Effect of Home Telehealth Data Quality on Decision Support System Performance

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Abstract

In this study, data quality analyses were performed on raw signals from two types of home telehealth measurements; the pulse oximetry and the blood pressure. The results have confirmed that home telehealth pulse oximetry and blood pressure data quality issues do affect the reliability of a decision support system (DSS) for the particular algorithms and data sets used in this study. Both techniques (the manual outlier removal and the automated signal quality analysis) have improved the performance of the DSS. Therefore, these automated signal quality tools are considered useful and will be included in the DSS for the purpose of data quality assurance. This finding has also provided an additional method that can reduce the workload imposed when performing signal recording verification manually.

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1. Introduction

Clinical DSSs linked to electronic medical records are dependent to the quality of data in the databases [1]. There are two main characteristics of data quality; the accuracy and the completeness. Accuracy is the belief that data are correct, and completeness is the notion that data are recorded in the database [2].

Some studies indicated that a decision support system (DSS) using poor data quality may generate and send false recommendations to clinical users. Consequently, the quality of data is a significant and a fundamental issue of the design of a DSS [1-5].

Unless DSS implementations can efficiently deal with such data quality problems, it is uncertain whether the guidance provided by these systems can be reliable. Subsequently, data quality needs to be assessed, because erroneous recommendations based on inaccurate data could influence DSS acceptance and may raise liability issues [4].

The effect of data quality onto DSS have been studied. Nonetheless, those studies either analysed medical data recorded in supervised clinical environments or used simulated data [1, 2, 4]. Consequently, it can effortlessly be claimed that home telehealth data quality is going to affect the performance of a DSS, as the measurement is accomplished in an unsupervised background [6]. Therefore, it is vital to extend the existing research by analysing the effect of home telehealth data quality on DSS accuracy.

In this study, the qualities of the automatically derived measurement data are evaluated using available signal quality algorithms [7, 8]. The analyses are performed on raw signals from two types of measurements collected using home telehealth system; the pulse oximetry and the blood pressure.

To demonstrate the effect of data quality on the DSS, the performance of the DSS is compared by using data that originally comes directly from the home telehealth device and against data extracted from the raw signals after performing signal quality analysis.

2. Background

2.1. Pulse Oximetry Signal Quality Analysis

Pulse oximetry is a technique that monitors SpO2 and heart rate. SpO2 represents the estimates of the oxygen saturation (SaO2) value; that is the ratio of oxygenated haemoglobin (HbO2) to the combined amount of HbO2 and deoxygenated haemoglobin (Hb) present in arterial blood.

The method of measuring SpO2 using pulse oximetry is based on the principle of photoplethysmography (PPG). A conventional PPG probe uses two wavelengths (red and infrared, often at 660 nm and 940 nm, respectively) and each wavelength is preferentially absorbed by HbO2 or Hb in the blood. This enables the derivation of a SpO2 estimate using a general empirical linear approximation (Eq. 1), where R is the ratio of red to infrared lights absorption [9, 10].

$$\text{SpO}_2 = 110 - 25R$$  \hspace{1cm} (1)

A pulse oximetry signal quality algorithm has been developed by our research group to detect and eliminate noise in noise contaminated pulse oximetry signals [8]. Fig. 1 shows one example of a PPG signal contaminated with noise. When the signal is analysed using the pulse oximetry signal quality algorithm [8], the section with bad pulses is removed and the SpO2 and heart rate values are recalculated based only on the segments of the signal containing acceptable quality beats.
2.2. Blood Pressure Signal Quality Analysis

Blood pressure usually refers to the arterial pressure of the systemic circulation. During each heartbeat, blood pressure varies between a maximum (systolic) and a minimum (diastolic) pressure; “systolic” and “diastolic” are two terms commonly used to summarise the blood pressure profile. Systolic blood pressure refers to the pressure in the systemic arteries as the heart expels blood during each beat, while diastolic blood pressure is the pressure as the heart relaxes [11]. Typically, noninvasive blood pressure monitor (NIBPM) applies two types of methods; auscultatory and oscillometric methods. The auscultatory method is based on the measurement of Korotkoff sounds while the oscillometric method is based on the oscillation of pressure in the cuff during its gradual deflation from above the systolic to below the diastolic pressure.

In the blood pressure signal quality algorithm [7], the distortions of the Korotkoff sound signals are the fundamental guide to estimate the reliability of systolic and diastolic blood pressure values. In the case of the Korotkoff signal shown in Fig. 2, the diastolic blood pressure is unable to be determined due to the signal corruption.

3. Methodology

3.1. Data and Home Telehealth System

The data and the evaluated DSS algorithm has been designed and presented in [6, 12]. The chronic disease patient’s data collections were using the TMC-Home system, commercialised by TeleMedCare Pty. Ltd., Sydney, Australia. The system’s function is to integrate a range of e-health services to manage chronic disease in the patient’s home. The central component of the TMC-Home system is a workstation that connects to a mobile computing platform, which has internet connectivity. Patient users can use the system to measure and monitor their vital signs, including blood pressure, blood oximetry, weight, lung function (forced and relaxed spirometry), temperature and blood glucose levels, on a regular basis. The patient users also have access to a range of lifestyle and health questionnaires, which can be used to measure general wellness and fitness [13, 14].
3.2. Statistical Analysis

Hypothetically, a parameter extracted from a good quality signal will have the same value before and after the signal quality evaluation. Thus, to test the hypothesis, we have performed a Wilcoxon signed rank test. The test is performed on features extracted from SpO2, heart rate, and systolic and diastolic blood pressure parameter values for each subject. The hypothesis is:

H0: the median difference in the data obtained before and after the signal quality analysis equals zero
H1: the median difference in the data obtained before and after the signal quality analysis does not equal zero.

H1 is accepted if the significance level (p-value) is less than 0.05 [15].

3.3. Outlier Removals

Since the home telehealth data acquisition protocol was performed in an unsupervised environment, data quality may affect the classifier performance. Therefore, the data collected during the intervention period were manually inspected for outliers; defined as data points that lie very far from the median of the corresponding variable for each patient’s data. To determine the allowable range; first, some statistical characteristics of the data were obtained; namely, the median (50th percentile), and the lower (25th percentile) and the upper (75th percentile) quartiles, and secondly, the lower and upper thresholds were calculated as the data value on the 25th percentile minus the 1.5 (interquartile range value) and the data value on the 75th percentile plus the 1.5 (interquartile range value) respectively. Any data values outside these limits were considered as possible outliers [16]. Next, if the possible outlier point was derived from a raw waveform signal (such as SpO2 from a photoplethysmograph signal, for example), the signal was retrieved and examined visually. Outlier data which was deemed by a human observer to have come from signals corrupted by movement artifact and noise were excluded from further analysis. Alternatively, if the possible outlier value was not derived from a waveform (such as weight or temperature), the values were physiologically validated; that is, only potential outliers still falling within the range of what is physiologically possible were included in the analysis.

3.4. Performance Measure

The performance of the DSSs were evaluated by reporting the accuracy, sensitivity, specificity, positive predictive value (PPV) and negative predictive value (NPV) and Cohen’s kappa ($\kappa$) values. Eq. 2 shows the calculation of $\kappa$ [17];

$$\kappa = \frac{p_0 - p_c}{1 - p_c}$$

Where;

$p_0$ = the total agreement probability, or accuracy

$p_c$ = the ‘agreement’ probability which is due to chance

The DSS outputs are compared with the reference standard that has been developed in [12]. DSSs were constructed using:

(i) data originally coming from the TMC-Home device without manually removing outliers
(ii) data originally coming from the TMC-Home device after manually removing outliers
(iii) data extracted from the raw signals after performing the above-mentioned signal quality analysis.

The methods of constructing the DSSs are describes in Table 1. The comparison are made between: DSS I, DSS II and DSS III, DSS IV, DSS V and DSS VI, DSS VII, DSS VIII and DSS IX.
Table 1. The descriptions of the nine types of DSSs.

<table>
<thead>
<tr>
<th>DSS</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Analysis performed using <strong>only</strong> the features extracted from pulse oximetry derived parameters obtained from the database</td>
</tr>
<tr>
<td>II</td>
<td>Analysis performed using <strong>only</strong> the features extracted from pulse oximetry derived parameters after excluding outliers manually</td>
</tr>
<tr>
<td>III</td>
<td>Analysis performed using <strong>only</strong> the features extracted from pulse oximetry derived parameters after performing signal quality analysis on the PPG signals which led to the recalculation of SpO2 and heart rate values</td>
</tr>
<tr>
<td>IV</td>
<td>Analysis performed using <strong>only</strong> the features extracted from blood pressure signals obtained from the database after excluding outliers manually</td>
</tr>
<tr>
<td>V</td>
<td>Analysis performed using <strong>only</strong> the features extracted from blood pressure signals obtained from the database after excluding outliers manually</td>
</tr>
<tr>
<td>VI</td>
<td>Analysis performed using <strong>only</strong> the features extracted from blood pressure signals after performing signal quality analysis which led to the removal of parameter values categorised to originate from ‘bad’ quality signals</td>
</tr>
<tr>
<td>VII</td>
<td>Analysis performed using features extracted from pulse oximetry parameters, blood pressure parameters and other parameters obtained from the database</td>
</tr>
<tr>
<td>VIII</td>
<td>Analysis performed using features extracted from pulse oximetry parameters, blood pressure parameters and other parameters obtained from the database after excluding outliers manually</td>
</tr>
<tr>
<td>IX</td>
<td>Analysis performed using features extracted from pulse oximetry parameters, blood pressure parameters and other parameters after performing signal quality analyses on the PPG and the blood pressure signals</td>
</tr>
</tbody>
</table>

* The recalculation of SpO2 is using Eq. 1. The heart rate value is estimated by averaging the time of arrival of PPG pulses (measured from peak-to-peak) as taken from the sections of good PPG signals [8].

b The other parameters were derived from spirometry (relaxed and forced), weight and temperature measurements.

4. Results

4.1. Statistical Analysis

The Wilcoxon signed rank test performed on each subject’s data before (without manual data pre-processing) and after the signal quality analysis shows that the SpO2 and heart rate parameter value, distribution mean and distribution standard deviation for all subjects have changed significantly after the signal quality analysis (p<0.05). However, SpO2 percentage changes and z-score from most subjects have not been affected by the signal quality analysis. A different scenario is observed on the features extracted from the blood pressure parameters. Significant changes are noticed on most subject’s distribution mean, distribution standard deviation, and percentage changes and z-score data.

4.2. Analysis Using Only Pulse Oximetry Features

The data set consists of 2467 pulse oximetry measurements. Out of these 2467 pulse oximetry recordings, 44 were removed due to being corrupted. Table 2 shows the results of the developed DSSs.

Table 2. The $\kappa$ value, accuracy, sensitivity, specificity, PPV, and NPV for DSS I, DSS II and DSS III.

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>$\kappa$</th>
<th>Accuracy (%)</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>PPV (%)</th>
<th>NPV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSS I</td>
<td>369</td>
<td>0.41</td>
<td>78.53</td>
<td>60.26</td>
<td>83.45</td>
<td>49.47</td>
<td>88.64</td>
</tr>
<tr>
<td>DSS II</td>
<td>366</td>
<td>0.43</td>
<td>78.71</td>
<td>64.63</td>
<td>82.70</td>
<td>51.46</td>
<td>89.18</td>
</tr>
<tr>
<td>DSS III</td>
<td>365</td>
<td>0.45</td>
<td>81.69</td>
<td>56.41</td>
<td>88.54</td>
<td>57.14</td>
<td>88.24</td>
</tr>
</tbody>
</table>

4.3. Analysis Using Only Blood Pressure Features

A total of 2703 blood pressure parameter values were obtained from the data set. Approximately 17.13% or 463 blood pressure parameter values were removed due to ‘bad’ signals as suggested by the signal quality indicator. This resulted in 332 cases for DSS VI construction. Table 3 show the results.
Table 3. The \( \kappa \) value, accuracy, sensitivity, specificity, PPV, and NPV for DSS III and DSS IV.

<table>
<thead>
<tr>
<th></th>
<th>( N )</th>
<th>( \kappa )</th>
<th>Accuracy (%)</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>PPV (%)</th>
<th>NPV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSS IV</td>
<td>373</td>
<td>0.14</td>
<td>65.15</td>
<td>46.34</td>
<td>70.45</td>
<td>30.65</td>
<td>82.33</td>
</tr>
<tr>
<td>DSS V</td>
<td>371</td>
<td>0.14</td>
<td>66.31</td>
<td>43.90</td>
<td>72.66</td>
<td>31.30</td>
<td>82.03</td>
</tr>
<tr>
<td>DSS VI</td>
<td>332</td>
<td>0.27</td>
<td>75.07</td>
<td>44.16</td>
<td>83.45</td>
<td>41.98</td>
<td>84.64</td>
</tr>
</tbody>
</table>

4.4. Analysis Using All Features

The analysis for DSS VII, DSS VIII and DSS IX used all available physiological measurement data. This included parameters from pulse oximetry, blood pressure, spirometry, weight and temperature measurements. Table 4 show the relative performance of the DSSs.

Table 4. The \( \kappa \) value, accuracy, sensitivity, specificity, PPV, and NPV for DSS VII, DSS VIII and DSS IX.

<table>
<thead>
<tr>
<th></th>
<th>( n )</th>
<th>( \kappa )</th>
<th>Accuracy (%)</th>
<th>Sensitivity (%)</th>
<th>Specificity (%)</th>
<th>PPV (%)</th>
<th>NPV (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>DSS VII</td>
<td>373</td>
<td>0.48</td>
<td>78.71</td>
<td>64.63</td>
<td>82.70</td>
<td>51.46</td>
<td>89.18</td>
</tr>
<tr>
<td>DSS VIII</td>
<td>371</td>
<td>0.52</td>
<td>81.40</td>
<td>74.39</td>
<td>83.39</td>
<td>55.90</td>
<td>91.98</td>
</tr>
<tr>
<td>DSS IX</td>
<td>366</td>
<td>0.51</td>
<td>82.79</td>
<td>65.38</td>
<td>87.50</td>
<td>58.65</td>
<td>90.32</td>
</tr>
</tbody>
</table>

5. Discussions and Conclusion

In this study, we only performed signal quality analysis on pulse oximetry and blood pressure signals and not spirometry signals. This was because; the TMC-Home spirometry measurement has adopted the international established standard for its quality assurance. The standard was developed by the ATS and European Respiratory Society (ERS) task force for standardisation of lung function testing. The TMC-Home spirometry quality module assures that the spirometry parameter values come from correctly acquired signals. For example, if patients were using wrong techniques in performing the spirometry measurements, the device will reject the measurements and prompt a notification on the TMC-Home monitor. The notification will advise the patient for the reasons of failing the measurement and request the patient to start the measurement again. The reasons that a failed spirometry measurement may occur include; the patient hesitates at the start of the measurement, the patient takes an extra breath during the measurement, the patient does not exhale fully or the patient exhales too slowly [18].

The technique performed in analysing the pulse oximetry signal quality is similar to the approach taken by [19] and [20]. These researchers equipped a system called Welfare Techno House with a quality indicator algorithm for the electrocardiogram (ECG) signal. The recorded ECG waveforms were categorised into three classes; ‘excellent’, ‘good’ and ‘not good’ [19-21].

Table 2 show the results for DSS I, DSS II and DSS III. DSS II and DSS III demonstrate an improvement in terms of \( \kappa \) value, accuracy, specificity and PPV when compared to DSS I. However, comparing DSS I and DSS III, the sensitivity has decreased from 60.26% to 56.41% \((p>0.05)\).

The removal of blood pressure parameter values which come from ‘poor’ quality signals does affect the performance of the DSS constructed using features extracted from blood pressure parameters alone. The \( \kappa \) value increased from 0.14 (DSS IV) to 0.27 (DSS VI), and the accuracy improved from 65.15% to 75.07% \((p<0.05)\).

Overall, the quality of the pulse oximetry and the blood pressure signals does affect the performance of the DSS. The result shows that both DSS VIII and DSS IX have improved the \( \kappa \) value of DSS VII, from 0.48 to 0.52 \((p<0.05)\) (comparison between DSS VII and DSS VIII) and from 0.48 to 0.51 \((p<0.05)\) (comparison between DSS VII and DSS XI). DSS XI has a slightly higher accuracy of 82.79% compared to DSS VIII accuracy of 81.40%.

Based on the results, it was found that both manual data pre-processing and signal quality analysis techniques have improved the usability of the parameters extracted from the pulse oximetry measurements. However, only signal quality analysis improved the blood pressure measurement usability in the DSS analysis.
Conventionally, in other studies, SpO₂ data derived from artifact-contaminated signals were ignored [22]. This analysis has provided a possible alternative solution to this approach, where, data from contaminated PPG signals have been ‘corrected’ before use.

Furthermore, the ability of the signal quality algorithms to detect ‘poor’ quality signals can be used as an early notification tool for pulse oximetry and blood pressure measurements in the unsupervised telehealth environment. In this manner, patients can be prompted to retake a measurement if the automated algorithms flag the initial measurement as corrupted.

There are assumptions made in this study: (1) there are enough acceptable waveform beats for the recalculation of SpO₂ and heart rate in the PPG signal after sections with artifact have been removed; (2) The TMC-Home device uses the same generally accepted equations in deriving the SpO₂ and heart rate values from the PPG signal and, (3) the major source of error in the pulse oximetry and the blood pressure measurements are contributed by motion artifacts. In the future, there are a number of improvements that could be made to improve the outcomes of this study: (1) the pulse oximetry measurements could be performed for a longer period of time, consequently increasing the likelihood of obtaining longer sections of acceptable pulses; and (2) the analysis could be enhanced by using signal quality algorithms that could detect all sources of poor signal quality, not only motion artifacts.

Nevertheless, the analyses performed in this study have confirmed that data quality issues do affect the reliability of the DSS, in the case of the particular algorithms and data sets [12].

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