Asset Tracking Solution with BLE and Smartphones: an Energy/Position Accuracy Trade-Off

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Abstract—This paper presents a novel asset tracking solution, preliminarily introduced in [1], aimed at tracking assets within construction sites or similar contexts. It is based on an ad hoc, heterogeneous sensor network, whose main components are: i) RFID tags, ii) Bluetooth Low Energy (BLE) tags and iii) smartphones.
It is sketched in Fig. 2. In more detail, the dashed lines represent wireless links and the continuous ones represent wired links. Two different mechanisms for tagging are jointly used: each asset is tagged by means of both RFID and BLE devices (indicated with “T” in Fig. 2). The Asset Management DataBase System (AMDBS) stores within its tables the relations between the assets and the associated tags. In this way, discovering and identifying tags permits to uniquely determine the asset itself; in the case of BLE tags, this allows modelling a one-to-one relation between the tables managed by the AMDBS and the information on the assets. In particular, when a BLE tag is detected, the AMDBS is queried and all the information, related to the asset which the BLE is associated to, is updated (e.g., its position).
RFIDs are employed to check when an asset is taken from a warehouse (or from an office) by a worker. Obviously, the involved buildings within the construction site are equipped with RFID readers. In addition, workers who handle assets are provided with another RFID tag in order to identify them through the AMDBS. In more detail, RFID tags of workers contain information such as employee name and registration number; tags on assets include data regarding asset typology, serial number, and maintenance expiration date. In this way, it is possible to determine which worker is using a given asset by means of the association between assets and workers in the AMDBS.
Foremen are equipped with a smartphone (also called Mobile Device and denoted as MD in Fig. 2), where two ad hoc apps, developed by the authors, called Asset Proximity Locator (APL) and Wandering Object Location Finder (WOLF), are installed.
The APL is automatically launched after the phone booting and runs as a background process; the WOLF is activated by the user whenever he desires to locate an asset. In practice, the APL implements all the functions needed to track the asset position. The proposed approach to discover assets, through BLE tags, trades precision and energy consumption (as illustrated in the performance evaluation section), thus guaranteeing the desired performance trade-off. The WOLF represents the interface for user interactions.
The devised system exploits a heterogeneous telecommunication network to convey information from/to its hardware and software components: BLE tags communicate to smartphones over IEEE-802.15; smartphones use GSM, GPRS or UMTS networks to share information with the Locator Server (LS) and the AMDBS. Mobile and fixed devices access the Internet via wired and/or wireless lines to get data from AMDBS.

The RFID readers are devices, coupled with a set of directive antennas, able to gain information from RFID tags. Readers are commonly deployed in the proximity of warehouses, garages, hangars, and workshops in order to monitor assets: specifically, they reveal that an asset has been taken by a specific employee and store the related notice into a local database that, in turn, updates the AMDBS by performing a remote insert query. All the technical details related to the management of the RFID data are not described here because they are entirely based on state of the art solutions currently off the shelf and out of the scope of this paper.

The employed RFIDs are passive and, consequently, need readers. Hence they cannot locate assets within a wide site area. The adoption of active RFIDs may represent a possible solution to locate assets but a number of expensive antennas is to be deployed, thus increasing the overall architectural cost. Modern BLE tags represent an alternative solution, which does not require any specific configuration to interact with smartphones. These tags may be stuck on the high-value assets, thus allowing their localization. The power is supplied by a 3-Volt battery that assures a long life, estimated in 2.5 years. The sole task they perform is the periodic transmission of the beacon, so that a smartphone may listen to it.

The mentioned AMDBS manages the database containing all the data related to i) asset handling, ii) asset location, iii) personnel, iv) associations between assets and Bluetooth MAC addresses, v) associations between assets and information
stored in RFID tags. The AMDBS may be accessed by means of several Web Applications, developed for both fixed and mobile devices, that permit browsing the data archived in order to obtain a possible track of each asset.

The APL is an application which runs over Android smartphones (MDs). It represents the core function of the asset tracking architecture because it allows locating assets in the construction site area. The strategy devised (hereinafter named "Asset Tracking Function") to localize the BLE tags is described and discussed in the next Section. The APL communicates the BLE MAC address, the Received Signal Strength (RSS), and the estimated position of the tag to the LS. The APL may use either a connection over the Internet, if a packet radio service is available, or the Short Message Service (SMS), always ensured in all areas covered by mobile telephony.

The Locator Server (LS) is aimed at managing data exchange to/from the APL. It is connected, via a serial link, to a GSM modem to receive the SMSs possibly generated by the APL. Furthermore, the LS accesses the Internet: consequently, the APL is able to establish a TCP connection if a packet radio service is provided by the base station which the smartphone running the APL is joined to. The LS function is composed of two software modules:

- Asset Management Client (AMC): it manages all the data acquired and gathered by the APL;
- Asset Tracker Application (ATA): it exploits the functionality of AMC in order to update the data hosted in the AMDBS.

Another software module is represented by the Web Application (WA), which plays the role of bridge between the user app named WOLF (described in the next subsection) and the AMDBS. Upon receiving a data request from the WOLF, the WA converts it into a structured sequence of SQL queries to be delivered to the AMDBS.

The WOLF is an Android application installed on smartphones that allows users searching for a certain asset in order to achieve information on which employee has taken it and its last recorded position. The user may perform a search by asset or by person. The WOLF generates a proper request for the WA which, in turn, enters a query into the AMDBS. Upon receiving a response from the WA, the WOLF shows the retrieved information to the user by using Google maps web-services in order to display the asset position. Fig. 1 reports the WOLF asset searching interface (left) and a screenshot of the scenario in which the presented architecture has been tested (right).

II. STATE OF THE ART

The efficiency of manufacturing and construction operations can be seriously affected by the amount of time spent searching for misplaced high value things, hereafter referred as assets [2]. The problem of asset localization and tracking is not new: a large number of research works faced it in different scenarios and under various constraints. For instance, the authors of [3] proposed an approach for tracking mobile robots in an indoor environment; the work presented in [4] addressed the problem of localizing assets by means of the joint use of two technologies, namely radio and ultrasonics: the assets to be monitored are equipped with ultrasonic devices and communicate with each other through a wireless sensor network in order to estimate their position.

In the last years, smartphones applications and have become popular (see [5] and references therein). The approach presented in [6] exploits smartphones for object localization and it requires the cooperation among users (i.e., the foremen). The method presented in [7] also aims at tracking mobile assets defined as GPS-aware devices. In practice, the smartphone is the asset to be tracked by means of its GPS receiver. Differently from our solution, this approach does not employ tags or other resources (e.g., images) to identify the assets (i.e., GPS-unaware objects). However, the authors attempt to save resources (e.g., energy), while limiting accuracy detriment. Furthermore, the relevance of asset tracking has been highlighted in [2]. In the first paper, passive RFIDs are employed while the second approach proposes several radio localization techniques. In fact, in addition to GPS, other radio interfaces are used, such as Wireless Local Area Network (WLAN) and Ultra-Wide Band (UWB).
To the best of authors knowledge, the architecture proposed in this paper is the first that uses, at the same time, smartphone and tags both RFID and BLE.

![Diagram](Image)

**Fig. 2.** The overall architecture of the proposed Asset Tracking scheme.

### Algorithm 1 The proposed APL application.

```plaintext
1: procedure GetBLEData() 
2:   start;
3:   Turn the GPS on;
4:   
5:   if !GPSsignal then
6:     goto top;
7:   end if;
8:   AllBLEcen ← Scan for BLE tags beacons
9:   loop for k = 1, k++, k < size (AllBLEcen)
10:  Read data from AllBLEcen (k)
11:  Send data to the database
12:  end loop;
13:  Turn the GPS off;
14:  Wait the Scan Period [s]
15:  goto start
16:  end procedure
```

### III. ASSET TRACKING FUNCTION

Considering that the accuracy of the asset location represents a crucial requirement in terms of precision, in this Section, a suitable approach to determine the asset position, employed by the proposed asset tracking strategy, is briefly presented, as well as its related accuracy, even if already introduced in [1], for the sake of completeness.

The asset position estimation is obtained by using the APL Android application that exploits the presence of BLE tags: when a BLE tag is detected, the application determines the smartphone location by using the GPS and senses the Received Signal Strength (RSS) of the received beacon so to estimate the distance between the tag and the smartphone itself. Finally, the MD sends to the LS all these data together with a timestamp and the detected BLE MAC address.

The APL calculates the distance \( d \) between the smartphone and the BLE tag. This distance estimation is achieved by exploiting the polynomial function reported in Eq. (1). Specifically, such equation converts the RSS acquired by the smartphone into the distance between the BLE tag and the smartphone itself.

\[
\hat{d} = \sum_{n=0}^{N} c_n W^n \tag{1}
\]

The quantity \( W \) is the actual RSS measured (in dBm) by the smartphone, \( \hat{d} \) is the estimated distance (in metres), and \( N \) is the polynomial degree. Solving Eq. (1) means to find the best set of the \( c_n \) coefficients, such that it provides the most accurate estimation of the distance in a least-squares sense. In the same way as reported in [1], the estimation was performed by collecting the RSS at 20 different distances ranging from 0 to 20 [m] with a fixed step size of 1 [m]. For each distance 30 different RSS values were acquired. A robust polynomial estimation was achieved by means of a Cross-Validation (CV) approach. The set of 30 values was divided in three subsets of 10 RSS values each. Two sets were employed to train the polynomial function and the third one was used to test the goodness of the approximation. The approach was repeated three times, in order to obtain three different trials corresponding to all the possible combinations of two 10-RSS values sets for training and one for testing. Finally, the achieved results were averaged.

Let us define with \( D \) the maximum considered distance which is 20[m], in our tests. The quantities \( I_Ψ \) and \( I_Φ \) are the number of RSS acquisitions used for the training and the testing phase, respectively. Let: \( i \) \( Ψ \) be a \( D \times I_Ψ \) matrix of the RSS values employed in the training phase, where the generic \( Ψ_{d,i} \) element represents the \( i-th \) acquisition of the RSS sensed at distance \( d \); \( ii \) \( Φ \) be a \( D \times I_Φ \) matrix of the RSS measures employed during the test phase, where the generic \( Φ_{d,i} \) element represents the \( i-th \) acquisition of the RSS sensed at distance \( d \).

Considering the notation previously reported, the bet values of the coefficients \( c_N \) (namely denoted with \( C^* \)) is computing by solving the expression in Eq. (2)

\[
C^* = \arg \min_{C \in \mathbb{R}^N} \sum_{d=0}^{D} \sum_{i=0}^{I_Ψ} \sum_{n=0}^{N} c_n \Psi_{d,i}^n - d \tag{2}
\]

For our tests we have employed three different degrees of polynomial approximation: \( N = 3, N = 4, \) and \( N = 5 \). The histograms shown in Fig. 3 reports the bar plots of the mean (\( \mu_N \)) and the Explained Variance (EV) of the estimation error when the polynomial orders \( N = 3, 4, \) and 5 are employed. They have been calculated by using the following equations

\[
\begin{align*}
\mu_N &= \frac{1}{I_Φ \cdot D} \sum_{d=0}^{D} \sum_{i=0}^{I_Ψ} \left| \sum_{n=0}^{N} c_n \Psi_{d,i}^n - d \right| \\
\sigma_N^2 &= \frac{1}{I_Φ \cdot D} \sum_{d=0}^{D} \sum_{i=0}^{I_Ψ} \left( \sum_{n=0}^{N} (c_n \Psi_{d,i}^n - d - \mu_N) \right)^2
\end{align*}
\tag{3}
\]

The bars in Fig. 3 clearly show that the mean positioning error \( \mu_N \) (which around 2 [m]) is not affected by the the degree of the polynomial approximation. In more detail, incrementing the degree of the polynomial approximation
does not result in a lower positioning error.

IV. ENERGY/POSITION ACCURACY TRADE-OFF

When MDs are considered, energy consumption is a crucial issue. In the following we describe and model the energy required by a smartphone to perform the asset tracking function. Such analysis, already reported in [1], has been provided also here to allow a better and a more complete understanding. Successively, an optimization of the rate at which the GPS receiver has to be kept off) is performed in order to ensure that the smartphone battery lasts for an entire working shift (i.e., 8 hours).

We tested the GPS power consumption of different Android mobile devices so to obtain reliable and robust results. Specifically, the Discharge Time (DT) of the smartphone’s battery depends on both the energy required by the smartphone and the Total Charge (TC) of the battery itself. In particular, power consumption strongly depends on whether the GPS is active or not. Table I shows, for two off-the-shelf Android Smartphones, the DT values referred to the case where the GPS is kept on for a continuous reading, all radio modules are disabled and LCD display is off. All the power measurements have been measured using the Power Tutor (PT) [8].

Obviously, considering that smartphones also execute different tasks (calling, sending messages), which may involve other hardware components, the aforementioned DTs represent an upper bound of the actual time the battery is able to supply the phone. The strategy of switching on and off the GPS receiver allows us to save energy, but has the drawback of does not permit a precise localization since a certain amount of time must be spent to (re)activate the GPS. It is straightforward that a suitable strategy must be adopted to achieve a reasonable energy/position-accuracy trade-off.

The estimation of background power was performed by monitoring the two smartphone classes (Class 1 and Class 2). All the devices were completely charged and used in the Regular usage pattern, according to the definition in [9], until their batteries have not been completely drained. The experiment was iterated several times and the results were averaged. As a result, smartphones, supplied with a 9.88 [Wh] and a 5.55 [Wh] battery (i.e., the TCs), presented an average Discharge Time (DT) of about 28.55 hours and 13.80 hours, as shown in Table I. Consequently, the mean background power is about $\frac{5.55}{28.55}=0.195$ [Wh/h] and $\frac{9.88}{13.80}=0.720$ [Wh/h] for Class 1 and Class 2, respectively.

<p>| TABLE I. THE TWO SMARTPHONES CLASSES CONSIDERED. |</p>
<table>
<thead>
<tr>
<th>Class 1</th>
<th>Class 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Charge [Wh]</td>
<td>5.55</td>
</tr>
<tr>
<td>Discharge Time [h]</td>
<td>28.55</td>
</tr>
</tbody>
</table>

The Asset Tracking Function periodically activates every Scanning Period (SP). The function periodically activates every Scanning Period (SP). The SP is divided in two sub-periods: $\tau_{on}$ and $\tau_{off}$, namely $SP = \tau_{on} + \tau_{off}$. The GPS receiver stays on for $\tau_{on}$ seconds and off for $\tau_{off}$ seconds. Considering that a Bluetooth scan lasts about 15 [s] (i.e., 12 [s] for the discovery process plus 2 [s] to deliver the results [10]) and that the GPS position can be exploited only when the Bluetooth scan is in progress, we have fixed $\tau_{on} = 15$ [s] for all the experiments. In other words, we keep the GPS interface active only for the time needed by the MD to complete a BLE scan.

Let $p_{on}$ and $p_{off}$ be the power consumptions when the GPS receiver is active and not active, respectively. $p_{gps}$ is the power required to execute all the background tasks. When GPS is on, $p_{on} = p_{off} + p_{gps}$, being $p_{gps}$ the power involved in the use of the GPS. Thereby, the overall energy $\Delta TC_i$ consumed in the $i$-th scanning period is

$$\Delta TC_i = p_{on} \cdot \tau_{on} + p_{off} \cdot \tau_{off}$$

If $N_{SP}$ is the number of SPs the device is able to perform, then the Total Charge (TC) of the battery can be expressed as

$$TC = \sum_{i=1}^{N_{SP}} \Delta TC_i$$

Supposing that the discharge time DT is a multiple of SP

$$N_{SP} = \frac{DT}{SP} = \frac{DT}{\tau_{on} + \tau_{off}}$$

Substituting Eq. (4) in Eqs. (5) yields

$$\sum_{i=1}^{N_{SP}} \Delta TC_i = \sum_{i=1}^{N_{SP}} p_{on} \cdot \tau_{on} + p_{off} \cdot \tau_{off}$$

Thereby,

$$TC = N_{SP} (p_{on} \cdot \tau_{on} + p_{off} \cdot \tau_{off})$$

Then the battery lifetime is given by

$$DT = \frac{\tau_{on} + \tau_{off}}{p_{on} \cdot \tau_{on} + p_{off} \cdot \tau_{off}} TC$$

Keeping $\tau_{on}$ fixed to 15[s], the critical parameter of Eq. (8) is $\tau_{off}$. Setting $DT^{*}$ to the working shift duration and using Eq. (9), the corresponding time period $\tau_{off}^*$ (during whitch the GPS receiver has to be kept off) is

$$\tau_{off}^* = \frac{TC - DT^{*} \cdot p_{on}}{DT^{*} p_{off} - TC} \tau_{on}$$

A usage pattern with extended time of listening to music, combined with more lengthy or frequent phone calls, messaging and a bit of emailing.
The proposed model highlights that the minimum battery lifetime corresponds to the case when the GPS receiver always stays active (viz. \( \tau_{\text{off}} = 0 \)). Let \( DT^{\text{min}} \) be the battery duration when \( SP = \tau_{\text{on}} \), then

\[
DT^{\text{min}} = \frac{\tau_{\text{on}}}{p_{\text{on}} \cdot \tau_{\text{on}}} TC = \frac{TC}{p_{\text{on}}} \tag{11}
\]

Consequently, when \( \tau_{\text{off}} > 0 \)

\[
DT^\ast > DT^{\text{min}} = \frac{TC}{p_{\text{on}}} \tag{12}
\]

Therefore, given a smartphone TC and the specific values for \( p_{\text{on}} \) and \( p_{\text{off}} \) (i.e., \( p_{\text{bg}} \) and \( p_{\text{gps}} \)), it is easy to check the condition in Eq. (12) and to determine \( \tau_{\text{off}}^\ast \) able to assure a battery lifetime equal to \( DT^\ast \).

In this paper, considering the measures related to devices of the Class 1 (see Table I), \( p_{\text{on}} = 0.802 \) [W], \( p_{\text{off}} = 0.402 \) [W], and \( TC = 5.55 \) [Wh]. Setting \( DT^\ast \) equal to 8 [h] (i.e., the working shift duration) the condition in Eq. (12) is satisfied, being \( DT^{\text{min}} = \frac{TC}{p_{\text{on}}} = 6.920 \) [h].

Concerning the Class 2, if \( DT^\ast = 8 \text{[h]} \), we have \( p_{\text{on}} = 0.746 \) [W], \( p_{\text{off}} = 0.346 \) [W] and \( TC = 9.88 \) [Wh]. In this case \( DT^{\text{min}} = \frac{TC}{p_{\text{on}}} = 13.24 \) [h] (as shown in the previous section). Consequently, when a smartphone from the Class 2 is employed the asset tracking function can continuously access the GPS receiver because the battery can provide energy for an entire working shift (\( SP = \tau_{\text{on}} = 15 \) [s]). When a smartphone from the Class 1 is used, we need to set \( \tau_{\text{off}}^\ast = 5.565 \) [s], which is rounded to 6 [s]. Hence, \( SP = \tau_{\text{on}} + \tau_{\text{on}}^\ast = 15 \text{[s]} + 6 \text{[s]} = 21 \text{[s]} \).

It is worth noting that the longer the SP, the longer the battery discharge time. Furthermore, if the Class 1 smartphones are considered, it is easy to compute that, when the SP is set to 21 [s], the battery lasts for about 8 hours (i.e., the common work shift duration). Consequently, a SP longer than 21 [s] should be chosen.

V. EXPERIMENTAL RESULTS

A. BLE Energy Consumption

We analysed BLE tags manufactured by StickNFind Technologies, which employ a normal watch lithium battery CR2016, whose nominal capacity is 90 [mAh]. In order to find out the amount of energy involved when a beacon is emitted, we carried out some practical measurements on several off-the-shelf BLE tags. More in detail, a 10-Ohm resistor was inserted between the button battery and the tag circuitry, as reported in Fig. 4. The voltage across the resistor was measured in order to estimate either the current traversing the tag and, as a consequence, the energy as function of time. This measures were repeated on different tags for several times and the achieved results were averaged.

The left part of Fig. 5 plots the temporal behaviour of the measured current traversing BLE tag when a beacon is transmitted. It should be noted that the BLE tags spend about 4500 [s] to emit a beacon and the current presents a series of peaks from about 6 to 11 [mA]. The time interval from 450 to 1700 [s] is partially spent to wake up the device from the sleepy mode to the full active one. The mean current is 3.44 [mA]. The right part of Fig. 5 shows the corresponding energy growth as a function of time: the total energy involved in a beacon emission amounts to 11.6 [mJ] and the mean power to 10.3 [mW]. The beacon is periodically emitted every 5 [s]. Moreover, the BLE tag requires about 0.9 [W] to keep itself active in sleepy mode. Therefore, the total energy consumed between two consecutive beacons amounts to 53 [J] and, consequently, the battery lifetime is longer than 2.5 years. This agrees with the technical specifications that highlight a maximum power of 15 [mW] at 1[Mbit/s] transmission rate.

B. Simulation Results

Even if the proposed platform has been designed, implemented and deployed, all the results reported in this section have been obtained through an ad hoc simulator, implemented in C++ by the authors. According to the the concept of accuracy of the asset location and completeness of the acquired information and considering that the accuracy of the location has been already evaluated in Section III, this sub-section presents the results concerning the Full Detection Probability (FDP) and the Ageing time. The first one is the probability to detect all the BLE tags in the construction area, at least once during a simulation run while, the second one, is the time between two successive detections of the same BLE tag. These metrics were evaluated versus the SP and the number of BLE tags. The total number of simulation runs amounts to 15000. The results achieved are reported in Fig. 6 and in Table II.

Fig. 6 reports the Aging time as a function of the SP and number of employed BLE tags. The plot highlights increasing values of the Aging while increasing the SP. This is motivated by the fact that when the time between two consecutive scans increases (i.e., the SP is longer), a smaller number of BLE tags is detected, thus increasing the Aging time.

In more detail, when the SP is around 120 [s] or longer, the plot presents significant variations while varying the number of BLE tags. Also in presence of few BLE tags the Aging time
CONCLUSIONS

An asset tracking architecture has been presented that jointly exploits the traditional asset tracking techniques and the facilities offered by modern Android smartphones. Specifically, the paper focused on the use of an ad hoc, heterogeneous sensor network, whose main components are: Bluetooth Low Energy (BLE) and RFID tags and smartphones. The final aim of the architecture is to guarantee a good level of tracking accuracy while saving smartphones’ resources, in particular, energy.

The two main functions of the proposed solution are: i) the Asset Proximity Locator (APL) discovers the BLE tags present in the area and it estimates the distance between the smartphone and the tags and ii) the Wandering Object Location Finder (WOLF) which is the user interface.

The paper demonstrates that a Energy/Position Accuracy trade-off can be found to allow saving enough energy to ensure smartphones’ battery lifetime equal to (or greater than) an entire working shift (8 hours, in typical construction sites). Indeed, simulations demonstrate that, when the scan period is lower than 21[s], the system is able to detect almost all the tags in the construction site with an Ageing time lower than 300[s].

REFERENCES


