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Continuous Vital Signs Monitoring: Benefits And Challenges For Real Time Big Data Analyses

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ABSTRACT

Remote patient monitoring (RPM) involves the collection of data from wearable sensors that typically requires analysis in real time. The real time analysis of data continuously streaming challenges data mining algorithms that have been developed for static data residing in central repositories. RPM also generates huge data sets that present storage challenges. These factors combine to make data analytics with continuous patient data challenging however, the careful design of RPM systems can lead to health care improvements. This is illustrated by drawing on a case study involving the real time analysis of patient vital sign data to detect deterioration in Indian hospitals.

INTRODUCTION

The continuous monitoring of patients with wearable sensors that stream data via wireless networks to repositories accessible by health care providers is emerging as a technology that promises to lead to new ways to realize early detection of conditions and increased efficiency and safety in health care systems (Chan, Estève, Fourniols, Escriba, & Campo, 2012). The approach combines body area wireless sensor networks (BSN) with systems that are designed to process and store the data for the purpose of raising alarms immediately or for data analytics exercises at a later point in time(Balasubramanian, Stranieri, & Kaur, 2015). Real time monitoring systems have been described for a number of remote applications including: continuous vital signs monitoring (Balasubramanian & Stranieri, 2014; Catley, Smith, McGregor, & Tracy, 2009), arrhythmia detection (Kakria, Tripathi, & Kitipawang, 2015), regulating oxygen therapy (Zhu et al., 2005), foetal monitoring (Balasubramanian, Hoang, &

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Ahmad, 2008), fall detection (Thilo et al., 2016), chemotherapy reaction (Breen et al., 2017) and glucose monitoring(Klonoff, Ahn, & Drincic, 2017).

(Kalid et al., 2018) notes that remote patient monitoring leads to large data repositories that presents serious challenges for Big Data analytics algorithms. A review by (Mikalef, Pappas, Krogstie, & Giannakos, 2017) reveals that Big Data is characterized in terms of the five main 'Vs:' volume, velocity, variety, veracity and value. Volume refers to large quantities data and velocity refers to the speed of data collection, processing and analysis in real time. The diversity of structured, unstructured, image, audio, video data is reflected in the variety of data. (Mikalef et al., 2017) note that though a great deal has been written about the Big Data explosion little is known of the conditions under which Big Data Analysis (BDA) leads to the generation of value for an organization. (Wang, Kung, & Byrd, 2018)

The openEHR standard that depicts the pragmatics of health care concepts described by (Kalra, Beale, & Heard, 2005) provides an important precursor to facilitate the application of Big Data analytics for RPM data. (Garavand, Samadbeik, Kafashi, & Abhari, 2016) survey the progress achieved in many healthcare systems toward the integration of digital health records into a consolidated virtual record. Government led electronic health record systems development tends to be enormously expensive and few countries have successfully implemented EHR systems despite the promise of potential efficiency gains and healthcare improvements that arise from access to so much data(Séroussi & Bouaud, 2016).

The development of electronic health records requires a very high level of interoperability between diverse computer systems and extensive use of standards(Sitton & Reich, 2016). Standards essential for electronic health records include OSI network communication standards, messaging standards such as HL7 (Schloeffel, Beale, Hayworth, Heard, & Leslie, 2006) and medical vocabulary standards such as SNOMET-CT (www.snomed.org/snomed-ct).

(Ramakrishnan, Hanauer, & Keller, 2010) attached a great deal of importance to the benefits of having standardized terminologies for data mining exercises some years ago when SNOMED-CT and Big Data were in their infancy. However, perhaps contrary to early expectations, the emergence of SNOMED-CT has not automatically facilitated Big Data Analytics(BDA)(Benson & Grieve, 2016). Reasons for this include the observation that coding of conditions, events, and

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test results to the appropriate SNOMED-CT code requires expertise and, in practice is often not done precisely or consistently, resulting in ambiguous data. The concept of "patient height" may appear to be terminologically unique and well defined as the distance between the top of the head and the bottom of the feet, however this concept is inappropriate if the patient cannot stand straight or is an infant. Height data collected inappropriately is likely to hamper analytics exercises.

In addition to terminological issues remote patient monitoring data requires additional abstraction due to the temporal nature of RPM. A patient's blood pressure measured continuously every 20 minutes over 24 hours may fluctuate between 140/70 mmHg and 110/90 mmHg for a particular patient. This level of fluctuation is not usually clinically significant so can be abstracted to a label like "Normal blood pressure". Conversely, a sudden drop in blood pressure from 150/80 mmHg to 90/60 mmHg in minutes warrants concern even if both measures are not clinically concerning in their own right.

RPM ANALYTICS

(Balasubramanian & Stranieri, 2014) designed and implemented an architecture that enables the transmission of patient data to Cloud-based repositories where software services invoked by health care providers can be instantiated, executed and terminated readily to securely and efficiently process all or part of a patient's data collected continuously with wearable sensors. Patients in participating hospitals were fitted with wearable sensors capable of monitoring ECG, blood pressure, temperature, respiratory rate and heart rate. The sensors were configured to continuously transmit data to a nearby Tablet running prototype software developed following (Balasubramanian & Stranieri, 2014).

The vast majority of data generated by RPM is found not to be of direct clinical interest for treating physicians, however once collected in digital form, health record legislation in most jurisdictions mandate that digital health data be stored and only deleted following onerous procedures. Most hospital information systems are not designed to store RPM data so storage must be done outside these systems with safeguards in place to ensure privacy and security.

As RPM continues to be adopted by healthcare systems, problems for data analytics exercises can be expected to emerge that dramatically reduce the utility of the data. However, data streams

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pose unique space and time constraints on the computation process (Aggarwal & Philip, 2007). Unlike conventional data mining, stream mining approaches must occur in real time which challenges computational processing efficiency. Most machine learning algorithms have been developed assuming all data is available to the algorithm. (Sanila, Subramanian, & Sathyalakshmi, 2018) review real time mining techniques to reveal the adaptation of algorithms for use when data streams incrementally in, is a pressing research problem. One approach to deal with this involves data summarisation where data is typically segmented into windows and reduced using filters. For instance, (Allami, Stranieri, Balasubramanian, & Jelinek, 2016) presents a low computational resource algorithm for reducing ECG data without losing key data points critical for diagnoses. Another approach involves incrementing subsequence counts (Abadia, Stranieri, Quinn, & Seifollahi, 2011) as each new data streams in. Sub-sequence counts can be directly used in classification algorithms advanced by (Quinn, Stranieri, Yearwood, Hafen, & Jelinek, 2008). Frequency counts profiles of interbeat heart rate variability has been shown by (Allami, Stranieri, Balasubramanian, & Jelinek, 2017) to predict future heart rate variability and some heart conditions.

Real time analytics with data streams is enhanced when it is linked with other data such as the patient's conditions, medication, demographic or other relevant data. However, accessing static data stored in other repositories during a real time analysis of the stream presents severe computational complexity challenges. Setting up processes to perform analyses that link stream data with static data requires a great deal of labor intensive work.

CONCLUSION

Remote patient monitoring systems collect data from patients, typically with wearable sensors, and transfer the data to servers so that health care professionals can remotely log in to view the data. Although these systems are emerging, to date little attention has been placed on the challenges inherent in analyzing data collected from remote patient monitoring systems.

REFERENCES

Abadia, R., Stranieri, A., Quinn, A., & Seifollahi, S. (2011). *Real time processing of data from patient biodevices.* Paper presented at the Proceedings of the Fourth Australasian Workshop on Health Informatics and Knowledge Management-Volume 120.

ISSN:0971-1260

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Aggarwal, C. C., & Philip, S. Y. (2007). A survey of synopsis construction in data streams. In *Data Streams* (pp. 169-207): Springer.

Allami, R., Stranieri, A., Balasubramanian, V., & Jelinek, H. F. (2016). *ECG Reduction for Wearable Sensor*. Paper presented at the Signal-Image Technology & Internet-Based Systems (SITIS), 2016 12th International Conference on.

Allami, R., Stranieri, A., Balasubramanian, V., & Jelinek, H. F. (2017). A count data model for heart rate variability forecasting and premature ventricular contraction detection. *Signal, Image and Video Processing*, 1-9.

Balasubramanian, V., Hoang, D. B., & Ahmad, N. (2008). *SOAP based Assistive Care Loop using wireless sensor networks*. Paper presented at the IT in Medicine and Education, 2008. ITME 2008. IEEE International Symposium on.

Balasubramanian, V., & Stranieri, A. (2014). *A scalable cloud Platform for Active healthcare monitoring applications*. Paper presented at the e-Learning, e-Management and e-Services (IC3e), 2014 IEEE Conference on.

Balasubramanian, V., Stranieri, A., & Kaur, R. (2015). *AppA: assistive patient monitoring cloud platform for active healthcare applications*. Paper presented at the Proceedings of the 9th International Conference on Ubiquitous Information Management and Communication.

Benson, T., & Grieve, G. (2016). *Principles of health interoperability: SNOMED CT, HL7 and FHIR*: Springer.

Breen, S., Kofoed, S., Ritchie, D., Dryden, T., Maguire, R., Kearney, N., & Aranda, S. (2017). Remote real-time monitoring for chemotherapy side-effects in patients with blood cancers. *Collegian, 24*(6), 541-549.

Catley, C., Smith, K., McGregor, C., & Tracy, M. (2009). *Extending CRISP-DM to incorporate temporal data mining of multidimensional medical data streams: A neonatal intensive care unit case study*. Paper presented at the Computer-Based Medical Systems, 2009. CBMS 2009. 22nd IEEE International Symposium on.

Chan, M., Estève, D., Fourniols, J.-Y., Escriba, C., & Campo, E. (2012). Smart wearable systems: Current status and future challenges. *Artificial intelligence in medicine, 56*(3), 137-156.

Garavand, A., Samadbeik, M., Kafashi, M., & Abhari, S. (2016). The Identification and Classification of Deployment Challenges Related to Electronic Health Records: A Review Article. *Shiraz E-Medical Journal, 17*(2).

Kakria, P., Tripathi, N., & Kitipawang, P. (2015). A real-time health monitoring system for remote cardiac patients using smartphone and wearable sensors. *International journal of telemedicine and applications, 2015*, 8.

Kalid, N., Zaidan, A. A., Zaidan, B. B., Salman, O. H., Hashim, M., & Muzammil, H. (2018). Based Real Time Remote Health Monitoring Systems: A Review on Patients Prioritization and Related "Big Data" Using Body Sensors information and Communication Technology. *Journal of medical systems, 42*(2). doi:10.1007/s10916-017-0883-4

Kalra, D., Beale, T., & Heard, S. (2005). The openEHR foundation. *Studies in health technology and informatics, 115*, 153-173.

Klonoff, D. C., Ahn, D., & Drincic, A. (2017). Continuous glucose monitoring: A review of the technology and clinical use. *Diabetes research and clinical practice, 133*, 178-192. doi:https://doi.org/10.1016/j.diabres.2017.08.005

ISSN:0971-1260

Vol-22-Issue-10-November-2019

Mikalef, P., Pappas, I. O., Krogstie, J., & Giannakos, M. (2017). Big data analytics capabilities: a systematic literature review and research agenda. *Information Systems and e-Business Management*, 1-32. doi:10.1007/s10257-017-0362-y

Quinn, A., Stranieri, A., Yearwood, J., Hafen, G., & Jelinek, H. F. (2008). AWSum-Combining Classification with Knowledge Aquisition. *Int. J. Software and Informatics, 2*(2), 199-214.

Ramakrishnan, N., Hanauer, D., & Keller, B. (2010). Mining electronic health records. *Computer, 43*(10), 77-81.

Sanila, S., Subramanian, D. V., & Sathyalakshmi, S. (2018). Real-Time Mining Techniques: A Big Data Perspective for a Smart Future. *Indian Journal of Science and Technology, 10*(42).

Schloeffel, P., Beale, T., Hayworth, G., Heard, S., & Leslie, H. (2006). The relationship between CEN 13606, HL7, and openEHR. *HIC 2006 and HINZ 2006: Proceedings, 24.*

Séroussi, B., & Bouaud, J. (2016). Adoption of a Nationwide Shared Medical Record in France: Lessons Learnt after 5 Years of Deployment. *AMIA Annual Symposium Proceedings, 2016*, 1100-1109.

Sitton, M., & Reich, Y. (2016). Enterprise Systems Engineering for Better Operational Interoperability. *Systems Engineering.*

Thilo, F. J., Hürlimann, B., Hahn, S., Bilger, S., Schols, J. M., & Halfens, R. J. (2016). Involvement of older people in the development of fall detection systems: a scoping review. *BMC geriatrics, 16*(1), 42.

Wang, Y., Kung, L., & Byrd, T. A. (2018). Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technological Forecasting and Social Change, 126*, 3-13. doi:https://doi.org/10.1016/j.techfore.2015.12.019

Zhu, Z., Barnette, R. K., Fussell, K. M., Michael Rodriguez, R., Canonico, A., & Light, R. W. (2005). Continuous oxygen monitoring—a better way to prescribe long-term oxygen therapy. *Respiratory Medicine, 99*(11), 1386-1392. doi:http://dx.doi.org/10.1016/j.rmed.2005.03.010