Contact-free Monitoring of Physiological Parameters in People with Profound Intellectual and Multiple Disabilities

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Outline

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Section 1: Introduction, motivation and problem definition

Section 2: Prototype system, deep learning enhancements

Section 3: Evaluation and results

Section 4: Demo video

Section 5: Summary and conclusion

Problem definition

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Q: How does she feel?
A: I can see her **smiling**

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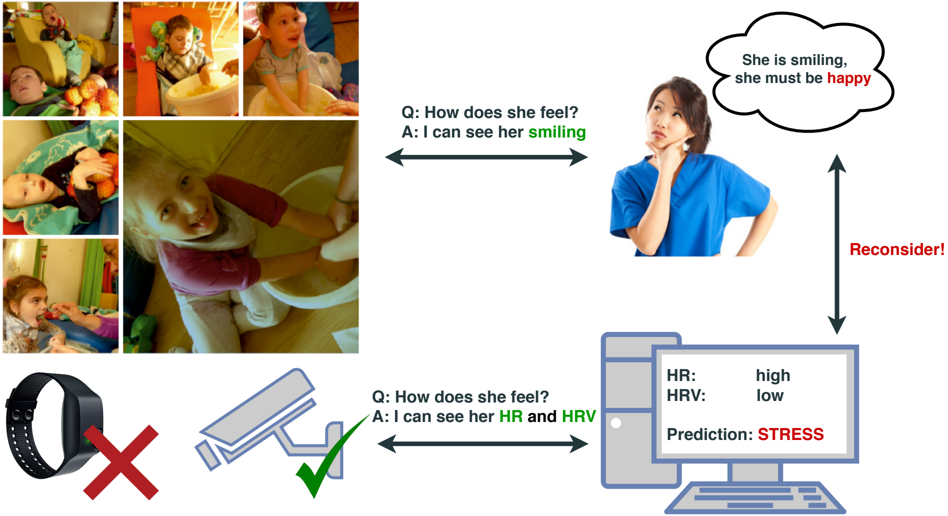
Problem definition

Q: How does she feel?
A: I can see her smiling

Q: How does she feel?
A: I can see her HR and HRV

Problem definition



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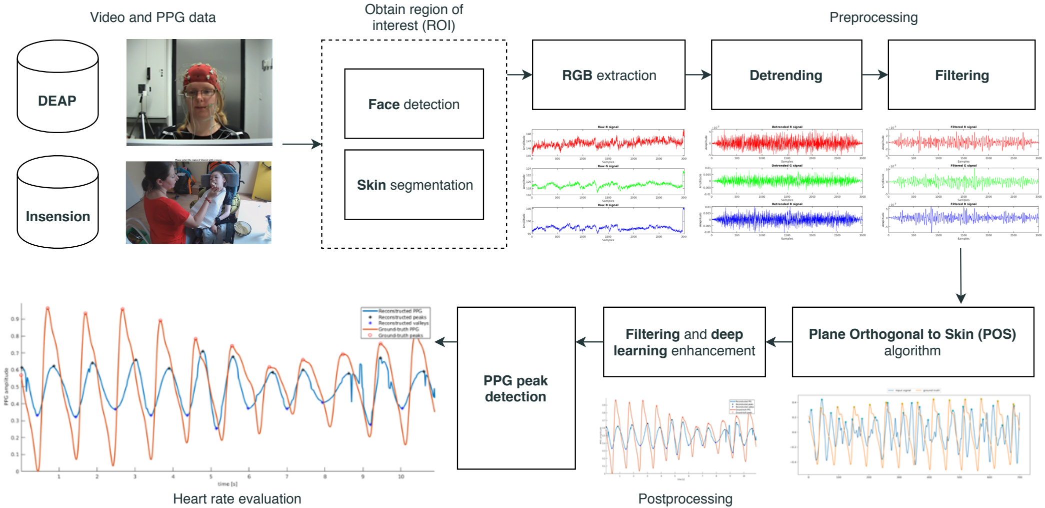
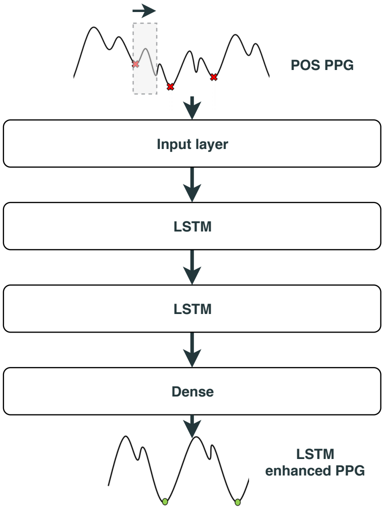
Prototype architecture



Deep learning enhancements

1. Convolutional autoencoder (CNN)
    - Should learn how to encode the PPG shape
2. Long-Short-Term-Memory neural network
    - Should learn temporal dynamics and predict the next sample based on previous trends



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Evaluation

1. Current evaluation done on the publicly available **DEAP dataset**
2. 16 subjects used for training, 2 for validation, 2 for test
3. **Compared** the following rPPG methods + enhancements:
    - Using just **POS**
    - **POS + Convolutional autoencoder (CNN)**
    - **POS + Long-Short-Term Memory neural network (LSTM)**
4. Used a robust PPG peak detection algorithm (Elgendi et al.) to evaluate HR
    - **Mean Absolute Error (MAE)** between nr. of peaks detected in ground-truth and in enhanced signals
5. Additionally computed the **correlation** between predicted HR and ground-truth HR

Errors and visual inspection

Method	**MAE** [BPM]	**Correlation**
Baseline	8.36	Inapplicable
POS	13.36	0.27
CNN-POS	**7.92**	0.24
LSTM-POS	8.09	**0.40**

Errors and visual inspection

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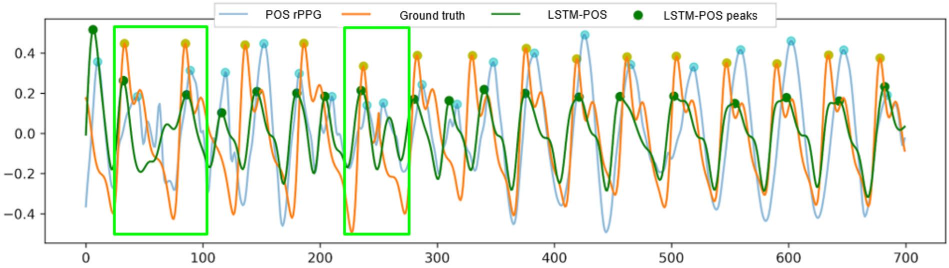
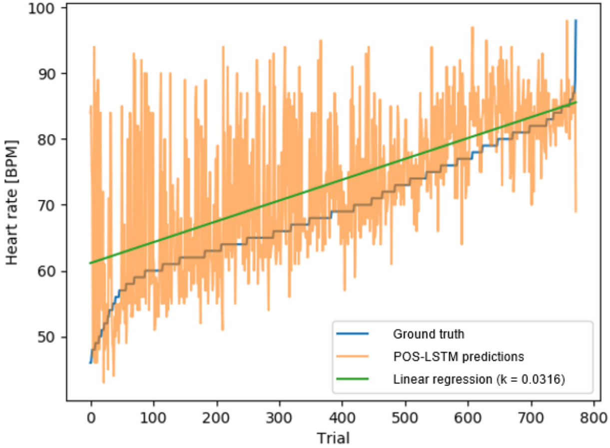


Correlation

1. Good correlation between predicted and ground-truth HR using LSTM-POS



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Demo video

The algorithm was ran on a sequence of facial images of one project participant

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Summary and conclusion

1. LSTM-POS method performs best, with error of 8 BPM on DEAP dataset
2. Good correlation between predicted and ground-truth HR
3. Better temporal alignment of peaks (important for HRV)

Summary and conclusion

1. LSTM-POS method performs best, with error of 8 BPM on DEAP dataset
2. Good correlation between predicted and ground-truth HR
3. Better temporal alignment of peaks (important for HRV)

4. Future work (in progress):
    - Evaluate on real-world data of PIMD people
    - Use the evaluated vitals of PIMD people to infer their mental state
    - Empower the PIMD people by having the system respond to their state (e.g., if stressed, play the music they enjoy)

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PSNC Pädagogische Hochschule HEIDELBERG University of Education Jožef Stefan Institute CTIC centro tecnológico stowarzyszenie na tak HARPO