MOBILE DEVICE POWER MANAGEMENT MODEL FOR LOCATION BASED SERVICE APPLICATIONS

by
Hettiarachchige Don Sajitha Priyankara (168256H)

A thesis submitted to University of Moratuwa in partial fulfilment of the requirements for the
Master of Computer Science, *Specialized in Mobile Computing*

Department of Computer Science & Engineering
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Declaration

I declare that this is my own work and this thesis/dissertation does not incorporate without acknowledgment any material previously submitted for a Degree or Diploma in any University or other institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgment is made in the text.

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I have supervised and accepted this thesis/dissertation for the award of the degree.

Dr. Indika Perera — Date
Department of Computer Science and Engineering
University of Moratuwa

Abstract

Location based solutions for smartphones and other smart hand-held devices have been significantly increased. Geo location is one of the key contexts which can be easily captured with the current localization or geo positioning technologies. Most recent geo-localized Points of Interest (POI) aware systems perform much intelligent decisions and proactive actions by identifying nearby places and the nature of the surrounding. For achieving that proactiveness, Location Based Service (LBS) approaches utilize continuous feed of Global Positioning System (GPS) which consumes more energy, makes a significant battery drain and generates heat resulting in a severe reduction of operation time.

Objective of this research is to introduce enhanced power utilization mechanisms for POI aware systems by implementing intelligent location extraction methods along with Application Programming Interface (API) level optimizations as well.

In the relevant research literature mobile device power optimization has been discussed and many solutions have been introduced and those have been discussed and referred during the research work.

Applicable use cases which can be integrated with power management mechanisms have been identified to address the above mentioned problem as the first step. GPS and WiFi based hybrid positioning system has been identified as the main supportive GPS adaptation. Then intelligent GPS sampling mechanisms and intelligent communication with the location based service provider have been studied and classified based on the state differentiation of the applications.

In the implementation phase a prototype called "DealTella" has been created. Activity recognition has been implemented for intelligent decision making in location sampling. GPS adaptation using Wi-Fi trace based reversed location extraction is the most important power utilization adaptation introduced during the research work.

A considerable percentage of energy saving could be achieved by enabling

all the mechanisms explained under the implementation section along with enabling intelligent sampling. Proposed implementation has been tested under three main scenarios while enabling better battery consumption strategies. Accuracy has been measured against the battery consumption and recommendations have been provided based on results.

Further as part of the research work, a prototype has been developed just to prove the concept and it will be enhanced and released as a marketable and production quality application.

Modern leading operating systems invest more on optimizing battery consumption natively. Since modern smart applications are heavy process oriented for providing the best and most context related user experience. Those applications consume more and more energy for achieving that proactiveness and to feed the intelligence into applications. Still there exist a lot of research opportunities in the context and some of the extensions have been proposed to be carried out in a future phase.

Acknowledgements

I would like to pay my sincere gratitude towards my supervisors, Dr. Indika Perera and Dr. Malaka J. Walpola, Senior Lecturers, Department of Computer Science and Engineering, Faculty of Engineering University of Moratuwa, for their valuable guidance, feedback and continuous support.

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Furthermore, I extend my heartfelt thanks to my wife Mrs. Hemani Herath, for her immense support, encouragement and faith in me and my mother and father for their heartiest blessings which made this work a success.

Abbreviations

A–GPS – Assisted Global Positioning System
AI – Artificial Intelligence
API – Application Programming Interface
CDF – Cumulative Distribution Function
CLA – Centroid location algorithm
CNP – Cellular Network Provider
EEPS – Energy-Efficient Positioning Scheme
GPS – Global Positioning System
GSM – Global System for Mobile Communications
HMM – Hidden Markov Models
IDC – International Data Corporation
iOS – iPhone Operating System
ISP – Internet Service Provider
KNN – K-nearest neighbor
LBS – Location Based Services
MAC – Media Access Control Address
NoSQL – Not Structured Query Language
POI – Points of Interest
RSS – Received Signal Strength
TTFF – Time to First Fix
Wi-Fi – Wireless Fidelity

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Chapter 1

Introduction

Technology has become an important part of everyday life, and it is difficult to live without technology in many aspects. Hand-held mobile devices play a major role in the above context. Forecast projection of worldwide smart phone shipment is 1.37 billion for the year 2019 [10] according to the sources from Worldwide Quarterly Mobile Phone Tracker by International Data Corporation (IDC) [6]. IDC provides quarterly figures on mobile device markets. According to IDC, the same above source, sales volume of smartphones passed the sales volume of personal computers in the 2010 fourth quarter. With the arrival of 5G smartphones, IDC predicts 5G smartphones volume will be highly increased where in 2020 it will be 7% out of all smart devices in the market. As a number it will be around 200 million as a forecast value with volumes to account for roughly 7% of all smartphones in 2020 [10].

Smart hand-held device based location based services which provide unique and broader experience limited only by human imagination have been significantly increased among other smart services. Geo-positioning, indoor outdoor navigation aids, geo-fencing based smart triggers and reminders, location based promotions and advertisements, push notifications, travel aids and companions kind of location based applications are becoming more popular in the current context of Location Based Services (LBS). Continuously monitored current location of the device is the primary input for many of the above mentioned services and it can be easily captured with current geo positioning technologies. Most recent geo-localized Points of Interest (POI) aware systems perform much intelligent decisions and proactive actions by identifying nearby places and the nature of the surrounding.

1.1 Research Problem

Current mobile applications have become more advanced in leveraging location services and injecting value additions to applications. To achieve proactiveness, LBS (Location based service) approaches utilize continuous feed of GPS which consumes more energy. This unmanaged way of continuous GPS feed consumes more energy and makes a significant battery drain which results in a severe reduction of operation time and it is the main problem area which mainly strives to address.

When the location service is enabled and while a location based application is being used in foreground mode, battery draining is a common experience which can be observed even with the bare eye. It is quite high while moving fast or accessing services in low signal strength areas. Basic assumptions would be, applications that continually keep fixing the location or the device is heavily working on communicating with cell towers and satellites or continuous location based service fetching from the server over the network. Before optimizing battery consumption, the first part of the problem is what are the exact causes of battery draining and by which activities the battery is being depleted.

Another problem is to find ways of optimally consuming battery without sacrificing the location related core functionalities or application specific value additions. Location accuracy is the main sacrifice and needs to be researched to determine the proportions of accuracy versus battery consumptions based on the application type.

Even though GPS is the first party which is being blamed in the context of battery draining in location based applications, the problem is that are these any other reasons and causes in which battery is being depleted. Both Android and Apple which are the leading mobile operating systems are highly incentivized and are continuously being updated in optimizing battery usage. But these optimizations are more general and targeting common issues. Because of that there may be some generally untouched application specific problems which need to be identified.

As mentioned above there exist many less considered problematic areas in the context of power management in POI aware location based service applications.

1.2 Research Objectives

As mentioned under the problem statement there exist a lot of research opportunities to be addressed in the mentioned context. As the first thing, all the reasons and the causes to the mentioned problem above need to be properly identified.

The main research objective is to introduce a power optimized location extraction model by adapting GPS with alternative location extraction mechanisms while keeping the accuracy within application desired margins with the aid of application modes classification based on their state differentiation.

All in all there is still a lot of room for improvements and broad research leads still to be addressed in the context. As mentioned above, This research work strives to overcome problematic areas in all battery draining causes in location based service applications. An intelligent and adaptive mechanism for resource and sensor utilizing is required to be implemented as the solution.

After performing the research on the mentioned context, one of the extended objectives is to enhance and release the created prototype as a marketable product.

1.3 Organization of the Thesis

The remainder of the thesis is structured as mentioned below.

- **Chapter 2: Location Based Services**
  This chapter introduces location based services. It describes the location based services, main components comprising LBS and applications of LBS. Further it describes location extraction technologies mainly including GPS based positioning and Wi-Fi or Mobile network cell identity base positioning.

- **Chapter 3 : Literature Review**
  This chapter refers and reviews the previous research work in energy management strategies in LBS mobile applications. It describes adaptive methods of location extraction. Further it reviews the literature on location extraction methods for indoor positioning, privacy concerns in LBS applications, location recognition and prediction methods as well.

- **Chapter 4: Methodology**
  This chapter describes the methodology for the proposed solution. Applicable use cases which can be integrated with power management mechanisms have been outlined to address the above mentioned problem as the first step. GPS and WiFi based hybrid positioning system has been proposed as the main supportive GPS adaptation. Then intelligent GPS sampling mechanisms and intelligent communication with the location based service provider have been studied and classifications based on the state differentiation of the applications have been illustrated.

- **Chapter 5: Implementation**
  This chapter includes the implementation of the proposed solution under the methodology and it describes the creation of a prototype called "DealTella" which is a location based deal telling application. This further describes how it has been implemented the activity recognition for intelligent decision making in location sampling and the reversed location extraction as it is the most important power utilization adaptation introduced during the research work.

- **Chapter 6: Results**
  This chapter illustrates the results of the proposed implementation which has been tested under three main scenarios while enabling better battery consumption strategies. Further it compares the accuracy against the battery consumption and recommendations have been provided based on results.

- **Chapter 7: Conclusions**
  This chapter summarizes the results obtained. At the end of this chapter it concludes the research work by discussing limitations and further introducing possible future extensions.

Chapter 2

Location Based Services

Technology has become an important part of everyday life, and it is difficult to live without technology in many aspects. Hand-held mobile devices play a major role in the above context. Forecast projection of worldwide smart phone shipment is 1.37 billion for the year 2019 [10] according to the sources from Worldwide Quarterly Mobile Phone Tracker by International Data Corporation (IDC) [6]. IDC provides quarterly figures on mobile device markets. According to IDC, the same above source, sales volume of smartphones passed the sales volume of personal computers in the 2010 fourth quarter. With the arrival of 5G smartphones, IDC predicts 5G smartphones volume will be highly increased where in 2020 it will be 7% out of all smart devices in the market. As a number it will be around 200 million as a forecast value with volumes to account for roughly 7% of all smartphones in 2020 [10].

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Continuously monitored current location of the device is the primary input for many of the above mentioned services and it can be easily captured with current geo positioning technologies. Most recent geo-localized Points of Interest (POI) aware systems perform much intelligent decisions and proactive actions by identifying nearby places and the nature of the surrounding.

To achieve that proactiveness, Location based services utilize continuous feed of Global Positioning System (GPS) which consumes more energy. This unmanaged way of employing continuous GPS feed consumes more energy and makes a significant battery drain which results in a severe reduction of operation time. An intelligent mechanism for resource and sensor utilizing is required to be implemented as a solution.

2.1 Location Based Services in Mobile Computing

Location based services are information providing soft service applications that offer various kinds of services utilizing geographical position of the location capturing capable smart device or based on any projected position by a mobile service consumer.

> *"Location-based services (LBS) are the delivery of data and information services where the content of those services is tailored to the current or some projected location and context of a mobile user [11]."*

> *"Location Based Service (LBS) is and information or entertainment service, accessible with mobile devices through the mobile network and utilizing the ability to make use of the geographical position of the mobile device [50]."*

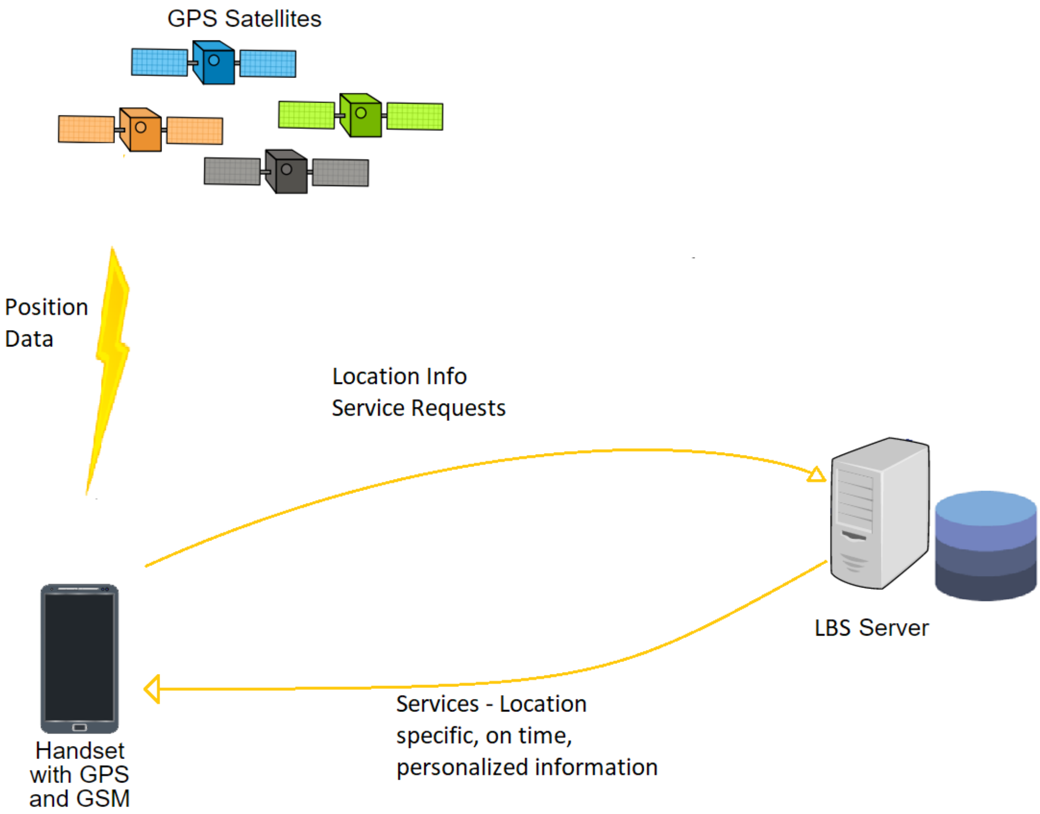

Figure 2.1: Architecture of Location Based Services

2.2 Components in LBS

The LBS system comprises six main components as shown in Figure 2.2. location extraction system, referencing system, service provider application, relevant content provider, consumer application with communication capability over network and existence of a network for bridging the consumer and the provider [2].

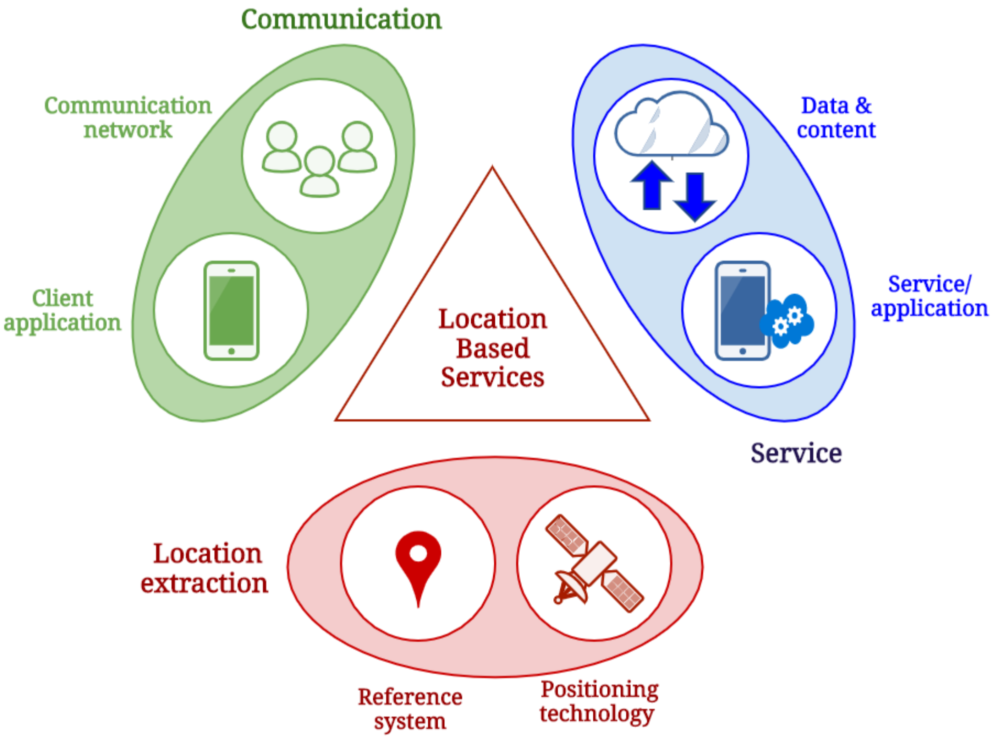

Figure 2.2: Components of Location Based Services [30]

2.2.1 Location Extraction and Mapping System

Geo location extraction is carried out mainly using the global positioning system or employing multiple positioning technologies in combination such as Wi-Fi based location extraction or sensor based location extraction. Referencing system is the other main part of the localization sub system, which maps the input signal to a formalized position.

Examples for reference systems include 2D-maps (e.g. building plan), 3D-maps (e.g. virtual model of a shop floor) or a database (e.g. list of available conference rooms).

Service provision is achieved by an IT service, i.e. a software application along with all the data required for the service.

2.2.2 Consumer and Provider System

Communication requires an adequate communication network (e.g. LTE or Wi-Fi) and a user interface (e.g. smart phone or computer). The implementation of location based service requires the specification of each component along with a close consideration of the existing infrastructure and other requirements for a specific use case.

- Geo position capturing device
- Service consumer application on mobile device with a positioning technology
- Mobile network which bridges the service and consumer
- Service provider application
- Geo specific content provider

2.2.3 Types of LBS Based on the Service Fetching Mechanism

Two types of location based services are functioning as push services and pull services. In push services, server pushes information without user request and notify at the end user level with an interruption or append to a queue at end user level. In pull services, end user requests for service information by itself or simply polls the server for information.

2.3 Applications of LBS

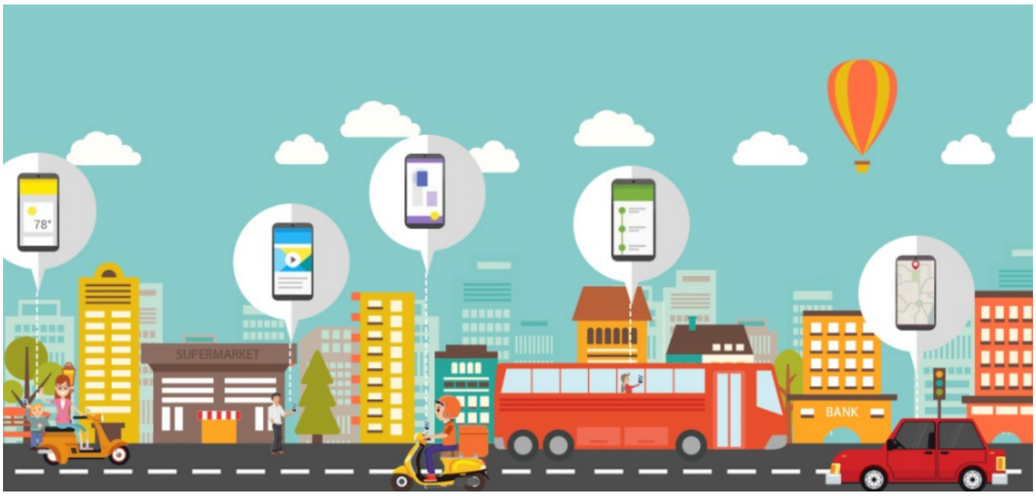

Figure 2.3: Applications of Location Based Services [5]

Location based applications can be found in many streams which bring unique value additions to each of them [49].

- Navigation and traveling
- Location based point of interests or information services
- Location based mobile marketing, local advertising and geo fencing based promotions and reminders
- Location based social media applications and geo tagging
- Security and emergency services
- Location based gaming and sports
- Fleet management, transportation, auto insurance and asset tracking
- Location sensitive billing, mobile fraudulent management

Figure 2.4: Overview of Location Based Service applications [4]

2.4 Geo-localized POI Aware System

Geo location based points of interest aware application services have been empowered with current location extraction capabilities and self-learning Artificial Intelligence (AI) based context extraction technologies. They perform much intelligent ahead of time decisions and context related personalized actions proactively by identifying nearby places and the nature of the user and surrounding context.

2.5 Location Extraction Technologies

Location extraction is one of the primary subjects in LBS applications and it can be easily extracted with the advancement of the current technology.

Below listed positioning technologies are being widely used in the context.

- Global positioning system based positioning
- Wi-Fi or mobile network cell identity based positioning
- Beacon kind of location broadcaster based positioning
- Code or sign reading and extraction based positioning
- Mobile sensor based relative positioning

2.5.1 Global Positioning System Based Positioning

GPS is a satellite based network for navigation and geo positioning purposes which was designed, launched and controlled by the United State government and initially intended for military purposes only. Full setup can be separated into three main segments [3].

2.5.1.1 Space Segment

The space satellite network setup is carried out with 24 to 32 satellites which are orbiting the Earth at an approximate altitude of 20200 km. Many of them are considered as core constellation units that transmit current satellite position, time and others are redundant measurement providers for precision enhancements.

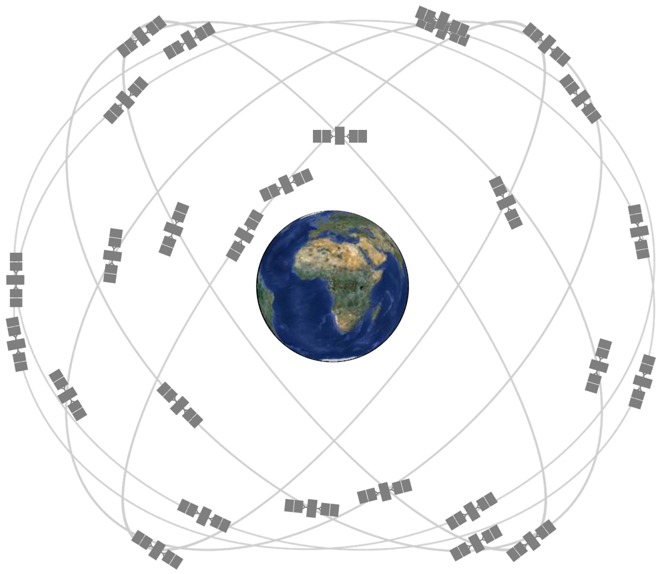

Figure 2.5: GPS constellation [44]

2.5.1.2 Control Segment

Controlling configuration contains a master controlling station with redundant mirror, ground antennas and monitor stations. All controlling operations are handled by this segment including orbit maintenance, clock adjustments, and navigational data management and overall status management of core constellations.

2.5.1.3 User or Consumer Segment

GPS initially designed and deployed for military operations by the US defense department as high precise positioning service and later less precise GPS service made available for general usages as a service which is a free 24 hours available service anywhere in the world. Millions of civil and commercial users consuming this service various streams such as travelling, transportation, surveying and farming etc. Scientific applications are empowered with GPS as well in applications such as weather forecasting, earthquake monitoring, ocean monitoring, environment monitoring etc.

2.5.1.4 Geo positioning with GPS

Figure 2.6 illustrates an example of geo position querying and extraction procedure with trilateration. The first satellite locates device position on a surface equidistant from its center (Figure 2.6a). The second satellite intercepts the first sphere and narrows the device location to a circle (Figure 2.6b). The third satellite intercepts the circle in two points and reduces the choice to two possible points (Figure 2.6c). Even though the Earth sphere should touch one from them and another point can be neglected, the fourth satellite contributes to calculate a timing and location correction (Figure 2.6d).

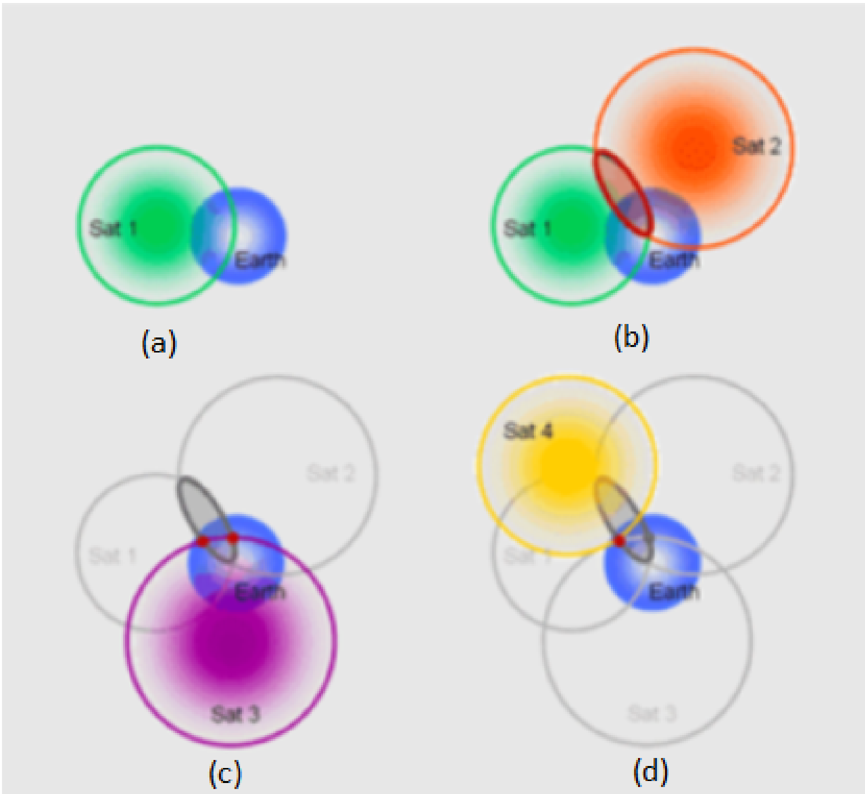

Figure 2.6: Trilateration in GPS [1]

2.5.2 Wi-Fi or Mobile Network Cell Identity Based Positioning

Wi-Fi and Mobile network cell identity based positioning is another geolocation extracting technique which uses the geo position of surrounding cell towers or Wi-Fi access points and calculates the geo position of the targeted point [?], [34], [45]. Trilateration triangulation and centroid localization are the basic methods of location extraction.

2.5.2.1 Trilateration

Location extracting using trilateration: Received Signal Strength (RSS) from at least three signal sources is converted into distance using various terrain and surrounding based models and feed into trilateration model for extracting the location querying position as illustrated in Figure 2.7.

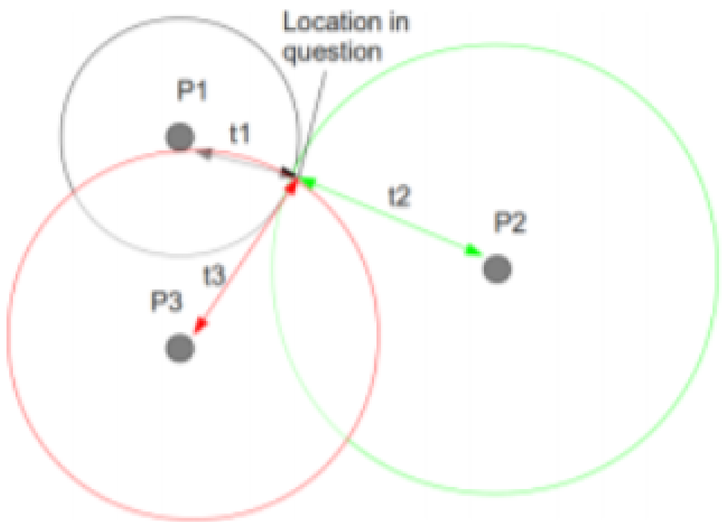

Figure 2.7: Trilateration

2.5.2.2 Triangulation

Location extracting using triangulation: Angle of arrival from two signal sources is measured and distance between them feed in to triangulation model for extracting the location querying position as illustrated in Figure 2.8.

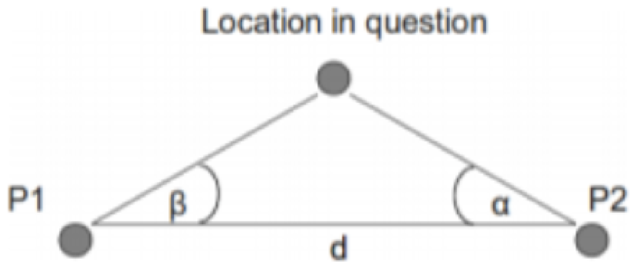

Figure 2.8: Triangulation

2.5.2.3 Centroid Localization

Location extracting using centroid localization: The location querying node calculates its position as the centroid of all received signal source reference positions by averaging them namely considering the arithmetic mean of it as illustrated in Figure 2.9. .

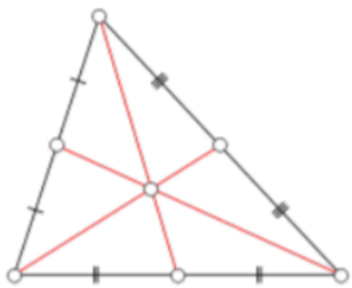

Figure 2.9: Centroid of a triangle

Chapter 3

Literature Review

3.1 Main Methods of Location Extraction

There are two main ways of location extraction in smart handheld devices which are GPS based positioning and network based positioning. GPS is a satellite based geo positioning mechanism launched by the United States and this technology is the most utilized standard way of positioning. One major issue with GPS is it does not work indoors. Wi-Fi and cellular based localization strategies came into play as a solution for this issue. Network-based location extraction mechanisms do not have a high accuracy and they do have a low Time To First Fix (TTFF) while their energy consumption level is considerably low. Comparatively GPS based geo position extraction mechanisms do have the best accuracy.

Few drawbacks of GPS utilization

- Only available in outdoor and open surroundings
- Very deficient in energy consumption.

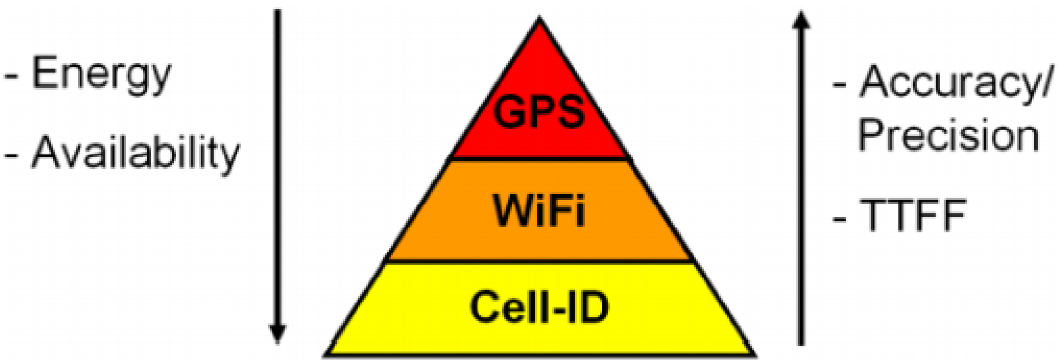

Figure 3.1: Geo positioning pyramid [16]

Other than GPS it can be utilized several positioning mechanisms and which are having different characteristics as mentioned above. Energy and Availability versus Accuracy and TTFF varying behaviors are illustrated in Figure 3.1. Early research on efficient power saving strategies have been recommended to the sensor-assisted GPS positioning methods to employ where they provide sufficient level of accuracy for most of the POI aware solutions. Bareth U. and Kupper A. have measured the energy consumption of the three main positioning technologies as shown in the table below [16].

Table 3.1: Properties of positioning techniques [2]

Technology	**Accuracy**	**Precision**	**Energy**
A-GPS	10m	95%	6.616Ws
Wi-Fi	50m	90%	2.852Ws
Cell-Id	5km	65%	1.013Ws

For example Thomas Graf et al. [32] points out three main approaches which can be followed in power efficient positioning.

1. Replacement of GPS by other peer technologies Wi-Fi, bluetooth beacon or cell identity.

2. Intelligent Switching of Localization Technology
3. Adaptive reduction of GPS operations

Accuracy of GPS with smart devices has generally been stated to be "about 5m". This has been proven by utilizing 1000 participants over 100 countries and the measured average accuracy of the research was 4.9m [28].

Additionally, this discusses that many of those systems are also bound and backed with well-formed APIs as well. But there is still a lot of room for improvements and broad research leads in intelligent decision making, pattern matching and route prediction kind of areas.

3.2 Adaptive Methods of Location Extraction

Jonas Willaredt [53] classifies mobile device localization techniques and Yu-Chung Cheng et al. [22] in accuracy characterization for Wi-Fi localization compare how each possible approaches in localization may vary with coverage as illustrated in Figure 3.2.

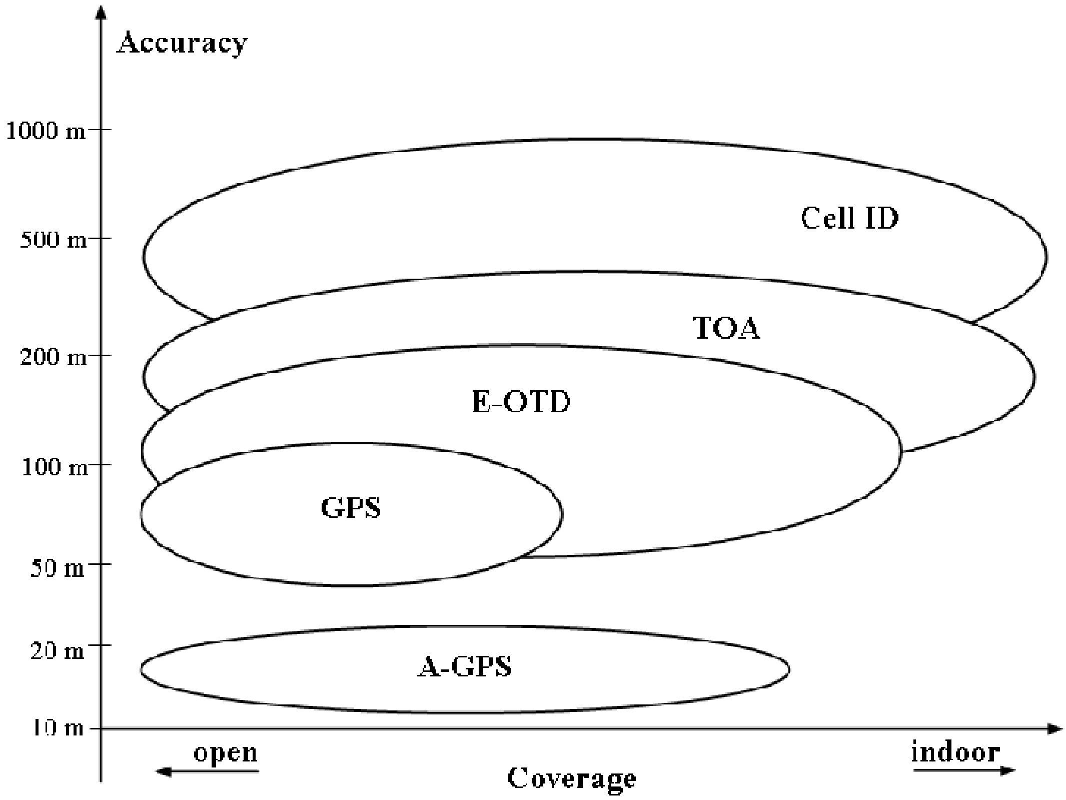

Figure 3.2: Different localization techniques and their accuracy details [53]

Chao-Hsien et al. [37] proposed a POI context related power saving mechanism for ubiquitous touring service using smart devices. A dynamically adjustable system of GPS sampling along with inbuilt sensors based on three main factors.

- Relativity to the last known or current geo position
- Movements and other activity behavior of the device
- Physical environment

Lee et al. [39] discussed a GPS based energy-efficient location middleware along with an accelerometer and a geomagnetic sensor. In their research it can be defined or configured a level of accuracy over which the system needs to be maintained and GPS sampling dynamically changes based on it.

Youssef et al. [54] researched out a hybrid GPS-accelerometer compass (GAC) mechanism. Power saving is done by controlling the GPS sampling in an intelligent way. Application predict the route of the user with the aid accelerometer and the compass and calculate the current position with relative to an initial exact GPS location sample. Infrequent GPS samplings are used for synchronization of the current calculated and derived position with the exact one.

Many research works have been performed to improve the accuracy of cell identity based positioning mechanism along with GPS. Paek et al. [48] introduced CAPS, which is mainly utilizing Cell-ID traces for geo positioning. The proposed system utilizes near continuous user location changes and gathered historical data of those movements for achieving significantly better accuracy than the conventional GPS and Network based positioning methods. In this method continuously capturing cell identity sequence is compared against a previously stored cell identity sequence fingerprint. CAPS uses a modified Smith-Waterman algorithm for cell-ID sequence matching and the highest score will be used. Once a user is moving on a frequent route a matched sequence is extracted and will be used as additional support for reducing GPS fixing frequency [43].

Chon et al. propose a cell-id sequence fingerprint based positioning system. Other than location extraction they argue mobile device usage pattern is having high correlation with the mobility pattern of the user, since a considerably high percentage of users routes are routine routes. As an example users tend to use multimedia applications while traveling from home to the workplace. These kinds of usage patterns are mapped with mobility patterns to extract out the required amount of battery power before the next charge. Based on the research findings they have

- Designed a low-power user location extraction and prediction mechanism based on scanned and pre-stored cell tower traces.

- Modeled the correlation between the mobility pattern of the user and the battery consumption behaviours of the device [25].

User's geo location determination based on cell tower triangulation or trilateration is not possible. The main reason is that the accurate geo positions of cell towers are not freely and publicly available without any cell tower location prepulalation. Therefore, instead of storing cell tower locations, cell identities of base transceiver stations have been monitored. When the device which is being monitored is in a cell border, ping pong effect can be frequently experienced which is a challenging task to distinguish actual user movements over automatic cell transition. Ping Pong effect means device connection with a cell is being changed among neighboring cells which are being associated with, even without device moving [38]. This is occurring due to fluctuations in receiving signal strength and cell breathing nature when balancing the cell load.

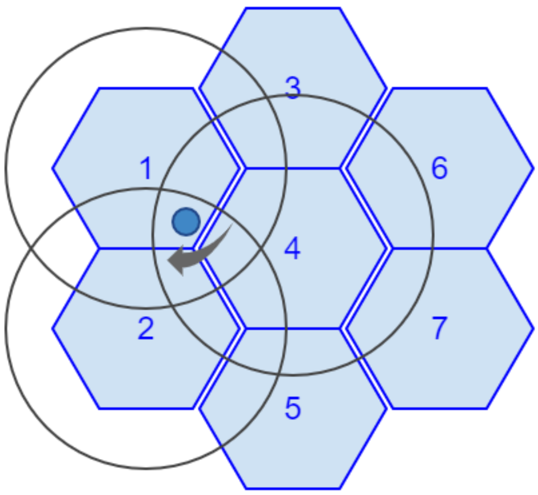

Figure 3.3: Ping pong effect [38]

As they have discussed Figure 3.3 shows a pingpong occuring scenario. When user is in a place as illustrated it is very much possible of giving cell identity changing sequences as 1→2 →1 or 1→2 →4 or 1→4 →1 or 1→4 →2 →1 . . . etc, even without any user movement which is really challenging to distinguish over transition sequences due to actual user movements. A process of using aggregated states has been proposed to overcome the pingpong issue by clustering cell tower sequences. User movement detection is delayed within the aggregated state size or area with this avoidance [25].

Below is the used methods to overcome pingpong issue

$$\begin{aligned}
C_t &= \text{Set of cell towers in the visibility at time t} \\
C_{t+1} &= \text{Set of cell towers in the visibility at time t+1} \\
N_{threshold} &= \text{Contextually derived threshold value}
\end{aligned}$$

For actual user movement recognition they have formulated the below mechanism.

$$\begin{aligned}
Movement &= \text{True if} \left| C_{t+1} \bigcap C_t \right| \geq N_{threshold} \\
&= \text{False if} \left| C_{t+1} \bigcap C_t \right| < N_{threshold}
\end{aligned}$$

For instance, if the aggregated set of current visibility is { 1,2,4 } and the active cell identity is 1 at time t has been changed to cell 2 as the active cell at time t+1 while remaining the aggregated state set of cell identities as same, they avoid that output as a ping pong effect [25].

Deblauwe et al. research out power efficient location tracking solution using GPS with cell identity matching for proactive location based service applications [26]. They propose a central server for location extraction for tracking mobile users. Core mechanism is based on

- Circle-based strategies which is an extension of Dynamic Centered Circles and GPS utilizing mechanism
- Cell-based strategy which is an algorithm for efficiently executing spatial queries [26].

Chen et al. have considered below five items and have examined the accuracy of positioning.

- Selecting the algorithm
- Size of the scanned set
- Parallel use of services from different service providers in the vicinity
- Training on multiple devices even with different specifications
- Testing and drive density calibration

A metropolitan environment was considered for the testing area with Global System for Mobile communication (GSM) beacon based location system and when selecting algorithm.

- A centroid algorithm without considering the radio propagation.
- An algorithm for matching fingerprints of radio signal strength
- Monte Carlo localization has been considered with a signal propagation model which is based on Gaussian Processes [21], [23].

Some recent research studies have considered Wi-Fi and in built sensor readings as well. Paek et al. introduce a positioning system which is mainly based on rate adaptation. They leverage sensors readings, cell identity readings, bluetooth aid as well to extract device position and to predict spatial user movement with intelligent GPS fixes over time to regain the predefined expected accuracy [50].

Kim et al. present an energy-efficient positioning scheme as EEPS for smart devices using location based applications. EEPS performs a position extraction mechanism of a smart device considering three main factors.

- Interesting regions of the device
- Predefined application required accuracy levels
- Level of the battery [35]

Lin et al. present a user geo position extraction model with the ability of self tuning power consumption and the location extraction accuracy leveraging in built sensor aid technologies [32]. Since present mobile devices are equipped with many and more powerful sensors which are capable of extracting more context related information, best sensor options should be chosen by considering both required accuracy and extraction cost. They have introduced a mechanism for selecting the most suitable algorithm, for switching between most power efficient sensors to gain the application related required location accuracy. As illustrated in the Figure 3.4 they have developed a model which automatically calculates the accuracy requirement for mobile dynamically. By considering the changes in the accuracy model and the sensor accuracy confidant level changes with the movement of the user.

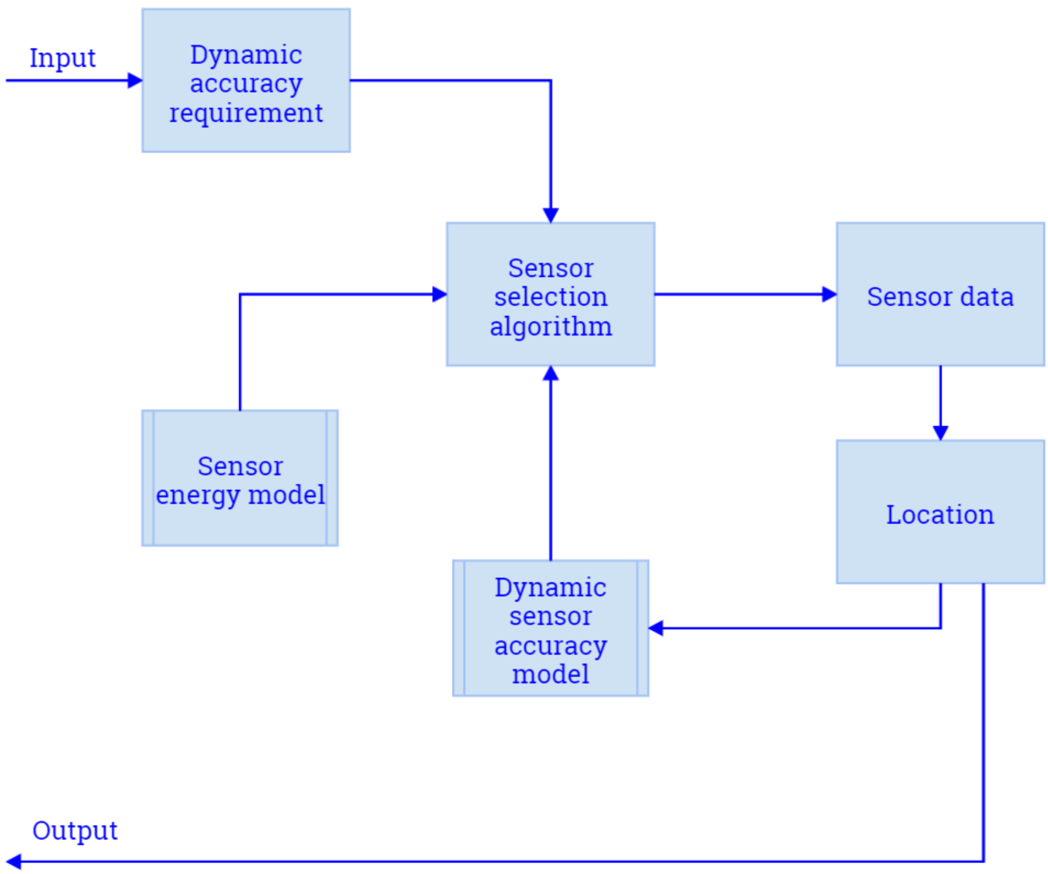

Figure 3.4: Dynamic model for calculating accuracy requirement [32]

Chon et al. present adaptive user location extraction scheme where intelligently switch among GSM, Wi-Fi, and GPS based on user movement prediction results [11],[18],[17]. In their work two main intelligent agents are presented as mobility learner and mobility predictor by utilizing motion of the user, usage of the device and mobility patterns of the user to build a user's context by combining employing many inbuilt positioning approaches such as Wi-Fi, accelerometer sensor, digital compass, thermometer, Bluetooth, and GSM.

3.3 Privacy Concerns in Location Based Services

LBS users have to consider their privacy when consuming location based services even if they are being served some useful facts. All of user activities, behaviors and routings can be captured and stored easily at the LBS side which raises a huge privacy issue [13], [14], [46]. Ulrich Bareth et al. [17] addressed this important factor by highlighting privacy issues and concerns in background tracking systems. A radio beacon based location resolvement method which avoids continuous background location lookups with LBS server, is proposed in opposition to conventional cellular location determination mechanisms with extra attention to privacy concerns while enhancing the energy saving as well.

3.4 Location Extraction Methods for Indoor Positioning

GPS is not the best positioning solution for indoor location based solutions. Some research works try to address this limited capabilities of GPS in indoor positioning systems [40], [20], [33]. Lamarca et al. present a beacon based positioning model to improve the indoor location coverage [21] and Wi-fi, bluetooth or cell identity based radio beacons are commonly utilized to fully and accurately coverage indoor areas.

Chintalapudi et al. present an indoor positioning system which fully leverages the 802.11 Wi-Fi access points [22]. Their model builds a learning positioning scheme by collecting location data at the device level that traverses the indoor area where users are moving around, while using the same scheme to extract out the locations of users within the building.

Location recognition and location prediction are the next most important concepts in the context of location based services in providing better service and achieving better performance at the same time as well. Simply knowing the current location and the next location of the user are the most important information in location based service context.

3.5 Location Recognition and Prediction

When examining current literature of the context of proliferating location based context aware applications, lots of attempts have been taken for having the knowledge of recognizing current location and predicting the next possible location of the user. Common models can be identified in the literature for location recognition and prediction.

3.5.1 Location Recognition

For location recognition below approaches have been widely considered [24], [31], [51].

- Decision tree based solutions
- K-nearest neighbor (KNN) and decision trees based hybrid approaches

KNN is a non-parametric, lazy learning and one of the simplest algorithms which is being commonly used for regression and classification tasks. Number of nearest neighbors which is used for the classification is denoted by K.

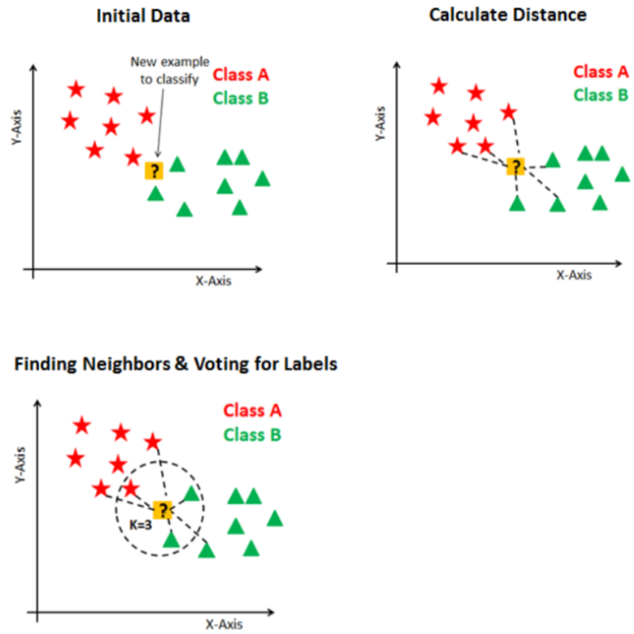

Figure 3.5: KNN illustration [7]

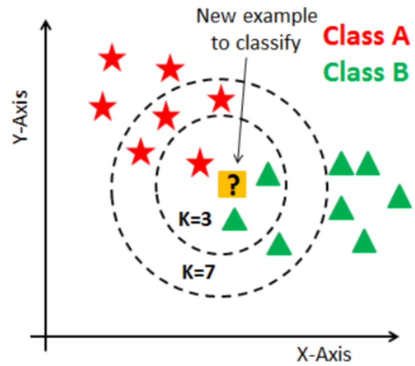

Figure 3.6: KNN based classification [7]

3.5.2 Location Prediction

For location prediction below approaches have been widely considered.

- Hidden Markov Models (HMM)

Yong et al. researched on extracting or recognizing user location and predicting users next location based on decision tree, K nearest neighbor with hidden markov models [36]. Over 90% of average accuracy on user's location prediction has been achieved by employing their researched model which has been proven by collecting everyday data set from ten individuals over six month of period. Most of the location prediction researches HMM has been used as the base model [12], [19], [42].

A method has been introduced as "Predestination" for determining next destination of moving vehicle by Krumm et al. [43]. Markov model has been utilized for recognizing device location from GPS data based systems by Ashbrook et al. which automatically clusters those collected data over an all-encompassing timespan and into places at multiple scales [15]. AlvarezGarcia et al. researched on a new mechanism based on Hidden Markov Model and local map with street views for predicting destination of a route by feeding already completed route details of the trajectory [10].

HMM capabilities have been utilized by Mathew et al. when designing a hybrid mechanism for the purpose of human mobility determination [27]. Destination and the route of a moving vehicle have been predicted real time by utilizing HMM capabilities with the aid of GPS and localized map database by Simmons et al. [52]. Indoor positioning and predicting the next location are widely researched areas in the context. Dynamic Bayesian network has been modeled to extract indoor location and predicting next location by Petzold et al. and then it has been compared with two other predicting models which are the state predictor and the multi-layer perceptron predictor [37].

Petzold et al. compared various location predicting models in the context for location prediction of a moving user [17]. Dynamic Bayesian network, Markov predictor and multi-layer perceptron, state predictor and Elman net have been considered during the comparison. Monreale et al. proposed route pattern tree for next location prediction of a moving device [25].

Morzy et al. created a collection of moving device geo-positions and created a frequent route recognizing model and movement rules, and compared and matched a particular route of a moving device with the collection of movement rules to construct a probabilistic model [47], [32]. Scellato et al. created a location predicting model by analyzing nonlinear time series [41].

Chapter 4

Methodology

4.1 Causes for Battery Draining in LBS Based POI Aware Systems

Location based POI aware systems are becoming more and more proactive with various kinds of intelligent features which leads to consume more power for processing them as well.

Three main cases can be identified as the main causes for draining the battery in LBS based POI aware applications.

1. Exhausting use of GPS.
2. Continuous location based service related data transmission via cellular network or Wi-Fi for service fetching.
3. Continuous processing for geofence based triggerings within the device.

All of the above battery draining causes will be addressed in this research work.

4.2 Classification of Location Based Services

Location based service can be classified into two main groups based on the

1. Required accuracy level of the geolocation

2. Fetching response times of the POIs from the LBS server

Based on the above classification criteria, dynamic GPS sampling based power saving strategies are hardly applicable for the applications requiring a very high level of positioning accuracy. Still many of the location based services which are not required a high level of accuracy and it is acceptable of having some latency in location specific service fetching can be integrated with power saving mechanisms.

4.3 Overview of Power Management Strategies

Power consumption management can be achieved by implementing assisted GPS mechanisms as proved by many other researchers. The assisted or supportive technology can be either a network based or a sensor based approach.

There exist some situations where the system can intelligently avoid location sampling. As an example when a device is not moving location sampling can be avoided. In-built sensors within the mobile device can be employed for checking the device behavior and managing and controlling the location sampling. Another example is when a device moving in constant velocity namely moving in a highway, location sampling can be controlled in more intelligent ways.

There exists some applications that users navigating or routing through the very same route most of the time and POIs are the only changing entity over time.

- Smart mobile applications which serve location based deals and promotions may route through the same path most of the time and nearby deals and promotions may only change over time.
- Smart mobile Applications which serve traffic volumes and ahead route conditions ahead of time, may route through the same way most of the time and serving results may only change over time.

For this kind of application route caching and pattern matching approaches along with core location sampling can be implemented for far better power management.

Assisted approaches management is one of the main concerns as well. Injecting the intelligence into the location sampling is carried out by employing some parallel jobs along with core GPS location sampling. These supportive approaches again can add power consumption overhead into the system which may consume more power than applications where only GPS itself works on location sampling if they are not properly implemented.

Geo fencing and other fence triggering, place identification kind of location based POI extractions are again carried out by some other parallel APIs as well. These keep adding extra overhead into the core application as well. Namely these supportive sampling approaches and mechanisms for achieving context awareness are consuming a considerable amount of portion of processing power.

Proper API management and inter process communication management need to be considered as well. Current web and mobile application development trends on progressive application concepts for application shelling and adding offline working capabilities can be introduced. Aggregated API usage for handling most of the tasks within one single API which processes interconnection and memory management done within itself can be introduced as well for better power management in POI aware systems.

Namely power saving in POI aware LBS systems is still prompting a lot room for improvements and broad research leads in intelligent decision making, pattern matching and route prediction kind of areas.

4.4 Implementation Aspects of Power Management Strategies

Equipped positioning technologies in mobile devices have different characteristics, especially concerning power consumption and the accuracy gaining. There is a huge potential to improve the energy-efficiency while keeping the required positioning accuracy. Below are the possible strategies researched out and verified in this research work.

1. Utilizing assisted technologies for GPS

2. Enabling intelligent GPS sampling mechanisms based on the state differentiations of the application
3. Enabling intelligent communication with the location based service provider based on the state differentiations of the application
4. Mobile task offloading
5. Route caching and route prediction

4.4.1 Utilizing Assisted Technologies for GPS

Utilizing assisted technologies along with core GPS sampling is the most widely researched and commonly used way of managing power in location based applications. In this context assisted technologies to GPS means not the natively utilization of Assisted-GPS or A-GPS which is used to enhance the response time.

4.4.1.1 Assisted-GPS

When it is considered about a GPS only system it will take from 30 seconds to two or three minutes of time to correctly acquire GPS signals and precisely locate the queried device. This time is introduced as TTFF which is the period of time from the device turning on the GPS device or starting location querying to receive the first location fix after finding visible orbiting satellites and clock data from them. It can take any value between the above period which is due to interference in between the device and the satellites. Especially in metropolitan or the same kind of highly GPS signal interfering surrounding, TTFF reading will be a higher number compared to open areas [29], [55].

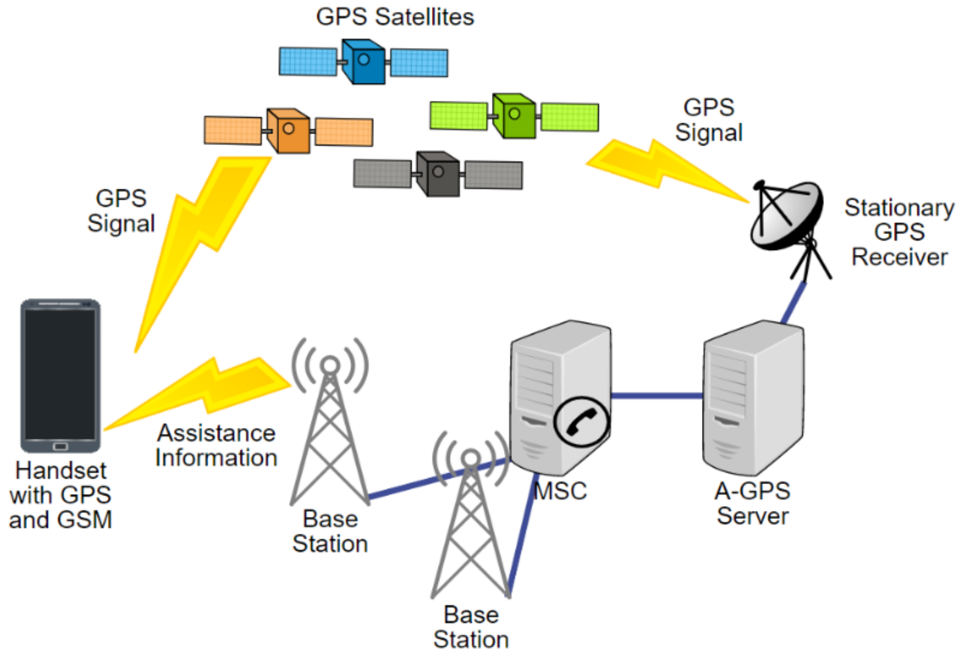

Figure 4.1: Architecture of Assisted-GPS

Assisted GPS or also known as Augmented GPS is a remedy mechanism or alternative utilization on top of conventional GPS which significantly speedup the process and enhance the response time at the starting up a system. GPS receivers which are deployed in base stations are constantly fetching satellite information and computing the data.

A-GPS has been designed in speeding up the process in two main ways.

1. By sending satellite information fetched at the base station to the mobile device for easily getting stuck with satellites quickly and speeding up the location extraction process.

2. By sending the mobile device approximately captured less accurate data to the A-GPS server via base station and get the job done in a more precise way. This mobile mobile task offloading as all the processing and

other processes completing GPS communications are carried out at the A-GPS server will bring up an extra advantage as well.

And overall by utilizing A-GPS it will acquire below advantages,

1. Faster location extraction.

2. Location acquisition in situations where no satellites are in the line of sight to the device but having CNP/ISP (Internet Service Provider/Cellular Network Provider) in the vicinity.

3. Process of loading and reducing the in device processing power.

4. Efficient battery usage

Most of the modern smart devices are capable of providing this facility autonomously. Even with this it is quite possible to occur battery draining due to unwanted GPS pollings or due to unwanted location acquisition attempts even in the situations where application required accuracy has been already achieved. There must be further actions to be taken to manage the device power in more advanced and intelligent ways.

4.4.1.2 GPS and Wi-Fi Based Hybrid Positioning System

The information broadcasting by Wi-Fi devices and other access points can be utilized for extracting the location of a smart device. Usage and the accuracy of this mechanism is totally based on the richness of the mapped Wi-Fi traces of a particular location against the accurate GPS location data of the same location. Once the device acquires the location using GPS, the device sends publicly readable nearby Wi-Fi device Media Access Control (MAC) addresses back to the vendor along with GPS data and makes rich the online Wi-Fi device location database. This location database of access points can be then queried against by sending identities of access points as query parameters and get back the early stored location if available.

This service is quite useful in situations where GPS is not available or the device is not capable of acquiring location via GPS but in a position of connecting to ISP and getting the location hosted by vendors. All vendors are continuously making their databases rich and keep updating the existing records for providing better and accurate service for their clients.

Similar strategy can be utilized for other location based services in centralized manner and even within devices upto some extent as well.

Most of the location based applications usually fetch location related information from a central location based service providing server. Within these servers it can be managed an application bound database of access points identities and/or even cell identities against the acquired location any other means as the same way vendors collect and enrich the locations of access points databases. Location based service consumer application can be utilized to piggyback nearby access points and other cell identity traces and enrich the database at the server side while querying for location related points of interests.

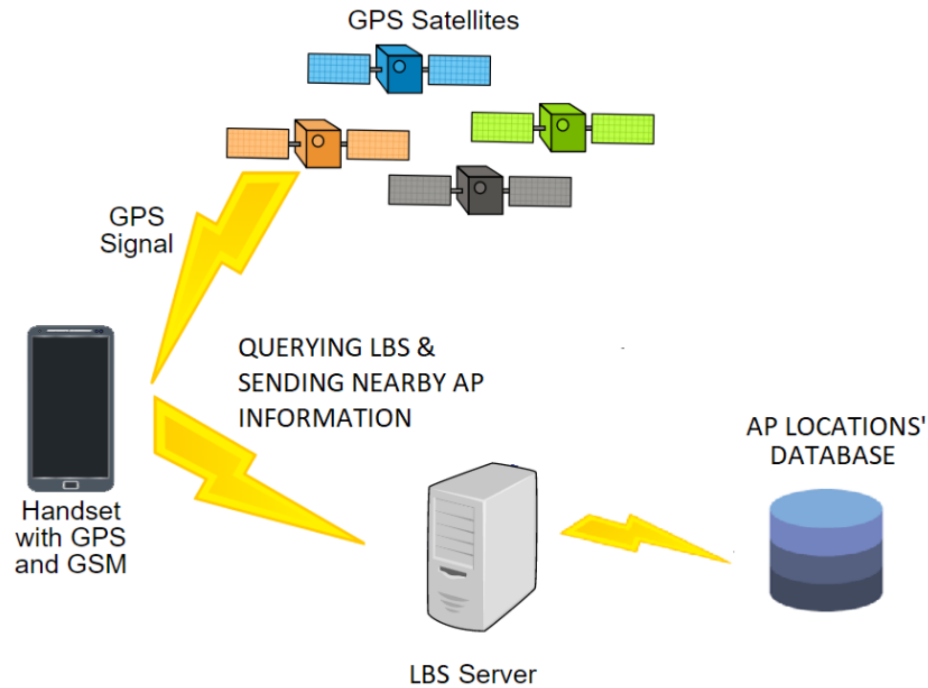

Figure 4.2: Application bound database of access point locations

This application bounded location awareness via the reverse querying location by sending publicly readable access point traces is quite useful in two main regards.

1. These kind of secondary services other than the main service of location based service providing is quite useful in situations where

    - GPS is not available or
    - Device is not capable of acquire location via GPS or
    - Even network based positioning is not possible due to manually switching of the location services in the device

    But in a position of consuming location based POI service via ISP and to acquire the location related context awareness not by querying using current location but by querying the service by access point traces in the vicinity.

2. LBS consumer applications which have been installed in the mobile device must communicate with the LBS for acquiring location-based POIs. This secondary service enables querying location related POIs without querying based on the current location of the consumer device but sending nearby access point identities.

This mechanism has been utilized in this research work in situations where it has been confidently identified that the device is in a previously visited place by device itself or even any of another consumer device of that particular service. This will fully save the energy to acquire the location by other mechanisms. Once the server realises that the device is moving into places where no previous traces are so far in the database and unable to extract out device location remotely, consumer applications will be notified to switch back to the next most energy efficient location acquiring method.

The location accuracy and the area coverage continuously increase when application is widely being used. Highly densified areas can be identified as user gathering areas or rather areas being served which contain lots of points of interests by location based service providers. In this research work an application bound central location database has been created. Normally those databases store Wi-Fi or cell identity traces against their respective locations in a common schema without considering any personalized content. In this research work while continuously populating the database it maintains personalized contents as well. Visited places of a particular user and tracing location sequences are stored in a tree structure.

4.4.2 Enabling Intelligent GPS Sampling Mechanisms Based on the State Differentiation of the Application

Applicable use cases which can be integrated with power management mechanisms should be identified as the first step.

1. Always high accuracy and fast response time required LBS applications
    - Location based security services
    - Location based emergency services
    - Location based gaming applications
2. Dynamic levels of accuracy and latency acceptable LBS applications
    - Location based advertisements and deals pushing application even a few kilometers radius accuracy is acceptable until the user hits on a particular interested advertisement.
    - Nearby attractions showing up applications which pop up some nearby attractions on the way, same as above case, even a few kilometers radius accuracy is acceptable until a traveler hits on a particular attraction.
3. Low accuracy required LBS applications

- Some non location based applications and still perform geo tagging as a value addition - Geo tagging in social media applications and location check in applications

- Some fleet and workforce management location based applications.

Considering above LBS classification, type 3 applications can be fully integrated with efficient power management strategies. Only distinguished medium and low accuracy acceptable modes in type 1 and 2 applications can be dynamically integrated with efficient power management mechanisms.

4.4.2.1 Differentiate High, Medium and Low Accuracy Acceptable Modes

Mode differentiation in a LBS application can be achieved using below parameters and their state values.

1. Application is being used either in live mode (L) or in background mode (B). Even in the live mode applications which can be categorized under type 1 and 2, can be further divided into
    - High accuracy required mode (H) or
    - Surfing mode or in low accuracy acceptable mode (S)
2. Device is moving (M) or stationary (S)
3. Nearby POIs are available (A) or not (N)

With the above three properties will create 12 total different states for a particular LBS application as shown in the table below.

Table 4.1: State differentiation for GPS sampling

	App Mode		Moving	Nearby POIs	GPS sampling mode
1	L	H	M	A	1
2	L	H	M	N	1
3	L	H	S	A	0
4	L	H	S	N	0
5	L	S	M	A	2
6	L	S	M	N	2
7	L	S	S	A	0
8	L	S	S	N	0
9	B		M	A	3
10	B		M	N	3
11	B		S	A	0
12	B		S	N	0

GPS sampling can be classified into several modes based on the application mode and other contextual property differentiation as illustrated in the table above as per the accuracy and latency acceptable for each of the state combinations.

GPS sampling modes

- 0 - No GPS sampling mode
- 1 - High accuracy GPS sampling mode
- 2 - Medium accuracy GPS sampling mode
- 3 - Low accuracy GPS sampling mode

Namely, other than state 1 and 2, all other states are applicable for enabling power saving mechanisms. State 3,4,7,8,11 and 12 can be fully avoided in GPS sampling. State 5 and 6 can be employed with medium accuracy GPS sampling strategies. State 9 and 10 are the states of minimum accuracy required where very low frequency GPS fixings will cater the accuracy requirements of the application.

4.4.3 Enabling Intelligent Communication with the Location Based Service Provider Based on the State Differentiation of the Application

Querying locations related POIs by sending any means of location information is the typical behaviour of LBS. Communication over the network for fetching location based services consume a considerable amount of energy as well. Applicable use cases which can be integrated with power management mechanisms in communication over network should be differentiated same as for the intelligent GPS sampling.

Considering the same above LBS classification under the intelligent GPS sample section, type 3 applications can be fully integrated with efficient power management strategies. Only distinguished medium and low accuracy acceptable modes in type 1 and 2 applications can be dynamically integrated with efficient power management mechanisms.

4.4.3.1 Differentiate High, Medium and Low Accuracy Acceptable Modes

The process of query data transmission to the location based service provider and receive location based service information can be differentiated using the same above parameters.

With the above three properties will create 12 total different states for a particular LBS application as shown in the table below. Transmission accuracy, acceptable latency and information fetching cycle frequency configuration can be intelligently controlled based on the modes. Transmission accuracy mode values are a bit different than GPS mods since continuous service information fetching needs to be performed even in standstill mode.

Table 4.2: State differentiation for data transmission over network

	App Mode		Moving	Nearby POIs	Data t/x over network mode
1	L	H	M	A	1
2	L	H	M	N	1
3	L	H	S	A	2
4	L	H	S	N	2
5	L	S	M	A	2
6	L	S	M	N	2
7	L	S	S	A	3
8	L	S	S	N	3
9	B		M	A	3
10	B		M	N	3
11	B		S	A	3
12	B		S	N	3

Data transmission over network can be classified into several modes based on the application mode and other contextual property differentiation as illustrated in the table above as per the accuracy and latency acceptable for each of the state combinations.

Data transmission over network modes

- 1 - High accuracy data transmission mode
- 2 - Medium accuracy data transmission mode
- 3 - Low accuracy data transmission mode

Data transmission over network or keep communicating with the location based service provider is still required even for device not moving states since there may be changes in points of interests in the vicinity as shown in state 3,4,7,8,11 and 12. State 5 and 6 can be integrated with medium accuracy data transmission mode since the application is in surfing mode and it is moving. States from state 7 to 12 can be integrated with low accuracy data transmission mode since application is not being surfed and device is not moving in state 7 and 8 and it is not being used in the states from 9 to 12.

4.4.4 Mobile Task Offloading

Complex processing within the device is again a costly operation. Mobile task offloading is a proven strategy to divide the processing cost and leverage inside processing capacity for other tasks and save energy.

Offloading is mainly to transfer the state of the application to a remote environment which is having more processing capacity and do the processing in the remote processor and get back the results. Proper analysis needs to be performed to distinguish offloadble segments before proceeding with the mobile task offloading. Network and the communication infrastructure of the application should be reliable and high bandwidth where it should be well capable of transmitting data over the network.

Mobile task offloading is not appropriate for all mobile applications because data transmission over network is again a costly job both in energy wise and cost wise. Therefore the balance point needs to be identified otherwise offloading will add extra overhead in all aspects such as energy consumption and charges for communication over the network.

Location based services do many continuous processing inside the device such as geofence monitoring.

- Some mobile applications are designed for parental controlling such as
  - Continuously monitor live locations of children on real time basis
  - Allow to define safe perimeters for children and trigger alerts and notify parents once they cross the boundaries
- Some applications are perform location based marketing
  - Continuously monitor current location and calculate the geofence triggering and perform retrieving relevant POIs from the remote server.

These kind of location based service provider applications anyway communicate over network with the remote server for retrieving services which means if any of off-loadable tasks segments can be identified those can be piggybacked with them.

State data piggybacking will not be added much overhead since devices must send the current location for the service querying purposes. Namely perimeters of geo fences can be maintained as personalized configurations and can be dynamically calculated at the server level and all the geofence based actions can be triggered at the same time in the server level itself.

Chapter 5

Implementation

Location Based Applications can be found in many streams which bring unique value additions to each of those applications. Location input is the primary input for those applications and continuous location fixing and location related service fetching are the most expensive tasks compared to limited power stored in a mobile device.

Three main cases can be identified as the main causes for draining the battery in LBS based POI aware applications.

1. Continuous and exhausting use of GPS.
2. Continuous data transmission and server communication via cellular network or Wi-Fi for location related service fetching.
3. Continuous processing for geofence based triggerings within the device.

All of the above battery consuming events will be handled intelligently in this research work while maintaining the best possible location related service information accuracy.

5.1 Prototype Creation

Location based service application prototype has been created for proving the concept. This application is named as “DealTella” which is a location

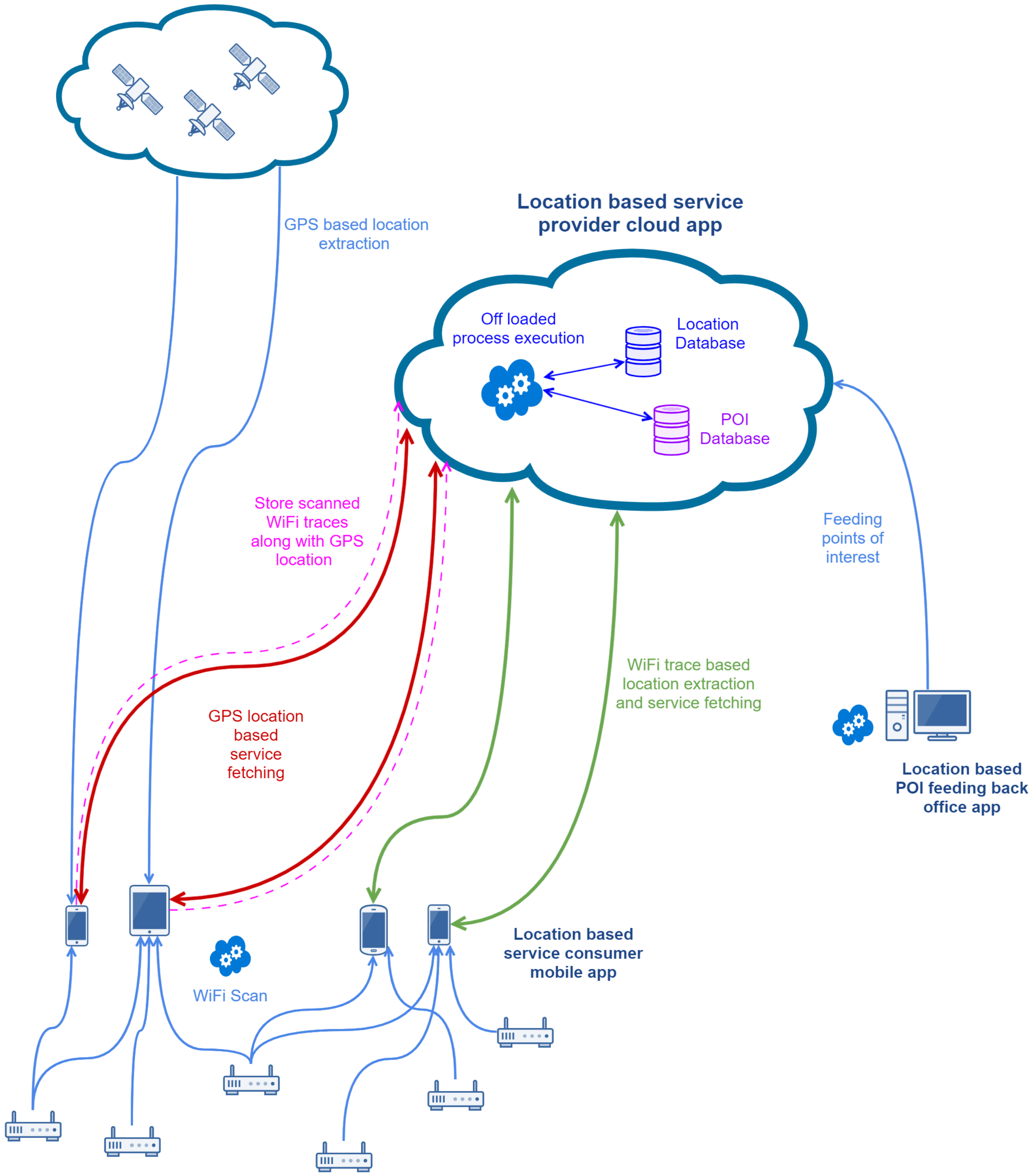

Figure 5.1: Enhanced architecture of the prototype Location Based Application

based deal telling application. Nearby deals and promotions will be fetched from a centralized location based service in a personalized manner.

For any kind of a client facing application there is a front end part and a back end part.

5.1.1 Location Service Client Implementation

For mobile application implementation cross platform frameworks have been considered over native scripting. Current cross platform frameworks are equally capable and applications with native look and feel can be created with quite less effort and cost within a single code base.

Flutter one of the cross platform toolkits developed and introduced by Google has been leveraged because of the above reasons and having intention to enhance the prototype into an actual working future product "DealTella" which should be compatible and easily manageable in all popular mobile operating systems with less effort and cost. Client application screens of the designed prototype are shown in Figure 5.2 and Figure 5.3

Natively compilation capabilities is one of Flutter's unique features where it provides the luxury to craft native like applications within a single code base with less effort and cost. Another best thing flutter provides is web and desktop support where if needed the same code base can be utilized for generating web or desktop applications.

5.1.2 Location Based Service Implementation

Google Firebase is a powerful platform for scalable and secure application creation which provides many useful services. Cloud Firestore is one of the cloud oriented real time NoSQL databases which is facilitating scalable infrastructure for serverless mobile and web application making in a more flexible and secure manner. It also provides Authentication services, Hosting facilities, Analytics, Monitoring facilities, Storage facilities, Advanced Machine learning and Artificial intelligence capabilities.

A flat NoSQL Firebase Cloud FireStore database has been designed and

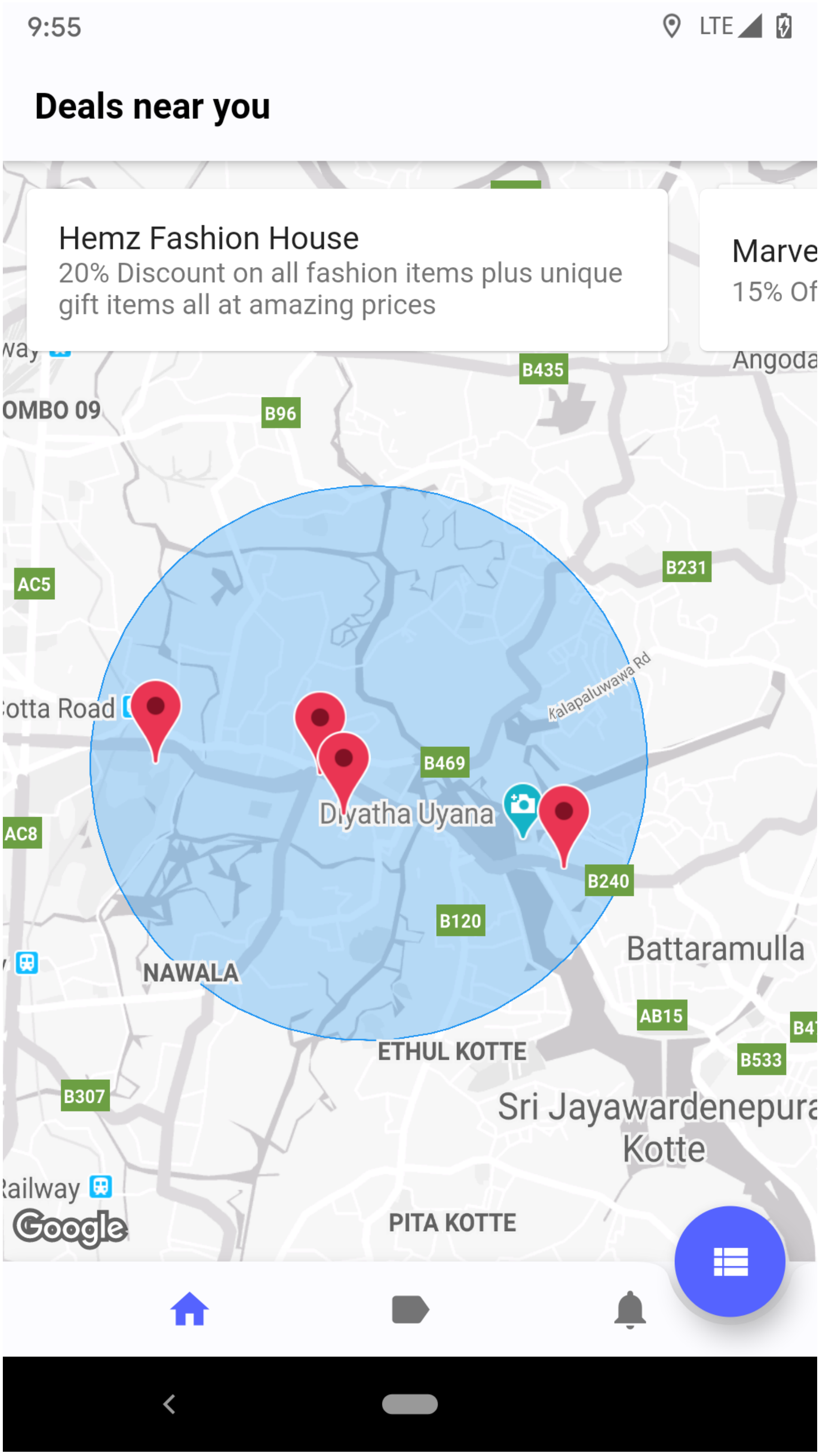

Figure 5.2: DealTella landing interface displaying nearby deals within 2 km radius - Map view

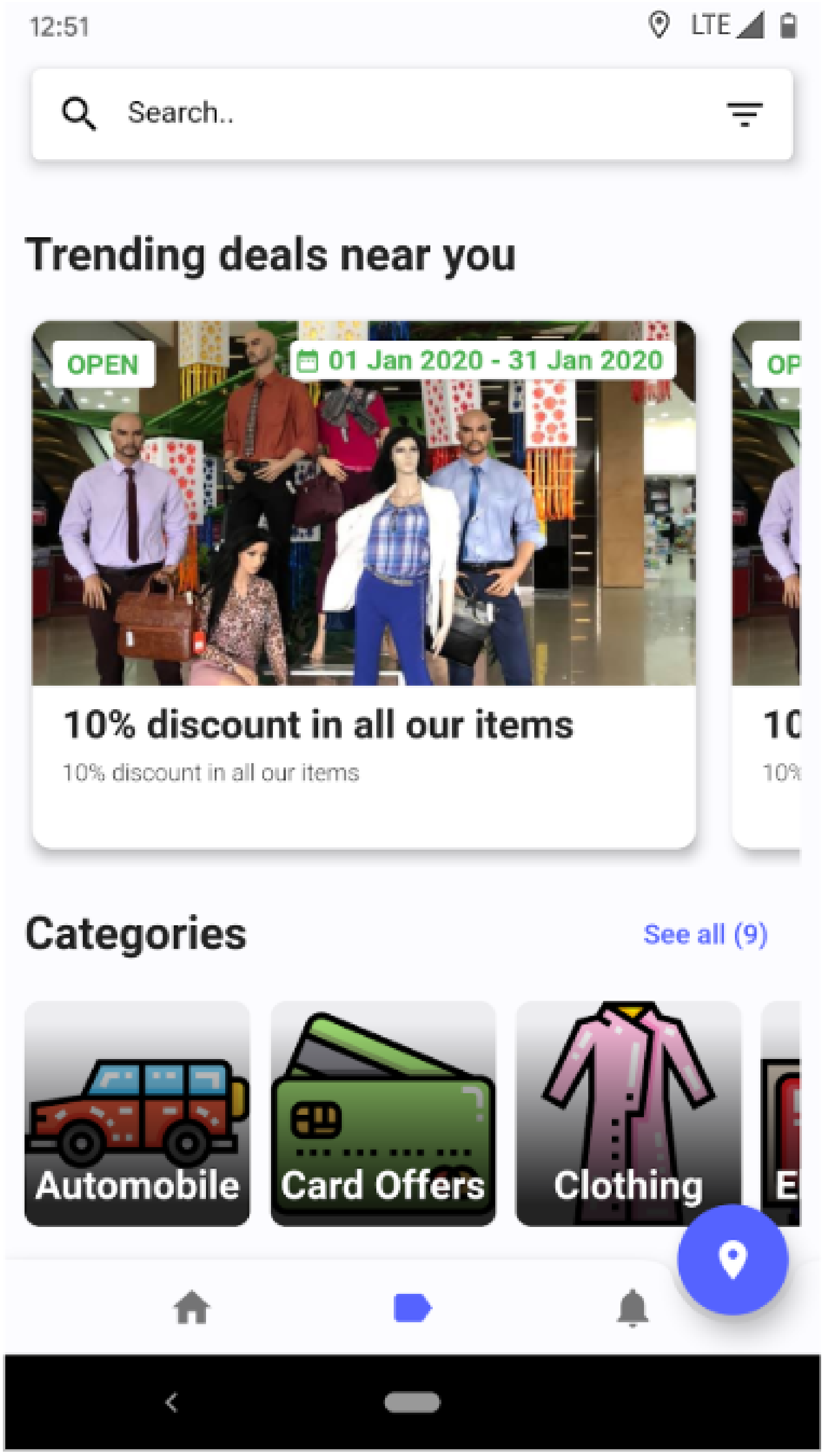

Figure 5.3: DealTella result listing interface - List view

hosted which is the location based service provider for the “DealTella”. Service consoles of the designed prototype application are shown in Figure 5.4 and Figure 5.5

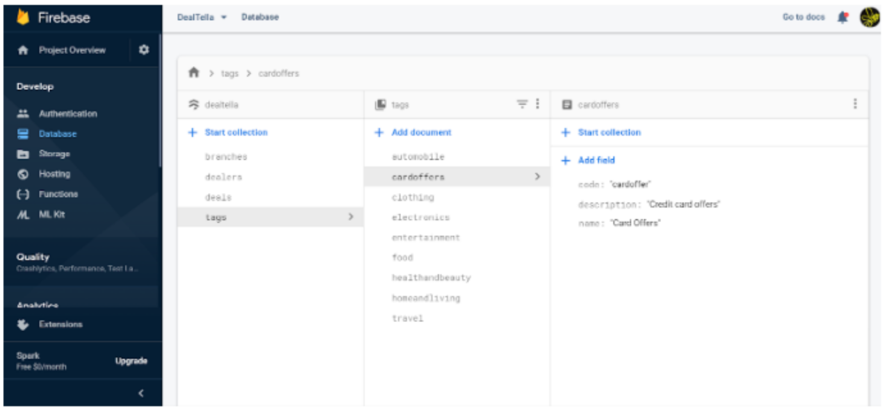

Figure 5.4: DealTella service - Collection of tags in Firebase database

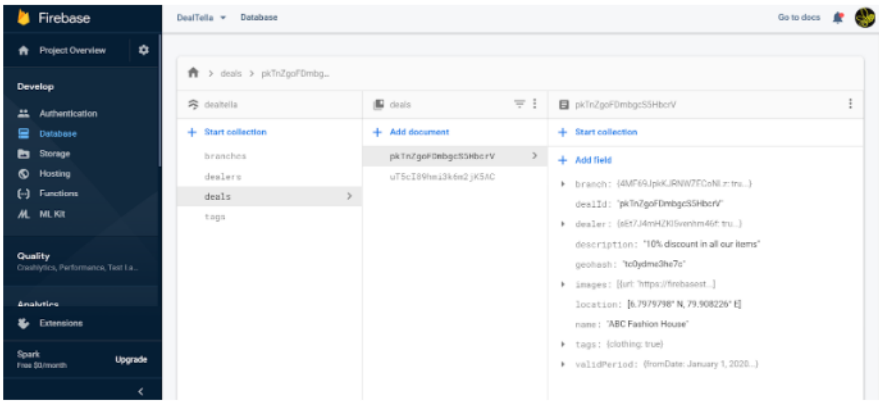

Figure 5.5: DealTella service - Collection of deals in Firebase database

5.1.3 Prototype Behavior

Dynamic levels of accuracy and latency acceptable LBS applications and low accuracy required LBS applications have been considered in energy optimization in this research work because of the larger portion of LBS apps included in this set and by applying correct optimizations high energy saving can be gained while having a better accuracy. Continuous GPS fixing is not required and has been controlled via various intelligent ways which will be described in upcoming next sections.

“DealTella” is a location based advertising application. Before applying the power consumption optimization remedies it continuously fixes the current location and continuously fetches location specific points of interest over the network by quring the location based service.

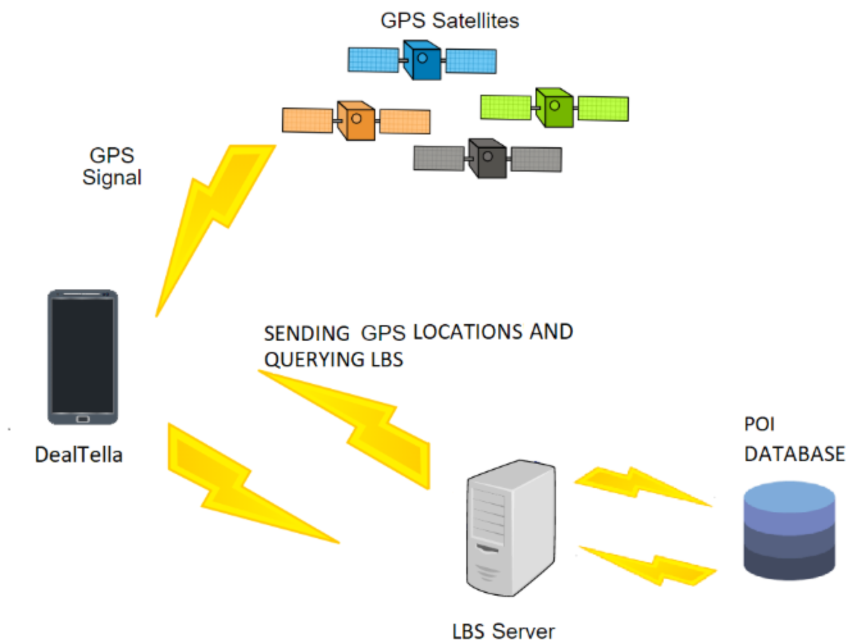

Figure 5.6: Reversed location extraction

All location based applications are common in providing real time services based on virtual geo fences where they all trigger actions based on the existence of the device within the perimeter or cross the virtual geofence in or out. There may be some offline or non real time services as well.

Geofence radius has been defined using configurations in the service level itself. Geo hashes have been used to store location details and search nearby POIs is performed by bit matching over current geohash and over neighbour geohashes. The radius configuration is a bit length which defines the bit depth or the bit resolution.

Based on the configured length of the first part of the current location geohash is searched in the all location hashes in the database for nearby POIs.

5.2 Optimizing Power Consumption

GPS sampling mode and the data transmission over network mode should be differentiated. Device sensors outputs have been utilized for recognizing the device activity. High level optimization of power consumption has been illustrated in Figure 5.7.

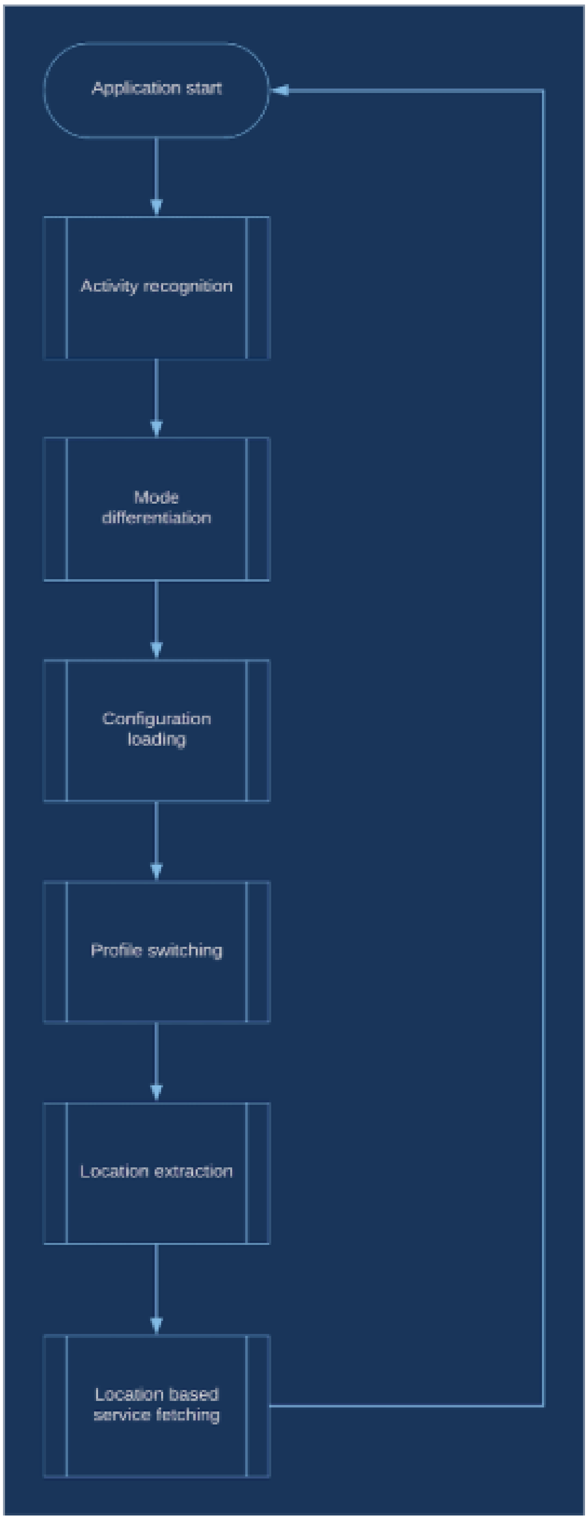

Figure 5.7: Optimizing power consumption

5.3 Supportive Technology Implementations

5.3.1 Activity Recognition

All the smart devices are now fully equipped with different kinds of sensors which are providing various useful measures and can be utilized in recognizing various user activities. Since smart applications are frequently incorporating these capabilities in their handy features, all the main mobile operating systems are now exposing these activity recognition capabilities as native functions.

Below is the list of inbuilt sensors.

- Accelerometer - This detects the acceleration of the device and simply using this sensor it can be measured how fast the device is moving in any linear direction.
- Gyroscope - This detects device orientation and device tilt and rotation accurately
- Magnetometer - This senses magnetic fields and is giving the compass output.
- GPS sensor - This is to locate the geo position
- Proximity Sensor - This is to detect any object in the proximity.
- Light sensor - This is to detect the light conditions outside.
- Pedometer - This is to track the number of steps taken by foot
- Thermometer - This measures inside temperature of the device

Other than these above common sensors high end smarts devices now equipped with sensors such as

- Heart Rate Sensor
- Air Humidity Sensor
- Geiger Counter

Utilizing output measures provided by the above mentioned sensors in making intelligent and smart applications is quite popular in smart applications creating industry which provide more context related than previous applications.

Activity recognition implementation which has been used in the prototype is illustrated below [8].

```
class _MyAppState extends State<MyApp> {
  @override
  Widget build(BuildContext context) {
    return new MaterialApp(
      home: new Scaffold(
        appBar: new AppBar(
          title: const Text('Plugin example app'),
        ),
        body: new Center(
          child: StreamBuilder(
            builder: (context, snapshot) {
              if (snapshot.hasData) {
                Activity act = snapshot.data;
                return Text("Your phone is to ${act.confidence}%
                    ${act.type}!");
              }

              return Text("No activity detected.");
            },
            stream: ActivityRecognitionAlt.activityUpdates(),
          ),
        ),
      ),
    );
  }
}
```

Core implementation of the location recognition is mentioned below [8].

```
class _ActivityChannel {
  StreamController<Activity> _activityStreamController =
      StreamController<Activity>();
  StreamSubscription _activityUpdateStreamSubscription;

  Stream<Activity> get activityUpdates =>
      _activityStreamController.stream;

  _ActivityChannel() {
    _activityStreamController.onListen = startActivityUpdates();
  }

  startActivityUpdates() {
    if (_activityUpdateStreamSubscription != null) return;

    _activityUpdateStreamSubscription = _eventChannel
        .receiveBroadcastStream()
        .listen(_onActivityUpdateReceived);

    _channel.invokeMethod('startActivityUpdates');
  }

  endActivityUpdates() {
    if (_activityUpdateStreamSubscription != null) {
      _activityUpdateStreamSubscription.cancel();
      _activityUpdateStreamSubscription = null;
    }
  }

  _onActivityUpdateReceived(dynamic activity) {
    debugPrint("onActivityUpdateReceived");
    assert(activity is String);
    var parsedActivity = Activity.fromJson(json.decode(activity));
    _activityStreamController.add(parsedActivity);
  }

  static const MethodChannel _channel =
      const MethodChannel('activity_recognition/activities');
```

```
  static const EventChannel _eventChannel =
      const EventChannel('activity_recognition/activityUpdates');
}
```

Above outlined activity recognition function used in determining below mentioned list of activity types along with the confidence level as well.

Table 5.1: Types of activity recognition

Output type	Detectable Activity type	Description
Integer	IN_VEHICLE	Device is in a car or some kind of a fast moving vehicle
Integer	ON_BICYCLE	Device is on a bicycle.
Integer	ON_FOOT	User with the device is running or walking.
Integer	WALKING	User with the device is walking and this is a sub occurence of the above.
Integer	RUNNING	User with the device is running and this is a sub occurence of the above.
Integer	STILL	User with the device is not moving.
Integer	TILTING	The device angle relative to gravity changed significantly.
Integer	UNKNOWN	When the system is unable to recognize the user's current activity.

5.3.2 Wi-Fi Tracing and Storing

Nearby Wi-Fi IDs can be collected and piggybacked with location based service fetching requests. Those collected Wi-Fi traces should be tagged with actual geo location as always as possible. All the geolocation tagged scanned Wi-Fi traces have been stored in the firestore as flat entries.

Wi-Fi tracing implementation is mentioned below [9].

```
static Future<List<WifiResult>> list(String key) async {
  final Map<String, dynamic> params = {
    'key': key,
  };
  var results = await _channel.invokeMethod('list', params);
  List<WifiResult> resultList = [];
  for (int i = 0; i < results.length; i++) {
    resultList.add(WifiResult(results[i]['ssid'],
        results[i]['level']));
  }
  return resultList;
}
```

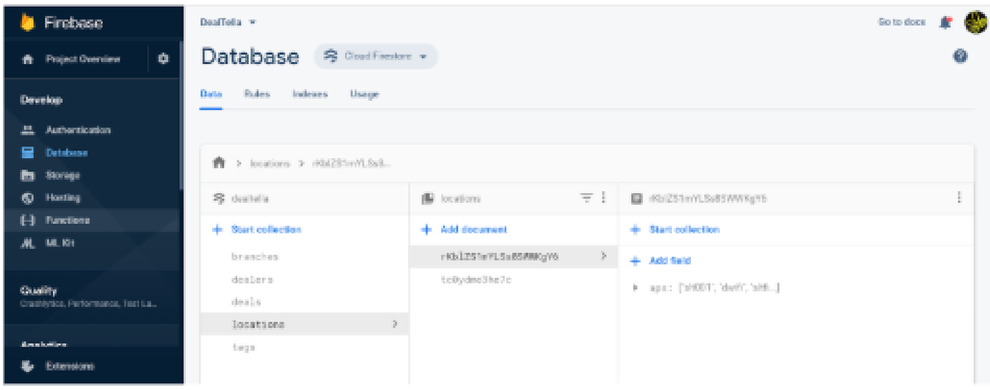

Figure 5.8: DealTella service - Collection of locations in Firebase database

This database will be a fast growing location verses scanned Wi-Fi traces collection. All the application installed devices contribute to this store and make it more rich on a continuous basis. Accuracy of the reverse queried location based on Wi-Fi traces will be continuously increased based on the data density of the location database.

5.3.3 Wi-Fi Trace Based Reverse Location Extraction

In this implementation, reverse location extraction has been tested and proven that once location collection is rich the application required accuracy can be gained and maintained while GPS sampling is switched off even when the device is moving.

For the testing purpose a route has been chosen to check the accuracy over power consumption.

- Collected and stored location mapped Wi-Fi traces over 20 times in the very same route from home to work with a configurable rate of GPS fixing.
- Then completely switched off the GPS sampling and reverse queried the location by only sending the scanned Wi-Fi traces to the application inbound location service over network again in configurable intervals.

It gives quite accurate location extractions and location related points of interests as it gives when the device is retrieving the location based on GPS.

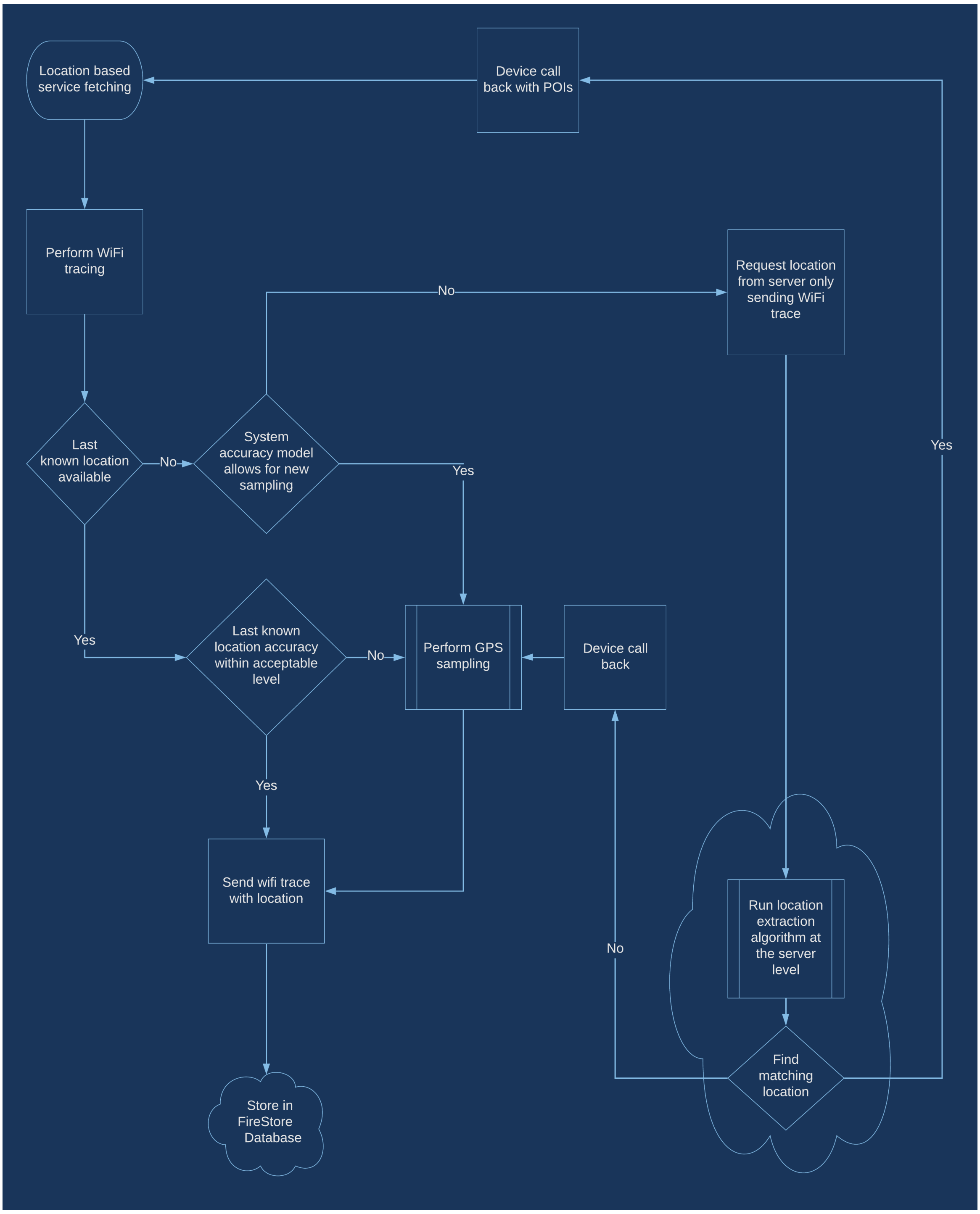

Figure 5.9: Wi-Fi trace based reverse location extraction

1. Geo location tagged Wi-Fi Access Point traces

   In a trajectory when device traveling from GeoLocation “m” to GeoLocation “m+k”

   $AP_{(m+k)n}$ will be the nth access point found in the location $GL_{(m+k)}$ where n is a positive integer.

$$
\begin{aligned}
\text{Start} = GL_m &= [AP_{m1}, AP_{m2}, ..., AP_{mn}] \\
GL_{m+1} &= [AP_{(m+1)1}, AP_{(m+1)2}, ..., AP_{(m+1)n}] \\
GL_{m+2} &= [AP_{(m+2)1}, AP_{(m+2)2}, ..., AP_{(m+2)n}] \\
&... \\
&... \\
\text{Destination} = GL_{m+k} &= [AP_{(m+k)1}, AP_{(m+k)2}, ..., AP_{(m+k)n}]
\end{aligned}
$$

2. Scanned Wi-Fi access point trace in the trajectory.
   AP_i = SSID of a scanned access point in the trajectory and
   $Array < AP_{ssid} >=$ Array of SSIDs scanned in a particular location in the trajectory
   $Array < AP_{ssid} >= [AP_i, AP_{i+1}, AP_{i+2}..., AP_{i+j}]$

3. Weighted map building for the traced access points in the array
   Input: Array of access points, Collection of geo location tagged access point arrays based on the last known location of the device.
   Output: Extracted geo location

```
weightedMap = {}
for i = 1, ... , [APssid] do
  for x = 1, ... , [{ GLx, [APssid] }]
    if [APssid] contains APi then
      if(!weightMap.hasKey(GLx)) then
        weightMap.set(GLx,1)
      else
        weightMap[GLx].value++
```

```
        end if
      end if
    end for
  end for
  return weightedMap
```

4. Extract location from the weightedMap
   Iterate over the map and extract key with the heights value and return the key as the extracted location.
   Input: **weightedMap**
   Output: Extracted geo location or "Unknown"
   highestWeightedLocations = []
   secondHighestWeightedLocations = []

```
forEach (value: <integer>, key: <string>) weightedMap
  if(highestWeightedLocations[0] &&
  value > weightedMap[highestWeightedLocations[0]].value)
    secondHighestWeightedLocations = highestWeightedLocations
    highestWeightedLocations = []
    highestWeightedLocations.push(value)
  else if( highestWeightedLocations[0] &&
  value == weightedMap[highestWeightedLocations[0]].value)
    highestWeightedLocations.push(value)
  end if
end for
  if(highestWeightedLocations.length === 1)
    return weightedMap[highestWeightedLocations[0]]
  else if(highestWeightedLocations.length >1)
    return
       getLocationHavingShortestDistanceToSecondHighestWeigtedLocations()
  end if
```

5. If valid location is extracted, all the location relevant points of interest can be responded back to the requested client application.

5.4 Mode Differentiation

Three main points have been taken into consideration when differentiating application power usage modes as mentioned in above.

1. Application is being used either in live mode (L) or in background mode (B). Even in the live mode applications which can be categorized under type 1 and 2, can be further divided into
   (a) High accuracy required mode (H) or
   (b) Surfing mode or in low accuracy acceptable mode (S)
2. Device is moving (M) or stationary (S)
3. Nearby POIs are available (A) or not (N)

5.5 Configuration Loading

Energy profiles have been defined and stored in the database which will be fetched and stored locally once the application is being initialized.

Those will be

- GPS sampling rate based on accuracy mode
- Data transmission and service fetching frequency based on accuracy mode
- Within device processing enabling or cloud offload enabling
- Enabling activity recognition.

Chapter 6

Evaluations

Modern leading operating systems invest more on optimizing battery consumption natively. Since modern smart applications are most of the time heavy process oriented for providing the best and most context related user experience. For achieving proactiveness and to feed the intelligence into applications it consumes more and more energy.

Location related service providing applications consume extra power on top of all the above mentioned consumption just for location extraction. In this research work main targets were to

- Reduce location extraction portion of power consumption
- Reduce service communication frequency
- Reduce internal process as possible by offloading possible calculations into cloud

by enabling all the mechanisms explained under the implementation section. By enabling intelligent sampling, a considerable percentage of energy saving could be achieved.

6.1 Results

Below results are based on the battery historian output for a selected period of time while only using prototype application only. While testing the implementation three main scenarios have been predefined as below.

- Scenario 1 - Scenario before enabling any power saving modes which is when the application is working under native behaviors of the operating system. This is the scenario where the actual problem exists.
- Scenario 2 - Scenario after enabling power saving mode. This will be the average case. GPS sampling has been controlled using adaptive location fixes using Wi-Fi based location extraction mechanism.
- Scenario 3 - Scenario after enabling extra power saving mode for identified routes. This is the best case scenario where the prototype application can hit the maximum power saving limits.

6.1.1 Scenario 1 - Before Enabling Power Saving Mode

Below are the maintained test conditions for all the test cases under scenario 1 testings.

1. Fully charge the device
2. Clean battery consumption data in the device
3. Switch on GPS and location service in the mobile device
4. Switch on mobile internet over Cellular Network Provider
5. Switch off Wi-Fi scan
6. Switch off all other client applications
7. Navigate through a route and let the application to communicate to LBS and fetch information
8. Measure drained battery percentage within a defined time window
9. Repeat the same upto defined number of occurrences under same test conditions

Under the above conditions, battery consumption details were collected over time while moving in a defined route for 5 times. Under these conditions one of the battery historian graphs is shown below.

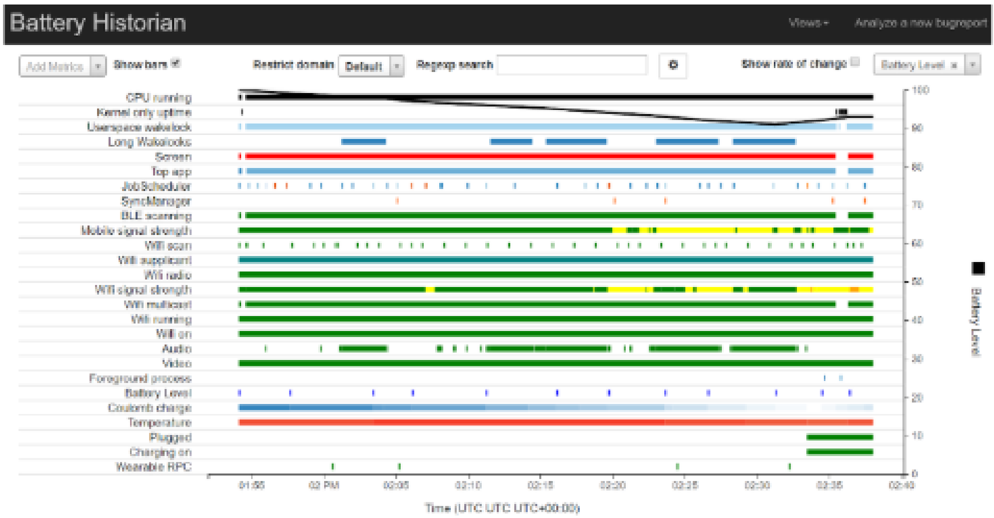

Figure 6.1: Battery history

As illustrated in the Figure 6.1, it does not show any Wi-Fi scan strips and Wi-Fi radio indications as Wi-Fi has been switched off during this period. The GPS fixing frequency is quite high compared to the illustration under scenario 2 as this is the native behaviour where the fixing frequency is determined by the operating system and the default nature of the application. Cases which have been derived under scenario 1 can be classified as highest accuracy providing cases while showing the highest power consumption out of these three scenarios.

Scenario 1 has been considered as the reference case for the research where the actual problem currently exists and the below two scenarios have been compared against it. In scenario 1 all the adaptive GPS utilization techniques haven't been enabled and measurements have been collected while the application behaves under pure and native conditions.

Measurements have been taken for 1 hour of period and battery consumption logs natively injected to the operating system have been extracted and illustrated using “Battery Historian”. The Android operating system running device has been used in the result collecting and validation process.

Below table illustrates the battery consumption percentages under scenario 1 in five occurrences. Average battery consumption was 24% for 1 hour of period.

Table 6.1: Scenariowise battery usage

Scenario	Battery usage
S1.1	23%
S1.2	24%
S1.3	20%
S1.4	28%
S1.5	25%

Accuracy of GPS with smart devices has generally been stated to be “about 5m”. But during this research GPS reading has been taken as the reference reading and GPS error has not been considered.

6.1.2 Scenario 2 - After Enabling Power Saving Mode

Below are the maintained test conditions for all the test cases under scenario 2 testings.

1. Fully charge the device
2. Clean battery consumption data in the device
3. Switch on GPS and location service in the mobile device
4. Switch on mobile internet over Cellular Network Provider
5. Switch on Wi-Fi scan
6. Switch off all other client applications
7. Navigate through a route and let the application to communicate to LBS and fetch information

8. Measure drained battery percentage within a defined time window
9. Repeat the same upto defined number of occurrences under same test conditions

Under the above conditions, battery consumption details were collected over time while moving in the same defined route for 5 times. Under these conditions one of the battery historian graphs is shown below.

Figure 6.2: Battery history

As illustrated in the Figure 6.2, both GPS and Wi-Fi radio scans can be identified in the Battery Historian output. Compared to scenario 1 the frequency of GPS sampling has been reduced as it shows a lesser number of strips under GPS scan row. Wi-Fi scanning has been enabled and based on Wi-Fi scanned output based reverse location extraction has been employed in parallel to the GPS sampling.

In this scenario the reading for the average battery was 18%. As it can be shown 6% of power saving could be achieved by enabling adaptive location extraction mechanisms along with pure GPS sampling.

While having positive reading in battery consumption point of view, the accuracy factor should not be highly deviated as well. Even though generally available GPS is having 0-5m error it has not been considered when calculating relative error in cases under scenario 2.

Below table illustrates the battery consumption percentages under scenario 2 in five occurrences. Average battery consumption was 18% for 1 hour of period. Once this is compared with average battery consumption of scenario 1, this shows 6% better battery consumption per hour.

Table 6.2: Scenariowise battery usage

Scenario	Battery usage
S2.1	18%
S2.2	17%
S2.3	19%
S2.4	19%
S2.5	17%

When configurations are set to on for controlling continuous GPS sampling, the accuracy of the extracted location may be reduced even though having 6% of reduction of battery consumption.

6.1.2.1 Accuracy Measuring

While the main process of the application is operating under adaptive GPS sampling mode, a completely separated independent thread has been triggered just to measure the accuracy of the adaptive GPS mode. Power consumption has been disregarded during this accuracy measuring activity since both adaptive GPS sampling and native GPS sampling were working parallelly. Only common thing that both processes shared was time where both jobs needed to synchronize up while location was being extracted. Extracted location using Wi-Fi supported adaptive mechanism was compared against the native GPS location. For all the location extraction samples were mapped against the location error and the robustness of the proposed system has been proven by carrying out the same over many occurrences. Cumulative Distribution Function (CDF) was used in presenting the measured accuracy readings.

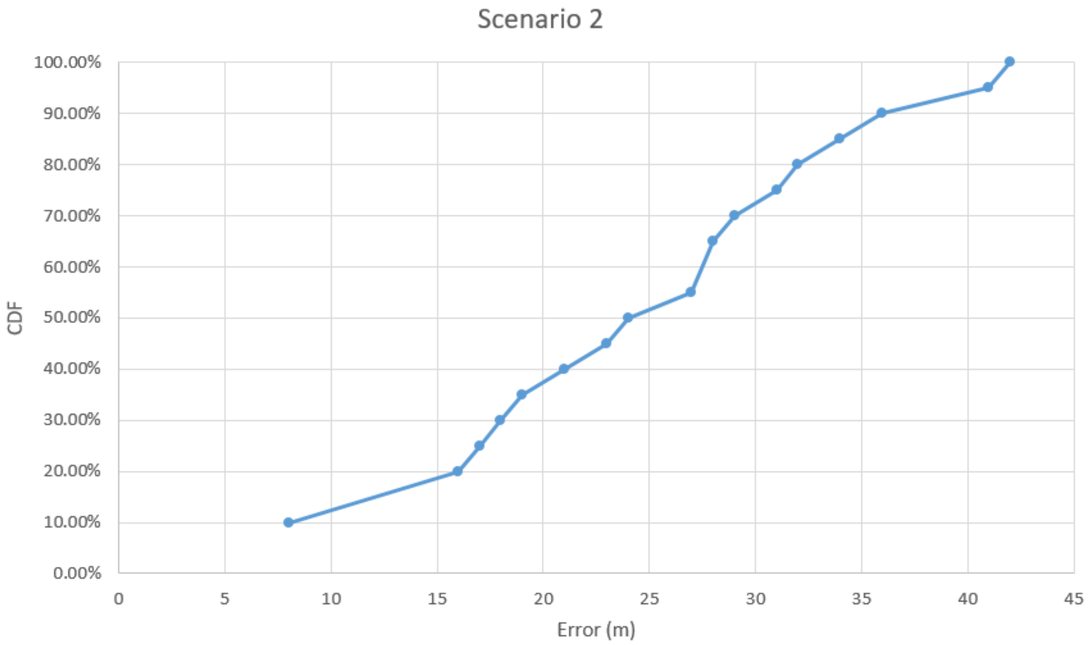

Figure 6.3: Precision of a single instance in scenario 2

6.1.3 Scenario 3 - Extra Power Saving Mode for Identified Routes

Below are the maintained test conditions for all the test cases under scenario 3 testings.

1. Fully charge the device
2. Clean battery consumption data in the device
3. Switch off GPS and location service in the mobile device
4. Switch on mobile internet over Cellular Network Provider
5. Switch on Wi-Fi scan
6. Switch off all other client applications
7. Navigate through a route and let the application to communicate to

8. LBS and fetch information only sending scanned Wi-Fi traces
9. Measure drained battery percentage within a defined time window
10. Repeat the same upto defined number of occurrences under same test conditions

This is the extra power saving enabled mode. Application is switched to this mode once application recognizes the route that the device is being moved as an early known trajectory. Once the Wi-Fi location map is rich enough to extract locations with highly dense locations along with location attached Wi-Fi traces map, this mode can be enabled for unknown routes as well. Since the accuracy of reverse location extraction is continuously increasing with the richness of the location mapped Wi-Fi traces volume.

Under the above conditions, battery consumption details were collected over time while moving in the same defined route for 5 times and one of the battery historian graphs is shown below.

Figure 6.4: Battery history

As illustrated in the Figure 6.4, it does not show any indications for GPS sampling and Wi-Fi radio sampling. Only radio network communication has taken place where location extraction happened only via the reverse location extraction mechanism. Since GPS is completely switched off battery consumption has been reduced by considerable percentage.

Below table illustrates the battery consumption percentages under scenario 1 in five occurrences. Average battery consumption was 7.8% for 1 hour of period.

Table 6.3: Scenariowise battery usage

Scenario	Battery usage
S3.1	8%
S3.2	9%
S3.3	7%
S3.4	7%
S3.5	8%

6.1.3.1 Accuracy Measuring

While the main process of the application is operating under fully reversed location calculation mode, a completely separated independent thread has been triggered just to measure the accuracy of this mode. Power consumption has been disregarded during this accuracy measuring activity since both reversed location extraction and native GPS sampling were working parallelly.

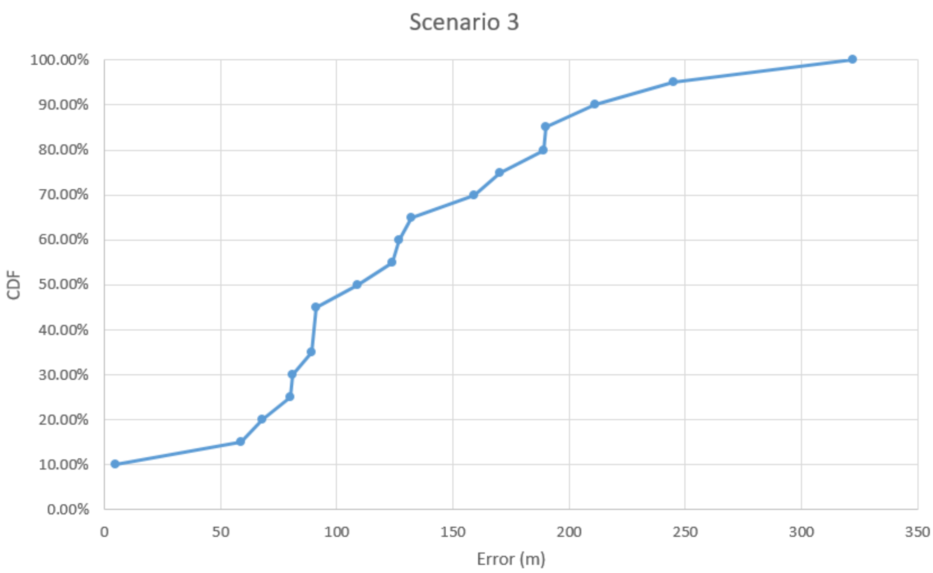

Figure 6.5: Precision of a single instance in scenario 2

6.2 Discussion

The graph below illustrates the holistic view of battery power consumption in all 15 scenarios.

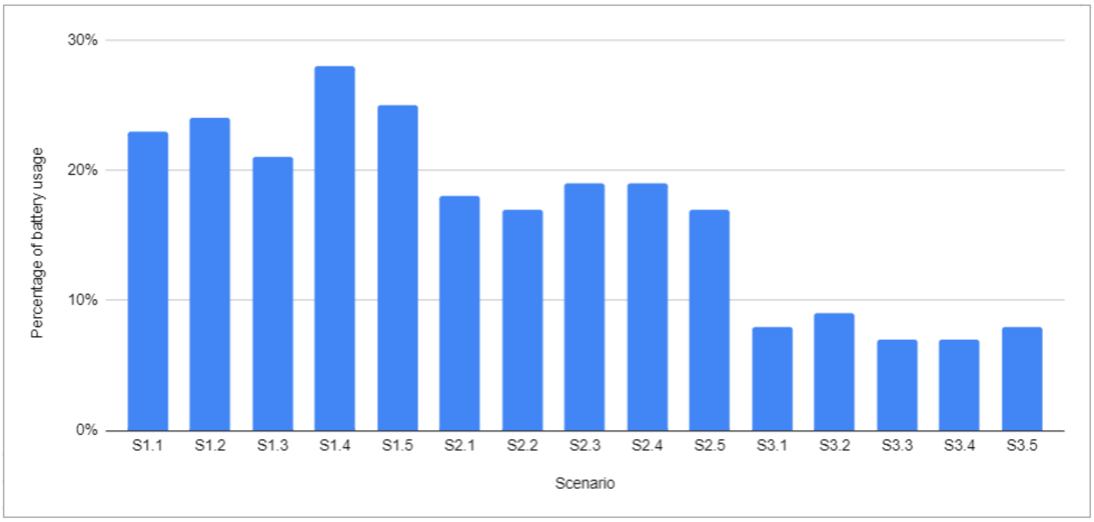

Figure 6.6: Scenario wise percentage of battery consumption

As it is illustrated scenario 2 and scenario 3 shows a considerable percentage of energy saving per hour. The average percentage gain of battery usage from scenario 1 to scenario 2 is 6%. The average percentage gain of battery usage from scenario 1 to scenario 3 is 16.2%. These are per hour battery usage readings while moving. In scenario 3 it is showing a considerable amount of energy saving where it gives a 16.2% percentage of gain over native situations. Under this scenario 3 mobile internet over Cellular Network Provider and Wi-Fi scanning have been switched on while GPS sampling is completely switched off which means by switching off the GPS it can save a considerable amount of energy.

But controlling GPS sampling directly sacrifices the accuracy of the location readings. That is where adaptive ways of location extraction have been introduced, implemented and tested. Because of that, the reverse location extraction mechanism has been introduced and tested in this research work in location extraction even without GPS. All the situations where applications can have an accurate GPS fix and if it is performed while having the device Wi-Fi is enabled as well, then application will collect nearby access point identities and upload to “DealTella” database. With the aid of this crowd-sourcing mechanism by employing mobile devices as mobile data collectors, prototype application could gain this much energy saving as illustrated in the table 6.4.

Table 6.4: Result summarization

Scenario	Average battery usage per hour	Average distance error (-5m or +5m)
S1	24%	-
S2	18%	24.5 m
S3	7.8%	133.8 m

As mentioned accuracy has been dropped as expected since GPS sampling has been controlled. Average distance error from scenario 1 to scenario 2 is 24.5 m and same from scenario 2 to scenario 3 is 133.8 m which is comparatively high error. This can be further reduced with the volume and richness of the Wi-Fi identity traces at the server level.

There exist two other supportive factors for this as well.

- Most of the Wi-Fi access points are stationary
- Coverage radius of an average access point is accommodating approximately 100 m.

Because of this for an already traced trajectory theoretically it is possible to gain 100 m accuracy due to identity interceptions. As illustrated in table 6.4 for an previously routed trajectory which means traces of the access points are available at the server side for reverse querying, the system could extract locations with a 133.8 m of average error distance.

Distribution of the measurements among their values has been graphed which gives a quick and summarized view of the distribution as illustrated in the CDF graph in Figure 6.7.

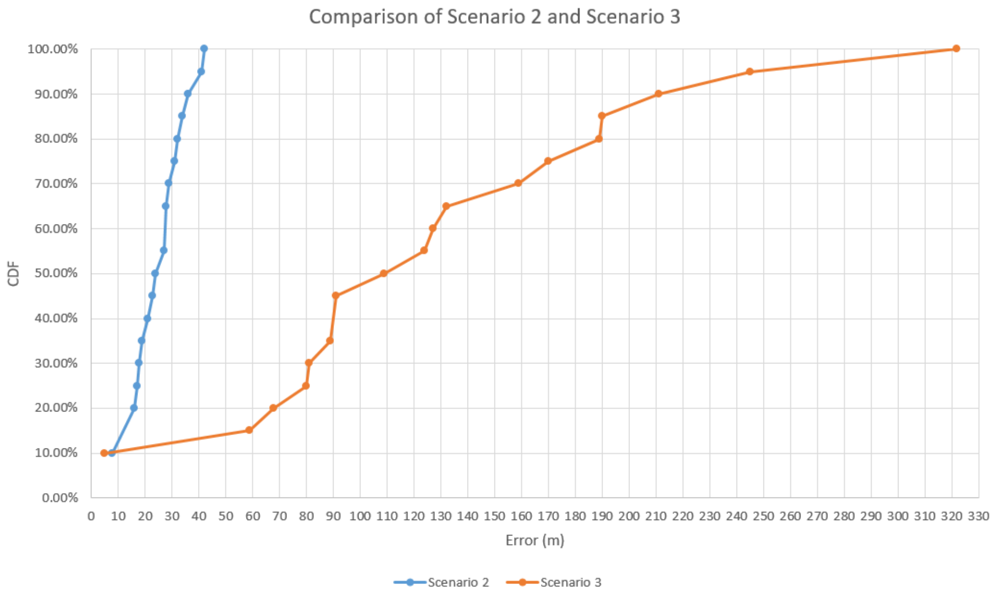

Figure 6.7: Comparison of Scenario 2 and Scenario 3

For scenario 2 the average error in meters is 24.5 m. and 80% of the error samples are below than 32 m which is a good reading while having 6% per hour battery usage gain as well. Worst figure for accuracy is 42 m.

For scenario 3 the average error in meters is 133.8 m. and 80% of the error samples are below than 186 m which is again a good reading while having 16.2% per hour battery usage gain as well. This is because GPS fixing is fully switched off during the measured period. Worst figure for accuracy is 322 m.

The same specification has been tested using three separate devices.

- D1: Google Pixel
- D2: Moto G7
- D3: Huawei Y6

Table 6.5 illustrates the accuracy and the distance error variation under each scenario tested using three separate devices. As it shows it can be clearly prove that the same battery draining pattern has been followed in all devices.

The reasons for those deviations are due to differentiation of operating system optimization and device hardware capabilities.

Table 6.5: Comparison of Scenario 2 and Scenario 3 tested using three devices

Scenario	Average battery usage per hour			Average error(-5m or +5m)		
-	D1	D2	D3	D1	D2	D3
S1	24%	25.6%	29.3%	-	-	-
S2	18%	20%	25.4%	24.5m	31.05m	43.15m
S3	7.8%	11.2%	16.5%	133.8m	161.3m	178.8m

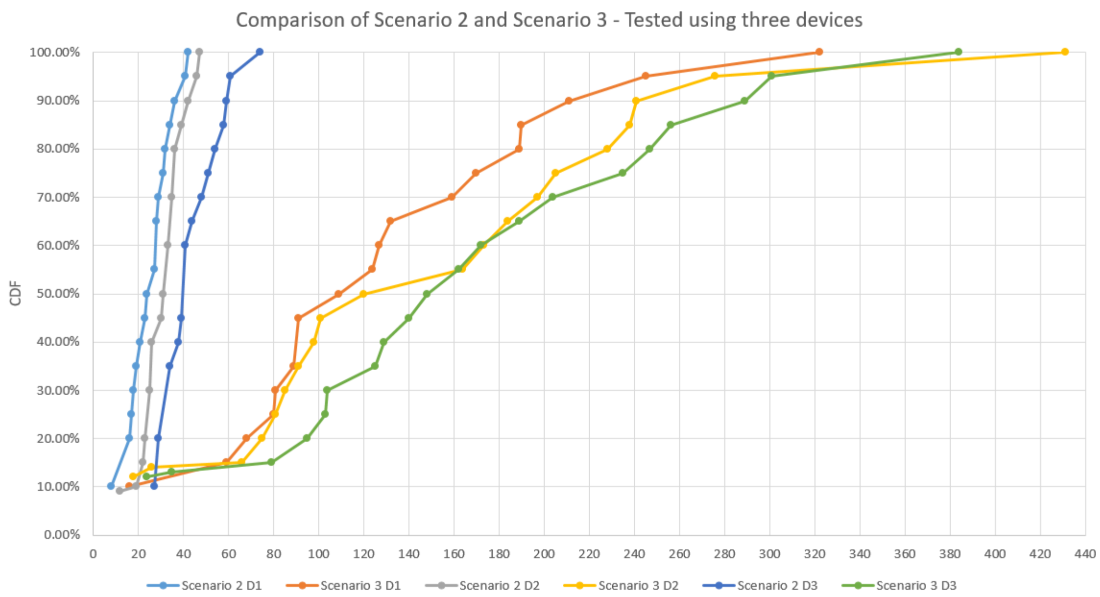

Figure 6.8: Comparison of Scenario 2 and Scenario 3 tested using three devices

As illustrated in 6.8 it shows the comparison in more graphical manner. Maximum error experienced has been measured as 322m, 384m and 431m in three devices respectively. As mentioned above the same pattern has been followed by all the cases.

Chapter 7

Conclusions

Based on the above accuracy measures and the battery historian graph readings under each scenario it can be proved that the optimized way of energy consumption which has been implemented by using intelligent location fixing through this research work is a success. Based on the accuracy readings this proposed solution can be utilized in many location based service applications while having their application specific thresholds for location fixing controlling configurations.

Modern leading mobile operating system building companies invest more on optimizing battery consumption natively. Battery charge life time is one of the main marketable concerns in every new release. While introducing new battery technologies for increasing the physical capacity, They research a lot in all possible soft solutions to gain the maximum efficiency in battery usage.

Those common solutions are natively available in mobile operating systems and most of the configurations are set to battery save modes by default. Since those solutions are designed as core implementations, it still does not support some application specific battery drains.

Since modern smart applications are most of the time heavy process oriented for providing the best and most context related user experience. To achieve this proactiveness and to feed the intelligence into applications it consumes more and more power. To achieve this context awareness and the proactiveness smart applications go beyond native battery usage recommendations and best practices.

In these kinds of situations, application specific power consumption optimization comes into play where there is still a lot of room for improvements in the context of power consumption optimization.

This research work, It was mainly focused on this concern in application specific power optimization by selecting a subset of applications which is location based service applications. Since location is one of the main context related knowledge which will add extra value to any kind of application but at a cost of location extraction effort. Since having the knowledge of current location is capable of injecting an extra level of user experience enhancement, Many application makers take location extraction into consideration even for applications which their main user case is non location oriented.

Battery draining in these kinds of situations is the main problem which has been addressed during this research work. As the end result shows, the concept has been proven with the implementation through the methodology followed.

7.1 Limitations

Proposed and implemented power saving mechanism can be extended in several directions as to gain more power optimization.

- Always high accuracy and fast response time required LBS applications will not be fully suitable with power management strategies introduced during the research. Applications such as location based security services, location based emergency services, location based gaming applications should always be integrated with best accuracy modes.

  But having these adaptive location extraction mechanisms for applications such as emergency locators, there is a possibility of location extraction which will be helpful when GPS is not available or devices are not capable of acquiring location via GPS even with a low accuracy.

- While comparing accuracy under scenario 2 and scenario 3 GPS error has not been considered as GPS positioning gives readings within 5 meters. All the accuracy measurements for the comparison have been taken by the GPS receiver in the device itself. When the accuracy is being measured the battery consumption has not been considered since GPS is enabled for capturing accuracy measurements.

- Another limitation is some of the proposed functionalities are not allowed or fully supported by iPhone OS (iOS). Even though the prototype is by design supported for all the main platforms (Android, Apple and Web) within the single code base, some of the core controlling has not been exposed by nature in iOS.

7.2 Future Work

Proposed and implemented power saving mechanism can be extended in several directions as to gain more power optimization.

- One of the main future enhancements for this application would be to transform the location fetching optimization core solution into a reusable library module and in a way that it can be used in any kind of location extraction situation.

  Required accuracy levels, possible location extraction sources should be able to pass via inputs to the library module along with application accuracy specific configurations as well. Then this library can be utilized as an importable module for all kinds of location extraction applications and obtain location with lesser cost.

- Wi-Fi trace matching has been offloaded as a cloud function and it can be optimized to match and extract out the locations quickly. This has not been addressed during the research since the main focus is to gain the maximum power gain at the device side. But if this application is going to be released as an actual working product this server side location extraction logic must be optimized.

- Personalize location extraction keeps user location traces which will collect and build up a user navigation profile. All of user activities, behaviors and routings can be captured and stored easily against users actual identity at the service side which raises a huge privacy issue. This must be decoupled with users actual identities as to protect the privacy of the users.

Ulrich Bareth et al. provided a solution for this important factor by mainly considering privacy issues and concerns in background trajectory tracking systems. A radio beacon based location resolvement method which avoids continuous background location lookups with LBS server, is proposed in opposition to conventional cellular location determination mechanisms with extra attention to privacy concerns while enhancing the energy saving as well.

But the exact same proposed solution by Bareth et al. will not be applicable for large scale or global applications.

As a future extension, this should be considered and honor users' privacy.

- Even though location recognition has been implemented in a more power optimistic mechanism, Location prediction has not been considered in this implementation. Although the same context has been considered and successfully implemented in many of the related literature which has been carried out mainly using hidden markove model.

  Next location of a moving device is one of the most important knowledge for any kind of location related service application to acquire. If that can be gained regular location fixings can be fully avoided since trajectory has been acquired.

  If the device is not retrieving services from a remote service, application can get the maximum energy saving by location prediction. For applications which is implemented in this research will be able to gain that much of a energy saving since it is communicating with the remote location service.

7.2.1 Creating the Product DealTella

One of the main future work is to develop the prototype into a shippable and marketable product which will notify the users with nearby deals and promotions for both mobile and web users.

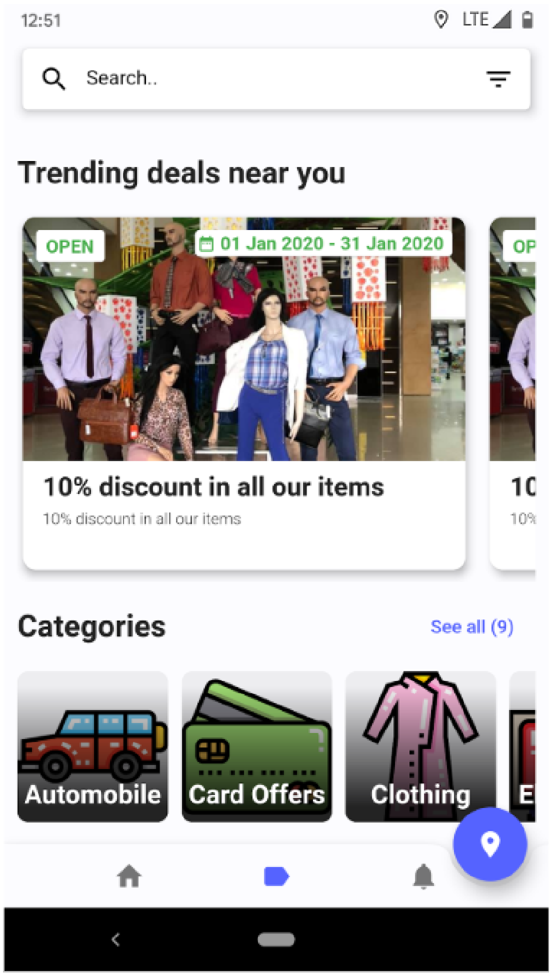

Figure 7.1: DealTella mobile application

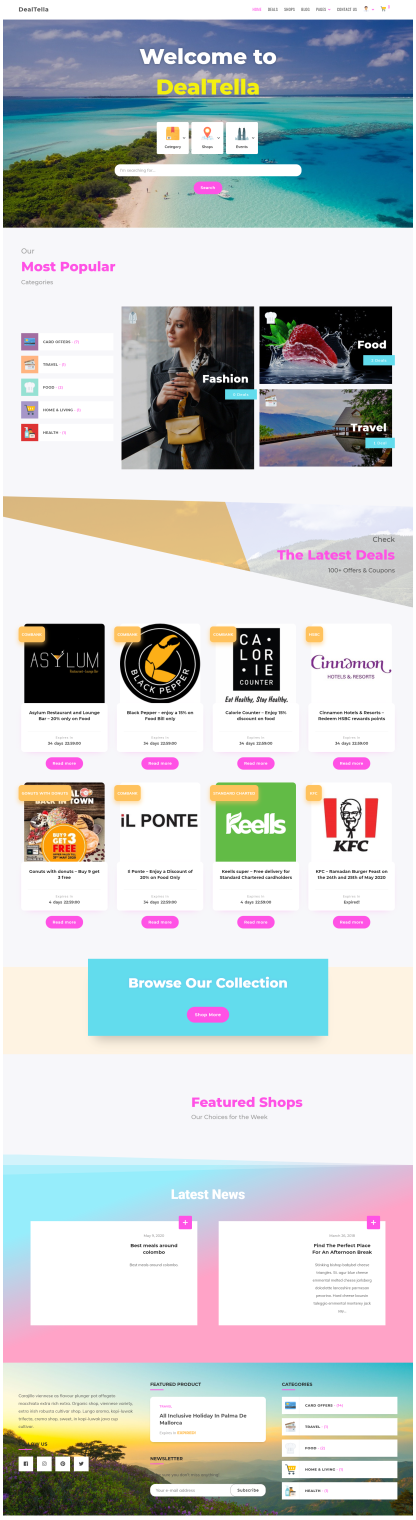

Figure 7.2: DealTella web application

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