Large Scale Remote Health Monitoring in Sparsely Connected Rural Regions

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***Abstract*—Remote health monitoring and intervention systems including wearable sensors, smartphones and advanced communication technologies are slated to be a game changer in the delivery of quality healthcare services, especially in developing parts of the world. However, we are yet to see large scale adoption of remote health monitoring systems due to many factors such as: lack of reliable data network coverage, high power requirements for smartphone analytics, and unreliability in the timely delivery of critical data to remote doctors. In addition to these, the huge volume of sensor data and alerts from multiple remote patients are unmanageable for already overloaded doctors. In this paper, we attempt to address each of these issues. First, we propose a novel healthcare communication architecture that connects remotely stationed telemedicine nodes and village clinics with remote doctors in specialty hospitals. Second, we present the development of disease severity pattern discovery and summarization algorithms, the result of which is a *Consensus Abnormality Motif (CAM)* and an associated *Alert Measure Index,* which suggests the immediacy of the patient data for doctor's consultative time. By frequently sending CAM as SMS in the absence of data network, we ensure timely delivery of critical data. Through a Detailed Data on Demand (DD-on-D) pull data mechanism doctors can further investigate complete data from the cloud. The CAM and DD-on-D mechanisms result in energy savings of up to 25%, while the data usage is reduced tremendously. Furthermore, we present a pilot deployment of the systems using a continuous cardiac monitoring device coupled with an intervention framework including more than 60 telemedicine nodes station in villages across India.**

Keywords—Remote health monitoring, Healthcare communication architecture, medical data summarization, tele-health.

I. INTRODUCTION

More than 60% of the population in the developing countries resides in rural villages. There is a startling lack of accessibility to hospitals in most villages. In most cases, patients have to travel at least 2-3 hours to reach the nearest hospital, leading to uncertain impact on their health or even loss of life. From an economic point of view, a break from their work and cost of travelling to hospital has a heavy impact on their family income. This is a major demotivating factor for patients. The doctors in tier II or tertiary hospitals advice frequent follow up visit or updates from the patient to monitor the progress of medication or recovery. Another major issue that is hurting the current healthcare system is the lack of experienced expert doctors in hospitals. In most parts of the developing world, the number of qualified healthcare professionals is not increasing to meet the demands of an increasing population. We are also witnessing a lack of willingness of qualified doctors to practice in remote rural regions. In spite of emergence of new technological advances, the rural population is unable to receive quality healthcare access in comparison to their urban counterparts. Together, these factors are contributing towards higher mortality as well as falling standards of health care. Inequitable affordability as well as inadequate timeliness of access to healthcare for underserved populations around the world are significant humanitarian concerns.

Fortunately, recent advances in wireless communications and embedded systems coupled with their falling costs have opened a whole new vista: Remote healthcare monitoring using wearable sensors and smartphones is one of the most promising affordable technological interventions in aid of economically backward rural populations in remote regions. One of the first such interventions widely dealt with in literature (elaborated in Section II on related work), naturally because of its prevalence, is in the area of cardiac health monitoring, with the aid of smartphones. However, we have not yet seen their noticeable adoption in rural communities.

In this research, a collaborative team of us consisting of researchers from wireless center and school of medicine at top ranked multi-disciplinary universities of India embarked on a project to develop and deploy a remote health monitoring system in our rural neighborhoods. We identify the major challenges in adopting remote healthcare monitoring (Section III) for such populations, and then propose a four step methodology (Section IV) to design a system that integrates into traditional healthcare setup. We then present our cardiac monitoring sensor device (Section V), followed by the communication and delivery platform that runs lean on energy and data (Section VI), discuss the algorithmic innovations to preserve timeliness and integrity of diagnostic decision making (Section VII), and move on to the performance evaluation of algorithms(section VIII). We then present the telemedicine interventional network being deployed (Section IX) followed by the deployment experiences (Section X) and conclusions (Section XI).

II. Related Work

Extensive survey and analysis of existing healthcare service models, communication frameworks and evaluation of the clinical usability of these remote health-monitoring devices is presented in [2]. They have also identified that the three main barriers of this technology are: reliability and efficiency of wireless technology, quality of physiological data and patient confidentiality and security. There are far too many remote vitals monitoring systems that have come out and we would be able to present only a non-exhaustive list here with no particular order or priority. This includes [3], [4], [5], and [6]. Most of the latest and widely used commercially available cardiac monitoring devices including smartphone monitoring systems, patch based ECG monitoring and implantable loop recorders are discussed from a clinical utility perspective in [7]. This study also points to the specific challenges related to the cost effectiveness of the solutions as well as the need for predictive analysis. It was also noted that most of these solutions do not address the challenges posed by energy and bandwidth constrained environments, and hence not exactly suitable for remote rural regions.

Kalahasty et al. [8] describes how technological advances have aided in the development of useful remote monitoring systems, though a large scale clinically validated system is yet to be seen. A relatively recent work [9] describes the potential of ubiquitous computing aided by smartphones in delivering tele-health and mHealth in remote and bandwidth-constrained regions. Steele et al. [9] also focuses on the fact that the urban communication technology infrastructure is far superior in terms of bandwidth, cost and quality compared to their rural counterparts. Our previous work on the "Amrita Spandanam" remote cardiac monitoring device [1] was especially designed for rural regions.

Through smart diagnosis and summarization in the patient"s smartphone, we can effectively use the scant bandwidth available in rural regions to transmit critical data. Banaee et al. [10] analyzes the existing data mining techniques on large time series data including healthcare data summarization. Some of the earlier works in effective pattern discovery is presented in [11] and [12]. More recently, Balasubramanian et al. [13] have worked on determining the temporal relationship between multi-sensor data for fall detection in elderly people. Our earlier work [20] on severity based quantization and motif discovery on multi-sensor data is an initial effort in this direction. In this paper, we present novel architecture, techniques and algorithms to diagnose, summarize and alert cardiac events from multiple ECG parameters, along with an intervention framework using telemedicine network linked to existing public healthcare facilities.

III. Problem Statement

Notwithstanding the phenomenal advances in mobile and sensor technologies, there are three major challenges that need to be overcome for rural adoption of remote health monitoring and intervention systems:

- Unavailability and/or unaffordability of high bandwidth wireless data networks in rural regions, even though there is high mobile penetration [14] [17]. A closely related issue is that of incremental energy consumed by smartphones when data is switched on, and the severe scarcity of energy supply in remote regions.
- Large data volumes that pour in from continuous monitoring that compete for already overloaded doctors' time.
- Lack of integration and interoperability with already existing public healthcare delivery outlets, mechanisms, and systems.

The first and the second challenge above are related to data, and its required energy for computation and transmission. Unlike other domains, data could be life-saving, and hence, we have to tread very carefully while trying to address this challenge. The third concerns legacy and sluggishness with which firmly rooted traditional healthcare practices embrace newer technologies and methods. Nevertheless, by transforming these challenges to opportunities, our goal remains: to deploy healthcare monitoring in sparsely connected remote rural regions that can be relied upon by both doctors and patients, using wireless, mobile, and sensor technologies as enablers.

IV. Methodology

Healthcare is a vast field that has to deal with large and complex variations in human illnesses. The very first step in our embarked upon project is to choose a sub-domain that is both of reasonably significant value to the population being served, and amenable to the kind of technological intervention that we are proposing. For this purpose, we chose cardio-vascular conditions since there is increased incidence in rural Indian populations possibly because of life-style sedentariness. We designed and fabricated a low-cost wearable ECG monitoring sensor that interfaces wirelessly with the mobile smartphone (refer figure 1).

The second step of our methodology is to define and develop a healthcare communication platform that enables patient data aggregation, forwarding, archival, and visual presentation, all in a timely manner. The platform is instrumented to measure data bandwidths, energy consumed, delay latencies, for various modes of communication: SMS, WhatsApp, Email, etc.

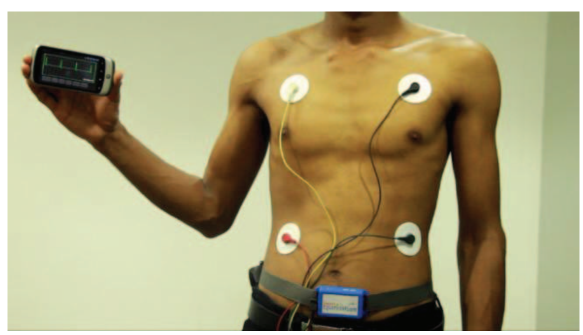

Figure 1: Amrita Spandanam wearable ECG monitoring sensor interfaced with the smartphone android application.

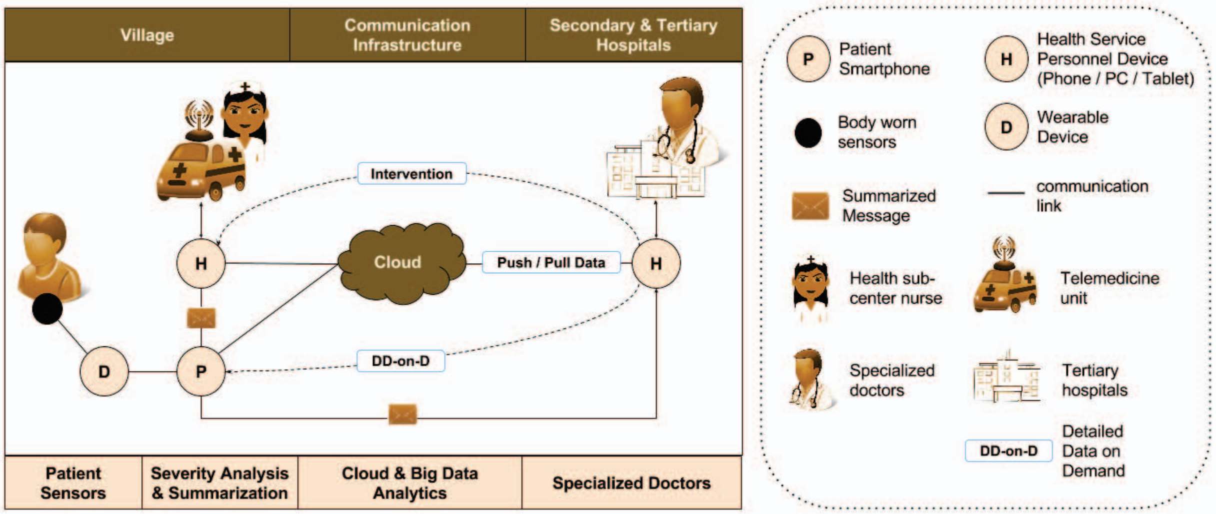

Figure 2: Healthcare communication platform. Whereas replies to DD-on-D are routed through cloud, AMI alerts go directly from patient smartphone to doctor's device.

The third step is to formulate techniques and algorithms for smart summarization of data to identify abnormal deviations in patient‟s vital data, and a subsequent criticality based communication protocol that reduces the dependence on data networks, while ensuring timely delivery of critical alerts to the doctors.

In the fourth step, we implement a remote intervention mechanism that enables telemedicine collaboration between doctors in tertiary hospitals with nurses stationed in village health sub-centers to implement the treatment plan at the closest point of care for remote rural patients. We are readying the entire system for scalable deployment in 108 villages across the Indian subcontinent, as a joint interdisciplinary initiative of our Amrita University and Amrita Institute of Medical Sciences, two of the best-known academic and medical institutions in India, both belonging to the world renowned charitable organization, Sri Mata Amritanandamayi Math.

V. WEARABLE CARDIAC MONITORING SENSOR

As an effort towards development of cost-effective wearable sensors, we have developed a cardiac monitoring device, named Amrita Spandanam [2], which is a 3-lead ambulatory continuous ECG monitoring sensor. This AAMI/EC13 compliant device can be worn in Mason-Likar configuration for limb leads as well as Holter-like lead system to obtain two chest leads, and the continuous recording can be done for up to several months through the use of a USB rechargeable battery. Figure 1 shows the usage of this device. This is one of the first devices to be integrated in to the healthcare communication platform, which is explained next.

VI. HEALTHCARE COMMUNICATION PLATFORM

The healthcare communication platform (see Figure 2) uses multiple wireless technologies to efficiently connect a gradation of devices: lightweight sensors, wearable device, patient smartphone, internet cloud, telemedicine station, and handhelds or PC type devices belonging to doctors and local healthcare support personnel. The platform automates the following data transports in a timely manner.

- Patient data aggregation: Sensor to patient smartphone via wearable wireless interface. The patients can wear the sensor devices (such as Amrita Spandanam ECG device), which sends data to the user‟s smartphone over Bluetooth (BT) or other short-range media.

- Alerts transmission: Patient smartphone to Doctor's device. The patient‟s smartphone analyzes and summarizes the data using a fast and effective disease severity discovery technique called *Multi-Parameter Consensus Abnormality Motif (here after referred to as CAM)*, elaborated in the next Section. The outcome of this algorithm is the patient's *Alert Measure Index (AMI)* indicative of the immediacy of patient priority for doctor's consultative attention. We consider three AMI thresholds as shown in the Figure 3. If the AMI is high, CAMs are transmitted without further ado, and among the available networks (cellular versus data), the least delay network and messaging application are used. The CAMs and AMI are transmitted directly to the doctor‟s device bypassing the cloud.

- Periodic Archival: Patient's smartphone to Internet Cloud. The summarized data in the form of CAM may be sent to the cloud for onward transmission to the remote health service personnel (HSP), or locally stored for delayed transmission. The latter option is exercised only if AMI is normal.

There are two network related limitations arising from our targeted population of remote rural regions: scarcity of data bandwidths, and paucity of energy for smartphones. As a result, we have incorporated several bandwidth and energy saving innovations:

- SMS/MMS: Taking into consideration the intermittence or total lack of data network availability in rural regions, at high AMIs, the CAMs are immediately sent to the doctors over SMS or MMS.

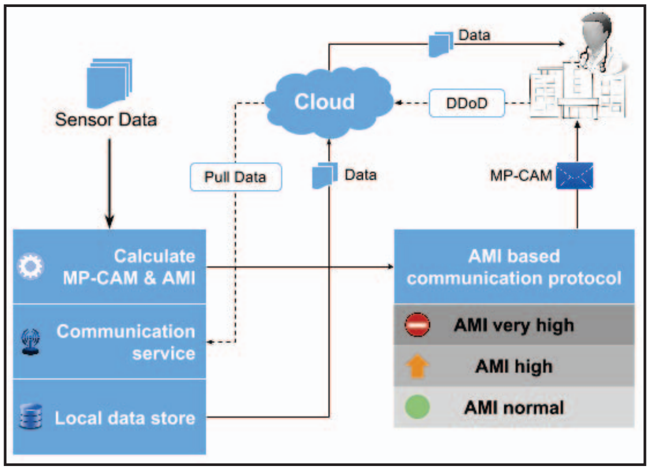

Figure 3: Alert message protocol based on AMI of the vital data.

- Detail Data on Demand (DD-on-D): Upon viewing the received AMI and CAM pertaining to a patient, the doctor may initiate a data pull mechanism, abbreviated as "*DD-on-D*" originating from the doctor's device to the cloud.

The DD-on-D may further propagate to the patient's smartphone (see Figure 3) if part or whole of the data requested is still remnant on the patient"s smartphone. The response to this request may trigger spontaneous switching on of the smartphone data if connectivity is available, and if not, a step-wise refined summaries are transmitted via successive sequence of SMSs or MMSs. The DD-on-D also handles other data related directives from the doctor, such as a request to increment (or decrement) the summarization frequency, so that he/she receives CAMs more (or less) often from that particular patient.

VII. Criticality Summarization and Alert Mechanism

Diagnostic data summarization, not only is it crucial for bandwidth and energy starved remote regions, but also has a pragmatic human dimension too: avoiding the significant overload on already very busy doctors to having to go through voluminous patient reports. Working hand in hand with our super specialty doctors, we have devised novel techniques to analyze and summarize the data in the patient"s smartphone itself. Needless to say, the analysis should not be computationally complex as otherwise it will result in further drain of mobile battery and be counterproductive to the energy constrained operation. Our summarization techniques attempt to discover medically accepted disease severity patterns, dubbed as, *Multi-Parameter Consensus Abnormality Motif (CAM)*. It starts with a severity quantizer applied on sensor reported health parameter values, which are then structured into a multi-parameter quantized value matrix, for abnormality pattern (henceforth called as *motif*) discovery and alert level calculator. The precise algorithms in the context of our cardiac monitoring device are described next.

A. Multi Parameter Quantized Value Matrix

Consider a continuous monitoring ECG sensor, S_N. Suppose we intent to monitor a number of different parameters, P_1, P_2, …, P_i, such as RR interval, ST deviation, ST segment etc. Let us also assume that the total number of parameters is N_P. Our goal is to identify any criticality and summarize this multi-parameter data such that a lucid report is sent to the doctors. Before we find the abnormalities, we preprocess the sensor data as follows.

First, the raw sensor data is processed by the parametric analyzer, which calculates the values of each parameter P_i, at a frequency of f_P. Next, these parameter values are quantized into any of K severity symbols defined for the respective parameters. The severity symbols are assigned as A+, A++, A-, A-- etc., based on the deviation from the medically accepted normal parameter value, which is denoted by the symbol A. The + and - symbols represent varying degrees of above-normal and subnormal severity levels. After this, the quantized values are sent to a mux, which constructs a multi-parameter quantized value matrix (MP-QVM). The columns of MP-QVM represent the different parameters, while the rows are time ordered quantized values. We describe a sample scenario below. Suppose we need to discover a CAM once in every ten minutes, denoted as summarization frequency $f_S = 1/600$ *(per sec*). Assuming the parametric analyzer frequency f_P=1 Hz, we discover CAM from an MP-QVM of $1/f_S$ rows (denoted as observation window size W_S) and N_P columns. Figure 4 depicts these processing steps. Next we describe how CAMs are discovered from an MP-QVM.

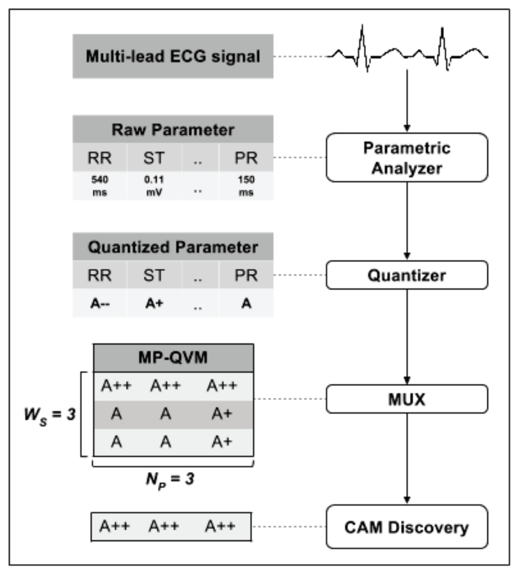

Figure 4: Computing the Multi-Parameter Consensus Abnormality Motif (CAM) from raw sensor data

B. Discovering CAMs

The doctors are often interested to discover the most frequent deviations from medically accepted levels of a parameter. The first step in the CAM discovery algorithm is to calculate the frequency of occurrence of each severity symbol in the MP-QVM. Based on this, a Multi Parameter Severity Profile Matrix (MP-SPM) is constructed with N_P columns and K rows (refer Figure 5). The MP-SPM is then analyzed to find out the most frequently occurring severity symbol. However, since we are interested only in deviations from the normal behavior, we employ a weighted element-wise multiplication of elements in MP-SPM with a predetermined corresponding severity weights to build a weighted MP-SPM.

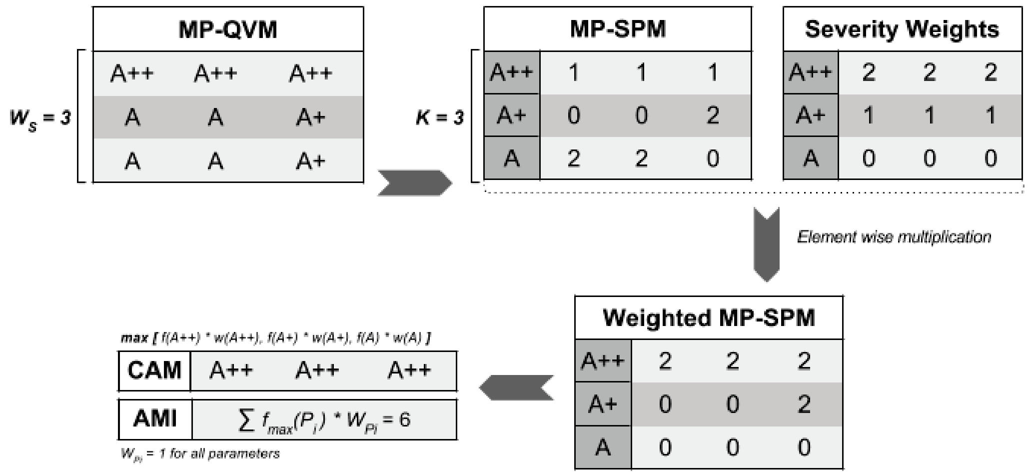

Figure 5: Discovering CAM and AMI from Multi-Parameter QVM using a weighted severity matrix SPM.

In the example shown in Figure 5, we give the normal severity level a weight of zero while other levels are given increasing weights such as 1, 2, etc. The result of element-wise multiplication of MP-SPM with Severity Weights Matrix is the Weighted MP-SPM. We now identify the severity symbols with the highest weighted frequency values to derive the CAM, which in this particular example is A++, A++, A++. We also note that though A+ and A++ had the same Weighted MP-SPM value for the third parameter, we selected the higher severity symbol to ensure that a severe condition is not missed out from being reported to the doctor.

The CAM represents the most frequent deviation of each parameter during an observation window W_S. However, many a time, we need to compare multiple CAMs to identify the W_S during which the patient showed relatively high criticality. Furthermore, not all parameters are considered equally important in identifying the overall criticality of the patient. Hence, we derive a single real value called *Alert Measure Index (AMI)* that factors in these two requirements.

C. Computing The Alert Measure Index

Alert Measure Index is an aggregate score of the maximum weighted frequencies of each parameter with a parameter specific weight (W_{Pi}). For instance, with $W_{Pi} = 1$ for all the parameters, we obtain the AMI for the example in Figure 5 as six. The AMI has another utility too. When multiple patients are remotely monitored, AMI gives us a method to classify the criticality of patients requiring immediate attention of the doctors compared to those who could be attended to later on.

We have now seen a technique to identify severity levels and classify the patients according to their criticality. Next, we evaluate the efficacy of this technique and the resulting energy savings in the smartphone.

VIII. PERFORMANCE EVALUATION

Apart from the acceptance among the medical practitioners during initial studies, our system was evaluated using two other metric. First we analyzed the integrity and accuracy of the CAM in representing the most frequent abnormalities. Second we evaluated the improvement in the power consumption in the smartphone while using CAM and DD-on-D technique.

For the first analysis we considered ECG data from PhysioNet [18] MIT-BIH supraventricular arrhythmia database [19], which contains 78 continuous ECG signals with 30 minutes of data per signal. To assess the effectiveness of severity quantization, we considered RR intervals between two successive beats as a representative parameter. The normal range of RR interval (0.6s to 1.2s) was assigned the symbol A, while different levels of tachycardia and bradycardia were assigned different degrees of „+" and „-" respectively. Figure 6 shows the RR interval plot for 1000 beats for record number 800 from the database.

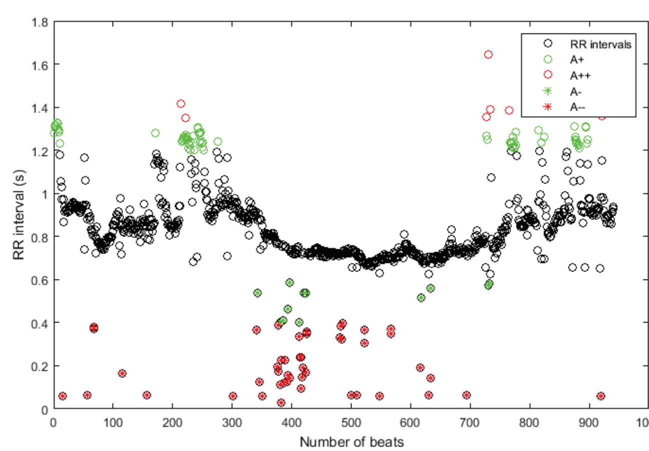

Figure 6: RR intervals quantized according to different severity levels

Using the severity quantization we see that during the time interval from beat number 350 till 450 there is a higher frequency of low RR intervals (**A- -**). Also, between beats 200 and 300 there is higher frequency of A+. Hence, if a CAM is generated every 100 seconds, then during the above said intervals, the severity symbol for RR interval parameter in that CAM would be (A- **-**) and (A+) respectively. As an example, in the first interval an SMS will be sent to the doctor, if the AMI threshold is passed due to extremely low RR interval that repeats for more than 23 times out of 100 normal beats. However, we also notice that the rare occurrences of A++ suggest that these are outliers not worthy of being considered seriously. The weighted frequency based CAM discovery ensures that these symbols do not become part of the CAM. Similar measurements are made for other parameters as well to form a multi-parameter CAM.

The second part of the analysis was carried out to evaluate the energy consumption in the smartphone. To provide a perspective, each minute of the 3-lead ECG data generates close to 180KB data, resulting in around 10MB of data per hour. On the other hand, the CAM consisting of 5 parameters would have less than 100 Bytes, and hence can be sent over an SMS to the doctor. Furthermore, if the doctor requests for a more detailed data through DD-no-D for an hour of ECG data, we send a summary consisting of 6CAMs, a 1s ECG snapshot corresponding to each CAM, and a textual summary of arrhythmia; the entire data totaling to around 100KB. Hence, we compare the processing and transmission power associated with each of these cases: CAM send as SMS, a DD-on-D reply and the entire data transmitted over the 3G networks. We present the results in Figure 7.

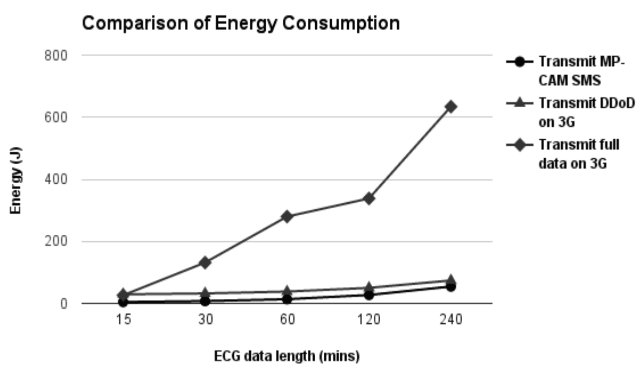

Figure 7: Energy consumption analysis of SMS based CAM transmission vs. other scenarios.

In the first scenario, the ECG data was received at the smartphone and directly forwarded to the cloud. In the second scenario, the ECG was summarized in the smartphone and only the CAMs were sent to the doctor using SMS. In the third scenario, a detailed summary (as explained above) was prepared and sent to the doctor through the cloud. The experimental setup included Android smartphones (running Android 5.1, 1.2 GHz, 1GB RAM) for testing of mobile nodes and Amazon cloud services (S3) for remote storage. The cloud processing was done on a machine instance with dual core 3.1 GHz processor and 4GB RAM running Ubuntu 14.04.

We observe that there is energy savings of 25% and above upon using SMS CAM messages to transmit summaries every hour compared to summaries sent to the cloud over data networks. Also, in comparison to transmission of the entire data to the cloud, the other two summarizations are an order of magnitude better. This suggests that CAMs are an accurate and efficient way to communicate the criticality to the doctors. The DD-on-D technique that fetches a fine-grained summarized data provides doctors with more insights in to the patient condition. The doctors can, then, based on the analysis request for complete data from the cloud. The energy savings are considerable given that reducing the battery usage in the smartphones is one of the challenges to be overcome for wide scale adoption of continuous health monitoring systems. In the following sections we present how remote intervention is made possible using the telemedicine network and our experience from initial pilot deployment.

IX. TELEMEDICINE INTERVENTIONAL NETWORK

As a country-wide initiative, our organization has adopted 108 villages comprising at least two remote rural villages in every one of the 30-odd states of the Indian Subcontinent. We have begun pilot deployment in several of these villages. Interventional telemedicine from doctor back to patients is administered through a network of terminals located at government established HSCs (health sub centers). HSCs, which cover around 6-10 villages and numbering about 143,000, are staffed by a few nurses and healthcare workers trained in basic and emergency medication, and they constitute the lowest rung of the public healthcare infrastructure ladder. Going up this ladder, up to eight HSCs are grouped to one Public Health Center (PHC), which sports a few beds. Up to eight PHCs are grouped to a community health center (CHC), which is a hospital staffed by at least one doctor. Up above are district and tertiary hospitals.

Our Amrita Institute of Medical Sciences (AIMS) uses a VSAT based satellite network (see Figure 8) to deliver the remote tele-consultation [15] from the doctor to the patient. There are clear advantages to such a telemedicine network:

- It provides a large coverage footprint, with reachability to the remotest village even, currently all of India, some of the islands in the Arabian Sea and Bay of Bengal, and some parts of Africa as well.
- The telemedicine terminals, stationed in HSCs are always on, to accommodate walk in appointments
- Provides for video conferencing for real-time visual tele-appearance between the doctor at one end and the patient plus local healthcare worker at the other end, as a timely follow up to any alerted CAMs received by the doctor.

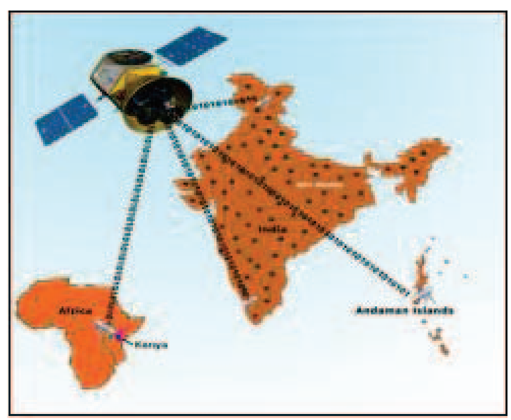

Figure 8: Amrita Telemedicine network, with a coverage footprint over India, Islands in the Arabian Sea and Bay of Bengal, and parts of Africa.

X. DEPLOYMENT AND EXPERIENCE

The system, to our pleasant surprise, has found favorable adoption by practicing physicians, who are otherwise too busy and cautiously skeptical of any newly claimed deviation from long-established traditional patient care methods. Of course, our decision to make the design and development of the system a truly collaborative venture in partnership with the medical fraternity right from the start has been a significant contributing factor to our application and deployment success. The simplicity of the architecture and the utility of the algorithms for analytics are often quoted advantages from the viewpoint of the doctors. To our greater surprise, upon guidance directly from our Chancellor and world renowned humanitarian leader Amma (Sri Mata Amritanandamayi Devi), the physicians readily agreed to even more ways of using our system: to extract discoveries of disease symptom representative patterns from the huge computerized hospital information system database (Amrita HIS) [16], as a learning aid to junior doctors, thereby significantly accelerating their experiential learning curve.

As an example, records of thousands of patients diagnosed with a specific type of cardiac disease are analyzed and their CAM discovery yields valuable insight into most commonly observable parameter variations. This becomes an invaluable diagnostic aid adding to the experiential capability of physicians. The same learning potential can be extended to the domain of knowledge acquisition about temporal outcome trends representing drug efficacies in treatments.

XI. Conclusion

In this paper we describe a healthcare data communication architecture that enables close collaboration between village stationed nurses and telemedicine units with specialist doctors in tertiary hospitals, ensuring quality healthcare delivery to sparsely connected rural population. Through the use of smart disease pattern discovery algorithms to find out CAMs and AMI, we are able to ensure critical data delivery through the use of SMS. As we see from the experimental results the energy and bandwidth savings are considerable, without compromising on the accuracy of data summarization. Our initial pilot studies are showing highly encouraging results. The acceptance among the larger medical community as well as rural population gives further impetus in working towards improving this framework. In the near future, we intend to conduct wide scale testing in more villages across India.

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