

Finding Needles in a Haystack: Reducing False Alarm Rate Using Telemedicine Mobile Cloud

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Abstract—Wearable body sensors have been widely used to monitor the health status of seniors or patients who live alone. Alarms are sent to e-Health providers when dangerous symptoms are detected. However, high false alarm rate significantly limits the effectiveness of medical monitoring. Telemedicine Mobile Cloud (TMC), leveraging recent advances in sensing, networking, and computing technologies, is an effective and promising solution. In this paper, a TMC based strategy has been proposed, which identifies needles (real dangers) among the haystacks (alarms) by taking advantage of the real-time, on-site monitoring capability of Android mobile device and the abundant computing power of the cloud. Extensive experimental study has verified that the TMC-enhanced strategy has effectively reduced the false alarm rate.

Keywords-Telemedicine Mobile Cloud, False Positive Alarms, e-Health Service, Remote Patient Monitoring.

I. INTRODUCTION

According to the World Health Organization (WHO) [14], the United States spends about 16% of its gross domestic product (GDP) on healthcare, the highest level in the world and twice the world average, far higher than the percentage for other developed countries (8.9% on average). The Department of Health and Human Services estimates that the figure will be 19.5% by 2017 [12]. Nevertheless, the use of health care services in the U.S. is far below that of comparable countries, reflecting greater inefficiency and higher prices for health care services in the United States. The skyrocketing health expenditures and the gradually aging population have been the two of the top concerns to the whole society.

Telemedicine, leveraging recent advances in sensing, networking, and computing technologies, has proven to be an effective and promising solution. A critical and costly part of healthcare systems is the monitoring of patients' vital signs and other physiological signals, which play significant roles in physicians' diagnostic processes. The highly specialized and extremely expensive medical monitoring equipment found in hospitals is neither easily accessible nor affordable for next-generation patient-centered, pervasive healthcare.

Fast growing mobile technologies have enabled and promoted the use of mobile-based health monitoring and alert systems (usually referred as "mHealth"), aiming at providing real-time feedback about an individuals health condition to either the user or to a medical center, while alerting in case of possibly imminent health-threatening conditions. Mobile

phones have become ubiquitous in people's daily lives. Recently, many mobile-based medical monitoring devices have been developed with the capability of processing certain types of physiological signals [8], [10].

However, the limited computational power and battery life of existing mobile devices, significantly limit their ability to execute computing-intensive tasks. Due to these constraints, many mHealth systems are built on top of naive threshold based alert generation algorithms. Consequently, the false alarm rate is very high. Several studies have reported the extremely high rate of false alarms (i.e., up to 90% of all alarms) in clinical settings [6]. Frequent false alarms are distracting and interfere with physician's ability to perform critical tasks effectively in practice, so that it may not be uncommon for nurses to simply turn off the monitor since they have been overwhelmed by those false alarms.

Cloud computing is a new computing paradigm that has gained interests from both industry and academia. Compared to the traditional distributed computing, cloud computing possesses a lot of favorable features, such as transparent service, good scalability and elasticity, supporting the pay-as-you-go service model, and omni-accessibility [9]. This paradigm not only enables users to enjoy the convenient, versatile, efficient services, but also relieves the burden required for maintenance. Government branches and private business sectors have recognized that cloud computing will promote telemedicine revolutionarily.

Integrating smart mobile devices and cloud computing platform, the Telemedicine Mobile Cloud (TMC) is a promising approach towards pervasive, affordable, versatile medical and health services of our future [13]. In this paper, we investigate the feasibility of reducing the high false alarm rate by outsourcing data intensive and computing intensive tasks in telemedicine to powerful cloud servers. A proof-of-concept TMC prototype has been developed and the experimental results are very encouraging since the false alarm rate has been reduced significantly.

The rest of the paper is structured as follows. Section II provides a brief introduction to the work related to cloud-enhanced telemedicine. Section III introduces our TMC architecture and algorithms to identify true medical conditions from a huge amount of alarms. The experimental results and performance evaluation are reported in Section IV. Finally, we wrap up this paper in Section V with conclusions.

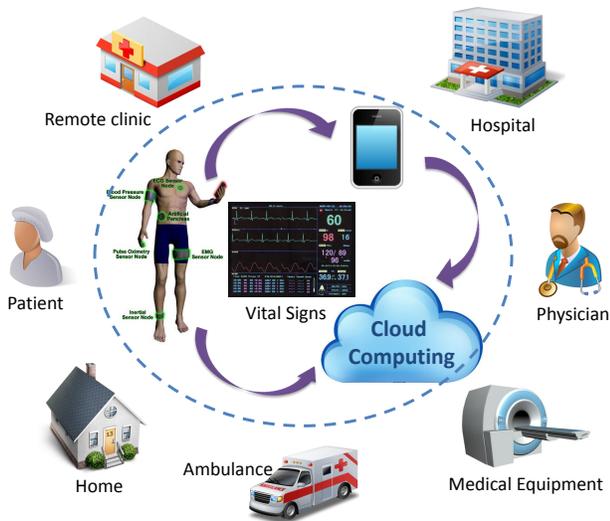


Figure 1. Telemedicine based on Mobile Cloud Medical Monitoring.

II. BACKGROUND AND RELATED WORK

Telemedicine represents the delivery of healthcare over long distances, by using information and communication technologies (ICTs) for the exchange of valid information for diagnosis, treatment and prevention of disease and injuries, and for the continuing education of healthcare providers [15]. Recent advances of wireless mobile technologies have created a tremendous amount of momentum toward increasing access to health care via telemedicine.

The use of portable/wearable physiological monitoring systems will enable physicians (and patients) to closely monitor patients' health status and effectively prevent major medical conditions without the costly and time-consuming hospital visits. Medical monitoring data can be routed to the physician for detailed evaluation or to a computer-aided diagnostic program to automatically identify any abnormalities in physiological measurements and provide the alerts or warnings to caregivers for timely response [1]. This type of telemonitoring is particularly effective for managing chronic conditions for elderly adults such as diabetes, hypertension, and cardiovascular diseases, and has been shown to reduce hospitalization and mortality rates [11].

As shown in Figure 1, mobile devices can be used to acquire various physiological signals from a set of ambient/body sensors. To alleviate intensive computations and extend the battery life of mobile devices, the acquired physiological signals will be transferred to a cloud service environment to perform desired, computation-intensive algorithmic signal processing. The processed results, recognized abnormalities, or diagnostic alarms will be automatically archived in the cloud or sent to the mobile devices owned by patients, physicians, or emergency teams. This application mode can be of particular significance to patients whose physiological signals need to be monitored continuously.

For instance, Hsieh and Hsu [5] presented a telemedicine

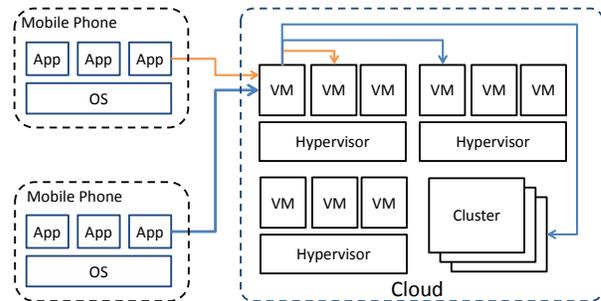


Figure 2. Software Architecture.

cloud service enabling ubiquitous delivery of inter-hospital ECG records. Shen *et al.* [3] proposed a cloud-based EEG signal analysis system to detect brain disorder, where the computation-intensive functions of feature extraction, feature selection, and support vector machine (SVM) classifier are implemented and deployed using cloud services.

In this paper, we seek to explore an optimal application model that synergistically leverages the mobile cloud for telemedicine. Instead of focusing on certain specific disease monitoring or signal analysis algorithm, cloud has been utilized to identify real abnormalities among a huge amount of alerts. This paper also presents our results that characterize the performance, energy, and complexity attributes of both mobile- and cloud-based solutions for medical monitoring.

III. REDUCTION OF FALSE ALARM RATE USING TMC

A. Architecture of a TMC

In clinical setting, vital signs are usually recorded, collected and stored in a frequency of one sample per second or minute, like the data in the MIMIC II database [7], we thus emulate the real-time vital sign data inputs of the mobile telemedicine device by loading the patients' records of MIMIC II database. Due to the constraints on battery life, computing power, and storage space, mobile devices often execute light-weight algorithms to serve as a simple real-time monitor with high false alarm rate. In this work, a TMC has been considered to validate how much a TMC can help to reduce the false alarm rate by implementing more complex algorithms on the powerful cloud. The TMC software architecture is shown in Figure 2. Each mobile device runs multiple local applications, which handle light-weight tasks. Virtual machines (VMs) are assigned to execute more powerful but computing intensive algorithms.

B. Algorithms

In patient monitoring, the collected signals may be from different types of sensors, for example, ECG signal is bioelectrical while BP is biomechanical. Based on the non-commensurate characteristic of the raw sensor data, observational physiological data cannot be combined directly and only can be fused at feature level or decision level. Past years

have witnessed the development and application of many patient monitoring signal processing and information fusion algorithms. In order to verify the effectiveness of TMC in reducing the false alarm rate, two algorithms have been selected: Fuzzy Logic and SVM (both the Linear SVM and RBF SVM are considered). Due to the limited space, only a brief introduction to these algorithms is given below. For interested readers, please refer to the references for details.

Fuzzy logic is a type of probabilistic logic dealing with the approximate situations rather than exact case. Since health, illness and disease are matters of degree and may be influenced by time, human activity, environment or many other factors [2], fuzzy logic could be suitable for monitoring the patients health status. It has already been applied in the medical area to determine the disease risk, medical control systems, drug dose and so on. Generally, the fuzzy logic system consists of 4 parts: fuzzification, fuzzy rules, aggregation and defuzzification.

Support vector machine (SVM) is a supervised model in pattern recognition algorithms. The main idea of SVM is to find a hyperplane to separate two classes of data so that the distance from the hyperplane to the nearest training data point of any class is the largest one. Sometimes linear SVM is not effective to handle all the cases, so nonlinear classification is created to deal with more complex situations and map the dataset into a higher dimensional space using a “kernel function”. The most commonly used nonlinear kernels are polynomial, Gaussian, and RBF functions [4].

IV. EXPERIMENTAL RESULTS

A. Experiment Setup

The mobile device used in this experiment is a Google Galaxy Nexus smartphone with the Android 4.1 Jelly Bean system. The Galaxy Nexus phone contains a 1.2 GHz dual-core ARM Cortex-A9 microprocessor, 1 GB memory and a 1,750 mAh battery. The computing server used for emulating a cloud environment is a Dell PowerEdge M620 server, equipped with 12 Xeon 2.5 GHz cores and 64 GB memory. The TMC software architecture is shown in Figure 2.

The metrics adopted to evaluate the performance of these algorithms includes true positive (TP), false positive (FP), true negative (TN) and false negative (FN). Among them, the most critical ones are the TP Rate, which is the detection rate, and the FP Rate, which is the ratio of false alarms that were raised when it is actually not a real medical condition.

B. False Alarm Rate Reduction

All of the fuzzy logic and (linear/RBF) SVM algorithms have been implemented on both the mobile device and the cloud server. In this study, we primarily focus on detecting the abnormalities of vital signs using the heart rate (HR) and arterial blood pressure (ABP). Two sets of data from MIMIC II database have been used. The first data set consists of numeric data (1 sample per minute) from 10 patient records

including 272 golden alarms. In some cases, there are more than one golden alarms within one minute period, which are merged into one alarm. There are 49,427 samples in total and no post-processing since the data is sampled in one minute. The second data set consists of waveform data (125 samples per second) from the same 10 patient records including 2,556,908 samples in total and 297 golden alarms. We tested the performance on the waveform data without post-processing and with post-processing of ± 60 seconds. The purpose of the post-processing is to reduce the miscounting of repetitive alarms within a very short period of time. For instance, there are three alarms reported for three consecutive samples to indicate a detected abnormal condition, while maybe only one alarm is activated in the middle sample to indicate the same problem. In this case, we can reasonably group those three detected alarms together without reporting any false alarms. The experimental results are summarized in Table I.

Case 1. Numeric Data-based Processing: Based on the numeric data set, the fuzzy logic algorithm has detected 88 out of 272 golden alarms and raised 1,515 false alarms. It is corresponding to a 32.35% detection rate and a 3.08% false positive rate. The linear and RBF SVM algorithms have detected 207 and 217 golden alarms respectively. RBF SVM obtained the highest detection rate 79.78%, but the false positive rate is also very high, 32.46%. In contrast, the linear SVM achieved a much lower false positive rate, 15.7%, with a detection rate of 76.10%.

Case 2. Waveform Data-based Processing, without Post-Processing: The performance of these algorithms is very interesting when the waveform data set is applied. The linear SVM achieved a detection rate of 91.25% with an acceptable 12.39% false alarm rate within the shortest processing time. With a detection rate of 58.25% and false alarm rate of 4.63%, the fuzzy logic algorithm outperformed the RBF SVM algorithm except a much longer processing time. Again, the linear SVM achieved a well balanced performance: shortest time, highest detection rate, and tolerable false alarm rate.

Case 3. Waveform Data-based Processing, with Post-Processing of ± 60 seconds: The post-processing has promoted the performance for all three algorithms, such that all three detection rates are higher than 90%. In particular, the linear SVM achieved a 97.98% detection rate. The advantage is not so clear. If a low false alarm rate is more critical as long as a satisfactory detection rate is achieved, RBF SVM or fuzzy logic algorithms are reasonable options. However, the linear SVM is still the preferable if the highest detection rate is the dominant factor.

Summary: The experimental results reveal a very interesting finding, that is, SVM algorithms consume much less time compared to the fuzzy logic algorithm, while SVM is often believed to be more complex and time-consuming than fuzzy logic. The reason behind that is,

Table I
PERFORMANCE OF MULTIPARAMETER MEDICAL MONITORING

Methods	TP	TN	FP	FN	TP Rate (%)	FP Rate (%)	Time on Cloud (second)	Time on Mobile (second)
Numeric Data-based Processing								
Fuzzy Logic	88	47,641	1,515	184	32.35	3.08	1.08	141.78
Linear SVM	207	41,434	7,721	65	76.10	15.70	0.07	15.79
RBF SVM	217	33,403	15,752	55	79.78	32.46	0.09	16.85
Waveform Data-based Processing								
Fuzzy Logic	173	2,438,138	118,473	124	58.25	4.63	31.44	4,601.36
Linear SVM	271	2,239,729	316,882	26	91.25	12.39	1.23	881.27
RBF SVM	129	2,502,986	53,625	168	43.43	2.10	5.34	1,108.87
Waveform Data-based Processing (with Post-processing of ± 60 seconds)								
Fuzzy Logic	273	2,447,283	109,328	24	91.92	4.28	31.65	4,718.86
Linear SVM	291	2,257,712	298,899	6	97.98	11.69	1.50	997.60
RBF SVM	270	2,509,801	46,810	27	90.91	1.83	5.55	1,225.54

the most dominant process in machine learning algorithms, such as SVM and ANN, is the complex training procedure. By carefully choosing and managing a fairly small training dataset, we can even observe the execution time for SVM is smaller than fuzzy logic. It is expected the execution time will be significantly increased as the SVM moves to a rather larger training data set (exponentially).

As the experimental results show, the cloud servers can afford more computing overhead and achieve high detection rate at the cost of an acceptable false alarm rate. The processing on the cloud can adequately meet the "real-time" requirement of patient monitoring by accomplishing the job in several seconds, which represents over 100X speed up against the mobile-based processing and indicates the superior advantage of cloud-based physiological signal processing over the pure mobile-based processing. Besides the challenges of processing time, mobile devices also face another challenge from the perspective of battery life, which will be discussed in the next subsection.

C. Mobile Device Performance Evaluation

Study 1. Maximum Battery Life: During the experiments, all peripherals (i.e., WiFi, Cellular, Bluetooth, and backlight) are turned off to maximize the battery life of the mobile device for telemedicine applications. The fully charged Android smartphone can only sustain for about 33 hours, significantly less than the claimed standby battery life of 270 hours. It shows that even with the most advanced smartphones, it is still infeasible to deploy and rely on the mobile devices for continuous medical monitoring and other telemedicine applications on a daily basis.

Study 2. Battery Life under Computing Intensive Tasks: In this experiment, we purposely turned off the automatic power scaling in Android devices to force the microprocessor to remain in power-draining active mode. To emulate the scenario of intensive computation, four vital sign signals are continuously fed into the device and processed by the fuzzy logic algorithm. The observed battery life is about 6.72 hours, a level that is prohibitive for analyzing large-scale, highly sampled physiological data and deploying more sophisticated processing algorithms on mobile devices.

V. CONCLUSIONS

Leveraging the recent advances in mobile technologies and cloud computing, telemedicine is on the verge of a substantial transformation that will strengthen the effectiveness and efficiency of healthcare delivery. In this paper, we present a preliminary performance study of mobile cloud to demonstrate its potential in performing continuous health monitoring in daily life and achieving higher diagnostic accuracy. Our findings also unveil the limitations of existing mobile devices in performing telemedicine by themselves.

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