Measuring Human-Plant-Interaction

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Measuring Emotions through Human-plant interaction
Motivation and Research

Motivation and Research

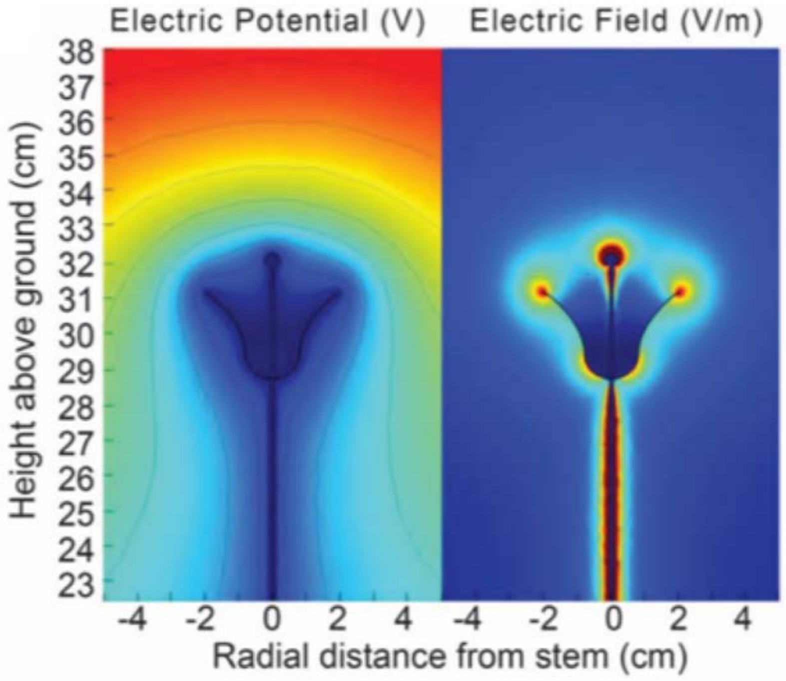
Data Acquisition

Pre-Processing

Model Building and Training

- Plants developed pathways for electrical signal transmission to respond rapidly when external stimuli are applied[1].
- The equivalent of these electrical signals in human beings are the ECG or EEG used by medical professionals
- Electric fields arising as a result of potential differences between flowers and insects[2]

[2]



[1]Volkov, Alexander. (2006). Plant electrophysiology: Theory and methods. 10.1007/978-3-540-37843-3.
[2] Clarke, Dominic & Whitney, Heather & Sutton, Gregory & Robert, Daniel. (2013). Detection and Learning of Floral Electric Fields by Bumblebees. Science (New York, N.Y.). 340. 10.1126/science.1230883.

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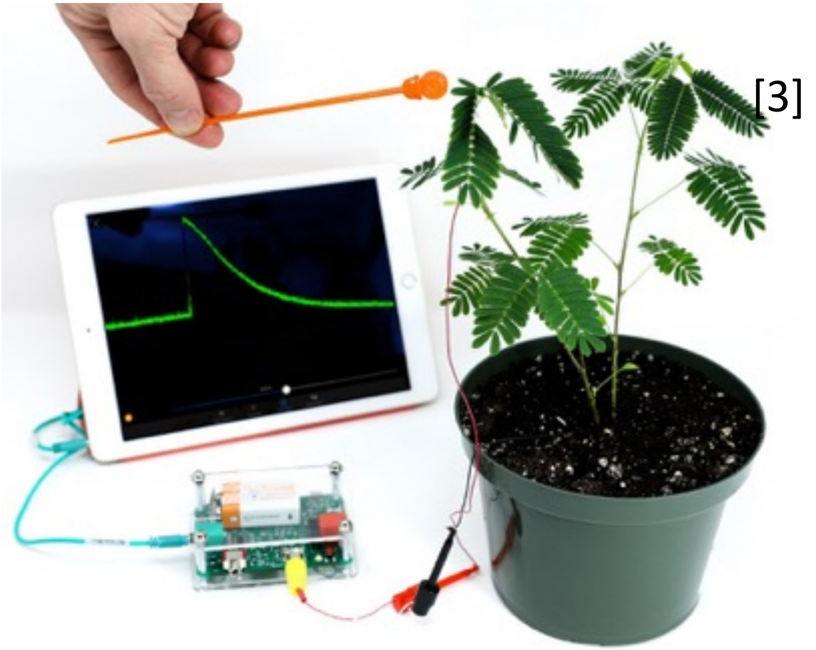
Motivation and Research

Motivation and Research → Data Acquisition → Pre-Processing → Model Building and Training

- Visually-expressing examples of plant electricity :
  - Mimosa Pudica
  - Venus Flytrap
- Mimosa folds its leaves when touched
- Venus Flytrap closes as soon as prey moves inside


[3]

→ Can we measure Human-plant-interaction through electrical signals or other means of communication ?

[3] Marzullo, Timothy & Gage, Gregory. (2012). The SpikerBox: A Low Cost, Open-Source BioAmplifier for Increasing Public Participation in Neuroscience Inquiry. PloS one. 7. e30837. 10.1371/journal.pone.0030837.

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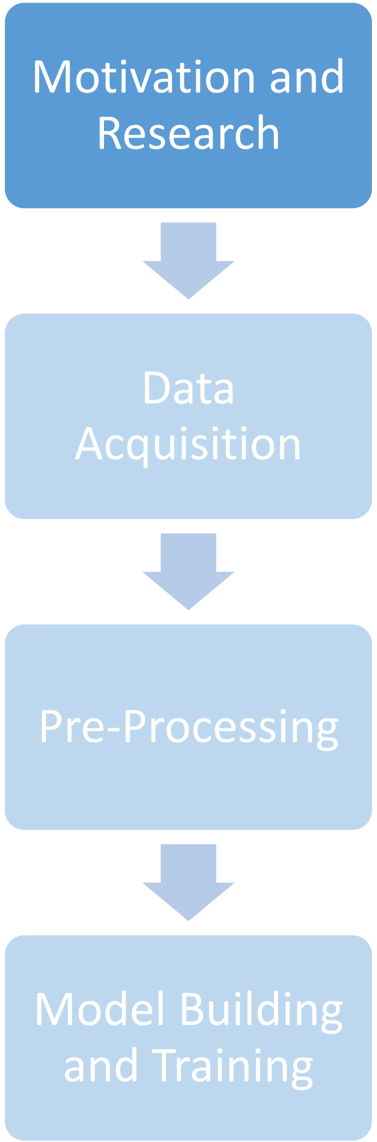
Motivation and Research - Current Research and Applications



- Plants employed as biosensors represent a natural and powerful extension of the Internet of Things
- Plants naturally pervade our environment, are significantly less expensive in terms of production, operating and maintenance costs than any artificial device[4]
- No Privacy or GDPR* concerns
- Current Research focus on applications in :[4]
  - environmental monitoring (e.g. pollution, fires),
  - agriculture (e.g. irrigation, plants health, use of chemicals),
  - area monitoring (e.g. avalanches, floodings)

[4] Manzella, Veronica & Gaz, Claudio & Vitaletti, Andrea & Masi, Elisa & Santopolo, Luisa & Mancuso, Stefano & Salazar, D. & Heras, J.. (2013). Plants as sensing devices: the PLEASED experience. SenSys 2013 - Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems. 10.1145/2517351.2517403.

*General Data Protection Regulation

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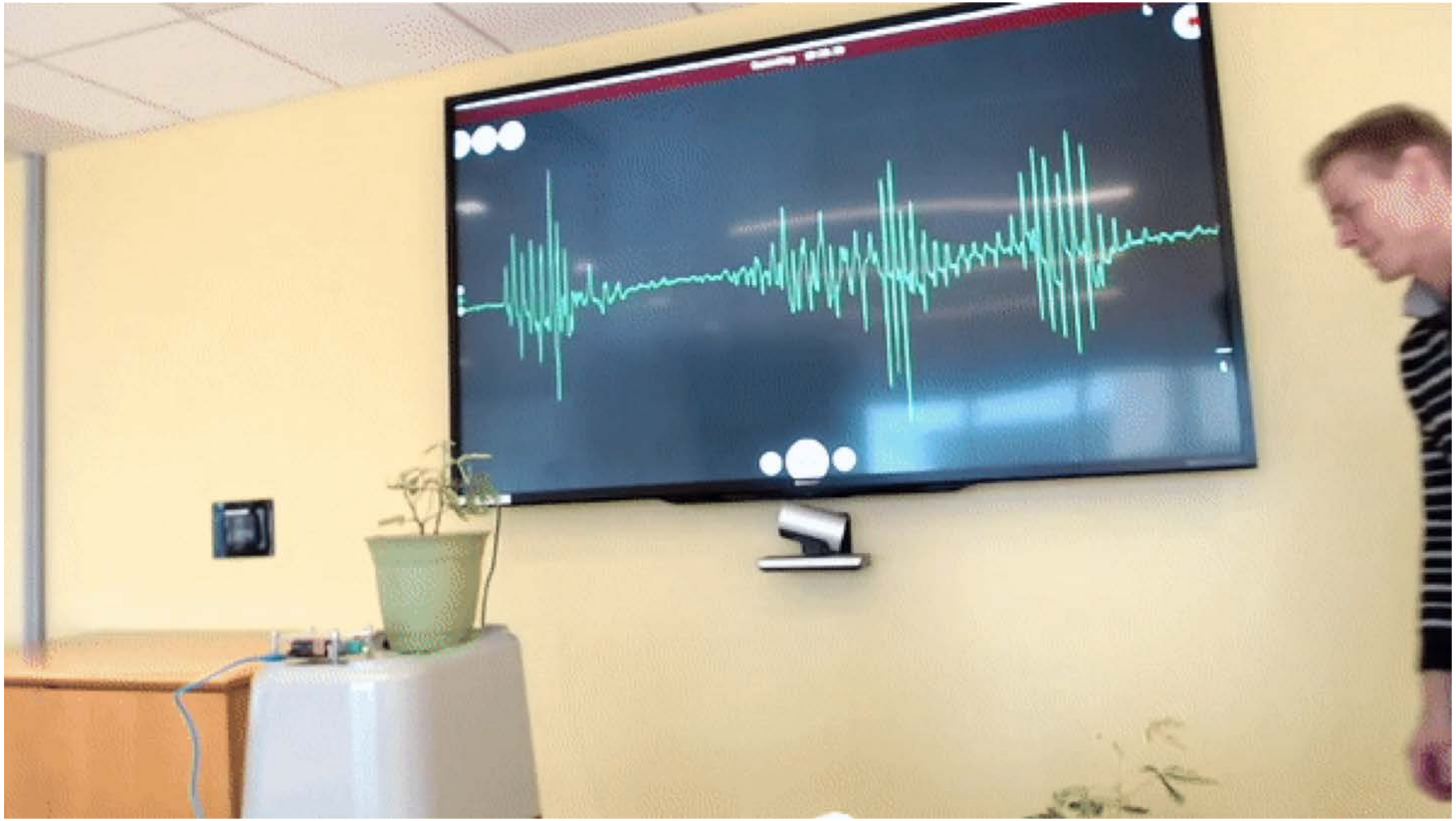
Data Acquisition – Walking by Plants

- Motivation and Research
- **Data Acquisition**
- Pre-Processing
- Model Building and Training



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Data Acquisition – Walking by Plants

Motivation and Research

Data Acquisition

Pre-Processing

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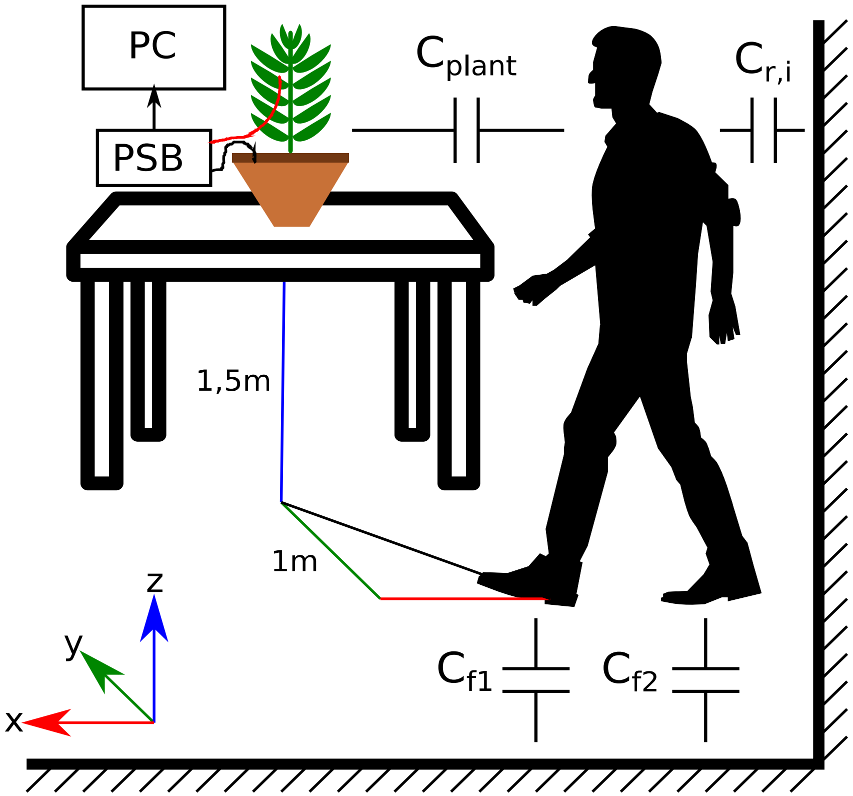
- Walking Sad[6]:
  - Reduced walking speed
  - Smaller amplitude in vertical movements of the upper body
- Static electricity is generated as a result of friction between the human body, clothing and ground.
- Human (foot-) movement perturbates the electric field surrounding the human and plant[5]



[5] Li, M., Tian, S., Linlin, S., Chen, X.: Gait Analysis for Post-Stroke Hemiparetic Patient by Multi-Features Fusion Method. Sensors 2019, 19, 1737 (2019)
[6] Michalak, J., Troje,N.F., Vollmar, P., Heidenreich, T., Schulte, D.: Embodiment of Sadness and Depression—Gait Patterns Associated With Dysphoric Mood, Psychosomatic Medicine 71:580–587 (2009).

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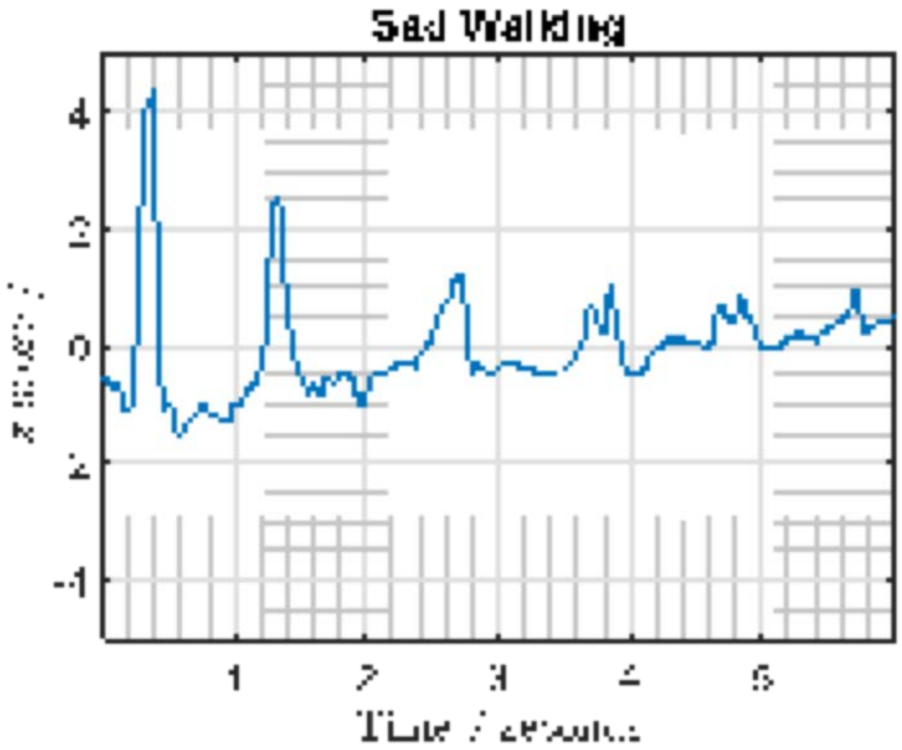
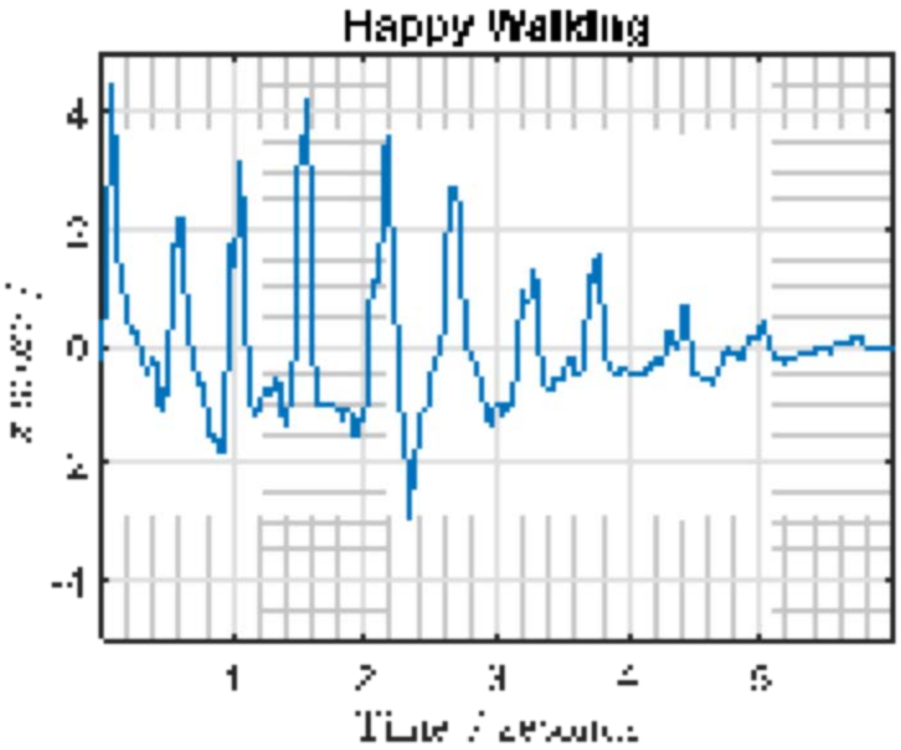
Data Acquisition – Walking by Plants (Emotion Prediction)

- Motivation and Research
- Data Acquisition
- **Pre-Processing**
- Model Building and Training

How is someone walking by the Plant?





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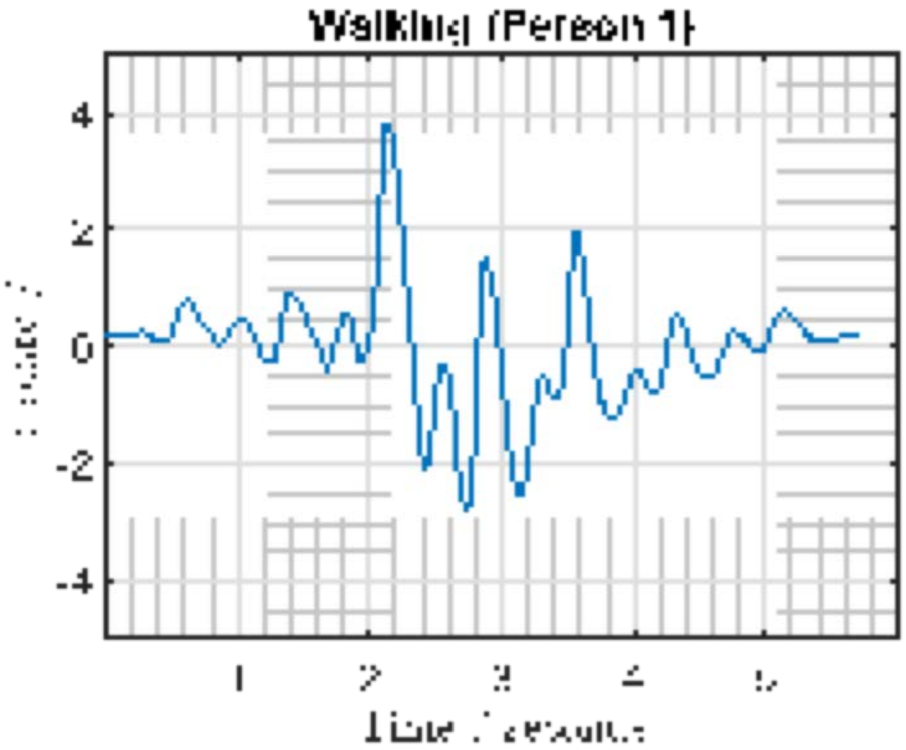
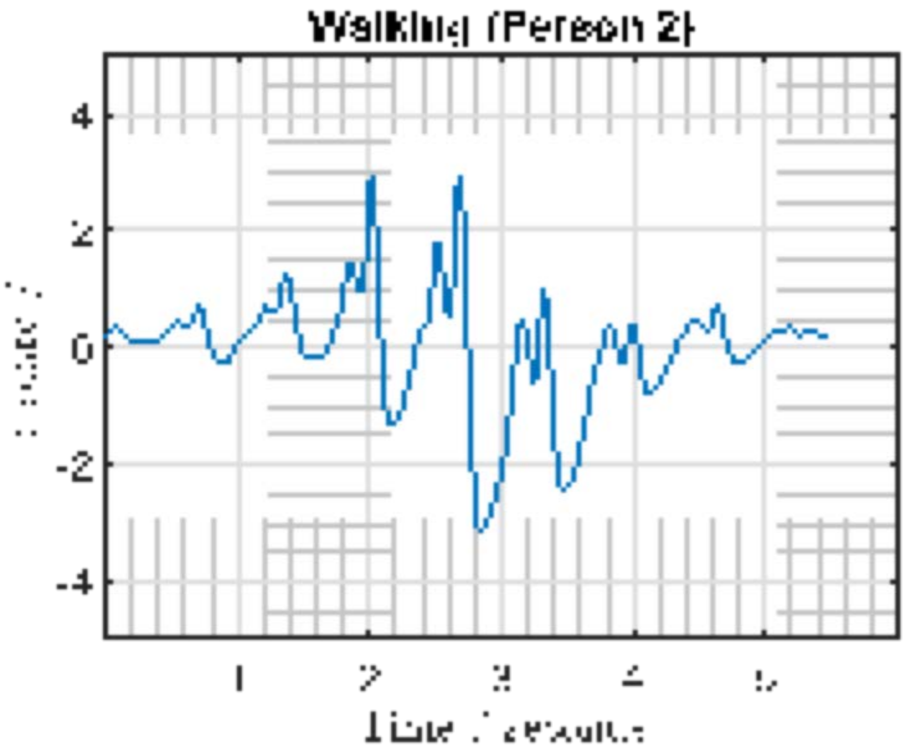
Data Acquisition – Walking by Plants (Individual Prediction)

- Motivation and Research
- Data Acquisition
- **Pre-Processing**
- Model Building and Training

Who is walking by the Plant?





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Model Building – Feature Extraction

Motivation and Research

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Data Acquisition

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Pre-Processing

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Model Building and Training

- Spectrograms can be used for ECG/EEG[7]- and Audio Classification in Machine Learning Applications[8]
- Extracting statistical features like MFCC of electrical signals in plants can yield a good accuracy on predicting dangerous chemicals using Decision Trees[9]

→ Develop Classification Models for Human-Plant-Interaction

[7] Colomer, Adrián & Fuentes, Félix & Naranjo, Valery & Guixeres, Jaime & Ausín, J. & Alcañiz Raya, Mariano. (2016). A Comparison of Physiological Signal Analysis Techniques and Classifiers for Automatic Emotional Evaluation of Audiovisual Contents. Frontiers in Computational Neuroscience. 10. 10.3389/fncom.2016.00074.
[8] Hershey, Shawn & Chaudhuri, Sourish & Ellis, Daniel & Gemmeke, Jort & Jansen, Aren & Moore, R. & Plakal, Manoj & Platt, Devin & Saurous, Rif & Seybold, Bryan & Slaney, Malcolm & Weiss, Ron & Wilson, Kevin. (2017). CNN architectures for large-scale audio classification. 131-135. 10.1109/ICASSP.2017.7952132
[9] Chatterjee, Shre & Das, Saptarshi & Maharatna, Koushik & Masi, Elisa & Santopolo, Luisa & Colzi, Ilaria & Mancuso, Stefano & Vitaletti, Andrea. (2017). Comparison of Decision Tree Based Classification Strategies to Detect External Chemical Stimuli from Raw and Filtered Plant Electrical Response. Sensors and Actuators B: Chemical. 249. 10.1016/j.snb.2017.04.071. .

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Model Building – Predicting Humans

Motivation and Research

Data Acquisition

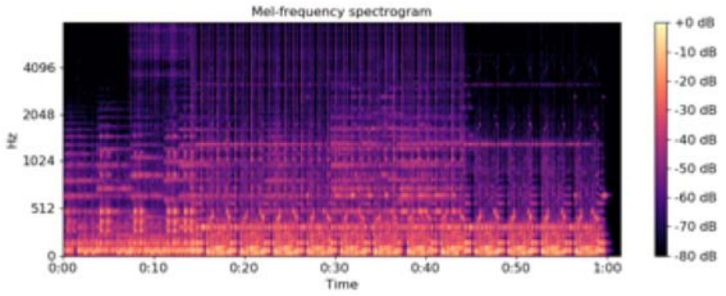
Pre-Processing

Model Building and Training

Mimosa Pudica

Cropping and Z-Transformation

Mel-Frequency-Spectogram



MFCC Feature Vector

Random-Forest Classifier

	Individual Prediction	Emotion Prediction
N	212	139
# Classes	6	2
Classifier	Random-Forest	Random-Forest
# Estimator	100	100
Cross-Validation	10-Fold-CV	10-Fold-CV
Accuracy	**67%**	**88%**

- Low-frequency MFCC are most the most predictive features
- Plant-type and location of experiment are not relevant

THANK YOU

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References

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1	Volkov, Alexander. (2006). Plant electrophysiology: Theory and methods. 10.1007/978-3-540-37843-3.
2	Clarke, Dominic & Whitney, Heather & Sutton, Gregory & Robert, Daniel. (2013). Detection and Learning of Floral Electric Fields by Bumblebees. Science (New York, N.Y.). 340. 10.1126/science.1230883.
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References

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