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ONLINE DYNAMIC MONITORING SYSTEM FOR PATIENT DIAGNOSTIC RECORDS

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ABSTRACT-Context-aware monitoring is an emerging technology that provides real-time personalised health-care services and a rich area of big data application. In this paper, we propose a knowledge discovery-based approach that allows the context-aware system to adapt its behaviour in runtime by analysing large amounts of data generated in ambient assisted living (AAL) systems and stored in cloud repositories.Major purpose of this paper evaluation shows estimate of detecting proper anomaloussituations for different types of patients in effective way. We are upload patient medical reports such as Blood Pressure, Blood Sugar, Heart Rate etc .The patient report encrypted binary format store to cloud using AES Algorithhm. Context Aggregation to aggregate different types of patient. It analysis and identify who are normal condition and abnormal condition. If abnormal condition means send SMS alert immediately corresponding patient.After that the patient will take treatment the hospital.

I.INTRODUCTION

AN ambient assisted living (AAL) system consists of heterogeneous sensors and devices which generate huge amounts of patient-specific unstructured raw data everyday. Due to diversity of sensors and devices, the captured data also have wide variations. A data element can be from a few bytes of numerical value (e.g. HR = 72 bpm) to several gigabytes of video stream. For example, if weassume a single AAL system generates 100 kilobytes data every second on average then it will become 2.93 terabytes in one year. If any system targets to support say, 5 million patients, then the data amount will be 14 exabytes per year 1. Even if a healthcare system targets to analyse only continuous ECG of cardiac patients in real-time inside the cloud environment ,then it will produce around 7 PetaBytes data everyday Including these dynamically generated continuous monitoring data, there are also huge amounts of persistent data such as patient profile, medical records, disease histories and social contacts. If we want to store all these data and patient histories to predict any future abnormality accurately, then the representation of data will be in zetabytes in a few years. Such concerns necessitate the development of cloud-based assisted healthcare infrastructure . Efficient processing of this large volume of medical, ambient and media data using computational power of cloud infrastructure, extraction of right context information , finding the correlationsamong different contexts for inferring knowledge, and prediction of a state using those inferred observationsto deliver proper situation-aware services, are

some primary challenges in the development of contextawaremonitoring applications.

According to IBM data scientists, big data can be characterized in four dimensions: volume, variety,velocity, and veracity (“the 4 V’s”) . Our model also satisfies these four V’s because the context-aware data we are referring to have massive variations (e.g.health data, activity data), is large in volume (severalpetabytes), continuous in terms of velocity and accurate to satisfy veracity. Such data also have great value and high impact on future healthcare infrastructure.The predictive analyses over large historical data provide robust solutions for disease prevention. This also simplifies the tasks of healthcare professionals and doctors by assessing the causes of any anomalous situation at an early stage and improving the quality of life of a patient. The physiological data of a patient varies with different activities and locations .

Traditional solutions for personalized AAL systems depend on standalone applications that run on a local server or a

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handheld device. These applications solve only specificcases [10]. The amount of information gathered from a personalized AAL system is so massive that it is almost impossible to store and manipulate them for knowledge-discovery in a mobile device. Furthermore, the growing ageing population and chronic diseases, particularly in Australia and other western nations, increase the demand for a common platform that is capable of handling many patients simultaneously and maintaining the personalized knowledge of every user. This necessitates the initialization of such big data-centric context-aware applications on cloud environments .An important feature of remote monitoring applications is to identify the abnormal conditions of a patient accurately and so send appropriate alerts to the care givers. In traditional systems, situations are classified by generalized medical rules or fuzzy rules which are not always applicable for every kind of patient. These systems cannot sense the future at an early stage. In some monitoring systems, when a patient feels unwell he/she needs to press a wearable panic button to notify a response centre about the emergency. Some systems try to understand a patient's discomfort level and the seriousness of the condition by asking automated sets of questions. Such systems can generate many false alarms to the monitoring centres; this is not desirable.

The flexibility of using low-cost cloud platforms such as Amazon web service (AWS) , Windows Azure and Google cloud has added greater advantage to learn of true abnormal situations by storing and analysing every past and current event of a patient, and generate personalized rules . Such an individualized rule-mining process also promotes the inference of more generalized medical rules for particular patient category. In a home healthcare system, a typical architecture involves body sensors, ambient and smart sensors, devices, actuators and software services that collect data from a target user who lives alone and has some kind of disability . The data is collected continuously at different times of the day and also, in some cases, on a demand basis. The data can be physiological (e.g. heart rate, blood pressure, ECG), environmental conditions (e.g. humidity, room temperature) that affect a patient's health condition and activities related to a patient's behaviour (e.g. sleeping, eating, toileting) that can be inferred by processing data from sensors, cameras, RFIDs etc.

Some data can be captured from persistence storage such as a patient's profile (e.g. thepatient has heart disease), recognized patterns (e.g. patient wakes up between 7-7:30 a.m., smokes five times per day on average), historical (e.g. patient had a heart attack two years ago) and medical recordse.g. last tested white blood cell count 7746). The definition of context varies according to the purpose of the application domain. In our model, context means any high level user-specific information obtained directly or inferred from raw sensor data. Generally, the aggregated contexts are sent to a monitoring centre (e.g. doctor, nurse, hospital) for decisionmaking about the patient's condition. In effecting our goal, we take this one step further by incorporating patient-specific intelligence that constantly learns from collected data and interprets new incoming data using that gained knowledge just as a medical expert would. This also allows doctors to make decisions with greater knowledge, to monitor chronic deterioration in a patient's condition, or to assess the patient's response to treatment. The identification of a patient's abnormal condition can warn the patient by activating a local device (e.g. medication reminder), or send an emergency message to the monitoring centre. Overall, our innovative learning technique on a massive volume of context data enables reliable classification of a patient's situation for qualitative remote monitoring support, using the advantage of cloud computing.

Motivation

We are motivated by our previous work wherewe developed a cloud-oriented context-aware middleware(CoCaMAAL) and proved its advantage forprocessing and managing large amount of contextsgathered from multiple AAL systems. In CoCaMAAL,we described the context-aware service identificationprocess using high level generalized medical rules.The model lacked an important feature such as personalizedknowledge discovery which could be derivedfrom a large amount of patient data stored inthe cloud repositories. Therefore we developed BDCaM,an extended version of the CoCaMAAL model.This includes the functionalities of learning and theknowledge discovery process to find patient-specificanomalies using large amounts of data. The mainmotivations are the following. The need for an abstract context-aware frameworkthat improves the confidence of abnormality detectionin the home healthcare environment bycorrelating physiological statistics with variousphysical activities and environmental factors.The use of cloud computing enables faster learningwith greater knowledge from continuously generatedbig data gathered from heterogeneous contextsof various assisted living systems. This alsoimproves the discovery of user-specific rules withstronger support. The improved knowledge of understanding thepatient's situation through iterative learning ofpresent contexts and substantial historical data can reduce the transmission of repeated false alertsto the remote monitoring systems.

Contributions

The primary contributions of our work are as follows.

- We build an innovative architectural model for context-aware monitoring, **BDCaM**that uses cloud

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computing platforms. Every generated context of AAL systems are sent to the cloud. A number of distributed servers

- in the cloud store and process those contexts to extract required information for decision-making using this novel technique.
- We develop a 2-step learning methodology. In the first step, the system identifies the correlations between context attributes and the threshold valuesof vital signs. Using MapReduceApriori algorithm, over a long term context data of a particular patient, the system generates a set of association rules that are specific to that patient. In the second step, the system uses supervised learning over a new large set of context data generated using the rules discovered in the first step. In this way, the system becomes more robust to accurately predict any patient situation.
- We demonstrate the performance and efficiency of BDCaM model in situation classification by implementing a case study. Our system refines patientspecific rules from big data and simplifies the job of healthcare professionals by providing early detection of anomalous situations with good accuracy.

Background

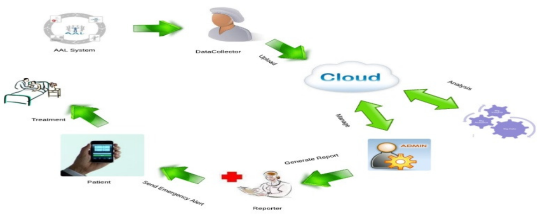
In the research literature, many examples introducean integrated system using big data for contextawarenessin assisted healthcare. However, most systemsare described from an architectural point of viewand there has been no practical implementation of any of those systems. In our previous paper, we described the CoCaMAAL model and here wehave extended that model to illustrate the learningprocess from big context-aware data to find abnormalitiesin an individual patient. In our system, we haveused the MapReduce-Apriori algorithms proposed in which is an effective process to measure correlationsbetween context attributes. MapReduce is alsoan efficient programming model to process big datausing distributed clusters. In an AAL system, mostof the generated contexts are numerical or categorical.Therefore, together withMapReduce-Apriori, weused the techniques described in to generate rulesusing numerical attributes of our model. As we do notintend to explore the generation, pre-processing andtransmission of real sensor data in the present work,we have assumed that subsystems are responsible fordoing this from existing knowledge.

II.PROPOSED SYSTEM

The proposed model facilitates analysis of big data inside a cloud environment.We can upload large amount of data such as patient medical report to the cloud.Regularly monitoring and updating patient report who are normal and abnormal condition.Send SMS alert to the abnormal patient.

SYSTEM ARCHITECTURE

The general architecture of the proposed knowledge discovery-based context-aware framework for assisted healthcare designed over big data model is visualized. The flow of raw data, context, rules and services between different distributed components are also shown. The overall architecture can be split into five cloud components.



Ambient Assisted Living (AAL) Systems

The sensors, devices and software services of each AAL system produce raw data that contain low level information of a patient's health status, location, activities, surrounding ambient conditions, device status, etc.

Personal Cloud Servers (PCS)

Each AAL System is connected to a personal cloud server. This is a virtual server inthe cloud that is highly scalable and managed bytrusted entities. It has secure storage facilities to store patient-specific information (e.g. Amazon S3,Microsoft HealthVault) such as the profile (e.g. age,sex, BMI), recognized patterns of his/her daily activities (e.g. smoking habits), identified threshold values of different vital signs, medication times, disease treatment plans, prescriptions, preferences,emergency contacts and personal medical records.

Data Collector and Forwarder (DCF)

Traditional context-aware systems process the lowlevel data and perform the computation in a localserver or mobile device and then forward the highlevel context data to the cloud.

Context Management System (CMS)

A Context Management System (CMS) is the corecomponent of the framework. The CMS consists ofa number of distributed cloud servers that hold thebig data. It stores the context histories of millions ofpatients.

Context Providers (CP)

The context providers (CPs) cloud is the main source for generating contexts. The CA distributes the low level data collected from different AAL systems to multiple CPs. Each CP applies well-known techniques to obtain primitive context from the low level data.

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USE CASE IMPLEMENTATION

In accordance with the BDCaM functional components described in the previous sections, a case study is implemented to evaluate our algorithms. The objectivesof this implementation are: (i) discover knowledge of BP and HR changes on different situations for different patients; (ii) find association rules for specific patient situations using a distributed cloud model, and (iii) classify an unknown situation basedon the learned model.

Description of use case

The continuous BP level of a patient is determined by examining systolic BP (SBP) and diastolic BP (DBP) values in mmHg using a body worn BP sensor, and HR is measured in bpm using the ECG sensor . Abnormal BP or HR is difficult to diagnose and treat if they are only measured once or twice a day. The variations in BP and HR occur due to changes in ambient temperature, physical activity, noise, sleep, fatigue, stress etc. (e.g. HR is high for exercise, BP is high for eating). The variations are also common from patient to patient for other factors such as disease history and family profile (e.g. BP is always high for a hypertensive patient).

The abnormal variations are not always dangerous in practical situations. Therefore, if a patient's situation is classified using only the generalized threshold value, for most cases this will trigger false alarms to the receiver. So it is important to consider the correlations of other contexts for making final clinical decisions. The goal of this experiment is to detect those abnormal cases which are not actually that critical for raising an alarm. The learning process utilizes large historical data of multiple patients and generates personalized knowledge for each patient.

The knowledge generation and abnormality detection cases are run in a cloud platform. For evaluating cloud platforms we have used Google App Engine and Amazon web services (AWS). The proposed model facilitates analysis of big data inside a cloud environment.We can upload large amount of data such as patient medical report to the cloud.Regularly monitoring and updating patient report who are normal and abnormal condition.Send SMS alert to the abnormal patient.

ALGORITHM:

Aggregate all contexts to a context state

Input: A set of context information ItDk forAAL systems
Output: Context state Cjt for each AAL system j
Procedure Mapper()
begin
for each AAL system j **do**
for domain 1 to k **do**
generate ItDk for time t
output(key=(j,t), value=ItDk)
end for
if IDs 6= _ **then**
output(key=(j,t), value=IDs)
end if
end for
end
Procedure Reducer(key=(j,t), value=set of ItDk)
begin
for each AAL system j **do**
Cj t
end for
for each ItDk at t in AAL system j **do**
Cjt Cjt [ItDk
end for
if Exists(IDs) in AAL system j **then**
CjtCjt[IDs
end if
output(key=(j,t), value=Cjt)
end

Disadvantages of the existing system

Analyzing and Monitoring Big data is difficult.
Not Accuracy and Efficiency.
Limited Storage Space

III.CONCLUSION

In this work, we have presented BDCaM, a generalized framework for personalized healthcare, which leverages the advantages of context-aware computing, remote-monitoring, cloud computing, machine learning and big data. Our solution provides a systematic approach to support the fast-growing communities of people with chronic illness who live alone and require assisted care. The model also simplifies the tasks of healthcare professionals by not swamping them with false alerts. The system can accurately distinguish emergencies from normal conditions. The data used to validate the model are obtained via artificial data generation based on data derived from real patients, preserving the correlation of a patient's vital signs with different activities and symptoms. The stronger relationship between vital signs and contextual information will make the generated data more consistent and the model will be more accurate for validation. The experimental evaluation of our system in cloud model for patients having different HR and BP levels has demonstrated that the system can predict correct abnormal conditions in a patient with great accuracy and within a short time when it is properly trained with large samples. In future, we intend to extend the model with more context domains.

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