Signal Analysis and Classification of Photoplethysmography (PPG) Waveforms for Predicting Clinical Outcomes

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Introduction

- Photoplethysmogram (PPG) is a non-invasive circulatory signal related to the pulsatile volume of blood in tissue and is typically collected by pulse oximeters [1].
- Each year, an estimated 390 million dengue infections occur around the world, of which 96 million manifest clinically (with any severity of disease) [2].
- Pulse oximeters are low-cost wearable devices that would monitor patients during epidemics to support medical triage and management in severe dengue.
- Our clinical partners, Oxford University Clinical Research Unit (OUCRU) in Vietnam has been collecting prospective clinical data from patients with dengue [3].
- However, these raw data collected via pulse oximeters can be subject to artefact and noise, and is very susceptible to patient movement; therefore, cannot be used directly to provide effective medical advice.

Aim

- We aim to analyse the raw PPG waveforms and develop signal quality indices (SQIs) to label the segmented data and visualise the signal quality clusters in 2-D space.
- The ultimate goal is to achieve automatic labelling of PPG quality, when a dataset with both the input features (SQIs, raw data, spectrograms) and quality outcomes (classes) are ready.

Method

- The flowchart of PPG analysis method is shown in Fig. 1.
- The Signal Quality Index (SQI) we use in this project:
- Skewness
- Kurtosis
- Signal-to-Noise Ratio (SNR)
- Zero-Crossing Rate (ZCR)
- Mean-Crossing Rate (MCR)
- Mean Signal Quality (MSQ)
- Perfusion

Results

1. Data Preprocessing

Dataset

- The 01NVa dataset collected by OUCRU from Vietnam [3].
- PPG data from adult patients are sampled 100 times per second. The statistics of the data are shown in Table.1.

Data Preparation

- The quality of the raw signal has four categories, see Fig.2.
- To simplify the classification, excellent and acceptable waveforms are collectively referred to as good waveforms. Then the three classes are: good, unfit, and zero.
- Concatenate the data of 4 patients (01NVa-003-2001, 2012, 2103, and 2104).
- PPG data of each patient are trimmed 5 minutes from head and tail, and the remaining data are normalised to [0,1]. The normalised data are truncated into 10-second windows. Each window has 1000 numbers. Total 20890 data samples (windows).

2. Feature Extraction

Signal Quality Index (SQI)

- 7 SQIs in Method are calculated to measure each PPG window. The resulting SQI feature is a 20890 * 7 matrix.

Spectrogram

- Tukey window with 1/8 of a window's length overlap at each end, and the size of an output spectrogram is 129 * 4. Three spectrogram examples of good, unfit and zero waveforms are shown in Fig.3.
- Since most of the frequency entries of the spectrograms are 0 from 21 to 129, the spectrograms are all cropped to 20 * 4.

3. Semi-Automatic Labelling

- Semi-automatic labelling is to generate quality labels (0, 1, 2) for the windowed PPG dataset. Will be the ground truth for subsequent visualisation and classification.
- Mini-Batch K-Means clustering algorithm. The number of each quality label is listed in Table.2.

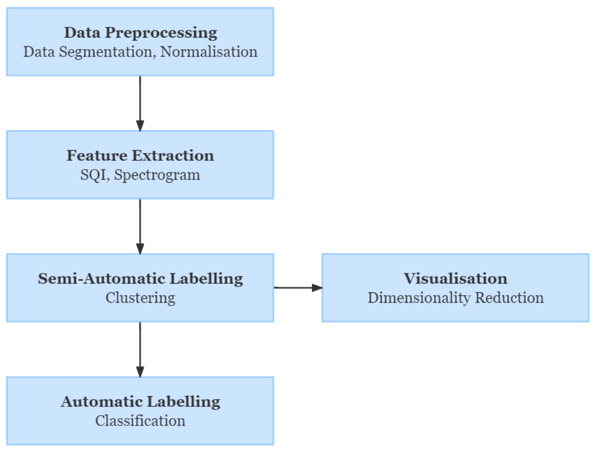


Fig. 1: Flowchart of PPG signal analysis and classification methods

Patient number	PPG length	Time (h)	Mean	Std	Min	Max
01NVa-003-2001	5626377	15.628	29698.443	17799.433	0	65535
01NVa-003-2012	5176634	14.379	17115.179	20088.398	0	65535
01NVa-003-2023	1645899	4.571	13441.664	18889.555	0	65535
01NVa-003-2023	2122127	5.894	25176.773	19579.210	0	65535
01NVa-003-2028	878261	2.439	32693.617	15787.726	0	65535
01NVa-003-2103	5297036	14.713	11461.761	17913.632	0	65535
01NVa-003-2104	5027951	13.966	28195.070	17829.383	0	65535
01NVa-003-2109	3896567	10.823	31364.225	16738.005	0	65535
01NVa-003-2110	4404269	12.234	26306.603	18766.272	0	65535
01NVa-003-2110	189207	0.525	20162.520	19859.245	0	65535
01NVa-003-2162	5464398	15.178	28381.130	18558.764	0	65535

Table. 1: 01NVa PPG dataset and statistics of some adult patients

Label	2	1	0
Quality	Good	Zero	Unfit
Number	9906	7076	3908

Table. 2: Result of semi-automatic labelling

Input data	Decision tree	Random forest	AdaBoost
Raw PPG signal	0.8422	0.9151	0.7436
SQI	1.0	1.0	1.0

Table. 4: Accuracy of 3 classifiers on raw PPG signal and SQI

Encoder	Activation	LR	Epoch	Batch	Optimiser	Loss
[20, 14, 8, 5, 2]	ReLU	1e-3	20	128	Adam	MSE

Table. 3: Autoencoder settings

Activation	LR	Epoch	Batch	Optimiser	Loss
ReLU, Softmax	1e-3	100	256	Adam	Cross Entropy

Table. 5: CNN settings

4. Visualisation

- The 7-D SQI features are reduced to 2-D by PCA and autoencoder. By using clustering in the 2-D space, we can intuitively see how the PPG samples are distributed.

Principal Component Analysis (PCA)

- See the results in 2-D in Fig.4.
- The good PPG samples are the yellow points at about (-33, 0). Zero samples are the blue points at (65.327, -0.461). Unfit samples are the purple points around the yellow dots.
- The labelling result: (Good: 10936, Zero: 7076, Unfit: 2878).
- The results of PCA dimensionality reduction method are stable and remain unchanged in different trials.

Autoencoder

- The settings are in Table.3. The 2-D result is in Fig.5.
- The good PPG samples are the purple dots at about (2, 0). Zero samples are the blue dots at (105.125, 6.918). Unfit samples are the yellow dots around the purple dots.
- The labelling result: (Good: 7132, Zero: 7077, Unfit: 6681).
- Autoencoder is very hard to tune, train, and converge.
- The clustering results of PCA are closer to the ground truth, while the results of autoencoders deviate much.
- The results after dimensionality reduction are all close to a straight line, which means that one SQI may play a leading role among the 7 in the classification of signal quality.

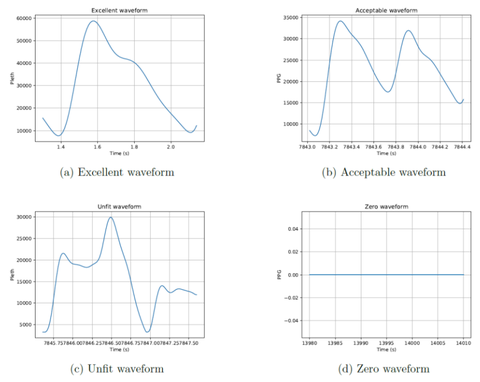
5. Automatic Labelling

Decision Tree, Random Forest, and AdaBoost

- 3 classifiers performed on the SQI and raw PPG data.
- The average accuracy on 10 trials of the three classifiers on the test set is shown in Table.4. Random forest > Decision tree > AdaBoost
- Raw data classification is very slow. SQI 100% accurate but hard to calculate SQIs for classification input.

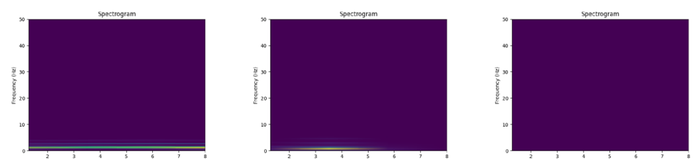
Convolutional Neural Networks (CNN)

- The accuracy and loss for training and validation (batch size=256) is shown in Fig.6.
- Test accuracy is 0.85352. The settings are in Table.5.
- The accuracy of CNN classification is slightly higher than decision trees and lower than random forests. The time taken by CNN to classify spectrograms is much lower than that of random forests to classify raw data.



(a) Excellent waveform (b) Acceptable waveform (c) Unfit waveform (d) Zero waveform

Fig. 2: Classes of PPG waveform



(a) Good spectrogram (b) Unfit spectrogram (c) Zero spectrogram

Fig. 3: Classes of PPG spectrogram

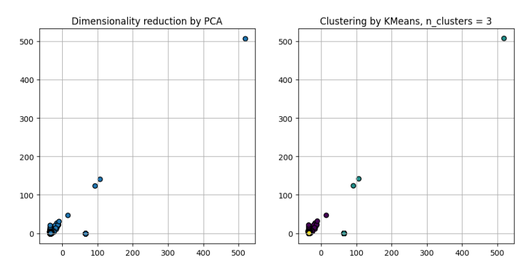


Fig. 4: SQI features dimensionality reduced by PCA and clustered by mini-batch k-means

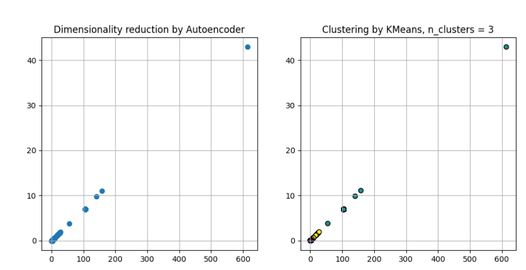


Fig. 5: SQI features dimensionality reduced by autoencoder and clustered by mini-batch k-means

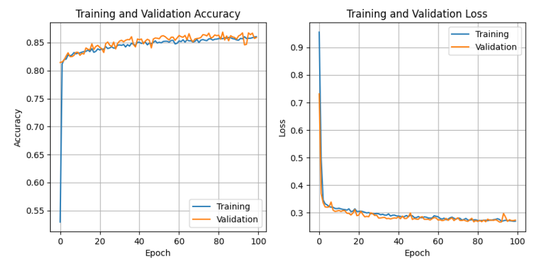


Fig. 6: CNN training and validation accuracy and loss

Conclusion

- SQI is an effective PPG feature that facilitates quality labelling and dimensionality reduction.
- Spectrogram is also an effective PPG feature, and the CNN classifier has good stability, good flexibility, high accuracy and fast speed.
- The classification accuracy of random forest is higher than that of decision tree and AdaBoost, but it is slow to calculate on raw data.
- For raw PPG waveform without labels, it is ideal to label with SQIs. For labelled PPG datasets, computing the spectrogram and using CNN for classification is preferred.

Future Work

- Continue the search on finding the most effective SQIs/features for measuring PPG quality. Try to get rid of some SQIs that do not measure quality well.
- Explore more advanced time-series clustering algorithms.
- Try to represent the PPG quality in continuous scores, and the classification problem becomes a regression problem.
- Real-time PPG signal quality analysis methods on wearable devices can be studied.

References

[1] M. Elgendi, "Optimal signal quality index for photoplethysmogram signals," *Bioengineering*, vol. 3, (4), pp. 21, 2016.
[2] S. Bhatt et al, "The global distribution and burden of dengue," *Nature*, vol. 496, (7446), pp. 504-507, 2013.
[3] The OUCRU datasets. Available: https://bahp.github.io/vital-oucru-clinical/datasets/overview.html#the-01nva-dataset.