Deep Physiological Sensing Toolbox

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ABSTRACT

Camera physiological measurement is a fast growing field of computer vision. Remote photoplethysmography (rPPG) uses video cameras (imagers) to measure the peripheral blood volume pulse (BVP). Simply, this enables heart rate measurement via webcams, smartphone cameras and many other imaging devices. The current state-of-the-art methods are supervised deep neural architectures that have large numbers of parameters and a signal number of hyper-parameters. Replication of results and benchmarking of new models is critical for scientific progress. However, as with many other applications of deep learning, reliable codebases are not easy to find. We present a comprehensive toolbox, rPPG-Toolbox, containing code for training and evaluating unsupervised and supervised rPPG models: https://github.com/ubicomplab/rPPG-Toolbox

Introduction

The vision of pervasive or ubiquitous computing is to embed computation into everyday objects to enable them to perform useful tasks. Sensing of physiological vital signs is one such task that plays an important role in how health is understand and managed. Cameras are both ubiquitous and versatile sensors, and transforming them into accurate health sensors has potential to make measurement more comfortable and accessible. Examples of applications of this technology, include systems for monitoring neonates¹, dialysis patients², and detection of heart arrhythmias³.

Building on advances in computer vision, camera measurement of physiological vitals signs has developed into a research field of its own⁴. Researchers have developed methods for measuring cardiac and pulmonary signals by analyzing subtle pixel changes across time. Recently, several companies have been granted FDA De Novo status for products that uses software algorithms to analyze video and estimate pulse rate, heart rate, respiratory rate and/or breathing rates.¹² There are hundreds of computational architectures that have been proposed to measure of cardiopulmonary signals. Unsupervised signal processing methods leverage tools such as Independent Component Analysis (ICA) or Principal Component Analysis (PCA) and assumptions about the periodicity or structure of the underlying pulse waveform. Neural architectures can be trained in a supervised fashion using videos with synchronized gold-standard signals.⁵–⁸. Innovative data generation and augmentation,⁹ meta-learning for personalization¹⁰ and semi-supervised learning¹², have led to significant improvements in the performance of these methods.

However, standardization in the field of physiological measurement is still severely lacking. Based on our review of literature in the space we identified four issues that hindered the interpretation of results in many of the paper. First, and perhaps most obviously, a lot of the published work is not accompanied by public code. While publishing code repositories with papers is now fairly common in the machine learning and computer vision research communities, it is far less common in the field of computer physiological measurement. While there are reasons that it might be difficult to release datasets, we cannot find good arguments for not releasing code. Second, many papers do not compare to previously published methods in a “apples-to-apples” fashion. This point is a little more subtle, but rather than performing systematic side-by-side comparisons between methods, the papers pull numbers from previous work. Unfortunately, this often makes it unclear if performance differences are due to preprocessing steps, model design, postprocessing or a combination of these. Continuing this thread, the third flaw is that papers use pre- and post-processing steps that are often lacking in detail. Finally, different researchers compute the “labels” (e.g., HR frequency) using their own methods from the contact PPG or ECG timeseries. Differences in these methods leads to different labels and a fundamental issues when it comes to benchmarking performance. When you

¹https://www.accessdata.fda.gov/cdrh_docs/reviews/DEN200019.pdf
²https://www.accessdata.fda.gov/cdrh_docs/reviews/DEN200038.pdf
Table 1. [Comparison of our toolbox with others.]

| Toolbox              | Multiple Dataset Support | Uns. Eval | DNN Training | DNN Eval |
|----------------------|--------------------------|-----------|--------------|----------|
| iPhys-Toolbox        | ✗                        | ✓         | ✓            | ✗        |
| Boccignone et al.    | ✗                        | ✓         | ✓            | ✗        |
| PPG-I Toolbox        | ✗                        | ✓         | ✓            | ✗        |
| pyVHR                | ✓                        | ✓         | ✓            | ✗        |
| rPPG Toolbox (our)   | ✓                        | ✓         | ✓            | ✓        |

Uns. = Unsupervised learning methods, DNN = Deep neural network methods.

combine these together it makes it very difficult to draw conclusions from the literature about the optimal choices for the design of rPPG systems.

Open source code allows researchers to compare novel approaches to consistent baselines without ambiguity about the implementation or parameters used. This transparency is very important as subsequent research invariably builds on prior art. Implementing a prior method from a paper, even if the most clearly written can be difficult, and it is not efficient for many researcher to implement all baseline methods. To address this, several open source toolboxes have been released for camera physiological sensing. These toolboxes have been a significant contribution to the community and provide implementations of methods and models\(^\text{13-15}\). However, these toolboxes are incomplete. McDuff and Blackford\(^\text{13}\) implemented a set of source separation methods (Green, ICA, CHROM, POS) and Pilz\(^\text{15}\) published the PPGI-Toolbox\(^\text{4}\) containing implementations of Green, SSR, POS, Local Group Invariance (LGI), Diffusion Process (DP) and Riemannian-PPGI (SPH) models. These toolboxes are implemented in MATLAB (e.g.,\(^\text{13}\)); however, Python is now the language of choice for a large majority of the computer vision and deep learning research. There are several implementation of the popular signal processing methods in Python: Bob.rppg.base\(^\text{5}\) includes implementations of CHROM, SSR and Li et al.\(^\text{2}\) and Boccignone et al.\(^\text{7}\) released code for Green, CHROM, ICA, LGI, PBV, PCA, an POS. Several published papers have included links to code; however, often this is only inference code and not training code for neural models.

In this paper, we present a comprehensive rPPG-Toolbox\(^\text{6}\) of methods for camera physiological measurement. We include: 1) supporting for multiple public datasets, 2) preprocessing code to format the datasets for training neural models, 3) implementations of neural model architectures and unsupervised learning methods, 4) building evaluation and inference pipelines for neural supervised and unsupervised learning methods for reproducibility. We hope that this toolbox helps the research community to establish clearer benchmarks and compare methods in a fairer way.

The rPPG Toolbox

To address the gaps in the current set of tools and to promote reproducibility and clearer benchmarking within the video physiological measurement and rPPG communities we present an opensource code toolbox. This toolbox is designed to support multiple public datasets, preprocessing steps, model training and evaluation.

Dataset and Preprocessing Support

The toolbox includes preprocessing code that converts multiple public datasets into a form amenable for training with the neural models. The standard form for the videos (features) we select includes raw frames and difference frames (the difference between each pair of consecutive frames) stored as numpy arrays in a \([N, W, H, C]\) format. Where \(N\) is the length of the sequence, \(W\) is the width of the frames, \(H\) is the height of the frames and \(C\) is the channels. Channels in this case is six, as the raw frames and difference frames are included. For faster data loading, each videos in the datasets is typically broken up into several “chunks” of non-overlapping 180 frame sequences. All these parameters (\(N, W, H, C\)) are easy to change and customize. The PPG waveforms (labels) are stored as numpy arrays in a \([1, N]\) format.

In the first version of the rPPG-Toolbox we provide preprocessing code for four commonly used public datasets: UBFC\(^\text{18}\), PURE\(^\text{19}\) and SCAMPS\(^\text{27}\).

UBFC-RPPG\(^\text{18}\): The UBFC-RPPG RGB video dataset, collected with a Logitech C920 HD Pro at 30Hz with a resolution of 640x480 in uncompressed 8-bit RGB format. A CMS50E transmissive pulse oximeter was used to obtain the gold-standard PPG data. During the recording, the subjects were seated one meter from the camera. All experiments are conducted indoors with a mixture of sunlight and indoor illumination.

\(^\text{3}\)https://github.com/danmcduff/iphys-toolbox
\(^\text{4}\)https://github.com/partofthestars/PPGI-Toolbox
\(^\text{5}\)https://pypi.org/project/bob.rppg.base/
\(^\text{6}\)https://github.com/ubicomplab/rPPG-Toolbox
Table 2. Baseline results on the UBFC-rPPG\textsuperscript{18} and PURE\textsuperscript{19} datasets generated using the rPPG toolbox. For the supervised methods we show results training with the UBFC-rPPG and PURE.

| Training Set | PURE\textsuperscript{18} | UBFC\textsuperscript{18} | UBFC\textsubscript{19} | PURE\textsubscript{19} |
|--------------|----------------|----------------|----------------|----------------|
| Testing Set  | MAE↓ RMSE↓ MAPE↓ ρ ↑ | MAE↓ RMSE↓ MAPE↓ ρ ↑ | MAE↓ RMSE↓ MAPE↓ ρ ↑ | MAE↓ RMSE↓ MAPE↓ ρ ↑ |
| Supervised   |                |                |                |                |
| TS-CAN\textsuperscript{7} | 0.99 2.41 1.17 0.99 | 5.75 16.3 6.04 0.74 |                |                |
| PhysNet\textsuperscript{6} | 1.99 4.49 2.09 0.97 | 8.39 19.2 16.9 0.71 |                |                |
| DeepPhys\textsuperscript{20} | 1.02 2.53 1.25 0.99 | 5.80 17.1 6.11 0.71 |                |                |
| Unsupervised |                |                |                |                |
| POS\textsuperscript{21} | 2.79 4.69 3.25 0.97 | 7.89 11.08 10.65 0.89 |                |                |
| PBV\textsuperscript{22} | 13.63 24.12 15.75 0.32 | 23.31 30.73 30.40 0.51 |                |                |
| LGI\textsuperscript{23} | 5.64 7.87 5.95 0.90 | 10.61 15.76 13.67 0.73 |                |                |
| CHROM\textsuperscript{24} | 3.13 5.11 3.68 0.97 | 7.29 10.33 10.06 0.90 |                |                |
| ICA\textsuperscript{25} | 7.50 11.43 7.09 0.80 | 5.67 8.89 6.84 0.88 |                |                |
| Green\textsuperscript{26} | 9.32 12.64 9.71 0.74 | 8.48 11.59 10.38 0.78 |                |                |

MAE = Mean Absolute Error in HR estimation (Beats/Min), RMSE = Root Mean Square Error in HR estimation (Beats/Min), ρ = Pearson Correlation in HR estimation.

Table 3. For the supervised methods we show results training with the SCAMPS\textsuperscript{27} dataset.

| Training Set | UBFC\textsuperscript{18} | SCAMPS\textsuperscript{27} | PURE\textsuperscript{19} |
|--------------|----------------|----------------|----------------|
| Testing Set  | MAE↓ RMSE↓ MAPE↓ ρ ↑ | MAE↓ RMSE↓ MAPE↓ ρ ↑ | MAE↓ RMSE↓ MAPE↓ ρ ↑ |
| Supervised   |                |                |                |
| TS-CAN\textsuperscript{7} | 6.86 16.1 6.68 0.76 | 6.67 18.9 7.93 0.62 |                |                |
| PhysNet\textsuperscript{6} | 6.46 12.2 6.50 0.823 | 19.95 27.57 0.16 31.54 |                |                |
| DeepPhys\textsuperscript{20} | 3.83 12.5 3.62 0.82 | 3.46 12.9 3.53 0.84 |                |                |

MAE = Mean Absolute Error in HR estimation (Beats/Min), RMSE = Root Mean Square Error in HR estimation (Beats/Min), ρ = Pearson Correlation in HR estimation.

PURE\textsuperscript{19}: The PURE datasets contains recordings of 10 subjects (8 male, 2 female) each during six tasks. The videos were captured with an RGB eco274CVGE camera (SVS-Vistek GmbH) at a resolution of 640x480 and 60 Hz. The subjects were seated in front of the camera at an average distance of 1.1 meters and lit from the front with ambient natural light through a window. Gold-standard measures of PPG and SpO2 were collected with a pulse oximeter CMS50E attached to the finger. The participants each completed six recording under different motion conditions.

SCAMPS\textsuperscript{27}: The SCAMPS dataset contains 2,800 videos (1.68M frames) with aligned cardiac and respiratory signals. The waveforms and videos were synthesized using a sophisticated facial pipeline that produces high fidelity data, almost photo-realistic renderings. The videos have a range of confounders including head motions, facial expressions and ambient illumination changes.

Models

The implementations of both following unsupervised and supervised learning algorithms are included in the toolbox.

Unsupervised

The following methods all use linear algebra to recover the estimated BVP signal.

Green\textsuperscript{26}: is an unsupervised learning method that use the green channel information as the proxy of PPG after spatial averaging of RGB video.

ICA\textsuperscript{25}: is an unsupervised learning method that using Independent Component Analysis (ICA) is applied to normalized spatially averaged color signal to recover demixing matrices.

CHROM\textsuperscript{24}: is an unsupervised learning method that uses a linear combination of the chrominance signals obtained from the RGB video.

POS\textsuperscript{21}: the plane-orthogonal-to-the-skin (POS) method uses a principled approach that calculates a projection plane orthogonal to the skin-tone based on physiological and optical principles. A fixed matrix projection is applied to the spatially
normalized averaged pixel values then be used to recover PPG waveform.

PBV\textsuperscript{22}: A signature, that is determined by a given light spectrum and changes of blood volume pulse, is used to derive PPG waveform to offset motion and other noises in RGB videos.

LG\textsuperscript{23}: A feature representation method that is invariant to motion of a differentiable local transformation.

**Supervised**
The following methods all supervised neural networks to recover estimated BVP signal.

DeepPhys\textsuperscript{5}: is a 2D convolutional attention network architecture. The two representations (appearance and difference frames) processed by parallel branches with the appearance branch guiding the motion branch via a gated attention mechanism. The target signal is the first differential of the PPG wave.

TS-CAN\textsuperscript{7}: is a 2D convolutional attention network architecture that leverages temporal shift operations information across the time axis to perform efficient temporal and spatial modeling. The target signal is the first differential of the PPG wave.

PhysNet\textsuperscript{6}: is a 3D convolutional network architecture. Yu et al. compared this 3D-CNN architecture with a 2D-CNN + RNN architecture finding that a 3D-CNN version was able to achieve superior PR prediction errors. Therefore, we included the 3D-CNN in this case.

**Postprocessing and Evaluation**
There are several standard postprocessing steps that are typically employed to improve model predictions. A 2nd-order Butterworth filter (cut-off frequencies of 0.75 and 2.5 Hz) is applied to filter the predicted PPG waveform. The choice of filtering parameters can have a significant impact on downstream results such as heart rate MAE. Fast Fourier transform is then applied to the filtered signal to calculate the heart rate.

**Baselining and Results**
To show that the implementations of the baseline methods are functioning as expected and provide benchmark results for consumers of the toolbox to reference and reproduce, we performed a set of baseline experiments using three commonly used video rPPG datasets: SCAMPS\textsuperscript{27}, UBFC\textsuperscript{18}, and PURE\textsuperscript{19}. Table 2 and Table 3 show mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE) and Person Correlation (\(\rho\)) computed between the video-level heart rate estimates and gold standard measurements.

**Conclusion**
Research relies on the sharing of ideas; sharing of this kind is vital because it allows methods to be verified, saves time and resources, and allows researchers to more effectively build upon existing work. Only a small percentage of the papers published on rPPG include public code. Without these resources fair comparison and evaluation of methods is difficult, creates needless repetitions and wastes resources. We present a comprehensive toolbox containing code for preprocessing multiple public datasets, implementations of supervised and unsupervised machine learning methods (including training code), and postprocessing and evaluation tools.

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