Building a Decision Support System for Automated Mobile Asthma Monitoring

Uwaoma, Chinazunwa, The University of the West Indies, Jamaica
chinazunwa.uwaoma@mymona.uwi.edu

Mansingh, Gunjan, The University of West Indies, Jamaica
gunjan.mansingh@uwimona.edu.jm

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ABSTRACT
Advances in mobile computing have paved way for development of several health applications using Smartphone as platform for data acquisition, analysis and presentation. Such areas where m-health systems have been extensively deployed include monitoring of long-term health conditions like Cardio-Vascular Diseases and pulmonary disorders, as well as detection of changes from baseline measurements of such conditions. Asthma is one of the respiratory conditions with growing concern across the globe due to economic, social and emotional burden associated with the ailment. The management and control of asthma can be improved by consistent monitoring of the condition in real-time since attack could occur anytime and anywhere. This paper proposes the use of smartphone equipped with built-in sensors, to capture and analyse early symptoms of asthma triggered by exercise. The system design is based on Decision Support System (DSS) techniques for measuring and analysing the level and type of patient’s physical activity as well as weather conditions that predispose asthma attack. Preliminary results demonstrate that smartphones can solely be used for monitoring and detecting asthma symptoms without other networked devices; thus, enhancing the usability of the health system while ensuring user’s data privacy, and reducing the overall cost of system deployment.

Keywords: Mobile computing, Decision support, Smartphone, Asthma monitoring
INTRODUCTION

Recent years have witnessed a paradigm shift from the conventional use of cellular phones in supporting only voice communication to multimedia services and healthcare applications. The massive availability and improvement on the storage, networking and computing capabilities of these devices have allowed the development of a wide range of mobile applications including healthcare systems. Combination of mobile computing technologies and wireless body sensor networks (WBSN) presents opportunities for unobtrusive monitoring of patient’s clinical data and seamless communication of the monitored data to healthcare professionals. Asthma is one of the long-term health conditions whose treatment can benefit from real-time and continuous monitoring, as an attack could occur anytime and anywhere. The rising increase in asthma cases has necessitated the development of technological support for asthma management and control (Seto et al., 2009; Uwaoma & Mansingh, 2014).

Asthma manifests in variant forms which can be categorized according to the trigger factors and temporal-spatial dynamics of the attack. Our study focuses on Exercise-induced Asthma (EIA) - an asthma flare due to strenuous physical exertion. McFadden and Gilbert (1994) report that asthmatics with chronic conditions manifest signs of asthma attack during exercise. However, there are many people without asthma who develop symptoms only during rigorous exercises like sporting activities. EIA is associated with wheeze and shortness of breath. Person experiencing asthma attack also tends to lean forward in an effort to get sufficient air into the lungs which invariably makes the patient to assume an inclined posture (Signs of a pending Asthma Attack n.d).

Wheezing is the most investigated vital sign among the common symptoms of asthma. However, not all wheezes points to asthma and not all asthmatics presents wheeze during an episode; hence, the need to include contextual information to help evaluate patient’s condition. Furthermore, the identification of ambient conditions associated with pathophysiology of asthma as well as measuring patient’s level of physical activities (Karantonis et al. 2006) on detection of any anomaly in breath pattern, could help in real-time medical intervention for asthmatics. This paper proposes a design for asthma monitoring based on embedded intelligent systems in smartphones, to assist asthma patients and their care givers in managing asthma flares induced by rigorous activities.
The rest of the paper is structured as follows. Section 2 provides enabling concepts for our design. In section 3, we present an overview of the design architecture. Design implementation and results from the preliminary testing are discussed in section 4 while section 5 summarises our discussion and direction for future work.

BACKGROUND

There has been notable increase in the use of advance information and communications technologies to improve overall asthma management and control. This spans from electronic peak-flowmetry and asthma diaries through asthma web-based tools to mobile phone applications (Glykas & Chytas, 2004; Hendler et al., 2012; Uwaoma & Mansingh, 2014). Building on their previous work – DexterNet, Seto et al., (2009) proposed an architecture for comprehensive asthma monitoring. The system consists of a mobile device as sink for the aggregation and processing of clinical and physiological data. The proposed system extends the functionalities of the existing asthma e-health systems to accommodate monitoring of physical activity and outdoor exposures to environmental triggers. The architecture also includes web-based applications which provides platform for collaborative work among the patients, healthcare providers and health researchers.

Lung sound is one of the most vital signs monitored in asthma given that its analysis provides medical doctors with critical information on how to adjust treatment for patients with asthma condition. Thus, detection and analysis of abnormal respiratory sounds like wheezes becomes paramount in the design of asthma e-health systems. Wisniewski and Zielinski (2010) argue that asthma e-health designs are not sufficient to provide comprehensive monitoring of asthma patients without the inclusion of lung sound analysis. The authors advance a ‘fully’ integrated asthma e-health system that will not only allow for detection of asthma wheeze but also include measurement of other vital signs and triggering factors.

Asthma wheeze detection systems are developed alongside classification models which make it possible to precisely qualify and distinguish adventitious sound from normal respiratory sounds (Shaharum et al. 2012; Reichert et al. 2008; Taplidou and Hadjileontiadis, 2007). Several approaches adopt machine learning techniques using advanced classifiers rather than threshold-based algorithms, to produce more elaborate and reliable results. Oletic et al. (2014), evaluated different wheeze detection algorithms based on Decision Tree classification. The aim is to
determine which metrics has the best classification accuracy and efficiency that could be implemented on a low-power wearable device for automated recognition of respiratory sound patterns.

Knowledge-based and Decision Support Systems for mobile healthcare are built to detect and alert on any anomaly, and also provide summary report on monitored health condition. These intelligent systems use context information from different sources to correlate data from a monitored event in order to arrive at a decision (Minutolo et al., 2010). In situation or context aware systems, extracted data from different sources are often validated using a set of conditional tests. Usually, a chain of conditions are applied to the given data to identify the condition(s) that matches the required pattern. These set of conditional tests are called production rules and can be combined with ontologies for efficient processing of information. An ontology provides formal framework for organization and representation of domain knowledge (Henriques et al., 2013).

In our study, we leverage the potentials of embedded sensors in smartphones for data collection, and the phone itself providing the platform for data processing, analysis, presentation and feedback. This is enhanced by incorporating contextual information through machine learning techniques and expert systems to assist in decision process. The ability of the system to automatically signal warnings on detection of abnormalities and to generate feedback would help to improve patient’s self-management and communication with health professionals. Also, by utilizing the capabilities of internal sensors, modern mobile phones can serve as veritable assistive tools for monitoring and alerting asthma patients and their care providers on early symptoms of asthma exacerbation. This removes the need of having external sensors and other networked devices attached on the user, which could increase installation cost and compromise user’s data which by default are sent over to a remote server for computation and analysis.

SYSTEM DESIGN

Figure 1 shows an overview of the proposed system architecture. The design comprises of both hardware and software components to realize an integrated monitoring system. The audio sensor, activity sensors and ambient sensors constitute the basic hardware for capturing both physiological and clinical data of the patient. The system architecture also includes data processing components which enable extraction and representation of important features of the data. The DSS kernel
houses data analysis components - classification algorithms and context recognition techniques, which provide analysis and description of context data sets, and also generate the required services for the user.

The design is conceptualized based on the premises that:

- Mobile phones are capable of recording breath sounds and performing analysis on the recorded signal using computer algorithms.

- Wheeze detection and analysis provide medical doctors with critical information on how to adjust treatment of patients with asthma condition.

- Smartphones are able to correlate patterns in the user’s movement and also recognize sudden changes in bodily position using embedded sensors like gyroscope, accelerometer and magnetometer. Table 1 provides brief description of available sensors in modern smartphones.

- Ambient data such as temperature, humidity and air pressure can be captured by built-in sensors to provide context on detected events.

- Expert systems can use the evaluation from the sensors’ measurements to decide on the severity of a patients’ condition.

Figure 1. An Overview of the Monitoring System Architecture.
Table 1. Embedded Sensors in Smartphones.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gyroscope</td>
<td>Measures the orientation of a device in pitch, roll and yaw; and also the rotational rate of the device in x,y,z axes.</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>Measures the acceleration force that is applied to the device including force of gravity.</td>
</tr>
<tr>
<td>Magnetometer</td>
<td>Measures the heading direction or the geomagnetic field of the device in three axes.</td>
</tr>
<tr>
<td>Barometer</td>
<td>Measures the ambient air pressure.</td>
</tr>
<tr>
<td>Hygrometer</td>
<td>Measures the humidity of ambient environment.</td>
</tr>
<tr>
<td>Thermometer</td>
<td>Measures the ambient (room) temperature.</td>
</tr>
<tr>
<td>MEMS Microphone</td>
<td>Records sound transmitted to the phone.</td>
</tr>
</tbody>
</table>

DESIGN IMPLEMENTATION AND PRELIMINARY TESTING

The first phase of the design implementation requires two procedures for feature extraction from sensors’ data namely; wheeze detection and activity recognition. The raw sensor data may need to be pre-processed on the firmware or at the application level before exposing them to the techniques used in the two subsystems.

Wheeze Detection

Wheezing is one of the frequent symptoms experienced by patients with asthma. Detecting the presence of wheeze, its duration and proportion in a breath cycle could assist physicians to ascertain the severity of attack. Wheeze detection systems are built on the basis of stethoscope principle. Several algorithms have been proposed for automated wheeze detection in respiratory sounds. These include Tonal Index [TI], Kurtosis [K], Energy Ratio [ER] (Wisniewski & Zielinski 2010), and Adaptive Respiratory Spectrum Correlation Coefficient [RSACC] (Yu et al. 2013).
In our design, we implemented Time-Frequency Threshold Dependent (TFTD) algorithm which by extension is a modification of RSACC algorithm with low computational requirement for resource-constraint devices like smartphones. Characteristic features used for determining the presence of wheeze include the frequency harmonics, continuity and duration of wheeze intervals in a breath cycle. For the preliminary testing of the TFTD algorithm we used pre-recorded lung sounds obtained from a repository. An android phone was also used to record simulated ‘wheezes’ and normal breath from a healthy individual. The major operations in the algorithm include segmentation and decomposition of the breath signal to extract spectral and temporal features using Short Time Fourier Transform (STFT) in (1).

\[ X[n] = \sum_{k=-\infty}^{\infty} s[n]w[n-m]e^{-j2\pi k/N} \quad (1) \]

Actual respiratory segments are isolated from the baseline signals using local minima and wheeze segments are identified by performing cross correlation (2) on adjacent respiratory segments. The proportion and duration of the detected wheezes is then determined from the respiratory cycle.

\[ C(n) = \frac{\sum_{k=0}^{N}[(x(k)-mx)(y(k)-my)]}{\sqrt{(x(k)-mx)^2}(y(k)-my)^2} \quad (2) \]

The overall performance of the algorithm has a mean accuracy of 0.88±2 with false alarm rate of about 10.6%. The erroneous detection is attributed to strong correlation of respiratory signals between wheezing sounds and other respiratory sounds due to existence of peaks in other breath sounds which are highly similar to peaks representing wheezes. To further discriminate between wheezing sound and other respiratory sounds we included other quantitative and qualitative measures in the analysis. These include ranges of dominant frequencies and visualization of the sound waveform, spectrogram and cross correlation plot (resulting from the TFTD algorithm).
Activity Recognition

In this section we describe two quantities of interest in the activity recognition subsystem using the motion sensors. These features are patient’s *posture change* obtained from the Orientation measurement and *activity level* provided by the linear motion parameter. With the device placed strategically on the body trunk, the linear movement is represented by the readings of the three accelerometer axes as follows:

- z-axis: captures forward movement (motions);
- y-axis: captures upward/downward movement and
- x-axis: captures horizontal movement.

For posture change, the orientation or attitude data is measure in degrees (between -180 and 180). Evaluating the posture of the trunk after a patient has undergone a burst of energetic or vigorous exercise helps to ascertain if there are remarkable degree of posture variations in terms of a patient bending forward or tilting sideways in order to get sufficient air in the event of airway obstruction.

The Movement Intensity (MI) metric also known as average resultant acceleration measures the instantaneous intensity of patient’s movements and it is generated from accelerometer readings of the three axes as show in (4).

\[
\text{Movement Intensity (MI)} = \sqrt{(x_i^2 + y_i^2 + z_i^2)}
\]  

(4)

To determine the level of activity, linear accelerometer readings resulting from patient’s movement are categorized into two:

(i) Sedentary (e.g. sitting, standing, lying)  (ii) Ambulation (e.g. walking, running, jogging).

To distinguish between the two categories of activities, we compute the movement intensity using average motion (AM) expressed as:

\[
\text{Average Motion (AM)} = \frac{1}{N} \sum_{i=1}^{N} |MI_i - SMA_i|
\]

(5)

Where N is the length of sampling/sliding window and SMA\textsubscript{i} is the combined Signal Magnitude Area of the three axes computed as:

\[
\text{Signal Magnitude Area (SMA\textsubscript{i})} = \frac{1}{N} \left( \sum_{i=1}^{N} |x[i]| + \sum_{i=1}^{N} |y[i]| + \sum_{i=1}^{N} |z[i]| \right)
\]

(6)

SMA is a metric used to track or predict energy expenditure in everyday activity. It is also used to discriminate between a resting state and high intensity movements in a classification frame work.

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Thus, using a threshold-based classification in a scenario where the patient is apparently NOT moving, the AM value is relatively low and where the activity status is “not resting” (noticeable strenuous movements), the AM value is relatively high.

In the following subsections, we describe strategies adopted to enhance the results obtained from the early implementation of the design. First we consider machine learning approach for classification of extracted features in the wheeze detection and activity recognition processes. We also consider using embedded intelligence to provide alerts to patients and caregivers on deviation from baseline measurements. This will be accomplished by developing Expert Systems to integrate the rules and contextual information in order generate the required services to the user.

**Machine Learning Techniques**

Machine learning (ML) has become an integral part of detection and context recognition systems particularly in healthcare. ML techniques provide light-weight algorithms for event detection and context recognition to reduce energy consumption by the monitoring system. Furthermore, in the wheeze detection that was tested on recorded breath sounds, we noted “false positives” detection in breath signals that contains no wheeze. Advance classification models and machine learning techniques could be used to minimize the occurrences of erroneous detections. This of course will involve searching for optimal classification parameters from extracted signal features. There are several classification models used for optimal parameter search in extracted features. These include support vector machine (SVM), MPL ANN algorithm and Decision Trees. The choice of the model however, will depend on the accuracy, efficiency and low computational and power requirements on a mobile phone. Figure 2 depicts the process flow of the machine learning process.
Embedded Expert Systems for Decision Making

Expert systems (ES) designs are based on artificial intelligence techniques involving expert knowledge expressed through rules. Rule-based DSS for m-Health systems require context information for ad-hoc reasoning in order to reduce false positive alarms on a detected event. For exercise-induced asthma monitoring, contextual data such as patient’s activity type (walking, running, jogging) and weather condition (ambient temperature, humidity) could help in quicker and correct recognition of asthma flares given the presence of potential triggers. Information on patient’s body postures (sitting, lying, standing, tilting forward, and tilting sideways) could also improve the accuracy in determining the severity of the attack.

A typical rule-based DSS for healthcare comprises of three main components namely:
- Fact base which contains physiological and contextual data from patients
- Inference Engine which handles the decision process
- Rule base which contains expert knowledge that determines what action or service is to be executed/provided.

These three components are represented as layers in a simplified DSS model as shown in Figure 3.
In our design we intend to combine production rules with ontologies in the DSS model for efficient processing of information specific to the problem domain. Production rules play important role in expert systems as they provide the basis for the computational model to draw deductions from the presented scenario. They are often structured using the IF-THEN statement. Ontology on the other hand, defines structures and descriptive logics used to establish and actively reason upon relationships among the structures in the domain. New relationships could also be discovered while querying the existing ones in a given ontology. Figure 4 shows a sample of ontological structure design for the specific issue we are considering which is Exercise-Induced Asthma (EIA).
Figure 4. Ontological Structure of the proposed DSS

CONCLUSION

The overall goal of the system design is to develop real-time application for monitoring and detection of early symptoms of asthma during exercise. The envisaged system would alert users on detection of any anomaly so as to avoid further exacerbation of the condition; and also generate feedback on patient’s health status. We have implemented the algorithms for breath sound analysis and we are currently working on activity recognition using advanced classification algorithms performed on a smartphone. As m-Health is gaining wider acceptance in modern medicine, inclusion of domain medical knowledge in decision making implemented in expert systems as part of the design, will help provide right diagnosis and treatment for the patient by health professionals. Thus, having all the operations performed exclusively on the mobile device, we believe our design approach will improve on the usability and reliability of the previous systems while ensuring patient’s data privacy.
REFERENCES


