Tradeoffs Between Sensing Quality and Energy Efficiency for Context Monitoring Applications

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***Abstract*—Mobile devices have gone far beyond their basic usage like calling, texting, etc. New generation mobile devices like smartphones contain a rich set of embedded sensors which enable them to perform sensing operations in different domains. To get user contextual information, both human centric & participatory sensing can be helpful. In order to accurately capture, recognize and classify various user states, sensors need to operate more in active mode. However, continuous sensing results in huge energy consumption, decreasing the battery lifetime. Hence, a tradeoff in between the sensing accuracy and energy-efficiency is required. In this paper, we have developed novel strategies to make this tradeoff. User contexts are monitored and multiplicative increase and multiplicative decrease (MIMD) approach is exploited to dynamically adjust the sensing frequency following the sensing quality requirements of the applications. We have developed a real-time android application to evaluate the effectiveness of the proposed method in terms of sensing accuracy and energy-efficiency. The results show a good level of improvement compared to a state-of-the-art work.**

I. Introduction

Mobile devices, especially smart mobile phones have emerged as the main electronic device not only for voice communication but also for running heterogeneous real-time applications. Today's mobile devices have a large number of embedded sensors like GPS, Bluetooth, camera, accelerometer, ambient light sensor, magnetic compass, Wi-Fi, etc. Data readings from these sensors may put tremendous impact in developing many applications, e.g., social networking, health care, transportation safety, smart office, smart home, etc.

Mobile sensing applications are of two categories: *participatory sensing* in which the parameters (how, when, what, where to sense) are determined actively by the users; and, *opportunistic sensing* in which sensing operations are performed without involving the user. In this paper, we have made our observations based on opportunistic sensing, although participatory sensing can also be enabled for the proposed method. Human beings are generally involved in a large variety of diverse context events. As mobile phones have become a constant part of our daily lives, inferring a particular context can be performed using the built-in sensors of the mobile phones. For instance, Jigsaw [1] has been developed for performing real-time monitoring of events that are driven by location, activity and sound. A noise mapping system named Ear-Phone [2] has been developed to create different area based noise maps. Another fine example is www.sensorly.com [3] which is a website offering access to coverage maps for various wireless networks while the information itself is entirely community powered.

However, there is a dilemma in the extensive use of mobile devices for sensing purposes. Optimal calibration of sampling frequency is a critical issue in context monitoring applications due to over sensing and under sensing. In case of over sensing, redundant samples are taken increasing the energy consumption and calculation overheads. On the other hand, under sensing might result in generating inaccurate results. In cases where user states remain unchanged for a long time, frequent sampling would result in consuming excessive energy. However, frequent sampling would be required if the user is in a dynamic state.

The situation becomes worse when multiple sensors are powered on simultaneously. In such situations battery life would be significantly reduced. Various researches suggest that modern mobile phones aren't capable of supporting all on-board sensors at the same time. For example, Nokia N95, a mobile phone that supports about 10 hours for phone conversation, loses all battery charge within only 6 hours if GPS is on continuously [4]. Therefore, a tradeoff in between the energy consumption and the sensing accuracy is of utmost requirement for the successful penetration of context monitoring applications. Another example can be found from the built-in accelerometer sensor in HTC Touch Pro which is activated with a fixed sampling frequency. While the sensor itself should consume less than 1 mW when data samples are received by the phone; total power consumption of the device is increased by 370 mW in such situations [5]. Most of the recent studies on participatory and opportunistic sensing [3] emphasized on the design and implementation of a particular sensing application. Also, operation specific adjustable duty cycle assignment and using adaptively changing sampling periods have been proposed as a suitable approach [6]. Other approaches like CoMon [7] shares phone sensors among adjacent users thus improving sensing capacity and reducing overall energy consumption. Another approach, ACE [8] introduced techniques for reducing energy consumption by leveraging context patterns occurred in real life.

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In this paper, we introduce a context monitoring scheme and multiplicative increase and multiplicative decrease (MIMD) based adaptive sensing frequency scaling so as to achieve higher accuracy even as expending reduced amount of energy from the resource-constrained sensor devices. The main contributions of this paper are summarized below.

- We have developed a framework for dynamic sensing and monitoring applications that makes a tradeoff in between sensing accuracy and the energy-efficiency.
- An intelligent context monitoring scheme has been developed using k-means clustering algorithm that can differentiate between redundant and useful data. Thus, it can decrease processing overhead as well as the energy consumption.
- MIMD based dynamic controlling of the sensing frequency makes the system more adaptive with the application environment and thus it enhances the system performance.
- The results of our performance evaluation study, carried out through implementing android application, depict that the proposed sensing strategy outperforms a state-of-the-art method in terms of sensing accuracy and energy-efficiency.

The remaining of the paper is organized as follows. Section II provides a study on the related works in this area of research. The proposed model and mechanism have been presented in Section III and Section IV gives an insight of our algorithms for efficient sensor management. Section V presents the performance evaluation of the algorithm. Finally, the paper is concluded in Section VI.

II. Related Works

For performing user activity recognition tasks, different embedded sensors on mobile devices like GPS, Bluetooth, accelerometer etc have been explored in details. Several research works have been carried out for recognizing user states accurately while reducing the energy consumption. Most of the existing works provide partial solutions for the energy accuracy tradeoff.

Wang et al. [4] proposed Energy Efficient Mobile Sensing System (EEMSS), which is a sensor management system that improves the battery life of the mobile devices by powering a minimum set of sensors applied with duty cycles. However, this approach uses a highly directional sensor which cannot cover the entire area. Also sensors have fixed duty cycles when they are active and aren't adjustable to different user behavior.

Optimization of sensor duty cycles to minimize user state estimation errors has been studied in [9]. Maintaining an energy consumption budget is also taken into consideration in this study. "SeeMon" is introduced in [10] which provides a hierarchical sensor management system. Energy efficiency and reduced computational complexity is achieved by the system through performing continuous context detection only when changes appear during the context monitoring.

In order to provide a solution for the accuracy vs. energy consumption tradeoff, a dynamic sensor selection scheme is demonstrated in [11]. Another approach to handle this tradeoff is provided in [12], [13], [14] which uses different sampling period schemes. These schemes are used to query sensor data in continuous sensing mode in mobile devices. They used a function based approach which can be dynamically adopted. They changed the sampling interval using some pre-defined advance and back-off functions (linear, quadratic, exponential etc). Depending on the stability of the context, the parameters switched among different functions of sampling intervals. Sensors cannot support sensing at any random sampling frequency, thus this type of methods are not applicable. In [15], a system named "SenseLess" that saves energy by sensing localization applications is described. Constandache et al. [16] suggested that humans can be profiled based on mobility patterns and using this information location can be predicted. "EnLoc", the system that was proposed, achieves localization accuracy with realistic energy budget. Approaches suggesting context monitoring mechanism along with adaptive sampling and duty cycling was presented in [5], [6] that exploited additive increase additive decrease (AIAD) approach.

In this paper, we provide a system model and necessary algorithms to solve the accuracy vs. energy consumption tradeoff. Our concept has some similarities with [5]. While their approach was novel, there were some shortcomings. For example, they introduced a parameter called t_{suf}. This parameter was used to adjust duty cycle and sampling frequency by measuring the stability of the context inference up to the time period denoted by t_{suf}. Due to comparison with min and max values for duty cycles and sampling frequency, convergence becomes slow. In the proposed algorithms, authors adjusted the parameters with reference to t_{suf} while not quantifying the amount of change in user context. As a result exact measurement cannot be ensured. Our approach is distinguishable from other proposed methods by the following key elements: *First*, we provide a system model to illustrate the overall process. *Second*, we introduce an algorithm for controlling data acceptance and rejection in the buffers which are used to store and compare sensed values. Decision making for currently sensed data is carried out according to this algorithm. *Third*, we introduce another algorithm for proper scheduling of sensors. Dynamic frequency calibration and duty cycle assignment operations are executed. *Finally*, we set the required parameters and calculate the efficiency and accuracy of the system.

III. System Model and Assumptions

We consider a smartphone with N number of sensors whose set is denoted by S_N. Let A_n is the set of n sensors required by a context monitoring application A to extract contextual information correctly where $A_n \in S_N$ and $n \leq N$.

The overall system model and it's functional components are illustrated in Fig. 1. n sensors produce discrete raw data which enter into a processing pipeline. Output of this pipeline indicates possible change in user context or not.

The first component of the processing block is a preprocessing structure which filters out necessary information

TABLE I

NOTATION TABLE

Symbol	Description
S_N	Set of all sensors
A_n	Set of sensors for a particular application
F	Set of available frequencies
D	Set of available duty cycles
B_i	Set of buffered values of sensor i
X_j	j^{th} data tuple sensed by the sensor
T_{in}	Sensor initialization time
T_{adj}	Sampling frequency and duty cycle adjustment time
T_c	Active cycle time
T_{ter}	Sensor termination time
T_{run}	Active running time
T_s	Sensing interval
t_s	Sampling period
n_i	Required samples between i^{th} and $(i-1)^{th}$ samplings
ψX	Max. allowable diff. betn. two consecutive samples
n_{req_i}	Supported number of samples in between i^{th} and $(i-1)^{th}$ samplings
μ_k	Mean of the k^{th} cluster
σ_k	SD of k^{th} cluster
N_{max}	Max. samples taken in one cycle
N_c	Total number of active cycles
$\mathcal{B}$	Base
$\mathcal{N}_{cur}$	Generated Number with base $\mathcal{B}$ and N_{req_i} as digits
$\mathcal{N}_{max}$	Generated Number with base $\mathcal{B}$ and N_{max_i} as digits
f_{min}	Minimum sampling frequency
f_{max}	Maximum sampling frequency
d_{min}	Minimum duty cycle
d_{max}	Maximum duty cycle
f_{next}	Calibrated frequency for next cycle
d_{next}	Assigned duty cycle for next cycle
$\varphi(f_{next})$	Frequency mapping for f_{next}
$\varphi(d_{next})$	Duty cycle mapping for d_{next}

from the raw sensor data. There is a dedicated buffer for each sensor. Each Buffer contains contextual information and stores N previous samples. Let B_i denotes the set of buffered values for sensor A_i. Here, $\mid B_i \mid \gg N$ where $N_{min} \leq N \leq N_{max}$. Buffers also consist of comparison variables which are obtained by statistical analysis on previously stored data such as standard deviation, variance etc. In the middle of the processing pipeline, there is a decision making component. Intelligent decision maker classifications are applied here among current and previous contextual information to determine whether further processing on the currently sensed data will be carried out or not. The feature extraction block extracts new and different contextual information to determine a possible user state transition.

The user state detection block recognizes user state transitions. This block also notifies the application about a new user state transition and also selects the required set of sensors for the recognition of current user state and possible user state transitions. The dynamic frequency and duty cycle adjuster block keeps track of the operational frequency and the length of the duty cycle of the sensor. To maintain tradeoff between energy efficiency and sensing accuracy, duty cycle and sampling period of the sensor can be adjusted dynamically. The notations used in this paper are summarized in Table I.

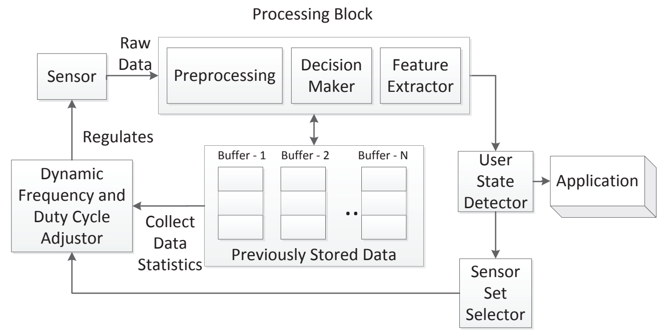

Fig. 1. The System Model

IV. PROPOSED STRATEGIES FOR ENERGY EFFICIENCY

Based on operation methods, smartphone sensors can be divided into 2 categories. The first category consists of sensors that support changing the sampling periods adaptively. Accelerometer and microphone belong to this category. Second category sensors like GPS, Wi-Fi, Bluetooth etc don't support setting different sampling periods [6]. The proposed techniques cannot be adapted to the second category sensors since their sampling frequencies are not allowed to be adjusted dynamically.

Despite the presence of several sensors in the mobile phones, we cannot use all of them simultaneously, the main reason being draining the battery life extensively. However, the energy requirements for different sensors vary significantly. According to studies [15], accelerometer is a sensor that works faster than other sensors. Accelerometer is followed by Bluetooth, microphone, GPS, Wi-Fi and video camera. As a result it would be wise to select accelerometer as the default sensor. Our proposed model provides an efficient way to improve the user context recognition vs. power consumption tradeoff.

Our basic model consists of 2 parts: a context monitoring mechanism and a dynamic frequency calibration system.

A. Context Monitoring Mechanism

In order to get user contextual information properly, the context must be monitored continuously. Such tasks cause heavy workloads which result in hampering the analysis of user context and reducing the battery life. Also redundant repetition of same information must be avoided.

In this paper, we have proposed an intelligent computational method to recognize contextual information of the user. Conventional methods process all raw sensor data, carrying them out through the whole processing pipeline. To reduce this overhead for required operation sequences, our proposed mechanism notifies the application about the user's state only when a state transition occurs. When a raw sensor data arrives, it is compared with previously buffered data to decide whether it indicates a possible change of user's current state or not. Decision on the raw data is taken using the following mechanism.

Let, for each sensor $A_i \in A_n$ there is a buffer B_i of size N which stores N previously sensed data where $B_i = \{X_1, X_2 ... X_N\}$ and X_j denotes the j^{th} data tuple sensed by sensor A_i. We applied K means clustering algorithm to partition B_i into K clusters, $C = \{C_1, C_2 ..., C_K\}$ using Eq. 1.

$$\underset{C}{\operatorname{argmin}} \sum_{k=1}^{K} \sum_{x \in C_k} \|x - \mu_k\|^2 \tag{1}$$

where μ_k denotes the mean of k^{th} cluster. Here k is the number of clusters generated by the algorithm thus the value of k is an important consideration. A small value of k will affect the accuracy of the context monitoring mechanism. On the other hand, a large value of k will lead to high computational overhead. We adopt a common approach that is choosing the value of k such that adding another cluster does not achieve much better gain in terms of minimizing within-cluster sum of squares (WCSS). Though our proposed mechanism does not restrict the type of algorithm used for clustering, in practice we found k means algorithm to be simple and sufficient to serve our purpose.

Let X_j is the current sample and X_{j-1} is the previous sample stored in the buffer. Now we calculate mean (μ_k) and standard deviation (σ_k) of k^{th} cluster, C_k such that $X_{j-1} \in C_k$ using Eq. 2 and Eq. 3.

$$\mu_k = \frac{\sum_{i=1}^{|C_k|} x_i}{|\, C_k \,|} \tag{2}$$

$$\sigma_k = \sqrt{\frac{1}{|\, C_k \,|} \sum_{i=1}^{|C_k|} (x_i - \mu_k)^2} \tag{3}$$

Now when sensor A_i senses a raw data X_j, whether this data is redundant is decided using Algorithm 1.

Algorithm 1 Decision making for currently sensed data

```
C_k = FindClusterWithPreviousValue(C, X_{j-1})
Calculate μ of C_k using Eq. 2
Calculate σ of C_k using Eq. 3
Calculate deviation of X_j from μ_k as, D_cur = | X_j − μ_k |
if D_cur ≥ σ_k × ξ then
    B_i ← B_i ∪ {X_j}
    Accept X_j for further processing
else
    Reject X_j
end if
```

B. Sensor Operation Structure

In Fig. 2, sensor operation structure is illustrated. It starts with sensor initialization time which is denoted by T_{in}, the required time for waking a sensor up and getting acknowledged response that the sensor is ready to operate. For other sensors a shorter period is sufficient to power them up and to set their initial system requirements before sampling operations begin. T_{adj} is the time required for adjusting sensor's current operational frequency f and current duty cycle d (portion of time of a cycle spend on sampling). If T_c denotes the time required for an operational cycle, then the number of samples N, taken in this cycle can easily be calculated as, $N = f \times d \times T_c$.

After initialization, sensors start capturing contextual information and continue this operation repeatedly until the starting of termination time T_{ter}. T_{ter} is the time required to terminate the operation of a sensor. After T_{ter}, sensor shuts down until a new duty is assigned. The total running time denoted by T_{total} is the time required from waking a sensor up until shutting it down. Now, sensor's active running time for taking samples t_{run} can be calculated as, $T_{run} = T_{total} - (T_{init} + T_{ter})$. The number of active cycles run by a sensor between T_{init} and T_{ter} can be calculated as, $N_{cycle} = \frac{T_{run}}{T_c}$. T_s denotes sampling interval within which time a sample is taken and can be calculated as, $T_s = \frac{T_c}{N}$. Here, $t_s (\leq T_s)$ is the sampling period and is given by, $t_s = \frac{1}{f}$.

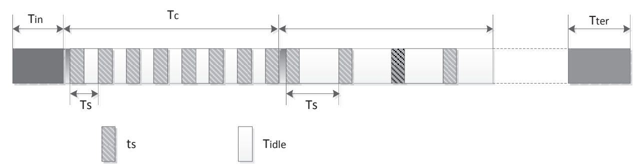

Fig. 2. Sensor Operation Structure

C. Dynamic Frequency Calibration

Let, X_i and X_{i-1} denote the i^{th} and $(i-1)^{th}$ data tuples respectively. Now, due to low sampling frequency some necessary data might be missed. On the other hand, in case of high sampling frequency some redundant data could be captured. So, the actual number of required readings between these two consecutive samples can be calculated as, $n_i = \frac{|X_i - X_{i-1}|}{\psi X}$. Here, ψX is the maximum allowable difference between two consecutive samples to extract contextual information accurately. But as the sampling frequency is limited to $[f_{min}, f_{max}]$ the maximum and minimum numbers of samples that can be taken during T_s are $N_{max} = (T_s + t_s) \times f_{max}$ and $N_{min} = (T_s + t_s) \times f_{min}$ respectively. So, the actual number of required samples is given by,

$$N_{req_i} = \begin{cases} min(N_{max}, n) & \text{if } n > 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

$$N_{req_i} = \lfloor (N_{req_i} + 0.5) \rfloor \tag{5}$$

In our proposed mechanism, the duty cycle length and sampling frequency are adjusted dynamically for each sensor. To reduce energy consumption, a pair of duty cycle and sampling frequency is assigned to each sensor. In this situation a tradeoff between energy consumption vs. accuracy arises, which has to be balanced efficiently. Too long sampling intervals cause insufficient sampling to represent real conditions which may lead to incorrect user state recognition. On the other hand, a short sampling interval enables a larger number of samplings thus consuming more energy. In case of duty cycle, a short duty cycle length will save energy, increasing sleeping period of a sensor. However, this causes higher detection latency and leads to false detection of user states. A long duty cycle length will increase data accuracy while wasting more energy. Our proposed mechanism dynamically adjusts sampling frequency and duty cycle to balance this tradeoff.

We define base $\mathcal{B}$ as,

$$\mathcal{B} = N_{max} + 1 \tag{6}$$

Now, n_{req_i}, which denote the required number of samples between i^{th} and $(i-1)^{th}$ samples and can be calculated using Eq. 6. We consider a number system of base $\mathcal{B}$ whose digits can be any values between 0 and $\mathcal{B}-1$. Now, for $N-1$ consecutive samples we generate two numbers $\mathcal{N}_{cur}$ and $\mathcal{N}_{max}$ taking N_{req_i} and N_{max_i} as digits respectively, where $0 \leq N_{req_i}, N_{max} \leq (\mathcal{B}-1)$.

$$\mathcal{N}_{cur} = \sum_{i=1}^{N-1} N_{req_i} \times \mathcal{B}^{i-1} \tag{7}$$

$$\mathcal{N}_{max} = \sum_{i=1}^{N-1} N_{max} \times \mathcal{B}^{i-1} \tag{8}$$

Now, using $\mathcal{N}_{cur}$ and $\mathcal{N}_{max}$ we can determine sampling frequency for the next cycle using the following equation.

$$f_{next} = \lfloor \frac{\mathcal{N}_{cur}}{\mathcal{N}_{max}} \times (f_{max} - f_{min}) + f_{min} \rfloor \tag{9}$$

Now, according to f_{next}, the duty cycle for the next cycle d_{next} can be adjusted as,

$$d_{next} = \lfloor \frac{f_{next} - f_{min}}{f_{max} - f_{min}} \times (d_{max} - d_{min}) + d_{min} \rfloor \tag{10}$$

Since sensor's frequency can't be calibrated to any continuous value, we must map the f_{next} and d_{next} pair to the available discrete values. Let F and D denote the sets of all available frequencies and duty cycles. So, the required mapping function can be defined as,

$$\varphi(f_{next}) = \begin{cases} f_i & |f_i - f_{next}| < |f_{i+1} - f_{next}| \\ f_{i+1} & |f_i - f_{next}| > |f_{i+1} - f_{next}| \end{cases} \tag{11}$$

where $f_i, f_{i+1} \in F$, $f_i \leq f_{next} \leq f_{i+1}$ and $i = 1, 2, \ldots \mid F \mid -1$. If $\mid f_i - f_{next} \mid = \mid f_{i+1} - f_{next} \mid$ then the mapping function can be modified as,

$$\varphi(f_{next}) = \begin{cases} f_i & \text{for power sensitive app.} \\ f_{i+1} & \text{for accuracy sensitive app.} \end{cases} \tag{12}$$

Using similar mapping function, we can map d_{next} to $\varphi(d_{next})$. Now the sensors sampling frequency is calibrated to $\varphi(f_{next})$ and $\varphi(d_{next})$ is assigned as the active duty cycle in the next cycle, as summarized in Algorithm 2. Overall sensor operation scheme is presented in Algorithm 3.

Algorithm 2 Dynamic Frequency Calibration

1. **INPUT:** B, f_{max}, f_{min} and ΔX
2. **OUTPUT:** $\varphi(f_{next})$ and $\varphi(d_{next})$
3. **for all** $X_i \in B$, i = 1, 2, 3, ..., $\mid B \mid$-1 **do**
4. calculate n_i and N_{req_i} using Eq. 4 to Eq. 5
5. **end for**
6. Calculate $\mathcal{N}_{cur}$, $\mathcal{N}_{max}$ and $\mathcal{B}$ using Eq. 5 to Eq. 8
7. Calculate f_{next} and d_{next} using Eq. 9 to Eq. 10
8. Find $\varphi(f_{next})$ and $\varphi(d_{next})$ using Eq. 11 and Eq. 12

Algorithm 3 Sensor Operation Scheme

1. **repeat**
2. Run Algorithm 2
3. Set sampling frequency and active duty cycle to $\varphi(f_{next})$ and $\varphi(d_{next})$ respectively
4. **repeat**
5. Take Sample for sampling interval T_S (sample is taken in t_s time and sensor remains idle for rest of the T_S before taking a new sample)
6. **until** active cycle time reaches to $T_c - T_{sch}$
7. **until** no of active cycle reaches N_{cycle}

V. Performance Evaluation

In this section, we study the performance of our proposed system with comparison to the methods described in [5]. For our convenience, we denote the methods described in [5] as ASDC (Adaptive Sampling and Duty Cycling). Performance measurement is done in terms of accuracy and power efficiency.

A. Simulation Environment

A smartphone application is implemented in order to evaluate the performance of the proposed system. The application collects contextual data using accelerometer sensor. Samsung Galaxy S-DUOS smartphone is used as the target device. Android Studio is used as software development tool. The target device supports a 3-axis accelerometer which is used to collect sensor data following the specifications provided in [5]. Parametric values for the simulation environment are summarized in Table II.

B. Performance Metrices

1) Accuracy: Accuracy between i^{th} and $(i-1)^{th}$ samples can be calculated as

$$\alpha_i = \begin{cases} \frac{1}{n_i} & \text{if } n_i > 0 \\ 1 & \text{otherwise} \end{cases} \tag{13}$$

TABLE II
SIMULATION PARAMETERS

Parameter	Value
F	{10Hz, 15Hz, 20 Hz}
D	{1, 0.75, 0.5}
T_c	2 sec
T_{total}	1 hour
ψX	0.1

Then, the average accuracy for N samples taken in T_{run} time is calculated as follows,

$$\alpha = \frac{1}{N} \times \sum_{i=1}^{N-1} \alpha_i \tag{14}$$

2) Power Efficiency: Power Efficiency is defined as the ratio of remaining energy and initial energy budget. For calculation of power efficiency ζ we adopt power consumption analysis of [5].

C. Simulation Result

Simulation results demonstrate satisfactory performance. In Fig. 3, we observe that the accuracy increases until it reaches its saturation level in both ASDC and our proposed method. However, the rate of increase in our proposed method is greater than that of ASDC. This is caused by the fact that, in ASDC, after every t_{suf} time a sensor adjusts its duty cycle and sampling frequency to the next possible index. Thus, it requires more time to converge to the appropriate duty cycle and sampling frequency. However, in our proposed method, according to the contextual information, sampling frequency and duty cycle are dynamically scaled for next time. So, convergence becomes faster and thus increasing the accuracy.

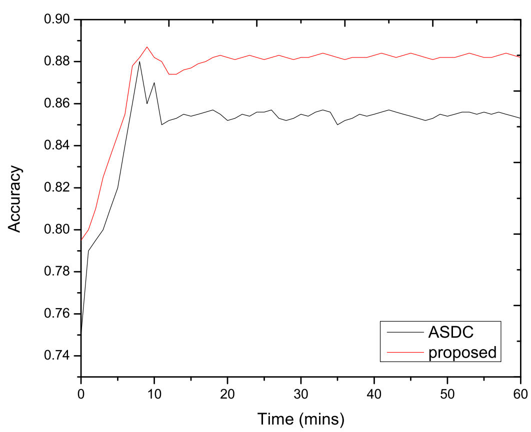

Fig. 3. Time vs. Accuracy

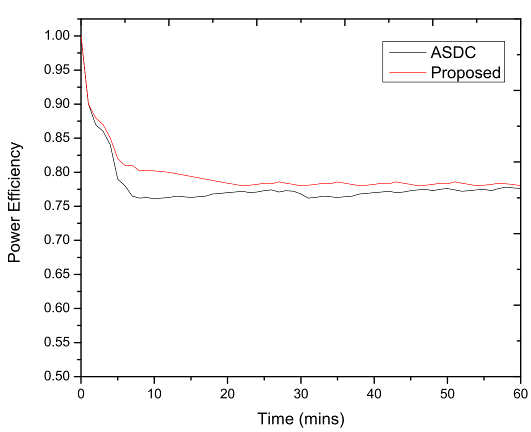

Fig. 4. Time vs. Power Efficiency

The Figure 4 shows that power efficiency decreases in time in both ASDC and our proposed method. But the rate of decreasing is slower in our proposed method. Since the convergence is faster in our method, it reduces unnecessary sampling thus reducing power consumption.

VI. Conclusion

We have presented novel approaches in this paper to address the energy accuracy tradeoff for smartphone sensing. Several algorithms have been developed to improve the energy efficiency of context monitoring applications while capturing accurate contextual information. The use of MIMD in adaptively scaling the sensing frequency has been explored and the results prove that it is more effective than AIAD (additive increase additive decrease). Implementation results showed satisfactory performance improvement both in accuracy and energy domains. Now, we are exploring the formulation of an optimization function to further improve tradeoff levels whenever the application environment parameters greatly vary over time. In addition to that the system stability analysis would be an indispensable part of this work.

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