RESEARCH ARTICLE

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Photoplethysmogram Signal Quality Assessment Using Support Vector Machine and Multi-Feature Fusion

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Background: Noise is unavoidable in the physiological signal measurement system. Poor quality signals can affect the results of analysis and disable the following clinical diagnosis. Thus, it is necessary to perform signal quality assessment before we interpreting the signal. *Objective*: In this work, we describe a method combing support vector machine (SVM) and multi-feature fusion for assessing the signal quality of pulsatile waveforms, concentrating on the photoplethysmogram (PPG). *Methods*: PPG signals from 53 healthy volunteers were recorded. Each had a 5 min length. Signal quality in each heart beat was manual annotated by clinical expert, and then the signal quality in 5 s episode was automatically calculated according to the results from each beat segments, resulting in a total of 13,294 5-s PPG segments. Then a SVM was trained to classify clean/noisy PPG recordings by inputting a set of twelve signal quality features. Further experiments were carried out to verify the proposed SVM based signal quality classifier method. *Results*: An average accuracy of 87.90%, a sensitivity of 88.10% and a specificity of 87.66% were found on the 10-fold cross validation. *Conclusions*: The signal quality of PPGs can be accurately classified by using the proposed method.

Keywords: Signal Quality Assessment, PPG, Feature, SVM.

1. INTRODUCTION

Physiological signal is characterized by small amplitude, wide spectrum and complicated noises. Noises from a variety of sources may corrupt the physiological signals, therefore, signal quality assessment (SQA) is an essential step for automated signal processing. SQA has been studied on a variety of physiological signals, such as electrocardiogram (ECG),[1,2] arterial blood pressure (ABP),[3] photoplethysmograms (PPG),[3] electroencephalogram (EEG),[4] electromyogram (EMG)[5] and phonocardiogram (PCG).[6]

Recently, PPG is widely used in clinical practices such as heart rate, respiratory rate,[7] gastric motility,[8] arterial stiffness[9] etc., and due to it is easy to obtain by a pulse oximeter. The signal quality of PPG is fine in rest measuring condition. But the signals are easily corrupted by various noises, such as ambient light changes, motion artifacts and electromagnetic noise coupling from other electronic instruments.[10,11] To reduce the noise, various signal processing techniques have been investigated, which include adaptive noise cancellation, wavelet-transform, adaptive filter techniques, cyclic moving average filter, and novel nonlinear approaches.[12–16] Although most of these filtering methods can used in low level noise situation, they may not reach the desired effect if the level of noise is high. To avoid making wrong diagnosis, using the signal with noise in clinical is forbidden. The effective quality assessment method is a great challenge in PPG signal processing research. How to improve the accuracy of SQA is attracting more attention from domestic and foreign researchers. Yu et al. provided a robust approach for automatically assessing the reliability of large quantities of the PPG waveforms, based on time-domain features.[17] Several studies used bispectral analysis, kurtosis and skewness measures.[18] Sukor et al. presented a novel waveform morphology analysis-based method for automatic rejection of artifact contaminated pulse oximetry waveforms.[19] Gil et al.[20] and Monasterio et al.[21] used Hjorth parameters for assessing PPG signal quality. Silvar et al. presented a new generic point-by-point signal quality index (SQI) that does not rely on morphological feature extraction from the target waveform, compared with the signal-to-noise ratio (SNR).[3] In addition, a stand-alone SQA algorithm for assessing

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Table I. Basic information of all 53 subjects.

Variables	Value
No.	53
Female/Male	27/26
Age (year)	24 ± 1
Height (cm)	168 ± 8
Weight (kg)	59 ± 11
Body mass index	21 ± 2
Heat rate (beats/min)	71 ± 9
Systolic blood pressure (mmHg)	119 ± 15
Diastolic blood pressure (mmHg)	71 ± 10

Note: Data are expressed as numbers or mean ± standard deviation (SD).

PPG signal quality by introducing dynamic time warping to stretch each beat to match a running template, achieving a classification rate of 95.2% on independent test set.[22] Orphanidou et al. presented an PPG SQA algorithm by providing a real-time assessment of the suitability of PPG signals for deriving reliable HR values.[23] Li et al. developed a unique onboard feature detection algorithm to assess the quality of PPGs obtained by a wireless pulse oximeter.[24] Some authors used higher order statistics (HOS) to identify corrupt data by motion artifact, but for a variety of noise, the feature is more limited. Template matching, and other quality assessment algorithms need a longer computing time, which cannot achieve the requirements of real-time clinical assessment.

In this study, a multi-feature fusion and SVM based PPG signal quality assessment method was proposed to explore an automated and efficient analysis of such signals. Twelve signal quality metrics were computed from each recording, and then eight metrics with better classification effect were used to classify PPG signal quality using SVM classifier.

2. METHOD

2.1. Data Collection

Fifty-three healthy volunteers (27 females and 26 males) were recruited in this study. They all had no history of cardiovascular disease, mental illness, or alcohol records. All subjects signed the informed consents before the experiment. The study received ethical permission from Shandong University and the Second Affiliated Hospital of Jining Medical College in China by the Committee for Ethical Affairs.

The details for the involved subjects are depicted in Table I.

The experiment was performed in a quiet and temperature controlled (24 ± 2 °C) room. PPG signals were recorded using RM6240B system (Chengdu Instrument Factory, Chengdu, China) with a sample rate of 1,000 Hz. The testing position for PPG sensors is the index finger of the right hand. 5 minutes PPG signals of each subject was collected.

2.2. Annotations of PPG Signal Quality

PPG recordings were manually annotated as good (SQI = 1) or poor (SQI = 0) for each beat pulse. Examples of good and poor signal quality beats are shown in Figure 1.

Each PPG recording was non-overlapped segmented into 5-s PPG segments, resulting in 13,294 5-s PPG segments totally. The signal quality of each 5-s PPG segment was determined based on

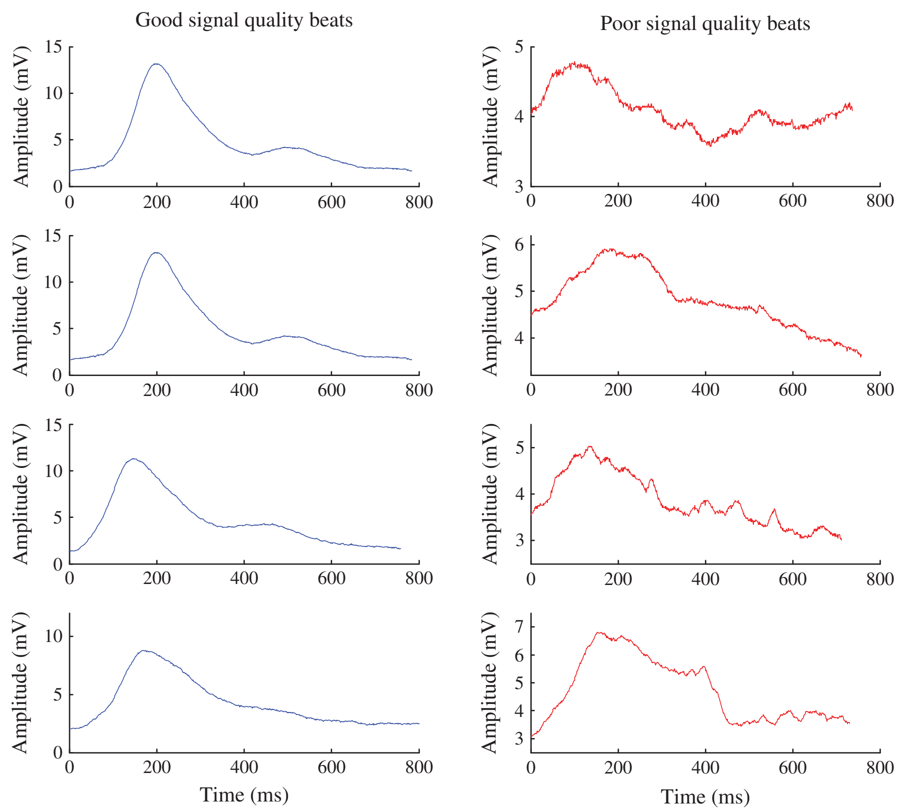

Fig. 1. Examples of good (left) and poor (right) signal quality pulse beats.

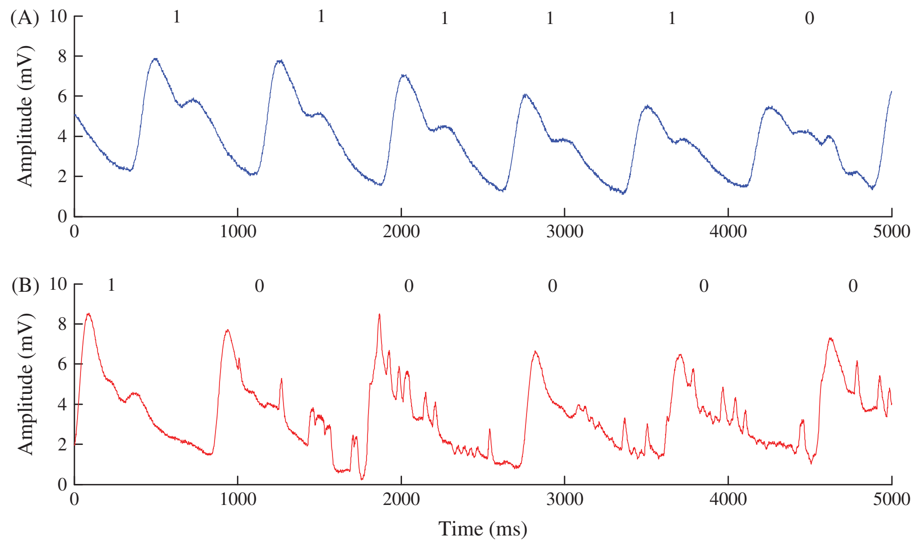

Fig. 2. Examples of 5-s pulse segments with good (A) and poor (B) signal quality. Signal quality labels for each beat are also shown. The 5-s pulse segment with good signal quality has an arithmetic mean of SQI of 0.83, and the 5-s pulse segment with poor signal quality has an arithmetic mean of SQI of 0.17.

the manual signal quality annotations for each beat pulse. The annotated rule for signal quality of 5-s PPG segment is listed as following.

If the arithmetic mean of SQIs is higher than 0.8, the 5-s PPG segment was labeled as good, otherwise was labeled as poor, resulting in a total of 12,641 good and a total of 653 poor 5-s PPG segments. Examples of 5-s PPG segments with good and poor signal quality are shown in Figure 2. The data profile is shown on Table II.

2.3. Signal Quality Features

The following features were calculated for each recording:

(1) kSQI: the kurtosis of the waveform, it is usually defined as follows:[18]

$$\text{Kurtosis} = \frac{\mu_4}{\sigma^4} - 3 \tag{1}$$

Where σ is the standard deviation, μ_4 are the fourth moments.

(2) svdSQI: the minimum ratio of the second to first singular value from the singular value decomposition (SVD) of varying window sizes of the autocorrelation function.[6]

$$[U, S, V] = svd(A)$$
$$\text{ratio} = S(1,1)/S(0,0) \tag{2}$$

where S is the diagonal matrix, $S(1,1)$ and $S(0,0)$ are the singular values of A.

(3) vSQI: the variance of the autocorrelation function.[6]

(4) skSQI: the skewness of the waveform, it is defined as follows:[18]

$$\text{Skew} = \frac{\mu_3}{\sigma^{3/2}} \tag{3}$$

Where σ is the standard deviation, μ_3 are the third moments.

Table II. Data profile of PPG recordings with good and poor signal quality.

	Good signal quality	Poor signal quality	Total
# beats	75,839	3,387	79,226
# 5-s PPG segments	12,641	653	13,294

(5) ccSQI: the correlation coefficient between waveform and a fitted, rectified sine waveform.

(6) seSQI: the sample entropy (SampEn) with different parameters of the waveform.[6] Two features with different parameters are put into use, seSQI1 with parameters of $m = 1$, $r = 1$; and seSQI2 with parameters of $m = 1$, $r = 0.15$.

(7) aaSQI: the average absolute amplitude of the normalized waveform after high-pass filtering with a frequency of 10–15 Hz.

(8) arSQI: the ratio of the maximum and minimum of the average absolute amplitude in all 1-s window normalized waveform.

(9) fqSQI: the percentage of the frequency component within 1–10 Hz of total frequency component.

(10) qrSQI: the ratio of the difference of the 95% quantile to the 5% quantile marked as qrSQI1, and the 90% quantile to the 10% quantile marked as qrSQI2, of the sorted data of the first 2.5 s with that of the last 2.5 s.

Thus, twelve SQIs were used in this study.

2.4. Support Vector Machine-Based Classifier

The classifier was based on SVM model, and widely used libSVM library[25] was used to train the classification model. As shown in Table II, the numbers of "good" class samples is almost ten times more than "poor" class samples, the data set is imbalanced, which will cause bias and poor generalization ability of the classification model. So we randomly selected 653 5-s PPG segments with good signal quality to match the 653 5-s segments with poor signal quality, to construct the experiment data for classifying good/poor signal quality segments.

Gaussian kernel was used in SVM model training. Considering the parameter C controls how strict the classifier is, which defines the relative importance of maximizing the margin and minimizing the amount of slack. A large value of C will assign a high penalty to errors and margin errors. Another parameter γ controls the width of Gaussian function. γ were optimized using a grid search method with the search range over C (from 0.5 to 724) and γ (from 4 to 32).[26] To evaluate the model performance, 10-folder cross validation method was used for testing the SVM classifier.

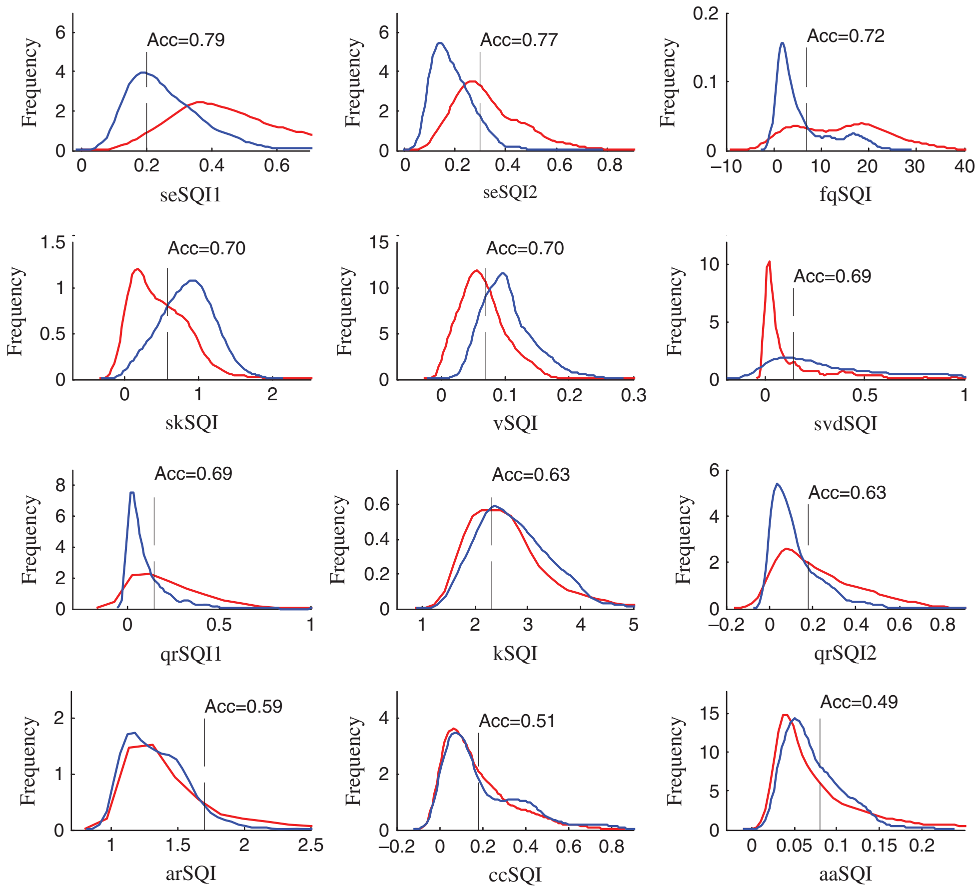

Fig. 3. Each of twelve SQIs with distribution of good (blue) and poor (red) parts is sorted. There are the threshold of each SQI with the peak classification accuracy.

3. RESULT

First, we ranked the classification accuracy for all 12 features as shown in Figure 3, which shows seSQI achieved the best classification accuracies: 0.79 for seSQI1 and 0.77 for seSQI2 respectively, followed by the features of seSQI (0.72), skSQI (0.70), vSQI (0.70), svdSQI (0.69), qrSQI1 (0.69), kSQI (0.63), qrSQI2 (0.63), arSQI (0.59), ccSQI (0.51). Feature aaSQI reported the worst classification accuracy of 0.49.

Then, 10-folder cross validation was performed by inputting different number of the ranked best features, from only one to the total of 12. Figure 4 shows the corresponding classification accuracy when using different numbers of the SQI features. The results indicate that the maximum classification accuracy achieved by using the first eight best features. The corresponding classification sensitivity and specificity were shown in Figures 5 and 6. It is clear that using total 12 features output the highest sensitivity and using the first seven best features reported the highest specificity.

Table III gives the detailed 10-folder cross-validation results using the first eight best features. The optimized parameters C and γ for each folder were also shown. The mean *Acc* of the

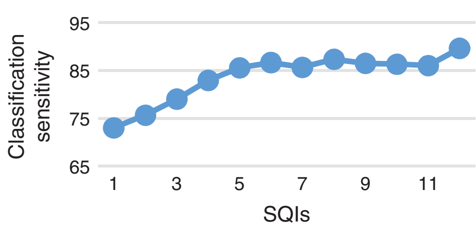

Fig. 5. The classification sensitivity with different numbers of the SQIs.

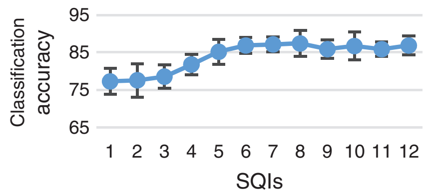

Fig. 4. The classification accuracy with different numbers of the SQIs.

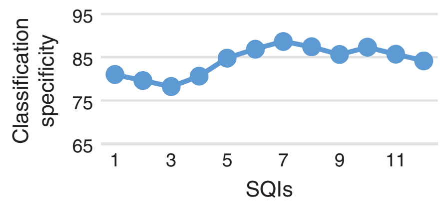

Fig. 6. The classification specificity with different numbers of the SQIs.

Table III. Classification accuracy of the 10-folder cross validation. SD: Standard deviation. True positive (TP), false positive (FP), true negative (TN), false negative (FN), sensitivity (Se), specificity (Sp) and accuracy (*Acc*).

Folder	*C*	γ	TP	FN	FP	TN	Se (%)	Sp (%)	*Acc* (%)
1	256.00	4.00	57	9	12	53	86.36	81.54	83.97
2	32.00	11.31	54	5	2	70	91.53	97.22	94.66
3	128.00	5.66	59	6	11	54	90.77	83.08	86.92
4	5.66	32.00	62	7	10	51	89.86	83.61	86.92
5	90.51	5.66	53	7	9	62	88.33	87.32	87.79
6	22.63	11.31	57	10	6	57	85.07	90.48	87.69
7	181.02	5.66	63	7	5	56	90.00	91.80	90.84
8	362.04	4.00	59	6	12	53	90.77	81.54	86.15
9	256.00	5.66	57	8	7	59	87.69	89.39	88.55
10	5.66	22.63	54	13	6	58	80.60	90.63	85.50
Mean	133.95	10.79	57.5	7.8	8	57.3	88.10	87.66	87.90
SD	125.46	9.36	3.34	2.35	3.33	5.54	0.03	0.05	3.00

10-folder cross-validation results was 87.90% with a standard deviation (SD) of 3.00%.

4. DISCUSSION AND CONCLUSION

PPG signal can be affected by noise obviously especially motion artifacts and electronic instruments. We presented several signal quality index (SQI) which is intended to provide a assessment for PPG signals. A SVM based classifier was trained for the task of PPG signal quality assessment, and it achieved mean sensitivity of 88.10% and mean specificity of 87.66%. Although the PPG quality assessment had been previously investigated, the gold standard was defined by computing not artificial.[17, 18] Results show that PPG signal quality can be estimated in more detail based on our method.

Previous quality assessment algorithms sometimes calculate few index and need a longer computing time, which cannot achieve the requirements of real-time clinical assessment. In this paper, an algorithm is studied to find more effective quality index to consume computing time and improve signal recognition accuracy. It does not depend on the parameter adjustment and is convenient for operator, which can be widely applied to clinical monitoring and diagnosis.

It can be seen on Table III and Figure 4 that classification effect not depend on parameters γ and C only, the number of features also makes a great difference. The mean γ used is 10.79, and mean C is 133.95. Some of them have C greater than 256, which may lead to over-fitting. Therefore, in the training of SVM algorithm, we should try to reduce the value of C to avoid overfitting. Besides, the use of eight SQIs across all datasets resulted in the best accuracy. The accuracy is reduced after increasing features, since the over-fitting is increased to a certain extent. The most frequently used features are the sample entropy and skewness.

Further investigation of other classification techniques are required particularly to improve the sensitivities. The better performance of classification also need effective and sensitive features to be further studied. And most of these kinds of studies are focused on single channel signal, recently. It is necessary of further research on multiple signals to improve estimation of vital signs.

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