README for dataset release

Dataset for Camera-Based Vital Signs Estimation in Narrow-Band Near-Infrared

Please cite the following paper when using the dataset:

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@inproceedings{magdalena2018sparseppg,
  title={Sparseppg: Towards driver monitoring using camera-based vital signs estimation in near-infrared},
  author={Magdalena Nowara, Ewa and Marks, Tim K and Mansour, Hassan and Veeraraghavan, Ashok},
  booktitle={Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops},
  pages={1272--1281},
  year={2018}
}
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Ewa M. Nowara, Tim K. Marks, Hassan Mansour, and Ashok Veeraraghavan (2018). SparsePPG: Towards Driver Monitoring Using Camera-Based Vital Signs Estimation in Near-Infrared. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops* (CVPRW 2018), pp. 1272-1281.

Dataset

We release the first dataset of face videos for remote photoplethysmography (rPPG) that were collected simultaneously in broadband RGB (with a standard color camera) and narrow-band NIR (near-infrared), with pulse oximeter recordings as ground truth of the vital signs. This dataset gives researchers the ability to understand the difficulties with using NIR for rPPG and the limitations of using a single color channel to achieve robustness, and to compare the performance to RGB recordings as a benchmark.

Accessing the Dataset

In order to download this dataset, please follow this link and fill out a request form.

The dataset contains a separate directory for each of the 8 subjects, each containing and still and motion experiment. Inside each subject's directory are four subdirectories:

1. *IR* contains the images recorded with the NIR camera.
2. *PulseOX* contains the pulse oximeter recordings, saved as the Matlab data file pulseOx.mat.
3. *RGB_demosaiced* contains the images recorded with the RGB camera that have been demosaiced into standard color images.
4. *RGB_raw* contains the original raw images captured with RGB camera (prior to demosaicing).

The two cameras and pulse oximeter recordings were synchronized at the beginning of the data collection, so the frame numbers in each directory are in correspondence.

Comparing Evaluation Results

When using this dataset, please compare your performance to the SparsePPG results summarized in the table below. (Do not compare directly to the results reported in the paper, since those results used an earlier version of the dataset.) The pulse oximeter occasionally output erroneous measurements of 0 beats per minute (bpm) due to slight finger motion. The results below were evaluated excluding the time points when the pulse oximeter data read 0 bpm. The rPPG signals were additionally normalized in each time window by computing the mean over the time window for each facial region, then subtracting and dividing by that mean to obtain the facial region's signal for the time window.

	NIR		**RGB**	
	RMSE [bpm]	PTE6 [%]	RMSE [bpm]	PTE6 [%]
SparsePPG (ours)	**1.06**	**95.18**	0.64	98.53
distancePPG	6.23	82.32	**0.50**	**99.05**
ICA	N/A	N/A	0.91	97.23
CHROM	N/A	N/A	2.34	94.2

In our publication [1], we initially evaluated the results on 12 subjects. However, 2 of the subjects did not agree to have their data publicly released, and there were technical problems with videos of 2 other subjects. For a fair comparison, we re-evaluated our performance as well as the previous methods (distancePPG, ICA and CHROM) on just the 8 subjects' videos that we are releasing here. The table here shows the results on this released version of the dataset.

Research summary

The goal of this work is to remotely estimate vital signs in order to improve driver safety. Remote photoplethysmography (rPPG) is a non-contact method for estimating vital signs, such as heart rate (HR) and heart rate variability (HRV), from subtle intensity variations in skin appearance due to blood flow that are observed with a camera. Methods for rPPG have improved considerably in recent years, but these methods are still not robust enough for measuring vital signs during driving. There are several challenges unique to the driver monitoring context that must be overcome. First, drastic illumination changes on the driver's face, both during the day (as sun filters in and out of overhead trees, etc.) and at night (from street lamps and oncoming headlights), which current rPPG algorithms cannot account for. Second, the amount of motion during driving of the driver's head and the camera inside the car is significant. The outside illumination variations are significantly reduced by narrow-bandwidth near-infrared (NIR) active illumination at 940 nm, with matching bandpass filter on the camera. Sunlight effects are reduced at 940 nm because of absorption due to atmospheric moisture. Unfortunately, the strength of rPPG signals decreases significantly in NIR compared to visible-light wavelengths due to lower hemoglobin absorption in NIR. Furthermore, the camera sensors are less sensitive in NIR. Because of these two factors, the signal-to-noise ratio (SNR) of rPPG signals obtained in NIR will be significantly lower than than that of signals measured using a broad-band RGB camera. However, by using NIR we are much more robust to large outside light variations that are present during driving.

Data Collection and Hardware Details

We recorded indoor videos of 8 healthy subjects (2 female, 6 male), aged 20-40 years old, with varying skin tones (4 Indian, 3 Caucasian, 1 Asian). Of the male subjects, 4 had facial hair. During the still experiments the subjects were asked to sit still, but to allow for natural head motion we did not use a headrest. During the motion experiments the subjects were asked to slightly move their head rigidly in different direction for 15 seconds and then to count out loud from 0 to 10. During the first and last 15 seconds of the motion experiments the subjects were asked to sit still as a control experiment.

The raw 10-bit images were recorded with 640 × 640 resolution at 30 fps. The exposure for the IR camera was fixed for all participants, but the RGB camera's exposure was manually adjusted at the beginning of each recording session to ensure that images of people with darker skin tones were well exposed. We turned off gamma correction and set gain to zero. The videos are each about 3 minutes long.

We simultaneously recorded videos with an RGB camera and an NIR camera. We used the following RGB cameras: Point Grey Flea3 FL3-U3-13E4C-C for subject 6 (sensor format: 'bggr'), and FLIR Blackfly BFLY-U3-23S6C-C for all other subjects (sensor format 'rggb'). To record NIR images, we used a monochrome camera, Point Grey Grasshopper GS3-U3-41C6NIR-C, fitted with a narrow-band 940 nm bandpass filter with 10 nm passband. We used two Bosch EX12LED-3BD-9W illuminators. Each illuminator was fitted with both the 95-degree diffuser in the vertical direction and the 80-degree diffuser in the horizontal direction, to widen the beam in order to more uniformly illuminate the face. We used ambient overhead lights to accommodate the RGB camera. We used a CMS 50D+ finger pulse oximeter to obtain a ground-truth PPG waveform recorded at 60 fps.

Subject details:

subject1 - male, facial hair
subject2 - female, no facial hair
subject3 - male, facial hair
subject4 - male, no facial hair
subject5 - male, no facial hair
subject6 - male, facial hair
subject7 - female, no facial hair
subject8 - male, facial hair

Due to a hardware issue during the data collection, the motion video of subject 5 was removed.

SparsePPG: Proposed method for estimating rPPG in NIR

To address the challenges of low SNR in NIR and motion, we developed a novel rPPG signal tracking and denoising algorithm, which we call SparsePPG, that is based on Robust Principal Components Analysis (RPCA) and sparse frequency spectrum estimation.

The results of SparsePPG on this dataset are summarized in the table above. For details about SparsePPG, please refer to the reference [1] below.

Reference

1. Ewa M. Nowara, Tim K. Marks, Hassan Mansour, and Ashok Veeraraghavan (2018). SparsePPG: Towards Driver Monitoring Using Camera-Based Vital Signs Estimation in Near-Infrared. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops* (CVPRW 2018), pp. 1272-1281.