INVESTIGATING PHYSIOLOGICAL SYNCHRONY IN PARAMEDIC TRAINEE DYADS

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Introduction

Goal: to investigate the physiological synchrony between paramedic trainee pairs in training situations.

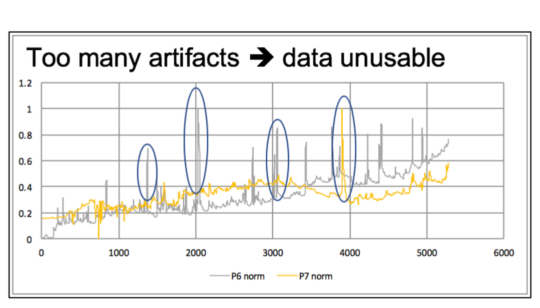
- **Physiological synchrony:** the unconscious, dynamic linking of physiological responses such as heart rate and electrodermal activity
- Physiological responses have been well-linked to several affective and mental states, e.g., arousal and cognitive load.

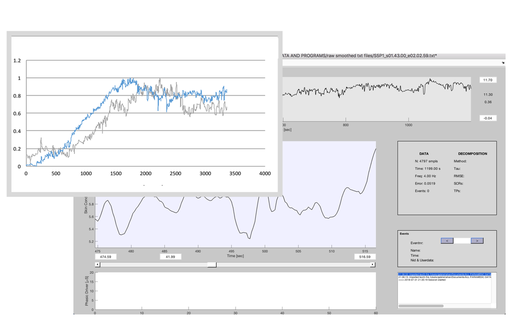
Motivation: understanding the role of physiological synchrony in a realistic, high-stakes environment can have an effect on the fatigue and stress levels of trainees' performance in carrying out life-saving tasks.
- moderate stress ➔ can improve cognitive performance
- severe stress ➔ can reduce fine motor performance and attention.


Empatica Wristbands

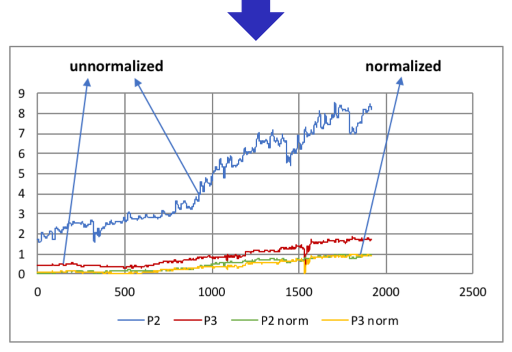
Data Preprocessing

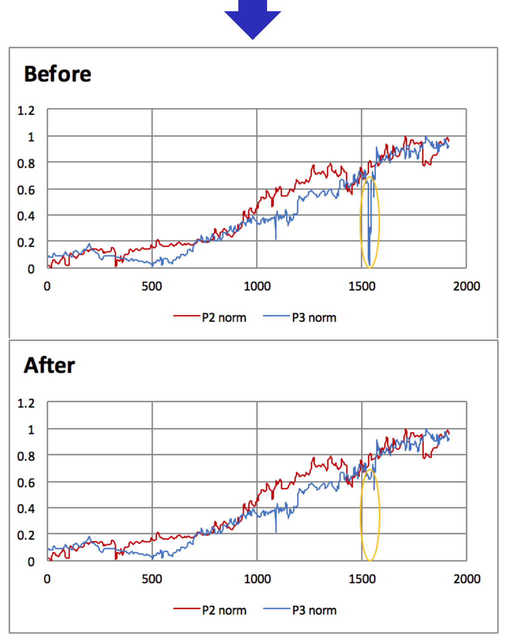
Our study monitors paramedic trainees as they work in realistic simulated emergency situations. Using E4 Empatica wristbands, we recorded the electrodermal activity (EDA) during simulation training. We then processed the raw EDA data like so:





1. Visual inspection of original data to assess quality
2. Filter out unusable data – left with 15 pairs' data
3. Use Ledalab to smooth data using 1 second window
4. Normalize data to 0-1 range to facilitate comparison between people.
5. Use Matlab findpeaks to identify artifacts. Then use Ledalab to correct them.



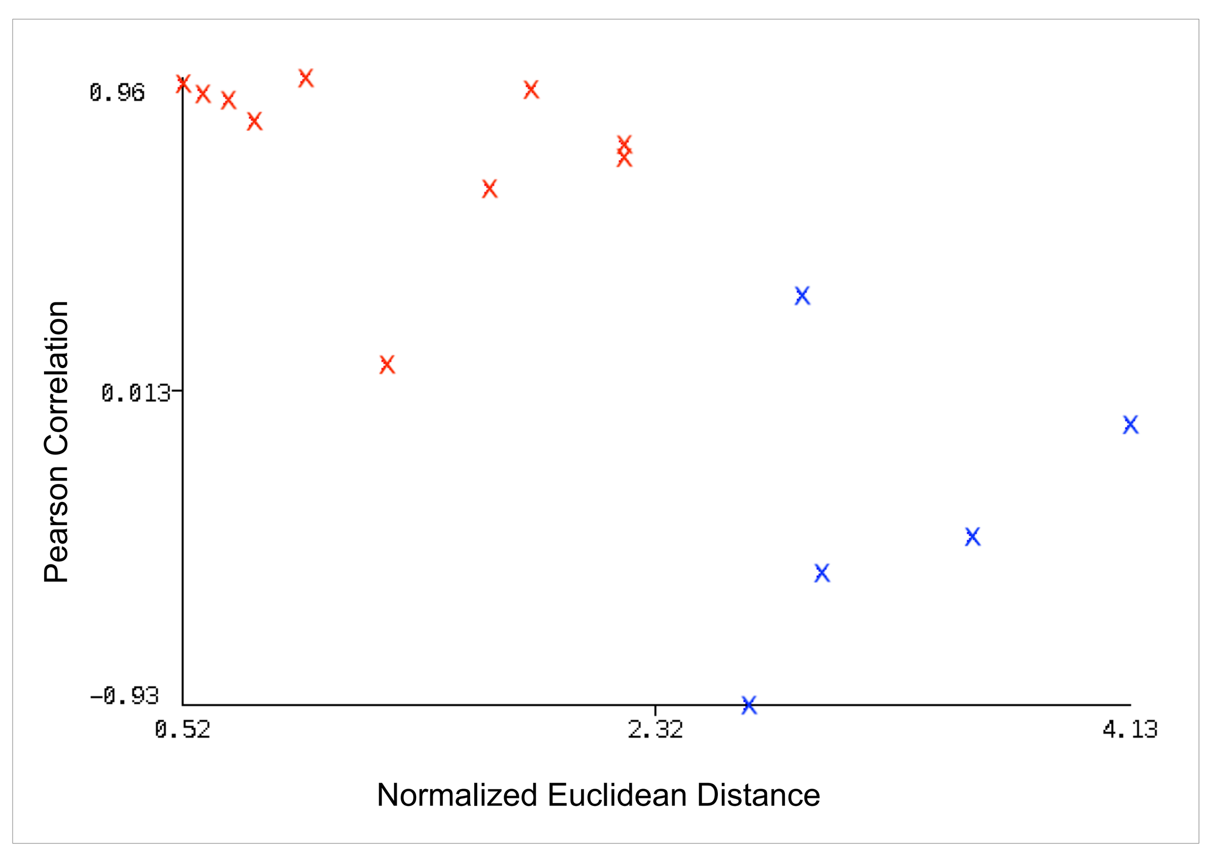


Feature Extraction

We computed a number of **synchrony features** which have been been shown and typically used to measure synchrony from EDA data. These included:
- Pearson correlation of each pair's EDA
- Difference between pair's average EDA
- Difference between pair's average peak amplitude
- Difference between pair's number of peaks
- Euclidean distance of the 3 difference measures

Analysis and Results

Using the machine learning application Weka, we ran *K*-means clustering (*k*=2 and *k*=3) on the 15 distinct pairs with the 5 synchrony features. *K*=2 showed the clearest distinction between the EDA of the paramedic trainee pairs.



Red X's mark pairs in cluster 0 (10 pairs) while blue X's mark pairs in cluster 1 (5 pairs)

Final cluster centroids:

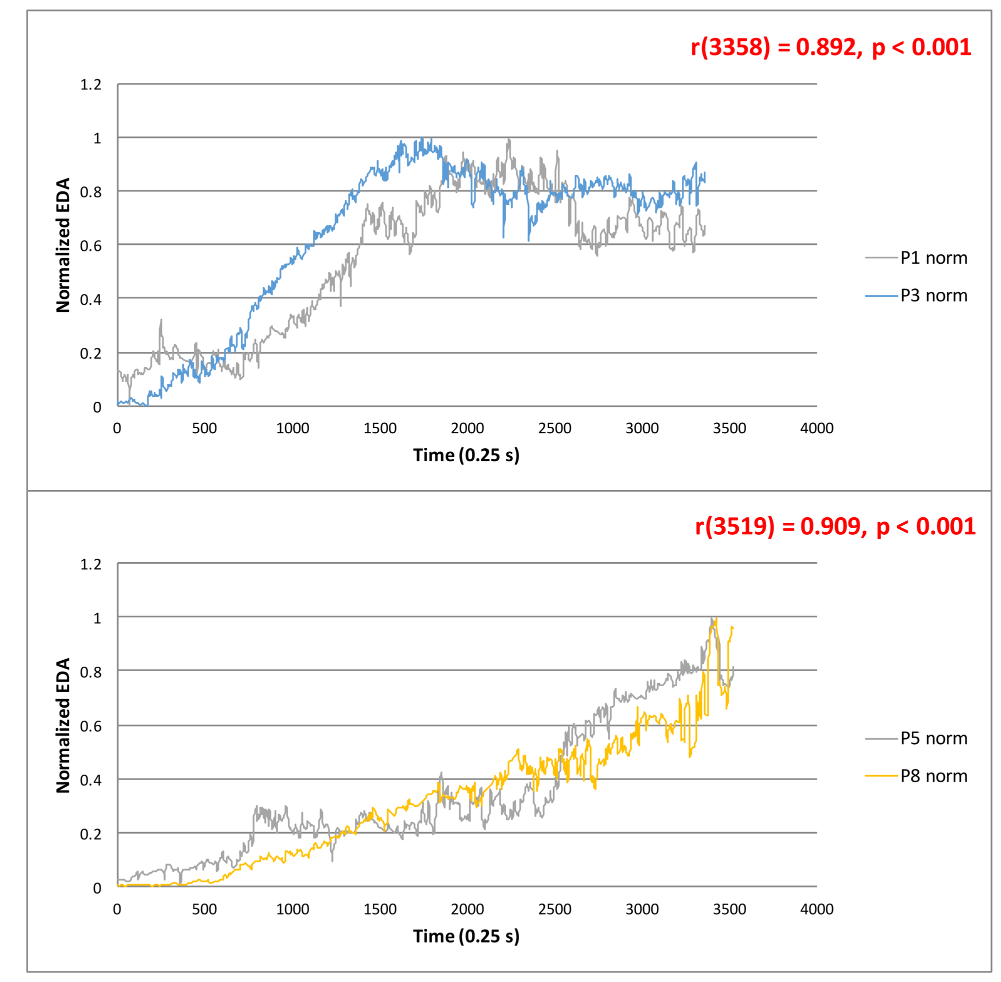
Attribute	Full Data (15.0)	Cluster# 0 (10.0)	1 (5.0)
mean distance	0.1577	0.1222	0.2288
number of peaks distance	79.3333	43.4	151.2
mean peak amp distance	0.0113	0.0067	0.0204
norm Eucl. Dist	1.9331	1.2823	3.2346
correlation	0.3972	0.7644	-0.3372

The most discriminative EDA features for clustering were:
- **Euclidean distance of the 3 difference measures**
- **Pearson correlation**

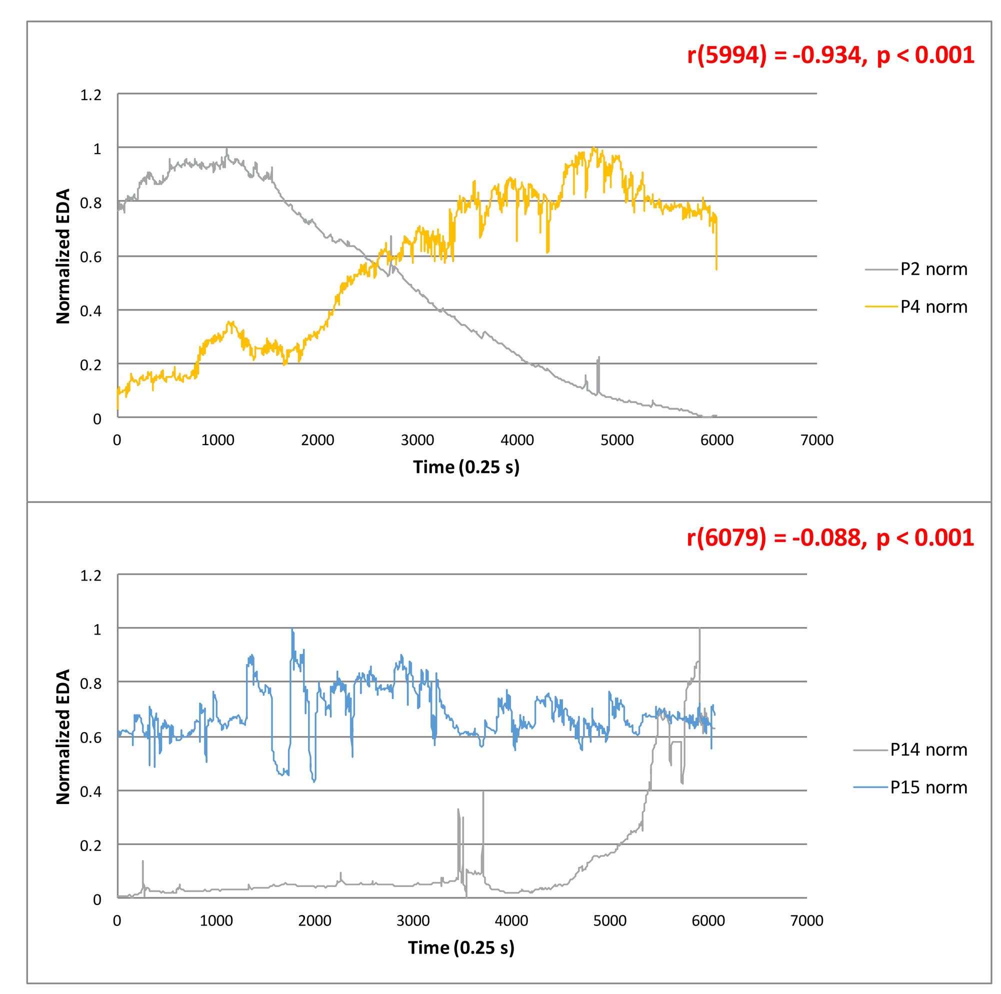
With the exception of an outlier pair in the 15th training session, all pairs in cluster 0 had a Pearson correlation of 0.6 and above, and all had a Euclidean distance of 2.201 or below. Further, with the exception of the pair in the 8th session, all pairs in cluster 1 had a negative Pearson correlation, and all had a Euclidean distance of 2.677 or above.
- **cluster 0 Eucl. Dist. range**: 0.518 - 2.201
- **cluster 1 Eucl. Dist. range**: 2.677 - 4.129

➔ no overlap in ranges

Cluster 0 Example Graphs



Cluster 1 Example Graphs



Conclusion

Our results demonstrate a clear distinction in our data between pairs for which the paramedic trainee pair's EDA data correlated more highly and had more similarities (as indicated by a lower Euclidean distance) and the rest of the pairs, whose EDA neither correlated highly nor had many similarities. From this we may conclude that these features, the Euclidean distance of 3 difference features and the Pearson correlation, are important features which may help identify synchrony. This is in agreement with similar studies on physiological synchrony.

We hope to use these measures to further investigate how the level of physiological synchrony can affect the stress and performance of working dyads by combining with behavioral analysis done on the video we captured of each session.

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