DETECTION OF LAUGHTER IN CHILDREN'S SPEECH USING SPECTRAL AND PROSODIC ACOUSTIC FEATURES

Hrishikesh Rao[1], Jonathan C. Kim[1], Agata Rozga[2], and Mark A. Clements[1]

[1] School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA, USA
[2] School of Interactive Computing, Georgia Institute of Technology, Atlanta, GA, USA

Expeditions in Computing

Motivation

- Laughter is an important para-linguisitc cue that can be useful in gauging the affective state of the speaker.
- Detection of laughter in children's speech is less explored and has important applications in clinical psychology.
- Laughter , along with other vocalizations, is an important marker for very early detection of autism spectrum disorder (ASD) [1].
- Diarization of para-lingusitic events would benefit psychologists who are interested in studying children's affective communication.

Datasets

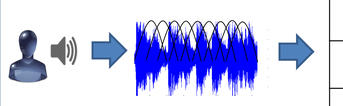
FAU-Aibo Emotion Corpus [2], [3]

- Interaction between adolescent and Sony's Aibo robot
- Data collected from 51 children (aged 10-13 years, 21 male, 30 female)
- Laughter annotated along with speech.
- Different types of laughter annotated (voiced, unvoiced, voiced-unvoiced, and speech modulated with laughter)
- Number of sample points – 13478 for speech and 236 for laughter.

Rapid ABC Dataset [4]

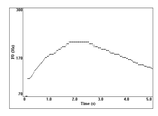
- Semi-structured dyadic interaction between toddler and examiner
- Activities include greeting the child, initiating a game of rolling the ball back and forth, bringing a book and inviting the child to through it, pretending the book to be a hat, and engaging the child in a tickling game.
- 20 Rapid ABC sessions (aged 15-29 months) used with laughter and other vocalizations annotated.
- Number of sample points – 17 each for speech and laughter.

Methodology and Results

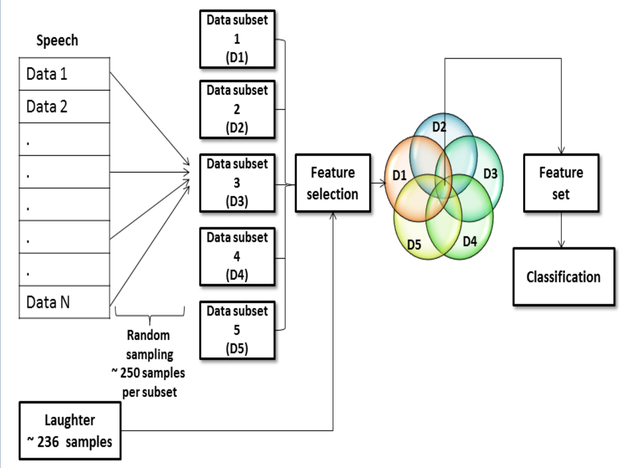


Hamming window of 30 ms with 10 ms overlap

Feature	Number of low-level descriptors
Intensity	2
Loudness	2
Mel-frequency Cepstral Coefficients	24
Pitch	2
Probability of voicing	2
Pitch envelope	2
Line spectral frequencies	16
Zero-crossing rate	2
Formant frequency and bandwidth	6
Ratio of formant frequencies	3
Ratio of bandwidths of formants	3
Euclidean distance between formant frequencies	3
Euclidean distance between formant bandwidths	3
Euclidean distance between ratio of formant frequencies	3



Statistical Measure
Max./Min. value and respective relative position within input, range, arithmetic mean, 2 linear regression coefficients and linear and quadratic error, standard deviation, skewness, kurtosis, quartile 1-3, and 3 inter-quartile ranges



- Five subsets of data consisting of randomly selected 250 speech samples
- Frame-level acoustic features extracted and statistical measures evaluated at the phrase level
- Features are ranked as per the information gain criterion
- $IG(w_i, Xj) = -\sum_{i=1}^{M} \Pr(w_i)\, log_2 \Pr(wi) + \sum_{j=1}^{N}\sum_{i=1}^{M} \Pr(X_j)\, \Pr(w_i|X_j)\, log_2 \Pr(wi|Xj)$
- Intersection of top 100 features for each subset results in final feature set

Feature	Number of features selected
Probability of voicing	12
Pitch	5
Mel-frequency Cepstral Coefficient	5
Line Spectral Frequency	3
First Formant Frequency	5

Task: 10-fold cross-validation using five subsets of data with a various classifiers

Classifier	Accuracy (mean ± standard deviation)
Multi-layer Perceptron	95.04±2.67%
Radial Basis Function Neural Networks	95.44±2.70%
SVM (Linear kernel)	95.30±2.68%
SVM (Polynomial kernel, degree = 2)	95.82±2.27%
SVM (RBF kernel)	95.96±2.28%
GMM - EM	95.16±3.25%

Task: Clustering with GMM-EM and k-Means using five subsets of data

Clustering algorithm	Error rate (mean ± standard deviation)
k-Means	7.19±3.67%
GMM-EM	5.71±3.16%

Clustering results indicate robust predictive power of selected features

Task: Classification using a support vector machine (SVM) with a polynomial kernel (degree = 1.65) on FAU-AEC dataset

	Predicted Speech	Predicted Laughter
True Speech	12726	752
True Laughter	13	223

Weighted accuracy : **94.43%**
Unweighted accuracy : **94.46%**

FAU-AEC's Results
Weighted accuracy : **81.95%**
Unweighted accuracy : **82.95%**

Absolute improvement of **12.48%** over FAU-AEC

Task: Classification using a support vector machine (SVM) with a linear kernel trained using FAU-AEC dataset and tested on Rapid ABC dataset

	Predicted Speech	Predicted Laughter
True Speech	12	5
True Laughter	5	12

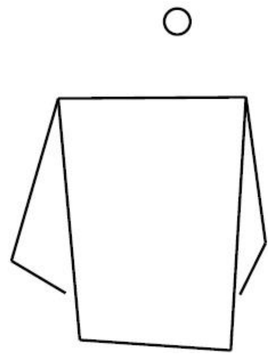
Weighted accuracy : **70.58%**
Unweighted accuracy : **70.58%**

Multi-Modal Analysis Ideas

Laughter and Smile Detector

- Laughter correlated with smiling.
- FaceTracker used for extracting visual features.
- Late fusion of scores from visual and audio classifier could be used for predicting emotion viz. joy.

Posture and Para-Lingusitic Event Detector



- Tickling involves movement of upper body and laughter.
- Use of upper body predicates along with laughter detection results.
- Fusion of visual and audio features for predicting level of engagement.
- Could be used to parse the tickling state of Rapid ABC.

Conclusions

- Robust detection of laughter is possible in children's speech using acoustic features
- Statistically relevant generalization on other datasets consisting of different recording conditions, ages of subjects, and languages.
- Multimodal analysis using vision and electro-dermal activity improves the understanding of the affective nature of laughter.

Acknowledgment

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