Survey on A Smart Health Monitoring System Based on Context Awareness Sensing

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Abstract

Wearable health monitoring systems, with a context-awareness sensing ability, can greatly improve the way such devices work, both in terms of its accuracy and efficiency. This paper summarises related work previously performed, their advantages and disadvantages, and how they can be incorporated in future work. The related work covers approaches using devices such as smartphones used in isolation, smartphones combined with wristbands and ARM based microcontrollers interfaced with different sensors. Different approaches for optimizing power usage in wireless systems are also investigated. For context awareness, various papers are analyzed to determine existing activity recognition patterns, and approaches to solve common problems experienced in this field. Furthermore, this paper proposes a system that can be considered for future work, combining methods that are found to be meet a certain set of criteria, to develop a device that would be applicable for use by underground mine workers.

Keywords: Activity Recognition, Acceleration Sensors, Context Awareness, Decision Trees, Defuzzification, Fuzzification, Human Wearable Health Monitoring Systems, Machine Learning, Ubiquitous Computing, Wireless Sensor Network

1. Introduction & Problem Description

The development of unobtrusive, low-powered wireless health-monitoring devices, using contextual information, have paved the way for underground miners. A need exists to monitor miner’s biometric signals together with activity recognition and environment sensing, which can prevent or alert relevant parties of dangerous events. These sensor devices can detect the activity of the miner, including fall detection, impact detection, as well as other activities which may give better context to the relevant sensors. The objective is that these sensors are

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to be worn without interfering with miner's normal operations, and share data amongst other miner's devices and a central system. This can assist with improved evaluation of the circumstances, especially because not one single source of information is considered, and the majority of nodes can determine whether there are any outliers which may be faulty or in danger.

This work falls under the research of context-aware systems. Various other papers discuss health or environmental monitoring using wireless sensor networks (WSN's), as found in papers such as [1] [2] [3], however, these papers mostly avoid context-aware models, and uses normal threshold levels instead; these result in being either true of false, and nothing in-between. However, this is not sufficient to detect context.

The first discussion on context-aware systems was by Schilit and Theimer [4]. The discussion covered aspects such as accessing information and services with various context parameters taken into consideration, which includes activity, location, time, identity and preferences.

Context-awareness is not only beneficial in improving accuracy of sensors, but can also plays an important role in overall power management of a system. The scope therefore allows implementation in more than one of the subsystems.

There are several aspects in Wearable health monitoring systems that should be met for the system to be practical. This includes (1) the construction of the device should be portable, wearable, and unobtrusive, (2) the device should meet processing and energy requirements to be capable of processing the required data, while lasting long enough to serve its purpose, (3) the selection of integrated sensors should be adequate for properly determining a miners status, (4) the entire system should be both scalable and flexible enough to support new users added to the system, without the requirement to reprogram or re-train the system, and (5), the security of the system is also important as it contains personal information of different users [1][5]. It is therefore required that the design approach of the device, both in terms of the actual technology that will be used, and the physical construction and design needs special consideration.

Possible options that may exist in terms of implementation, is that the device is implemented within a hard hat, on a vest, as a wrist band, using built-in sensors of a smartphone, or a combination of one or more of these options.

With wireless monitoring systems, there are typically three stages that consume energy; sensing of the data, processing of the data and then transmitting the data wirelessly. The wireless transmission consumes the most energy, and should therefore be designed carefully, and possibly managed with context awareness methods to maximise efficiency from the system. The possibility of implementing a power management control system, based on contextual awareness, is possible by implementing fuzzy logic [6]. Such system would control when to transmit data wirelessly. This could allow for a much more efficient system, without unnecessary data overhead.

The deciding factor of where to process data also plays a crucial role in the deployment of the system. Factors that need to be considered includes, but is not limited to (1) power usage required for processing versus the power usage for wireless transmission, (2) whether it is more important to convey data more often or keep back transmission if data has not changed significantly, (3) sensor node processing capabilities, and (4) storage capabilities with build-up of backlogs.

Wireless technology in a mining environment is another crucial point of consideration that cannot be overlooked. Connectivity can prove difficult, especially due to the lack of underground cellular connectivity, and wireless communication signals being subjected to multipath fading in these environments - with narrow and branching corridors. A WSN is required to be implemented and interconnected amongst the miners and the statically placed sensor nodes. Because each Wearable Health Monitoring System (WHMS) needs to disseminate data on this network, building both a scalable and maintainable WSN infrastructure is required. There are some protocols and open-source software packages that look promising in this regard. Some which provide self-configurability, even with new devices/users being added to the network. The decision on wireless technology should also consider power consumption and range.

Often, systems are developed to merely bring a minimum viable product to the market. Just as often, these systems end up being the final product, as long as the results seem promising. However, maintainability and scalability is often overlooked. The infrastructure of the central system should be developed to be future maintainable, generic, and scalable, otherwise it may become almost impossible to migrate to improved systems. It could therefore be considered to develop a restful API. So, if the core system would be changed or upgraded to an entirely new framework, due to advancements in technology, the access layer can simply be developed to accept the same format of data. In this case, client devices would not be affected, as long as the black-box inputs and output structure remain the same. If any of the client-side layers were to be replaced or added, this could be done programming-language and framework independent.

2. Related Work

2.1 Wearable Health Monitoring System

Wearable Health monitoring systems has been a research area that attracted lots of interest in the past few years [7] [8], driven by various factors, such as increasing healthcare costs, and the requirement of monitoring people at risk such as underground miners, and the elderly. In [6], the author has summarised a list of various related work on health monitoring systems, both in terms of prototypes and commercially available products. The summary includes the communication platforms, type of sensing performed as well as discussing the appearance and design of the devices, and to what external devices they connect to.

In [8], a real-time activity recognition system has been developed, which uses a spiroergometry mask attached to the user, and a tri-axial acceleration sensor attached to the user's vest. The system operates using an ARM processor, and conveys data via Bluetooth. Various recognition patterns are analysed here; the author has found that Classification and Regression Trees (CART) and Adaptive Neural Fuzzy Inference Systems (ANFIS) patterns were the best for online monitoring. The implementation is however too obtrusive, especially with the mask, and the fact that the sensors are attached to the persons clothing. The system also does not disseminate the data amongst other users.

In [1], the author presents an approach towards establishing an operation framework for an individualised, and intelligent WHMS.

An approach followed by [9], is integrating a smartphone to obtain user activity information. The author relies solely on data obtained from the smartphone sensors, avoiding the need for an external sensor device. Furthermore, the research goes into feature extraction methods, by comparing ten different classifier algorithms to determine which perform the best (k-nearest neighbors (k-NN) and kStar ranked the highest). Only offline activity recognition is considered here, and the device is designed to only consider independent user activity, thus, data is not found in the context of other users in the area. Methods discussed also include avoiding the dependency on smartphone orientation, by implementing the concept of square summing. This combines the data from the accelerometer for all three axes. The approach followed here mostly conforms to the requirements of a WHMS, but may lack some accuracy due to its operation in isolation. Since no fuzzy logic is implemented, the system's power efficiency could also be improved in future work.

"Sensors" [10] uses a smartphone for the analysis of user activity based on hand and leg movement. Since hand gestures cannot be detected only via a phone in the user's pocket, a wrist strap is used, which has an accelerometer, gyroscope and linear acceleration sensor integrated. Using these the two devices in conjunction provides richer context information. The author also investigates the effect of changing the analysis window time. A problem that may arise with the approach followed is that the activity recognition is biased towards more common activities, which may result in inaccurate readings when more uncommon activities are performed.

2.2 Context-awareness Recognition

Several research papers discuss context-awareness, with [11] [12] [13] leveraging on sensors built into mobile phones to collect data from the user's activities and the environment, while others [8] leverage on ARM or other type of microcontrollers. Authors in [8] and [11] investigates and discusses a comparison of different methods for recognition of daily-life activities. In [8], FFT (Fast Fourier Transform) analysis is performed on the acceleration data to distinguish dynamic acceleration (activity) from static acceleration (gravity), and its possibility to determine the angle of the user to further determine his or her context, based on the AC and DC components of the signal. In [14], the frequency domain features are replaced with the polar coordinate converted equivalent data. This reduces the dimensions of the feature vector, enabling the acceleration data to be expressed in a three-dimensional coordinate system (X, Y, Z). The existing patterns that are considered in this field of research include kStar, ANFIS, CART decision tree, ID3 decision tree, k-NN and Naïve Bayesian. The selection between these patterns are made by considering computational power, accuracy and the likes. Figure 1 illustrates the flow of a generic human activity recognition system. The feature extraction subsystem considers time/frequency domain data, in terms of its statistical data over a timeframe. The rule based classification and model training uses patterns, as discussed above, based on rules stored in a database. Finally, the activity is transformed into a human understandable activity, which is the semantic activity.

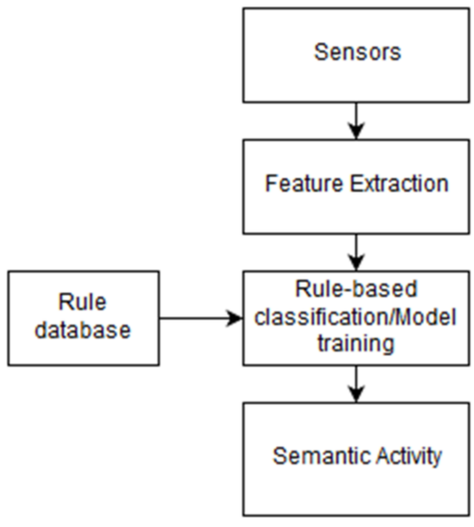

Figure 1: Human Activity Recognition flow diagram

Table 1, below, summarises a list of advantages and disadvantages of various classification patterns that are of interest.

Table 1: Activity classification pattern comparison

Pattern	Pros	Cons
kStar [15]	- performs well in scenarios with imbalanced attributes and attribute noise	- High error rates
ANFIS [16]	- tolerant to marginal errors - able to model nonlinearity - easy integration into common automatic control methods - easy to understand - flexible	- input-output mapping not possible - simple patters exist
CART [17]	- easy to understand data - inexpensive processing, immediate results - interactions between variables easily identifiable in model - automatically handles missing values - ability to use combination of discrete and continuous values - can establish interactions between variables - independent of monotonic transformation of predictive variable	- possibility of unstable decision trees - non-parametric - splits by single variable
decision tree [15]	- performs feature selection implicitly - not affected by outliers - easy to interpret. Little effort required for data preparation. - ability to discover nonlinear relationships and interactions	- classification error rate high - requires discrete data for certain construction algorithms
k-NN [18]	- easy to implement - flexibility with feature and distance choices - can handle multi-class cases, naturally - performs well with sufficient representative data	- inefficient finding nearest neighbours - storage of data an issue
Naïve Bayesian [19]	- fast - easy to implement - resistant to missing and noisy data (in classification and training set)	- large error margin, due to algorithm not properly handling complex hypothesis - biased results due to assumption of conditional independence - difficult to determine reason for feature vector classification

In [20], context-aware modelling using fuzzy logic is investigated. Here, both present and past values are considered in the fuzzy set, in order to handle the concept of partial truth. The fuzzy logic system consists of four parts, namely: the fuzzifier, the interference scheme, the rule base, and the defuzzifier. The fuzzifier maps the input value (from sensors) to a fuzzy value (i.e. fuzzy linguistic terms and membership functions). The interference scheme does an if-then statement and works with the rule base, which is a dictionary with a set of rules. These rules may consider the previous and current values to define the current situation. Lastly, the defuzzifier outputs crisp values based on the decision made. In this paper, the researchers added classical logic to the system by having implemented a mechanism that detects if the system loses connection to other nodes, whereby the data is stored to a buffer to be sent whenever a connection is re-established. This also has the advantage of a user to capture the missing values, if the system has failed, in the case where manual investigation is needed. The ability to program the possible contexts is also covered in the mentioned paper. Hereby, if the environment of sensors changes, the context definitions may also change.

2.3 Selection of sensors and attributes

The selection of attributes that should be considered for the health and safety of an underground miners include the following groups: acceleration, environment, physiological data and location.

(1) Acceleration: Image recognition techniques and accelerometer data can be used to recognise ambulation activities. More complex recognitions can be made using image recognition, however, it may not always be as practical as accelerometers, due to its portability. Triaxle accelerometers are found to be the most widely used for determining human activities [11] [10] [5]. Certain activities may however be confusing from an acceleration point of view. Placement of the accelerometer is also an important point of consideration, with papers such as [21] [9] indicates that it should be placed in a user's trouser pocket, while [22] suggests to attach the device on the user's belt, since this position provides information on the upper and lower part of the body. Authors in [23] suggests attaching it on the dominant arm's wrist, however, it all depends on the type of activity that needs to be recognised.

(2) Environment: Attributes including temperature, humidity, sound-pressure levels, various gas levels and lighting conditions form part of describing a user's surrounding context [5]. However, no single attribute can be considered in isolation. It is therefore required to accompany a combination of sensors to model an activity, as found in [24], where the difference between sitting and standing could not be detected while the device is attached to the wrist.

(3) Physiological: The physiological signals that may be determined include skin temperature, heart-rate, skin conductivity, respiration rate, etc. [5], however, in [23] it is found that heart-rate monitoring does not render useful where lots of physical activity takes place, as in a mining environment. However, it may determine whether the individual is busy working or resting, depending on the accelerometer's data.

(4) Location: GPS data is not an option in underground environments, therefore, other techniques need to be considered to determine the user's indoor location. These include ultra sound, optical, WLAN RSS (Received signal strength), ZigBee RF RSS and other methods. In [25], the methods are categorised into four domains, namely; (1) Wireless direction-range measurement system, (2) Indoor beacon matching system, (3) Inertial Navigation System and (4) Mixed system. According to [25], category no. 2 - indoor beacon matching system, has been the most popular amongst the four categories, between years 2010 and 2013. Category no. 2 is based on information of ultrasonic beacons, RFID beacons, WLAN beacons, etc.

2.4 Low-powered wireless-sensor networks

The implementation of 6LoWPAN has gained rapid growth in implementations over a wide variety of applications. It is a low-power, self-configurable, IP-based protocol built on IEEE 802.15.4, used in applications such as industrial monitoring, home automation, and healthcare - especially with wearable health-monitoring systems (WHMS's) [6]. With WHMS, sensors [27] collect parameters from the body (e.g. Heart-rate, blood-pressure temperature, etc.) and transmit the data to portable base stations LBR (6LoWPAN border Router).

In [20], the authors make use of Contiki, an open-source operating system developed for networked, memory-constrained wireless systems, which focusses on IoT devices. This OS is perfectly fit for any 6LoWPAN devices, as it provides for IPv6 networking. According to the official Contiki documentation, a device with Contiki installed only requires system memory in the order of kilobytes, and power budget in the order of mill-watts. Contiki also contains the Cooja simulator counterpart, whereby the author could simulate 19 sensor nodes, using the Routing Protocol for Low power and Lossy Networks (RPL), although this is not the limit.

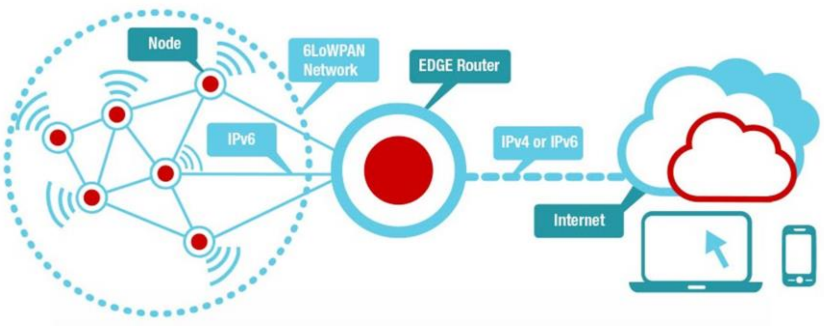

Figure 2: Contiki-6LoWPAN network [26]

The first simulation performed by the authors was to analyse the advantages of implementing fuzzy-logic for context-aware monitoring for the decision of data transmission. The fuzzy logic (implemented on some of the nodes) controls the interval in which data is transmitted, whereas the other nodes (without fuzzy logic), transmits data at a fixed, 10 second, interval. The fuzzy rule-set used detects whether the current temperature rating has changed from the previous measurement, and if so, would monitor or action an event, depending on the severity. In this simulation, it is found that the node with fuzzy-logic implemented, transmitted as little as 1/16th the amount of times as the normal node, purely based on the contextual awareness that found that it unnecessary to transmit as often. It was also found in the work that as the temperature rose to more concerning levels, the number of transmission started to increase.

In the second simulation performed by the authors, another parameter has been added to detect whether an external connection has been lost, which determines whether all the nodes should be notified about the change, so that their local buffers should be used until further notification.

In the last two simulations performed, it was found that network traffic decreased as much as 65%, and the power consumption could benefit, correspondingly, which has great enough advantages to implement in all such future systems.

3. Proposed Solution

Having reviewed various implementations for wearable health monitoring systems, and weighing each one's pros and cons, it is possible to combine these methods to propose a solution for future implementation of a health monitoring system for miners.

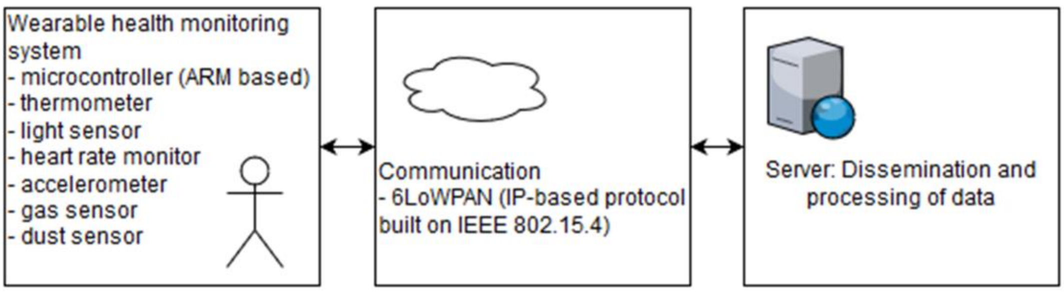

Figure 3: Data dissemination and processing architecture

The proposed system is one that is integrated into the hard-hat of a miner. This does not add to additional obstruction to the normal activity of the miner, as long as the sensor system adds negligible weight to the hard hat. An advantage of this implementation is that the sensor system has direct access to the battery source which already powers the lamp attached to the hard-hat. Because the hard hat also fits tightly against the user's head, temperature, heart-rate and skin conductance could also be measured rather conveniently.

The core of the sensor could be an ARM based microcontroller, which is interfaced with an accelerometer, and a 6LoWPAN network device. It is also proposed that an additional wristband is added to the system, so that better context could be obtained by the user's activities, as discussed in section II.A. For the communication system, it would be beneficial to disseminate the data within the entire network of users to obtain context amongst various miners, and not just from a single person in isolation, also reviewed in section II.A. The system can then have fuzzy logic for two aspects; the controlling of wireless transmissions, as discussed in section II.B, and fuzzy logic for determining each user's context based on past present values, also discussed in section II.B. For activity monitoring, an online approach is required, since each device would not be operating in isolation. Some of the best recognition patterns that could be used for this is CART and ANFIS, according to [8].

For location tracking, section II.C discusses that beacon based object is the most popular. Each of these methods have their challenges and setbacks, however, the best one, within this category, for underground mining will be investigated for implementation.

For sensing attributes, the environmental parameters that will be considered is sound pressure, humidity, gas, dust and temperature, since these are of the most crucial in a mining environment [28]. For physiological parameters, body temperature, heart rate and skin conductance are the most practical and logical to measure. Furthermore, these parameters will be considered in combination with the user's activities.

4. Conclusion

In this paper, different approaches for smart health monitoring devices are compared and discussed as documented by the referenced related work. The paper summarized different methods to determine user activity and discusses the advantages and disadvantages of each, in order to obtain contextual information. The selection of sensor attributes is then covered, which include acceleration, environmental, physiological, and location parameters. The paper then analyses various works relating to wireless sensor networks to determine the optimal solution, of which 6LoWPAN, a low-power wireless mesh network, looks promising. Finally, a possible product implementation is proposed with a selection of possible technologies in each part of the research.

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Biography

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