A Novel Approach to Unify Robotics, Sensors, and Cloud Computing Through IoT for a Smarter Healthcare Solution for Routine Checks and Fighting Epidemics

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Abstract. This paper attempts to project a novel concept where medical sensors, cloud computing and robotic platform are unified to offer state-of-the-art healthcare solutions to a wide variety of scenarios. The proposed solution is most effective if there is scarcity of healthcare providers or if putting them in the field expose them into a high risk environment such as fighting epidemics. In addition, the proposed system will also benefit routine checks in quarantine wards of hospitals where human reluctance of performing routine task by the healthcare providers can be avoided. Finally, it can also assist a doctor as a decision support system by using machine's capability of number crunching while it examines through patient's complete history, goes through every medical test reports and then applies data mining for catching possible ailments from his/her symptoms.

Keywords: Robot · IoT · Cloud · Healthcare · Sensing

1 Introduction

Using robots in healthcare is becoming more and more popular every day. Robots carrying out surgery [1], nano-bots delivering drugs inside human body [2], or therapeutic usage [3] are already in place. Similarly, using IoT for telemedicine and telepathology [4] or cloud computing for context based data mining are all nothing but a reality today [5]. These demonstrate a tremendous potential of today's technology and if all these technologies are clubbed into a single system, then it can bring us to the next-generation healthcare solution.

In this paper, we propose a methodology to unify all the above mentioned technologies in a single platform to have a powerful system that can move, measure, analyze and infer medical condition of patients without or with minimal human intervention. This can come handy in situations like epidemic outbreaks where robots can be deployed in contagious areas, collect samples, analyze the results and send the diagnosis to doctors for their advice. These robots can also be deployed in quarantine wards in hospitals for regular and effective patient monitoring. In contrast to these high risk scenarios, doctors can use this system for their everyday out-patient chambers to take advantage of the number crunching power of machines to eliminate any missed instances in patient's

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medical records as well as getting inference about the ailment in fraction of a second. In fact, we have already worked on building innovative and portable digital medical gadgets (ideal for easy mobility with robots), a framework for cognitive engine, and robotics that are supported by a wide range of publications in recent years. To be specific, we have exploited smartphone camera and microphone to extract blood pressure (BP), heart rate (HR) and heart rate variability (HRV) [6, 7]. In addition, we also exploited LED based reflective photoplethysmography (PPG) sensor to extract blood pressure information from wide variety of body positions that supports wearable sensing [8]. In our lab, we have developed an algorithm to enable a robot to identify sound source from 3D augmentation obtained from a camera and an array of microphones [9], Moreover, we worked on building a cognitive engine that addressed smart city public alerting system having novel features like stream windowing, incremental reasoning etc. [10–12]. Although the system was trained for smart-city use case, it can be re-trained for healthcare applications as discussed in Sect. 3. Furthermore, we have also investigated medical data compression techniques and came up with a novel adaptive approach that is best suited for preserving critical information related to abnormalities in the medical data [13]. Finally, our lab has developed a cloud hosted IoT PAAS solution named TCS Connected Universe Platform (TCUP)[1] that provides a set of restful services to manage devices, to store sensor data, to do complex event processing, to run analytics and to develop IoT applications. We are now integrating all those in a single platform to come up with our first prototype of the envisioned healthcare system, an early version of which is presented in this paper.

We describe need of such system in Sect. 1.1, the proposed system architecture in Sect. 2, and our initial implementation and result in Sect. 3. Finally, we summarize our work along with scope of future improvements in Sect. 4.

1.1 Why It Is Important

It is a grim reality that at the time of Ebola attack in 2012 [14], healthcare providers were reluctant to go to the field and help patients because of the possibility of getting infected. An IoT-enabled robotic solution would have helped the scenario dramatically as the robots could have been deployed in the field and performed both physiological and pathological tests and sent the results to remote healthcare team for further diagnosis, since now-a-days connected digital medical instruments are readily available [15]. Similarly, healthcare workers in quarantine wards in hospitals may feel fatigue to perform periodic routine checks specially to take adequate measures like disinfecting the area, putting mask etc. every time they enter the ward. This situation can also be helped by robotic solutions. In addition to many such scenarios a variant of the proposed system can also be useful for healthcare in sparsely populated areas. For example, in sparsely populated countries where a family doesn't have neighbor in a few square km of area, it is very difficult for them to get medical attention in case of emergency. Here, a drone robot could fly to the patient, take measurements and inform the hospitals about patient's condition. While there are limitless possibilities and use cases, one common

[1] http://tcup.web2labs.net/tcup/assets/TCUPWebpages-Kol-v1.4/TCUP-Mainpage.html.

factor in all would be to use computing capabilities of the cloud connected robot to conduct machine-assisted diagnostics. To summarize, it can be foreseen that a system incorporating computing power of a cloud, measuring capability of digital connected instruments, and mobility capability by robotic platforms along with the intelligence to understand the medical knowledge from web can have tremendous potentials in health-care. Neither such complete end-to-end system exists nor has it been conceptualized.

2 Proposed System Architecture/Methodology

In this section, we would present the end-to-end system architecture and operational methodology to describe how to actually instantiate such a system. Figure 1 depicts the proposed system architecture. It mainly has three different functional components. The first layer is composed of digital medical devices both for physiological and pathological sensing, a second layer is composed of alert generation system (on finding anomaly/abnormality in the measurements) and finally a third layer is composed of cloud based cognitive engine that maps abnormalities to disease and send the report to a doctor/caregiver. The measuring instruments are carried by a sophisticated robotic platform capable of movement as well as fine mechatronics. The cognitive engine is connected to this robotic platform via internet for real-time data exchange.

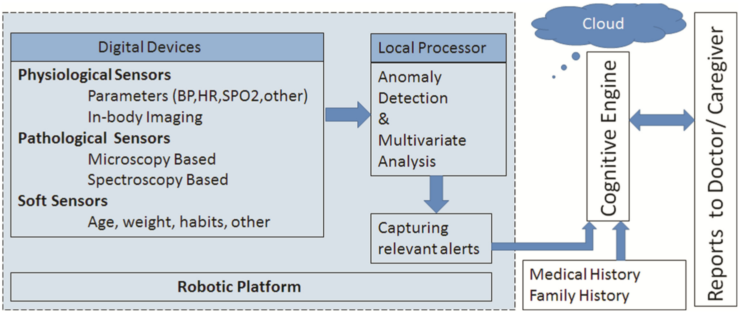

Fig. 1. System architecture and working methodology.

The robot first comes to the patient and takes measurements through the comprehensive medical sensors consist of physiological, pathological and in-body imaging. This is to note that in-body imaging system (say, ultrasound imaging) with robotic arm could be far more efficient than usual manual scans as robotic arm can conduct very precision movements for scanning. Although only a few parameters like BP, HR etc. are highlighted in the figure they are just indicative placeholders and the actual set can include all sorts of other parameters. Similarly, auto-analyzer[2] based measurements can include a large set of pathological tests including detection of virus/bacteria, blood glucose level, cholesterol etc. [15]. All these measurements are fed to the anomaly detection module that derives critical information mostly related to abnormalities of the

[2] http://hydrology1.nmsu.edu/teaching/soil698/student_material/AutoAnalyzer.

measurements with reduced false positives and negative. Only these relevant anomalies are then sent to cognitive engine that resides on the cloud. The job of this cognitive engine is to relate this set of anomalies to possible disease and send the report to doctors/hospitals for their use. This is to note that the reasoning section (i.e. mapping anomalies to disease) requires lot of computational power as one needs to build the knowledgebase by going through the vast digital knowledge available in the web. Moreover, since the medical information is always updated in the web, the cognitive engine needs to update its rules continuously much like how IBM Watson[3] learns and updates itself. An in-depth understanding of such Big Data analytics on healthcare system can be found in our published work in 2012 [16].

3 Initial Implementation and Result

In our initial work, we use our smartphone based BP, HR, HRV solutions [6, 7] along with off-the-shelf available eHealth[4] sensor to additionally include breathing rate, ECG, SPO2, temperature and blood glucose measurements. Smartphones are particularly attractive for its wireless connectivity and multipurpose sensing capabilities via built-in sensors and readily available attachments like flir[5], lens[6], etc.

An Arduino board, connected to the iPhone via blue-tooth and connected to eHealth sensors through eHealth shield, is used for sensor data acquisition. It then sends the data to a PC via USB connection for alert generation (Fig. 2a). At this stage, we built the anomaly detection layer as well as a cognitive engine both hosted in a PC. Although, implementation of the cognitive engine for healthcare is still in progress, we briefly outline our design approach. The cognitive engine is based on deriving meaningful actionable inferences by reasoning on the combined knowledge of static facts (like user profile), ontologies (like disease taxonomy) and dynamic facts (like sensed data) [10] as depicted in Fig. 2b. For handling streaming data, a snapshot of it is usually used for reasoning, the snapshot window being determined by various strategies [11]. Sensed data is put in a queue and processed by Data Handler (that performs tasks like data filtering and transformation) before being put into Working Memory where matching rules are fired and registered queries are triggered at specified intervals to produce results. The above module is developed by extending Apache Jena[7] and is based on Semantic Web framework. The rules are being written in a triple format and so is the query in SPARQL, for knowledge clubbing. Rules are written from medical books and consultation with doctors. A sample rule is to entail stress condition of a patient based on heart rate and blood pressure readings: *(?patient <p:hasHeartRate> <s:high>) (?patient <p:hasBloodPressure> <s:high>) -> (?patient <p:possibleDiagnosis> <d:Stress>).*

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[3] http://www.ibm.com/smarterplanet/us/en/ibmwatson.

[4] https://www.cooking-hacks.com/documentation/tutorials/ehealth-biometric-sensor-platform-arduino-raspberry-pi-medical.

[5] http://www.flir.com/flirone/.

[6] http://www.instructables.com/id/10-Smartphone-to-digital-microscope-conversion/.

[7] https://jena.apache.org/.

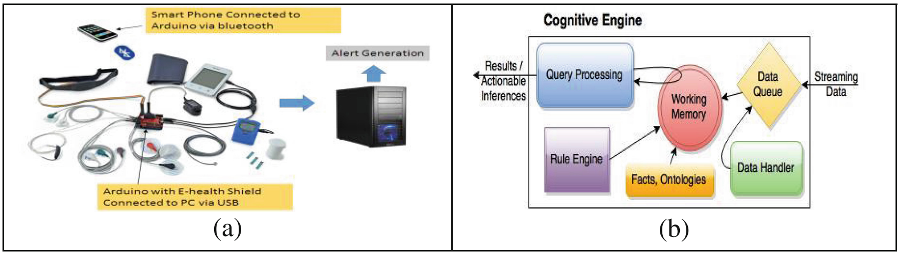

Fig. 2. (a) Initial implementation, and (b) working principle of cognitive engine

A sample query is: *select ?disease where {<u:user123> <p:possibleDiagnosis> ?disease}.*

We report successful measurement of BP and HRV parameters when tried on 10 participants following our earlier work [6, 7]. For example, mean error for diastolic (Pd) and systolic pressure (Ps) are under 5 % when validated against Omron sphygmomanometer[8]. Similarly, the maximum error in HRV parameters (RMSSD, SDSD, SDNN, nn50, pnn50, nn20, pnn20) are also found to be under 14 % when validated against HRV calculated from AliveCor ECG[9] data. The rest of the sensing is done with e-Health medical grade sensors and hence, reporting measurement accuracy is not required. These measures are then fed to anomaly detection to raise alert. For example, Fig. 3b depicts successful detection of anomalies (shown in red) from ECG dataset[10] based on Brute Force Discord Discovery (BFDD) [17]. The anomaly detection algorithm was executed on the web hosted dataset as all our measurements taken from our colleagues came out to be normal.

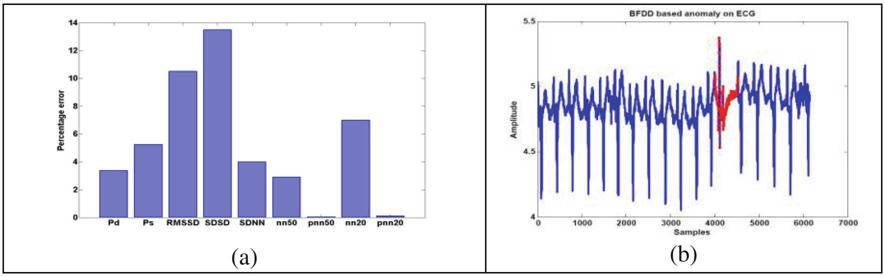

Fig. 3. (a) Error in BP, HRV measurement (b) BFDD based anomaly detection in ECG data

4 Summary

Our preliminary work supports feasibility of automatic alert generation by measuring healthcare parameters through portable digital gadgets. In addition, if a robotic platform

8 http://omronhealthcare.com/blood-pressure/upper-arm/.
9 http://www.alivecor.com/.
10 http://www.cs.ucr.edu/~eamonn/discords.

comes into place to actually carry the sensors then this proposed system would cater for a variety of situation in healthcare that would otherwise be difficult to be handled by humans. Specially, the robotic platform will reduce or even eliminate the need for humans to come close to patients in high risk environments like contagious virus attacks. Alternatively, it can also address the problem of unavailability of trained healthcare workers in remote villages of under developed countries or for countries with sparsely populated areas. Moreover, the cloud hosted cognitive engine may assist the doctors by checking detailed patient's history and medical reports that would have been left unattended due to human limitation in terms of their memory and processing ability. Our future work would include hosting the cognitive engine on TCUP as well as choosing a robotic platform to carry the sensors.

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