Inferring Autonomic Nervous System Activation from Noisy Wearable Electrodermal Activity Data with the Goal of Investigating the Relationship Between Vocal Hyperfunction and Emotional Arousal

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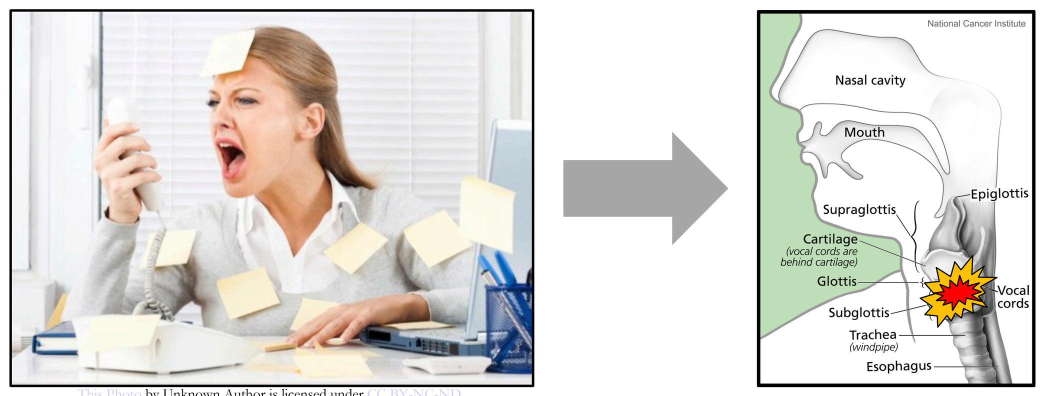
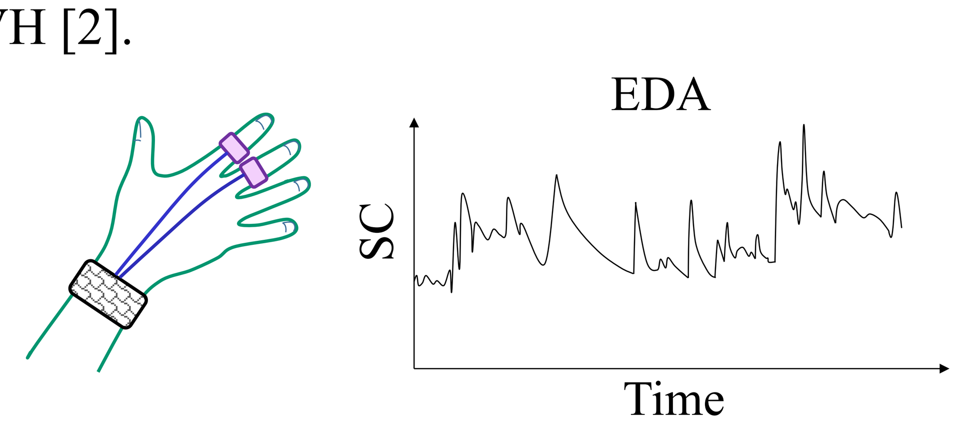
Introduction

- Vocal hyperfunction (VH) is a condition characterized by chronically excessive or unbalanced vocal muscle recruitment [1].

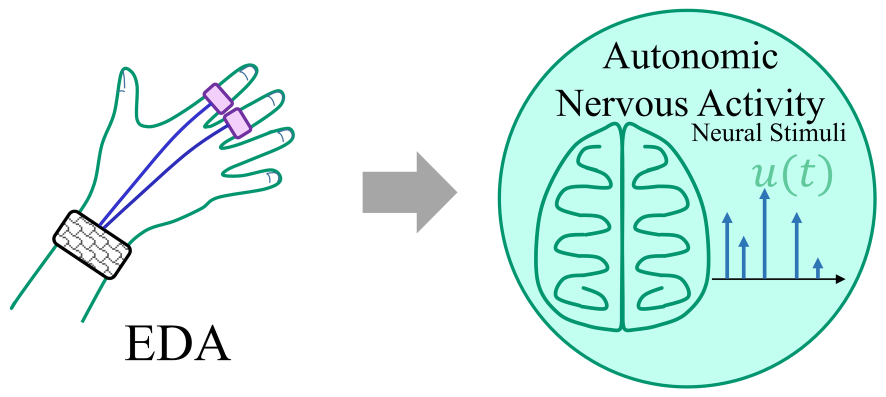


- Literature has demonstrated that patients with non-phonotraumatic vocal hyperfunction (NPVH) experience higher than normal levels of psychological stress while speaking, which could imply a correlation between high arousal and VH [2].
- Investigating the relationship between arousal level and voice recording may provide insights into the prevention, diagnosis and treatment of VH [2].

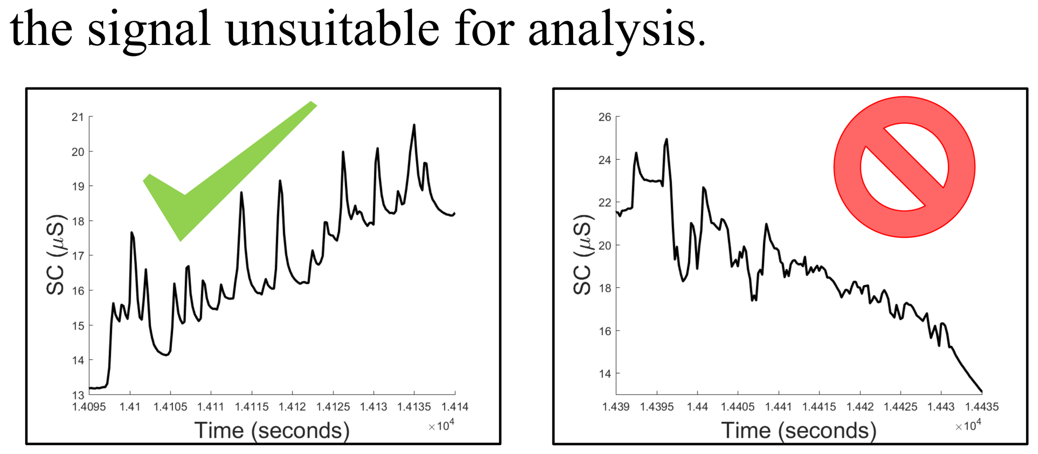


- Electrodermal activity (EDA) reflects the stimulation from the autonomic nervous system (ANS) to the eccrine sweat glands due to arousal.
- Skin conductance (SC), a measure of EDA, can be used to retrieve arousal level information.

Goals & Challenges:

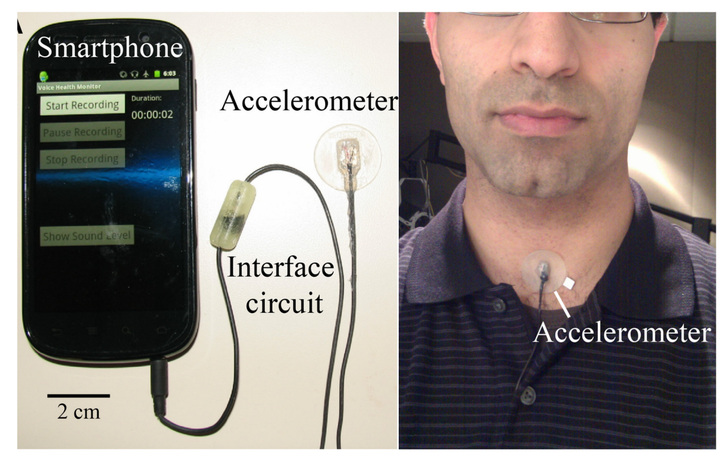


- Our goal is to infer ANS activity from EDA measurements.
- However, extracting ANS activity solely using EDA is challenging as the underlying physiological system is also unknown.
- Moreover, artifacts originating in real-world settings can corrupt the EDA, making portions of the signal unsuitable for analysis.

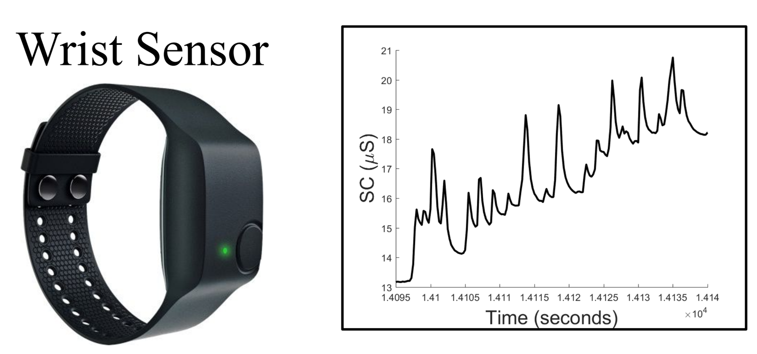


Dataset Description

- Voice recordings and physiological data are collected in a real-world environment, in order to investigate the relationship between high-arousal and VH [2].
- Accelerometer located at the base of the neck measures voice data [2].



- EDA data is collected using the wrist-worn Empatica E4.

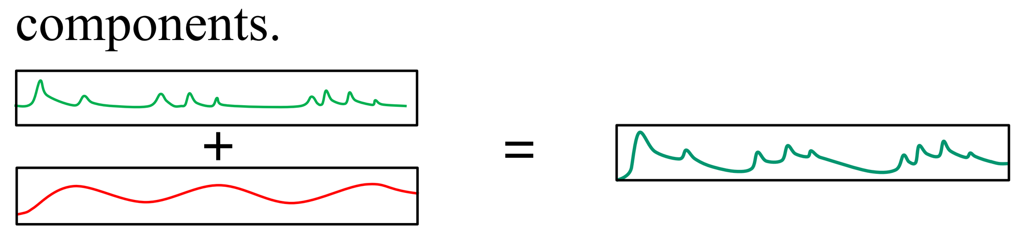


- The patients participating in this study had either healphonotraumatic vocal hyperfunction (PVH), non-phonotraumatic vocal hyperfunction (NPVH) or no VH at all.

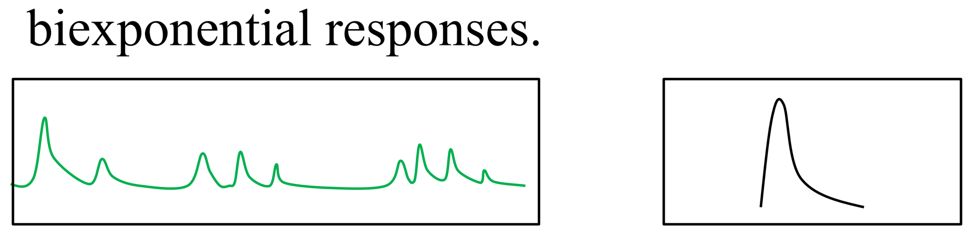
	PVH	NPVH	Normal
# of female patients	96	36	50
# of male patients	0	8	2

Nature of Clean EDA Data:

- Patient SC can be modelled as the sum of two components.

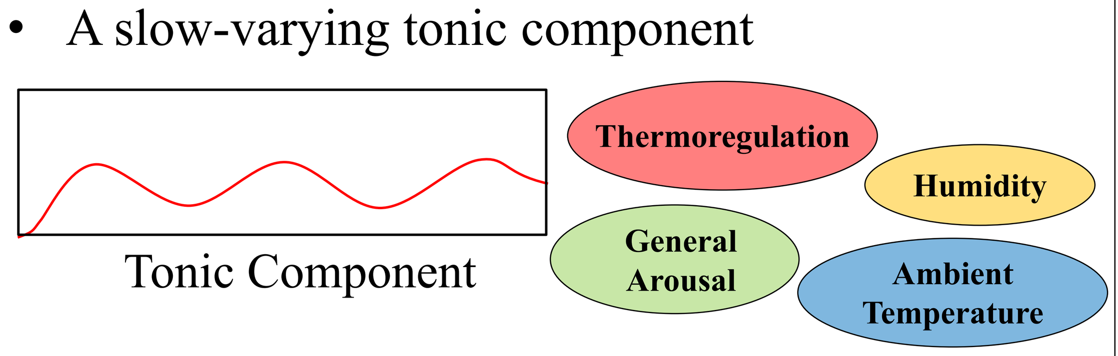


- A fast-varying phasic component, i.e. a series of biexponential responses.



Phasic Component   Biexponential Response

- A slow-varying tonic component



Tonic Component

- We analyze data which includes natural EDA behavior, avoiding signals corrupted by artifacts.
- We investigate two published automatic methods for identifying EDA segments suitable for analysis: EDAQA and EDA Explorer.
- We also visually inspect the data and compare with automatic methods.

Automatic Methods for Identifying Artifacts

EDAQA:

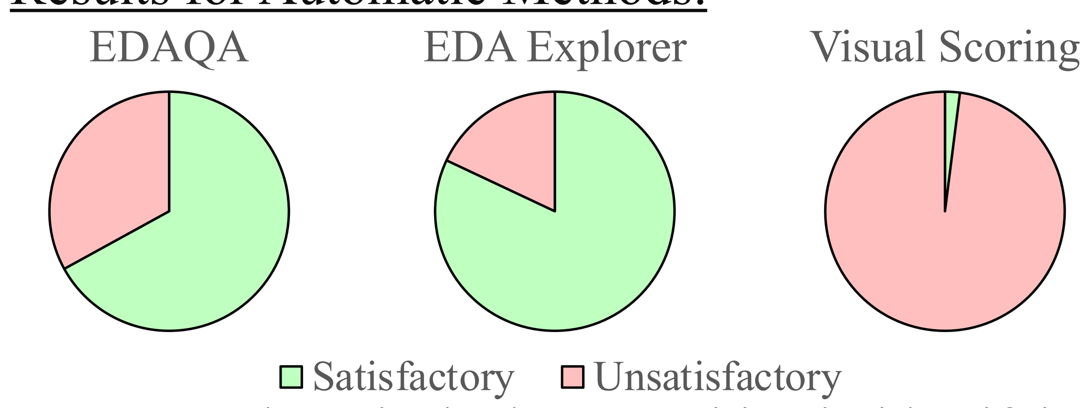
- The *Electrodermal Activity Automated Quality Assessment (EDAQA)* program is based on four criteria:
  1. a bounded range of possible SC values,
  2. a maximum slope of SC data,
  3. a bounded range of temperature values, and
  4. whether surrounding SC data violates any of the previous rules [3].

EDA Explorer:

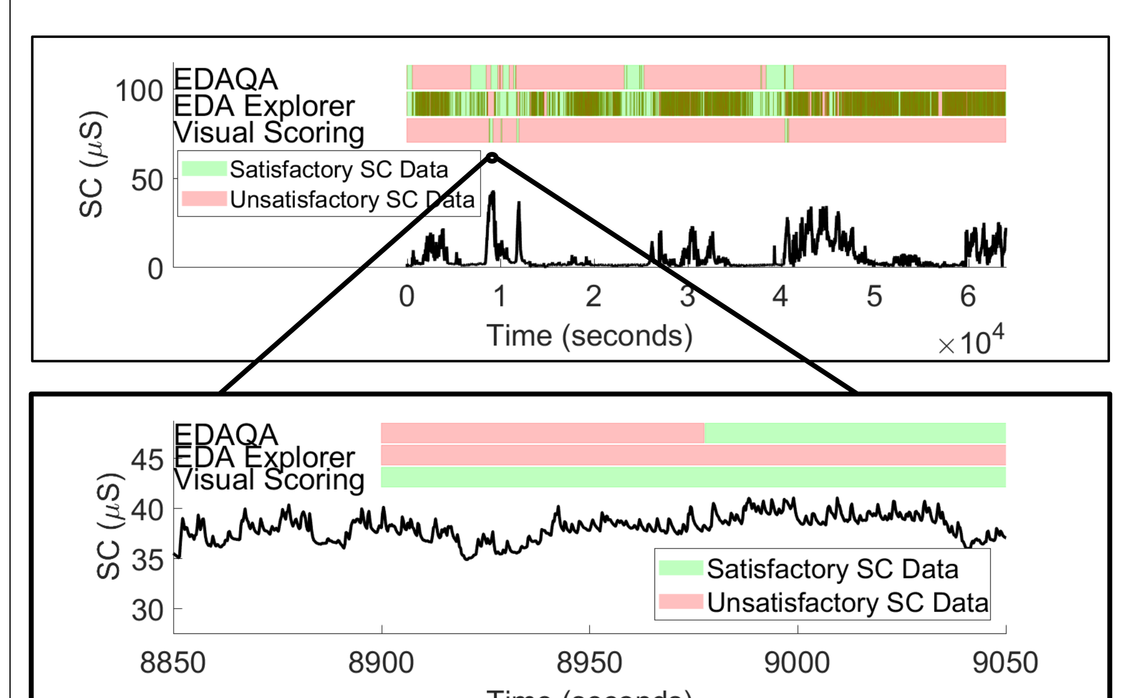
- *EDA Explorer* program is a machine learning algorithm for the automatic detection of EDA artifacts [4].
- Trained by two reviewers on a data set of 1560 non-overlapping 5-second epochs of EDA data [4].

- We perform these automatic methods on 5 EDA data series to compare the relative performance of each method.

Results for Automatic Methods:



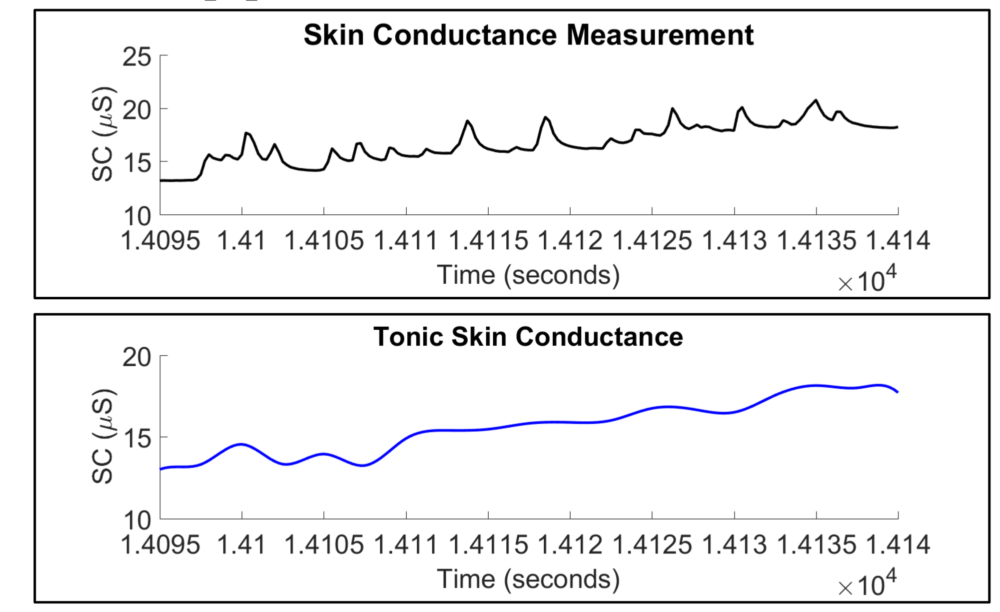
- EDA Explorer is the least sensitive in identifying corrupted EDA data on average.
- EDAQA excludes more data than EDAQA but still includes more corrupted data than Visual Scoring.
- Visual Scoring is the most conservative method for identifying EDA data suitable for analysis, selecting the least number of points of all three methods.



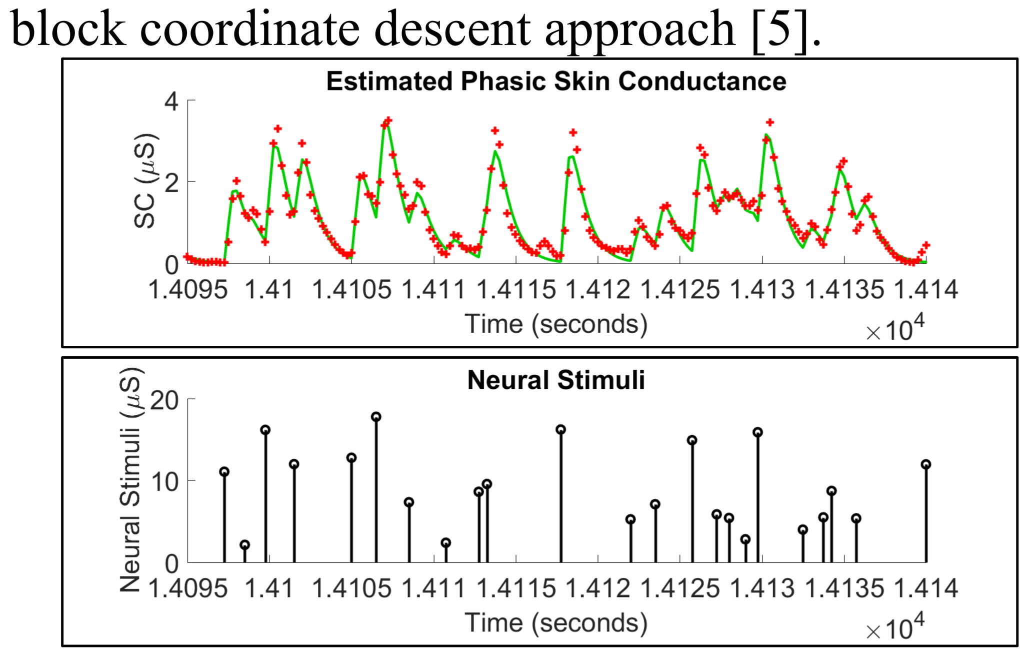
- A conservative method is preferable to a lenient method, in that a conservative method has a higher standard for good data.
- No automatic method to reliably identify EDA data suitable for analysis exists.
- Using the Visual Scoring data labels, we isolate the good segments of EDA data from the raw signal for analysis.

Inferring ANS Activation

- We first estimate the tonic component of the clean EDA data [5].



- We recover underlying neural stimuli and model parameters from the phasic component of the SC signal, using a generalized-cross-validation-based block coordinate descent approach [5].



Conclusion and Future Work

f the current methods available for identifying good regions of SC data for deconvolution, manually selecting regions is the most reliable and the most conservative.

- There is disagreement between methods in identifying artifacts in EDA data.
- We plan to improve the automation of motion artifact correction for EDA data.
- We plan to investigate the relationship between voice data and the underlying neural stimuli and model parameters recovered from the deconvolution of EDA data.

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