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On the Impact of Lateralization in Physiological Signals from Wearable Sensors

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Lateralization Impact **Justification & Approach**



EDA

Lateralization of physiological signals^[20, 22]







Wrist device position







Left vs Right analysis



Impact on ML model



Train and test on different sides

"Worst case" scenario













USILaughs^[6] **Setup**



Limited User Movements







Empatica E4©

- ElectroDermal Activity (EDA)
- Blood Volume Pulse (BVP)
- Skin Temperature (ST)
- Accelerometer (ACC)



)

USILaughs^[6] **Data Collection**





Relax







Show Videos Record Laughs

Clapping Hands

Fake Laugh

Cognitive Load

Multiple Events



USILaughs⁶ Data Cleaning & Preparation [1]





• 4Hz

- 64Hz
- 1st Butterworth low-pass (0.4 Hz)
- Phasic Component^[3, 9]
- Norm mixed
 EDA

 1st Butterworth
 Not used by [6]
 Avg 3-axis low-pass (5 Hz)

MIN-MAX NORM USER-WISE



• 4Hz



• 32Hz





Quantification of Lateralization





In the literature Lateralization of physiological signals



• Can differ! [10, 20, 22, 29]



Phasic

What to expect



[11, 23]

• Should not **differ** [5,6,7]







Correlation Event Correlation Results

Consistency!

Correlation coefficient per event (BVP)

Event

baseline -	0.71	0.74	0.57
clapping hands -	0.72	0.74	0.57
cognitive load -	0.71	0.74	0.57
fake laughter -	0.72	0.74	0.56
funny videos -	0.71	0.75	0.57
laughter episodes -	0.57	0.55	0.45

Event

Pearson's ρ Spearman's ρ Kendall's τ

Variations

Correlation coefficient per event (EDA phasic)

baseline -	0.14	0.34	0.24		
clapping hands -	0.23	0.33	0.24		
cognitive load -	0.094	0.45	0.33		
fake laughter -	0.17	0.47	0.35		
funny videos -	0.44	0.37	0.26		
laughter episodes -	0.6	0.47	0.35		
Pearson's ρ Spearman's ρ Kendall's τ					













Effect size Analysis of raw signals



LEFT features



Clapping Hands



Effect size of features

RIGHT features



Per-event

Cliff's δ

Fake Laugh

Cognitive Load



Effect size Cliff's δ Results

Event

Cliff Delta values (BVP) baseline - 0.098 -0.044 0.043 -0.187 -0.022 -0.169 0.013 clapping hands 0.122 -0.045 0.089 -0.256 -0.023 -0.109 0.089 cognitive load - 0.106 0.065 0.089 -0.137 0.008 -0.254 0.089 fake laughter - 0.019 - 0.028 - 0.006 - 0.141 - 0.079 - 0.143 - 0.006 funny videos- 0.04 -0.045 0.016 -0.137 0.063 -0.137 -0.026 laughter episodes 0.151 0.063 0.127 -0.154 0.043 0.059 0.004 hr mean slope std 111 Feature





ML Task





Idea **Real-world applications**













640 values (50/50)



Laughter vs Relaxation



ML training







ML Models Classical Machine Learning



- KNN
- SVM
- Gaussian Process Gaussian Naïve Bayes

Leave-One-Subject-Out Cross Validation





- Random Forest
- XGBoost

Accuracy





Training and testing Paradigms implemented





Worst case scenario





Train/test different sides!

Results Laughter Recognition ML

Side/Sensor	EDA	PPG	
Train Left, Test Left	59.0 ± 0.6	57.1 ± 0.6	
Train Right, Test Right	54.4 ± 0.7	54.7 ± 0.7	
Train Random, Test Random	49.2 ± 0.7	56.5 ± 0.6	
Train Left, Test Right	54.8 ± 0.6	53.0 ± 0.5	
Train Right, Test Left	58.7 ± 0.6	54.7 ± 0.5	
Random Baseline	50.9 ± 2.2		



Conclusions





 We confirmed EDA lateralization We found small differences in BVP Worst case scenario ML trained models might decrease performance

Reduction in performance for EDA-

Training and testing on different sides



Thank you!





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