De-identification of facial videos while preserving remote physiological utility

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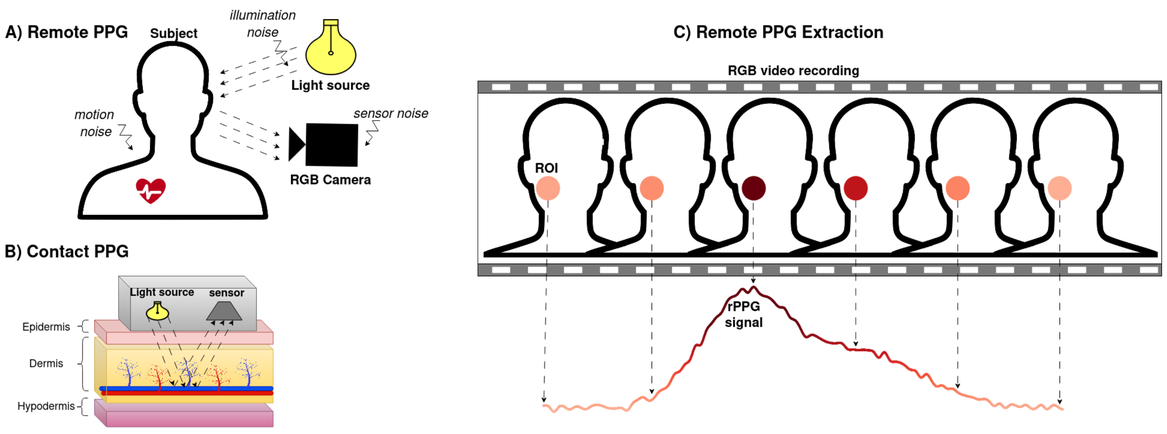
What is Remote Photoplethysmography (rPPG) ?

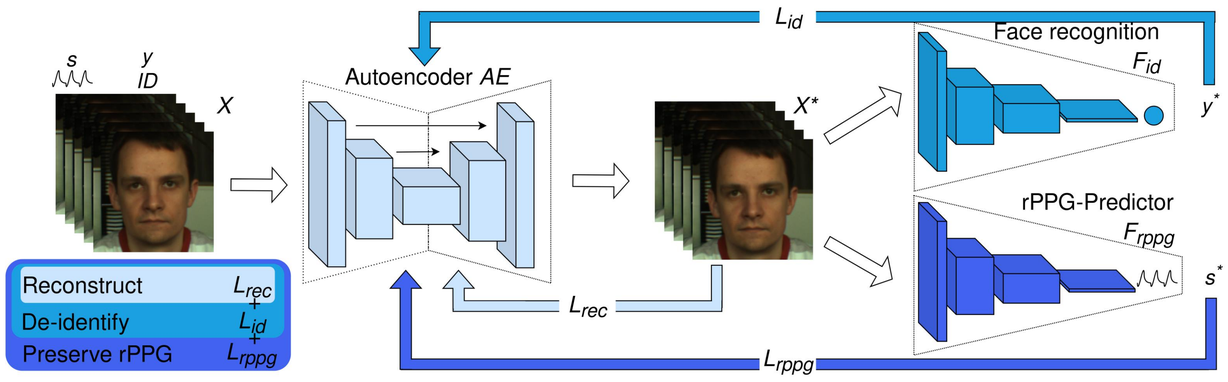
- Convenient non-contact method for cardiac signal estimation
- rPPG signals are extracted from facial videos recorded with RGB cameras
- Derived from subtle periodical variations in facial colour (sensitive to noise)



Potential Privacy issues

- Data contains both sensitive physiological signals and facial videos, which are biometric data subject to special restrictions (GDPR, EU AI Act)
- Big data and Machine Learning allow to extract sensitive data like Identity, Race, Gender, etc. → high risk of intentional or unintentional unethical practices
- De-identification from machines is crucial for future applications

Our rPPG preserving De-identification method



- Retains data utility (underlying rPPG signals and visual appearance) while removing identity related features, rendering videos un-recognisable by machines
- Unobtrusive perturbations added to input by semi-adversarial training of Autoencoder
- Learning constraints imposed by pre-trained Face recogniser and rPPG predictor
- Trained with three objectives: Reconstruct, De-identify and Preserve rPPG.

1. Reconstruct

- Reconstructs input video with visually imperceptible perturbations

$$L_{rec}(X,X^*) = |X - X^*|_2 + \frac{1}{T}\sum_{t=1}^{T}\frac{1}{W}\sum_{i=1}^{W} SSIM(w_i x_t, w_i x_t^*)$$

2. De-identify

- Deceives the identity recognizer, resulting in wrong and non-confident identity predictions

$$L_{id}(X^*,F_{id},y) = \frac{1}{K}\sum_{x_k^* \in X_K^*} l_{id}(x_k^*,F_{id},y) \quad where \quad X_K^* = \{X^*(i)\}_{i=1}^{K}$$

$$l_{id}(x_k^*,F_{id},y) = \frac{1}{N}\sum_{i=1}^{N} y_i log(F_{id}(x_k^*)) + \lambda \frac{\|F_{id}(x_k^*) - [(1/N)_{\times N}]\|_2}{\|F_{id}(x_k^*)\|_2 + \|[(1/N)_{\times N}]\|_2}$$

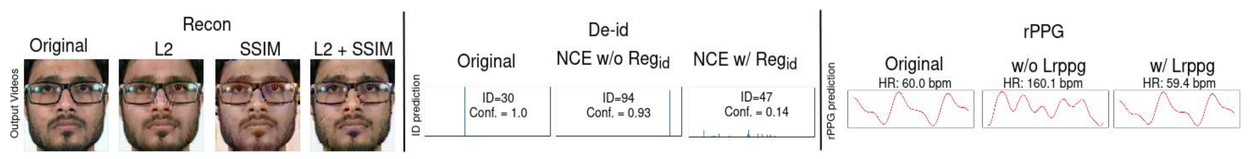
3. Preserve rPPG

- Ensure that the perturbations do not deteriorate the rPPG signal

$$L_{rppg} = \frac{\sum_i (s_i - \bar{s})(s_i^* - \bar{s}_i^*)}{\sqrt{\sum_i (s_i - \bar{s})^2 (s_i^* - \bar{s}_i^*)^2}} \quad i \in [0, T[$$

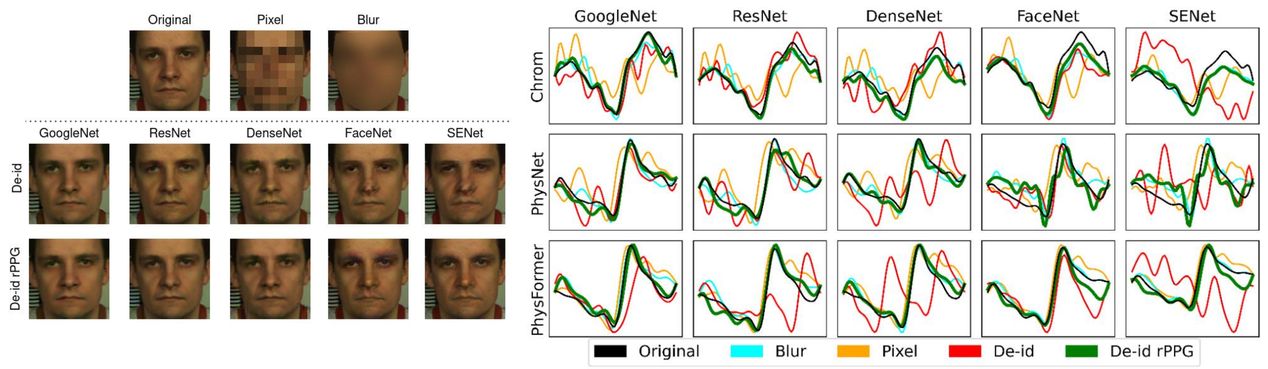
Total loss function

$$L = \alpha L_{rec} + \beta L_{id} + \gamma L_{rppg}$$

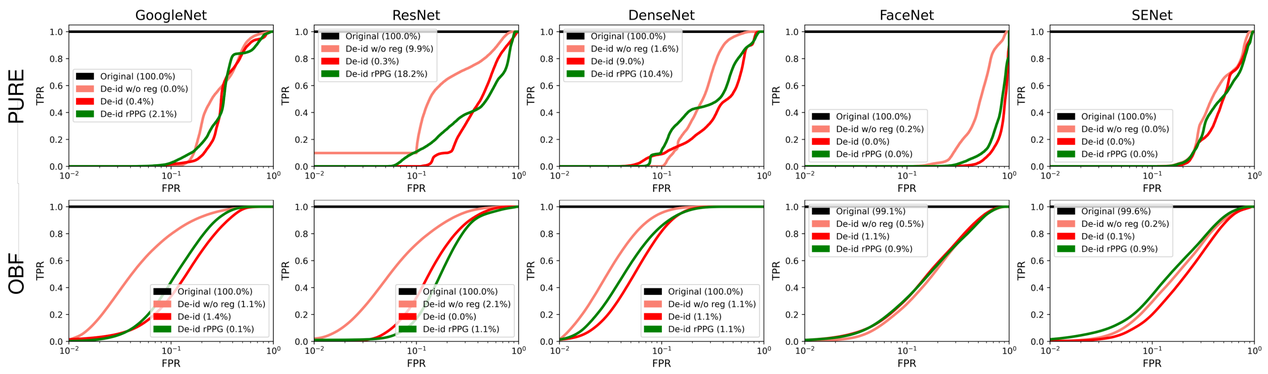


Results

- Visual acceptance PSNR>30dB and SSIM approx. 0.97
- Signals and heart rates extracted of high quality (R = 0.99, RMSE < 1)



- De-identification is successful, with accuracy below random guessing and high EER



Results

- First learning based method for facial video de-identification that preserves the physiological and visual fidelity, while protecting user's privacy from machines
- Experiments on two public datasets show effectiveness of our method in deteriorating biometric performance, while preserving visual information and rPPG signal.
- Future work will include more challenging biometric attack scenarios and removal of soft biometrics while preserving rPPG.

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