Adaptive Motif-Based Alerts for Mobile Health Monitoring

Ekanath Rangan[1] and Rahul Krishnan Pathinarupothi[2(✉)]

[1] School of Medicine, Amrita Vishwa Vidyapeetham (University), Kochi, India
[2] Center for Wireless Networks and Applications, Amrita Vishwa Vidyapeetham (University), Kollam, India
rahulkrishnan@am.amrita.edu

Abstract. We have developed a rapid remote health monitoring architecture called RASPRO using wearable sensors and smartphones. RASPRO's novelty comes from its techniques to efficiently compute compact alerts from sensor data. The alerts are computationally fast to run on patients' smartphones, are effective to accurately communicate patients' severity to physicians, take into consideration inter-sensor dependencies, and are adaptive based on recently observed parametric trends. Preliminary implementation with practicing physicians and testing on patient data from our collaborating multi-specialty hospital has yielded encouraging results.

Keywords: Mobile healthcare · Severity detection

1 Introduction

Remote health monitoring through the use of clinically approved wearable sensors, integrated with the smartphones, are emerging as a promising technological intervention to overcome the lack of affordable access to quality healthcare and timely delivery of critical care. Sensors are now available for monitoring as many as 30 vital cardio-metabolic health indicators, including blood pressure (BP), blood glucose, electrocardiogram (ECG), and oxygen saturation (SpO2) to alert any impending cardiac conditions such as ischemic events or syncope. Perego et al. [1] propose that wearable sensing can be employed even as early as in newborn babies. Frederix et al. [2] present a mobile smartphone based application for monitoring coronary artery disease. Such systems enable physicians, who are located in specialty hospitals far from the patients, to assess the patient's physiological condition based on received sensor values, viewed in the context of patients' historical electronic health records (EHR). The physicians can then initiate delivery of timely treatment through proximally located healthcare service providers.

Extensive survey of remote health monitoring devices is presented in [3]. However, in an experimental deployment of such systems of sensors and smartphones, we observed the following limitations:

P. Perego et al. (Eds.): MobiHealth 2016, LNICST 192, pp. 168–176, 2017.
DOI: 10.1007/978-3-319-58877-3_23

- **At the physician end:** Physicians started to receive voluminous data from the sensors attached to their patients. The data volume is amplified by the increased number of patients, multiplicity of sensors on each patient, and frequent sensing of vital parameters. Physicians, overwhelmed by this data volume, practically started to ignore, let alone even attempt to interpret, and there was diminished chance of making a suitable treatment decision in real-time.
- **At the patient end:** The use of popular smartphones to receive, multiplex, and transmit sensor data continuously causes rapid power draining. As a result, there is a good chance of inadequate power just when all sensors are required to fire in the event of an unforeseen health condition.

A solution to overcome these challenges is to summarize the data on the patients' smartphones prior to transmission. Recent hardware advances in both sensors and mobile wireless devices have led to increasing quantum of interest and research in this area. Banaee et al. [4] recognize that, recently, research in health monitoring systems has shifted from simple reasoning of wearable sensors readings to the advanced level of data processing.

Much of the recent research in summarization has focused on complex machine learning techniques to aid in disease diagnosis [5]. Whereas this is a promising direction for the future, our interactions and observations with our medical collaborators in our inter-disciplinary research team is that, physicians are not yet ready to accord an influential role for automated diagnosis in their patient care. We have chosen a practical compromise: Summarization whose outcome is alerts with following attributes:

- Alerts have to accurately communicate the severity of the patient's condition to the physician. Alerts are computed from the sensor measurements and can take multiple levels.
- Alerts should take into consideration observed trends in intra-sensor measurements, and also inter-sensor severity dependencies.
- Alerts should have a feedback influence on adapting the frequency of both the sensor measurements and summarization. By dynamically reducing the frequency during low severity conditions, significant savings in the power can be achieved, without compromising on the accuracy. Conversely, during high alert conditions, rapidity of measurements and related summarization can be accelerated since delays can be life threatening. So, in this paper, we set forth to address the challenge of accurate and timely processing of alerts.
- Alerts should be dynamically adjustable based on the physicians' perception of the patients' vulnerability to health conditions.
- Alerts should be computationally inexpensive to run efficiently on edge devices such as smartphones.

To our best knowledge, the alert mechanisms already proposed in literature, like the one proposed by Bai et al. [6] are targeted towards generating alarms in an ICU, and could not satisfy all of the above requirements that we set out with.

In this paper, we propose a novel interventional time-inverted adaptive feedback alert mechanism, which we call as RASPRO (Rapid Alerts Summarization for Effective Prognosis) to analyze the data at the edge devices (e.g., smartphones), followed by transmission of alerts to the remote physician. We have based this mechanism on our previous work [7], where we have used a motif-based representation for multi-sensor medical data.

The remainder of this paper is organized as follows: Sect. 2 presents the overall architecture of the RASPRO remote health monitoring system. Section 3 presents the adaptive feedback based alert computation techniques. Section 4 presents implementation and preliminary results, and Sect. 5 concludes the paper.

2 RASPRO Architecture

The patient side architecture (see Fig. 1) begins with sensors attached to human body for measuring and monitoring a variety of physiological parameters such as, pulse rate, blood pressure, blood oxygen, ECG, respiratory rate, blood sugar, temperature, etc., together constituting the sensing subsystem. Each of the sensors output analog signals that are then digitized into a raw data sequence. In general, let us consider $\boldsymbol{N}$ vital sensors, $\boldsymbol{s_1, s_2, \ldots, s_N}$, each with a sampling frequency, $\boldsymbol{F}$. The sampling proceeds continuously for an interval of $\boldsymbol{I}$ time units, following which there may be a gap of $\boldsymbol{\Gamma}$ time units, and then the sampling resumes for the next interval $\boldsymbol{I}$, etc. Many such intervals constitute the total observation window $\boldsymbol{\Phi}$. For instance, sampling may occur for $\boldsymbol{I} = 1$ h every day in a week, in which case, $\boldsymbol{\Gamma} = 23$ h and $\boldsymbol{\Phi} = 7$. The relative durations $\boldsymbol{I}$, $\boldsymbol{\Gamma}$, and $\boldsymbol{\Phi}$ are patient and disease specific and are set by the physician.

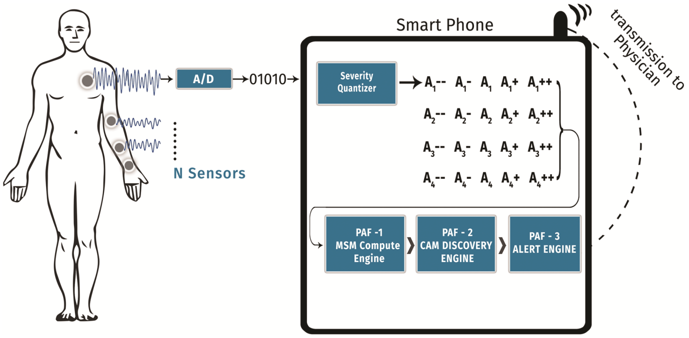

Fig. 1. RASPRO remote health monitoring patient-side architecture, with three physician assist filters (PAFs) running on patient's smartphone. Matrices (MSM) and Motifs (CAM) are introduced later in this section.

Then a sensor data specific comparator quantizes the digital sequence into one of Q possible severity symbols. For instance, if Q is taken to be five, the levels are labeled A−−, A−, A, A+ , and A++ with the symbol A indicating normality, and subscripts "−" and "+" indicating sub-normal and above normal levels of increasing severity. More complex parameters could be derived from sensor data and can employ domain specific reference patterns corresponding to various severity levels. The different severity levels are selected from the medical interpretation as well as physician's input based on the patient profile. For instance the normal range of BP is 120/80 to 140/90 and there are different severity levels of hypertension and hypotension above and below this normal range.

The severity symbol sequences, all assumed to be of same frequency, are multiplexed at the granularity of one symbol per sensor. Its output is a sequence of timed vectors, with each vector consisting of N values, one from each sensor sampled at that particular instant. Any missing sensor values (for whatever reason), are filled in by duplicating the most recent value of that particular sensor.

These vectors become the elements of a three dimensional Multi-Sensor Matrix (MSM), with F * I columns, and Φ rows, and each element depth equal to N. The MSM can be thought of as consisting of N two dimensional Single Sensor Matrices (SSM [1], SSM [2],…, SSM[n],… SSM[N]), each of F * I columns and Φ rows. In the next stage of RASPRO, the MSM is used for discovering frequent trends in sensor values that is called consensus abnormality motifs (CAM). This is dealt with in detail in our previous work [7].

The above modules are implemented as Physician Assist Filters (PAFs), and are named MUX-MSM Compute Engine, CAM Discovery Engine, and Alert Delivery Engine and they run on the patient smart phone. The computed alerts and its semantic interpretation are promptly transmitted to the physician by the Alert Delivery Engine via popular messaging platforms such as SMS and Whatsapp, based on the network bandwidth availability, power constraints and severity of the alerts.

3 Alert Computation Techniques

Building on our previous works on developing a rapid severity detection and summarization algorithm, we propose the use of consensus abnormality motifs as a representation of frequent abnormality in a large time series data.

3.1 Motifs

Candidate Motif, μ_{CAN}[n] is a temporally ordered sequence of quantized values, **A^*_t, A^*_{t+1}, A^*_{t+2}, …, A^*_{t+L}** of length L that is selected from SSM [n]. So, the first row of an SSM can be selected as a **μ_{CAN}** by selecting $L = F * I$ and starting symbol as element (1,1) in SSM.

Normal Motif, μ_{NOR}[n] is a candidate motif in which all values represent the normal severity level, which means each and every value is equal to **A**.

Consensus Motif, μ_{CON}[n] is a candidate motif satisfying the following two conditions: its hamming distance from **μ_{NOR}[n]** does *not* exceed a physician prescribed sensor-specific near normality bound, d_{NOR}[n] and, its total hamming distance from all other **μ_{CAN}[n]** is the minimum. **μ_{CON}** represents the observed patient-specific near normal trend.

Consensus Abnormality Motif, μ_{CAM}[n], is a candidate motif satisfying the following two conditions: its hamming distance from **μ_{NOR}[n]** exceeds a physician prescribed sensor-specific near normality bound, d_{NOR}[n] and, its total hamming distance from all other **μ_{CAN}[n]** is the minimum (Fig. 2).

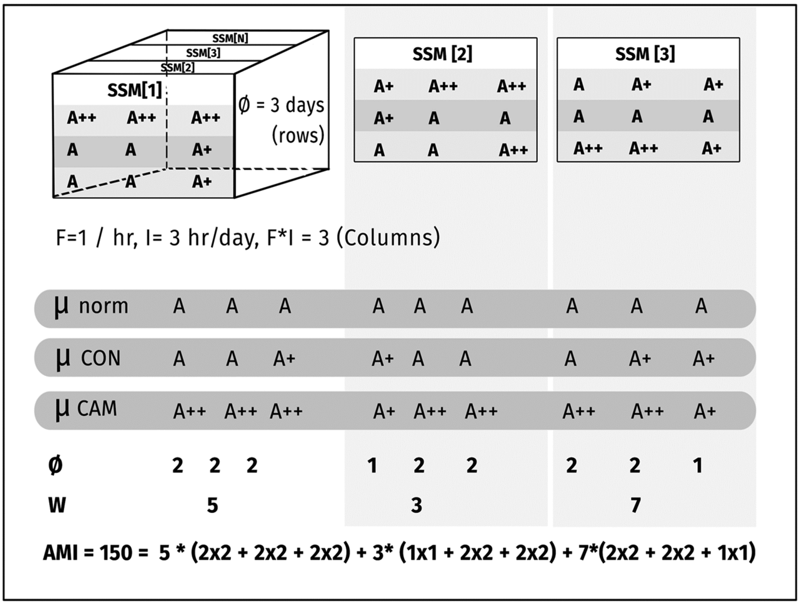

Fig. 2. Computation of the Motifs and Alerts from sensor matrices

It should be noted that, whereas an isolated abnormal sensor reading is indicated by A++, A+ , A–, A−−, etc., $\boldsymbol{\mu}_{\mathbf{CAM}}$ represents the most frequently occurring abnormality trend over the entire observation period. The parameter d_{NOR} can be set specific both to the patient and to the vital parameter, by the attending physician. The discovery of the motifs is dealt with in detail in our previous work [7]. In this paper, we now present novel techniques for computing alerts from these motifs.

3.2 Alert Measure Index

At the end of each observation window $\boldsymbol{\Phi}_{\mathbf{r}}$, for every patient, we define an aggregate alert score, called the **Alert Measure Index (AMI)**. This is calculated as

$$\mathbf{AMI}[\boldsymbol{\Phi}_r] = \sum\nolimits_{i=1}^{N} W[\mathrm{i}] * \sum\nolimits_{j=1}^{F*I} \mathbf{num}(\boldsymbol{\mu}_{\mathbf{cam}}[\mathrm{i}][\mathrm{j}]) * \boldsymbol{\Theta}[\mathrm{j}] \quad (1)$$

Wherein, the inner summation takes each severity value in the $\boldsymbol{\mu}_{\mathbf{CAM}}$ of the i^{th} sensor, converts it into a numerical value (e.g., A± is assigned 1, A++/−− is assigned 2), scales it up by a severity specific factor ***Θ[j]***, and the outer summation scales it up by a sensor specific weightage ***W[i]***, both of which are derived from medical domain expertise. We call these two factors ***W*** and ***Θ*** as severity factors, and the resulting ***AMI*** is indicative of the immediacy of patient priority for physician's consultative attention.

3.3 Interventional Time-Inverted Alerts

We propose a goal directed approach to determining the severity factors $\boldsymbol{W}$ and $\boldsymbol{\Theta}$. The goal of delivering the alerts to the physician is to indicate the upper bound on the time that can elapse before which the physician's intervention is imperative to pull the patient out of danger. In order to capture this, we define the severity factors $\boldsymbol{W}$ and $\boldsymbol{\Theta}$ as follows:

$$\Theta[\alpha] = \frac{\mathrm{K1}}{\Delta[\alpha]}, \quad \mathrm{W}[\mathrm{n}] = \frac{\mathrm{K2}}{\Delta[\mathrm{n}]} \tag{2}$$

where, $\Delta[\alpha]$ is the upper bound on the time for intervention for severity level α (which can take on values A++, A+ , etc.), $\Delta[n]$ is the upper bound on the time for intervention for sensor n. In (2), constants K_1 and K_2 can be set by the physician considering the context of patient's health condition (including historical medical records and specific sensitivities and vulnerabilities documented therein). The inverse linear equation relating the severity factor to interventional time may be substituted by more complex equations for progressively complicated disease conditions. For instance, cardiologists prefer an exponential increase in alert levels if the monitored patients' ECG shows significant ST level depression: a direct indicator of myocardial infarction.

$$\Theta(\alpha) = e^{\left(\frac{K1}{\Delta(\alpha)}\right)} \tag{3}$$

We are currently engaged in active dialog with collaborating physicians from our medical school to determine the severity level - interventional time relationships for different specialties.

AMIs also serve as a feedback mechanism to modulate sensing frequency and alert computation instants. A low AMI is used to effect three adjustments: (1) Reduce the frequency $\boldsymbol{F}$ of future sensor measurements to a medically allowed minimum bound, (2) Increase the gap $\boldsymbol{\Gamma}$ between successive monitoring intervals, and (3) Increase the subsequent inter-alert window $\boldsymbol{\Phi}$, thereby saving power and bandwidth of transmission. By the same token, a high AMI causes $\boldsymbol{F}$ to increase, $\boldsymbol{\Gamma}$ to decrease, and $\boldsymbol{\Phi}$ to increase. We have used a linear model to relate each of these factors:

$$\begin{aligned} \boldsymbol{F}_{\mathrm{r+1}} &= \boldsymbol{F}_{\mathrm{r}}[1 + \boldsymbol{C}_1 * \left(\mathrm{AMI}\left(\boldsymbol{\Phi}_{\mathrm{r}}\right) - \mathrm{AMI}\left(\boldsymbol{\Phi}_{\mathrm{r-1}}\right)\right] \\ \boldsymbol{\Gamma}_{\mathrm{r+1}} &= \boldsymbol{\Gamma}_{\mathrm{r}}[1 - \boldsymbol{C}_2 * \left(\mathrm{AMI}\ \left(\boldsymbol{\Phi}_{\mathrm{r}}\right) - \mathrm{AMI}\ \left(\boldsymbol{\Phi}_{\mathrm{r-1}}\right)\right] \\ \boldsymbol{\Phi}_{\mathrm{r+1}} &= \boldsymbol{\Phi}_{\mathrm{r}}[1 - \boldsymbol{C}_3 * \left(\mathrm{AMI}\ \left(\boldsymbol{\Phi}_{\mathrm{r}}\right) - \mathrm{AMI}\ \left(\boldsymbol{\Phi}_{\mathrm{r-1}}\right)\right] \end{aligned} \tag{4}$$

where, $\boldsymbol{C_1}$, $\boldsymbol{C_2}$, $\boldsymbol{C_3}$ are positive feedback constants adaptively set by physician's preferences. A very high frequency causes redundancy in summarization while a lower frequency may result in missing sudden short duration spikes in parameters. An optimum frequency for SDS has to be specific to the patient, sensor and severity. A detailed discussion on setting of these constants is outside the scope of this paper.

4 Implementation and Preliminary Results

We have built an initial implementation of the RASPRO architecture (see Fig. 3), and carried out preliminary testing of the alerting techniques on anonymized patient data at our 1500-bed super-specialty hospital, namely, the Amrita Institute of Medical Sciences. Secure network protocols are used to transmit alerts (AMIs) over mobile networks, and standard encryption techniques are used to ensure privacy. Upon viewing the received AMI pertaining to a patient, the doctor may initiate a data pull mechanism called Detail Data on Demand, abbreviated as "***DDoD***", originating from the doctor's device to the cloud. The DDoD may further propagate to the patient's smartphone if part or whole of the data requested is still remnant on the patient's smartphone.

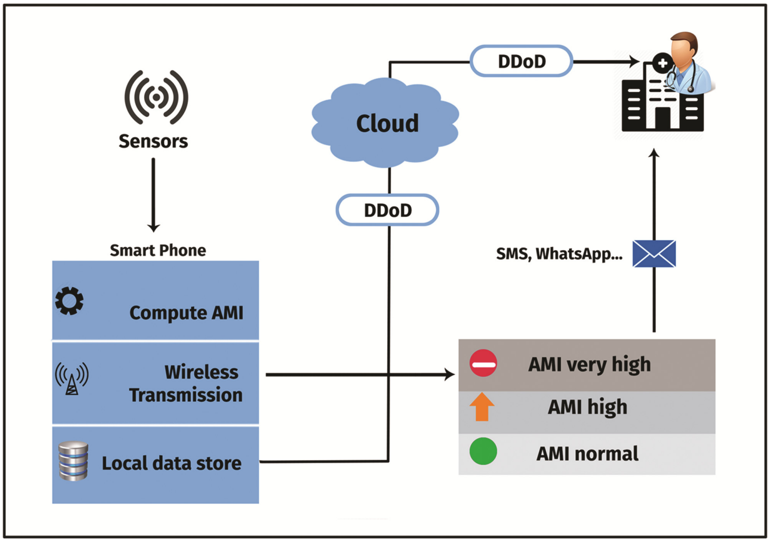

Fig. 3. Implementation of the alert delivery mechanism on Mobile networks with Detail Data on Demand (DDoD) feature

We have seen very encouraging results during the early trials of the system at the hospital, both among the physician community as well as the patients. As early adopters of the RASPRO system, the physicians identified the following target patient groups. Cardiac patients with history of ischemia, diabetes, syncope and hypertension have been using our wearable monitoring and alerting devices [8] and integration of RASRPO alerting technique is slated to be a key enabler in identifying patients who need immediate help. Another target group are patients who need to be identified with sleep apnea and given warnings when their heart rate and respiratory rate variability is asynchronous in nature.

Figure 4 shows blood glucose levels measured using interstitial chips from two patients as a representative of this group. The continuously collected 24 h raw values are analyzed for severity and summarized at a fixed frequency and then using the adaptive feedback technique of (4), where $\Phi = 3$ h in the beginning and then decreased to 2 h, 1 h, and then finally to 20 min, corresponding to increasing severities.

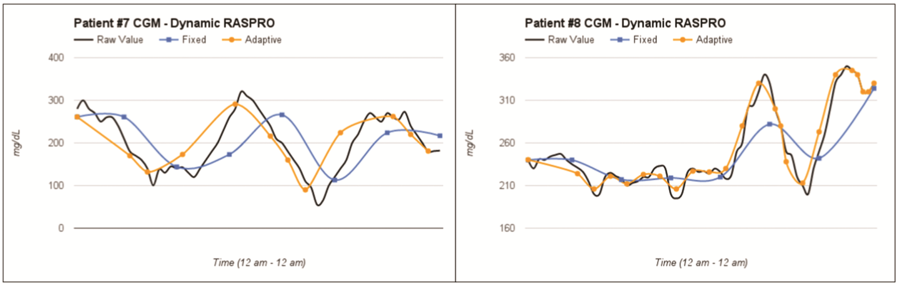

Fig. 4. Performance of adaptive feedback based alerts for blood glucose level variations, as compared to fixed frequency alerts, for multiple patients

We have very interesting observations from these data: (a) fixed frequency alerts might lead to missing spikes of high severity, which might lead to even life-threatening scenarios, (b) since feedback-based alerts adapt the frequency according to rising or falling trends, they are able to pick higher severities with much better accuracy, and (c) both adaptive and fixed alerts are similar in performance during normal times. Similar observations were made in other patient data as well, all though due to space constraints we have omitted from reporting here.

5 Conclusion

We have developed a novel adaptive feedback technique for timely computation of healthcare criticality alerts and a system architecture called RASPRO for their delivery over mobile remote health monitoring networks. The alerts are computed from severity trends represented as motifs, and capture the inter-sensor dependencies. Alerts have great advantages of reducing the bandwidth and energy on smartphones, as well as, avoiding the significant data overload on already very busy doctors saving them from the need to go through voluminous patient reports. Results from our initial pilot implementation carried out jointly with practicing physicians are highly encouraging.

Acknowledgments. We express our deep gratitude to our Chancellor and world renowned humanitarian leader Sri Mata Amritanandamayi Devi (Amma) for her inspiration and support towards working on inter-disciplinary research that has direct societal benefit.

References

1. Perego, P., Andreoni, G., Zanini, R., Bellù, R.: Wearable biosignal monitoring system for newborns. In: EAI 4th International Conference on Wireless Mobile Communication and Healthcare (Mobihealth), pp. 271–274. IEEE (2014)

2. Frederix, I., Sankaran, S., Coninx, K., Dendale, P.: MobileHeart, a mobile smartphone-based application that supports and monitors coronary artery disease patients during rehabilitation. In: IEEE Annual Conference on Engineering in Medicine and Biology, pp. 513–516. IEEE (2016)
3. Mukhopadhyay, S.C.: Wearable sensors for human activity monitoring: a review. IEEE Sens. J. **15**(3), 1321–1330. IEEE (2015)
4. Banaee, H., Ahmed, M.U., Loutfi, A.: Data mining for wearable sensors in health monitoring systems: a review of recent trends and challenges. Sensors **13**(12), 17472–17500 (2013)
5. Keogh, E., Lin, J., Fu, A.: Hot sax: efficiently finding the most unusual time series subsequence. In: Fifth IEEE International Conference on Data Mining (ICDM 2005), 8 p. IEEE (2005)
6. Bai, Y., Do, D., Ding, Q., Palacios, J.A., Shahriari, Y., Pelter, M.M., Boyle, N., Fidler, R., Hu, X.: Is the sequence of super alarm triggers more predictive than sequence of the currently utilized patient monitor alarms. In: IEEE Transactions on Biomedical Engineering, vol. 99. IEEE (2016)
7. Pathinarupothi, R.K., Rangan, E.: Discovering vital trends for personalized healthcare delivery. In: Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct, pp. 1106–1109. ACM (2016)
8. Dilraj, N., Rakesh, K., Krishnan, R., Ramesh, M.: A low cost remote cardiac monitoring framework for rural regions. In: Proceedings of the 5th EAI International Conference on Wireless Mobile Communication and Healthcare, pp. 231–236. ICST (2015)