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

Highly Survivable Bed Pressure Mat Remote Patient Monitoring System for mHealth

Vilas Joshi, Megan Holtzman, Amaya Arcelus, Rafik Goubran, *Fellow, IEEE*, and Frank Knoefel

Abstract— **The high speed mobile networks like 4G and beyond are making a ubiquitous remote patient monitoring (RPM) system using multiple sensors and wireless sensor networks a realistic possibility. The high speed wireless RPM system will be an integral part of the mobile health (mHealth) paradigm reducing cost and providing better service to the patients. While the high speed wireless RPM system will allow clinicians to monitor various chronic and acute medical conditions, the reliability of such system will depend on the network Quality of Service (QoS). The RPM system needs to be resilient to temporary reduced network QoS. This paper presents a highly survivable bed pressure mat RPM system design using an adaptive information content management methodology for the monitored sensor data. The proposed design improves the resiliency of the RPM system under adverse network conditions like congestion and/or temporary loss of connectivity. It also shows how the proposed RPM system can reduce the information rate and correspondingly reduce the data transfer rate by a factor of 5.5 and 144 to address temporary network congestion. The RPM system data rate reduction results in a lower specificity and sensitivity for the features being monitored but increases the survivability of the system from 1 second to 2.4 minutes making it highly robust.**

I. Introduction

Mobile Health (mHealth) delivers health services using mobile and wireless technologies including Remote Patient Monitoring (RPM). The RPM system provides patient monitoring by transmitting physiological and environmental sensor data from the patient to a central node using wireless technology [1]. The mHealth market is growing and will see significant maturation over the next decade. It is predicted that the monitoring needs for chronic diseases such as Asthma, COPD and diabetes, could claim a significant proportion of the overall patient monitoring market [2].

With its high data rate, 4G network opens the door to feature rich RPM systems with the ability to monitor patient conditions using audio/video/infrared and other high bandwidth sensors. Wireless networks suffer from dropped connections and congestion due to demand being higher than the capacity of the network, sudden increases in traffic, changes in routes, links going down etc. Congestion-related packet loss or loss of connectivity can have a significant impact on the quality of care provided by the RPM system, since it can result in loss of critical patient data, which could be disastrous for the patient's health [3].

If the RPM systems are to achieve wider penetration, the RPM system architecture must be cost effective and highly survivable under temporary adverse network conditions. An Adaptive Information Content Management (AICM) methodology using a sender buffer caching scheme has been proposed for the RPM systems to improve the system survivability under adverse network conditions [4].

In this paper we propose a RPM system that can monitor the characteristics of bed-exit analysis, movement, and breathing rate using bed pressure mat. It also presents how the survivability of the bed pressure mat based RPM system can be improved using the AICM method under network congestion.

II. A Wireless RPM System Using Bed Pressure Mat Sensor Array

The AICM methodology divides the raw data stream from the RPM system in to 'n' multiple levels L_1 to L_n where 'n' is a design parameter. The pre-processing algorithm progressively reduces the information content from one level to the next, e.g. Level #L_i has lower information content than Level #L_{i-1} and correspondingly has lower data rate. Fig. 1 shows the architecture of the proposed bed pressure mat sensor based RPM system using the AICM method. The proposed RPM system employs centralized data processing architecture where raw data from the bed pressure mat sensors is sent directly to the central node using high data rate wireless networks like 4G without any processing in the local node. The architecture presented in the Fig. 1 is scalable since new sensors can be added with ease.

The centralized data processing architecture simplifies the setup needed at the patient's home significantly. All that is needed at the patient's home are the bed mat pressure sensors and a wireless device that will receive and transmit the sensor data to the central node over wireless network. Any changes to the processing software can be applied at the central node with no disruption to the patient's life. Also the raw pressure mat data is stored at the central node for backup which is then available for future analysis; data can also be used for trialing newer algorithms.

In this paper we use data from earlier clinical trials to show how our proposed RPM system is capable of providing improved survivability when network bandwidth drops for any reason temporarily.

This work was supported in part by the Natural Sciences and Engineering Research Council (NSERC) and industrial and government partners, through the Healthcare Support through Information Technology Enhancements (hSITE) Strategic Research Network.

V. Joshi, M. Holtzman, R. Goubran and F. Knoefel are with the Department of Systems and Computer Engineering, Carleton University, Ottawa, ON, Canada (email: vjoshi@sce.carleton.ca)

F. Knoefel is also with Élisabeth Bruyère Hospital and the, Elisabeth-Bruyère Research Institute, Ottawa, ON, Canada (email: fknoefel@bruyere.org).

A. Arcelus is with Department of Occupational Science and Occupational Therapy, University of Toronto, Toronto, On, Canada

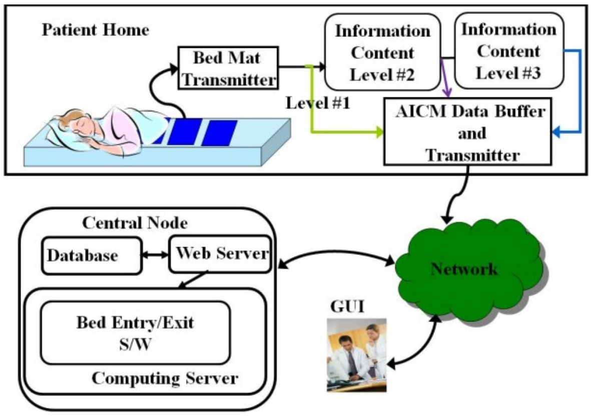

Figure 1: Bed pressure mat based RPM system

III. Bed Pressure Mat Sensor for Patient Monitoring

A smart home design that implements pressure sensing throughout the home was introduced by Arcelus et al [5] and Holtzman et al [6]. It embedded bed pressure mat sensor into the bed to monitor an occupant's behavior patterns over time. Clinical trials were conducted in the rehabilitation ward of the Élisabeth Bruyère Hospital in Ottawa, ON, Canada. Patients were monitored continuously during rehabilitation beginning with the day of the operation and ending when they were released from the hospital. Fig. 2 shows the clinically significant features which were extracted from the bed pressure mat.

A. Bed Sensors

The proposed RPM system uses a pressure sensitive mat called Bed Occupancy Sensor (BOS™) by S4 Sensors Controls Inc. Each bed pressure mat has 24 embedded sensors. The pressure mat works well with mattress types commonly used in home and hospital bed. Placed under the bed mattress, the mats provided unobtrusive monitoring suitable to the home environment.

The clinical trial used 6 mats for each patient providing a total of 144 sensors positioned in 8 columns across the bed and 18 rows from the headboard to the footboard. The sensors were sampled at 10 Hz. Samples from each sensor were forwarded over the network as three semi-redundant 2-byte words, resulting in a data rate of ~10 KBps.

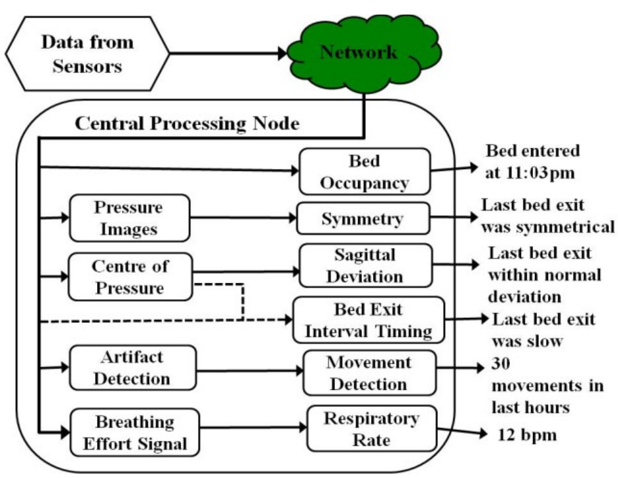

Figure 2: Information extraction.

B. Clinical Feature Extraction

The Following clinical features, bed occupancy, symmetry, sagittal deviation, bed-exit interval timing and movement detection and respiratory rate, were extracted from the clinical data to monitor patient mobility, bed occupancy patterns etc.

1) Bed Occupancy

The presence of the occupant in the bed was determined using the point-source modality of the sum of all sensors introduced in [5].

2) Symmetry

The body symmetry as the occupant exited the bed is a significant parameter in the estimation of an occupant's level of functional mobility [7].

3) Sagittal Deviation

The deviation of the body along a sagittal plane was measured by analyzing the center of pressure trajectory as the body exits the bed. Monitoring this feature over time can indicate changes in balance and stability of an occupant.

4) Bed-exit Interval Timing

Timing of the Bed-exit interval defined as intention to exit the bed and actual exit from the bed is an important feature of a patient' stability [7].

5) Movement Detection

The detection of muscular movements can be used in the measurement of sleep restlessness and overall sleep quality.

6) Respiratory Rate

Respiratory rate during sleep is widely monitored as it is a predictor of mortality in older adults [8] [9].

IV. AICM Method the Proposed Bed Pressure Mat RPM System

This study shows how a very simple information content reduction method without the need for extensive local node processing can be used to improve the survivability of the RPM system. Here we demonstrate how information content can be reduced to achieve higher survivability under adverse network conditions and the impact of reduced information content on system performance in terms of

- Loss of features compared with full information content.
- Effect on specificity and sensitivity for extracted features.

The AICM scheme proposed here as shown in Fig. 1 is a 3-Level AICM where each level reduces the transmitted sensor data rate as the network data rate drops due to network congestion or loss of connectivity. Feature extraction algorithms used in this paper were developed by researchers at Carleton University. The analysis was done using 31 bed occupancy data collected during the trial. The data rate reduction factor at each level is defined as D_i where i is the level number.

1) Level 1

Full information content is available at Level 1. At the processing node, all information is extracted once data is received. No change should be detected in the output since full information content is transmitted.

2) Level 2

Under moderate congestion or medium-term connectivity loss, a simple summation scheme to reduce the amount of data (and hence information) can be managed on the local device. To simultaneously keep centre of pressure information yet reduce the data, the sum of the rows and sum of the columns is buffered instead of the full sensor data. This results in only 8+18 = 26 data streams rather than the original 144. The data rate reduction factor D_2 is

$$D_2 = 144/26 = 5.54$$

3) Level 3

When heavy congestion limits sending bandwidth, or a connection loss lasts longer than what the medium buffer storage allows, only the sum of the sensors is buffered. Since some sensors constructively interfere with each other, there would be a loss in signal to noise ratio of some extracted signals, such as the respiratory signal. Features dependent on localization would be unavailable. The data reduction factor D_3 is 144.

B. Results

1) System Survivability

For analysis purpose it a 10 KB sender buffer was used. This allows storage of one second of full data content. This is a small amount of memory, but reflects only a single component of the full RPM system. By using the proposed method, the survivability of the system can be increased from one second with full information to 2.4 minutes with partial information (by a factor of 144 given by D_3). Fig. 3 displays the time to live of the system for each information content reduction scheme.

Table I displays the features that are retained at successive data reduction levels. Of the six features available with full data, two thirds of them are still available at Level 3. The loss of accuracy in the features is denoted by the * marks.

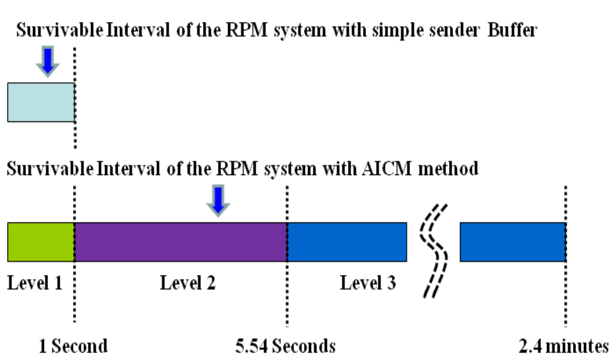

Figure 3: Comparison of survivability time for conventional RPM system and system using AICM.

The accuracy and sensitivity of the estimation and detection algorithms are dependent on the quality of the extracted movement and breathing effort signals, which are in turn dependent on the received sensor data. To compare the changes between levels, all available bed exits (31) were compared, while respiratory rates and movement detection sensitivity was compared over 120 30-second epochs. Respiratory rates were counted as valid if less than five seconds of the epoch was detected as movement. Table II presents the deviation from the original feature extracted from Level 1 data at both Level 2 and Level 3. Features that are not available at those levels are marked N/A.

For some features, the loss of accuracy at Level 3 may be enough to warrant dropping the feature, but this depends on the application. Although movements are detected at Level 3 with a sensitivity of only 50%, it is mostly small movements that are no longer discerned.

TABLE I. INFORMATION RETAINED, RATE REDUCTION, AND SURVIVABILITY AT EACH LEVEL

* INDICATES SOME LOSS OF ACCURACY COMPARED TO LEVEL 1

Information Retained	Level 1	Level 2	Level 3
Bed Occupancy	Yes	Yes	Yes
Bed-Exit Interval Timing	Yes	Yes	Yes*
Sagittal Deviation	Yes	Yes	No
Symmetry	Yes	No	No
Movement Detection	Yes	Yes*	Yes*
Respiratory Rate	Yes	Yes*	Yes*
Data Rate Reduction D_i	1:1	144:26	144:1
Survivability with 10 KB buffer space	1 sec	5.54 sec	2.4 min

TABLE II. DEVIATION OF FEATURES AT LEVEL 2 AND 3 COMPARED TO LEVEL 1

Feature	Level 2 mean (s.d.)	Level 2 (%)	Level 3 mean (s.d.)	Level 3 (%)
Bed-Exit Interval Timing (s)	0	0	12.9 ± (14.7)	29.2
Sagittal Deviation (cm)	0	0	N/A	N/A
Symmetry	N/A	N/A	N/A	N/A
Movement Detection		Sensitivity: 65.1% Specificity: 92.7%		Sensitivity: 49.4% Specificity: 91.4%
Respiratory Rate (bpm)	0.24 (0.86)	1.55 (6.67)	2.52 (5.93)	9.66 (22.19)

The movement detection feature would still be useful for further analysis where large movements are most important, such as for position change detection.

Fig. 4 displays the calculated bed exit interval times at all levels compared with the bed exit interval times calculated for the full data at Level 1. If no modification to the results occurs due to lower information content, all of the points would lie along a 45° line. Level 1 and 2 show identical results, while Level 3 is generally similar with some outliers.

Fig. 5 shows a similar plot for extracted respiratory rates. For Level 2 data, respiratory rates are very well correlated to the original respiratory rates at Level 1. However, Level 3 data is less likely to properly detect movements, and some epochs at Level 3 are marked as holding valid respiration when they are in fact corrupted by movement.

V. DISCUSSION

This study presents an example of the AICM method. Three levels of data buffering were presented, but further levels could also be defined. The algorithms have not been optimized for each level of information content, and such optimization could result in better accuracy.

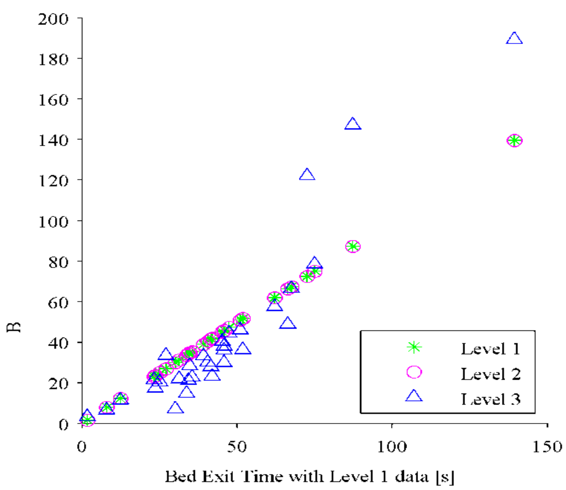

Figure 4: Bed exit times at all three levels

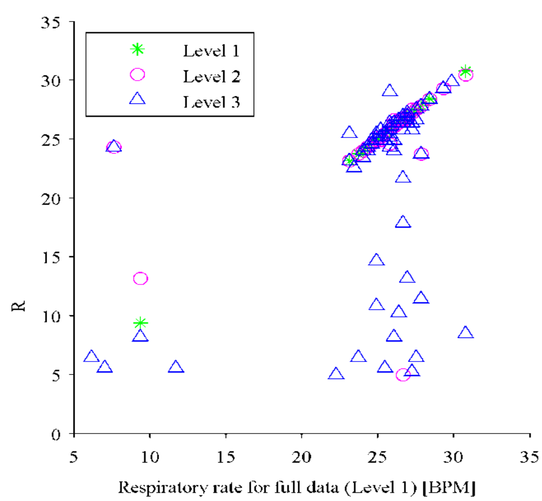

Figure 5: Respiratory rates at all three levels

The factors that will affect information content reduction are the specific patient condition(s) being monitored, sensors used, real-time response requirements, the need to reduce false alarms and the response time of the healthcare providers [10] [11].

VI. CONCLUSION

High data rate RPM systems will need to be robust to survive temporary network congestion and/or loss of connectivity. We have demonstrated how adaptively reducing the information content being transmitted by the RPM system; the survivability of the system can be significantly improved under adverse network conditions. Improved survivability comes at the cost of reduced sensitivity and specificity of the monitored features and may even result in complete loss of a feature. There is a tradeoff between loss of features, data rate reduction, criticality of the lost information, and survivability time of the RPM system.

REFERENCES

[1] R.S.H. Istepanian and Y. T. Zhang, "Guest editorial Introduction to Special Edition: 4G Health—The Long-Term Evolution of m-Health". *IEEE Trans. Information Technology in Biomedicine.* Volume: 16, No. 1 pp. 1-5, Jan. 2012.

[2] Juniper Research. (2010 March). Mobile Healthcare Opportunities Monitoring, Applications & mHealth Strategies 2010 – 2014**.** Juniper Research Ltd, Basingstoke, England. [online]. Available: http://www.juniperresearch.com/reports/mobile_healthcare_opportunity

[3] A. Alinejad, N. Philip and R.S.H. Istepanian, "Mapping of Multiple Parameter M-health Scenarios to Mobile WiMAX QoS Variables ",*in Proc. IEEE Int. Conf. Engineering in Medicine and Biology Society (EMBS)*, Boston, Massachusetts USA, 2011, pp. 1532-1535.

[4] V. Joshi, R.Goubran and F. Knoefel, "Adaptive Information Content Management and Buffer Caching Design for Robust Real-Time Streaming over IP Network", *in Proc. IEEE Int. Conf. on Comm (ICC)*, Ottawa, Canada, 2012.

[5] A. Arcelus, R. Goubran, F. Knoefel, H. Sveistrup, and M. Bilodeau, "Context-aware smart home monitoring through pressure measurement sequences," *Proc. IEEE Int. Workshop Medical Meas. and Applicat.(MeMeA),* Ottawa, ON, Canada, 2010, pp. 32-37.

[6] M. Holtzman, D. Townsend, R. Goubran and F.Knoefel, "Validation of Pressure Sensors for Physiological Monitoring in Home Environments", *Proc. IEEE Int. Workshop Medical Meas. and Applicat.(MeMeA),* Ottawa, ON, Canada, 2010, pp. 38-42.

[7] A. Arcelus, I. Veledar, R. Goubran, F. Knoefel, H. Sveistrup, and M. Bilodeau, "Measurements of sit-to-stand timing and symmetry from bed pressure sensors," *IEEE Trans. Instrum. Meas*., vol. 60, no. 5, pp. 1732 – 1740, May 2011.

[8] M. A. Dew, C. C. Hoch, D. J. Buysse, T. H. Monk, A. E. Begley, P. R. Houck, M. Hall, D. J. Kupfer, and C. F. R. 3rd, "Healthy older adults' sleep predicts all-cause mortality at 4 to 19 years of follow-up," *Psychosomatic Med.*, vol. 65, no. 1, pp. 63-73, Feb. 2003.

[9] M. H. Jones, R. A. Goubran, and F. Knoefel, "Reliable respiratory rate estimation from a bed pressure array," in *Proc. 28th Int. Conf. IEEE Eng. Med. Biol. Soc.*, New York, NY, USA, 2006, pp. 6410-6413.

[10] M. G. Martini, R. S. H. Istepanian, M. Mazzotti, and N. Philip, "Robust Multi-Layer Control for Enhanced Wireless Tele-Medical Video Streaming," *IEEE Trans. Mobile Computing*, vol. 9, no. 1, pp. 5-16, January 2010.

[11] C. Hewage, M. G. Martini and N. Khan, "3D medical video transmission over 4G networks", in Proc. *4th Int. Symp. on Appl. Sci. in Biomedical and Commun. Technologies,* Barcelona, Spain, Oct. 2011.