Hindawi
Wireless Communications and Mobile Computing
Volume 2023, Article ID 2880229, 9 pages
https://doi.org/10.1155/2023/2880229

Research Article

Analysis and Evaluation of Tracker Tag Efficiency

Enrique Hernández-Orallo,[1] **Antonio Armero-Martínez**,[2] **Carlos T. Calafate**,[1] **and Pietro Manzoni**[1]

[1]*Department of Computer Engineering (DISCA), Universitat Politècnica de València, Valencia, Spain*
[2]*Department of Engineering Projects, Universitat Politècnica de València, Valencia, Spain*

Correspondence should be addressed to Enrique Hernández-Orallo; ehernandez@disca.upv.es

Received 12 July 2022; Revised 21 December 2022; Accepted 26 December 2022; Published 12 January 2023

Academic Editor: Patrick Seeling

Tracker tags, such as Apple's AirTags and Tile's trackers, are small and cheap devices for finding lost items. Tags use Bluetooth technology and community tracking to find the location of lost tags whenever a compatible smartphone passes nearby. When we lose a tag, several questions may arise, like what are the chances of finding it? Or, when will we receive a notification of its detection? Unfortunately, companies such as Apple or Tile do not provide technical information about the efficiency of their tags. Thus, this paper is aimed at answering those questions based on a methodological analysis and evaluation of tags' efficiency. The main aspects that impact the efficiency of finding a lost tag are the detection range, community size, and human mobility. These aspects are evaluated in a campus scenario, showing that the probability of finding lost tags is very high: more than 98% of them were found, and the average detection time was about 1 hour.

1. Introduction

Tracker tags (tags for short) are small and cheap devices to help find lost things. They are attached to someone's most prized possessions and leverage technologies such as the Internet of Things (IoT), mobile crowdsensing (MCS), and opportunistic networking (OppNet). They allow tracking their location without using more expensive and energy-consuming technologies such as GPS (Global Positioning Systems) and cellular communications.

The most successful and known tag devices are Apple's AirTags, although there are alternatives such as Samsung's Galaxy SmartTag and Tile's tags. In essence, all these devices work the same way. When lost, they use Bluetooth Low Energy (BLE) to regularly broadcast short messages (advertisements) to potential nearby smartphones to get tracked. If a compatible smartphone receives such a message, it will relay the tag's location using its broadband communication capabilities.

The tracking is mainly based on the *opportunity* of contacting a nearby smartphone and, consequently, on human mobility patterns. For example, if a tag is lost in a crowded place (such as a metro station), a nearby smartphone will likely detect the lost tag. Nonetheless, if the tag is lost in a forsaken place (such as a remote field or a parking lot), the opportunity of finding the tag will be very low. Summing up, a key aspect for evaluating the efficiency of tags is human mobility and social behaviour.

This paper is aimed at evaluating the efficiency of tags based on known diffusion models and mobility patterns. The idea is to assess critical aspects of the tracker tags' performance, such as the probability of finding a lost tracker and the delay incurred. Firstly, we provide an expression to obtain this probability depending on time and the flow of people in an area. Secondly, we evaluate the efficiency in a real university campus scenario. We performed real and simulated experiments based on human mobility, which is a crucial issue in finding a lost tag.

As a general conclusion, we state that the most important factors that can improve the detection of a lost tag are increased people's mobility and detection range. Particularly, we studied that people's flow rate in a location is the key factor to increase the detection (that is, it not only depends on the number of devices in a place, as we can obviously think, but mostly on their mobility). The experiments confirm these facts: the success of finding a lost tag as well as its detection time depends on the flow rate of the place where the tag was lost and the tag's detection range.

On the other hand, the proposed evaluation methodology, based on simulating real human mobility traces, is generic and suitable for any tag tracker. It can be used in other scenarios by providing a mobility trace and considering their main performance parameters such as detection range and the size of the community (number of users that can detect lost tags). For example, the results of our experiments show that the probability of finding the lost tags is very high: more than 98% of the lost tags were found, and the average detection time was around 1 hour.

This research fills a gap in the evaluation of this practical technology. Unfortunately, companies like Apple, Samsung, and Tile have not provided technical information about the performance and efficiency of their tracker tags. Furthermore, this is the first research paper that evaluates their efficiency as far as we know.

The paper is organised as follows: Section 2 describes the related work. Section 3 introduces how tracker tags work, detailing their main limitations. Section 4 is devoted to presenting the proposed methods to evaluate the efficiency of tags. Section 5 describes the experiments performed and the main results. Finally, Section 6 summarises the paper.

2. Related Work

Tracking systems (or locating systems) are very common nowadays. Generally speaking, the goal of a tracking system is to track the location of persons or objects. Most tracker systems are based on GPS and/or cellular phones and have been used extensively to track vehicle fleets, ships, and containers, to name a few. Nevertheless, localisation by GPS or cellular networks implies the use of more expensive, bulkier, and energy-consuming devices which are not suitable for the tracking of small personal items, such as backpacks, wallets, or keys.

The emergence of cheaper and low-energy communications technologies, such as Bluetooth and RFID (radiofrequency identification), has allowed the development of new tracking models. Bluetooth Low Energy (BLE) and RFID have been used extensively for indoor tracking and localisation [1, 2]. Some proposals combine the use of these technologies and smartphones to track assets in construction sites [3, 4].

For short-range localisation, all tracker tags use BLE radio technology to locate the tags. The latest tags combine BLE with UWB (ultrawideband) to increase location accuracy to the range of 5 to 10 centimetres. Nevertheless, it was its combination with smartphone localisation capabilities which gave them a supplemental advantage: the opportunity of using other smartphones to detect lost tags and share their location with their owners. This idea was initially devised by the Tile company in 2012 [5], followed by Apple's AirTag and Samsung Galaxy SmartTag, both in 2021.

The technology behind finding lost track tags is the result of combining mobile crowdsensing with opportunistic networking, which allows mobile users to share sensed data (in this case, the location of the lost tags) without requiring the use of fixed infrastructure in the tags. Mobile crowdsensing has become a new way to monitor and collect data of interest using the sensors integrated into mobile devices (such as smartphones, tablets, and wearable devices) [6–8]. Novel applications can share this data using opportunistic networking, a networking paradigm where communications occur upon the establishment of ephemeral contacts among mobile nodes using direct communication (i.e., Bluetooth) [9–11]. This combination of MCS and OppNet is usually referred to as opportunistic mobile crowdsensing [12].

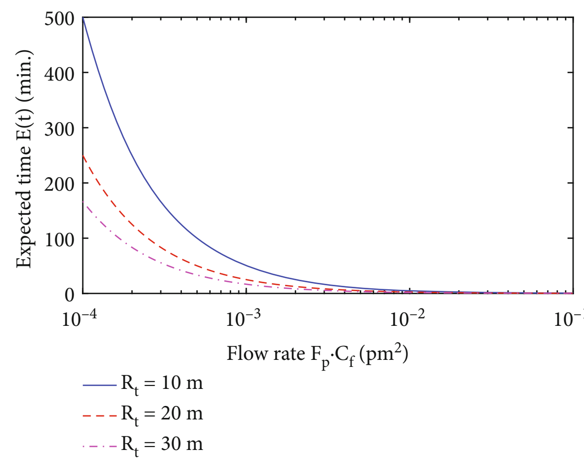

Figure 1: Expected time ($E(t)$) in minutes to find a lost tag depending on the flow rate of people wearing compatible smartphones ($F_p C_f$) for different detection ranges (R_t). Note that the x-axis is in log scale.

Table 1: Detection range and average detection times in the studied spaces.

Space	AirTag range	Tile range	AirTag detection
Park	32 m	52 m	72 min
Classroom	16 m	27 m	20 min
Canteen	14 m	26 m	15 min
Corridor	12 m	15 m	45 min
Office room	9 m	14 m	32 min

The main advantage of OppNet is that it supports low-cost and seamless communication between devices regardless of location, as tracker devices require. Still, its effectiveness depends mainly on the users' mobility. The dependence between mobility and the performance of OppNets has been studied extensively; see, for example, [13–17]. The study of human mobility and social behaviour is also essential for evaluating information dissemination in these opportunistic networks [18–20].

Only a few academic papers have studied tracker tag models and their efficiency. For example, Kulshrestha et al. [21] propose SmartITS, which combines the use of a smartphone as a sensing unit that scans the frames transmitted by nearby wireless devices (Wi-Fi/Bluetooth) and extracts their unique MAC address in order to localise the tags using the

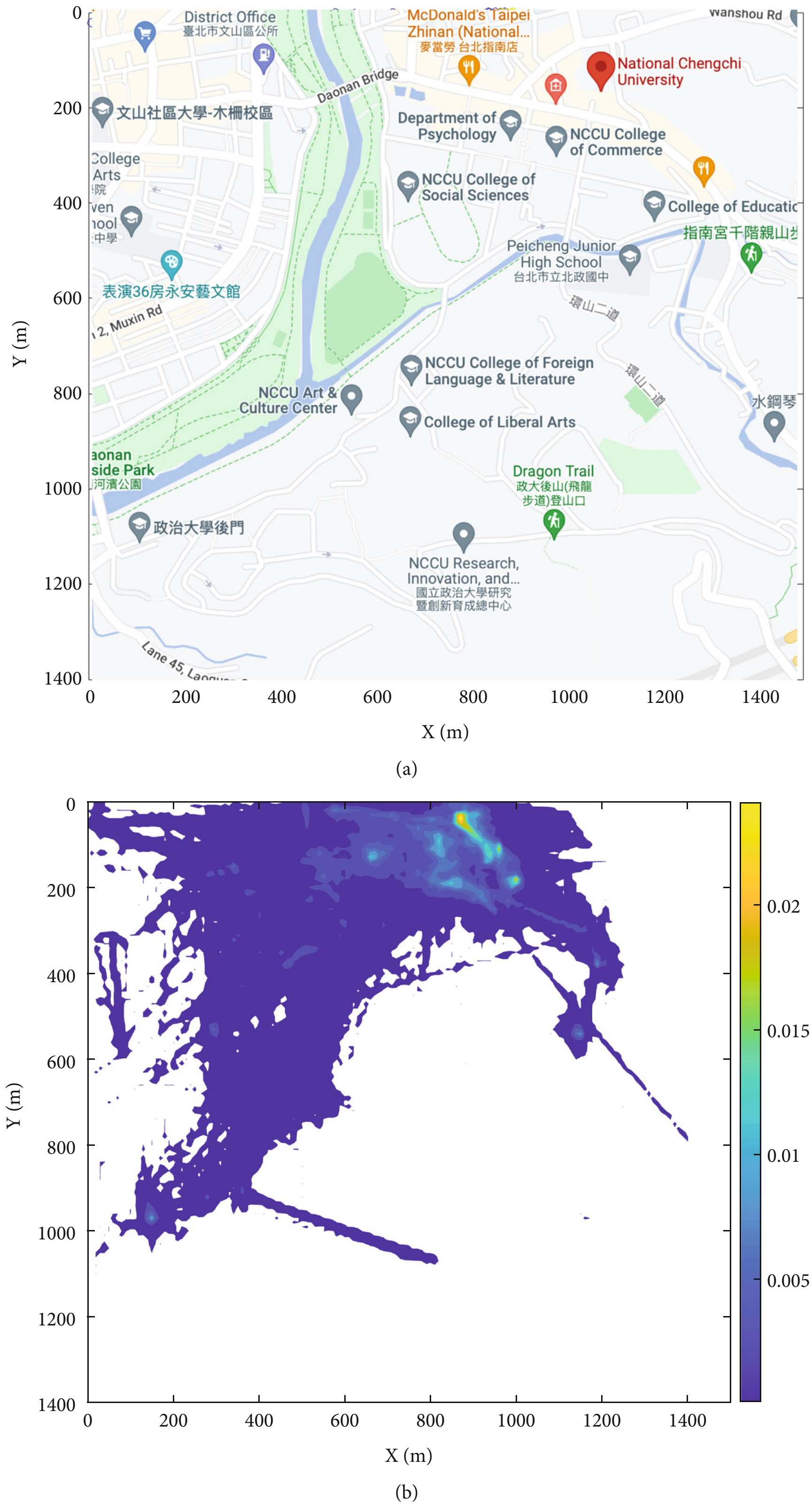

Figure 2: NCCU campus environment. (a) Map of the area. (b) Flow rate in pm^2.

smartphone location coordinates. A more specific application study in [22] is a tracking system for dementia patients, which used small BLE devices. Finally, in [23], the authors studied the efficiency of detecting BLE small tags in a real experiment for tracking the mobility of people. A similar experiment was performed in [24] for sensing the crowd.

Table 2: Main results for the different experiments performed. The columns show the number of tags not found (from a total of 10.000 tags lost), the percentage of tags found, and the average and maximum time of the first detection.

Range (R_t)	Not found	Avg. time	% found	Max. time
10 m	198	99.65 min	98.02	2406 min
20 m	59	55.28 min	99.41	2340 min
30 m	41	35.91 min	99.59	2086 min
40 m	34	24.31 min	99.66	1595 min
50 m	25	19.34 min	99.75	1425 min

With regard to commercial devices, Roth et al. [25] analyse the hardware and firmware used in Apple's AirTags. Mayberry et al. [26] study some malicious tracker techniques that have been used to track persons and propose several protection mechanisms.

Summing up, the vast majority of studies on BLE-based tracking systems have focused on evaluating the efficiency of finding the tags in their proximity. Nevertheless, one of the main advantages of tracker tags is the possibility to find lost tags, and no studies have been found to evaluate their performance. Thus, this paper fills a gap in providing a methodology to evaluate the efficiency of tracker tags depending on human mobility traces.

3. Tracker Tag Architecture

This section is devoted to describing how tracker tags work, along with their main limitations. Based on this study, we can determine the main parameters that can impact the efficiency of tracking and finding the lost tags, which will be used in our evaluation and experiments.

Tags are small devices based on Bluetooth Low Energy (BLE) location capabilities and are powered by tiny batteries. They provide two different ways of tracking: local tracking and community tracking. *Local tracking* is when you lose the tag while your smartphone is within Bluetooth range of your phone (for example, at home). In this case, the smartphone will be able to provide an approximate location by using Bluetooth-based proximity or even allows to play a sound in the tag to help finding it. Some tag devices can even use ultrawideband (UWB) to guide you to the precise location of the lost tag.

The second mode, *community tracking*, is when your smartphone cannot detect the tag. This is the case when you, after a while, become aware of a lost tag and want to know about its location. Then, you use your smartphone to mark the tag as lost to start the tracking process. When another compatible smartphone passes within proximity of your lost tag, it will relay its position, and you will be notified, so you can go and retrieve it. The broadcasting of the tags' location is based on repeatedly sending a BLE advertisement. In the studied devices, the advertising period ranges from one to two seconds, which is enough to warrant reception by a nearby pedestrian's smartphone. BLE is particularly good at this because it needs very little battery power to ping its location, meaning that batteries will last for more than a year.

Our study is focused on evaluating this second mode, community tracking, which depends on several factors such as the detection range, the community involved and their mobility, and the particular location of the lost tag.

A key factor for finding a tag is the range within which the tag can be detected. A long detection range will increase the number of smartphones that could pass near to your lost tag and, therefore, improve the opportunity of finding it. The detection range depends on the Bluetooth range (with a technical maximum of 100 meters, but with an effective range between 10 and 30 meters). The experiments performed in Section 5 with real tags confirm these effective ranges.

Another crucial aspect is the size of the community available to detect the lost tags. The greater the community, the higher the chances to find the lost tags. One strong limitation of tags is their incompatibility among brands, which reduces the community of possible trackers: only Apple devices will locate the AirTags, and only Samsung devices will locate the SmartTag. Tiles tags, although being compatible with iOS and Android devices, require the installation of an app, and only the smartphones with this app can detect lost Tile tags. Thus, the effectiveness of the detection of Tile tags is limited by the number of currently active users of each tag network.

Finally, the definitive factor for finding a tag is the location where the tag was lost. If your tag was lost in a crowded area, where many compatible smartphones are coming and going, its location will be updated frequently. On the other hand, if your tag is lost in a deserted area, the messages broadcasted by the tag will not reach any smartphone in its detection range, and you will not receive any update on its location.

4. Evaluating Tag Tracking Efficiency

In this section, we propose two methods to evaluate the efficiency of tag tracking, considering the human mobility and several factors that depend on the tags' particular brand and technology. Although companies, such as Apple, Samsung, or Tile, may have real and accurate data about the efficiency of their tags, collected from the real deployed tags, such information has unfortunately not been shared. Nevertheless, we have performed some real experiments, as described in Section 5.

Particularly, when a tag is lost, we are interested in knowing the chances of finding the tag and also knowing when we will receive the first location notification. These two aspects are interdependent, so we can talk about the probability of finding a tag depending on the time t since it was lost. We can obtain a simple expression for this probability. When a tag is lost in a given location, the probability of being detected will depend on the tag's detection range and people's mobility in the surrounded area.

Since we are interested in measuring the people moving around the lost tag, we can use *Crowd Science* metrics such as the *flow rate* [27]. The people moving passing through a

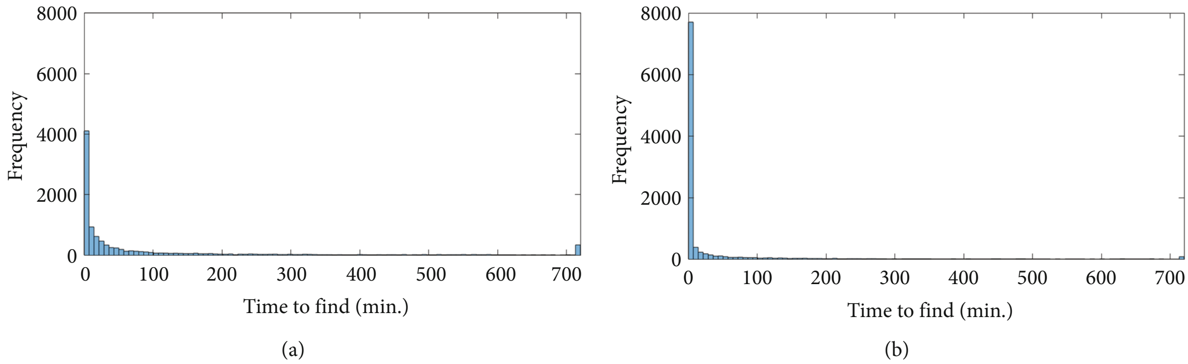

Figure 3: Histogram of the time to find the lost tags for different detection ranges: (a) 10 meters; (b) 30 meters.

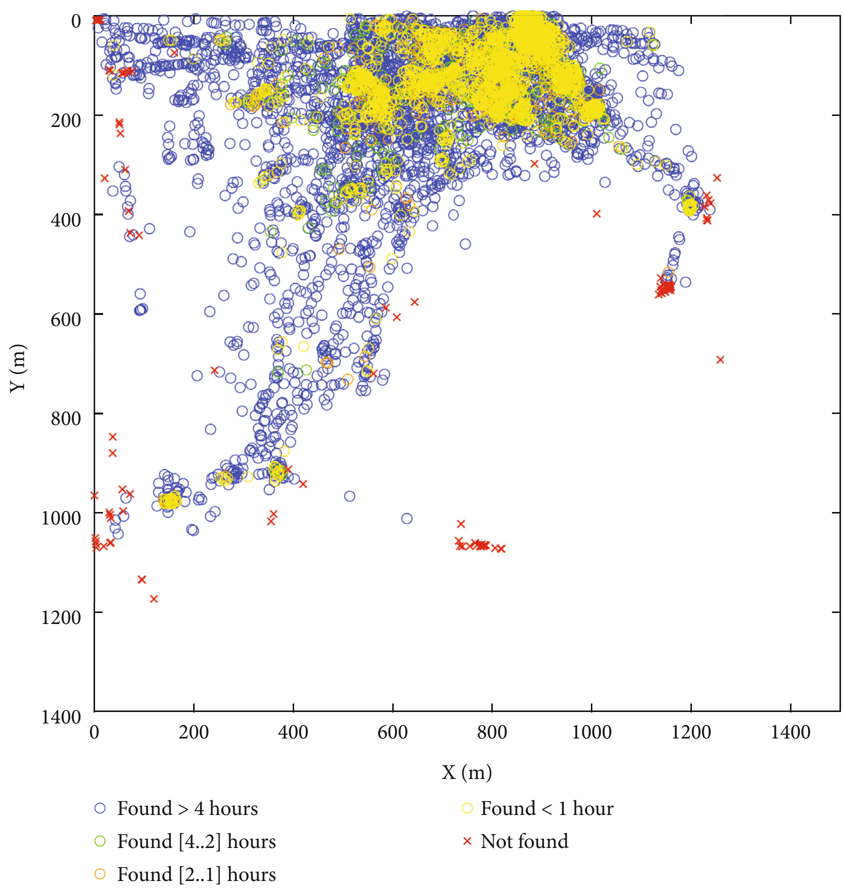

Figure 4: Map with the location of both found and not found tags, for a detection range of 10 meters. The graph shows tags that were found with a circle, using different colours to represent the time range to find these tags, and a red "x" is used to represent tags that were not found.

location can be expressed as a flow rate (F_p), measured as people per meter per minute (pm^2). As shown in [27], flow rates can range from 0 to 82 pm^2. Nevertheless, as detection is based on community tracking, from these people moving around, we can only consider the ones that have smartphones compatible with the tags. Therefore, we consider a community factor, C_f, which is the ratio of people wearing a compatible smartphone.

Thus, F_pC_f is the flow rate of people wearing compatible devices. Considering the range of detection, the average flow rate of people that could detect the lost tag is $\lambda = 2R_tF_pC_f$. That is, we consider the people who pass through a line centred in the lost tag, with a length $2R_t$. For obtaining the probability of a lost tag being detected, we should consider a people arrival pattern. To simplify, we use a *Poisson point process* with a mean equal to the obtained flow rate of people who could detect the tag (λ). Therefore, the accumulative distribution function is the probability of finding a tag:

$$P_f(t) = F(t;\lambda) = 1 - e^{-\lambda t}, \quad \lambda = 2R_tF_pC_f, \tag{1}$$

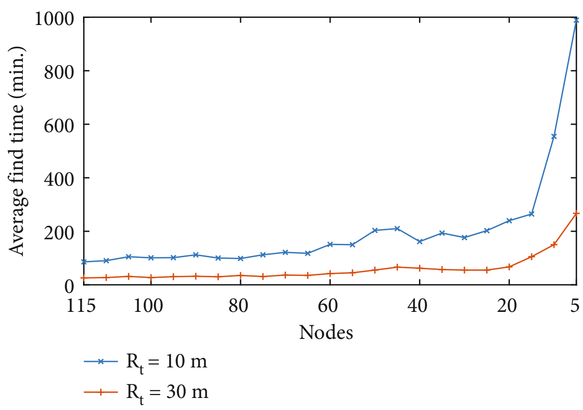

FIGURE 5: Average time to find a lost tag depending on the hour of the day (detection range is 10 meters).

and the expected time on finding the tag is $E(t) = 1/\lambda$. This expression gives a rough estimation of the expected time, in minutes, to find a lost tag. Considering a given flow rate of people in a place (F_p), it is easy to see that the time on finding the tag will be reduced by increasing the detection range or by increasing the number of compatible devices.

In Figure 1, we can see the expected time to find a lost tag ($E(t)$) depending on the flow rate of people wearing compatible devices and considering different detection ranges. Note that, for flow rates greater than $10^{-2}\,\mathrm{pm}^2$, the time is less than a few minutes. For flow rates less than $10^{-4}\,\mathrm{pm}^2$ (around 0.14 persons per day and meter), which can be considered a deserted place, the expected time could be as far as 300 minutes for a detection range of 10 meters. We consider some real scenarios with typical values extracted from [27]: in a train station with $F_p = 0.5\,\mathrm{pm}^2$, the expected detection time is immediate (0.02 minutes). In a restaurant (during meals time) with $F_p = 0.01\,\mathrm{pm}^2$, the expected detection time is around 1 minute. In a park with $F_p = 0.0001\,\mathrm{pm}^2$, the expected detection time is around 106 minutes. In all the cases, we are considering a community factor of $C_f = 0.3$ (a typical iPhone penetration ratio in most countries) and a range of 10 meters.

Nevertheless, this expression gives a limited vision of how efficient the community tracking of tags are. It can help to determine the probability and expected time in case you remember (more or less) the location(s) where you lost the tag. The strongest limitation is that the flow rate cannot reflect real mobility patterns. For example, in the previous example of the station, people's flow rate will be higher in the turnstiles than in adjacent passageways, so the probability of finding the tag will depend on the particular mobility pattern close to the exact location where the tag was lost. Thus, we should consider human mobility to obtain more realistic results, as it plays a crucial role in determining the opportunity of finding a lost tag. Human mobility is a well-studied topic in OppNet and MCS: many mobility models have been used to evaluate the transmission of messages. Several synthetic models have been devised to capture this human mobility [9], from the basic models, such as *random walk* and *random waypoint*, to more realistic models that consider some social aspects of human movements, like working days and meal hours [28, 29]. Nevertheless, these synthetic models can only capture some specific characteristics of human mobility. Therefore, the alternative is to use real mobility traces containing the location of the individuals of a given area [30–32].

The use of location-based mobility traces allows us to evaluate the impact of the community on detecting the lost tags and the location where the tag is lost. Specifically, we consider a set of individuals with smartphones moving around the area to study. Some will carry tags (for example, attached to their rucksacks). The idea is to simulate both the loss of tags carried by individuals and the detection of these tags by smartphones of nearby people. To this end, we have developed a custom simulator that is fed with a location-based trace in the format [time, latitude, longitude, node] and generates the time and node that detects a missed node tag. Individuals lose their tags at a random time t_l and are not aware of this until time t_a, when they notify the app of the lost tag, and so the community tracking starts. The process is as follows:

(1) Generate the trajectories of all the nodes (individuals) in the area to study using a location-based trace

(2) A node n_i is randomly chosen, who will lose the tag at time t_l, and will notify of its loss at time $t_a > t_l$

(3) Simulate the trajectories of the nodes:

  (a) At time t_l, the tag of node n_i is marked as lost, and its location is stored

  (b) At time t_a, the search of the tag starts. Then, the simulator checks if there are nodes within the detection range (R_t) of the lost node

  (c) For each of those nodes within range, the simulator generates a new detection output as [time, latitude, longitude, node], which represents the time and location of the detected tag

The simulation resolution is 1 second and 1 meter, enough to detect the nearby tags. In order to obtain average values, this simulation is repeated, so we can process the output to generate statistics such as the probability of finding the tag and the average time of detection.

5. Performance Evaluation

In this section, we describe the real and simulated experiments performed to evaluate the efficiency of tag discovery. All the experiments were centred on a university campus.

5.1. Real Experiments. We performed some experiments with real tags. Specifically, we evaluated Apple's AirTag and Tile's Pro tag. Firstly, we evaluated the detection range in several spaces of our university's campus: an outdoor space such as a park and indoor spaces such as a classroom, canteen, corridor, and office room. For all the experiments, we measured the distance when the signal was lost walking away from the tag location. Several measures were taken in each case in different directions, including, in some cases, obstacles.

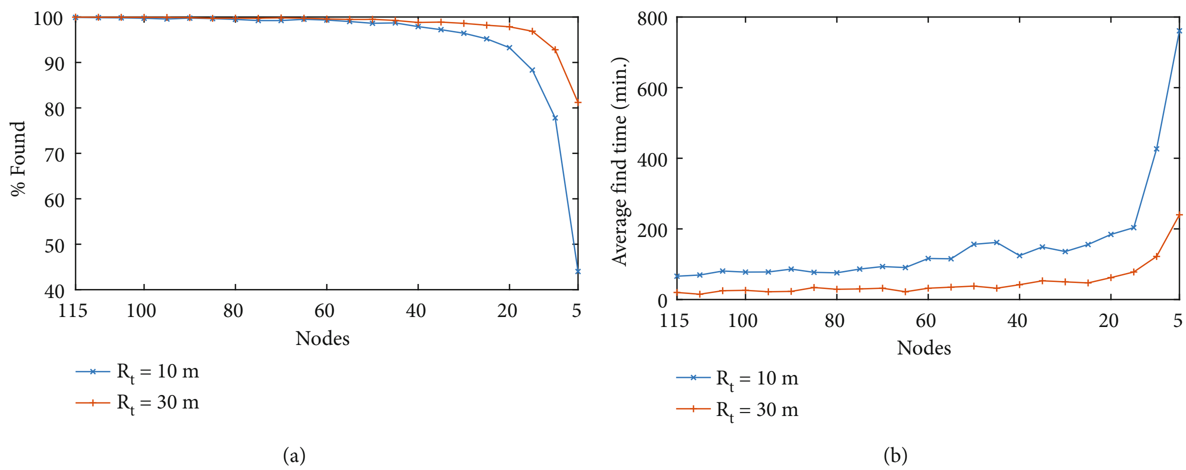

FIGURE 6: Tag tracking efficiency depending on the number of nodes for two different detection ranges (R_t): (a) percentage of tags found; (b) average delay to find the tags.

The average results are shown in Table 1. As expected, in open spaces, the range is higher than in indoor spaces with obstacles. In general, Apple's AirTags seem to have a lower range (10-30 meters) than the Tile Pro, which achieves a higher range (15-50 meters).

In the second set of experiments, we evaluated the efficiency of the community tracking of tags. These experiments were performed only with the AirTags as no smartphones compatible with the Tile App were detected in our campus. In these experiments, we left an AirTag in the places described above, and, after 10 minutes, we marked the AirTag as lost. Then, we obtained the elapsed time to the first location notification. These experiments were repeated several times at different day times. The results are shown in Table 1 in column AirTag detection. We can see that the average detection time ranges from 20 to 70 min. As expected, this time is lower for more crowded spaces such as the canteen and the classroom.

5.2. Simulated Experiments. Now, we evaluate the efficiency of the tracking of tags using a real mobility trace (NCCU trace) obtained at a university campus (the National Chengchi University campus, Taiwan) [32]. This trace was collected using an Android app installed on the smartphones of 115 students, and it was recorded for 15 days, starting on December 17, 2014, at 06:00:00 (am). It contains the GPS data, Wi-Fi access points, and Bluetooth devices in proximity in an area of 1.5 km × 11.4 km (see Figure 2(a)). Time is specified with a resolution of one second, and the location is rounded to meters.

As people flow rate is key to detecting lost tags, Figure 2(b) shows the people per meter per minute (pm^2) considering a cell of 10 × 10 m. Note that this is an average value, and the flow rate varies throughout the day. We can clearly see that students concentrate on the northeast side of the map, and the higher flow rates are on the NCCU buildings. For a broader study of the trajectories and crowd density of this trace, see reference [33] (particularly, the appendix of this paper).

Initially, we consider that all individuals of the trace wear compatible devices and, therefore, are part of the community to track the lost devices. At the end, we will study the case when not all devices belong to the community.

The first experiment evaluates the efficiency of community tracking depending on the detection range. We performed 10.000 simulations considering detection ranges from 10 to 50 meters (step 10). In each simulation, a random node was selected as the one that would lose the tag. The lost time t_l was randomly generated in the range [0, 24*60 min], that is, from 0 to 24 hours, and the aware time t_a in the range [30 min, 2*60 min], that is, from 30 minutes to 2 hours.

From the trace generated, we obtained the total number of tags not found, as well as the average and maximum detection times (measured from the aware time t_a). These results are shown in Table 2. We can see that the results are excellent. For a detection rate of 10 meters, the number of tags not found was of 198 tags (out of 10.000 simulated tags lost), and the average detection time was of about 100 minutes. As expected, if we increase the detection range, we can see that the number of tags not found is reduced (even for 50 meters, all the tags were found), and the average detection time is reduced. In general terms, the percentage of tags found was always greater than 98%.

We also obtained the time distribution to find the tags for detection ranges of 10 and 30 meters, which is shown in Figure 3. Note that we have limited the time to 12 hours. So, any detection times greater than these values are accumulated at the end of the histogram plot. In these distributions, we can clearly see that most of the tags were found in a relatively short time (less than an hour).

Now, we study how the location and time of day impact the tag tracking effectiveness. In all cases, we consider a detection range of 10 meters. In Figure 4, we can see the location and the time to find considering four ranges. We display the location of the found tag with a circle using four different colours to represent the required time to find them. The ranges are greater than 4 hours, between 4 and 2 hours, between 2 and 1 hour, and less than 1 hour. If we compare this map with the flow rate map in Figure 2(b), we can see that the areas with greater flow rate are the ones where most tags were lost and also with the lower times to find them. We can also see in this map those tags that were not found; these are represented with a red "x." As expected, we can see that the location of tags that were not found matched the areas with very low flow rates. Figure 5 shows the average time to find a lost tag depending on the hour of the day. As expected, from 6 to 20 hours, when people's mobility is higher, the time required to find a tag is lower than for the rest of the day.

The previous results show that the results are excellent for a community of 115 nodes. Yet, what would happen if the number of nodes is reduced? We repeated the same scenario as the previous experiments reducing the number of nodes from 115 to 10 and considering two different detection ranges: 10 and 30 meters. The main results are shown in Figure 6. We can clearly see that the efficiency is reduced when the number of nodes is reduced (that is, the percentage of tags found is reduced, and the average time required to find them is increased). This is particularly significant when the number of nodes is less than 20, situation where the percentage of found tags falls dramatically, and the detection time increases exponentially.

Summing up, the evaluation performed using the NCCU trace shows that community tracking is very efficient when the number of nodes is greater than 60. When considering fewer nodes, the efficiency is clearly reduced. This was also confirmed in the real experiments performed. That justifies the success of Apple's AirTags in countries with a high penetration of iPhone phones, such as the USA, Canada, and the UK. It also highlights the poor expected performance for any tag technology that fails to achieve a significant market penetration. Finally, the detection range has also a significant impact on finding the lost tags, as it helps to better find those tags lost in remote places, or in less crowded places.

6. Conclusions

In this paper, we have studied and evaluated the efficiency of tracker tags, focusing on the community tracking mode. The main aspects that impact the efficiency of finding a lost tag are the BLE detection range, community size (ratio of compatible devices), and human mobility.

Human mobility is key to detecting a lost tag, particularly the people's flow rate. We have provided an analytical expression to get the expected time to find a lost tag depending on this flow rate, confirming that places with greater people mobility have more chances to find the tags with lower detection times.

We also used a campus scenario to evaluate all these aspects: detection range, community size, and human mobility. We showed that, for a relatively low number of individuals (more than 60), the efficiency of finding the lost tags is very high: more than 98% of the lost tags were found, and the average detection time was close to 1 hour.

A key aspect to the success of tag tracking is the size of the community; nowadays, it depends on the brand penetration of the country. Hence, it would be desirable to make the tags compatible between them (maybe through a standard) to increase their efficiency.

As future work, we plan to perform more experiments in other scenarios following the methodology described in this paper.

Data Availability

All the data and code used in the models and experiments of the paper are available on the following GitHub repository : https://github.com/GRCDEV/TagsTracking.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work is derived from R&D project PID2021-122580NB-I00, funded by the MCIN/AEI (10.13039/501100011033) and ERDF "A way of making Europe."

References

[1] R. Faragher and R. Harle, "Location fingerprinting with Bluetooth low energy beacons," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 11, pp. 2418–2428, 2015.

[2] L. M. Ni, D. Zhang, and M. R. Souryal, "RFID-based localization and tracking technologies," *IEEE Wireless Communications*, vol. 18, no. 2, pp. 45–51, 2011.

[3] I. Bisio, A. Sciarrone, and S. Zappatore, "A new asset tracking architecture integrating RFID, Bluetooth low energy tags and *ad hoc* smartphone applications," *Pervasive and Mobile Computing*, vol. 31, pp. 79–93, 2016.

[4] D. Chen, K. G. Shin, Y. Jiang, and K.-H. Kim, "Locating and tracking BLE beacons with smartphones," in *Proceedings of the 13th International Conference on Emerging Networking EXperiments and Technologies, CoNEXT '17*, pp. 263–275, New York, NY, USA, 2017.

[5] K. Vahnemert, *Tile Might Be a Revolutionary Gizmo for Finding Lost Keys and Stolen Purses*, Wired, 2013.

[6] A. Capponi, C. Fiandrino, B. Kantarci, L. Foschini, D. Kliazovich, and P. Bouvry, "A survey on mobile crowdsensing systems: challenges, solutions, and opportunities," *IEEE Communications Surveys Tutorials*, vol. 21, no. 3, pp. 2419–2465, 2019.

[7] N. D. Lane, E. Miluzzo, L. Hong, D. Peebles, T. Choudhury, and A. T. Campbell, "A survey of mobile phone sensing," *IEEE Communications Magazine*, vol. 48, no. 9, pp. 140–150, 2010.

[8] W. Zamora, C. T. Calafate, J.-C. Cano, and P. Manzoni, "A survey on smartphone-based crowdsensing solutions," *Mobile Information Systems*, vol. 2016, Article ID 9681842, 26 pages, 2016.

[9] J. Dede, A. Förster, E. Hernández-Orallo et al., "Simulating opportunistic networks: survey and future directions," *IEEE Communications Surveys and Tutorials*, vol. 20, no. 2, pp. 1547–1573, 2018.

[10] L. Pelusi, A. Passarella, and M. Conti, "Opportunistic networking: data forwarding in disconnected mobile ad hoc networks,"

IEEE Communications Magazine, vol. 44, no. 11, pp. 134–141, 2006.

[11] S. Trifunovic, S. T. Kouyoumdjieva, B. Distl, L. Pajevic, G. Karlsson, and B. Plattner, "A decade of research in opportunistic networks: challenges, relevance, and future directions," *IEEE Communications Magazine*, vol. 55, no. 1, pp. 168–173, 2017.

[12] J. G. P. Rodrigues and A. Aguiar, "Opportunistic mobile crowdsensing for gathering mobility information: lessons learned," in *2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC)*, pp. 1654–1660, Rio de Janeiro, Brazil, 2016.

[13] A. Chaintreau, P. Hui, J. Crowcroft, C. Diot, R. Gass, and J. Scott, "Impact of human mobility on opportunistic forwarding algorithms," *IEEE Transactions on Mobile Computing*, vol. 6, no. 6, pp. 606–620, 2007.

[14] K. Garg, S. Giordano, and A. Förster, "A study to understand the impact of node density on data dissemination time in opportunistic networks," in *Proceedings of the 2nd ACM Workshop on High Performance Mobile Opportunistic Systems, HP-MOSys '13*, pp. 9–16, New York, NY, USA, 2013.

[15] M. Grossglauser and D. N. C. Tse, "Mobility increases the capacity of ad hoc wireless networks," *IEEE/ACM Transactions on Networking*, vol. 10, no. 4, pp. 477–486, 2002.

[16] Y. Lin, X. Wang, L. Zhang, P. Li, D. Zhang, and S. Liu, "The impact of node velocity diversity on mobile opportunistic network performance," *Journal of Network and Computer Applications*, vol. 55, pp. 47–58, 2015.

[17] X. Zhang, G. Neglia, J. Kurose, and D. Towsley, "Performance modeling of epidemic routing," *Computer Networks*, vol. 51, no. 10, pp. 2867–2891, 2007.

[18] Ó. Helgason, S. T. Kouyoumdjieva, and G. Karlsson, "Opportunistic communication and human mobility," *IEEE Transactions on Mobile Computing*, vol. 13, no. 7, pp. 1597–1610, 2014.

[19] E. Hernández-Orallo, C. Borrego, P. Manzoni, J. M. Marquez-Barja, J. C. Cano, and C. T. Calafate, "Optimising data diffusion while reducing local resources consumption in opportunistic mobile crowdsensing," *Pervasive and Mobile Computing*, vol. 67, article 101201, 2020.

[20] J. Herrera-Tapia, A. Förster, E. Hernández-Orallo, A. Udugama, A. Tomas, and P. Manzoni, *Mobility as the Main Enabler of Opportunistic Data Dissemination in Urban Scenarios*, Springer International Publishing, Cham, 2017.

[21] T. Kulshrestha, D. Saxena, R. Niyogi, V. Raychoudhury, and M. Misra, "SmartITS: smartphone-based identification and tracking using seamless indoor-outdoor localization," *Journal of Network and Computer Applications*, vol. 98, pp. 97–113, 2017.

[22] Y.-J. Lin, H.-S. Chen, and S. Mei-Ju, "A cloud based Bluetooth low energy tracking system for dementia patients," in *2015 Eighth International Conference on Mobile Computing and Ubiquitous Net- working (ICMU)*, pp. 88-89, Hakodate, Japan, 2015.

[23] S. Jamil, A. Basalamah, and A. Lbath, "Crowdsensing traces using Bluetooth low energy (BLE) proximity tags," in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication, UbiComp '14 Adjunct*, pp. 71–74, New York, NY, USA, 2014.

[24] A. Basalamah, "Sensing the crowds using Bluetooth low energy tags," *IEEE Access*, vol. 4, pp. 4225–4233, 2016.

[25] T. Roth, F. Freyer, M. Hollick, and J. Classen, "AirTag of the clones: shenanigans with liberated item finders," in *2022 IEEE Security and Privacy Workshops (SPW)*, pp. 301–311, San Francisco, CA, USA, 2022.

[26] T. Mayberry, E. Fenske, D. Brown et al., "Who tracks the trackers? Circumventing apple's anti-tracking alerts in the find my network," in *Proceedings of the 20th Workshop on Workshop on Privacy in the Electronic Society, WPES '21*, pp. 181–186, New York, NY, USA, 2021.

[27] G. Keith Still, *Introduction to Crowd Science*, CRC Press, 2013.

[28] K. Lee, S. Hong, S. J. Kim, I. Rhee, and S. Chong, "SLAW: a new mobility model for human walks," in *INFOCOM 2009*, pp. 855–863, Rio de Janeiro, Brazil, 2009.

[29] A. Mei and J. Stefa, "Swim: a simple model to generate small mobile worlds," in *INFOCOM 2009*, pp. 2106–2113, Rio de Janeiro, Brazil, 2009.

[30] S. M. King, F. Nawab, and K. Obraczka, "A survey of open source user activity traces with applications to user mobility characterization and modeling," 2021, https://arxiv.org/abs/2110.06382.

[31] P. Sapiezynski, A. Stopczynski, D. D. Lassen, and S. Lehmann, "Interaction data from the Copenhagen networks study," *Scientific Data*, vol. 6, no. 1, p. 315, 2019.

[32] T.-C. Tsai and H.-H. Chan, "NCCU trace: social-network-aware mobility trace," *IEEE Communications Magazine*, vol. 53, no. 10, pp. 144–149, 2015.

[33] M. Mahmood, J. Mateu, and E. Hernández-Orallo, "Contextual contact tracing based on stochastic compartment modeling and spatial risk assessment," *Stochastic Environmental Research and Risk Assessment*, vol. 36, no. 3, pp. 893–917, 2022.