b>0.053</b>	0.014	<b>0.053</b>	0.056	0.015	<b>0.057</b>
F3	0.033	0.013	<b>0.063</b>	0.035	0.015	<b>0.064</b>
F4	0.075	0.031	<b>0.107</b>	0.077	0.038	<b>0.102</b>
F5	0.080	0.032	<b>0.113</b>	0.081	0.040	<b>0.109</b>
F6	0.062	0.073	<b>0.117</b>	0.063	0.089	<b>0.114</b>
F7	0.038	<b>0.153</b>	0.048	0.040	<b>0.184</b>	0.043

### The effect of lexical-dependent models

- $\Delta(\%)$  = The difference of  $RM_n(m, F)$  in lexical-independent and lexical-dependent

Div#	Syllable Level		Word Level	
	Emotion	$\Delta(\%)$	Emotion	$\Delta(\%)$
F1	0.070	1.44	0.069	-2.28
F2	0.053	0.00	0.053	-7.01
F3	0.068	7.93	0.063	-1.58
F4	0.115	7.47	0.103	0.98
F5	0.122	7.56	0.111	1.83
F6	0.123	5.12	0.115	0.87
F7	0.067	<b>39.58</b>	0.063	<b>46.51</b>



## Conclusions

### Conclusions:

- Emotion mostly affects the middle and upper face regions
- Lexical independent model
- Lexical influence is localized in the orofacial region
- Constraining on the lexicon increases emotion variability
- Lexical dependent model

### Future Directions

- Fusing lexical dependent and lexical independent models
- Find suitable lexical unit (e.g., visemes instead of syllables)
- Finding lexical unit with similar trajectories (e.g., clustering)

### References:

C. Busso, M. Bulut, C. Lee, A. Kazemzadeh, E. Mower, S. Kim, J. Chang, S. Lee, and S. Narayanan, "IEMOCAP: Interactive emotional dyadic motion capture database," Journal of Language Resources and Evaluation, vol. 42, no. 4, pp. 335-359, December 2008