Unsupervised Motion Artifact Detection in Wrist-Measured Electrodermal Activity Data

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ISWC 2017

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Wearables and Physiological Data

- Wearables allow collection of physiological data in minimally invasive manner
  - Heart rate via photoplethysmogram (PPG)
  - Electrodermal activity (EDA) via galvanic skin response (GSR)
- Data collected from wearables often contain many motion artifacts (MAs)
- Our focus: detection of MAs in wrist-measured EDA data

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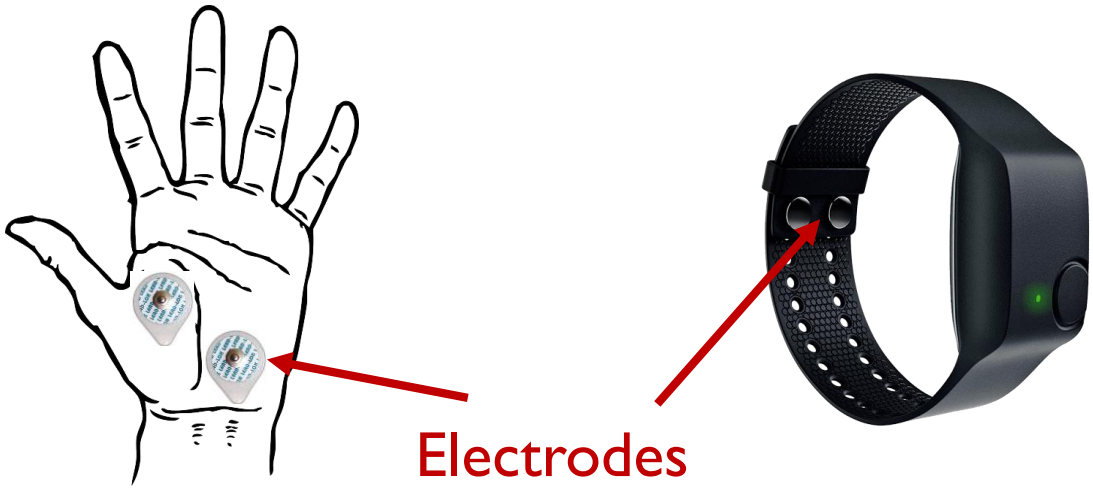
Electrodermal Activity (EDA)

- Reflects the emotional and sympathetic responses of a person
  - Applications include estimation of stress levels, seizure detection, analysis of mental health disorders, etc.
- Measured via galvanic skin response (GSR)
  - Change in electrical conductance between a pair of electrodes touching the skin
  - Usually referred to as skin conductance (SC)



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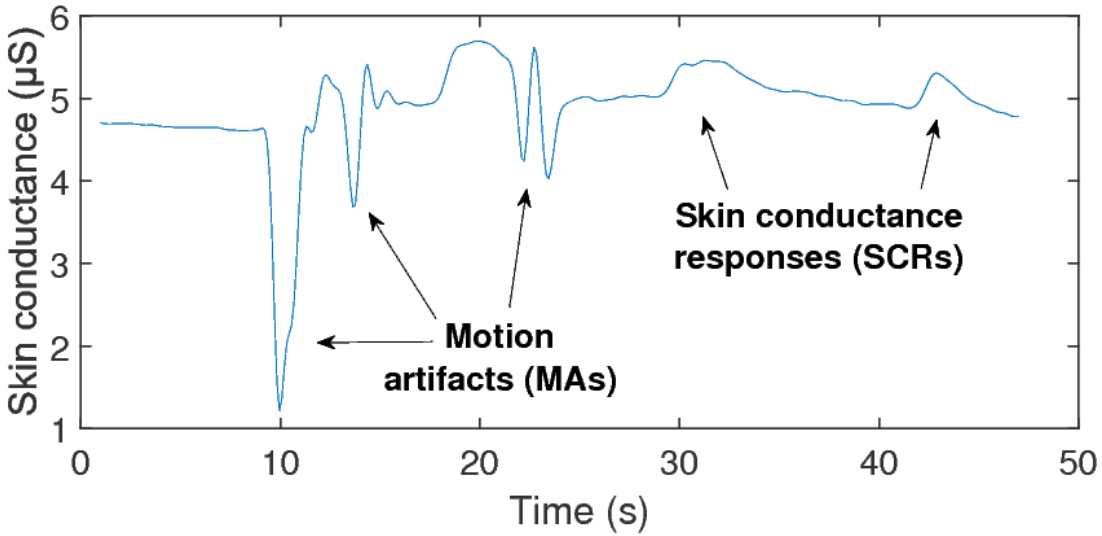
Motion Artifacts (MAs) in EDA

- Caused by change in amount of contact between the skin and the electrodes
  - Possible causes: motion, rotation, bumping the wearable, etc.
- MAs might be misidentified as skin conductance responses (SCRs)
  - SCRs and MAs can both generate a peak in SC
- Identification of the SC portions that contain MAs becomes extremely important as a pre-processing step



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Prior Work on MAs in EDA

- MA suppression: pass entire SC signal through a smoothing filter (Sano and Picard, 2013; Hernandez et al., 2014; Chen et al., 2015)
  - Distorts SC signal including SCRs
- Redundancy: use two independent EDA sensors and compare the two (Hedman, 2010)
  - Impractical for general use
- MA detection: automatically detect portions of SC with MAs using machine learning (Taylor et al., 2015)
  - Trained supervised machine learning algorithms on a small EDA data set collected in a lab environment
  - Requires lots of human effort to label MAs!

Our Contributions

- Apply 8 different machine learning algorithms for MA detection: 5 supervised and 3 unsupervised
  - Supervised: classification
  - Unsupervised: anomaly detection
- Evaluate on 1 lab-based and 1 real-world EDA dataset totaling ~23 hours of data
- Examine the usefulness of the accelerometer data in identifying MAs

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Datasets Used

- UT Dallas Stress (UTD) Data (13 hours lab-collected)
  - 20 college students subject to 3 types of stress: physical, cognitive, and emotional
- Alan Walks Wales (AWW) Data (10 hours real-world)
  - Collected by Alan Dix while he walked around Wales for ~3 months
  - We extracted 5 hours of walking data and 5 hours of resting data
- We use both EDA and 3-axis accelerometer (ACC) data collected by Affectiva Q sensor

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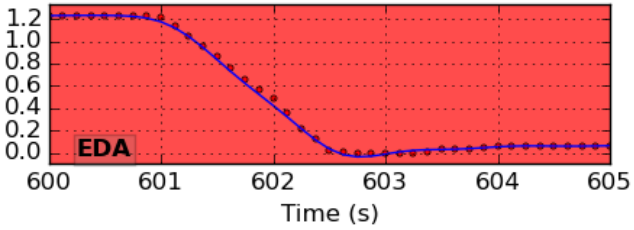
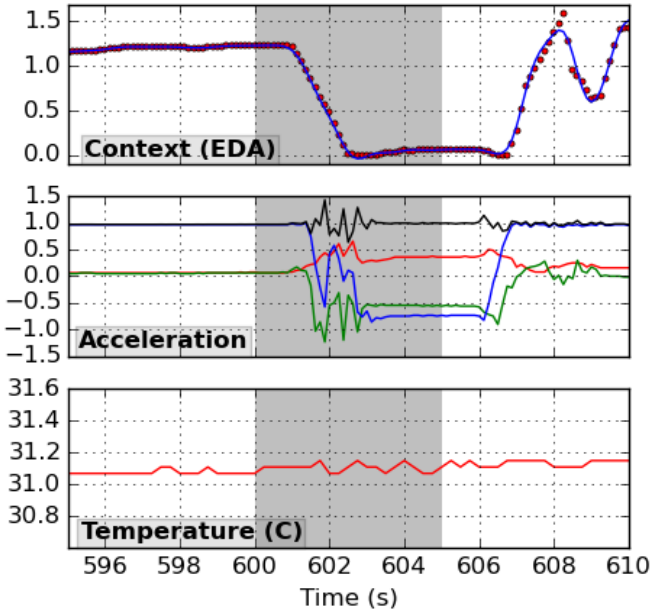
Methods Used

- Split EDA and ACC data into 5-second time windows and compute a variety of statistical features
- Feed feature set into machine learning algorithms
  - 5 supervised algorithms for binary classification:
    - Support vector machines
    - k-nearest neighbor classifiers
    - Random forests
    - Logistic regression
    - Multilayer Perceptron
  - 3 unsupervised algorithms for anomaly detection:
    - 1-class support vector machines
    - k-nearest neighbor distances
    - Isolation forests

Experiment Set-Up

- 3 experts use EDA Explorer software to label windows as MA or clean following a common set of criteria
  - Combine labels by majority vote
- Evaluate on 3 different feature sets separately:
  - ACC features only, EDA only, and ALL (ACC+EDA)
- Code and data available at https://github.com/IdeasLabUT/EDA-Artifact-Detection





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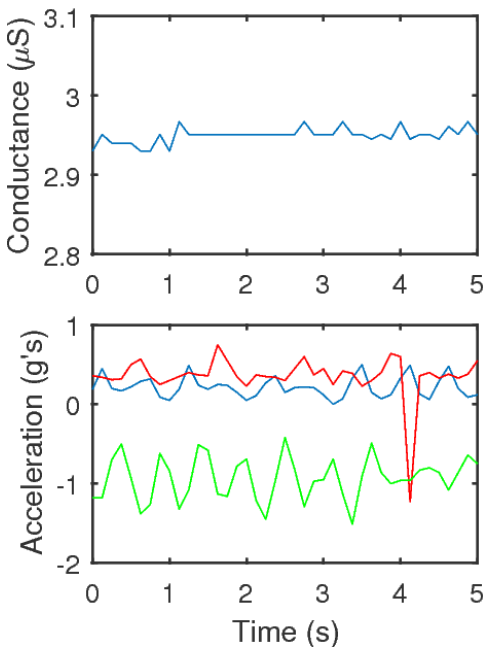
Overview of results

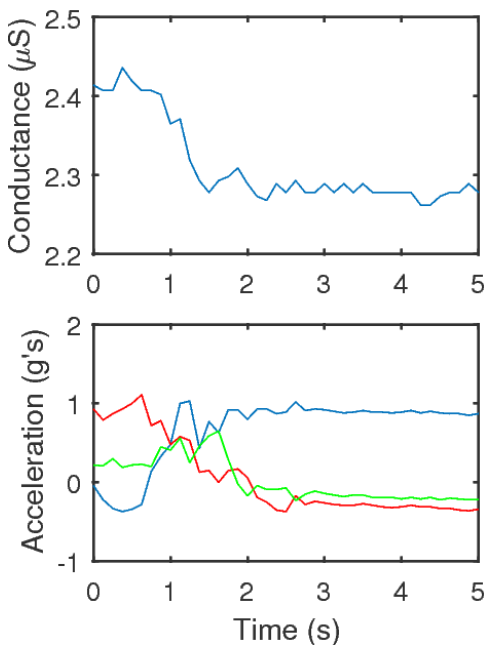
- Using ACC only features results in poor predictor: AUCs around 0.6-0.8
- Using EDA only or ALL (ACC+EDA) features results in much stronger predictor: AUCs around 0.8-0.95
- Unsupervised algorithms perform very competitively and sometimes better than supervised!
  - Both for in-sample and out-of-sample prediction
  - Best predictor on AWW data is unsupervised kNN distances (AUC of 0.90 on resting and 0.85 on walking)
- Using ALL features provides minimal benefit compared to EDA only
  - AUCs of supervised algorithms improve by 0.4%
  - AUCs of unsupervised algorithms decrease by 4.3%

Why ACC Appears Not to Help

- On many occasions, sudden changes in ACC do not affect EDA at all!
  - Motion that may not affect contact between electrodes and skin
- Maybe chosen features are not good for MA detection using ACC



Example where using ACC leads to incorrect prediction



Example where using ACC leads to correct prediction

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Summary

- Found unsupervised ML algorithms to be highly competitive with supervised algorithms for automatically detecting MAs in EDA
  - Highly accurate MA detection is possible without requiring significant human effort for labeling data!
  - Evaluation on ~23 hours of data in both lab- and real-world settings
- Accelerometer data does not appear to be very helpful in MA detection
  - Perhaps due to poor feature construction
- Next steps: incorporate output of ML algorithms into automatic SCR detection algorithms

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