Using Embedded Sensors in Smartphones to Monitor and Detect Early Symptoms of Exercise-induced Asthma

Chinazunwa Uwaoma and Gunjan Mansingh
Department of Computing, The University of the West Indies, Kingston, Jamaica

Keywords: Mobile Computing, Sensor Fusion, Health Monitoring, Smartphone, Asthma, Context Recognition.

Abstract: This paper describes work in progress on integrated design architecture for monitoring and detecting early symptoms of asthma attack using smartphone as sensors' platform for data capturing, processing, presentation and feedback. We present an application scenario of exercise-induced asthma where a patient wears a smartphone equipped with built-in sensors which are capable of providing clinical data and context on detection of any anomaly in the monitored vital signs. Our design architecture extends the functionality of "Nine-degree of Freedom" (9-DoF) sensor fusion model and context recognition using expert system frameworks. The design centers on the idea of creating a simple and portable asthma monitoring system that is able to detect asthma vital signs, perform signal analysis and context generation; and also send information to other mobile devices worn by caregivers and physicians. This approach removes the need to have external monitoring sensors patched on the user's body, thereby enhancing the usability and reliability of the system in providing timely information on the state of a patient's health.

1 INTRODUCTION

Asthma is of one the long-term respiratory conditions that require real-time and continuous monitoring, as an attack could occur anytime and anywhere. The ailment has considerable social and economic impact on the life of an individual sufferer and the society (Braman, 2006). The growing concern to reduce the cost of healthcare utilization due to asthma, the burden of personal management of the disease and the workload both on the patients and healthcare providers, has necessitated the development of asthma healthcare monitoring and delivery systems.

Combination of mobile computing technologies and wireless body sensor networks presents opportunities for unobstructive monitoring of patient's clinical data and seamless communication of the monitored data to healthcare professionals. Recent studies have focused on utilizing the potentials of intelligent mobile devices and wireless body sensors for data acquisition, signal processing and context recognition in health applications (Seto et al., 2009; Zhou and Zhang 2011). However, many heterogeneous wireless body sensors used for health monitoring do not always provide precise information on the sensed signals. Oberoi (2011) argues that these sensors come with different Operating Systems as well as proprietary network and middleware protocols, which makes it difficult to have a single sensing system that can comprehensively monitor and detect events of interest. Furthermore, the inability of patients to choose and setup different sensors and monitors; and also, difficulty in analyzing the circumstances surrounding the sensed data may result in delayed communication and uncertainty of data presented to healthcare professionals. A design platform that will allow integration of multiple sensor modalities and implementation of context recognition frameworks on a Smartphone could help overcome these issues.

As mobile computing evolves, mobile phones are being turned into high performance computer systems which are handy, discreet and pocket fit devices (Fernandes and Afonso, 2011). Modern smartphones come readily equipped with advanced sensors for detection and recognition of events, internet access, improved processing and memory units as well as flexible communication system and connectivity. Weghorn (2013) notes that these intelligent mobile devices also run open software system (e.g. Android) with better User Interface features compared to stand-alone sensors and monitors which use 'closed' system, specialized

Uwaoma C. and Mansingh G..
Using Embedded Sensors in Smartphones to Monitor and Detect Early Symptoms of Exercise-induced Asthma.
DOI: 10.5220/0004806901450150
In *Proceedings of the 3rd International Conference on Sensor Networks* (SENSORNETS-2014), pages 145-150
ISBN: 978-989-758-001-7

hardware and also, bulky in size. The enhanced capabilities provided in smartphones allow for development and use of third-party software such as asthma monitoring applications. Premised on the above considerations, our design objective centers on integrated system architecture that allows the use of personal mobile devices to monitor, detect and alert early signs of asthma attack.

2 RELATED WORK

Research has focused on the use of advance information and communications technologies to improve overall asthma management and control ranging from electronic peak-flowmetry and asthma diaries through asthma web-based tools to mobile phone applications (Seto et al., 2009). Seto et al. (2009) discuss several approaches that have been used in the design of asthma e-health systems. These solution methods however, are not quite sufficient to provide comprehensive monitoring of asthma patient without the inclusion of lung sound monitoring.

A new paradigm in asthma management and control is monitoring wheeze rate which involves signal analysis of asthma breath sounds. Mobile phones are capable of recording breath sounds and performing analysis on the recorded signal (Anderson et al., 2001; Zhou and Zhang 2011).Wheeze is one the frequent symptoms experienced by patients and doctors have described it as a clinical predictor of asthma exacerbation .

Wheeze detection and analysis provides medical doctors with critical information on how to adjust treatment of patients with asthma condition. There are several computer algorithms which can detect and evaluate percentage of wheeze on normal breath. Wisniewski and Zielinski (2010) provide detailed review on these algorithms. Nonetheless, acoustic signal analysis is only one of many tasks in preventing asthma attack. There is need to measure and analyze other vital signs including environmental effects as well as patient's level of activity, in order to provide accurate and reliable information in controlling asthma exacerbation.

Leveraging the potentials of the internal sensors, Smartphones can be configured to provide reliable and timely medical intervention for patients dealing with asthma crises. Smartphones are able to correlate patterns in the user's movement using embedded sensors like GPS, gyroscope and accelerometer. They can also recognize sudden changes in bodily position and decide on the severity of patient's condition by evaluating sensors' measurements (Kiss, 2011). The embedded microphone can record patient's breath sound, while ambient data such as air pressure, humidity and temperature can be captured by barometer, hygrometer and thermometer in the smartphone, to provided context on detected events.

2.1 Monitoring Exercise-Induced Asthma

Exercised-Induced Asthma (EIA) is triggered by exercise and physical exertion. 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. An important characteristic feature of asthma condition is the hypersensitivity of the airways to environmental factors. McFadden and Gilbert (1994) observe that persons with EIA have airways that are very sensitive to changes in temperature, humidity, and altitude. Common symptoms of EIA are wheeze and shortness of breath. Besides wheeze and difficulty in breathing, another vital sign of EIA attack is change in patients' posture. Persons experiencing asthma attack tend to lean forward in an effort to get sufficient air into the lungs, as shown in the presentation (Signs of a Pending Asthma Attack n.d).

There are preventive measures against EIA attack such as inhaled medications and Peak–Expiratory Flow (PEF) measurements (Casa et al., 2012). However, asthma patients at times find it tasking to adhere to prescribed medications and action plans which results in poor management and control of the condition. Hence the need for a personal assistive monitoring tool to alert patients and their care givers on signs of pending asthma attack as the patients engage in rigorous physical activities. Figure 1 depicts how a smartphone could be worn to monitor asthma vital signs during exercise.

Figure 1: Exercising with Smartphone strapped on the neck to monitor asthma vital signs (Source: Google Image).

2.2 Sensor Fusion and Context Recognition

A new development in sensor applications is multi-dimensional sensing which enhances the user's experience through sensor fusion. Sensor fusion is a technique that uses special filtering algorithms to compensate limitations of individual sensors in order to generate a desired output. Integrating inputs from multiple sensors using sensor fusion allows for more accurate and reliable sensing, which consequently produces much higher levels of recognition for appropriate response. Pattern-matching algorithms can identify and correlate events that will assist with delivering awareness to the user or the monitoring system. Through training and experience, the monitoring system adapts to changing circumstances and responses based on the generated context (Lee et al., 2008).

The importance of context awareness has continued to gain wider recognition in healthcare monitoring applications. By combining sensor fusion and context recognition techniques, we can develop smart systems that can help manage patients with chronic conditions such as asthma; and alert the patient or the healthcare providers of any anomaly.

3 THE EXTENDED 9-DOF SENSOR FUSION MODEL

Our design methodology builds on the platform of sensor fusion solution that combines triaxial-accelerometer, triaxial-gyroscope and triaxial-magnetometer.

These 3D-sensors have the capability of performing basic sensing (Ristic, 2012). An accelerometer measures linear motion, a gyroscope defines orientation while the magnetometer provides direction sensing. Their capabilities notwithstanding, these sensors are characterized by certain limitations that affect accuracy in applications. However, sensor fusion can be used to overcome the shortcomings of individual sensors. It eliminates deficiencies in separate devices by using intelligent algorithms and unique filtering techniques to produce synthesized and more sophisticated output; thus satisfying the impression that "*The whole is greater than the sum of its parts*" (Karimi, 2013).

An important feature of 9-DoF sensor fusion solution is its flexibility to accommodate several sensors. More sensors can be added on need basis and this automatically transforms the sensor fusion solution to an m-DoF solution where '**m**' implies '**multiple**' (see Table 1).

The design of the proposed asthma monitoring system includes activity and motion sensors, location sensor, ambient temperature and humidity sensors, air pressure sensor, and an embedded MEMS microphone for recording and monitoring asthma wheeze rate. The design is based on m-DoF solution (see Figure 2). The model allows two data paths to be used in processing the sensed data (Ristic, 2012).

1. Pass Through data path - sends raw data directly to the application.
2. Sensor Fusion path - allows initial raw data to be processed and synthesized into a smart output.

In our design, the monitored wheeze signal will require a separate application for analysis and need not to go through the sensor fusion path. Also data from ambient sensors may have to be sent 'raw' for analysis. This scenario, thus, makes the model suitable for the proposed design.

Table 1: m-DoF Sensor Fusion Models.

m-DoF	Sensors	Mobile Platforms
6-DoF	3D-gyroscope, 3D-compass	Android, Linux and Windows
9-DoF	3D-gyroscope, 3D-compass, 3D-accelerometer	Android, Linux and Windows
12-DoF	3D- gyroscope, 3D-compass, 3D-accelerometer, Barometer, Thermometer, ALS	Windows and Android

4 INTEGRATED DESIGN ARCHITECTURE

The integrated system architecture consists of three main layers: Data Acquisition Layer, Data Processing Layer, and Data Analysis Layer (see Figure 3). Implementing m-DoF sensor fusion algorithms at the Data Acquisition Layer allows multi-modal data collection. Data Processing components enable extraction and representation of important features of the data while Data Analysis components provide analysis and description of context data sets.

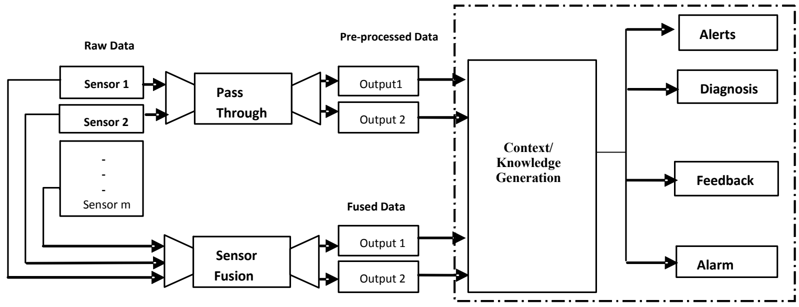

Figure 2: An extended 9-DoF sensor fusion model for asthma monitoring system using embedded sensors in Smartphones (Ristic, 2012).

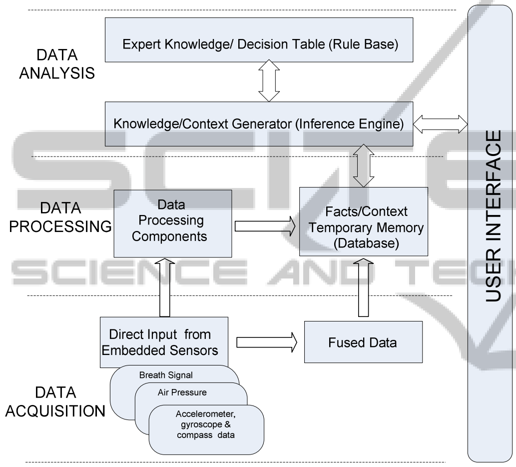

Figure 3: Layered architecture of the asthma monitoring system.

5 DESCRIPTION OF THE ARCHITECTURAL COMPONENTS

In this section, we explain the functionality of the integrated system architecture.

5.1 Data Collection and Signal Processing

Embedded sensors in the Smartphone collect signals and quantities of interest - physiological, activity, ambient and location data. Sensed data can be distorted due to noise, interference, or other environmental factors; hence the need for signal processing to obtain meaningful data. *Readers* and *Filters* algorithms are data processing components that can interface with the sensors and perform signal cleansing on the recorded data respectively. However, these components may not be used for the fused data since we are applying the m-DoF sensor fusion solution that performs the two tasks on the firmware at the Runtime (Ristic, 2012).

5.2 Data Fusion

The described Sensor Fusion model in section 3 provides flexibility for certain aspects of the sensed signals to be combined to extract desired features while other data “pass through” as calibrated direct input to the application processor as shown in Figure 2. With exercise-induced asthma in view, candidate parameters for fusion are linear motion, gravity, orientation and direction; derivable from accelerometer, gyroscope and compass sensors. Combining these features gives better description of patient’s level of activity in terms of motion and position of the body. To obtain these key features, the accelerometer compensates for gravity loss in gyroscope which provides the orientation estimates, while the compass corrects the heading error.

5.3 Wheeze Detection

Wheeze detection systems are designed based on the idea and principles of stethoscope. Previous designs involve the use of external sensitive microphones placed on the chest to record lung sound or on the neck to record tracheal sound (Sen and Kahya 2006). However, our design uses an embedded MEMS microphone located at the mouthpiece of the Smartphone.

Sovijarvi et al. (as cited in Wisniewski & Zielinski 2010) note that asthma wheeze signal has a dominant frequency usually above 100 Hz and with duration of about 80ms to 100ms. The breath sounds is pre-processed by applying High pass *filters* to remove noise or other low-frequency signals that may manifest similar morphologies. Characteristic features used for determining the presence of wheeze include the tone, location, duration and number of wheeze in a breath cycle.

Frequency domain algorithms are considered to be more efficient for wheeze detection and classification. However time-domain analysis using classification features like *Kurtosis* and *Renyi entropy* will be faster for real-time applications; and also, computationally effective for low-power mobile devices like smartphones.

5.3.1 Kurtosis

Kurtosis (1) shows the degree of peakedness of a probability distribution for a random variable X and it is defined as:

$$k = \frac{E(X-\mu)^4}{\sigma^4} \tag{1}$$

Kurtosis value k around or larger than 3 indicates normal distribution for non-wheeze signals while a value less than 3 shows that the breath sound contains wheezes and thus would have a uniform or sub-gaussian distribution (Aydore et al., 2009).

5.3.2 Renyi Entropy

This feature, also known as generalized Shannon entropy is a measure of uncertainty of signals and uniformity of distributions (2). For random variable X, Renyi entropy is defined as:

$$H_\alpha(X) = \frac{1}{1-\alpha} \log\left(\sum_{i=1}^{n} p_i^\alpha \right) \tag{2}$$

Study in (Aydore et al., 2009) shows that wheeze signal distribution has higher degree of uniformity when compared to non-wheeze signal.

By applying filter algorithms, the signal features are extracted into the temporary facts/ context database for further classification.

5.4 Context Generation, Analysis and Classification

It is important to select algorithms that will allow the system to generate intelligent information on the reported event or sensed data. Thus, we consider classification method based on decision rules obtained from medical experts and literature, as has been used in previous studies (Aydore et al., 2009; Basilakis et al., 2010; Borgohain and Sanyal, 2012; Bae et al., 2013). Rule-based classifiers label records or facts using a collection of "condition-action" rules defined as follows;

Rule: (condition) → ***l***, where 'condition' is a conjunction of attributes and ***l*** is the class label.

Processed data from different sensor modes can be grouped into four categories namely: Physiological data, Activity data, Ambient data and Location data. For the purpose of analysis however, we use only two categories as summarized in Table 2. In the exemplary classification and analysis of the sensed data, we illustrate how sensor fusion technique and rule-based expert system can be combined to handle multi-parameter sensing and context recognition.

Table 2: Classification of Processed Sensor Data.

Category A: Physiological Data

Sensor	Measurement	Duration	Kurtosis (k)	Class Label
MEMS Micro-phone	Breath Sound Signal	≥ 80ms	< 3	Wheeze
		< 80ms	≥ 3	Non-wheeze

Category B: Activity Data

Sensor (Fused)	Measure-ment	Motion	Orientation	Class Label
Accelero-meter, Gyroscope and Compass	Activity Level	Fast	Upright	Very active
		Slow	Inclined	Active
		None	Inclined	Non-active

The generated context is annotated using JSON-based description. The annotations can be displayed directly to the Smartphone console or stored temporarily in the context database for subsequent analysis. Context or situational analysis and pattern recognition can be performed by using Rete Algorithm (Figure 4) to combine decisions and confidence levels from experts in the application domain.

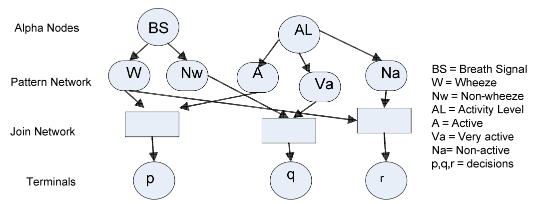

Figure 4: Rete Decision Tree - Network for Context Recognition.

Knowledge inferred from context analysis provides classes of services: alerts, diagnosis, feedback and alarm. The information can be stored as patient's health history on the SD card or shared with healthcare providers for further diagnosis and treatment. Alarm and Alert messages are sent in the event of emergency or detection of any anomaly on the monitored signals.

6 CONCLUDING REMARKS AND FUTURE WORK

The emerging IC MEMS sensory technology in Smartphones defines a new path in healthcare monitoring. Benefits of using mobile phone as multi-parameter sensing device include the ability of an asthma patient to carry an accurate all-in-one monitor anywhere; and the ability to make baseline measurements at anytime thereby generating a database that could allow for improved detection of disease state and control.

Our emphasis has been on sensor fusion and context modelling given that data fusion and context awareness are critical for optimal performance of any health monitoring system. Whereas data fusion provides accurate value, context recognition provides knowledge on what to do with the data. The sensor fusion requires substantial MCU power which may not be fully provided by Smartphones given the limited power source for these devices. Using a dedicated sensor processor may be an efficient way of performing sensor data computing. Optimal performance and cost however, are major considerations for independent sensor processor. The wheeze signal also, needs to be analyzed in a separate application. We are investigating how the application can run concurrently with data fusion in order to have a synchronized output.

REFERENCES

Anderson, K., Qiu, Y., Whittaker, A. R. & Lucas, M., 2001. Breath sounds, asthma, and the mobile phone. *The Lancet*, *35*(9290), 1343-1344.

Aydore, S., Sen, I., Kahya, Y. P. & Mihcak, M. K., 2009. Classification of respiratory signals by linear analysis. In EMBC *2009, Annual International Conference of the Engineering in Medicine and Biology Society.* IEEE. 2617-2620.

Bae, W. D., Alkobaisi, S., Narayanappa, S. & Liu, C. C., 2013. A Real-time Health Monitoring System for Evaluating Environmental Exposures. *Journal of Software, 8*(4), 791-801.

Basilakis, J., Lovell, N. H., Redmond, S. J. & Celler, B. G., 2010. Design of a decision-support architecture for management of remotely monitored patients. *IEEE Transactions on Information Technology in Biomedicine, 14*(5), 1216-1226.

Borgohain, R. & Sanyal S., 2012. Rule Base Expert System for Cerebral Palsy Diagnosis. *International Journal of Advance Networking and Application*, viewed 01 October 2013. http://arxiv.org/ftp/arxiv/papers/1207/1207.0117.pdf.

Braman, S. S., 2006. The global burden of asthma. *CHEST Journal*, 130, suppl. 1, 4-12.

Casa, D. J., et al. 2012. National Athletic Trainers' Association position statement: preventing sudden death in sports. *Journal of Athletic Training*, 47(1), 96.

Fernandes, B., Afonso, J.A. & Simões, R., 2011. Vital signs monitoring and management using mobile devices. In *6th Iberian Conference on Information Systems and Technologies (CISTI).* IEEE. 1-6.

Karimi, K., 2013. Sensor Fusion and Internet of Things (IoT). *The Embedded Beat*, 14 May, viewed 01 October 2013. https://community.freescale.com/community/the-embedded-beat/blog/2013/05/14/sensor-fusion-and-the-internet-of-things-iot.

Kiss, G., 2011. Using smartphones in healthcare and to save lives. In *Internet of Things (iThings/CPSCom), International Conference on Cyber, Physical and Social Computing*. IEEE. 614-619.

Lee, H., Park, K., Lee, B., Choi, J. & Elmasri, R., 2008. Issues in data fusion for healthcare monitoring. In *Proceedings of the 1st international conference on Pervasive Technologies Related to Assistive Environments.* ACM. 3.

McFadden Jr, E. R. & Gilbert, I. A., 1994. Exercise-induced asthma. N*ew England Journal of Medicine*, *330*(19), 1362-1367.

Oberoi, S., 2011. Sensor fusion brings situational awareness to health device. *Embedded*, 01 June, viewed 01 October 2013. http://www.embedded.com/design/embedded/4216526/2/Sensor-fusion-brings-situational-awareness-to-health-devices.

Ristic, L. J., 2012. Sensor Fusion and MEMS for 10-DoF Solutions. *EE Times,* 03 September, viewed 01 0ctober 2013. http://www.eetimes.com/document.asp?doc_id=1279870.

Sen, I. & Kahya, Y. P., 2006. A multi-channel device for respiratory sound data acquisition and transient detection. In *EMBS 2005, 27th Annual International Conference of the Engineering in Medicine and Biology Society*. IEEE. 6658-6661.

Seto, E. Y. W. et al. 2009. A wireless body sensor network for the prevention and management of asthma. In *SIES'09, International Symposium on Industrial Embedded Systems.* IEEE. 120-123.

Signs of a Pending Asthma Attack n.d. *WebMD*, viewed 01 October 2013. http://www.webmd.com/asthma/asthma-symptoms-7/slideshow-asthma-attack.

Weghorn, H., 2013. Applying mobile phone technology for making health and rehabilitation monitoring more affordable. In *2013 ISSNIP Biosignals and Biorobotics Conference (BRC*), IEEE. 1-5.

Wisniewski, M. & Zielinski, T., 2010. Digital analysis methods of wheezes in asthma. In *International Conference on Signals and Electronic Systems (ICSES)*. IEEE. 69-72.

Zhou, S., Zhang, Z. & Gu, J., 2011. Time-domain ECG signal analysis based on smart-phone. In *EMBC 2011, Annual International Conference of the Engineering in Medicine and Biology Society.* IEEE. 2582-2585.