A Real-time Health Monitoring System for Evaluating Environmental Exposures

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***Abstract*—Several recent studies have addressed the topic of "exposome", an approach for evaluating environmental exposures and their influence on human health conditions. Environmental exposures affecting human health range from a combination of factors like air pollution, tobacco smoke, and pollen, to climate, such as heat and humidity. With continued advances in information technology, and the worldwide deployment of mobile and wireless networks, patients' health conditions can be continuously monitored by numerous intelligent devices. Sensors can be integrated into their mobile devices such as smart phones for continuous health assistance and disease attack prevention. However, researchers must overcome many challenges, such as data acquisition, data scales and data uncertainty, in order to evaluate environmental exposures. In this paper, we propose a framework for a generic health monitoring system for modeling and analyzing individual exposure to environmental triggers. We propose to integrate a wide range of individual exposures using wireless sensors and mobile devices for exposure assessment. This paper provides a solid framework by considering asthma as a specific case and presents challenges and opportunities in developing a data management system for continuously changing data and algorithms for evaluating environmental exposures.**

***Index Terms*—health monitoring, exposome, GIS, asthma, wireless sensors, mobile data, data uncertainty**

I. INTRODUCTION

The relationship between negative health effects like asthma and lung cancer and elevated levels of environmental factors, such as air pollution, tobacco smoke and humidity, have been detected in several large scale exposure studies [24]. Monitoring and assessing trends of environmental exposures and related health problems require appropriate information in a timely manner for public health planning, management and surveillance purposes.

Health monitoring systems often need to to track, monitor, and analyze moving data objects, such as humans, vehicles, mobile devices, and satellite images, and find relationships between patients' environmental exposures and their diseases in order to delineate the causes and prevent environmental diseases. However, these systems present significant challenges in terms of data size, data scales, complex structures and relationships, uncertainty, and space and time constraints. Tracking moving objects has been a prominent issue recently due to the large number of applications that depend heavily on it. Continued advances and cost reduction in personal mobile devices such as smart phones made them widely used in daily-life practices such as en route navigation and vehicle tracking. However, monitoring of individual exposure to environmental conditions did not follow the same pace despite its great impact on public health; the general effect of environment and climate has more been the concern. Limited research has been done on techniques for retrieving, storing and analyzing real-time data of patients' trajectories along with the environmental conditions patients are exposed to.

Since exposures vary across locations and time-intervals, the exposure dataset is often managed by geographic information systems (GIS) as well as spatial database management systems and analyzed via spatial statistics and spatial data mining. Particularly, asthma triggers vary by patient, region, and time. Thus, individual-based measurement of exposure to certain levels of environmental factors is needed for developing more accurate understanding of the causes of acute asthma episodes [16]. Therefore a health monitoring system requires the integration of GIS components to facilitate knowledge discovery technologies for public health decision support [17].

This paper proposes a health monitoring system framework for modeling and analyzing individual exposure to environmental triggers of asthma attack. The proposed system gathers time/location data from patients through location aware devices such as GPS. The system also collects various environmental measurements such as hu-

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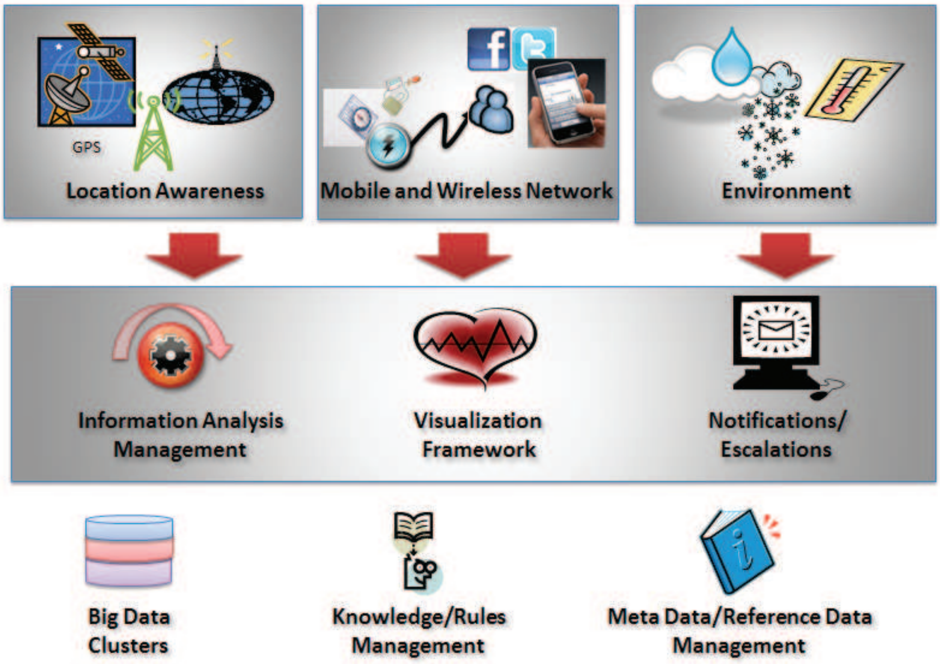


Fig. 1. Health monitoring system context

midity level and smoke concentration through wireless sensors. The data collected by these location devices and sensors are transmitted continuously through wireless sensor and mobile networks to a database server. Then, the developed analysis model at the server analyzes the collected data using a spatio-temporal integration model and derives conclusions. The system helps health specialists to have a better insight into the causes of asthma, to develop and evaluate policies and actions for disease prevention and management. Fig. 1 illustrates the contexts of our proposed health monitoring system.

The main advantages of the proposed system can be summarized as follows: (1) continuous monitoring and early attack detection associated with environmental factors, (2) data analysis on individual-level to provide risk alerts, (3) reducing time, effort and cost spent on emergency visits to hospitals and clinics, and (4) individual-level health care and long term treatment based on spatio-temporal data analysis, and (5) provide a better understanding of the effect of environmental exposures for improving public health care plans and strategies. Although we propose a framework targeting patients with asthma for a more focused study, it should be noted that the proposed system could be used to assess the effect of environmental exposures on other chronic diseases.

The remainder of this paper is organized as follows: We discuss our motivation and background in Section II. We then present related work in Section III. In Section IV we present the system architecture and discusses the system development challenges. In Section V, we introduce three components of the proposed system and we discuss the implementation considerations. Finally, we provide a conclusion in Section VI.

II. Motivation: Asthma and Environment

According to the World Health Organization asthma is a serious public health problem with over 100 million sufferers worldwide. It continues to be one of the major causes of hospitalization of children in many countries. Asthma is the leading cause of absenteeism from school and the third leading cause of work loss [1]. It ranks among the most common chronic conditions in the US, affecting an estimated 34.1 million persons in 2004 [18], [35], [37], [44]. The number of reported adults and children diagnosed with asthma in the U.S in 2009 was 17.5 million and 7.1 million, respectively [18], [35]. Moreover, the number of visits (to physician offices, hospital outpatient and emergency departments) with asthma as primary diagnosis in 2007 was 17.0 million in the U.S. only [37]. In the same year, the number of discharges with asthma as first-listed diagnosis was 456,000 with an average length of stay being 3.4 days [28], [37], [43]. The annual economic cost of asthma in the US was \$56.0 billion between 2002 and 2007. Direct health care costs of asthma, which include medial/nursing care and medication, made up \$50.1 billion of that total, and indirect costs such as lost productivity add another \$5.9 billion [44]. The prevalence of asthma has been increasing since the early 1980s for all age, sex, and racial groups and the burden in prevalence and health care use remains high. Yet, very limited health monitoring services are available for asthma patients.

In asthma sensitive people symptoms are initiated by breathing in allergy-causing substances also known as triggers. Most people diagnosed with asthma have attacks separated by symptom-free periods. Since there is no cure for asthma the goal of treatment is to control it by avoiding substances that trigger symptoms in the hopes of extending symptom-free periods. Research has identified several factors associated with the development of asthma, such as exposure to traffic exhaust fumes, tobacco smoke, pesticides, heat and humidity, and changes in the weather, but none have proven to be the causative agent [2], [20]. Rather, the development is a combination of underlying susceptibility with environmental exposures [2], [25].

Asthma specialists have also shown that the combination of extreme weather conditions, such as heat and high humidity, escalates some asthma attacks and consequently leads to mortality [2]. It has been also observed that people who remain in air-conditioned rooms for a long time can become easily susceptible to some diseases when exposed to extreme temperature. In many of these studies environmental conditions related to asthma have been measured in a broad manner, (i.e. studies were based on summarized data collected in large scale areas such as cities). Asthma triggers vary by patient, region, and time. Thus, individual-based measurement of exposure to certain levels of environmental factors is needed for developing more accurate diagnoses on the causes of acute asthma episodes.

There have been strong efforts made on developing health monitoring systems in both academia and industries internationally. A research group at the University of Technology in Australia [3] has been implementing personal health monitor software. The patient has one or more sensors (e.g. electrocardiogram and accelerometer) attached to their body. External devices are also used, such as a blood pressure monitor and weight scale, to periodically collect additional health data. Mobile phones provide communication channels between the patient and the system to receive the data and provide feedback. Another Example is HeathGear, a real-time wearable system by Microsoft Research for monitoring and analyzing physiological signals. In this system, physiological sensors transmit data such as oxygen levels in blood via Bluetooth to a mobile phone [33]. Yet, there do not appear to be any devices on the market that synchronize the environmental conditions (environmental sensors) with health monitoring (health conditions). With continued advances and cost reduction in mobile devices and wireless sensor technologies, it is feasible for medical device manufactures to implement a sensor equipped mobile device that can collect time/location data along with environmental data. Efficient and effective methods for combining individual health tracking with data analysis for the purpose of assessing the cause and treatment of health problems need to be developed for effective environmental health decision support.

The proposed system introduces healthcare providers to a tool that is able to develop more accurate asthma prevention and care plans enabled by real-time patient monitoring and communication through alerts for potential environmental triggers. This can reduce the cost and burden of hospital emergency visits for asthma patients and their families. Patients, especially children, can be easily equipped with light, wearable mobile devices in their daily-life. They can conveniently communicate with the system and avoid the triggers of asthma attacks.

III. Related Work

The emerging term "exposome" has been introduced in health care literature to assess the effect of different environmental exposure on human health [40], [45], [34]. These environmental exposures range from air pollution sources such as tobacco smoke to more dangerous chemicals such as lead. The general idea of exposome is to complement molecular level view of genomes and genomics with community-level view of exposures to understand the relationships among exposures, symptoms and diseases. Exposure to environmental conditions varies across different locations and time intervals. This spatio-temporal nature of the exposure data is best managed by spatio-temporal databases and geographic information systems that allow efficient analysis of the collected data.

Different tools and approaches exist to measure the exposome such as sensor technologies, imaging and mobile technologies and portable computerized devices [40]. Great advances have been made in the scale and battery life of sensors and GPS devices. In addition, advances have been made in the range, reliability and coverage of wireless communication networks such as Bluetooth, WiFi, and 3G. Each wireless technology addresses different system requirements based on coverage area and speed. Moreover, new algorithms and models have been developed to process data produced by mobile devices more efficiently and thus elongating the battery life of these mobile devices [22].

The technological advances made in ubiquitous mobile devices have turned them into ideal tools for monitoring environmental pollution. The authors in [36] developed an air pollution monitoring system. The proposed system provides real-time interpolated maps of air quality using GIS which analyzes and displays data collected by sensors. Such successful deployment of mobile devices in environmental monitoring have led researchers to use them in health assistant systems like the "EnviroFlash" model [4], which is used to notify patients about up to date information on air quality.

The rapid development in sensor networks, location tracking devices, and mobile networks, have enabled the creation of health care systems like Telemedicine applications [5] and eHealth [6] services. Through these health related technologies, "virtual visits" of patients to doctors became possible. Some patients are now able to skip actual "face to face" visits with doctors for simple tasks like blood pressure and sugar level measurement assessment. Moreover the application of ubiquitous mobile technology in healthcare has led to the development of commercial "emergency alert" systems that provide immediate support to patients with severe maladies such as heart disease and diabetes. An example is the "Invisible Bracelet" (iB) [7], a wearable device that utilizes mobile network technology to provide emergency identification and notification for patients.

Health monitoring systems range in scale and flexibility from ones that monitor entire homes such as the smart home monitoring device [21], that consist of several intelligent devices built in homes which monitor and provide help to the elderly and disabled people, to very tiny sensor chips that can be implanted in the body of patients to provide continuous monitoring of blood pressure, sugar level, and other measurements [19], [39]. These types of health monitoring systems are very useful but are limited in scope to specific requirements. For example, smart home systems are useful for continuity of care where patients spend most of their time at home. On the other hand, implanted sensor chips are capable of continuously monitoring patients regardless of their location making them suitable for patients who are suffering from chronic diseases that are not necessarily debilitating. However, the use of implanted sensor chips is limited by its high cost and social acceptance. In addition, health monitoring may not work for some diseases using these sensors since the development of their attacks may not be measured by sensors. In the case of asthma, it is not enough to depend on physical measurements of implanted sensors as many other factors play a role in triggering an attack. For example, it can be a result of the environmental factors stated earlier. [31] proposed personal health monitors based on a wireless body area network of intelligent sensors. Individual monitors were integrated into a distributed wireless system for synchronized monitoring of a group of subjects. The proposed system used measures of heart-rate variability to quantify stress level prior to and during training as well as to predict stress resistance. This system could be used during the selection process and as part of a psychophysiological evaluation of military members undergoing intense training. Authors in [10], [15] discussed ideas and challenges in developing a health monitoring system for asthma patients and provide an architecture framework.

Asthmapolis [1] is perhaps the first health monitoring system for asthma that associates asthma patients' locations to the potential time of asthma attacks. The system combines GPS sensors with asthma inhalers to provide tailored information through mobile phones to Asthma patients. The patient's data is based on analyzing the geographical location and time of the inhaler use. However, the Asthmapolis system does not provide an accurate depiction of all the triggers involved in an Asthma attack, particularly, environmental triggers. Our proposed health monitoring system provides a prototype in analyzing individual exposure to several environmental triggers and thus, a more comprehensive study of the correlation between exposome and asthma attacks. Other alternatives such as environmental data collected by sensors, mobile phones and online maps are considered.

The main obstacle associated with developing a hybrid health-environmental monitoring system is in processing the potentially large data sets and extracting useful feedback to the patient in real time. Data produced by such a system would be aggregated spatio-temporal data that are voluminous in nature. If data sampling is too fine, the data sets will be too large to store or process in a reasonable amount of time. On the other hand, if data sampling is too sparse, this will create "blind spots" in the data sets that may depreciate the utility of data. Current systems used for health and environmental monitoring and tracking rely on manual processing and analysis of data which lack real-time data acquisition and communication capabilities. Hence, integration of different technologies is critical for developing a system that can synchronize environmental condition monitoring with health monitoring to determine the effects of an individual' surroundings on his/her health. Such a system should have a real-time data analysis capability in order to communicate useful information to a patient and is the aim of this research study.

IV. System Framework and Challenges

In this paper we provide a framework for a generic health monitoring system by considering asthma as a specific case. This section identifies the essential components and provides a basis for estimating a more elaborate system to be implemented. Challenges related to the system implementation are also discussed.

A. System Overview

The general framework of the proposed system addresses the following aspects:

- Scope of exposome: the exposome is composed of every exposure an individual is subjected to from consumption to death. However, it would be unrealistic to measure all the exposures of every individual continuously. The target is rather to consider the nature of certain exposures and their changes over time. The targeted exposures can be these that have been proven to have an effect on asthma, such as air pollution, heat and humidity.
- Dynamics of exposome: the dynamic nature of the exposome is a main challenge. Exposures need to be considered in relation to their temporal variation, as an individual will have a particular profile of exposure at any given point in time. Thus, based on an initial analysis of data collected, a more precise timestamp defining data measurement periods/snapshots need to be defined. This contributes in building a continuous real-time profiling and monitoring of individuals.
- Exposome measurement: a range of tools should be considered to capture the exposome; these include sensors, mobile phones, GIS and other technologies. The integration of state-of-the-art exposure assessment can allow future exposure assessment of complex mixtures such as tobacco smoke.

The proposed system is able to retrieve an individual patient's location/time data (GPS data) and several environmental data (such as air pollution, tobacco smoke, temperature and humidity) through sensor equipped mobile devices. With the integration of these data, the system

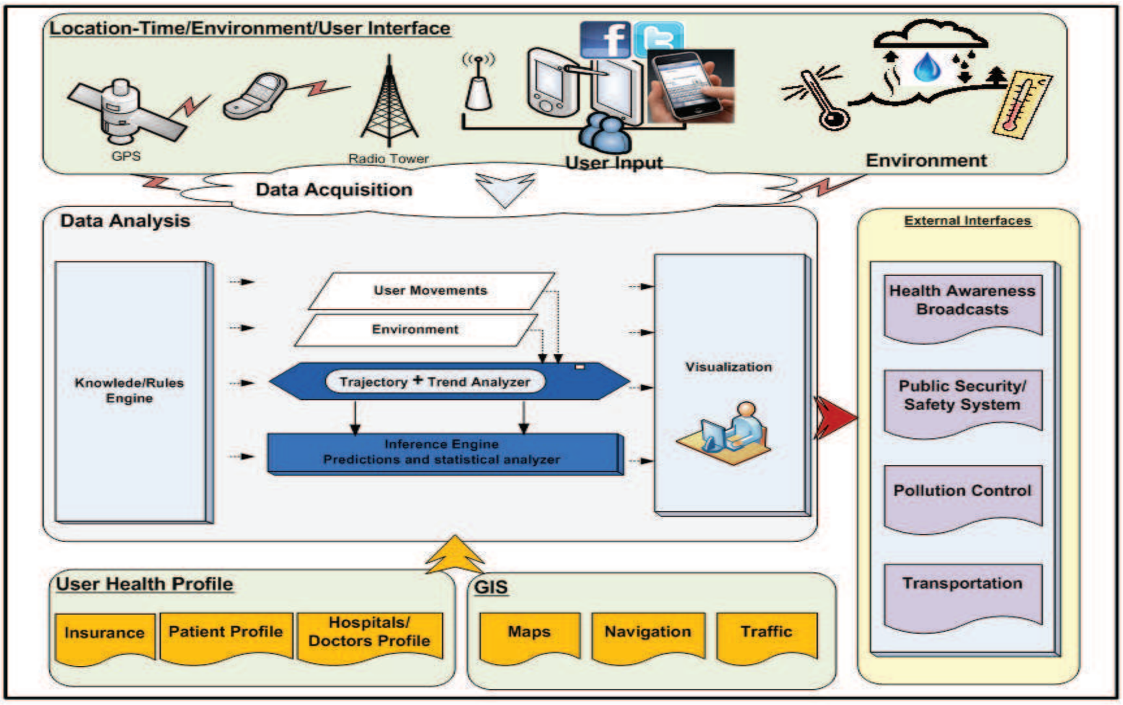


Fig. 2. A health monitoring system overview

can calculate the patient's exposure to certain levels of the environmental surroundings. Using statistical methods and efficient data analysis algorithms, the system can retrieve intelligeny information from relations between asthma and various environmental conditions.

Users' interaction with social networks or communication via mobile phone (phone number tied to business) etc., are other possible data collection methods. The communication via mobile and sensor networks can provide other information of the user such as the current health condition of the user (e.g., users post that they are feeling difficulty in breathing or chest wheezing). These unstructured data can be used to predict the environmental conditions such as traffic, congestion, smoke level, etc. Moreover, the user profile tied to user mobile devices provides intimate profile of the user. Based on the input, area of interest, reference data trajectory and trend analysis, the system computes the interesting output based on the rules configured in the system. In addition, The system can provide the output to external systems such as health awareness broadcast systems, public safety systems, pollution control systems, etc. Several rules of filtering and inference provide specific configurations to change the systems behavior without having to change the entire system. Fig. 2 presents an overview of the proposed system.

B. *Challenges*

The main obstacle associated with developing a hybrid health-environment monitoring system is processing the potentially large data sets generated by the mobile devices and sensors and extracting useful feedback to the patient in real time. All of the data contain spatio-temporal components with relevant environmental conditions. This obstacle is summarized in the following three interrelated challenges:

(1) Location uncertainty: A patient's trajectory is represented as spatio-temporal data and can be defined as space-time paths of a moving object. Due to database limitations and limited battery-life of mobile devices trajectories are modeled as discrete points representing locations in time. Sampling results in uncertainty in the location values recorded in the database of the moving object [12], [13], [38].

(2) Environmental conditions uncertainty: An environmental condition (e.g., humidity-30%) is also a spatio-temporal measurement that can be modeled as a raster grid for discrete time stamps. Each cell in the grid represents the average value of the environmental factor at a given time for the area. This average value is associated with positional and temporal uncertainties because of the approximations and interpolations used in modeling [24], [29].

(3) Analyzing and processing spatio-temporal data: Data analysis is a process of extracting useful and interesting information from large datasets. It is a fundamental and time-consuming process in spatio-temporal databases. Existing data analysis techniques do not adequately fit the nature of our datasets that continuously change their properties in time and that contain complex relationships. Therefore, flexible and scalable data analysis tools are crucial in order to analyze individual exposure to environmental triggers of asthma attacks.

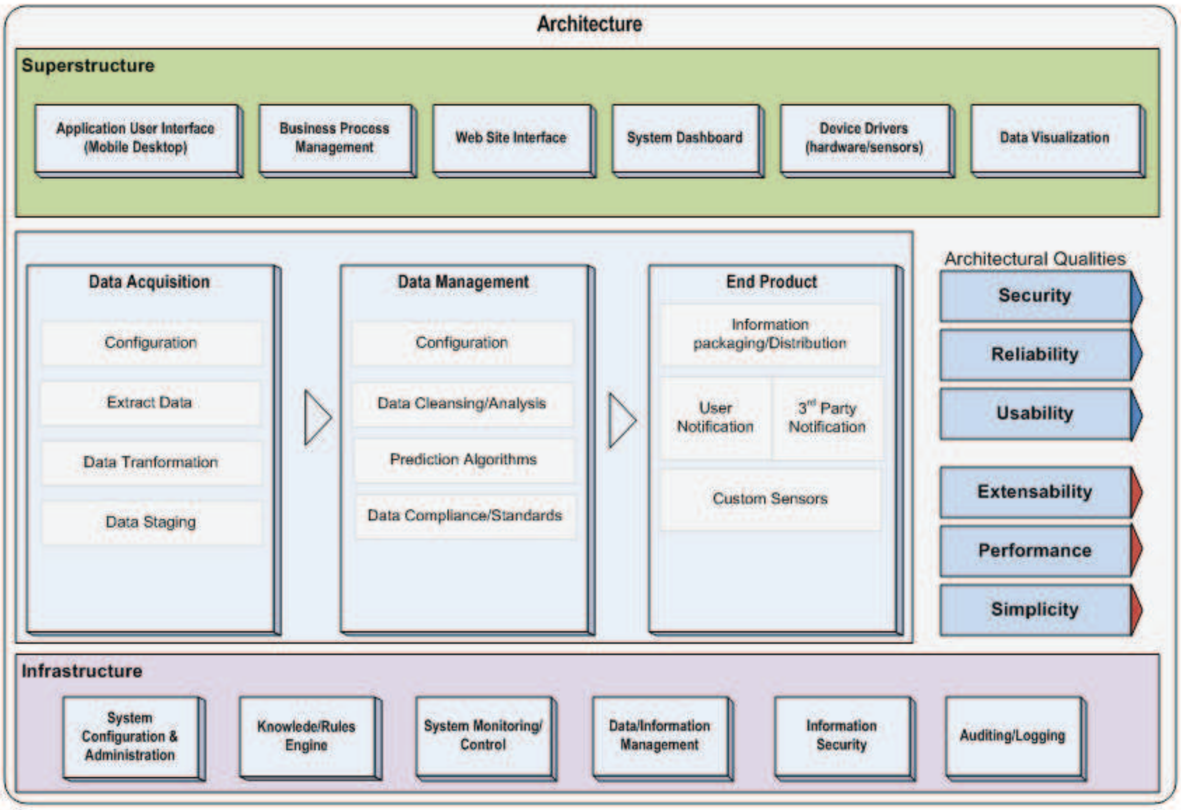


Fig. 3. System architecture

V. System Architecture

This section presents an architecture of the proposed system as shown in Fig. 3. The system and subsystems, and their relationships should be interpreted as a logical (or conceptual) view of the system. There are other subsystems, such as application downloads, software version upgrade system, and system installation, for implementing the proposed system. These must be identified on a case by case basis. The architecture must be augmented with technology choices (for example, database, programming language, etc.). Although some specific implementations for Android is given, the choice for interaction to subsystems must be clearly identified whether it is via API, messages, web service using Simple Object Access Protocol (SOAP) or Representational State Transfer (REST). Therefore, the presented architecture is generic and not tailored specifically for a particular implementation.

Our proposed architecture consists of several main system components (subsystems): (1) a real-time data acquisition system using sensors and mobile devices, (2) data management system that deals with spatio-temporal data modeling, data analysis algorithms, and visual evaluation tools, (3) superstructure system, and (4) infrastructure system. Implementation considerations for each of these subsystems are presented in this section.

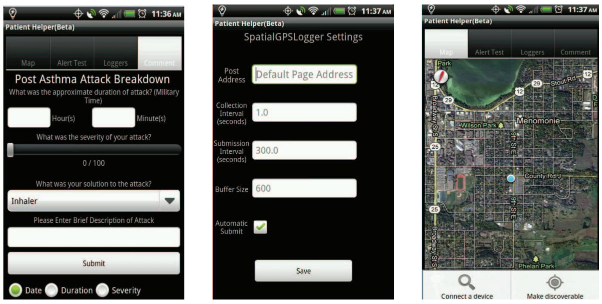
A. Data Acquisition System

Data acquisition system is responsible for obtaining data from external systems. This includes patient's data, hospital data, 3^{rd} party data, etc. The acquired data must be configured and extracted, transformed to local needs and finally staged for data analysis. Different techniques for data sampling need to be considered for both energy-efficiency and data accuracy. Cost models for optimizing continuous tracking of data with limited resources (e.g., sensor cover radius, mobile device life time, etc.) need to be developed.

In the proposed system, we focus on two data components: individuals' moving trajectories and environmental data. The first component can be obtained by location tracking devices using GPS/GSM technologies. The second component involves the use of sensors and the mobile phone to measure air quality. Our data acquisition system is a microprocessor based system to interface the sensors with a mobile phone running on Android operating system. The real-time data collected via the GPS/GSM modules are sampled and transferred to servers and stored in XML format, which can be later easily converted to other formats and integrated with other GIS datasets.

Environmental data such as air pollution and tobacco smoke cannot be obtained by the mobile phone without proper external hardware design. In the mobile phone system implementation in Fig. 4, the application interfaces are implemented using standard Google's API's. The first allows Android devices to communicate with external hardware. The second shows the Android open accessory and the third is accessory development kit (ADK). The development kit allows a mobile phone to communicate with sensor hardware on an external microprocessor board. It also allows building external accessories for Android devices with data collection, measurement, and data logger functions. Using a flexible and convenient system such as a smart phone is the key to continue our study to collect environmental data.

Sensors for patients' biological signals (e.g., peak flow levels) can be integrated to the system. The communication via mobile and sensor networks can also provide other information of the user such as the current health condition of the user (e.g., chest wheezing). Moreover, the user profile tied to user mobile devices provides intimate profile of the user. Fig. 4 illustrate user interface through mobile devices.



(a) User interface (b) System setting (c) Map integration

Fig. 4. User Interface

B. Data Management System

The data management system extracts data from the acquired raw data and applies statistical analysis and mining algorithms to the collected data. The goal is to find some rules that can help in identifying meaningful relationships among the datasets that would be useful in measuring the effect of environmental conditions on the health of asthma patients. To achieve this goal, a geostatistical model of spatial autocorrelation need to be developed to capture the correlation between a patient's data and the environmental factor datasets.

Both, location of moving objects [9], [13], [42] and environmental conditions are spatio-temporal data that are uncertain in nature [24]. For example, the concentrate of a specific air pollutant found in satellite data varies from one region to another and from a given time to another and depends on the accuracy of sensors. Also, a GPS device may report a location of a moving object 2-5 meters away from the actual location.

The concentration $C(t, s)$ of an environmental factor is a spatio-temporal variant phenomenon represented by grid cells for discrete time steps, with the grid cell value representing a spatially and temporally averaged estimate of the true concentration. In this case, uncertainties are often dominant to positional and temporal uncertainties due to the relatively coarse scale of modeling. Individual trajectories $I(t, s)$ are space-time paths as defined by [27]. By definition only positional and temporal uncertainties can occur for $I(t, s)$, as the only attributes are position and time. For GPS data the spatial uncertainty usually lies within 3 to 5 m and the temporal < 1 sec. Quantified uncertainties are characterized by their probability distribution functions which are joint probabilities if the variables are correlated which is the case for both data types [29]. By integrating these autocorrelation models [24], [27], [29], a spatial correlation model can be developed to measure the exposure time of individuals to certain levels of environmental factors.

The integration of spatio-temporal datasets (e.g., environmental data and trajectories) can provide information about the exposure measurement of a patient to environmental factors. Probabilistic methods [11], [14], [30], [32], [41] can be used for estimating the exposure of a specific patient to different environmental factors.

Research done in statistically and computationally efficient data analysis algorithms provide means that can be used in analyzing the effect of various environmental factors on the health of asthma patients. The system can find patterns, outliers, and classification, and provide recommendations and predictions of incidence, prevalence, and mortality based on individual exposure to various environmental factors. The proposed system requires investigation of data analysis methods using statistics; information associated with data density, samples drawn from the population and distribution of the samples. Statistical data analysis algorithms can analyze the effect of various environmental factors on the health of asthma patients. We propose the use of Bayesian Item Response Theory [23]. Item Response Theory (IRT) is an established mathematical model for measuring latent variables through other manifest variables. The method was used successfully in other applications such as profiling insider threat [8]. The goal would be to apply this mathematical model to create an inference engine that could predict the combined effect of spatial-temporal variables on the susceptibility of a user to an asthma attack. The model also allows measuring the effect of each variable on instigating an Asthma attack based on prior knowledge and user response data. A general framework for analyzing data through the proposed inference engine is depicted in Fig. 5.

Suspect triggers can be calibrated in terms of their effectiveness in instigating an asthma attack from collected data using Item Characteristic Curves (ICC). Example of such curves for the hypothetical variables humidity and temperature are shown in Fig. 6. The calibrated scores for the combination of spatio-temporal/environmental variables are measured in terms of their effect in inducing an Asthma attack for each individual. Example of such a curve is shown in Fig. 7. This method allows the system to measure the susceptibility of each individual to an asthma attack as the value of the exposure to variables change through time.

The inference engine can provide recommendations and predictions of an asthma attack incidence based on an individual's exposure to various environmental factors. It should also provide estimates on the prevalence of asthma

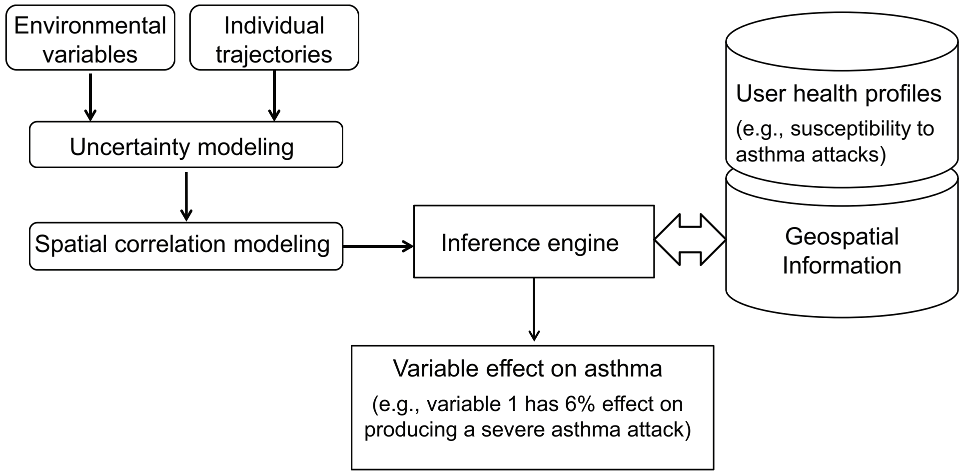
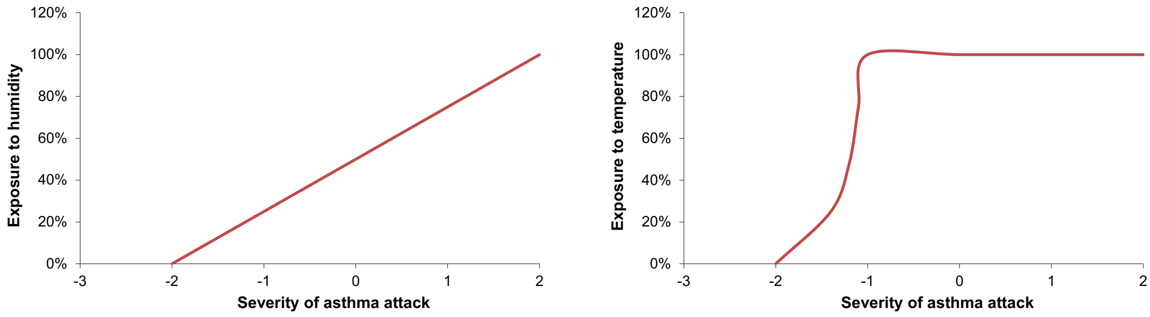


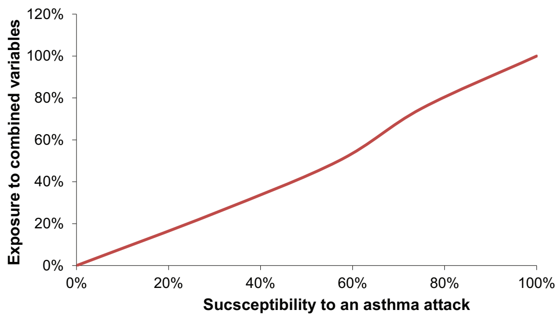
Fig. 5. A framework for data analysis



(a) Response data for humidity

(b) Response data for temperature

Fig. 6. Examples of IRT Curves for the variables humidity and temperature



(a) Response data of exposure to combined variables

Fig. 7. An example of an ICC Curve for Measuring user susceptibility to an asthma attack

attacks based on the occurrence of different combinations of environmental factors. One approach is to examine the IRT model and investigate new approaches to accomplish this task.

Due to spatial and spatio-temporal properties, query processing dealing with moving objects is a time-consuming process. Hence, optimizing techniques for developing an efficient database system is essential in the implementation of this system as well as investigating methods using statistics; information associated with data density, samples drawn from the population and distribution of the samples. In addition, physical database issues, e.g., storage and access methods such as indexing, and cost models of query processing should be investigated and assessed.

C. Superstructure

The superstructure system identifies all the systems (and subsystems) that the users are facing:

- User interface: This subsystem consists of all the user interfaces. It includes mobile, desktop, and web based interfaces for all types of users. For our proposed system, we identify the following types of users: 1) end users (asthma patients), 2) system administrators, 3) 3rd party (hospitals, insurance, doctors, pharmacists, etc.), 4) casual users (public). This subsystem uses the security model identified in the infrastructure subsystem.
- Business process management: This module captures all the business processes of the health monitoring system. An example of a business process for data acquisition could be: 1) external data configuration, 2) document/data acquisition and validation, 3) data extraction and transformation, 4) data loading/committing into the system. This subsystem handles all business processes, and transitionary work items for smooth information flow.
- Web site interface: this consists of user web interfaces, web site, contact information, etc.
- System dashboard: this subsystem displays the performance characteristics of the system. The actual measurements are derived from identifying the performance metrics (SEI's technical performance metrics, Trusted Platform Module (TPM) methods, could be used to identify the measures). This system is only responsible for displaying performance characteristics in terms of charts and tables. The system aids in identifying the current and future needs of the system as well as in showing the current outstanding issues and outages.
- Device drives and software downloads: this subsystem captures the sensors hardware and software, user downloadable software, software upgrades, etc.
- Data visualization: data visualization is the process of exploring data visually in order to extract information of complex data and to assist in deriving useful information. The system needs to provide the means to allow users to analyze the effect of various environmental factors on the health of patients. Strategies include the exploration of different combinations of technologies (and tools, such as tables, bar charts, graphs, maps, and 3D modeling) and the development of generic framework to build a flexible and scalable prototype. Development of a new type of cartographic interface is also required for the multidimensional exploration of environmental and health indicators.

D. Infrastructure

The infrastructure system identifies all the systems (and subsystems) that are essentially used by all other systems except the components that the users are facing:

- System configuration and administration: this subsystem handles system rules and configuration related issues.
- Knowledge/rules management: knowledge management consists of capturing the information related to standard patterns and anti-patterns. Rule engines (such as JESS, a Java rule engine that implements RETE algorithms) help to process the rules efficiently.
- System monitoring and control: this subsystems is responsible for collecting statistics on various performance measures. It ensures that the system operates as expected by monitoring the key performance indicators.
- Data/information management: this is responsible for database and information management including reference meta data management. It also includes customer profile, subscription, and product inventory customer billing. Any information requiring special qualities must be identified in this subsystem.
- Auditing/logging: the health monitoring system should be highly traceable from start to end. Therefore, auditing module traces the information by tracing metadata for each piece of information.
- Information security: this module captures the followings: user security (roles, users, authentication, authorization); information separation (patients personal medical data, payment information etc.); data encryption for data distribution and packaging; data separation for personal indemnifications information protection; information access violations.

The end product system is responsible for packaging the information (after data analysis) for various target users. In order to insure high architectural quality of a health monitoring system, the system should consider the following components:

- Security, reliability, and usability: these are considered for user service qualities.
- Extensibility: this is ranked high because the system will have many new algorithms and components as new products are identified.
- Performance: this component is critical to process large data and segregate and extract meaningful data in a timely manner.

- Simplicity: this quality is a complement to other qualities. In order to make the system extensible and usable, the architecture must be highly organized. However, this prioritization must be redone, taking into consideration the presented vision for a specific purpose.

The other concepts required in the fully executable systems include customer/issue management system, help/language support system, traceability, etc.

VI. Conclusion

Health monitoring systems can be thought of as a natural extension to advances in health services and technology including mobile and wireless sensor networks, and web and Internet. Their main objective is to analyze in real-time patients' data and environmental datasets collected over time and other GIS datasets in order to provide individual-based healthcare to patients. Such a system, if developed successfully, promises to reduce the cost, effort and time put in traditional health visits to hospitals.

In this paper, we proposed a framework for a real-time health monitoring system by targeting asthma as a specific case in order to evaluate environmental individual exposures. This system is expected to find utility in improving public health care strategic planning against asthma attacks. The paper presented an overview of the system architecture, components of each sub-systems and major challenges of system implementation.

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