Speech Processing and Natural Language Processing

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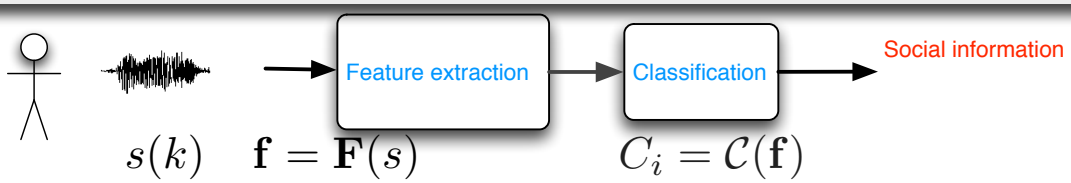
Speech processing in Social Interactions

Problem statement: From speech samples to social information: Identity, Emotion, Intention, Pathology...



LPC, MFCC, TRAPs, NPC...

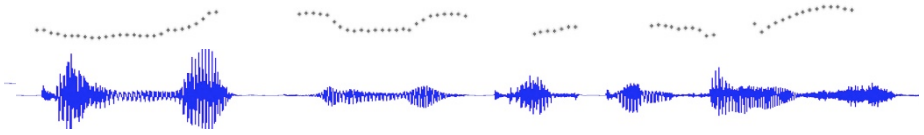
k-ppv, GMM, HMM, SVM...

Idea: Characterization of speech signals by feature extraction, time-scale and classification methods

Units?

Voiced, unvoiced, vowels...

Subjectivity?

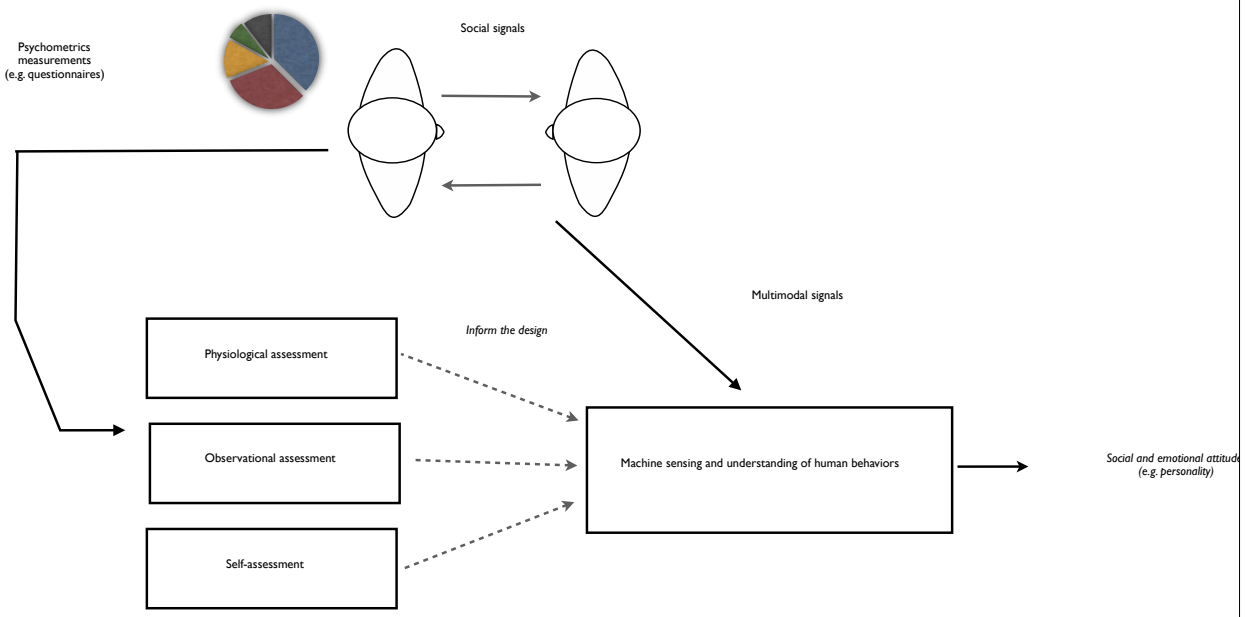


Statistical nature of speech signals?

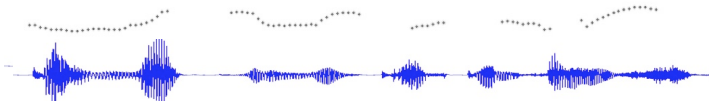
Gaussian vs Non-gaussian, Stationarity...

Manual vs Automatic annotations

Affective Computing



Speech Affective Computing Methodology



(1) Extraction of Low-Level Descriptors (LLD):
- Pitch (fundamental frequency)
- Energy
- Spectrum
- …

(2) Application of functionals
- Statistics
- Duration
- Linear prediction
- …

(3) Classification
- Speech turn
- Utterance turn

Speech Affective Computing
Lessons learnt from the First Computational Paralinguistics Challenge

Table 6
ComParE acoustic feature set: 65 provided **low-level descriptors** (LLD).

4 Energy Related LLD	Group
Sum of Auditory Spectrum (Loudness)	Prosodic
Sum of RASTA-Style Filtered Auditory Spectrum	Prosodic
RMS Energy, Zero-Crossing Rate	Prosodic
55 Spectral LLD	**Group**
RASTA-Style Auditory Spectrum, Bands 1−26 (0−8 kHz)	Spectral
MFCC 1−14	Cepstral
Spectral Energy 250−650 Hz, 1 k−4 kHz	Spectral
Spectral Roll Off Point 0.25, 0.50, 0.75, 0.90	Spectral
Spectral Flux, Centroid, Entropy, Slope, Harmonicity	Spectral
Spectral Psychoacoustic Sharpness	Spectral
Spectral Variance, Skewness, Kurtosis	Spectral
6 Voicing Related LLD	**Group**
F_0 (SHS & Viterbi Smoothing)	Prosodic
Probability of Voicing	Sound Quality
Log. HNR, Jitter (Local, Delta), Shimmer (Local)	Sound Quality

Björn Schuller, Felix Weninger, Yue Zhang, Fabien Ringeval, Anton Batliner, Stefan Steidl, Florian Eyben, Erik Marchi, Alessandro Vinciarelli, Klaus Scherer, **Mohamed Chetouani,** Marcello Mortillaro, Affective and behavioural computing: Lessons learnt from the First Computational Paralinguistics Challenge, Computer Speech & Language (2019)

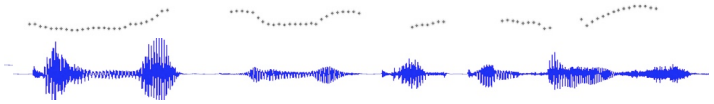
Speech Affective Computing
Lessons learnt from the First Computational Paralinguistics Challenge

Table 7
ComParE acoustic feature set: **functionals** applied to LLDs as defined in Table 6.

Mean Values
Arithmetic Mean$^{A\triangleq, B}$, Arithmetic Mean of Positive Values$^{A^\Delta, B}$
Root-Quadratic Mean, Flatness
Moments: Standard Deviation, Skewness, Kurtosis
Temporal Centroid$^{A\triangleq, B}$
Percentiles
Quartiles 1−3, Inter-Quartile Ranges 1−2, 2−3, 1−3
1%-tile, 99%-tile, Range 1−99%
Extrema
Relative Position of Maximum and Minimum, Full Range (Maximum−Minimum)
Peaks and Valleys^{A}
Mean of Peak Amplitudes,
Difference of Mean of Peak Amplitudes to Arithmetic Mean
Mean of Peak Amplitudes Relative to Arithmetic Mean
Peak to Peak Distances: Mean and Standard Deviation
Peak Range Relative to Arithmetic Mean
Range of Peak Amplitude Values
Range of Valley Amplitude Values Relative to Arithmetic Mean
Valley-Peak (Rising) Slopes: Mean and Standard Deviation
Peak-Valley (Falling) Slopes: Mean and Standard Deviation
Up-Level Times: 25%, 50%, 75%, 90%
Rise and Curvature Time
Relative Time in which Signal is Rising
Relative Time in which Signal has Left Curvative
Segment Lengths^{A}
Mean, Standard Deviation, Minimum, Maximum
Regression$^{A\triangleq, B}$
Linear Regression: Slope, Offset, Quadratic Error
Quadratic Regression: Coefficients a and b, Offset c, Quadratic Error
Linear Prediction
LP Analysis Gain (Amplitude Error), LP Coefficients 1−5

^{A}Functionals applied only to energy related and spectral LLDs (group A)
^{B}Functionals applied only to voicing related LLDs (group B)
$^{\Delta}$Functionals applied only to ΔLLDs
$\triangleq$ Functionals **not** applied to ΔLLDs

Speech Affective Computing Methodology



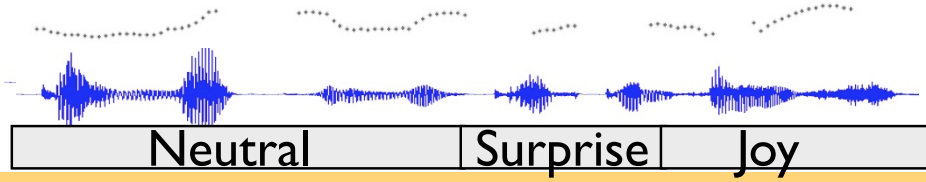
INTERSPEECH 2013 configuration:
6373 features

Group A: 4 energy related LLDs + 55 spectral LLDs
Group B: 6 voicing related LLDs

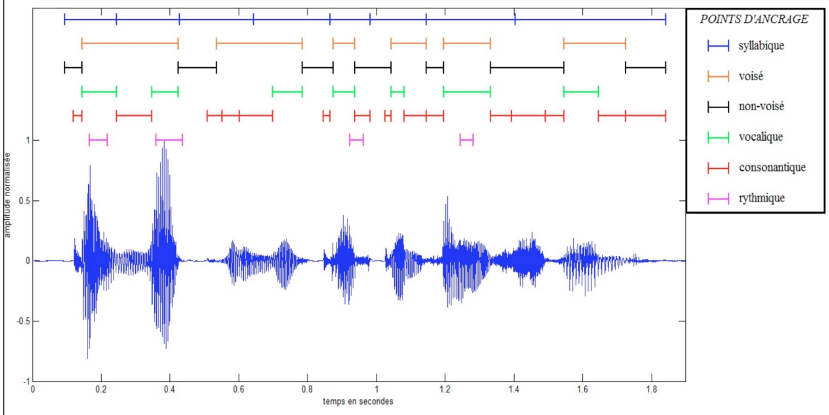
54 functionals applied to Group A + 46 applied to Delta LLDs -> 5900 features
39 functionals applied to Group B and Delta LLDs -> 468 features
5 temporal static descriptors for voiced segments: mean length, standard deviation of the segment length, minimum and maximum of voiced segments, ratio of non-zero F0

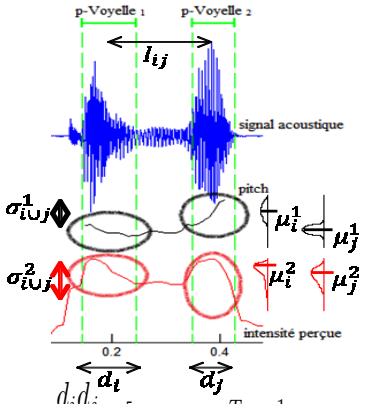
Total: 5900 + 468 + 5 = **6373 features**

Speech Affective Computing



Units for emotional speech processing:
- Acoustical, Prosodic and Rhythmic prominence
- Dynamics of units: Huang-Hilbert transform, Hotelling distance...



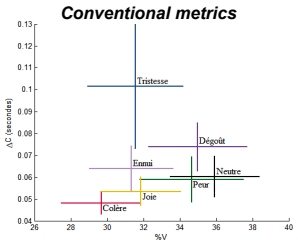


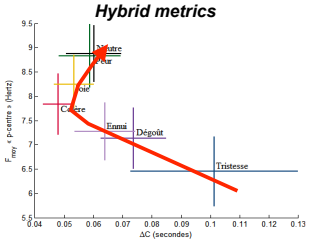
$$HD_{ij} = \frac{d_i d_j}{d_i + d_j}\left[(\mu_i - \mu_j)^T \Sigma^{-1}_{i\cup j}(\mu_i - \mu_j)\right]$$

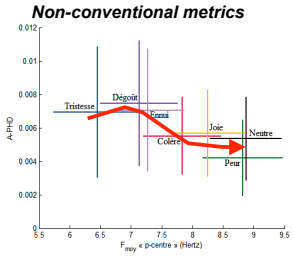
Speech Affective Computing

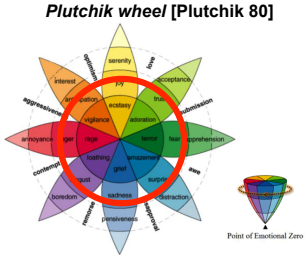
Applications

- Acted emotion recognition
- Children assessment: Autism, Pervasive Developmental Disorders, Language impairment
- Spontaneous and atypical emotions

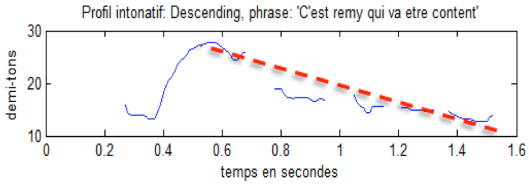


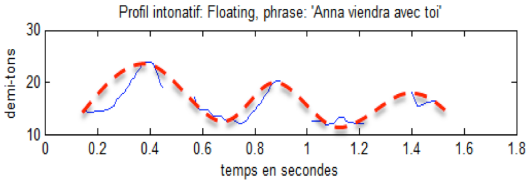






Automatic evaluation of prosody

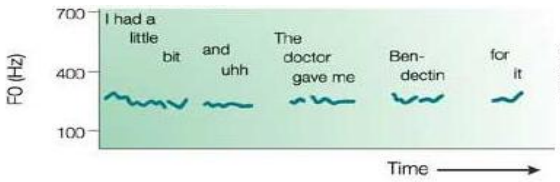




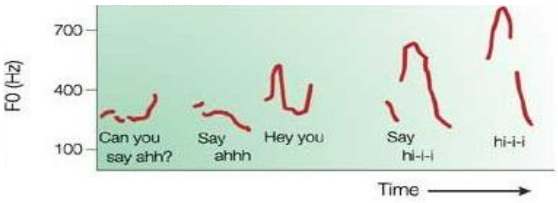
F. Ringeval et al. : Automatic intonation recognition for the prosodic assessment of language impaired children. *IEEE Trans. Audio, Speech and Language Processing* **19**(5) 1328-1342 (2011).

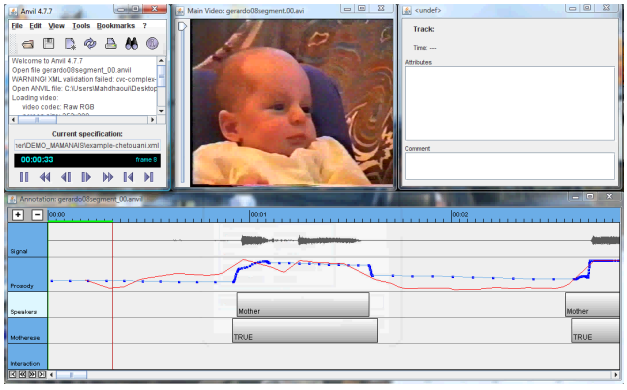
Speech Affective Computing Methodology

Adult-directed speech



Infant-directed speech



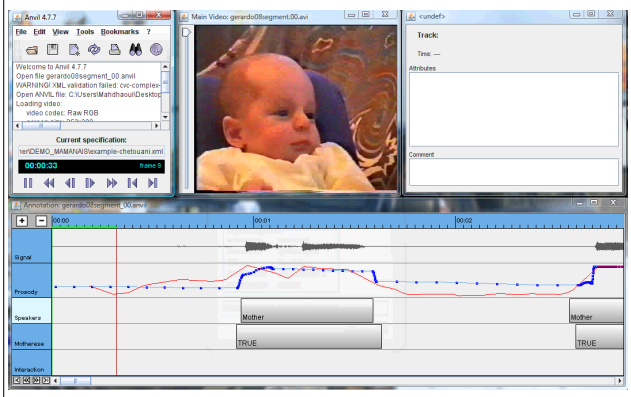


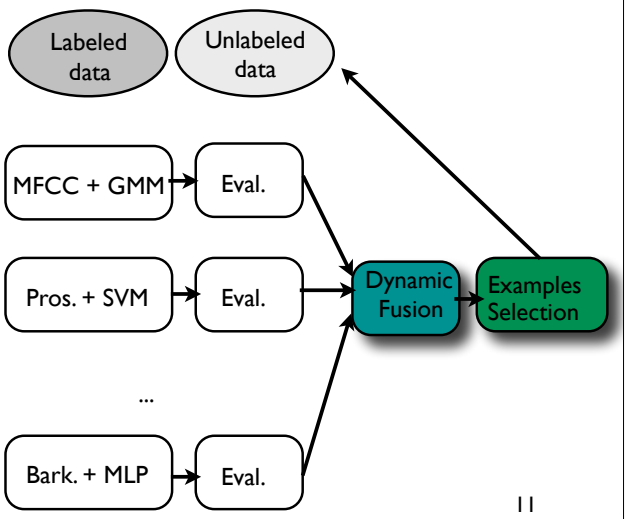
C. Saint-georges et al. : Motherese in Interaction: At the Cross-Road of Emotion and Cognition? (A Systematic Review) *Plos One*, 2013

Speech Affective Computing
Co-Learning approaches

Annotation and Subjectivity of social signals

- Semi-supervised learning: combining labeled and unlabeled data
- Co-training and fusion: Multi-view characterization





Speech Affective Computing
Co-Learning approaches

Table 3: Self-training algorithm

Given:
a set L of Labelled examples
a set U of Unlabelled examples
a number n of examples to be added to L in each iteraction
Loop:
Use L to train the classifier h
Allow h to label U
Let T be the n examples in U on which h makes the most confident predictions
Add T to L
Remove T from U
End

Table 4: Co-Training algorithm

Given:
a set L of Labelled examples
a set U of Unlabelled examples
Loop:
Use L to train each classifier h_1
Use L to train each classifier h_2
Allow h_1 to label p_1 positive and n_1 negative examples from U
Allow h_2 to label p_2 positive and n_2 negative examples from U
Add these self-labelled examples to L
Remove these self-labelled examples from U
End

A. Mahdhaoui and M. Chetouani : Supervised and semi-supervised infant-directed speech classification for parent-infant interaction analysis. *Speech Communication* **53**(9) 1149-1161 (2011).

Speech Affective Computing
Co-Learning approaches

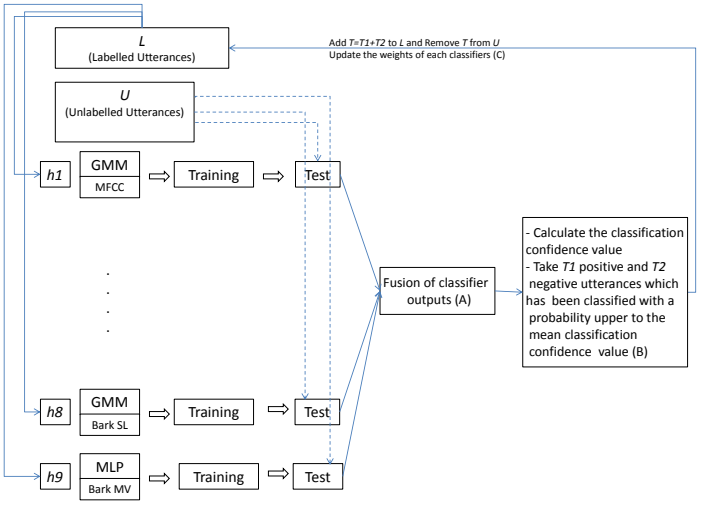


Figure 5: Structure of the proposed Co-training algorithm

A. Mahdhaoui and M. Chetouani : Supervised and semi-supervised infant-directed speech classification for parent-infant interaction analysis. *Speech Communication* **53**(9) 1149-1161 (2011).

Speech Affective Computing
Co-Learning approaches

Table 5: The proposed Co-Training algorithm

Given:

a set L of m Labelled examples $\{(l_1^1, ..., l_1^v, y_1), ..., (l_m^1, ..., l_m^v, y_m)\}$ with labels $y_i = \{1, 2\}$

a set U of n Unlabelled examples $\{(x_1^1, ..., x_1^v), ..., (x_n^1, ..., x_n^v)\}$

v = number of view (classifier)

Initialization:

ω_k (weights of classifier)= $1/v$ for all the view

While U not empty

A. Classify all the example of the test database:

Do for $k = 1, 2, ..., v$

1. Use L to train each classifier h_k
2. Classify all examples of U by each h_k
3. Calculate the probability of classification for each example x_i from U, $p(C_j|x_i) = \sum_{k=1}^{v} \omega_k \times h_k(C_j|x_i^k)$
4. $Labels(x_i) = argmax(p(C_j|x_i))$

End for

B. Update the training (L) and test (U) databases:

$U_j = \{z_1, ..., z_{nj}\}$ the ensemble of example classified C_j

Do for $i = 1, 2, ..., nj$

$p(C_j|z_i) = \frac{\sum_{k=1}^{v} \omega_k \times h_k(C_j|z_i^k)}{\sum_{k=1}^{v} \omega_k}$

End for

$margin_j = \frac{\sum_1^{n_j} p(C_j|z_i)}{n_j}$

Take T_j from U_j the examples which has classified on C_j with a probability upper to $margin_j$.

$T = \sum T_j$

Add T to L and remove it from U

C. Update weights: $\omega_k = \frac{\sum_{i=1}^{size(T)} h_k(z_i^k)}{\sum_{k=1}^{v} \sum_{i=1}^{size(T)} h_k(z_i^k)}$

End While

A. Mahdhaoui and M. Chetouani : Supervised and semi-supervised infant-directed speech classification for parent-infant interaction analysis. *Speech Communication* **53**(9) 1149-1161 (2011).

Speech Affective Computing
Co-Learning approaches

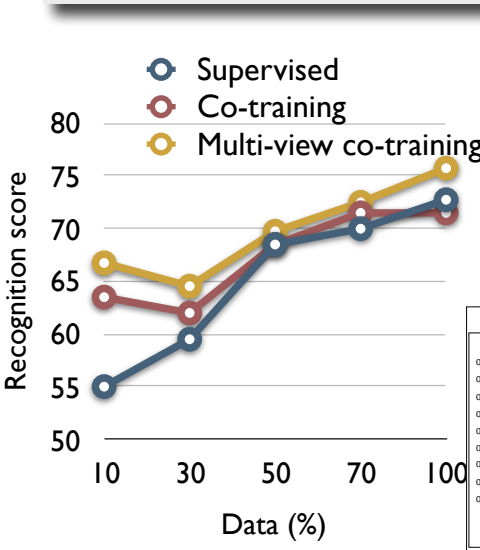
Table 8: Classification accuracy with different numbers of annotations

Number of annotations	10	20	30	40	50	60	70	80	90	100
Proposed Co-training method	66.75	65.25	63.5	67	69.75	72.25	72.5	71.75	74	75.75
Co-training standard (using h1 and h4)	63.5	62.5	62	64.5	68.5	69.75	71.25	69.5	71	71.5
Co-training standard (using all the classifiers h1-h9)	57	58.5	58.5	61	64	67	67.25	68	69	68.5
Self-training (using h1: MFCC-GMM)	52	50	50	54	55	62.5	61	65	69	70.25
Self-training (using h2: prosody-GMM)	54	52.5	53	52	53.5	58	59	62	64.5	67.75
Supervised method: MFCC-GMM (best configuration)	55	59.25	59.5	61.5	68.5	71	70	69.75	71.5	72.75

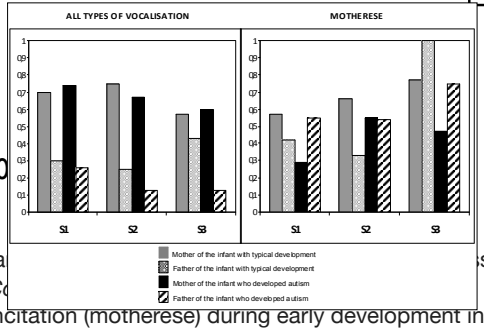
A. Mahdhaoui and M. Chetouani : Supervised and semi-supervised infant-directed speech classification for parent-infant interaction analysis. *Speech Communication* **53**(9) 1149-1161 (2011).

Speech Affective Computing
Co-Learning approaches

- Motherese detection in Family Home Movies
- Early signs of Autism Spectrum Disorders



Motherese detection



A. Mahdhaoui and M. Chetouani : Supervised a sification for parent-infant interaction analysis. *Speech Co*

R. Cassel et al.: Course of maternal prosodic incitation (motherese) during early development in autism: an exploratory study. *Interaction Studies. Vol 14 Pages 480-496 2014.*

Lessons learnt from the First Computational Paralinguistics Challenge

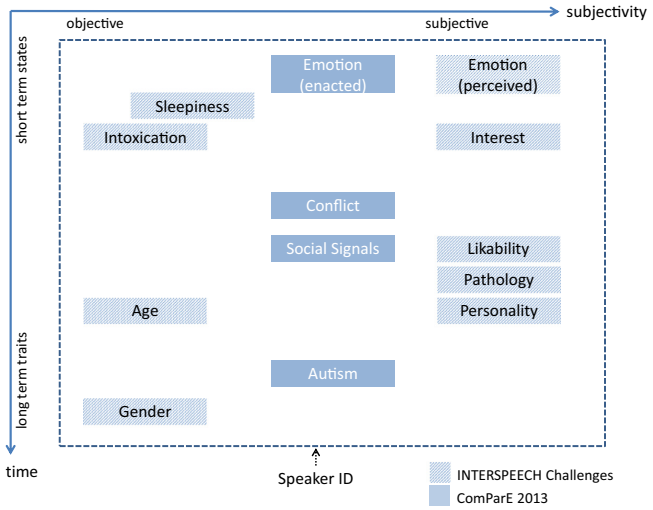


Fig. 1. Speaker characteristics investigated in the INTERSPEECH Challenges 2009–2012 and the First Computational Paralinguistics Challenge (ComParE) 2013.

Björn Schuller, Felix Weninger, Yue Zhang, Fabien Ringeval, Anton Batliner, Stefan Steidl, Florian Eyben, Erik Marchi, Alessandro Vinciarelli, Klaus Scherer, **Mohamed Chetouani,** Marcello Mortillaro, Affective and behavioural computing: Lessons learnt from the First Computational Paralinguistics Challenge, Computer Speech & Language (2019)

Lessons learnt from the First Computational Paralinguistics Challenge

Table 4
Partitioning of the GEMEP database into train, dev(elopment), and test set for 12-way classification by emotion category, and binary classification by pos(itive)/neg(ative) arousal (A) and valence (V).

#	Train	Dev	Test	A	V	Σ
Admiration[+]	20	2	8	pos	pos	30
Amusement	40	20	30	pos	pos	90
Anxiety	40	20	30	neg	neg	90
Cold anger	42	12	36	neg	neg	90
Contempt[+]	20	6	4	neg	neg	30
Despair	40	20	30	pos	neg	90
Disgust[+]	20	2	8	–*	–*	30
Elation	40	12	38	pos	pos	90
Hot anger	40	20	30	pos	neg	90
Interest	40	20	30	neg	pos	90
Panic fear	40	12	38	pos	neg	90
Pleasure	40	20	30	neg	pos	90
Pride	40	12	38	pos	pos	90
Relief	40	12	38	neg	pos	90
Sadness	40	12	38	neg	neg	90
Shame[+]	20	2	8	pos	neg	30
Surprise[+]	20	6	4	–*	–*	30
Tenderness[+]	20	6	4	neg	pos	30
Σ	602	216	442			1260

[+] Mapped to 'other' and excluded from evaluation in 12-class task.
* Mapped to 'undefined' and excluded from evaluation in binary tasks.

Björn Schuller, Felix Weninger, Yue Zhang, Fabien Ringeval, Anton Batliner, Stefan Steidl, Florian Eyben, Erik Marchi, Alessandro Vinciarelli, Klaus Scherer, **Mohamed Chetouani,** Marcello Mortillaro, Affective and behavioural computing: Lessons learnt from the First Computational Paralinguistics Challenge, Computer Speech & Language (2019)

Deep Learning for Human Affect Recognition: Insights and New Developments

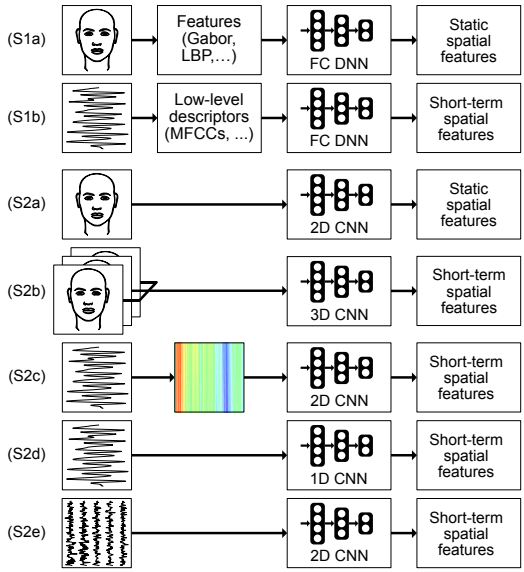


Fig. 2. Applications of deep learning for spatial feature learning with fully-connected DNNs (S1a–S1b) and CNNs (S2a–S2e).

P. V. Rouast, M. Adam and R. Chiong, "Deep Learning for Human Affect Recognition: Insights and New Developments," in IEEE Transactions on Affective Computing, doi: 10.1109/TAFFC.2018.2890471.

Deep Learning for Human Affect Recognition: Insights and New Developments

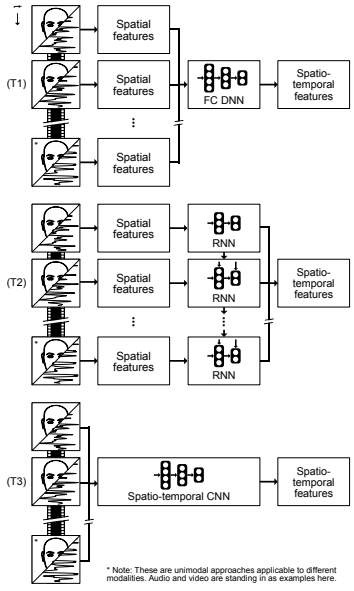


Fig. 5. Applications of deep learning for temporal feature learning with fully-connected DNNs (T1), RNNs (T2), and CNNs (T3).

P. V. Rouast, M. Adam and R. Chiong, "Deep Learning for Human Affect Recognition: Insights and New Developments," in IEEE Transactions on Affective Computing, doi: 10.1109/TAFFC.2018.2890471.

Deep Learning for Human Affect Recognition: Insights and New Developments

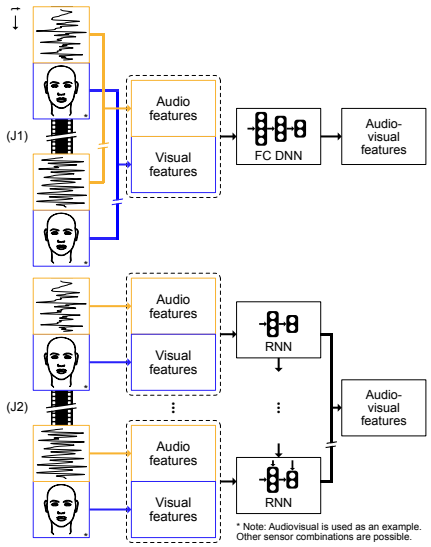
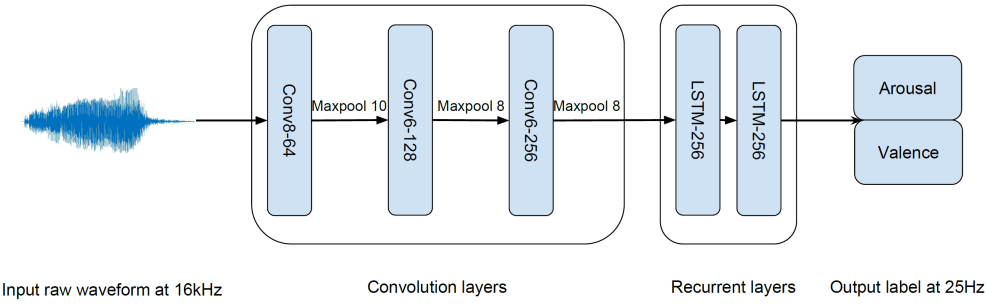


Fig. 6. Applications of deep learning for joint multimodal feature learnin with fully-connected fusion DNNs (J1) and fusion RNNs (J2).

P. V. Rouast, M. Adam and R. Chiong, "Deep Learning for Human Affect Recognition: Insights and New Developments," in IEEE Transactions on Affective Computing, doi: 10.1109/TAFFC.2018.2890471.

End-to-end approach

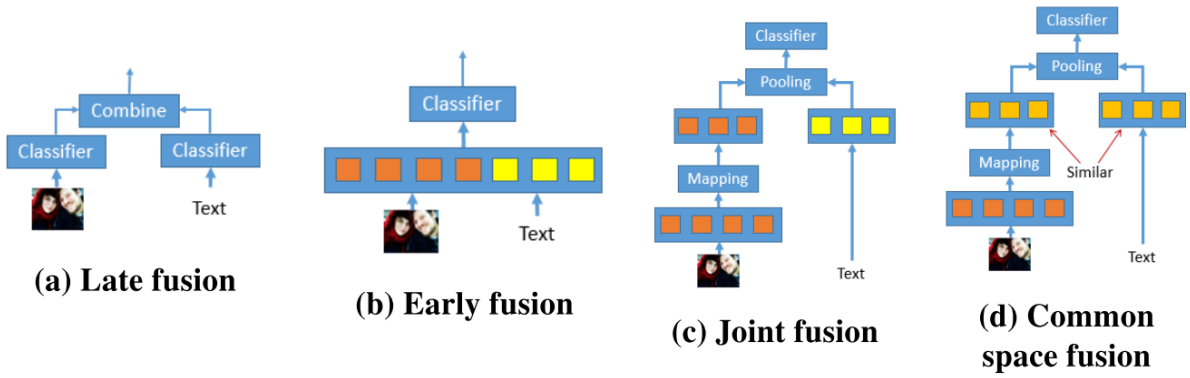


Convolution operation:

$$(f \star h)(i,j) = \sum_{k=-T}^{T} \sum_{m=-T}^{T} f(k,m) \cdot h(i-k, j-m) \quad (1)$$

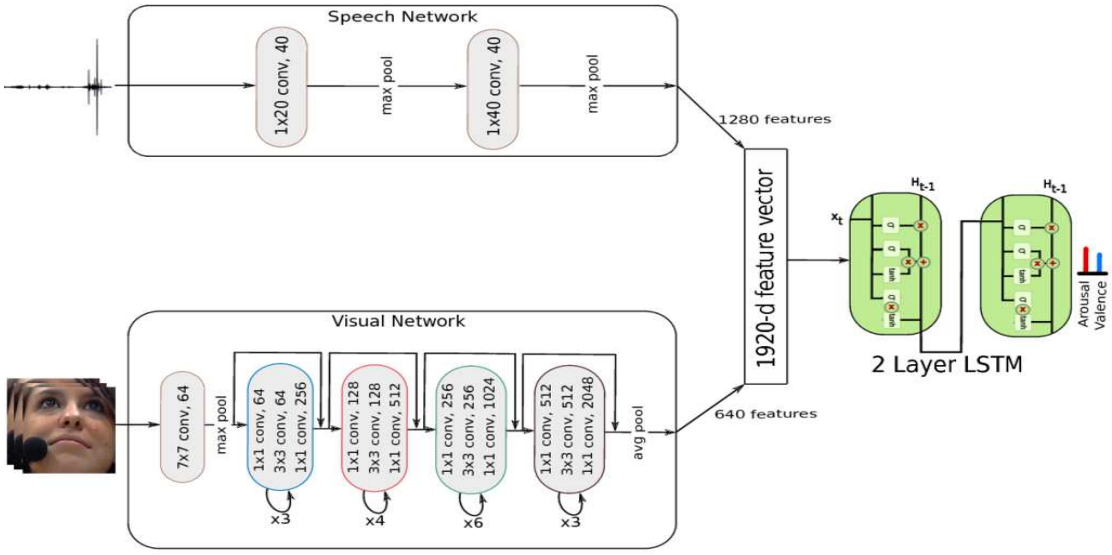
P. Tzirakis, G. Trigeorgis, M. A. Nicolaou, B. W. Schuller and S. Zafeiriou, "End-to-End Multimodal Emotion Recognition Using Deep Neural Networks," in IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 8, pp. 1301-1309, Dec. 2017, doi: 10.1109/JSTSP.2017.2764438.

End-to-End Multimodal Emotion Recognition



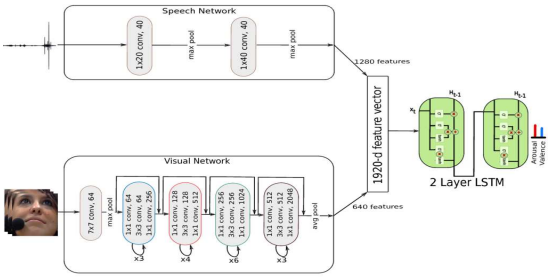
P. Tzirakis, G. Trigeorgis, M. A. Nicolaou, B. W. Schuller and S. Zafeiriou, "End-to-End Multimodal Emotion Recognition Using Deep Neural Networks," in IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 8, pp. 1301-1309, Dec. 2017, doi: 10.1109/JSTSP.2017.2764438.

End-to-End Multimodal Emotion Recognition



P. Tzirakis, G. Trigeorgis, M. A. Nicolaou, B. W. Schuller and S. Zafeiriou, "End-to-End Multimodal Emotion Recognition Using Deep Neural Networks," in IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 8, pp. 1301-1309, Dec. 2017, doi: 10.1109/JSTSP.2017.2764438.

End-to-End Multimodal Emotion Recognition



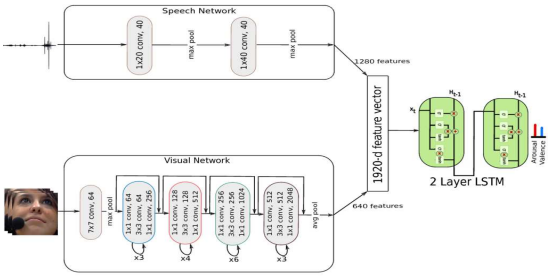
ResNet

Speech Network:

- Raw waveform (6s)
- Temporal Convolution (F=20): space time finite impulse filters with 5ms window in order to extract fine-scale spectral information
- Pooling across time: Half-wave rectifier (analogous to the cochlear transduction step in the human ear) and then downsampled to 8kHz (pool size = 2)
- Temporal convolution (F=40): Extract more long-term characteristics of the speech signal
- Max pooling across channels
- Dropout

P. Tzirakis, G. Trigeorgis, M. A. Nicolaou, B. W. Schuller and S. Zafeiriou, "End-to-End Multimodal Emotion Recognition Using Deep Neural Networks," in IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 8, pp. 1301-1309, Dec. 2017, doi: 10.1109/JSTSP.2017.2764438.

End-to-End Multimodal Emotion Recognition



Sequence length	Arousal	Valence
Visual network		
75	.293	.276
150	.363	.488
300	.193	.496
Speech network		
75	.727	.345
150	.744	.369
300	.685	.130

Table II: Results (in terms of ρ_c) on arousal and valence after 60 epochs when varying sequence length for speech and visual networks.

Objective function:
Instead of MSE, correlation

$$\mathcal{L}_c = 1 - \rho_c = 1 - \frac{2\sigma_{xy}^2}{\sigma_x^2 + \sigma_y^2 + (\mu_x - \mu_y)^2} = 1 - 2\sigma_{xy}^2\psi^{-1} \quad (3)$$

where $\psi = \sigma_x^2 + \sigma_y^2 + (\mu_x - \mu_y)^2$ and $\mu_x = \mathbb{E}(\mathbf{x})$, $\mu_y = \mathbb{E}(\mathbf{y}), \sigma_x^2 = \text{var}(\mathbf{x}), \sigma_y^2 = \text{var}(y)$ and $\sigma_{xy}^2 = \text{cov}(\mathbf{x}, \mathbf{y})$ Thus, to minimise $\mathcal{L}_c$ (or maximise ρ_c), we backpropagate the gradient of the last layer weights with respect to $\mathcal{L}_c$,

$$\frac{\partial \mathcal{L}_c}{\partial \mathbf{x}} \propto 2\frac{\sigma_{xy}^2(\mathbf{x} - \mu_y)}{\psi^2} + \frac{\mu_y - \mathbf{y}}{\psi}, \quad (4)$$

where all vector operations are done element-wise.

P. Tzirakis, G. Trigeorgis, M. A. Nicolaou, B. W. Schuller and S. Zafeiriou, "End-to-End Multimodal Emotion Recognition Using Deep Neural Networks," in IEEE Journal of Selected Topics in Signal Processing, vol. 11, no. 8, pp. 1301-1309, Dec. 2017, doi: 10.1109/JSTSP.2017.2764438.

Summary

- Multiple features
- Deep learning architectures for speech processing
- Interplay between speech and machine learning approaches

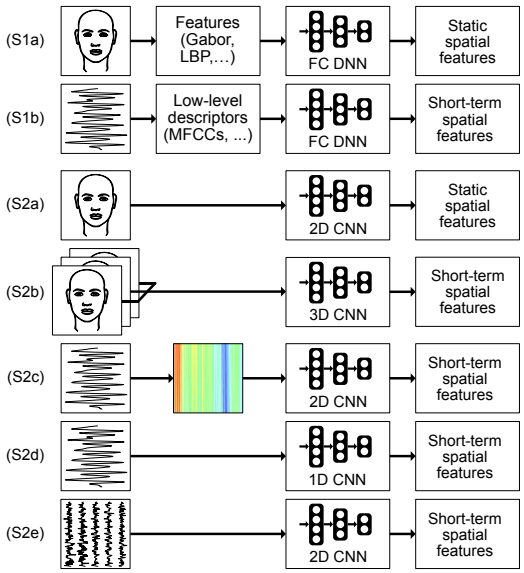


Fig. 2. Applications of deep learning for spatial feature learning with fully-connected DNNs (S1a–S1b) and CNNs (S2a–S2e).

Next steps

Practicals

Intention recognition from speech signals

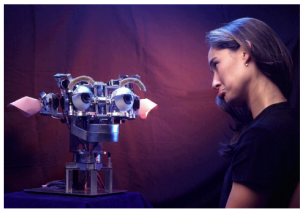


Fig. 2. Kismet is an expressive robotic creature designed for natural social interaction with people. See text.

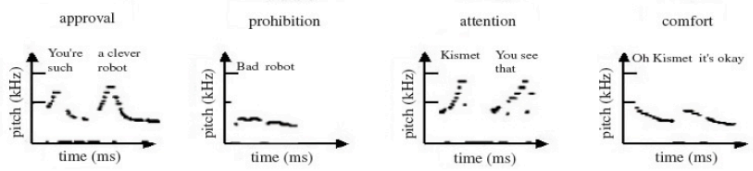


Fig. 2. Fernald's prototypical prosodic contours shown in robot directed speech for approval, attentional bid, prohibition, and soothing.

Next steps

Short project

Application of Natural Language Processing

Development of NLP pipeline

Thank you for your attention

Questions?