Synthesizing Physiological and Motion Data for Stress and Meditation Detection

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Overview

1. Motivation
2. Contribution
3. Model: Physiological and Motion Data Synthesis
4. Data
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6. Conclusion and Discussion

Motivation

Improving mental health via synthesizing signal for predicting affective states

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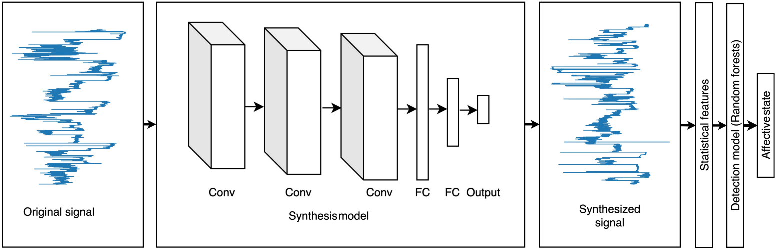
Improving mental health via synthesizing signal for predicting affective states

1. Can we synthesize (predict) physiological and motion signal (data) ahead of time?
2. If so, can we use the data to predict affective states?

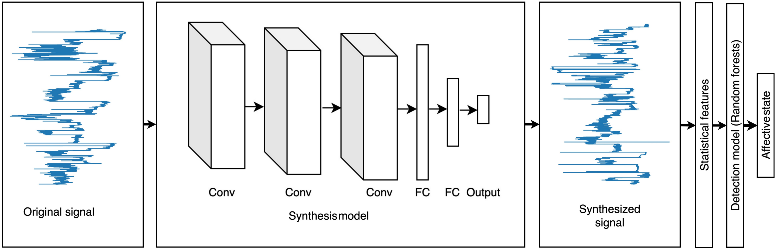
Contributions

- Synthesized (predicted) physiological signal ahead of time
- Predicted affective states from the synthetic data
- Published first baseline results on meditation (/ relaxed state) detection from WESAD dataset.

Physiological and Motion Data Synthesis



Physiological and Motion Data Synthesis



- Predict (synthesize) futuristic data from current and previous observations

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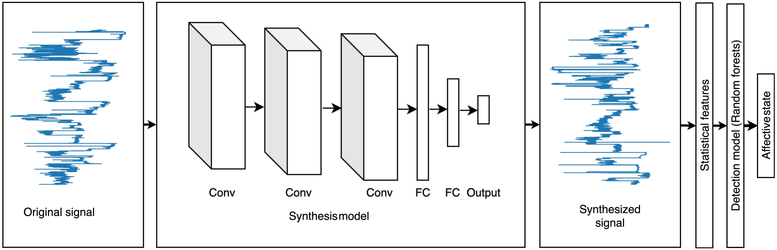

- Predict (synthesize) futuristic data from current and previous observations
- Feed features (computed from the synthetic data) to affect detection model

WESAD (Schmidt et al., ICMI 2018) Dataset

- Devices: RespiBAN and Empatica E4
- Signals: Acceleration, ECG, EMG, EDA, Temperature, Respiration
- Subjects: 15 (12 males and 3 females) grad students
- Data Collection
  1. **Neutral**: induce neutral affective state. 20 mins long
  2. **Amusement**: induce happy state. 6.5 mins long
  3. **Stress**: induce stress via public speaking and mental math tasks. 10 mins long
  4. **Meditation (/ relaxed)**: breathing exercise. 7 mins long

Note: *In this work, we only used data collected via RespiBAN device*

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- **Model validation**: 3-fold subject independent (non-overlapping subjects)

Performance: Synthesis

Input feature vector size $= 25$
CCC Score: higher $\longrightarrow$ better
Time T1: Use **0.25** second of data to predict **0.01** second of data

Signal		CCC score	
	Time T1	-	-
ACC X	0.9909±0.0054		
ACC Y	0.9675±0.0272		
ACC Z	0.9957±0.003		
ECG	0.8104±0.0327		
EMG	0.4381±0.6313		
EDA	0.9928±0.0012		
TEMP	0.95±0.0268		
RESP	0.9895±0.0009		

Performance: Synthesis

Input feature vector size $= 25$
CCC Score: higher $\longrightarrow$ better
Time T2: Use **1** second of data to predict **0.04** second of data

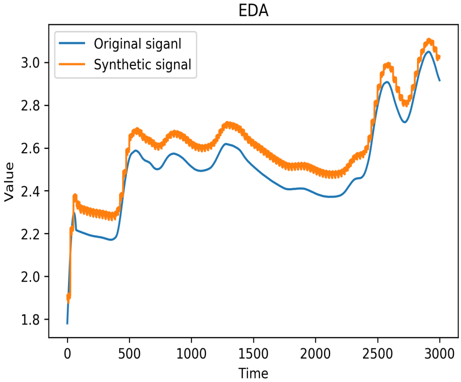
Signal		**CCC score**	
	Time T1	Time T2	-
ACC X	0.9909±0.0054	0.9856±0.0119	
ACC Y	0.9675±0.0272	0.9711±0.0081	
ACC Z	0.9957±0.003	0.992±0.0026	
ECG	0.8104±0.0327	0.5001±0.0922	
EMG	0.4381±0.6313	0.5837±0.0561	
EDA	0.9928±0.0012	0.9964±0.0009	
TEMP	0.95±0.0268	0.9401±0.0437	
RESP	0.9895±0.0009	0.9697±0.0065	

Performance: Synthesis

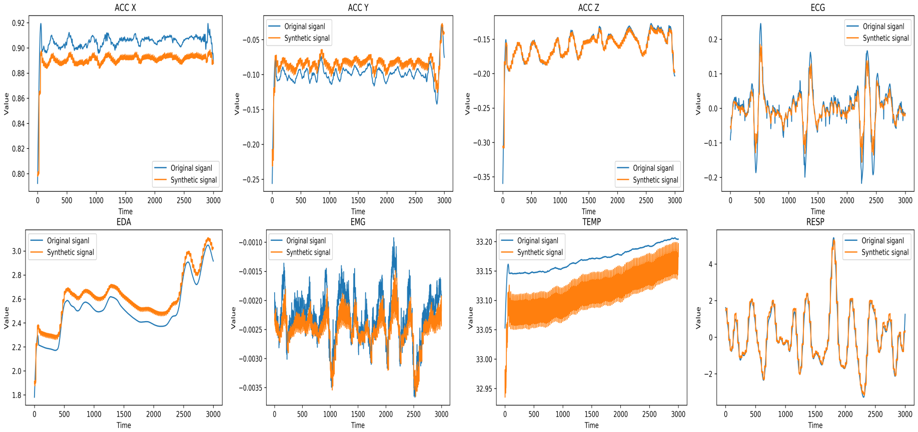
Input feature vector size = 25
CCC Score: higher $\longrightarrow$ better
Time T3: Use **2** seconds of data to predict **0.1** second of data

Signal		**CCC score**	
	Time T1	Time T2	Time T3
ACC X	0.9909±0.0054	0.9856±0.0119	0.9899±0.0014
ACC Y	0.9675±0.0272	0.9711±0.0081	0.7882±0.2552
ACC Z	0.9957±0.003	0.992±0.0026	0.9943±0.0024
ECG	0.8104±0.0327	0.5001±0.0922	0.3995±0.0602
EMG	0.4381±0.6313	0.5837±0.0561	0.3407±0.4757
EDA	0.9928±0.0012	0.9964±0.0009	0.9927±0.0036
TEMP	0.95±0.0268	0.9401±0.0437	0.7405±0.1785
RESP	0.9895±0.0009	0.9697±0.0065	0.9563±0.0094

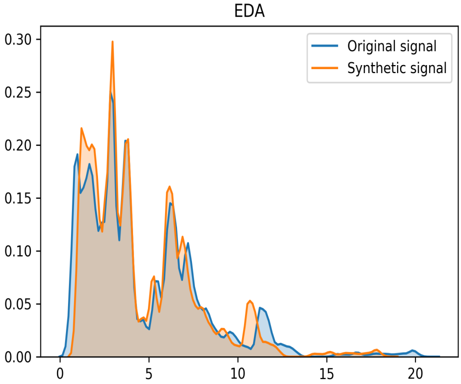
Sample Signals (Original and Synthesis)



Sample Signals (Original and Synthesis)

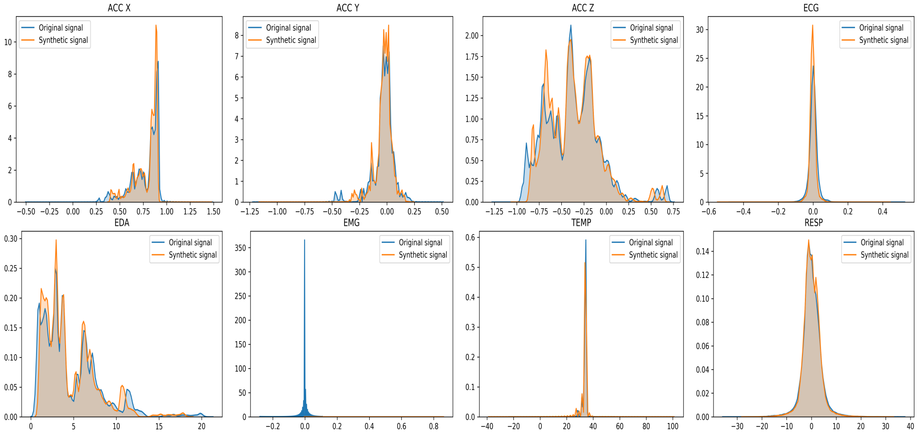


Signal Distribution (Original and Synthesis)



Signal Distribution (Original and Synthesis)

Learned the distribution for all signals except EMG



Performance: Affect Prediction vs. Classification

Detection Setting		Original data			Synthetic data	
	Precision	Recall	F1-score	Precision	Recall	F1-score
Stress vs Baseline	0.71±0.06	0.68±0.10	0.69±0.08	0.71±0.10	0.66±0.11	0.68±0.10

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Stress vs Amusement	0.54$\pm$0.11	0.61$\pm$0.06	0.57$\pm$0.10	0.55$\pm$0.15	0.56$\pm$0.07	0.55$\pm$0.11

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Stress vs Meditation	0.72±0.05	0.71±0.06	0.71±0.06	0.71±0.02	0.7±0.02	0.71±0.02

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Stress vs Meditation	0.72±0.05	0.71±0.06	0.71±0.06	0.71±0.02	0.7±0.02	0.71±0.02
Stress vs Rest	0.76±0.03	0.7±0.06	0.73±0.04	0.74±0.03	0.67±0.07	0.7±0.04

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  - Predicted signal ahead of time using CNN
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  - Achieved comparable results
- **Challenges and Future Work**
  - Synthetic data to synthesize data. (Noise, drift) $\longrightarrow$ out of distribuution (Alcorn et al., CVPR 2019)
  - Influence of gender (male & female)
  - Explore EMG and ECG