

# AUTOMATIC CLASSIFICATION OF VOLUMES OF WATER USING SWALLOW SOUNDS FROM CERVICAL AUSCULTATION

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Poster Session: WE3.PG.12: Biomedical Signal Processing

Wednesday, 6 May, 2020, 16:30-18:30



# Flow of presentation



- Introduction
- Data
- Proposed Study
- Results
- Conclusion



# Plan

- 1** Introduction
- 2 Data
- 3 Proposed Study
- 4 Results
- 5 Conclusion



# Swallow physiology and Dysphagia

- Swallow - Movement of food bolus from mouth through pharynx to the esophagus
- Process in sync with respiration
- Swallowing disorders (Dysphagia) can occur due to
  - Neurological disorders - Parkinson's disease, stroke
  - Irregularities in esophageal and pharyngeal muscles
  - Amyotrophic lateral sclerosis
  - Head and Neck cancer, etc.
- Common clinical assessments - Videofluoroscopy, Fiber-optic endoscopy - **invasive and expensive methods**
- Cervical Auscultation<sup>[1]</sup> (CA) characterizes swallow in terms of signal - **non-invasive**

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[1]Geovana de Paula Bolzan, Mara Keli Christmann, Luana Cristina Berwig, Cintia Conceição Costa, and Renata Man-cope Rocha, "Contribution of the cervical auscultation in clinical assessment of the oropharyngeal dysphagia," *Revista CEFAC*, vol. 15, no. 2, pp. 455-465, 2013.

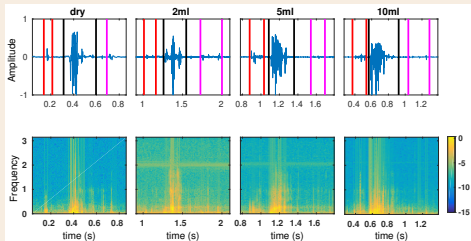


# Applications of Swallow Sound analysis

- Wearable MIB (Monitoring of Ingestive Behaviour) devices for food intake characterization
- Identification of dysphagia through Spontaneous Swallowing frequency analysis
- Volume specific models can help in studying the severity of dysphagia

# Swallow signal characterization

- Swallow signals are characterized by their Swallow Components<sup>[2]</sup>



Red, black and magenta lines represent SC1, SC2 and SC3 regions, respectively

- Why volume-specific features?:** Signatures of **SCs** are found to vary with bolus volume
- Objective:** Learn features for bolus volume characterization through classification of swallows of water against dry swallows

[2] Divya Giridhar, Achuth Rao, Prasanna Hegde, and Prasanta Ghosh, "Analysis of swallow sounds of healthy controls for different volumes of water," in Int. Conf. on Engg. in Med. and Life Sci., PSG College of Technology, Coimbatore, India, 2019.

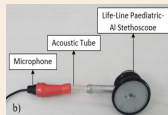
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- 1 Introduction
- 2 Data**
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- 5 Conclusion

# Swallow Sound Recording

- 56 subjects: 34 male, 23 female (20 - 30 years of age)
- Subjects made to swallow water of volumes 2ml, 5ml and 10ml, and also perform dry swallow - each 6 times per subject
- CA setup
  - Life-Line Paediatric-AI Stethoscope
  - Acoustic tube
  - Sorella'z portable 3.5mm microphone (frequency range of 30Hz - 15000Hz)
- Device placement site<sup>[3]</sup>: Posterior inferior to the cricoid cartilage encircling the trachea



[3]Q Pan, Naoto Maeda, Yousuke Manda, Naoki Kodama, and Shougo Minagi, "Validation of the optimal site in the neck region for detecting swallowing sounds," Journal of oral rehabilitation, vol. 43, no. 11, pp. 840-846, 2016.





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- 1 Introduction
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## Feature sets

- **Baseline Feature set (BLF)**: 12 features - duration of SSW1, SSW2, SC1, SC2, SC3, intervals between swallow components (I1, I2), duration to peak intensity (DPI), peak intensities (PI\_SSW1, PI\_SSW2, PI) and total duration (TD) of the swallow signal.
- **ComPARE 2016 Feature set (OSF)**: 6373 features - Voice source based (group A) and glottal excitation based (group B) features

Classes	Feature name / Abbreviation / Dimension	Total
Group A (59 features + 59 delta features)	Loudness (Ldns)(1), RASTA (26), MFCC(14), RMS energy (RMSe)(1), Modulated Loudness (MLdns)(1), ZCR(1), Band energy (BE)(2), Spectral: ROP (SR)(4), Flux (SF)(1), Centroid (SC)(1), Slope (SSI)(1), Entropy (SE)(1), Variance (SV)(3), Harmonicity (SH)(1), Sharpness (Shs)(1)	59 X 54 functionals + 59 delta X 46 functionals = 5900 features
Group B (6 features + 6 delta features)	F0(1), Prob. Voicing (PV)(1), Jitter (J)(2), Shimmer (Shr)(1), log(HNR)(1)	6 X 39 functionals + 6 delta X 39 functionals = 468 features

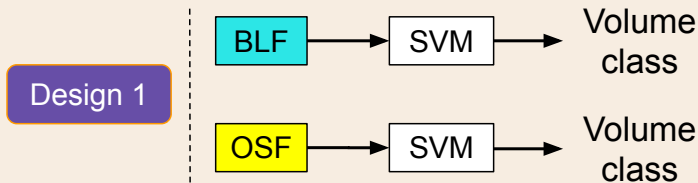


# Experimental setup

- Baseline features computed from swallow signals annotated by a clinical expert
- ComPARE 2016 features computed using OpenSMILE Audio Extraction and Analysis Tool - **require no manual annotation**
- 10-fold cross-validation step (no common subjects across folds)
- Three classification tasks: Dry-vs-2ml, Dry-vs-5ml, Dry-vs-10ml
- Classifier: Linear SVM
- Grid search for optimal C-parameter selection
- **Evaluation metric:** F-score
- **Significance test:** Wilcoxon signed rank test for zero median

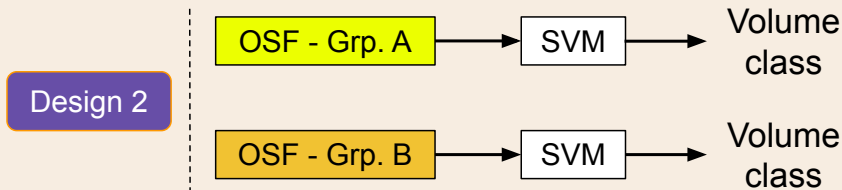
# Study Design 1 - BLF vs OSF

- Assessment of overall performance of BLF and OSF  
Features **requiring** manual annotation vs features **not requiring** manual annotations



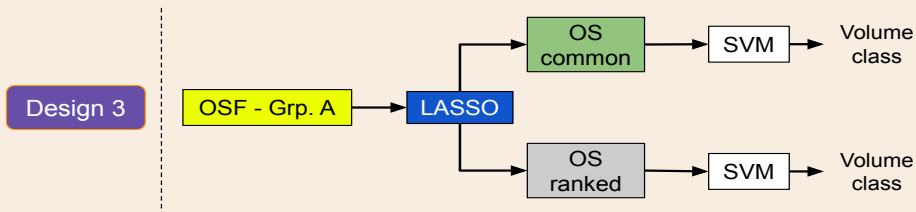
# Study Design 2

- Assessment of performance of subgroups of OSF  
vocal tract related features vs glottal excitation related features



## Study Design 3

- Feature ranking for each fold and each task can be different
- Joint features: Forward Feature Selection is computationally expensive!
  - LASSO<sup>[4]</sup> feature selection algorithm used to rank order OSF features
  - Features selected in two ways
    - OS-ranked: 12 features for each of the three classification tasks
    - OS-common: 12 features common across all three classification tasks



[4]Valeria Fonti and Eduard Belitser, "Feature selection usinglasso," *VU Amsterdam Research Paper in Business Analytics*, pp. 1–25, 2017

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## Results of Study 1: BLF vs OSF

Table: Mean **F-scores** (%) of the three classification tasks

Classification task	BLF	OSF	<i>p</i> -value
Dry vs 2ml	37.26 (15.05)	<b>70.14</b> (8.56)	0.03
Dry vs 5ml	57.77 (15.05)	<b>73.44</b> (3.03)	0.0098
Dry vs 10ml	69.10 (9.67)	<b>77.45</b> (6.65)	0.002

- OSF outperformed BLF by an average of around **18.9%**
- Reduced standard deviation in OSF indicates the robustness of OSF, across subjects and volumes





# Results of Study 2: OSF - Group A vs Group B

- Features unrelated to voice source outperformed features related to voice source by **21.02%**, BSF by **24.65%** and also OSF by **5.7%**
- Top performing features - MFCC, RASTA filtered audio spectrum and RMS energy

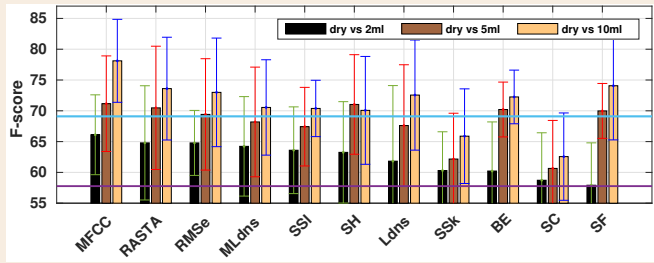


Figure: Mean F-scores(%) of different Group A features (ranked by F-scores of dry-vs-2ml classification); violet and blue horizontal lines are the baseline F-scores of dry-vs-5ml and dry-vs-10ml respectively



## Results of Study 3

Mean F-scores (%) of OS-common and OS-ranked features with standard deviations in (.)

Volume / Feature set	OS-common	OS-ranked	<i>p</i> -value
Dry vs 2ml	73.55 (6.78)	74.84 (4.85)	0.6523
Dry vs 5ml	75.88 (9.05)	77.67 (8.17)	0.4316
Dry vs 10ml	80.68 (4.88)	80.36 (7.61)	1.0

- Performance of OS-common & OS-ranked features similar to each other

Top 12 OS-common features with Pearson correlation coefficient (PCC) between feature value and the volume of water in [.].  $P_k$  indicates  $k$  percentile

Loudness	Derivative of Loudness
Inter-quartile range [0.14] ( $P_{75} - P_{50}$ )	$P_1$ [0.39], Standard deviation[0.41], Kurtosis [0.03], Mean segment length [0.25], Minimum segment length [0.18], Up-level time 25,50,75,90 [0.03] (%) Risetime [0.023], Left curvature time [0.06]

- LASSO selected features seem to indirectly indicate swallow components' boundaries



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# Key Takeaways

- Eliminated need for expert manual annotation
  - Improved F-score of OSF over BLF
  - LASSO selected functionals provided cues & indirectly indicated the boundaries of SCs
- 12 functionals of **Loudness** outperformed (significantly different from) the 12 baseline features
- Lower standard deviations - proposed features more robust to variations in signal characteristics with volume



## Future Works

- Exploring swallow sounds specific features unlike the generic OS features designed for speech analysis purposes
- Expanding the swallow sounds dataset with the inclusion of patient data of dysphagic swallows
- Classification of healthy and dysphagic swallows



## References

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- Sylvain Morinière, Patrice Beutter, and Michèle Boiron, "Sound component duration of healthy human pharyngoesophageal swallowing: a gender comparison study," *Dysphagia*, vol. 21, no. 3, pp. 175–182, 2006.
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**THANK YOU**



**Have questions/suggestions?**

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