GEMAT - Internet of Things Solution for Indoor Security Geofencing

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ABSTRACT

A geofence is a virtual perimeter for a real-world positioning area. Geo-fencing involves a location-aware device of a location-based service user or asset entering or exiting a virtual area. Rather than geofences being static, in indoor positioning systems they need to be dynamically updated, frequently, efficiently and on-demand. Furthermore, the underlying geofencing framework must work to incorporate the changes in the system's operational context (signal obstruction, static and dynamic obstacles, etc.) and compensate for their influence on the location calculations. In this paper, we propose the Geofencing Micro-location Asset Tracking (GEMAT) framework for dynamic security geofencing management and notification/actuation based on the Bluetooth Low Energy Micro-location Asset Tracking (BLEMAT) IoT system. We show how an indoor geofencing framework that includes and compensates for contextual updates provides more functional geofencing capabilities, both in terms of precision and sophisticated use cases. We present the main functionalities of the geofencing framework and test them in a real-world IoT environment. Furthermore, we elaborate on a performance analysis model for geofencing frameworks with ten criteria defined. Conducted experiments and performance analysis show that the proposed GEMAT framework is a good candidate for solving problems in a wide range of indoor geofencing use cases.

CCS CONCEPTS

• **Information systems → Spatial-temporal systems**; *Sensor networks*; • **Networks → Location based services**; • **Computer systems organization → Distributed architectures**.

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KEYWORDS

Internet of Things, geofencing, location-based services, context-awareness

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1 INTRODUCTION

Indoor asset tracking and positioning are an increasingly important aspect of the Internet of Things (IoT) solutions across industries. Businesses using location-based services (LBS) can confidently locate, monitor, manage and secure fleets of connected devices in real time. Location data can be used as a qualifier to interpret, organize and translate the vast collections of IoT data into actionable insights. This location context and data can be integral to core business processes such as data management, compliance, operational assessments, and reporting.

A geofence is a virtual perimeter that encapsulates a target area. User's or object's coordinates are used to determine whether they're inside or outside the target area, as well as when they cross in or out of it. Depending on how a geofence is configured it can prompt mobile push notifications, trigger text messages or alerts, send targeted advertisements on social media, allow tracking on vehicle fleets or deliver location-based marketing data. A retailer might put a virtual geofence around its stores to trigger mobile alerts for customers who have downloaded the retailer's mobile application [9]. Geofencing can be used to control and track vehicles in the shipping industry [16] or cattle in the agriculture industry [22]. Applications in e-health are also abundant [8]. Another important role of geofencing in industry relates to the security and safety of personnel [24].

The importance of LBS and geofencing for IoT systems cannot be overstated [5]. However, IoT systems lack inexpensive and easy-to-deploy geofencing solutions that work well with the existing network stack already deployed in indoor spaces (Wi-Fi, Bluetooth). Also, most of the above-mentioned indoor positioning systems (IPS) that have geofencing capabilities focus on proximity-based geofencing and disregard more sophisticated use cases where a geofence is an arbitrary polygon in the observed space. Furthermore, there are few geofencing frameworks for IoT that allow for dynamic creation of geofences and their on-demand updates, as well as those that consider high levels of geofence specification (geofence relations and transitions from one geofence area to another, duration of stay inside a geofence, etc.). In our previous work, we have implemented Bluetooth Low Energy Micro-location Asset Tracking (BLEMAT) IoT indoor positioning system. We have shown how BLEMAT successfully adapts to continual updates of dynamic IoT systems (varying resource utilization, node losses, signal obstruction, etc.), while increasing the accuracy of the underlying positioning techniques [18, 19]. While understanding context increases overall IPS accuracy, it also ameliorates machine-to-machine (M2M) communication performance, which is an essential element for the IoT [17]. Geofencing frameworks need to account for contextual changes in the underlying IPS.

Built on top of BLEMAT, the Geofencing Micro-location Asset Tracking (GEMAT) framework is a semi-unsupervised geofencing system that constantly learns about the operational context of the environment it is deployed. In an operational context like BLEMAT, geofencing capabilities are automatically enhanced by the solution's own functionalities that aim to correct positioning calculations, based on the changes in the context of the managed system. By using BLEMAT's data streams and services, in this paper, we propose a context-aware, self-adapting geofencing management solution with straightforward, on-demand geofence updates. Our main contributions are:

(1) Offering design, discussion, and implementation of a context-aware geofencing framework for IoT systems.
(2) Showcasing how geofencing calculations and triggers are automatically adapted to the changes in the operational context (moving physical obstacles and unaccounted interference).
(3) Testing and evaluating the implemented framework in a real-world IoT deployment through several experiments.
(4) Developing a performance analysis model for geofencing frameworks and using it to compare GEMAT to similar frameworks.

The rest of the paper is structured as follows: in Section 2 we elaborate on the related work; in Section 3 we explain the BLEMAT framework and its capabilities; in Section 4 we present the geofencing framework for the platform; Section 5 presents the experiments and their results; in Section 6 we provide conclusions and elaborate on future work.

2 RELATED WORK

Geofencing, especially outdoor geofencing is not a novel topic for LBS [15]. There have been many research advancements in tourism geofences [12], crowdsensing and mass gatherings management [3], parking spaces management [20], location-based marketing [2], etc. While outdoor geofencing has been well researched, indoor geofencing lacks a large number of research results – deployments considering efficient resource utilization and adapting to contextual changes in the physical environment.

Results similar to this paper were proposed in [13]. As an alternative to WiFi or Bluetooth, the authors use IMES [25] to create an IPS. However, sophisticated use cases for geofencing were not explored (chains of geofences, temporal geofences). Also, the authors of [10] propose a camera-based vision-analysis geofencing framework for thermal comfort and energy savings by tracking indoor area occupancy. It is a step forward in discussing the collaboration of IPS, geofencing and IoT M2M notifications/actuation. In this paper, we aim at the same goal, with elaborate experiments and discussions about the importance of IoT systems' context-awareness. Cardone et.al present MoST [4], a geofencing framework that is a complete and complex framework for geofencing. MosT is resource and context-aware, while also providing with additional geofencing functionalities (temporal geofences, geofence relations, etc.). MoST will be discussed more in Section 5.

As another approach, the authors of [14] argue that location-based geofencing could be replaced with network proximity-based geofencing. By using spectral fingerprinting and Received Signal Strength Indicator (RSSI) for proximity deduction, geofence areas can be set up as a set of basic point with statically calculated fingerprints. While this is a novel approach, one must carefully consider contextual-awareness of the systems [6]. If a context in which the system operates change, the spectral fingerprint of the indoor area must be regenerated as well. If not, it might lead to false positioning and proximity information. To address this challenge, BLEMAT and GEMAT have a mechanism for refreshing spectral fingerprints.

As presented in [11, 21], the concept of a single, independent, non-temporal geofences is often insufficient for encompassing more sophisticated use cases and the delivery of appropriate location-based notifications. We take these concepts into consideration in this paper and allow for generating chains of geofences, as well as specifying a temporal component to the chain or individual geofence.

Lastly, not many geofencing papers tackle the idea of privacy protection. As the user's privacy is important for LBS, authors of [7] tackle the challenge with proposing a LBS and geofencing framework based on homomorphic encryption of a user's location [23]. GEMAT and BLEMAT are fog computing systems, thus, they achieve a high level of privacy – all sensory data stay in the edge of the network. Furthermore, accessing location data is based on specific access-control policies, and location data is being stored in an encrypted manner, by leveraging Key-policy attribute-based encryption. However, the privacy of location data will not be discussed further in this paper and will be a part of our future work.

3 BLEMAT OVERVIEW

BLEMAT is a Bluetooth Low Energy-based indoor positioning system that rests on a deployed infrastructure of fog gateways, that we call *scanners* [18, 19]. BLEMAT scanners have the capability of scanning the indoor environment for active beacons and calculating their position in space using trilateration and with the help of machine learning. BLEMAT beacons rely on the deployment of *fog computing gateways* that come in the form of scanners. The beacons represent devices or objects being tracked within the BLEMAT system. The beacons are mobile and constantly emitting Bluetooth signal.

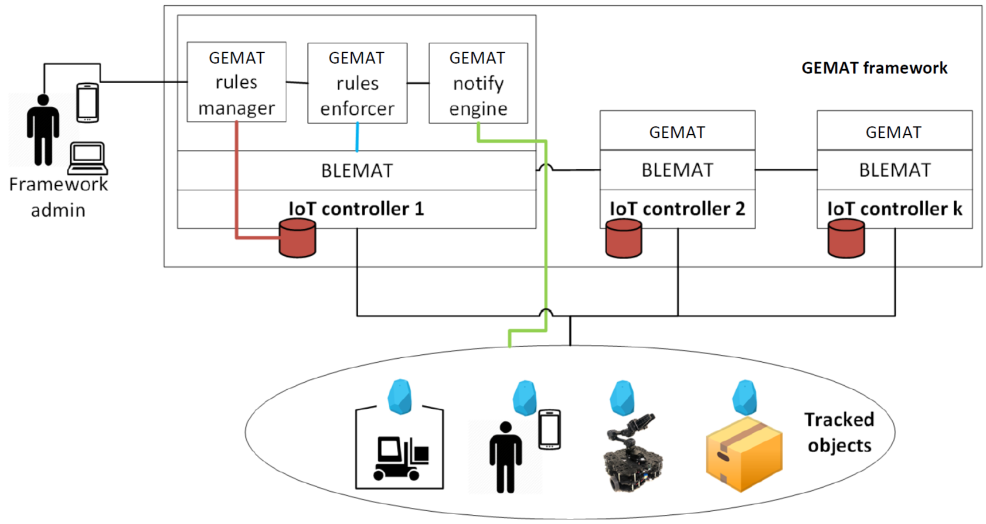

Figure 1: GEMAT workflow

BLEMAT has constant access to the systems operational context (flow of people, mobile and static obstacles, other signal sources that cause signal distortion, failure of devices, etc.), and this contextual information is used to filter signal measurements and correct positioning calculations. Large signal deviations can be detected and the information is propagated to the filtering components handling raw RSSI data collection and preprocessing (Auto-regressive moving average). The filters account for signal deviation and include that information in function resulting in final RSSI data output for position calculation. Large deviations in positioning calculations are detected and handled by the Kalman filter. By correcting both raw RSSI and final positioning data, BLEMAT uses the current context to increase the overall accuracy of the IPS. With the utilization of fog/edge computing, the BLEMAT brings 5G solutions to indoor positioning challenges.

Additionally, BLEMAT uses real-time and online machine learning in place of the traditional offline and manual fingerprinting approach for building signal propagation maps and floor plan layouts. By constantly examining signals from other scanners and Bluetooth devices, scanners are capable of learning about other sources of Bluetooth signals around them. Based on that, each scanner creates its own signal propagation map. At a certain point, all propagation maps are merged and based on that information a fingerprinting database is extracted for known devices. This is an online process, without requiring system downtime or manual recalibration.

Finally, for a specific object that is tracked inside BLEMAT, the BLEMAT system is capable of learning the *mobility pattern* of the tracked object, detect deviations from it, and trigger notifications/actions based on the detected abnormal behavior (i.e. a tracked forklift has left the storage area it is assigned to).

BLEMAT provides solid ground for implementing an indoor area security geofencing framework capable of both proximity-based and area-based geofencing. It can quickly respond to proximity information and has a foundation for management of proximity-based location data, as well as perform precise indoor positioning and detecting if an object is inside a specific area. Additionally, as an alternative approach to existing indoor geofencing solutions, BLEMAT geofencing uses the underlying BLEMAT framework to keep track of changes in the system's context and account for compromised positioning measurements.

4 INDOOR SECURITY GEOFENCING FRAMEWORK - GEMAT

The indoor security geofencing framework we are proposing in this paper rests on three main components: GEMAT area and rules manager, GEMAT rules enforcer and GEMAT notify engine (see Figure 1).

The GEMAT area and rules manager is the component in charge of persisting geofencing areas and rules for notification or actuation. An area is dynamically determined and marked in the GEMAT as an arbitrary polygon or a line on the indoor area floor plan. On top of defining geofences, this component includes the possibility of creating temporal relations between geofences as well as duration constraints for the time being within a geofence or in transition between geofences. These are two highly important aspects (also underlined in [21]) in order to cover sophisticated scenarios in which a notification should be triggered only in case the user crosses multiple geofences in a defined temporal order or leaves a geofence after a certain amount of time. Geofencing rules are defined in *"if this - then that"* manner. The first part of the rule refers to creating a relationship between a geofencing area and a tracked object. It also includes creating relationships between different geofencing rules. The second part of the rule defines communication actions towards the GEMAT notify engine, in order to deliver the information about the geofencing rule that was triggered. The GEMAT rules enforcer represents an automated geofencing workflow that works with positioning data provided by the BLEMAT system and the GEMAT

Paper/Criterion	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
(1) GEMAT	Dynamic	✓	Arbitrary	✓	<1m	✓	Low	✓	✓	<2s
(2) Google Geofencing	Inherited	✗	Radius	✗	Inherited	✗	Low	✗	✓	Unknown
(3) MoST	Dynamic	✗	Arbitrary	✗	~100m	✗	Controlled	✓	✓	Unknown
(4) Geofencing 2.0	Unknown	✓	Arbitrary	✓	Unknown	✗	Controlled	✓	✓	Unknown
(5) Geofencing Cooling Fan System	2s	✗	Object	✗	<1cm	✓	Medium	✓	Unknown	Unknown

Table 1: Comparison of geofencing frameworks

area and rules manager to determine whether there is an action to consider (i.e. a geofencing rule has to be triggered).

The GEMAT notify engine takes the outputs of the GEMAT rules enforcer the notify engine and turns them into action – it sends a notification or an actuation command to the desired device. The frameworks notification system works on delivering important system or user notifications. Furthermore, in an IoT system where actuation is an integral part of normal system operation, the GEMAT notify engine can be used to send actuation commands to other IoT devices and managed actuation systems.

The GEMAT allows for detection of entrance and exit event to certain indoor secured areas. Geofences for GEMAT can be supplied through BLEMAT's dashboard, where there is a possibility to place arbitrary geofences on the underlying floor plan. This is suitable for use cases where moving across the boundaries of a secured area needs to be recorded and/or controlled, such as: controlling access to specific segments of a larger area (i.e access to specific production machines/static assets), recording a mobile asset's through multiple geofences, etc. The GEMAT solution, through the BLEMAT system functionalities, dynamically adapts the geofencing parameters (referent spectral maps, derived positions and security lines) to address the changes in the system's operational context (moving obstacles for signal propagation, unaccounted interference and flow of people and devices through the area). This way, GEMAT is constantly learning contextual information from the underlying system's physical environment, thus progressing further the approaches listed in the Related Work section.

5 EXPERIMENTS AND RESULTS

Before proceeding to the discussion of the experimental results, we are going to present an elaborate performance analysis model of geofencing frameworks that we used to evaluate GEMAT. Furthermore, we will compare GEMAT to other solutions through the presented model.

5.1 Performance analysis model for geofencing frameworks

To measure the capability and performance of a geofencing framework, ten criteria need to be taken into consideration. The set of criteria is based on papers referencing geofencing frameworks design and implementation (mentioned also in Section 2). The criteria are as follows:

C1. Location sampling interval;
C2. Support for temporal geofences;
C3. Geofence shape;
C4. Support for geofence relationships;
C5. Positioning accuracy;
C6. Adaptation to changes in the system context;
C7. Resource consumption;
C8. Visualized geofences specification;
C9. Support for other LBS;
C10. Timestamps deviation.

Location sampling interval should be dynamically adjusted to save battery life without affecting the geofencing capabilities. If the tracked object is close to a geofence, the interval should be lower, and vice-versa. Temporal geofences refer to being able to specify an action if an object stays inside a geofence a certain amount of time. Geofence shape is relevant for more sophisticated use cases. Being able to create geofence chains in a form of geofence relationships is useful in use-cases where it is important to track objects through multiple geofences to perform a single action. Positioning accuracy and precision are tied to the underlying positioning technique used. Dynamic adaptation to system context is important for dynamic system environments where signal propagation changes, and/or obstacles are dynamically introduced. Resource consumption is relevant from the standpoint of where the geofencing system is deployed (devices' capabilities). It is important to have a straightforward geofences specification process (i.e. through a visualized dashboard). The percentage of missed geofences is a relevant factor, although it is also tied to the trade-off between positioning accuracy and location sampling. Also, we need to evaluate the support for other LBS, other than geofencing, and how easy is their integration with the geofencing system. Lastly, the deviation between the recorded and actual timestamps of geofences triggering needs to be reduced to minimal, for highest geofencing precision and support for sophisticated use cases.

To the best of our knowledge, Table 1 is the first to summarize a performance analysis model for geofencing frameworks and compare them. Table 1 shows how GEMAT compares to other similar geofencing frameworks taking into consideration C1-C10. While the Google Geofencing Library [1] provides an extension of Google LBS, it is not a standalone geofencing system thus the sampling interval and positioning accuracy are inherited from the application use-case leveraging geofencing. It does not provide with temporal of geofence relationships, and geofences are specified only as circles. MoST, on the other hand, is the most complete geofencing framework we have found, having functionalities to every criterion, however, it is focused on outdoors. It is relevant to notice that in

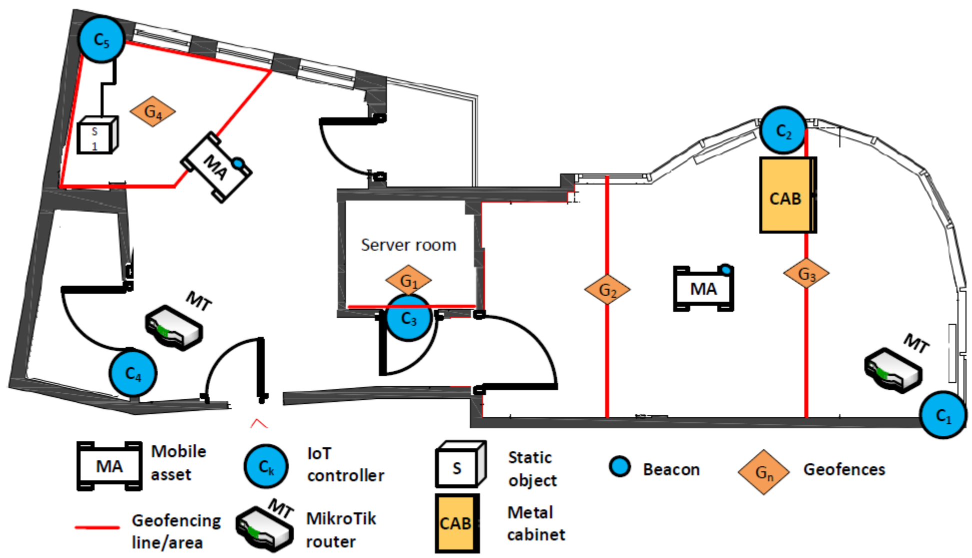

Figure 2: Experiment indoor area

MoST, the resource consumption is controlled through controlling the sampling interval. Also, the sampling interval is dynamically adapted based on the distance between the tracked object and the nearest geofence. The Geofencing 2.0 [21] framework ((4) in Table 1) also supports controlled resource consumption, and satisfies most of the criteria. GEMAT and (5) from Table 1) are the only two frameworks considering design towards context-awareness. Furthermore, (5) is a camera-based framework providing sub-centimeter accuracy, but with a heavier load on resources consumption (because of the camera and image processing) [10]. Also, the shape of the geofence is rather peculiar with this approach – objects that the camera captures can also be defined as geofences (i.e. a table), and are triggered when the object is involved with an action. Lastly, GEMAT is the only framework to consider the metric of timestamps deviation.

In conclusion, GEMAT compares well with other similar frameworks. The summarization of GEMAT through criteria C1-C10 is presented below:

C1. Location sampling interval – the underlying positioning system BLEMAT handles specification of location sampling intervals. Since GEMAT is not the only LBS using positioning data from BLEMAT, sampling intervals cannot be automatically updated as in MoST.

C2/C4. Support for temporal geofences and geofence relationships – although support for temporal geofences and geofence relationships definition is enabled, a deeper theoretical model (i.e. a domain-specific language) for defining them (such as in Geofence 2.0 [21]) and translating their specification to a programming language of choice (to be incorporated as a geofencing rule) is not yet researched, and will be a part of our future work.

C3. Geofence shape – support for arbitrary shapes is enabled in GEMAT, and this is a general flexibility need for indoor geofencing frameworks.

C5/C6. Positioning accuracy and adaptation to changes in the system context – are inherited BLEMAT functionalities. The accuracy is sub-meter (which is enough for most of IPS), and the process and workflows of how the IPS adapts to contextual changes are well described in our previous papers [18, 19], as well as in Section 3.

C7. Resource consumption – as BLEMAT was designed as a fog-computing system, without any cloud resource dependencies, and with strict resource utilization policies in mind, GEMAT is inherently resource-preserving.

C8. Visualized geofences specification – BLEMAT has a dashboard to track and explore positioning data for the underlying floor maps, and as an extension of the dashboard, GEMAT offers visualized geofences specification on the floorplan by drawing of arbitrary shapes. Visualized specification of temporal geofences and geofences relationships will be a part of our future work.

C9. Support for other LBS – having BLEMAT as an underlying IPS opens up possibilities for implementing other LBS that leverage past or present positioning data.

C10. Timestamps deviation – GEMAT is the only framework, out of the analyzed ones, to consider the metric of timestamps deviation. This makes a step forward in defining general quality metrics for other geofencing frameworks. In GEMAT, the deviation is small due to the low location sampling interval. The expected result for an increased location sampling interval would be a higher deviation between recorded and actual geofence triggering timestamps.

5.2 Experiment Setup

For the experiments, two datasets were collected. For the first dataset (DS1), positioning data was collected within one week, every day from 8h-20h, and during that time we have collected 300.000 position estimations (sampling interval of 1s). For the second dataset (DS2), positioning data was collected within one day from 8h-20h, and during that time we have collected 7.000 position estimations (sampling interval of 10s). Six users (BLEMAT system developers) have had their phones tracked via GEMAT, and all of them were included in geofences triggering scenarios. Geofences were triggered 6.000 times over the data collection period, and for each triggering, we have collected information about the scenario it tackled, and the scenario success.

The proposed GEMAT framework and it's functionalities were tested in two experiments, in a real-world indoor area (office space of VizLore Labs) with BLEMAT system deployed. The indoor area where the experiments were conducted in is a $100m^2$ single level office space where IoT controllers, static assets, and geofences are placed like in Figure 2. The experimental setup consists of five IoT controllers with BLEMAT and GEMAT systems running on them. Mobile assets (MA) are simulated by users (six are present in the experiments), and during the experimental phase, users have triggered the programmed geofences (by walking) 6.000 times. Mikrotik routers (MT) are introduced to the experiment as a means to increase the signal disturbance in certain areas and act as context changes of the spectral characteristics of the system. Metal cabinets (CAB) are also introduced as signal obstructors: they block a clear path between a Bluetooth signal source and destination. Presence of people, metal objects, or other obstacles or radio frequencies (RF) reflective surfaces causes perturbation in signal propagation. Other electrical equipment emitting strong RFs might do the same. Because WiFi uses the same 2.4 GHz bandwidth, these two signals often interfere with each other. The Static object (S_1) is a Zigbee E26 Smart Light Bulb, capable of execution of actuation commands that are received via Bluetooth, from BLEMAT IoT controllers.

5.3 Experimental Scenarios, Results and Evaluation

With GEMAT experiments we are confirming the following hypothesis:

(EX1): the GEMAT system is capable of handling both simple and sophisticated geofencing use cases (multiple geofences are tied, and there is a temporal component to them).

(EX2): the GEMAT achieves consistent accuracy when the operational context is changed (signal is obstructed on purpose).

EX1 was motivated by the IPS systems and geofencing approaches described in the Related Work Section of the paper (Section 2), in order to show how GEMAT can provide advanced geofencing capabilities while also being able to learn about the system's context. The motivation behind **EX2** was to explore the geofencing capabilities of GEMAT, while introducing constant signal obstruction, and thus directly impacting the system's capabilities to provide accurate positioning calculations.

Through our office space, we have emulated a smart warehouse scenario where mobile objects are tracked through BLEMAT and based on positioning data, and the geofencing rules defined with the GEMAT, appropriate actions are taken. Let us examine the geofences we have programmed into the GEMAT experiments:

(SC1): G_1 represents the entrance to the server room. When a user triggers this geofence ("if this" part of the rule), this information is persisted in GEMAT's database ("then that" part of the rule).

(SC2): G_2 and G_3 work together in order to achieve the following: when a mobile asset (MA) has passed geofence G_2, it has under 20 seconds to pass geofence G_3. If this does not happen in this order and under this time constraint, then a notification is sent to the system administrator mentioning a potential problem with the mobile asset (asset has stopped moving) so that it can be inspected.

(SC3): G_4 represents a secured area, with a static object S_1 inside. When a mobile asset crosses the boundaries of geofence G_4, the GEMAT generates an actuation command towards S_1. In a real-world warehousing environment, S_1 might represent a production machine/moving product line that is triggered when an MA passes into G_4. In our case, to demonstrate the actuation framework and the GEMAT collaboration in the underlying system, when G_4 is triggered, the light is turned on (S_1 is a Zigbee E26 Smart Light Bulb).

During the tests performed in the environment, for experiment **EX1**, we have confirmed all three scenarios (**SC1**, **SC2**, **SC3**) to be successful in executing geofencing rules. Mobile assets were represented by users carrying Bluetooth beacons on them (smartphones). G_1 was straightforward to implement and test. Also, G_1 rule triggers a database operation (no notification or actuation) so it was straightforward. Geofences like G_2 and G_3 are more complicated to implement. The GEMAT rule enforcer must continue to check both G_2 and G_3 at all times, and if there is a rule breach the appropriate action is taken (in this case notification to a particular system user). Geofence G_4 is an area-based geofence, with the rule that triggers an actuation command to turn on the lights.

In an experimental setup with low signal disturbances and a low location sampling interval of 1s (**DS1**), GEMAT was successful to trigger geofences G_1 and G_4 100% of the time. Temporal/relationship geofences G_2/G_3 were triggered correctly 97% of the time (considering both success and failure scenarios described above). However, for **DS2** where the location sampling interval was set to 10s, the percentage of triggered geofences is only 42% for G_1 and G_4 and 37% for G_2/G_3. With the lowest positioning sampling interval of 1s, the deviation between actual and captured timestamp is minimal. While increasing the sampling interval in an IPS where geofences are relatively close to each other is not recommended, we have increased the sampling interval to 10s (**DS2**). For IPS the sampling interval needs to be as low as to correspond to the type of the indoor area, and expected movement patterns and velocity of tracked objects.

For the second experiment (**EX2**) we have introduced signal obstruction obstacles in two ways: (a) we add two additional access points (MikroTik HAP AC routers - Figure 2, MT) on the same frequency, and (b) we placed a metal cabinet is in front of one of the IoT controllers (Figure 2, CAB). Furthermore, the following GEMAT's geofencing capabilities have been tested: (1) when the BLEMAT contextual learning is disabled and (2) when it is enabled. This means that for (1) GEMAT was working with raw, non-filtered, and uncorrected RSSI and positioning values, while for (2) context was taken into account and values were filtered and corrected through BLEMAT. In our previous paper [19] we have confirmed the influence of the contextual environment on the BLEMAT's positioning capabilities, and have since worked on how to account for them in positioning calculations [18]. Without the BLEMAT context-learning, geofences were triggered in 62% of cases, which is below operational functionality for a geofencing framework. On the other hand, where BLEMAT contextual learning is included, geofences were triggered in 96% of the cases, which is a significant improvement over the first experiment. Additionally, for the experimental use case with G_2 andG_3 for the experiment (1), there were 17% cases where G_3 was correctly triggered and G_2 was not, thus the notification was omitted.

Lastly, we have studied how the actual timestamp of passing the geofence boundaries relates to the timestamp recorded by GEMAT. Our conclusion is that the timestamps deviation is directly related to the location sampling interval, which was confirmed through both **EX1** and **EX2**, and especially from the point of view of both datasets **DS1** and **DS2**. The lowest timestamps deviation in GEMAT is achieved when the location sampling interval is 1s, and that deviation is always below 2s. However, for **DS2**, the timestamps deviation is higher, as expected, and varies between 2-10s.

6 CONCLUSION AND FUTURE WORK

In this paper, we have proposed the GEMAT geofencing framework for IoT systems. Built on top of the BLEMAT IPS, the GEMAT framework assimilates its unique context-learning capabilities which help in correcting position estimation calculations, thus directly making an impact on the quality of geofencing, possibility for defining sophisticated use cases and geofences' relationships. Furthermore, we have presented and elaborated on a performance analysis model for geofencing frameworks and summarized comparison with 5 frameworks to illustrate how the model is used.

To show that the conclusions from this paper can be extrapolated on a larger, and more populated indoor environments, as part of our future work we are going to explore GEMAT's capabilities in large-scale deployments and perform experiments with longer emulation periods. Next, although support for temporal geofences and geofence relationships definition is enabled in GEMAT, as part of our future work, we will develop a deeper theoretical model, a domain-specific language for defining sophisticated geofences and translating their specification to a programming language of choice (to be incorporated as geofencing rules). Lastly, we will also work on enhancing the current capabilities of the visualized specification of temporal geofences and geofences relationships.

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