34th Annual International Conference of the IEEE EMBS
San Diego, California USA, 28 August - 1 September, 2012

# Using Accelerometry to Identify Poor Signal Quality in Telehealth Blood Pressure Recordings

Sayuri Tamura, *Student Member, IEEE*, Stephen J. Redmond, *Member, IEEE*, Nigel H. Lovell, *Fellow, IEEE*

*Abstract*—**Telehealth is the support of healthcare using information and communication technologies and is seen as a possible alleviator of the burden on healthcare systems struggling to adapt to an increasing trend in chronic disease among an ageing population. Due to the unsupervised nature of the telehealth recording environment, poor signal quality is frequently associated with telehealth biosignal recordings. Algorithms to automatically detect this poor signal quality would ensure that unreliable measurements are discarded, and subsequently enable further automated analysis of general health by a decision support system. This study attempts to detect movement artifact arising during blood pressure measurement using a triaxial accelerometer attached to the pressure cuff. Blood pressure measurements were performed by twelve subjects, seven measurements for each person. The subjects were requested to perform a set of tasks to induce artifact in the cuff pressure and auscultatory signals. The gold standard was created by manually scoring the signals using a graphical user interface. The algorithm identified acceleration magnitudes which exceeded a heuristically set threshold of 0.05 G (G = 9.81 m/s$^2$) to detect sections of movement artifact. An average sensitivity of 45.9%, specificity of 93.8% and accuracy of 86.5% was obtained. While the accelerometer proved useful in detecting gross movements of the arm, the low sensitivity was caused by subtle noise and vibration which appeared to be dampened by the pressure cuff and hence not detected, indicating that the auscultatory or cuff pressure must also be analyzed in tandem with the accelerometry signals to improve artifact detection.**

## I. Introduction

According to a recent United Nations report on world population prospects, the world's population aged 60 and over was 11% in 2010 and is predicted to increase to 22% by 2050 [1]. In developed countries this percentage over 60 years has already reached 21% and is expected to 33% by 2050 [1]. It is required that healthcare systems accommodate the needs of these ageing populations, which include an obvious overall increase in demand for healthcare, trained personnel and long term care. The World Health Organization report that chronic diseases caused 60% of globally deaths in 2005; this is predicted to have risen by 17% in the period 2005-2015 [2]. Average health care expenditure in Organisation for Economic Co-operation and Development (OECD) countries is expected to rise from 5.7% of GDP in 2005 to 9.6% in 2050, with part of this cost attributed to the increasing prevalence of chronic diseases in an ageing population [2].

A suggested solution to this problem is the use of telehealth. Telehealth supports patients in a remote, unsupervised environment using information and communication technologies, allowing self-management of disease, early detection of deteriorating health, efficient transmission of individual data and the possibility of creating a decision support system that analyses data in order to signal a change in the patient's condition, possibly suggesting the next course of action for the patient [3-5]. It has been suggested that healthcare spending on chronically ill patients in the United States could be reduced by approximately 7.7-13.3% (US$312–US$542) per patient per quarter if a telehealth paradigm was used [6].

One physiological measurement which may be frequently acquired in the home using a telehealth monitoring device is blood pressure (BP). Systolic and diastolic blood pressure are useful indicators of the person's well-being. Non-invasive blood pressure measurement (NIBP) uses either the auscultatory or oscillometric methods. The auscultatory method requires the clinician to listen to the Korotkoff sound generated while the brachial artery is occluded using a pressure cuff and the pressure gradually reduced; a beating sound is heard as the pressure drops to the systolic pressure and stops again (or is softened) after the diastolic pressure is reached. For the oscillometric method, the changing pulse pressure is transmitted to the pressurized cuff and analyzed using heuristic methods to estimate the systolic and diastolic pressures [7]. Namely, there are several algorithms to estimate the systolic and diastolic blood pressures from the oscillatory waveform, such as the maximum amplitude algorithm, the linear approximation algorithm and a method which analyses the slope of the waveform [8].

Good quality signal is paramount if a reliable estimate of blood pressure is to be obtained. Movement artifact is a cause of poor signal quality. With automated, unsupervised blood pressure measurement, signals can be corrupted by movement of the arm or the cuff [4].

There are some existing methodologies for rejecting movement artifact using Kalman filters to predict the next oscillometric amplitude and measuring the resulting error due to the unpredictable artifact [9], a fuzzy logic regression algorithm that reconstructs the oscillometric amplitude depending on the truth degree [10], and a recent method by our research group which uses a decision tree applied to filtered versions of the Korotkoff, oscillometric and cuff pressure signals [11].

However, these algorithms cannot resolve sudden artifact events, caused by abrupt movement or tapping the device, from normal beats. The hypothesis of this paper is that simple movement detection using an accelerometer would help address this shortfall in algorithms which rely only on the existing set of acquired BP signals.

S. Tamura, N. H. Lovell and S. J. Redmond are with the Graduate School of Biomedical Engineering, University of New South Wales, Sydney, NSW 2052, Australia.

Others have investigated a similar approach for various applications. Charbonnier *et al.* investigated the correlation between heart rate and body acceleration to explain the large variance seen in 24-hour ambulatory systolic blood pressure (ASBP) measurements; raised ASBP is seen after activity [12]. On average 59% of the variation was accounted for by monitoring activity. This however is a very different application than that of telehealth BP monitoring and does not address the issue of BP recordings being spoiled by movement, but rather accounts for the true variance if BP readings over the course of a day.

Koo *et al.* performed a preliminary study of the usefulness of accelerometry to reject movement artifact in oscillometric signals in an ambulance setting. Accelerometer signals were used to construct a pressure signal caused by movement which is subtracted to obtain a clean BP signal [13]. This method is not capable of correcting artifact induced in the Korotkoff waveform of the more accurate auscultatory NIBP measurement method. Furthermore, in some extreme cases it would be more appropriate to entirely discard the signal rather than attempting to correct the interference.

Hasnain *et al.* attempted to remove movement artifact during walking by from a continuous oscillometric recording, using accelerometery and muscle movement signals [14]. Again, this is not applicable to the auscultatory method and the continuous measurement is not compatible with the normal telehealth measurement procedure. Furthermore, the method is only tested using a motorized mannequin arm.

This study aims to detect sections of movement artifact in both the cuff pressure and auscultatory waveforms using a three-axis accelerometer. This study also aims to discover if an accelerometer is sufficient to identify artifact caused by different types of movement thought to occur in telehealth environments. Previous studies have focused on artifact rejection while this study is centered on artifact detection. By recognizing the presence of movement artifact, low quality signals can be discarded, ensuring that the measurements are reliable enough for use in an automated telehealth decision support system [3].

The following describes the method of data collection, gold standard (GS) development, algorithm development and considers the feasibility of using an accelerometer to identify movement artifact in blood pressure signals.

## II. METHODS

### A. Data collection

The cuff pressure, auscultatory waveform and three accelerometer axes signals were acquired simultaneously while performing a BP measurement. A calibrated three-axis accelerometer (MMA7260Q) with a sensitivity of 6 G (G = 9.81 $ms^{-2}$) was attached to the cuff outer surface of the cuff (on the side opposite that in contact with the arm). The cuff pressure and auscultatory waveform (Korotkoff sounds) were recorded using a TeleMedCare Home Monitor device (TeleMedCare, Sydney, Australia) and the output of the analog front-end of this system sampled using PowerLab at a sampling frequency of 1000 Hz. The accelerometer signals were also acquired by PowerLab at the same sampling frequency.

Measurements were made by twelve young healthy subjects aged in their 20s (6 male, 6 female); each subject took seven measurements starting from the left arm and alternated arms for each measurement. Some of the measurements were intentionally corrupted with movement. Specifically, subjects were required to perform a set of tasks during the measurement such as: (1) staying still; (2) moving their arm; (3) moving fingers; (4) tapping the cuff; (5) moving the arm contralateral to the arm on which the cuff was placed; (6) adjusting the cuff, and; (7) bending the ipsilateral arm. (1) was applied for the whole duration of the measurement, while (2)-(7) were performed at random times during the recording. Movements that were likely to occur in a telehealth NIBP measurement were chosen to simulate artifact generation in these signals.

### B. Gold standard development

A MATLAB graphical user interface (GUI) was created to allow a scorer to select sections of the recording containing artifact. This annotation was considered the gold standard measure of artifact and was performed by observing obvious artifact on either the cuff signal or the Korotkoff waveform. The scorer was presented with the cuff pressure signal, Korotkoff sound waveform and the processed accelerometer signal (described later), as shown in Fig. 1. They could also listen to the Korotkoff sound recording through a headset, or change the timescale of the GUI window.

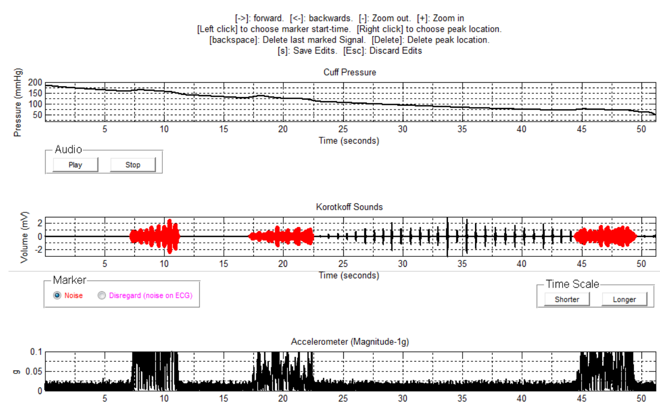


Fig. 1. GUI used by experts to manually score the signals. 'Audio' allowed the scorer to listen to the Korotkoff sounds, 'Marker' was selected to highlight artifacts and 'Time Scale' was used to change the signal duration shown. The plots shows the BP cuff pressure (top), the Korotkoff waveform (middle) and the processed accelerometry signal, *m*, described later (bottom).

### C. Algorithm development

#### 1) Signal preprocessing

After each accelerometer axis was calibrated, the vector magnitude was calculated and the gravity component was then approximately subtracted from the magnitude signal using a high-pass 4th order Butterworth filter with a cutoff frequency of 0.1 Hz, using zero-phase forward-backward filtering. Finally, the absolute value of this signal was taken to form the processed acceleration signal, *m*. Only the portion of recording corresponding to cuff deflation was analyzed; the cuff inflation phase and the final cuff release were ignored. This final processed signal is shown in the lower plot of Fig. 1

*2) Setting threshold and detecting movement*

A histogram was generated using the acceleration values of *m*. By inspection, a heuristically chosen threshold of 0.05 G was set.

*3) Selecting areas of movement artifact*

All samples with acceleration values above the 0.05 G threshold were selected as movement artifact. As a further processing step, if two samples labeled as containing artifact occur within 1 s of each other, the entire interval in between is also marked as artifact.

*4) Evaluating algorithm performance*

The performance of the algorithm was evaluated by calculating sensitivity, specificity, positive predictive value, negative predictive value and accuracy for each signal. The mean and standard deviation of the values above were calculated for each task. The performance is also analyzed by movement type and summarized by averaging these statistics across all movements.

## III. Results

Table I shows the results for each of the seven movement tasks. Listed are the mean and standard deviation of the sample-wise misclassification of artifact, as defined by the human annotated gold standard. When calculating the statistics, a true positive is considered artifact which is correct identified as such. Also shown in the last row is the average of the mean and the average of the standard deviation (SD) of each statistic. The average of the mean sensitivities when detecting artifact was 45.94%, specificity was 93.76% and accuracy was 86.45%.

Table I: Artifact detection performance. Mean ± SD of all 12 signals for each of 7 tasks.

| Tasks | Mean ± SD (N=12) | | | | |
|---|---|---|---|---|---|
| | **Sens %** | **Spec %** | **PPV %** | **NPV %** | **Accu %** |
| Remain still | 12.0 ± 27.2 | 98.2 ± 5.3 | 42.2 ± 50.5 | 98.7 ± 1.7 | 97.0 ± 5.1 |
| Move arm | 66.1 ± 26.3 | 94.6 ± 5.0 | 78.7 ± 26.7 | 87.4 ± 9.3 | 86.4 ± 7.0 |
| Move fingers | 19.0 ± 22.8 | 97.2 ± 4.6 | 82.1 ± 24.5 | 76.8 ± 13.8 | 76.5 ± 12.6 |
| Tap cuff | 78.0 ± 15.9 | 82.8 ± 14.7 | 57.3 ± 21.2 | 94.8 ± 3.7 | 82.5 ± 11.2 |
| Move other arm | 19.6 ± 30.4 | 95.8 ± 5.6 | 38.1 ± 36.7 | 96.1 ± 3.2 | 93.1 ± 5.5 |
| Adjust cuff | 80.5 ± 11.4 | 91.8 ± 6.8 | 78.7 ± 15.7 | 92.3 ± 5.4 | 88.2 ± 4.1 |
| Bend arm | 46.4 ± 32.8 | 95.9 ± 5.0 | 87.0 ± 14.4 | 81.1 ± 13.8 | 81.6 ± 8.6 |
| **Average statistics mean(mean) ± mean(SD)** | **45.9 ± 23.8** | **93.8 ± 6.7** | **66.3 ± 27.1** | **89.6 ± 7.3** | **86.5 ± 7.7** |

Sens: sensitivity; Spec: specificity; PPV: positive predictive value; NPV: negative predictive value; Accu: accuracy; SD: standard deviation.

Fig. 2-4 show the cuff pressures, Korotkoff waveforms, and processed accelerometer signals, *m* (further transformed using the logistic function $2(1/[1+\exp(-m)] - 0.5)$, to map the values of *m* into the interval [0,1) , for the purposes of visualization).

The human annotation is shown in the top subplot of each figure as an intermittent solid black line (drawn at 0 mmHg) and also highlighted on the cuff pressure waveform in grey. The algorithmically determined artifact is overlaid on the Korotkoff and accelerometry signals in grey (middle and bottom subplots of each figure). The threshold value (transformed for visualization) is also drawn on the last subplot of each figure as a solid line; most apparent in Fig. 2 and Fig. 4.

Fig. 2 corresponds to the subject moving the fingers of the ipsilateral arm, Fig. 3 corresponds to tapping the cuff with the finger of the contralateral arm, and Fig. 4 corresponds to bending elbow of the ipsilateral arm.

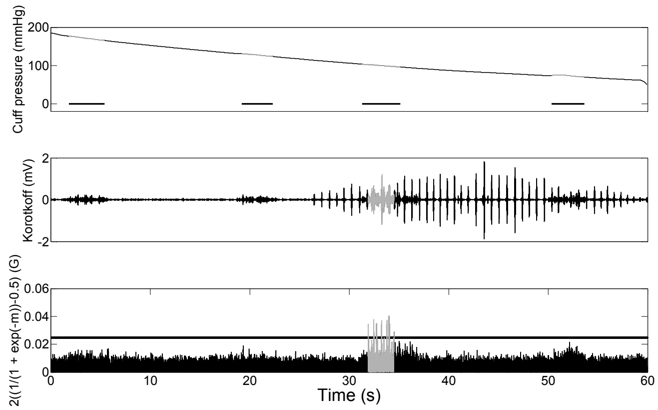


Fig. 2. Cuff pressure, Korotkoff waveform and processed accelerometer signal for subject moving their fingers at random times. Some artifact was not detected by the algorithm due to low acceleration. Results: Sens=18.83%, Spec=100.00%, PPV=100.00%, NPV=80.35% and Accu=81.21%.

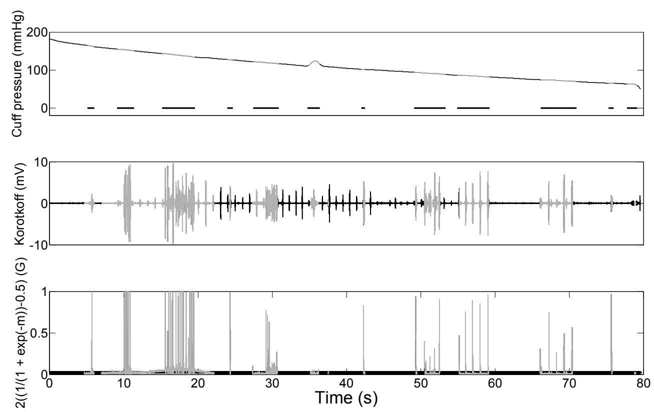


Fig. 3. Subject 'tapping the cuff'. Baseline shift from 10 s to 20 s (bottom subplot) causes that region to be rejected. Results: Sens=78.35%, Spec=81.90%, PPV=71.86%, NPV=86.51% and Accu=80.58%.

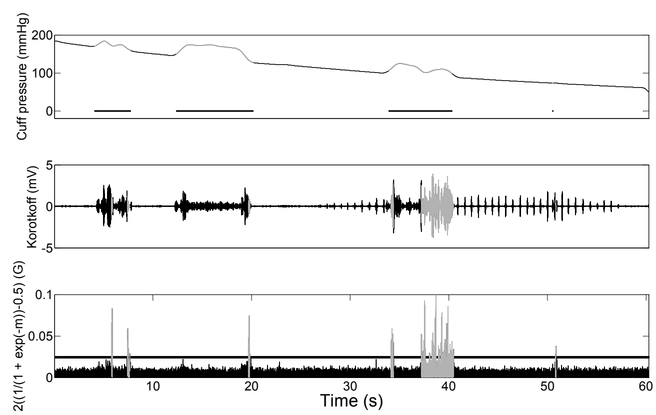


Fig. 4. Subject 'bending the arm'. Artifact was generated in the BP signals. However, the whole section of artifact was not detectable due to low acceleration magnitudes. Results: Sens=21.76%, Spec=99.61%, PPV=96.08%, NPV=74.60% and Accu=76.07%.

## IV. Discussion

The sensitivity of the algorithm is dependent on the type of task performed; tapping the cuff (Fig. 3) and adjusting the cuff resulted in high artifact detection sensitivity due to the larger acceleration generated for these activities. However, moving the finger generated low acceleration magnitudes which were not always detectable by the algorithm, as shown in Fig. 2, resulting in low sensitivity.

During the cuff tapping experiment a baseline shift (at 10-20 s in Fig. 3) occurred in $m$, possibly caused by a concurrent sudden movement of the arm causing the entire section to be erroneously detected as artifact (according to the gold standard annotation), resulting in a slightly lower specificity.

Bending the arm, and in some cases, adjusting the cuff generated artifact due to compression of the cuff. However, when the subject compressed the cuff while staying otherwise stationary, the algorithm failed to detect the artifact, as illustrated in Fig. 4. It may be that the air filled cuff is damping the vibrations originating at the arm-cuff interface, which are clearly visible in the Korotkoff waveform recording.

There was some difficulty in annotating the signals when tapping the cuff produced artifacts in the Korotkoff waveform, producing spikes which are difficult to differentiate from the normal Korotkoff sounds or what could be ectopic beats. The use of a simultaneous electrocardiogram in future work would solve this issue [11].

The converse is also true, that it may be possible to distinguish cardiac arrhythmia from Korotkoff sounds when using the accelerometer to rule out such movements events which would generate similar artifact.

Recent work by our group has investigated the sole use of the cuff pressure (and the oscillometric signal extracted from this) and the Korotkoff waveform to detect artifact in the NIBP measurement for telehealth environments [11]; achieving a sample-wise accuracy, sensitivity and specificity of 97.0%, 80.61% and 98.16%, respectively, when identifying noise in 100 BP recordings. The method presented here using a triaxial accelerometer (averaged accuracy = 86.5 ± 7.7%) achieves similar results.

Future research will investigate the fusion of these two approaches, applying pattern recognition to both the accelerometry, pressure and Korotkoff signals. Furthermore, supervised learning will be employed to optimize the decision rule, rather than using a heuristic threshold.

It is hoped to test these improved algorithms in real telehealth environments with elderly sufferers of chronic disease.

## V. Conclusion

In this study, the detection of movement artifact during NIBP measurement using a triaxial accelerometer has been presented. This study was motivated by the increasing use of telehealth where low quality signals may be generated due to patient movement. From the results, it can be seen that an averaged accuracy of 86.5% was achieved, indicating the potential usefulness of this approach to signal quality validation. However, there were several limitations such as inability to detect cuff compression or low acceleration magnitudes generated by certain movements, both of which possibly causing significant artifact in the BP recording. Future improvements include incorporating artifact detection based on signal morphology analysis. By detecting movement artifacts in self-performed telehealth physiological measurements, it is possible to eliminate poor quality recordings and generate accurate measurements of blood pressure. The ability to robustly acquire good quality signals in such unsupervised environments will foster the development of automated health monitoring services, relieving the current burden on out healthcare systems.

## VI. References


[1] "World population prospects: The 2008 revision," Department of Economic and Social Affairs. Population Division. United Nations, New York. 2009.

[2] F. Sassi and J. Hurst, "The prevention of lifestyle-related chronic diseases: an economic framework," Organisation for Economic Co-operation and Development, 2008.

[3] J. Basilakis, N. H. Lovell, S. J. Redmond, and B. G. Celler, "Design of a decision-support architecture for management of remotely monitored patients," *IEEE Transactions on Information Technology in Biomedicine,* vol. 14, pp. 1216-1226, 2010.

[4] N. H. Lovell, S. Redmond, J. Basilakis, and B. Celler, "Biosignal quality detection: An essential feature for unsupervised telehealth applications," in *12th IEEE International Conference on e-Health Networking Applications and Services (Healthcom)*, Lyon, France, 2010, pp. 81-85.

[5] M. S. Mohktar, J. Basilakis, S. J. Redmond, and N. H. Lovell, "A guideline-based decision support system for generating referral recommendations from routinely recorded home telehealth measurement data," in *Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Buenos Aires, Argentina, 2010, pp. 6166-6169.

[6] L. C. Baker, S. J. Johnson, D. Macaulay, and H. Birnbaum, "Integrated telehealth and care management program For medicare beneficiaries with chronic disease linked to savings," *Health Affairs,* vol. 30, pp. 1689-1697, 2011.

[7] D. Zheng, J. N. Amoore, S. Mieke, and A. Murray, "Estimation of mean arterial pressure from the oscillometric cuff pressure: comparison of different techniques," *Medical and Biological Engineering and Computing,* vol. 49, pp. 33-39, 2011.

[8] S. Chen, V. Groza, M. Bolic, and H. Dajani, "Assessment of algorithms for oscillometric blood pressure measurement," in *IEEE Instrumentation and Measurement Technology Conference*, Singapore, 2009, pp. 1763-1767.

[9] T. Dorsett, "Application of a prediction and smoothing algorithm to non-invasive blood pressure measurement," in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Orlando, FL, USA, 1991, pp. 468-469.

[10] C. T. Lin, S. H. Liu, J. J. Wang, and Z. C. Wen, "Reduction of interference in oscillometric arterial blood pressure measurement using fuzzy logic," *IEEE Transactions on Biomedical Engineering,* vol. 50, pp. 432-441, 2003.

[11] J. Abdul Sukor, S. J. Redmond, G. S. H. Chan, and N. H. Lovell, "Signal quality measures for unsupervised blood pressure measurement," *Physiological Measurement,* vol. 33, pp. 465-486, 2012.

[12] S. Charbonnier, J. Siché, and J. Mallion, "Toward a portable blood pressure recorder device equipped with an accelerometer," *Medical Engineering & Physics,* vol. 21, pp. 343-352, 1999.

[13] Y. Koo, J. Kang, I. H. Shin, M. Y. Jung, G. J. Suh, and H. C. Kim, "Preliminary study of motion artifact rejection for NIBP measurement in an ambulance," in *29th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, Lyon, France, 2007, pp. 705-708.

[14] A. Hasnain, M. Awan, and M. Farooq, "A ubiquitous real-time motion artifact rejection technique for remote NIBP monitoring of hypertensive patients," in *World Congress on Medical Physics and Biomedical Engineering*, Munich, Germany, 2009, pp. 913-916.