Signal Quality Measures on Pulse Oximetry and Blood Pressure Signals Acquired from Self-Measurement in a Home Environment

Jumadi Abd Sukor, Mas S. Mohktar, *Member, IEEE*, Stephen J. Redmond, *Member, IEEE*, and Nigel H. Lovell, *Fellow, IEEE*

Abstract—Recently, decision support system (DSSs) have become more widely accepted as a support tool for use with telehealth systems, helping clinicians to summarize and digest what would otherwise be an unmanageable volume of data. One of the pillars of a home telehealth system is the performance of unsupervised physiological self-measurement by patients in their own homes. Such measurements are prone to error and noise artifact, often due to poor measurement technique and ignorance of the measurement and transduction principles at work. These errors can degrade the quality of the recorded signals and ultimately degrade the performance of the DSS system, which is aiding the clinician in their management of the patient. Developed algorithms for automated quality assessment for pulse oximetry and blood pressure (BP) signals were tested retrospectively with data acquired from a trial that recorded signals in a home environment. The trial involved four aged subjects who performed pulse oximetry and BP measurements by themselves at their home for ten days, three times per day. This trial was set up to mimic the unsupervised physiological self-measurement as in a telehealth system. A manually annotated "gold standard" (GS) was used as the reference against which the developed algorithms were evaluated after analyzing the recordings. The assessment of pulse oximetry signals shows 95% of good sections and 67% of noisy sections were correctly detected by the developed algorithm, and a Cohen's Kappa coefficient (κ) of 0.58 was obtained in 120 pooled signals. The BP measurement evaluation demonstrates that 75% of the actual noisy sections were correctly classified in 120 pooled signals, with 97% and 91% of the signals correctly identified as worthy of attempting systolic and/or diastolic pressure estimation, respectively, with a mean error and standard deviation of 2.53 ± 4.20 mmHg and 1.46 ± 5.29 mmHg when compared to a manually annotated GS. These results demonstrate the feasibility, and highlight the potential benefit, of incorporating automated signal quality assessment

algorithms for pulse oximetry and BP recording within a DSS for telehealth patient management.

Index Terms—Blood pressure (BP), pulse oximetry, signal quality.

I. INTRODUCTION

A USEFUL telehealth medical records are dependent to the quality of data in the databases [1]. There are two main criteria of data quality; the precision (accuracy) and the completeness. Accuracy is the belief that data are correct, and completeness is the impression that data are recorded in the database [2].

A study by Aronsky *et al.* has used routinely recorded computerized patient records in a decision support system (DSS) to assess the risk of mortality in patients with community-acquired pneumonia. The data quality issue affected 27.9% of the DSS output, with the system underestimating the patient's risk of mortality [3]. The study above indicated that a DSS using poor data quality may generate and send false recommendations to clinical users. Consequently, the quality of data area becomes a significant and fundamental issue in the design of a DSS [1]–[5].

Three studies have examined the impact of data quality on DSS performance. However, two of the studies analyzed medical data recorded in supervised clinical environments and the third study used simulated data [1]–[3]. It can easily be argued that home telehealth data quality is going to affect the performance of a DSS, as the measurement is performed in an unsupervised environment [6].

Thus, to ensure the guidance provided by the DSS is reliable, the quality of the data used in the system should be assessed prior to utilization. The data collected by the home telehealth system should be free from erroneous values [2], [3].

Measured home telehealth vital sign data, such as peripheral blood oxygen saturation (SpO_2), heart rate (HR), and systolic and diastolic blood pressures are derived automatically from acquired signals. Currently, to our knowledge, there are no standard approaches in handling contaminated raw signals in such unsupervised telehealth recordings. Therefore, if an extracted measurement parameter is of concern because it is excessively high or low, it is difficult to determine the credibility of the given parameter [7]. Pulse oximetry is a noninvasive method for monitoring a patient's oxygen (O_2) saturation. Heart rate can also be derived from the signal. SpO_2 represents the estimates of the oxygen saturation (SaO_2) value; that is the ratio of oxygenated hemoglobin (HbO_2) to the combined amount of HbO_2 and deoxygenated hemoglobin (Hb) present in arterial blood.

The way of measuring SpO$_2$ using pulse oximetry is based on the principle of photoplethysmography (PPG). A typical PPG probe uses two wavelengths (red and infrared) and each wavelength is preferentially absorbed by HbO$_2$ or Hb in the blood. This enables the derivation of SpO$_2$ estimate using a general empirical linear approximation [8].

Despite the considerable advantages obtained by employing pulse oximetry for SpO$_2$ estimation, there are some factors that may degrade the accuracy of the estimation. The introduction of ambient light at the photodetector, wearing nail polish, poor blood perfusion of the peripheral tissues, motion artifact (including the relative movement between the fingertip and the oximetry probe), are all well-known sources of error [9].

The measurement of blood pressure (BP) through noninvasive blood pressure monitors (NIBPMs) is highly vulnerable to artifact such as patient movement; external vibration and coughing that subsequently leads to degradation in the accuracy of the measurement. When the measurement is contaminated with motion artifact, the air flow in the deflating cuff is typically interrupted, causing corruption of the small pressure oscillations from each heartbeat, which constitutes the oscillometric waveform [10], as well as introducing acoustic artifact that will be picked up by the microphone used to detect the Korotkoff sounds [11], [12]. As well as pulse oximetry measurement, the motion artifact is likely to occur in an unsupervised home environment.

Pulse oximetry and BP signal quality algorithms have been developed by our research group to detect and eliminate artifact in noise contaminated pulse oximetry signals and to assess the quality of an NIBPM measurement, respectively [13], [14].

The main objective of this paper is to assess the performance of the developed algorithms as in [13] and [14] when measuring the quality of the respective signals acquired from self-measurement performs by the subjects in their homes, which involved the presence of a trainer nearby but not actually intervening during the subject's signal acquisition process. This is a preliminary study before the developed algorithms are tested with the actual data recorded in a telehealth system. The methodology for assessing the performance of the algorithms is by comparing the output from each algorithm against a manually annotated gold standard (GS).

II. Methods

A. Subjects

In general, the preferred subjects for this study were aged people (since home telehealth systems are commonly used with older people) who were able to perform the physiological measurement protocols. Therefore, the general criteria for inclusion were: over 50 years old, able to operate a mouse using the hand contralateral to the hand being measured, willing to use a computer, independently living and ambulant. The specific exclusion criterion was peripheral vascular disease, since it may cause physiological artifacts (this was determined from information in a pretest questionnaire that was completed by subjects beforehand). The study required subjects to perform self-administered measurements of pulse oximetry and BP in their own homes.
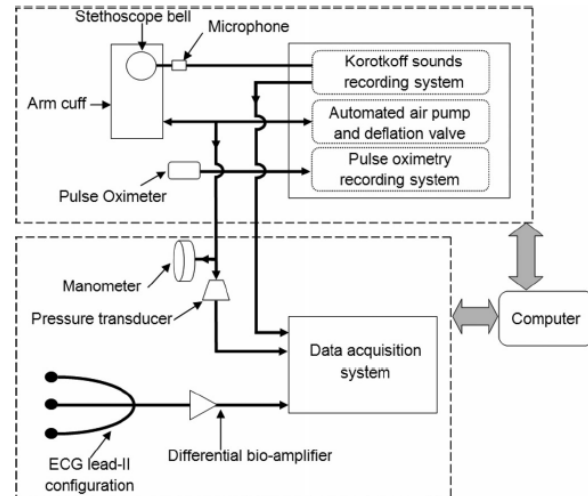

Fig. 1. System used to acquire simultaneous ECG, BP and pulse oximetry signals.

There were four qualified subjects, two males (65 and 67 years old) and two females (59 and 62 years old), who participated in the study.

B. Data Acquisition

In this study, simultaneous electrocardiography (ECG) and pulse oximetry, and simultaneous ECG and BP signals were recorded using a data acquisition system, which was set up as shown in Fig. 1. Note that the ECG was simultaneously recorded in order to be used as a reference signal for pulse oximetry and BP signals as described in detail in [13] and [14].

Signals were acquired from each subject for over ten days, with the subject performing pulse oximetry and BP measurements in a closed room at their homes three times per day: before 9 A.M., between 1 P.M. and 2 P.M. and after 5 P.M. This condition was purposely set up to mimic the unsupervised telehealth environment.

Before the study took place, subjects had a brief training session on the study background and the measurement protocols and devices. This session was conducted by a trainer at the subjects' homes. During the session, the trainer first briefly explained the background of the study then verbally and practically explained each protocol that was to be performed to measure pulse oximetry and BP, demonstrated in their home as they would use it. Finally, in order for the subjects to familiarize themselves with, and correctly perform the measurement protocols, the trainer supervised while they practiced until they were able to complete them unassisted.

On every occasion before the subject performed the pulse oximetry and BP measurement during the study, the trainer placed ECG leads on the subject, to ensure that a good quality ECG as a reference signal would be acquired, and then, left the subject's house so that the subject could perform the measurements unsupervised.

C. Measurement Protocol

The pulse oximetry recording was executed first, followed by BP. The subject placed the BP cuff on an arm and clipped the pulse oximeter on the middle finger, of the hand ipsilateral to the BP cuff. On the provided computer screen, a measurement graphical user interface (MGUI) was presented to the subject.

The subject started the pulse oximetry measurement by clicking the "Pulse Oximetry" icon using the hand contralateral to the measured hand, causing a new window to appear on the laptop screen, indicating that the measurement was being performed. After 1 min, the window automatically closed and the MGUI reappeared on the screen, indicating that 1 min of pulse oximetry had been completed.

When measuring BP, the subject clicked on the "BP" icon and a new pop-up window was displayed. After clicking the "Start" icon electronically controlled mechanical pump automatically started inflating the cuff. During this measurement, cuff pressure, Korotkoff sounds, and the ECG signal were simultaneously recorded by the data acquisition system. When this automated BP measurement was complete, the displayed window automatically closed.

D. GS Development

The GS development was based on the same methods applied in [13] and [14], for pulse oximetry and BP, respectively. In the development processes, two human experts (known as Rater 1 and Rater 2) for each signal first manually annotated the recorded signal to classify any noise section in the signals. Then, as a group of two (for each signal), any discrepancy in the marking was reconciled.

E. Algorithm

1) Pulse Oximetry: The pulse oximetry noise detection algorithm (NDA) is based on waveform morphology analysis of the PPG to automatically identify noise artifact in contaminated pulse oximetry waveforms. The output of the algorithm comprises sections of clean pulses free of various forms of artifact. In a simulated environment, the performance of the algorithm is compared to a manually annotated GS. The results show that the algorithm can increase the accuracy of SpO_2 estimation as well as HR derivation.

The pulse oximetry NDA has been designed to automatically classify bad, poor, and good pulses in an artifact contaminated pulse oximetry PPG signal. Three stages are involved in the classification process; 1) the pre-processing; 2) the removal of bad pulses known as Morphological analysis I, and 3) the removal of poor pulses Morphological analysis II [13].

2) BP: The BP signal quality algorithm automatically assessed the quality of a BP measurement by determining the feasibility of accurately estimating the diastolic and systolic pressures from various levels of artifact contaminated BP signals. A manually annotated reference scoring is developed and compared to the performance of the algorithm. The results from the laboratory testing demonstrate the robust performance of the

TABLE I
INTERSCORER AGREEMENT ON 120 POOLED PPG SIGNALS—NOISE DETECTION

Measure	Rater 1 v. Rater 2	Rater 2 v. Rater 1	Rater 1 v. GS	Rater 2 v. GS
Accuracy	94.86%	94.86%	95.26%	99.52%
Sensitivity	94.84%	99.70%	99.85%	99.66%
Specificity	95.25%	53.00%	55.00%	98.30%
Cohen's Kappa	0.66	0.66	0.68	0.97

algorithm, which indicates the readiness of the algorithm when implemented into existing NIBPM devices.

The function of the signal quality algorithm is first to detect noise sections (if any) from the raw signals. Then, the algorithm determines if it is possible to estimate the systolic and diastolic values from the waveform. The algorithm can be elaborated in three stages: preprocessing, noise classification, and feasibility of systolic and diastolic values estimation. A detailed description on the development of the BP signal quality and the BP NDAs can be found in [14].

F. Algorithm Performance

A comparison was undertaken between the performances of the developed algorithms [13], [14] with the relevant GS. When evaluating the performance of the developed algorithms in classifying noise sections in the pulse oximetry signals, Cohen's Kappa coefficient, accuracy, sensitivity, and specificity were calculated. When measuring the performance of the developed algorithm for the BP signal quality estimation, the following metrics were employed: the accuracy in determining if an estimate of systolic or diastolic BP should be attempted; the error in those estimated systolic and diastolic pressures (for signals where attempting such an estimate was deemed appropriate) ; and capability of classifying noise sections, as indicated by the derived accuracy, sensitivity, and specificity. Moreover, the results from the developed algorithms and the GS were compared by using Bland–Altman analyses [15].

III. RESULTS AND DISCUSSION

A total of 120 measurements for each signal (pulse oximetry and BP) were recorded throughout the study.

A. Interscorer Agreement

1) Pulse Oximetry: Table I details the interscorer agreement between the two experts when annotating the noise artifact in the 120 PPG signals. All signals are pooled to calculate the total agreement between experts (Rater 1 and Rater 2) when identifying noise artifacts. Cohen's Kappa coefficient, as shown in Table I, shows low specificity of "Rater 2 v. Rater 1" and "Rater 1 v. GS" (53% and 55%, respectively) and the high specificity of "Rater 2 v. GS" imply that the judgment in classifying noise in the PPG signal during the reconciliation process was dominantly influenced by Rater 2. The major contribution to these results is simply caused by the discrepancy in classifying the first and last pulses in each recorded signal. The discrepancy from both experts occurred when the first and/or the last trough
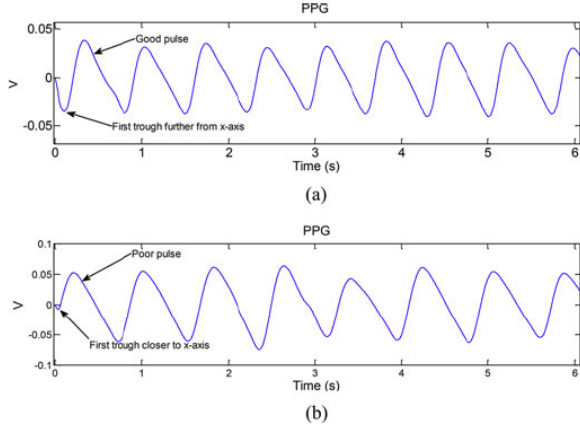
Fig. 2. Example of initial pulses in the filtered version of the PPG when (a) first trough further from x-axis and (b) first trough closer to x-axis. The initial pulse in (b) becomes a poor pulse, although it might be a good pulse in the unfiltered version of PPG.

TABLE II
INTERSCORER AGREEMENT RESULTS—POSSIBLE
SYSTOLIC AND DIASTOLIC DIFFERENCE

Approach	Mean ± standard deviation (mmHg)	n
Possible systolic difference	1.85 ± 3.57	119
Possible diastolic difference	3.00 ± 3.40	109

TABLE III
INTERSCORER AGREEMENT ON 120 POOLED BP SIGNALS—NOISE
CLASSIFICATION DETECTION

Measure	Rater 1 v. Rater 2	Rater 2 v. Rater 1	Rater 1 v. GS	Rater 2 v. GS
Accuracy	97.73%	97.73%	97.07%	97.28%
Sensitivity	92.39%	80.72%	93.24%	90.13%
Specificity	97.90%	99.81%	98.16%	97.35%

of the initial and the last pulses were closer to the x-axis. Fig. 2 (a) and (b) illustrates an example of two initial pulses with the first trough further from and closer to the x-axis, respectively. It should be noted that the scoring on pulse oximetry is based on pulse-by-pulse assessment.

2) BP: Tables II and III show the interscorer agreement results between the two human scorers in identifying possible systolic and diastolic events and classifying noise sections in 120 pooled signals, respectively.

For systolic and diastolic event, not all the systolic and/or diastolic events were detectable by the experts in each signal, due to the presence of noise that altered the visual and audio characteristics of the signal. Consequently, from 120 signals, only 119 signals were analyzed for systolic estimation, and 109 signals for diastolic estimation.

TABLE IV
ALGORITHM PERFORMANCE RESULTS—DEVELOPED ALGORITHM PPG [15]
VERSUS GS FOR VARIOUS SIGNAL CONDITIONS

Signal condition	n	κ	Accuracy (%)	Sensitivity (%)	Specificity (%)
Totally clean signal	18	undefined	93.80 ± 6.06	93.78 ± 0.06	undefined
Partly noisy signal	101	0.60 ± 0.25	91.73 ± 9.46	94.52 + 0.08	75.23 ± 0.26
Totally noisy signal	1	undefined	51.68	undefined	52.00
Pooled signals	120	0.58	91.84	94.71	66.71

The classification of signal condition (except the pooled signals) is based on the manually annotated GS.

B. Classification Performance

1) Pulse Oximetry: Table IV and Fig. 3 show the results of the noise classification when comparing the output of the developed algorithm with the GS. Note that in Table IV, "pooled signals" (in signal condition column) refers to a single long record that comprises the entire 120 signals.

In Table IV using the GS, from 120 pulse oximetry signals, 18 signals are totally clean, while only one consisted entirely of noise. The remaining 101 signals contain at least some noise. This demonstrates that approximately 85% (101 + 1) of the study data were contaminated with noise to some extent. However, the Cohen's Kappa value of 0.58 (for all signals pooled together) when detecting this noise, implies that the NDA has successfully identified many of these noise sections in the signals.

2) BP: Fig. 4 shows the results of the classification performance of the BP NDA when compared with the GS for the 61 noise-contaminated signals. Figs. 5 and 6 show Bland–Altman plots of possible systolic and diastolic pressures, respectively, with the NDA compared with the GS. Figs. 7 and 8 show Bland–Altman plots of possible systolic and diastolic pressures, respectively, without the NDA compared with the GS. In the cases in which the NDA and the GS could not determine the systolic and diastolic pressures, these signals were excluded from the calculation and the scatter plot.

In general, the noise classification from the experts (i.e., the GS) shows that artifacts that could corrupt the signals do occur when measuring pulse oximetry and BP in unsupervised home environments. Moreover, only 15% of the recorded pulse oximetry (see Table IV) and less than half of the recorded BP signals were free from noise artifacts. When observing the number of noise-contaminated signals and the summarized duration of the noise in these contaminated signals (as illustrated in Fig. 4), it can be concluded that noise artifacts have a high tendency (61.67% in this study) to occur during self-measurement of BP in the home environment; but artifacts are likely to be of short duration (less than 3 s in this study). Nevertheless, these artifacts could cause the measurement of BP to fail; in this study, for example, four of the signals may have failed to give accurate systolic pressure estimation and eight for diastolic pressure estimation.

The Bland–Altman plots comparing systolic pressures (see Fig. 5) estimated by the GS with those estimated by the developed algorithm, demonstrate that approximately 95% of the

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