Situation-Aware Mobile Health Monitoring

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ABSTRACT
Recent advances in mobile computing coupled with the widespread availability of inexpensive mobile devices are the key motivating factors for the development of mobile health monitoring systems. However, to leverage the full potential of such systems for continuous and real time monitoring, there are a number of challenges that need to be addressed. This paper proposes a situation-aware mobile health monitoring framework that aims to increase not only the accuracy in identifying the occurring health conditions but also the cost-efficiency of running algorithms (e.g. the activity recognition classifier) using a situation-aware adaptation technique. The proposed framework integrates high level knowledge (i.e. user activity) with low level sensory data (e.g. heart rate) in situation reasoning and data fusion. Such holistic situational information can significantly improve accuracy of clinical decision making and self-management of chronic diseases. The implementation and evaluation of the framework for a health monitoring application is described.

Categories and Subject Descriptors
C.3 Special-purpose and Application-based systems - Real-time and embedded systems, and D.4.7 Organization and Design - Real-time systems and embedded systems.

General Terms
Algorithms, Design, Experimentation.

Keywords
Situation-aware computing, data fusion, mobile healthcare, activity recognition, energy management.

1. INTRODUCTION
Mobile health monitoring is a fast growing area of research that capitalizes on mobile technologies and communication to provide real-time and continuous monitoring and analyzing of vital signs of patients at anytime and anywhere [1, 2]. Mobile health monitoring applications can be used for self-management of a chronic disease, remote monitoring of patients out of the hospital, early detection of abnormalities such as cardiac ischemia and arrhythmia and generating different levels of alarms [3, 4]. Despite the rapid advancement in mobile healthcare, there are still many challenges for users before they widely adopt these applications in their everyday lives.

Most mobile health monitoring applications mainly perform reasoning or analysis on an individual sensory data such as the heart rate [2-6]. Situation-aware computing [7, 8] is one of the branches of context-awareness that uses data fusion and reasoning methods to aggregate multiple sensory data and identify occurring situations. With regard to health monitoring, situation-awareness provides a wider view and better understanding of the patient's current health-related condition, which can be affected by multiple physiological data [7]. Examples of situations that we studied include 'hypertension stage 1', 'hypertension stage 2', 'hypertension stage 3' and 'healthy'.

Situation reasoning methods produce high level information from combining multiple low level sensory data. In health monitoring systems, accuracy of reasoning and identification of patients' health-related situations can be also affected based on physical activities such as walking, sitting or running, which is high level information per se [9]. The user activity knowledge is usually obtained by performing machine learning (e.g. classification) on the accelerometer data that can be collected from external wearable biosensors or directly from the in-built accelerometers of current mobile phones. A user's physical activities can cause changes in the other vital signs and the lack of this knowledge can reduce accuracy of situation-awareness. For example, rapid heart rate can represent two different situations depending on whether the patient is sitting or running. Inclusion of the user activity knowledge in the situation reasoning can improve accuracy and enhance clinical decision making. In the above example, it will allow reasoning about two different situations of 'Fast Moving Hypertension Stage 1' and 'Stationary/Not Moving Hypertension Stage 1' instead of identifying only 'Hypertension Stage 1'.

To enhance situation-aware mobile health monitors, we propose a Situation-Aware Mobile Health Monitoring (SA-MHM) framework that combines a fuzzy rule based reasoning approach,

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named FSI (Fuzzy Situation Inference) [7, 8] with the user activity knowledge. The hybrid reasoning approach aggregates the user's activity data which is already high-level information with other low level sensory data such as heart rate and blood pressure data.

Since performing activity recognition on mobile phones can be expensive in terms of energy consumption, the SA-MHM framework incorporates an intelligent adaptation strategy inspired by [10] to improve the algorithm's cost-efficiency. The proposed situation-aware adaptation strategy adjusts the operations of the activity recognition classifier according to the accuracy requirement of occurring situations in a gradual and fine-grained manner. In non-critical situations such as healthy, which is a state in which the application does not require high accuracy (concerning mining results), it is unnecessary to perform a closer monitoring. Thus, the adaptation process can produce the classification results with a lower level of accuracy. Since the accuracy level is directly proportional to the resource consumption level, this will result in preserving energy and extending the mobile phone's battery lifetime. In critical situations in which the application requires closer monitoring, the accuracy level can be increased.

This article is structured as follows. Section 2 provides a review and analysis of related works. Section 3 describes the architecture of the proposed SAMHM framework and its components. Section 4 discusses the implementation of the proposed approach for a mobile health monitoring application and details the evaluation of the prototype in terms of accuracy and efficiency. Finally, Section 5 concludes the paper and discusses future work.

2. RELATED WORK

In recent years, there has been a growing interest in the area of Mobile Health Monitoring (MHM). However, there are still many open issues that need to be addressed before leveraging the full potential of such systems for continuous and real time monitoring. Alemdar and Ersoy [11] suggest a list of design considerations for the healthcare monitoring applications. These include privacy, security, reliability, user-friendliness, middleware design, scalability, interoperability and context-awareness. In this paper our main focus is on the latter issue.

Context can be any information that is related to the user, device, application, environment or network. Context-awareness enables applications to adapt their behavior according to context changes and perform their tasks in an intelligent and efficient manner [8]. In mobile healthcare systems, context-awareness has been utilized to achieve different purposes. MediNet [12] is a mobile healthcare system that uses context-awareness to personalize the information presented to a patient based on the patient's profile, context and location. Motivate [13] is a context-aware system that provides users with personalized advice on physical activities considering the time, the weather and the user location.

In the health monitors introduced in [14, 15], contextual information is used to issue alerts. Harmoni [9] is a remote healthcare monitoring system that uses context-awareness for reducing transmissions to the backend. A context-aware traveler healthcare service system proposed in [16] enables the user to find a more convenient healthcare service.

In most of the above-mentioned systems, context-awareness is performed based on individual pieces of context. There are few studies that attempt to aggregate multiple contextual parameters using context reasoning or sensor fusion technique to provide a composite view of the user's situation. Situation-aware systems provide better understanding of the user's health conditions, particularly those that can occur due to changes in multiple contextual parameters. The work proposed in [7] is one of the first situation-aware mobile health monitoring systems that enables the fusion of different contextual information using a fuzzy logic based reasoning method. In this paper, we extend this work with the user activity knowledge.

The user activity is very important contextual information in health monitoring which can increase the accuracy of monitoring when it is combined with other pieces of information [9, 17]. User activities are generally determined by performing machine learning algorithms (also known as Activity Recognition methods) over accelerometer data that can be obtained from wearable sensors or in-built sensors in smart phones. The examples of activity recognition methods include neural networks, decision trees, Naïve Bayes, or nearest neighbor algorithms. However, performing real-time and continuous mining onboard mobile devices exhausts the limited computational resources and can drain battery quickly.

Most of the current health monitoring systems that infer user activities [17-21] do not employ energy management techniques to preserve battery on mobile phones. To address this issue, we employ situation-aware adaptation strategies to improve cost-efficiency of machine learning algorithms, thereby extending lifetime of mobile application.

3. THE ACTIVITY ENHANCED FUZZY SITUATION INFERENCE (AEFSI) FRAMEWORK

3.1 An Overview

This section presents the SA-MHM framework for situation-aware mobile health monitoring. Figure 1 shows an overview of the proposed framework. The five key components of the framework include: 1) Data Collector, 2) Data Pre-Processor, 3) Activity Enhanced FSI (AEFSI) which extends the FSI approach [5] with the user activity knowledge, 4) Machine Learning Classifier for activity recognition, and 5) Classification Adaptation Manager to perform the situation-aware adaptation.

3.2 Data Collector

The Data Collector is responsible to collect data streams from wireless sensors and wearable biosensors, and convert raw sensory data like ECG signals into heart rate values if necessary. Depending on the application, different external sensors can be used. These sensors will use mobile technologies like Bluetooth for wireless communication. To collect the accelerometer data, the framework will support both external sensors and the 3D accelerometer built internally into the mobile device. The data collector passes the data to both the situation reasoning component and machine learning algorithm.

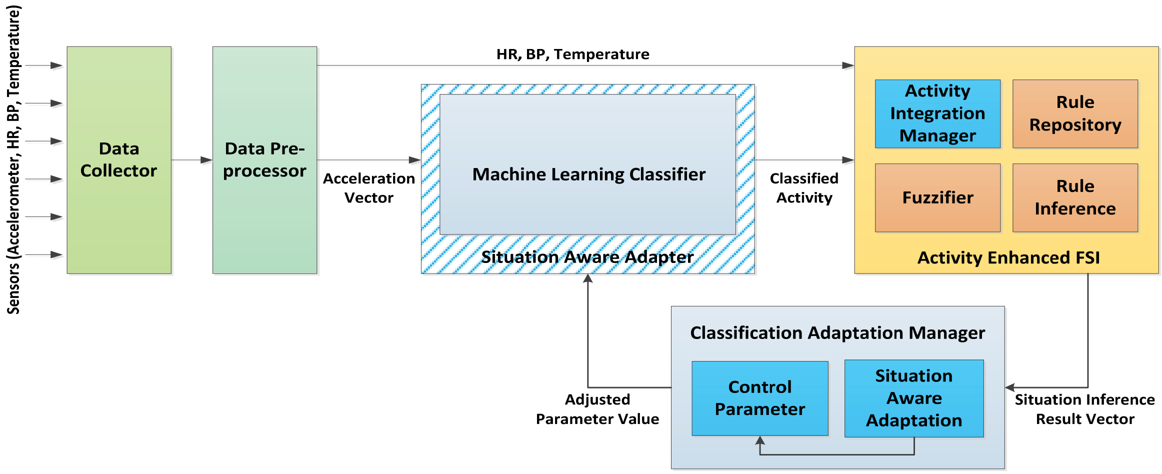

Figure 1. The SA-MHM framework.

3.3 Data Pre-Processing

On the latest smartphones and mobile devices, 3D accelerometers are capable of continuously capturing acceleration data streams in the x, y and z directions. In order for sensory data to be meaningful for learning algorithm these data streams need to be pre-processed and transformed [22]. The Data Pre-Processing component handles all pre-processing of raw input data to prepare them in a format and structure required by the machine learning classifier. An example of the acceleration force pre-processing is shown in Figure 2.

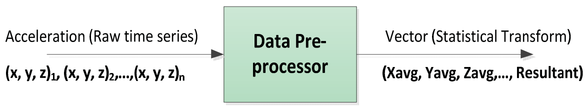

Figure 2. Data preprocessor.

In the acceleration pre-processing, time series of acceleration force for each axis are converted to statistical mathematical transforms. It means if the acceleration force was captured for a 10 second period with a 20Hz sample rate (1 sample every 50ms), this would produce 200 raw time series acceleration samples. The statistical conversation produces a single activity vector that represents the 200 raw accelerometer records.

Unlike other sensory data such as temperature which can be passed directly into the fuzzifier without the need for pre-processing, the raw acceleration samples need to be first transformed into a single tuple vector as described earlier and then passed into the machine learning classification algorithm.

3.4 Machine Learning Classifier

Depending on the application, any suitable supervised machine learning classifier can be used within this component. The current implementation of the SA-MHM framework supports decision trees and k-nearest neighbors (kNN).

Training data is an essential component of the classification process and is usually collected by recording predetermined physical movements of participants through a training phase [22]. Each predetermined physical movement is represented by a training vector and identified within the instance vector as an activity class label. These class labels are used in the classification process to determine the identity of unlabeled activity instance vectors. The new classified activity is then passed onto the Activity Enhanced Fuzzy Situation Inference (AEFSI) as an input. This high level information will be combined with other sensory data (i.e. low level information) to reason about occurring situations. In the personalized health monitors, it is important to prepare training data based on the user's activities to improve the accuracy.

In the SA-MHM, we perform classification on the mobile device rather than sending data to a remote server. However, running data mining algorithms continuously over data streams on mobile phones can be expensive in terms battery usage. To address this challenge, the framework incorporates a situation-aware adaptation strategy that sits like an extra layer on top of the algorithm. The adaptation strategy enables the adjustment of the operations of data stream mining according to the occurring situations. The details of situation-aware adaptation are described in Section 3.6.

3.5 Activity Enhanced Fuzzy Situation Inference (AEFSI)

The Activity Enhanced Fuzzy Situation Inference (AEFSI) component is the core of the proposed framework. It provides a novel, hybrid situation reasoning approach which combines rule-based reasoning with the learning-based method to improve accuracy of situation reasoning in mobile health monitoring applications. It extends the capabilities of the Fuzzy Situation Inference (FSI) [7, 8] with incorporating the user's activity knowledge.

Fuzzy Situation Inference (FSI) [8] is a situation modelling and reasoning approach which integrates fuzzy logic into the Context Spaces (CS) model [23] and infers situations from the multiple sensory data. FSI uses the benefits of the CS model to support the pervasive computing environments in terms of addressing the inaccuracy associated with sensory data, and applies the strengths of fuzzy logic to reason about imprecise and ambiguous real-life situations. The FSI approach consists of three main modules: Fuzzifier, Rule Repository and Rule Inference.

3.5.1 Fuzzifier

The input data to FSI includes crisp input (i.e. sensory data). The fuzzifier is a software component that maps crisp input into fuzzy sets by applying a trapezoidal membership function. With regard to FSI modelling, the greater the membership degree of elements defined in a fuzzy situation rule, the greater confidence is for the occurrence of the situation.

3.5.2 Rule Repository

In the FSI approach, situations of interest (i.e. health-related situations) are represented by fuzzy rules. Each fuzzy situation rule consists of two or more conditions. FSI uses the AND operator to join the conditions. These rules are stored in the Rule Repository, and are pre-defined by system designers or domain experts. In our implementation, we have used the information provided in 'Guide to Management of Hypertension' by National Heart Foundation [24] to define the situations. An example of a FSI rule is as follows.

If systolic blood pressure is 'very high' AND diastolic blood pressure is 'very high' AND user activity is 'fast moving' THEN situation is 'fast moving hypertension stage 3'.

3.5.3 Rule Inference

To reason about a situation, fuzzy rules need to be evaluated to compute a single output that determines the membership degree of the rule's consequent. Inspired by the CS model [23], the situation reasoning technique incorporates three notions of weights, contribution and confidence.

Weights are values between 0 and 1 that are assigned to the linguistic variables (e.g. heart rate) according to the relative importance of attributes in representing a situation. For example, systolic and diastolic blood pressures are stronger indications of the 'hypertension' situation compared to heart rate and therefore they can be assigned with higher weights (e.g. each 0.4). The heart rate value can change due to performing physical activities and can be given a lower weight (e.g. 0.2).

The membership degree of each variable represents the variables' contribution level to the occurrence of a situation. The FSI applies the following technique for evaluation of FSI rules and conditions joined with the AND operators to compute the confidence value for each situation:

$$\text{Confidence} = \sum_{i=1}^{n} w_i \mu(x_i) \qquad (1)$$

The membership degree of each variable represents the variables' contribution level where w_i represents a weight assigned to a linguistic variable, and $\mu(x_i)$ denotes the membership degree of the element x_i in the fuzzy set associated with the linguistic variable. The result of $w_i \mu(x_i)$ represents a weighted membership degree of x_i and *i* represents a fuzzy condition in a rule ($1 \leq i \leq n$). If the output of a rule evaluation for the 'hypertension' situation yields the value of 0.885, we can suggest that the level of confidence in the occurrence of 'hypertension' is 0.885. This value can be compared to a predefined threshold ε between 0 and 1 to determine whether a situation is occurring. For more details about FSI, we refer the reader to [7, 8].

3.6 Activity Integration Manager (AIM)

The Activity Integration Manager (AIM) is responsible for the integration of user activity knowledge into the situation reasoning of FSI. The AIM continuously receives the classified activity labels from the machine learning classifier component. Activity recognition methods can be used to learn about different categories of movements such walking, jogging, walking upstairs, walking downstairs, sitting, standing, etc. Compared to the other low-level contextual information (i.e. crisp sensory data like temperature) which are directly fuzzified and processed as FSI inputs, the activity knowledge needs to be treated as high-level information and processed differently by the Rule Inference component.

The activity knowledge is processed through a function named the Activity Membership Function (AMF) which only computes a value of 1 or 0 for each class. If the classified activity matches the activity defined within the condition of the fuzzy rule being evaluated, the AMF will return 1, otherwise it returns 0. This value is then processed along with the other membership degrees in the FSI rule evaluation according to Equation 1. Figure 3 shows the algorithm of how the AMF is incorporated the Rule Inference process.

3.7 Classification Adaptation Manager (CAM)

The Classification Adaptation Manager (CAM) uses the situation confidence level, i.e. the weighted sum that is a value between 0 and 1 per situation, as an input to perform a situation-aware adaptation.

The CAM consists of Situation-Aware Adaptation and Control Parameter components. The CAM controls the classification sleep time interval based on the criticality of the occurring situations to preserve energy. For example, when the occurring situation is non-critical (e.g. the patient is healthy), it means the application does not require close monitoring. On the other hand, when the situation becomes critical (e.g. hypertension), the application needs to monitor the user's activity closer, and the CAM will decrease the parameter value. To implement situation-aware adaptation in CAM, there is a need to identify the criticality level of each situation.

```
Get sensory data (Linguistic variables xi) from Data Collector
Get classified_Activity from Classifier
Get fuzzy_Rules from Rule Repository
Initialize situationInference_Vector
For each fuzzy_rule (Sj) in Rule Repository
  Initialize confidence = 0
  Initialize membership_degree μ= 0
  For each conditionLV in the fuzzy_Rule(Sj)
    If conditionLV = "activity"
     Compute μ(activity) by calling AMF
    Else
     Compute μ(xi) by calling Fuzzifier
    End If
 Get weight of variables (xi) in conditionLV
  confidence(Sj)  = Σ_{i=1}^{n} weight_i μ(x_i)
 End
For SituationInference_Vector.add(confidence(Sj))
End For
```

Figure 3. Integration algorithm.

Let all situations for a specific application be denoted by $S = \{s_1, s_2, \dots, s_n\}$ where s_i is an element of S and $1 \le i \le n$. The criticality of a situation s_i can be expressed using any value between 0 and 1 where $C(s_i) \in [0, 1]$ and each s_i has been given a predefined value of $C(s_i)$.

The situation criticality values for an application are subjective and assigned by system designers or domain experts at the time of defining fuzzy rules. These application-specific criticality values signify the importance of a situation relative to other situations in the set. When designing a system for mobile health monitoring, a particular situation can be identified as critical if its occurrence signifies a critical risk to the patient/user. Situations that fall into this category should be assigned a high criticality value close to 1. Yet, when situations are considered low risk they should be assigned a criticality value close to 0 (e.g. Healthy = 0.1, HypertensionStage1 = 0.7, HypertensionStage2 = 0.8, HypertensionStage3 = 0.9). These criticality values can be then used for situation-aware adaptation to calculate the initialized control parameter. This is explained in the next subsection.

3.7.1 Control Parameter

The control parameter here is considered as the parameter of the machine learning classifier that controls the operations of data mining such as input, output and iteration rate. Situation-aware adaptation computes the adjusted value of the control parameter based on the situation inference results and their corresponding initialized control parameter values. The initialized control parameter value is a pre-defined value per situation that represents its accuracy requirement. A non-critical situation's accuracy requirement for closer monitoring is typically lower than a critical situation. The initialized control parameter is calculated based on the equation below which is adapted from [10].

$$p_j = LB_t + \left((UB_t - LB_t) \times \left(1 - C(s_i)\right) \right) \quad (2)$$

where LB_t denotes the lower bound time interval and UB_t denotes the upper bound time interval for machine learning classification and $C(s_i)$ is the situation criticality value per situation. The initialized control parameter value p_j calculated by Equation 2 will produce lower time interval values for high criticality situations while producing higher time interval values for low criticality situations.

Here, the LB_t lower bound time interval would include the time taken for acceleration capture and processing, while the UB_t upper bound time interval value for p_j is defined based on the activity classification requirement of the low criticality situations. This upper bound time interval would include the lower bound time interval plus an additional sleep/wait period. Setting the lower and upper bound of the control parameter is important to maintain an acceptable level of accuracy.

3.7.2 Situation-Aware Adaptation

Generally supervised machine learning classifiers perform iterative operations and as discussed earlier can become computationally expensive and effect resource availability. They were originally developed for intensive data mining operations on powerful desktop/server based computer systems which had sufficient amount of memory, processing power and limitless energy/power capacity. In order to bring the strengths of supervised machine learning classification to mobile platforms with limited memory, processing power and battery, there is a need for intelligent adaptation techniques. The situation-aware adaptation aims to address this urgent problem.

Situation-aware adaptation operates based on situation inference results received from the AEFSI. As the AEFSI generates the confidence values for each pre-defined situation, these confidence values can be used to identify the current occurring situation. The higher the confidence value (e.g. 0.9 or 1) generated by the AEFSI, the higher the probability that this is the occurring situation.

In order to provide a smooth and fine grained parameter control approach the situation-aware adaptation strategy introduced in [10] is adopted here. The Equation 3 presents this method to compute the adjusted value of the control parameter $\hat{p}_j$ considering the confidence value of all situations.

$$\hat{p}_j = \frac{\sum_{i=1}^{n} \mu(s_i) p_j}{\sum_{i=1}^{n} \mu(s_i)} \quad (3)$$

Here $\mu(s_i)$ denotes the inferred confidence level per situation and p_j denotes the corresponding pre-defined control parameter for a situation s_i, where $1 \le i \le n$ and n represent the number of pre-defined situations in the application which aggregates to produce the adjusted control parameter $\hat{p}_j$ [10]. The pre-defined control parameter value for situation s_i denoted by p_j is application specific and evaluated using Equation 2.

The situation-aware adaptation strategy is able to reduce energy consumption when the occurring situations are non-critical and there is no need for closer monitoring, and it reduces the sleep time interval as soon as situations transition towards critical.

The SA adapter, mentioned earlier, will act as an extra layer on top of the machine learning classifier and controls its operations in a situation-aware and efficient manner. It will receive the output from the Classification Adaptation Manager which are the adjusted values of the classifier's control parameter, and will apply them to reduce the energy consumption according to the occurring situations.

4. IMPLEMENTATION AND EVALUATION

The health monitoring application was developed in Java for the Android platform. Figure 4 shows two screenshots of our implementation where the user's inferred situation is healthy with two different activities of stationary and slow moving. In this implementation, the Machine Learning Classifier (MLC) for activity recognition supports two classifiers, k-nearest neighbors (kNN) and J48 Decision Tree but the design of the prototype ensures that different classifiers can be used in the system. The kNN and J48 algorithms were chosen for the evaluation purposes after the model selection process and accuracy tests were conducted over the user activity data set published by Kwapisz et al. [22] (discussed in Section 7.3). The prototype's interface allows the user to select one of the two algorithms and specify the data split of the training and test sets as shown in Figure 5.

The interface also provides an option to enable or disable the Situation-Aware Adaptation. The status bars are used for visualization of the level of confidence in the occurrence of each situation that is inferred in real-time based on the data collected from the ECG sensor and other data sources.

The Classification Adaptation Manager (CAM) for Situation-aware adaptation was implemented by selecting the sleep time interval as the adaptation's control parameter. At run time, this parameter is dynamically adjusted according to the current situation criticality and situation inference results of the AEFSI.

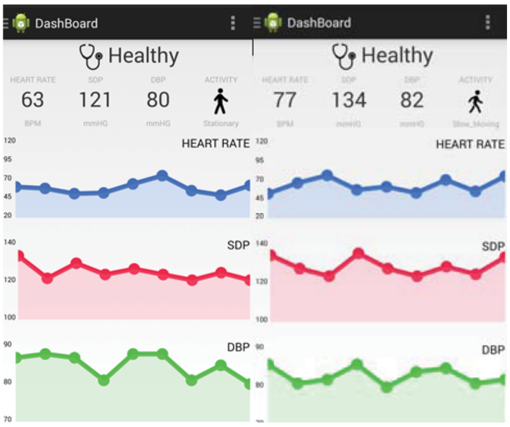

Figure 4. Situation-Aware health monitoring screenshots.

A higher value of the sleep time will result in a lower level of accuracy while a lower value of the sleep time interval will increase the accuracy of classification.

To evaluate the prototype, two Samsung Galaxy S2 I9100 Android mobile phones with the following hardware specifications were used:

- Processor: Dual-core 1.2 GHz Cortex-A9
- Ram: 1GB
- Battery: Li-Ion 1650 mAh battery
- Operating System: Android 4.1.2 Jelly Bean

4.1 Test Data

In the health monitoring application, we defined the situations based on four linguistic variables of systolic and diastolic blood pressure, heart rate and user activity. The heart rate data was obtained using the Alive Heart Monitor from Alive Technologies™. The high blood pressure data for different stages of hypertension was simulated using a random data generator program. The system was able to collect and use the accelerometer data from both the Alive Heart Monitor and the mobile phone's in-built sensor.

As previously mentioned, the classification model used in the evaluation was trained and tested using the dataset produced by Kwapisz [22] called WISDM Lab dataset.

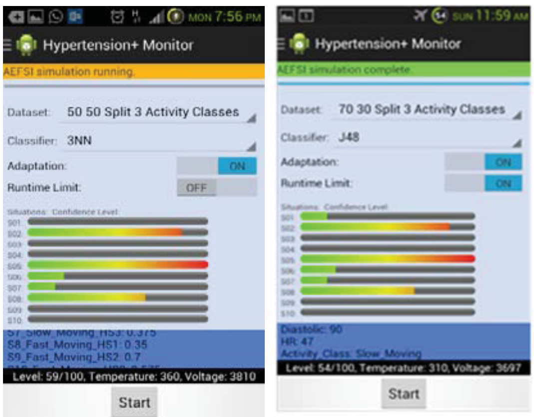

Figure 5. The simulation interface.

Table 1. Statistics of WISDM dataset

	Raw Data	**Transformed Data**
Samples	1,098,207	5,424
Attributes	6	46
Class Distribution		
Walking	38.6%	38.4%
Jogging	31.2%	30.0%
Upstairs	11.2%	11.7%
Downstairs	9.1%	9.8%
Sitting	5.5%	5.7%
Standing	4.4%	4.6%

Twenty nine volunteers involved during the data collection. The dataset consisted of two different sets, the raw data set and the transformed data set.

The transformed data set contained pre-processed accelerator data. Table 1 shows the comparison between the two data sets. The transformed acceleration dataset in the WISDM dataset package [20] is a statistical representation of the raw time series acceleration dataset with the 46 attributes:

- UNIQUE_ID (not used in classification)
- USER_ID
- Axis bins: X0, …, X9, Y0,…,Y9, Z0, ..., Z9 (30 attributes)
- XAVG, YAVG, ZAVG
- XPEAK, YPEAK, ZPEAK
- XABSOLDEV,YABSOLDEV, ZABSOLDEV
- XSTANDDEV, YSTANDDEV, ZSTANDDEV
- RESULTANT
- ACTIVITY_CLASS

The evaluation performed in this research used the transformed data set as the basis of the test data. However, we modified the existing data set that supported six types of activities into the three classes of stationary, slow moving and fast moving. The three activities of walking, walking up stairs and walking down stairs were considered as slow moving, and the sitting and standing activities were regarded as stationary. This significantly reduced the total number of pre-defined situations from nineteen to ten, and improved reasoning accuracy and system performance. Table 2 shows the details of the new class distribution of the data set.

Table 2. Customized user activity classes

Transformed Dataset Activity Class Distribution	**Customized Dataset Activity Class Distribution**
Sitting (5.7%)	Stationary (10.3%)
Standing (4.6%)	
Walking (38.4%)	Slow Moving (59.9%)
Walking Up Stairs (11.7%)	
Walking Down Stairs (9.8%)	
Jogging (30%)	Fast Moving (30%)

4.2 Accuracy of Situation Reasoning

The original FSI [8] is limited to reasoning over low level sensor data and does not have the ability to support the user's physical activity. Our proposed SA-MHM framework integrates the low level sensory data with the high level user activity knowledge. The inclusion of the activities in situation reasoning increases the accuracy and information granularity. For example, the Hypertension Stage 1 with the addition of the three activities classes (Table 2) can be defined as *Stationary Hypertension Stage 1, Slow Moving Hypertension Stage 1* and *Fast Moving Hypertension Stage* 1.

Table 3 compares the situation definitions using FSI that has no support for the activity knowledge and the AEFSI approach that includes user activity. The table shows how AEFSI is able to provide a better understanding of the user's health condition compared to the FSI. This rich and holistic knowledge increases the granularity of the situation-awareness and improves the accuracy of clinical decision making as well as self-management of the disease.

As Table 3 shows, the AEFSI does not use the user activity (stationary, slow moving, and fast moving) for the reasoning about the Healthy situation, which is a non-critical situation. This is because when the situation is healthy, the heart rate and blood pressure are normal and the activity information will not add any value.

Table 3. Comparison of FSI and AEFSI

Situations	Support for Activities
Four situations defined in FSI:	
S01- Healthy	No
S02- Hypertension Stage 1	No
S03- Hypertension Stage 2	No
S04- Hypertension Stage 3	No
Ten situations defined in AEFSI:	
S01- Healthy	Yes
S02- Stationary Hypertension Stage 1	Yes
S03- Stationary Hypertension Stage 2	Yes
S04- Stationary Hypertension Stage 3	Yes
S05- Slow Moving Hypertension Stage 1	Yes
S06- Slow Moving Hypertension Stage 2	Yes
S07- Slow Moving Hypertension Stage 3	Yes
S08- Fast Moving Hypertension Stage 1	Yes
S09- Fast Moving Hypertension Stage 2	Yes
S10- Fast Moving Hypertension Stage 3	Yes

4.3 Efficiency of Situation-Aware Adaptation

A core component of the SA-MHM framework is the Situation Aware Adaptation. This component was evaluated to demonstrate its ability to improve energy management of mobile supervised machine learning.

4.3.1 Evaluation of classification algorithms

The objective of this evaluation was validating the use of the published activity dataset for the machine learning classification component within the SA-MHM implementation.

The chosen WISDM Lab acceleration dataset [22] was evaluated on the Weka 3 data mining tool for accuracy with 10 fold cross validation experiments using the J48 Decision Tree and K Nearest Neighbour classification algorithms.

After customizing the original dataset to suit the requirements of this research, the customized dataset was used to create training and test datasets for the implementation. These datasets were used in the final experiment where the training dataset was used to build classification models for J48 and kNN.

The evaluation compared the accuracy of the classification models on the mobile implementation of the Weka Activity Classifier component (developed using Weka API Java) and the Weka 3 Desktop data mining tool.

The comparison produced identical results indicating the accuracy of both J48 and kNN at 97.60% and 97.64% respectively (as shown in Table 4). The results for the mobile implementation validated its capability for user activity recognition within the SA-MHM implementation.

We also tested the kNN with different values of K (1, 3, and 5). Based on the results, we considered K = 3 as the optimal value of K in our experiments (87.117 % correctly classified).

4.3.2 Experiment 1: Hypertension Stage 1

As discussed earlier, the energy savings with Situation-Aware adaptation are mostly achieved in non-critical situations like Healthy. However, based on Table 3, the healthy situation in AEFSI is not incorporating any user activity. Therefore, to show the energy savings in the two classification algorithms (i.e. J48 and kNN), we conducted this experiment for the situation of Hypertension Stage 1, which is the least critical situation in our list after the Healthy situation. The data generator for systolic and diastolic blood pressure and heart rate was set to generate values in the range of hypertension stage 1.

Table 4. Statistics of WISDM dataset

Summary	**J48 Unpruned Tree**		**3NN**	
	Desktop	Mobile	Desktop	Mobile
Correctly Classified Instances	2644 (97.60%)	2644 (97.60%)	2645 (97.64%)	2645 (97.64%)
Incorrectly Classified Instances	65 (2.40%)	65 (2.40%)	64 (2.36%)	64 (2.36%)
Kappa statistic	0.9553	0.9553	0.9555	0.9555
Mean absolute error	0.0188	0.0188	0.0211	0.0211
Root mean squared error	0.1216	0.1216	0.1152	0.1152
Total Number of Instances	2709	2709	2709	2709

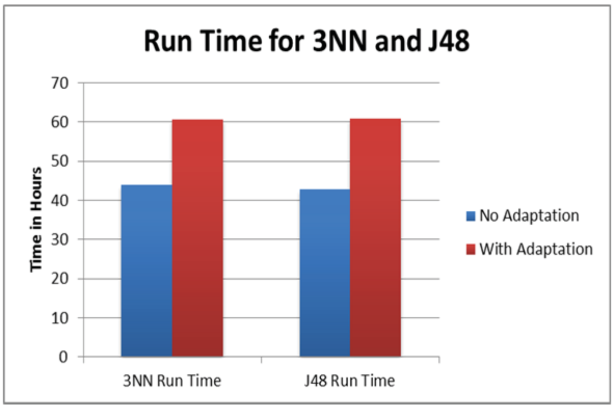

Figure 6. Energy efficiency evaluation results.

By including the user activity, we tested three situations of Stationary, Slow Moving and Fast Moving Hypertension Stage 1.

In this comparative evaluation, we measured and recorded the battery levels with and without situation-aware adaptation. To provide uniform testing situations for the two different implementations, the activity data was not read directly from the accelerator sensor in the mobile phone. Instead, a constant stream of activity data from the modified WISDM data set was read into the system. At the start of each test run, the stored data was read and fed into a data generator program that published the data with at a rate of 1 record/100 msec.

To consider the energy consumption by the Bluetooth communication between the sensor and the mobile phone, it was important to include the ECG and accelerometer sensors in the experiments. Hence, we decided to use the sensors during the experiments but overwrote the data by the simulated data (for blood pressure and heart rate). Figure 6 shows the comparison of battery lifetime in hours when the situation-aware adaptation is enabled and disabled. The tests were conducted for both 3NN and J48 classifiers. The results show that the battery lifetime was significantly increased when the situation-aware adaptation was applied. The difference between the results of the two algorithms was marginal. The battery on the phone without adaptation drained completely after 43.9 hours while with the adaptation the phone's battery lasted longer (i.e. 60.7 hours). This validates the benefits of the situation-aware adaptation approach in extending battery lifetime up to 38.26%.

4.3.3 Experiment 2: Hybrid Situations

In the Experiment 1, we generated the data for the Hypertension Stage 1 to show the ability of the SA-MHM approach to save energy. To investigate the mobile phone's overall energy savings when different situations occur, in Experiment 2, we configured the data generator such that the data can represent all the ten pre-defined situations in Table 3. Figure 7 depicts how situations gradually change from non-critical to critical and it also shows how the control parameter of the classifier algorithm (i.e. the sleep time interval) is smoothly adjusted from 90 to 27 second according to minor changes in situations.

In non-critical situations, the adaptation strategy increases the sleep time to reduce the accuracy, leading to the efficient use of resources. Alternatively, in critical situations such as Stationary Hypertension Stage3, the adaptation decreases the parameter value (to 27 sec), and therefore increases the accuracy which is required for closer monitoring.

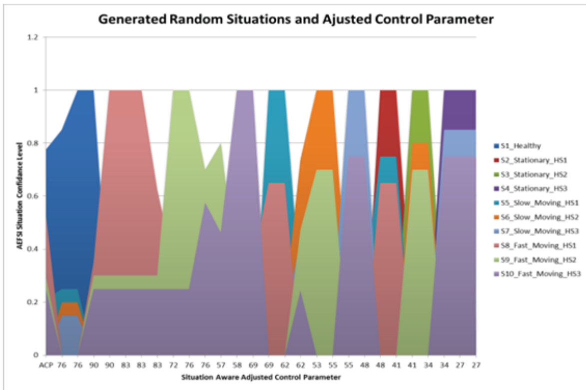

Figure 7. Experiment 2 for ten situations.

As Figure 7 shows the adaptation of the algorithm parameter occurs in a smooth and fine-grained manner while situations evolve from one to another. Without adaptation, the control parameter of the algorithm will remain fixed and unchanged and result in energy waste.

5. CONCLUSION

In this paper, we proposed a Situation-Aware Mobile Health Monitoring (SA-MHM) framework that integrates the user activity knowledge with other sensory data to increase the accuracy in identifying the occurring health conditions. The SA-MHM also incorporates an intelligent adaptation strategy that controls operations of the activity recognition algorithm according to current situations and their accuracy needs to preserve energy. We described the implementation of the SA-MHM for patients with hypertension. The evaluation results showed an increase of 38.26% in the application's lifetime.

As future work, it is important to evaluate our health monitoring system with domain experts and using a lab experiment in order to identify possible issues that could be faced in real world application of such systems.

We also intend to extend the SA-MHM framework from a standalone system to a distributed architecture. The extended system will allow medical professionals to remotely monitor a large group of patients in real time and utilize data analytics to identify clusters with common trends and patterns.

6. REFERENCES

[1] Silva, B., Rodrigues, J. J., Lopes, I., Machado, T. M. and Zhou, L. 2013. A Novel Cooperation Strategy for Mobile Health Applications. *IEEE Journal on Selected Areas in Communication*, 31, 9, 28-36. DOI= 10.1109/JSAC.2013.SUP.0513003.

[2] Pantelopoulos, A. and Bourbakis, N.G. 2010. A Survey on Wearable Sensor-Based Systems for Health Monitoring and Prognosis. *IEEE Transactions on Systems, Man, and Cybernetics*, Part C, 40, 1 (January 2010), 1-12. DOI: 10.1109/TSMCC.2009.2032660

[3] Kumar, S., Nilsen, W. et al. 2013. Mobile Health Technology Evaluation: The mHealth Evidence Workshop. *American Journal of Preventive Medicine*, 45, 2, (August 2013), 228-236. DOI= 10.1016/j.amepre.2013.03.017/

[4] Leijdekkers, P. Gay, V.C. and Barin, E. 2009. Trial Results of a Novel Cardiac Rhythm Management System using Smart Phones and wireless ECG Sensors. *the 7th*

International Conference On Smart homes and health Telematics (ICOST 09), ed Mokhatari,M et al, Springer, 2009, 32-39. DOI= 10.1007/978-3-642-02868-7_5.

[5] Jones, V., Gay, V., and Leijdekkers, P. 2010. Body sensor networks for mobile health monitoring: Experience in Europe and Australia. *ICDS'10, Proceedings of Fourth International Conference on Digital Society* (February 2010), 204-209. ACM Digital Library. DOI: 10.1109/ICDS.2010.41.

[6] Jong Hoon, A., and Potkonjak, M. 2013. mHealthMon: Toward Energy-Efficient and Distributed Mobile Health Monitoring Using Parallel Offloading. *Journal of Medical Systems,* 37, 5 (2013), 1-11.

[7] Delir Haghighi, P., Zaslavsky, A., Krishnaswamy, S. and Gaber, M. 2009. Mobile data mining for intelligent healthcare support. *In Proceedings of the 42nd Annual Hawaii International Conference on System Sciences (HICSS)*, (Big Island, Hawaii, 5-8 January 2009), IEEE. 1-10. DOI= 10.1109/HICSS.2009.309.

[8] Delir Haghighi, P. Krishnaswamy, S. Zaslavsky, A. and Gaber, M. Reasoning about context in uncertain pervasive computing environments. *In Proceedings of the 3rd European Conference on Smart Sensing and Context (EuroSSC 2008*), (Zurich, Switzerland, 2008), Springer-Verlag Berlin, Heidelberg, 112-125. DOI= 10.1007/978-3-540-88793-5_9 .

[9] Mohomed, I. Misra, A., Ebling, M. and Jerome, W. 2008. Harmoni: Context-aware filtering of sensor data for continuous remote health monitoring. *Sixth Annual IEEE International Conference on Pervasive Computing and Communications (PerCom 2008).* (17-21 March 2008), IEEE, 248-251. DOI= 10.1109/PERCOM.2008.110.

[10] Delir Haghighi, P., Krishnaswamy, K., Zaslavsky, A. Gaber, M., Sinha, R., and Gillick, B. 2013. Open Mobile Miner: A Toolkit for Building Situation-Aware Data Mining Applications. *Journal of Organizational Computing and Electronic Commerce (JOCEC),* 23, 3, (2013), 224-248. DOI= 10.1080/10919392.2013.807713.

[11] Alemdar, H. and Ersoy, C. Wireless sensor networks for healthcare: A survey. Computer Networks. *The International Journal of Computer and Telecommunications Networking* 54, 15, (October, 2010), 2688-2710. DOI= 10.1016/j.comnet.2010.05.003.

[12] Mohan, P., Marin, D., Sultan, S. and Deen, A. 2008. MediNet: Personalizing the Self-Care Process for Patients with Diabetes and Cardiovascular Disease Using Mobile Telephony. *30th Annual International Conference of the IEEE*, (20-25 Aug. 2008), 755-758. DOI= 10.1109/IEMBS.2008.4649262.

[13] Lin, Y., Jessurun, J., De Vries, B. and Timmermans, H. 2011. Motivate: Towards Context-Aware Recommendation Mobile System for Healthy Living. *5th International Conference in Pervasive Computing Technologies for Healthcare (PervasiveHealth)*, (Dublin, Ireland, 23-26 May 2011), 250-253.

[14] Mitchell, M., Sposaro, F., Wang, A. and Tyson, G. 2011. Beat: Bio-Environmental Android Tracking. *Radio and Wireless Symposium (RWS)*, (16-19 January, 2011), IEEE,402-405. DOI= 10.1109/RWS.2011.5725489.

[15] Lv, Z., Xia, F., Wu, G., Yao, L. and Chen, Z. Icare: A Mobile Health Monitoring System for the Elderly. In Proceedings of the IEEE/ACM Int'l Conference on Green Computing and Communications & Int'l Conference on Cyber, Physical and Social Computing, (Hangzhou, China, 18-20 December, 2010), 699-705. DOI= 10.1109/GreenCom-CPSCom.2010.84.

[16] Kim, H. and Jo, H. 2006. A Context-Aware Traveler Healthcare Service (THS) System. *Pervasive Health conference and Workshops*, Innsbruck, (Austria, November 29-December , 2006), IEEE, 1-3. DOI= 10.1109/PCTHEALTH.2006.361682

[17] Al-Bashayreh, M.G., Hashim, N.L. and Khorma, O.T. 2013. Context-Aware Mobile Patient Monitoring Frameworks: A Systematic Review and Research Agenda. *Journal of Software*, 8, 7, (2013), 1604-1612. DOI= 10.1016/j.ieri.2013.11.023

[18] Nachman, L., Baxi, A., et al., 2010. Jog Falls: A Pervasive Healthcare Platform for Diabetes Management. *Pervasive Computing*, Springer, (2010), 94-111.

[19] Gao, C., Kong, F. and J. Tan, J. Healthaware. 2009. Tackling Obesity with Health Aware Smart Phone Systems. *IEEE International Conference on Robotics and Biomimetics* (ROBIO), (2009), (Guilin, China, 19-23 December 2009), 1549-1554. DOI: 10.1109/ROBIO.2009.5420399

[20] Hong, Y., Kim, J., Ahn, S. and Kim, H. 2010. Mobile health monitoring system based on activity recognition using accelerometer, *Simulation Modelling Practice and Theory,* 18, 4(April 2010), 446-455. DOI= 10.1016/j.simpat.2009.09.002.

[21] Healey, J. and Logan, B. 2005. Wearable wellness monitoring using ECG and accelerometer data, *9th IEEE International Symposium on Wearable Computers*, (18-21 October, 2005), 220-221. DOI= 10.1109/ISWC.2005.59

[22] Kwapisz, J.R., Weiss, G.M. and Moore, S.A. 2011. Activity recognition using cell phone accelerometers, ACM SigKDD Explorations Newsletter, 12, 2 (December 2010), 74-82. DOI=10.1145/1964897.1964918.

[23] Padovitz, A., Zaslavsky, A. and Loke, S. 2006. A Unifying Model for Representing and Reasoning About Context under Uncertainty, *11th International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems (IPMU),* (Paris, France, 2006).

[24] Duggan, K., Anderson, C. Arnolda, L. 2008, Guide to management of hypertension 2008 - Assessing and managing raised blood pressure in adults, *National Heart Foundation*, Melbourne, 1-34, ISBN 978-1-921226-28-1.