Energy Efficient Adaptive GPS Sampling Using Accelerometer Data

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Abstract. Internet of Things (IoT) is a major component of the connected world. With billions of battery-powered devices connected to the internet, energy and bandwidth consumption become significant issues. Embedding intelligence/cognition in the apparatus is recognized as one of the solutions to mitigate these issues. Global Positioning System (GPS) is recognized as one of the most energy-consuming mobile sensors in smart vehicles/systems. This paper proposes a smart adaptive sampling method for GPS sensors using the accelerometer data. Our approach adapts the sampling frequency of the GPS sensor according to the data stream of the accelerometer, without causing significant distortions to the data. In our experiment, we could reduce the GPS sensing by 78% while preserving an accuracy of 91.4%.

Keywords: Internet of Things · Cognitive IoT · Adaptive sampling · GPS · Accelerometer

1 Introduction

Nowadays, cities worldwide encounter new challenges such as spectacular population growth, massive pressure on city infrastructure (power, water, health-care, transportation), and pollution. The smart city concept came in response to some of those contemporary challenges. Intelligent infrastructure, smart grids, and electric cars provide synergistic advantages for smart cities. One of the principal premises of smart cities is to enhance the quality of life by establishing "smart mobility". With billions of connected devices, the so-called "Internet of Things (IoT)" is quickly becoming a dominant milestone in the next generation of smart communication.

IoT is expected to have enormous economic and social impact. In essence, IoT devices may use internet connection to report, measure, and perform actions autonomously. Many of these devices consist of embedded sensors, actuators, or RFID tags, which are generally low-powered, and require network access, which may not be energy-efficient [8].

With billions of battery-powered devices connected to the internet, data volume, energy efficiency, and bandwidth consumption are believed to be three of

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the most significant challenges to overcome in IoT. One of the techniques to mitigate these issues is Adaptive Sampling (AS). AS consists of adapting the connected device's sampling frequency to the changes in the measurements, i.e., decrease (increase) the sampling frequency when the changes are small (large), while not exceeding a tolerable distortion to the data. This paper proposes a smart adaptive sampling method for Global Positioning System (GPS) sensors based on accelerometer sensor data. GPS sensor is a receiver that uses a satellite-based navigation system to provide position, timing, and velocity information at a given rate/frequency (ranging from 1 to 10 Hz) and consuming around 30 mA per data record. Compared to other typical motion-related sensors, GPS sensors are very demanding in energy (Fig. 1).

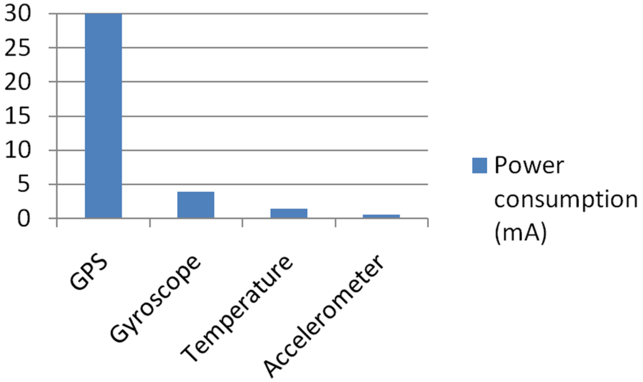

Fig. 1. Power consumption per sample for different sensors

We introduce the SAAF system, which stands for "Sense Acceleration & Adapt Frequency". SAAF is a new approach that senses acceleration data and adapts the frequency of the GPS sensor to reduce the amount of insignificant information, which leads to saving energy and bandwidth consumption and data storage. The proposed approach could form the basis of several IoT GPS-based applications, such as smart-phones, wearable devices, drones, and connected cars [4].

The rest of the paper is organized as follows. The second section summarizes the existing studies on adaptive sampling and filtering techniques. The proposed methodology is outlined in the third section. Section 4 describes the data acquisition process, and the evaluation of the experimental results. The last section concludes this paper and outlines the future work.

2 Related Works

In the literature, there are various approaches to adaptive sampling. Some preliminary work was carried out several years ago. Law et al. [6], proposed to use an adaptive sampling solution based on the Box-Jenkins approach in time series analysis. In [8], the authors focused on developing an energy-efficient adaptive sampling technique that uses temporal correlation among sensor measurements to find the best sampling rate. Kiran and co-workers [13] proposed a healthcare application based on intelligent sparse sensing, which reconstructs the original signal using an on-chip context predictor.

Yurur et al. have used the accelerometer for activity detection to save the energy of human-related sensors [16]. In a similar context, Chan et al. [2] combined the accelerometer and GPS sensors to improve the displacement information accuracy using empirical mode decomposition and adaptive filtering.

As adaptive filtering might save the storage space, it tends to consume more energy when the filtering is performed on the sensor side. Recent approaches use adaptive filtering on GPS data to improve its accuracy [1,7,12].

Several other studies, for instance, [10,14], and [5], have been carried out on adaptive sampling using event detection or penalty functions using the recent records of the same sensor. However, these approaches cannot be generalized. As highlighted by [8], critical applications cannot tolerate the risk of losing data, such as healthcare, and road safety systems. The approach proposed in this paper differs from the existing ones, as it uses low-power sensors to adapt the sampling frequency of greedy power-consuming sensors.

3 Approach

As mentioned in the previous section, adaptive filtering strategies can preserve data storage space and bandwidth but at the cost of higher energy consumption. In this era of big data and connected cities, data storage and bandwidth are not real concerns compared to the energy problem. Thus, we adopted the adaptive sampling strategy over adaptive filtering because of its practicality in solving the aforementioned challenges.

The proposed process design is presented in Fig. 2, which is composed of a four-step loop. The initial step consists of sensing the acceleration record (in time t_i), which allows us to calculate the velocity (v_i) in the next step using the three-dimensional acceleration data. As soon as these steps have been carried out, a new sampling frequency ($T_G\ (t_i)$) can be calculated using Eq. (4). The next step is a conditional one, compares the new GPS sampling frequency to the previous one. Finally, based on this comparison, it decides either to update the GPS frequency or to keep the old one. Below, we elaborate on each step of our approach.

3.1 Acceleration Sampling

The constant Accelerometer frequency allows us to sample the acceleration information at a fixed rate. The Accelerometer sensor yields three-axis acceleration information, which is used to calculate the velocity in the next step.

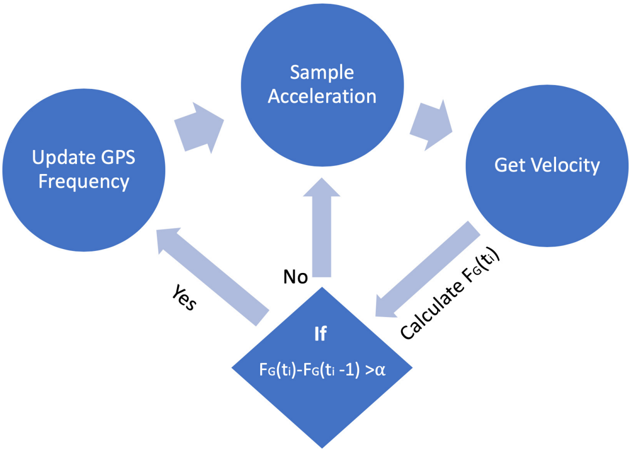

Fig. 2. Process design.

3.2 Velocity Calculation

The proposed algorithm adapts the GPS sampling frequency based on velocity values. Velocity records are calculated by exploiting the three-dimensional accelerometer data, as shown in Eq. (1) for each axis.

$$\begin{cases} v_x(kT_a) = v_x((k-1)T_a) + a_x(kT_a)T_a \\ v_y(kT_a) = v_y((k-1)T_a) + a_y(kT_a)T_a \\ v_z(kT_a) = v_z((k-1)T_a) + a_z(kT_a)T_a \end{cases} \tag{1}$$

Where v_x and a_x stand respectively for the velocity and acceleration according to the x-axis, T_a and k denote respectively the accelerometer sampling period and the sample index.

3.3 New Frequency Calculation

Let pT_a denote the sampling period of the GPS sensor. We would like to adapt the value of p, while making sure that the difference between the actual GPS record and the record at time instant $(k+p)T_a$ does not exceed a predefined threshold ϵ, i.e.,:

$$|u((k+p)T_a) - u(kT_a)| < \epsilon \tag{2}$$

Where $u(kT_a)$ and $u((k+p)T_a)$ stand respectively for the GPS record's value at time kT_a, and at time $(k+p)T_a$. It is worth noting that ϵ can be set to be the uncertainty value associated with the studied GPS sensor.

$$u((k+p)T_a) \approx u(kT_a) + \left[\sum_{i=0}^{p-1} v((k+i)T_a)\right] T_a \tag{3}$$

Considering (3) means

$$\sum_{i=0}^{p-1} v((k+i)T_a) < \frac{\epsilon}{T_a} \tag{4}$$

The objective is to find the optimum value of p that verifies the Eq. (3) and (4).

We use function (5) to adapt GPS sampling frequency, which takes in input the velocity of time t and outputs the new sampling period pT_a.

$$T_G(t) = f(p) = \begin{cases} T_{min} & v(t) > v_{max} \\ T_{max} & v(t) < v_{min} \\ pT_a & Otherwise \end{cases} \tag{5}$$

$T_{max}, T_{min}, v_{max}$ and v_{min} are predefined variables and depend on the use case. This function controls the frequency range (between T_{max} and T_{min}) by setting velocity limits (v_{max} and v_{min}).

3.4 Frequency Update

Once the new GPS frequency $F_G(t_i+1)$ is calculated, compare it to the previous one $F_G(t_i)$. If $F_G(t_i+1) - F_G(t_i)$ is greater than α then the GPS frequency is updated, else we go back to the first element in the cycle: acceleration sampling. Where α stands for the maximum allowed GPS frequency rate.

4 Experimental Results

In this section, we empirically evaluate our approach.

4.1 Dataset Acquisition

Measurements were taken using purpose-built equipment composed of a Raspberry Pi Model B, Accelerometer, Gyroscope, Thermometer, and two GPS sensors, one with a fixed frequency 1 Hz and the other with adaptive frequency. The data collection was carried out in Rabat, Morocco, using a recent model of Mercedes Benz. The tests were performed on a volunteer's vehicle. One driver participated in the experiment setting, which consisted of three days driving in different paths, including highways, motorways, and local roads. The driver was told to drive as he does in his daily routine.

The complete data set has a size of 412 MB and consists of 3.17 million samples. The content of each column is described below:

- Timestamp (ms)
- Acceleration in X (Gs)
- Acceleration in Y (Gs)
- Acceleration in Z (Gs)
- Latitude coordinates (degrees)

- Longitude coordinates (degrees)
- Altitude (meters)
- Vertical accuracy (degrees)
- Horizontal accuracy (degrees)
- Speed (km/h)
- Roll (degrees)
- Pitch (degrees)
- Yaw (degrees)

The Accelerometer and Gyroscope sensors provide records at 10 Hz frequency.

4.2 Research Questions (RQs)

Our evaluation addresses four research questions:

- ***RQ1. What is the optimal ϵ value?*** The value of ϵ controls the configuration of our approach. RQ1 identifies the configuration that produces the best overall results.
- ***RQ2. How efficient is our approach in a real experiment?*** Using the best configuration from RQ1, RQ2 assesses the effectiveness of our approach in energy, storage, and bandwidth reduction versus regular sampling.
- ***RQ3. How accurate is our approach to preserving the initial signal information?*** After evaluating the effectiveness of our approach, we calculate the distortion error and information loss, providing the accuracy of signal preservation.

4.3 Experiments

RQ1: To answer RQ1, we observed the impact of varying the *epsilon* values as summarized in Table 1. Higher *epsilon* values lead to higher sensing reduction but also higher distortion (higher error). This value is an empirical choice and depends on the use case and the tolerated error. In our case, we assume the intolerance of high distortion, thus taking into account the average GPS error, which is around 5 m, we choose $epsilon = 5.10^{-7}$.

RQ2: The next set of analyses examined the impact of the proposed approach on energy and bandwidth consumption and data storage. Data analysis and comparison were performed on two parallel data issued from two GPS sensors described in the previous section to measure these points. Figure 3 compares the standard GPS signal sampled with default frequency and adaptive GPS signal acquired by applying the proposed approach. It can be seen that the adaptive GPS signal skips noisy/unnecessary values while keeping essential changes.

The concluded results to emerge from the data is that the new signal reduces the data volume and bandwidth consumption of GPS sensor by 78.4% and reduces the energy consumption by 39.2%. Figure 4 shows the reduced power consumption for the used GPS model. These tests also revealed that, in the first ten minutes, our model reduced the data volume of the GPS sensor by at least 1.2 Mb.

Table 1. Comparison between different ϵ values

ϵ	10^{-6}	$7.5.10^{-7}$	5.10^{-7}	10^{-7}	5.10^{-8}
Reduced data (%)	94.29	88.14	78.40	63.45	30.94
Reduced energy (%)	47.14	44.07	39.2	31.72	15.47
Distortion (meter/sample)	7.34	5.76	3.95	1.03	0.57

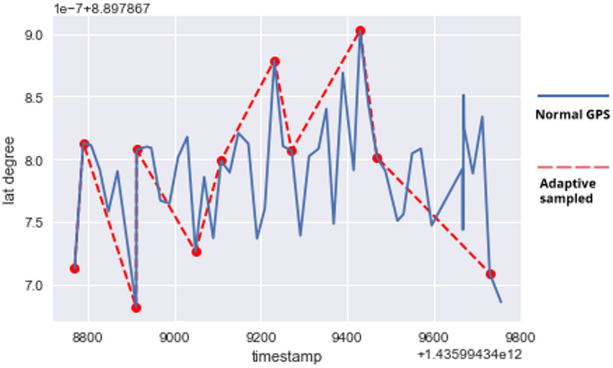

Fig. 3. Normal GPS signal versus adaptive GPS signal

RQ3: To evaluate the accuracy of our method, we measured the distortion between both signals. The average error of the proposed model is around 4 meters/sample. GPS signal is known to be noisy. Thus a preprocessing phase is required to clean and filter the noisy data. In our case, we can deduct the average GPS error from the resulted distortion to have a fair accuracy evaluation. After removing this noise, our model achieves an average accuracy of 91.4%. We believe that those results emphasize the validity of our method.

5 Discussion

As expected, there were some discrepancies in the proposed method due to multiple sensors with different sampling rates. Therefore, this approach will output almost in each use case an irregular time series. Considering the dataset's index is the GPS data, this will require using preprocessing techniques or algorithms for irregular time series.

As an essential step, preprocessing improves the performance and accuracy of the machine learning process by handling topics such as missing data [5], noisy data [15], and data quality [5]. More use cases of preprocessing are investigated by [5,15].

Generally, time series are generated by a regularly spaced interval of time, in which our proposed method fails to guarantee. This violation is caused by the variability of the GPS sampling frequency based on the velocity. In this section,

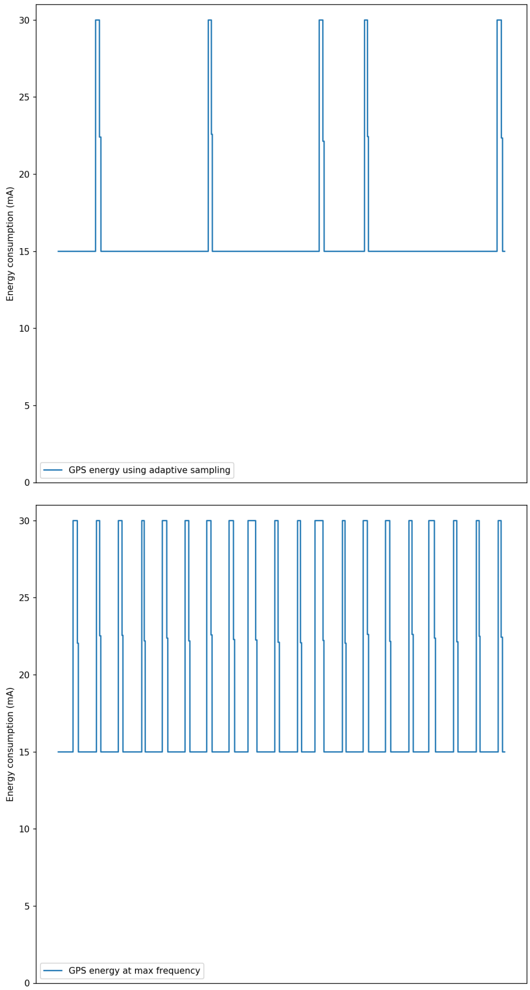

Fig. 4. GPS energy consumption before and after adaptive sampling

The main objective is to discuss the solutions and strategies to deal with this problem.

In the literature, there are few methods for keeping the structure of unevenly time series, such as rolling operators [3], weighted moving averages [9], and exponentially weighted moving averages [9]. The methods that keep working on the non-gaped subsequence of the data are functional for some use cases. Most of the powerful statistical tools for time series could not be applicable theoretically and directly to our data. We propose transforming irregular times series to regular data by using interpolation techniques to apply regularly spaced data methods.

The interval of time should not be highly irregular to transform the data into an equally spaced time series. Such a critical assumption can lead to severe biases in our data [11]. To solve this issue, our method fixes two parameters suggested in Sect. 2, F_{max} and F_{min} reduce the high variability in terms of the time interval.

Some solutions can be disastrous. Using the irregular time series with imputation methods, which can lead to white noise or transform a high irregular time series, can change the initial structure of the series (i.e., in terms of seasonality) completely. Therefore, the transformation cannot be the best solution. Analyzing the series in their unchanged form can be a valid choice [3,9,11].

6 Conclusion and Future Work

This paper has proposed a novel approach that applies adaptive sampling to optimize GPS sensing, using Accelerometer's data. Based on the collected dataset, this study's results indicate the capability to reduce energy, data volume, and bandwidth consumption by 78% while preserving a relatively high accuracy: 91.4%. Our work's strength lies in using a second less-energy-consuming sensor (Accelerometer) to produce energy-efficient sensing of a more energy-consuming sensor (GPS). These findings add to a growing body of literature on the adaptive sensing field. The present study has important implications for solving the energy problem of embedded systems and IoT.

Future work should focus on enhancing the performance of this approach. Therefore, we intend to collect a more significant and more varied dataset to verify our work's validity. This will allow us to do more analysis and improve our model's performance.

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