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Geolocation analysis for Search And Rescue systems using LoRaWAN

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Summary

Low-power wide-area network (LPWAN) technologies are aiming to provide power-efficient solutions to the field of Internet of Things (IoT). Over the last years, we have seen a significant development within the area of IoT applications. For many applications, the problem of localization (i.e., determine the physical location of nodes) is critical. An area study of such use case is also the rescue monitor systems. In this study, we start by describing a solution designed for the long range wide area network (LoRaWAN) to localize position of IoT modules such as wearables used from vulnerable groups. Through performance study of the behavior of a LoRaWAN channel and using trilateration and RSSI information, the localization of an IoT wearable can be acquired within a small range. Routing people in need is one of the use cases the above mechanism could be integrated so as to be able to be tracked by familiar people. After that, we evaluate the usage of mathematical model of multilateration algorithms using time difference of arrival (TDoA) as a solution for positioning over LoRaWAN. The research is carried out using simulations in Python by configuring the constant positions of the Gateways inside an outdoor area. The proposed algorithms can be integrated in application for tracking people at any time and especially routing people from vulnerable groups. Through multilateration and algorithm's prediction, we can have an accuracy of 40–60 m in location positioning, ideal for search and rescue use cases. We finally summarize the above algorithms' estimation and general behavior in a SAR system.

KEYWORDS

IoT, LoRaWAN, LPWAN, monitor, TTN, Wi-Fi

1 | INTRODUCTION

The world of Internet of Things (IoT) commits to the interconnection of data among smart devices and sensors. Nowadays, an explosion of IoT applications can be seen in many industries, many of which focusing on long-range communication, low data rate, and power consumption. These requirements lead to the need of new wireless technologies studies and the development of applications using low-power protocols. Simultaneously, the rapid growth of low-power applications and protocols has led to their incorporation into applications of great importance such as locating an individual or object. Among these value-added services, tracking is one of the most important factors for search and rescue (SAR) systems.

For localization of IoT devices, the literature, giving attention to accuracy has introduced the global positioning system (GPS). It is already known that GPS modules have position accuracy on about 15 m mainly on outdoor environments. Based on this, the above solution is quite attractive for SAR systems. Using GPS, IoT modules consume even more energy than Long Range (LoRa) use case, when localization packets are transmitted to the same rate. This deviation can be up to 20 times, if LoRa is configured both on spreading factors (SF) and bandwidth factors. In addition, GPS has higher power consumption, as GPS requires an extra module for communication on an IoT device.[1] Datta et al.[2] implement and deploy a smart IoT framework for location tracking using GPS/GPRS module. In our case, we want to guarantee the expandability of the battery, something that is not offered through GPS as it is quite costly in terms of power consumption. Having this in mind, we started our research on how to use protocols and networks that consume less power to communicate with gateways and central servers. For this reason, a candidate introduced is low-power wide-area network (LPWAN) for the whole IoT communication and localization.

LPWAN supported technologies are LoRa, Sigfox, and Narrowband-IoT (NB-IoT). Field of our study in this research work is focused on LoRa and Sigfox as well. Sigfox is an ultra narrowband wireless communication technology. Sigfox is aimed for IoT devices where one of its services is geolocation estimation. Many times, Sigfox uses machine learning techniques in order to achieve better accuracy of the position. However, this technology is able to locate devices with an accuracy precision (<500 m), using information from nearby Wi-Fi access points which is compared to crowd-sourced data. The above accuracy has been improved by many researchers, where position is calculated through RSSI power value. This leads to an increase of accuracy especially in small areas (less than 20 m).

With the great impact of the IoT applications, a large number of devices are used to operate on their own for many periods of time, often in long distance from Wi-Fi access points. For this reason, LPWAN technologies have attracted a lot of research attention from companies and global organizations. Practically, the above technology gives the ability to such devices to communicate in long distances on about 15–20 km in good conditions, using comparatively low power.

A geolocation application service built-in using LoRaWAN can be useful for location positioning, with the benefit of consuming fewer and low-cost devices with long-lasting batteries. Such devices could be wearable devices worn by people in need of help. In this case, because we do not know the actual time of location detection, the battery life as well as the cost of the device are considered important factors and should be considered when designing such a system. Some use cases that the above devices could be used are positioning monitor systems for a vulnerable group of people. In this use case, the goal is to locate people in need such as tracking them as they are moving or by creating geo-fences. A use case could be an alert message, if the person in need moves outside a defined area. Another use case could be a child moving unattended in a neighborhood. Geolocation includes the generation of a pair of geographic coordinates and is very close to the use of positioning systems. LoRa operates in various frequencies depending on the region. The value that is useful for us is 868 MHz for Europe citizens.[3]

In this paper, we begin our approach based on IoT devices and the integration of LoRaWAN gateways. After studying the LoRaWAN channel and using multilateration, localization of a person inside an area can be obtained within a small range (about 40–60 m). The proposed approach is a low power and cost solution and with a good possibility to operate even in indoors cases such as universities, playgrounds, or even shopping malls. Even though many candidates have been proposed in the literature to estimate the location, such as triangulation, trilateration, and multilateration, in this study, we evaluate the performance of trilateration and multilateration through simulations and real experiments that took place near the University of Patras, Greece.

After the study, we analyze the results as received from both candidates in order to examine if these methods could be integrated in SAR systems for position estimation in terms of position accuracy as well as per cent distance error on position estimation. The remaining part is described below. In Section 2, we analyze the related work. Section 3 contains an overview of LoRaWAN approach and describes the motivation behind our work and the theoretical background of geolocation. In Section 4, we make some experiments at LoRaWAN simulation testbed for IoT concepts, and we present the simulation results and the results of the real experiments. Section 5 includes the conclusions of our study; while in Section 6, some concepts and ideas that could be part of future study are described.

2 | RELATED WORK

The rapid growth of IoT devices has lead industries, organizations, and individual to the development of significant worth including IoT applications in section of rescue monitoring. In an ever-evolving technology-driven society living, IoT can certainly help develop better solutions and added value in real time. In rescue and general health care area, there are several occasions, such as rescue monitoring and tracking, where sensors can play an important role.

Many researches have already used the traditional GPS in terms of global navigation satellite system (GNSS) receivers for location estimation. Note that GPS systems use a similar approach but need to be more accurate by estimating the distance between a GPS end-client and at least three GPS satellites. This can also be done by measuring the time delay that a signal takes to be sent from the satellite to the GPS end-node and converting this time delay into a distance. GNSS systems have the possibility to provide great accuracy in a few meters but require devices with more power and cost. For localization of IoT devices, the state-of-the-art technology proposes GPS as an ideal candidate for more suitable accuracy results. However, GPS has higher power consumption, as mentioned in Cheng et al.[4] Using GPS IoT modules consumes more than 10 times the energy of LoRa, when localization packets are sent to the same rate. The difference can even be up to 20 times, if LoRa is configured in an efficient way on both spreading factors and bandwidth factors. In addition to a GPS module, a module will also demand for the communication an extra module. So, we start by studying the LPWAN as an ideal candidate in IoT devices.

An approach compared to our study is the one described in Thomas and Ros.[5] In this paper, authors exploit trilateration in order to locate a robot moving inside an area from known base stations. The mathematical model uses geometric arguments, coordinate-free formulas in order to find the position of the robot inside an area. Having this in mind, we start by examining a scenario for SAR systems using trilateration in LoRaWAN networks by using existed gateways, network server, and the IoT device such as a wearable. Moreover, in Moradi Zaniani et al.,[6] authors review the localization techniques that are broadly categorized into two sub-categories, which are range-based and range-free techniques. Then, they focus with algorithm presentation and diagram implementations to ensure that these algorithms can be used to develop a small low-cost low-power LoRa tracking device without global positioning satellite GPS. This is very important as GPS has a significant disadvantage in terms of battery life extension. This study helped us to understand and implement the above algorithms in our simulations as well as in real experiments. In addition,[7] researchers propose a system to locate a mobile device in case of emergency rescue need within the GSM network using a method integrating the known positions of the three base stations and the signal strength received. Compared to the above studies, in our study, we try to locate a person in need (wearing an IoT device) with LoRa connectivity and the known positions of already existed LoRaWAN gateways.

It is referred that through deep learning and machine learning, we can localize the object with the accuracy better than GPS. In the present research work, we will not use machine learning; however, the following references provided us important information regarding the localization algorithms of state of the art. Jondhale and Deshpande[8] propose a better performance on localization accuracy over traditional trilateration irrespective using a generalized regression neural network (GRNN) algorithm. Moreover, Yi et al.[9] exploit Wi-Fi trilateration-based indoor localization system which involves minimum labor-cost calibration to achieve a good accuracy that makes this method a prominent research solution to location-based services. Finally, Wang et al.[10] propose a new machine learning-based localization method to predict the location of a Sigfox module by dividing the space around each base station into sectors. After that, they train a path-loss-to-distance model for each sector to reflect its site-specific multipath propagation environment and predict the location of the user.

In this research, we test localization algorithms in terms of multilateration able to be integrated in SAR systems as an extension to localization methodologies from previous studies. Following, Schmidt algorithm[11] introduced in 1972 present person's location at foci rather than a hyperbola. From the other hand, Friedland[12] introduced a least squares (LS) method, where a linearization algorithm is used to estimate person's position from TDoA. Solutions like Robinson's and Foy[13] using Taylor Series[14] require a priori solution or guess in order to calculate the actual position of an object or a person. The above algorithms' usage will help us to study their performance through simulations and analyze the generated results. The performance is mainly focus on measure distance error and accuracy in positioning an object or people inside a LoRaWAN area. The next section introduces the LoRaWAN overview and localization study.

3 | LORAWAN LOCALIZATION APPROACH

3.1 | LoRaWAN overview

The motivation LoRaWAN is one of the LPWAN technologies presented in IoT market. The above technology has been constructed ideally for IoT modules that consume low power data and transfer data, as a technology can also be used for monitor use cases like vulnerable groups of people. The LoRaWAN standard determines MAC and network management protocols for devices using the LoRa modulation. The network topology of LoRaWAN is a star-of-stars, consisting of a peripheral node that connects only through the LoRa PHY, an end-node; a network server (NS): A centralized entity that is responsible to control the network parameters, exchange messages through the application, and reply to the end-nodes using gateway(s). Finally, a gateway (GW) is required in order to give access to end-nodes connect to internet and push their data. EDs and GWs are interconnected using LoRa. From the other hand, GWs and NS are communicating through legacy IP technologies. The LoRa physical layer operates usually in different frequency bands. In Europe, the available bands are 868 and 433 MHz. In the 868-MHz band case, there are three 125-kHz channels that are able to be implemented in every ED. Also, there are another five 125-kHz channels that can be used for the LoRa communication. By using ultra-narrow band (UNB), LoRaWAN utilizes bandwidth efficiently and experiences high receiver sensitivity, low noise levels, low ultra-low power consumption, and inexpensive antenna design. For this reason, LoRaWAN has been selected as one of the most suitable candidates for IoT network application development.[15]

3.2 | Localization

Real time tracking of people, objects and animals are one of the most attractive applications for companies, researchers, and individuals as well. Nowadays, a few technologies have been introduced to track people and objects in real time, as tracking is one of the most famous applications for developers and researchers. Many researchers through the literature have studied the algorithms and mathematical models that calculate the position. In the field of IoT location estimation, there are three ways of estimating a location through triangulation, trilateration, and multilateration.

3.2.1 | Triangulation

Out of the three techniques, triangulation measures angles rather than distances and is used in many location estimation cases. Building a SAR system through triangulation starts by initiate two points (point 1 and point 2) with an already known distance between them (Figure 1). Between these two points, the angle can be measured by lines from distant points where they intersect with the base line using a device (theodolite). The result of this calculation is the identification of unknown distances and the detection of distant points.

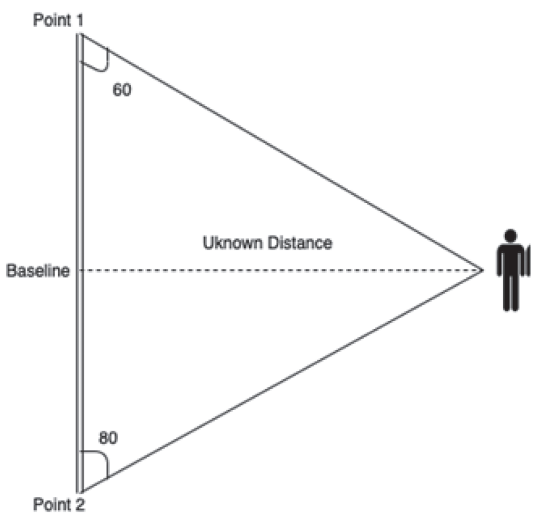

FIGURE 1 Geolocation based on triangulation

Two anchors are needed to determine a location in a two-dimensional (2-D) space in a SAR system and at least three anchors to determine a location in a three-dimensional (3-D) space. Triangulation as a methodology mostly fits in navigation, metrology, and astrometry. It is also an ideal candidate when examining a hilly area due to the ease of establishing stations at appropriate distances and areas; the LoS is hugely impacted and can only be overcome by the use of towers, which significantly increases the cost.

However, triangulation is hard to be implemented in a LoRaWAN use case for SAR systems. The main disadvantage is that requires knowing not just the location of GWs' position. The measurements in this case are significantly sensitive due to the way that they are measured. It also relies on timing differences in the reception of tags' signals where the time differences during transmission are quite small. For the above reason, it is an expensive solution and not preferable to be integrated on a SAR system.

3.2.2 | Trilateration

Trilateration is one more frequently encountered technique that is also used by the traditional GPS. The general idea is that a satellite broadcasts a signal for a GPS receiver to pick up. This is how the distance is calculated between a satellite and a GPS receiver. Having this in mind, a GPS receiver can be in any area along the radius of the circle (or sphere in case of a real-time scenario). Simultaneously, when three or more GPS satellites contact with a GPS receiver, the location can be calculated with higher accuracy.

Figure 2 shows that every satellite is located in the center of a circle. The point where circles intersect gives the location of the GPS receiver. In real-world scenario, the circles become spheres, and thus, four satellites are required to pinpoint the location with better accuracy.

Following our previous research on trilateration for a SAR system, we used more than one links that a LoRaWAN node establishes with surrounding GWs. All established GWs in our area are suitable to receive a data packet coming from an IoT device and forward it to the network server. This leads the network server to have multiple copies of the same package. Next step was to filter the duplicate copies and send a copy to the application service.

The above data can be extracted through the application service by developing a simple API. In this scenario, message queuing telemetry transport (MQTT) used to get the above information. The basic concept is the deployment of a broker, publishers/subscribers and topic creation. A JavaScript Object Notation (JSON) containing all the data and several details about the data channels and GWs is being created.

The critical condition in our approach is that the client in any position inside an area has connectivity with a minimum of three GWs. This can lead to the use of trilateration. The locations of the GWs inside a SAR system are to be installed, and the total number of required GWs is strongly dependent on the context in which the localization process has to take place. The setup of the LoRaWAN GWs has to be done into consideration of factors like the physical dimensions of the area that we want to extend over, the total of devices that can be tracked and any buildings that may be inside.

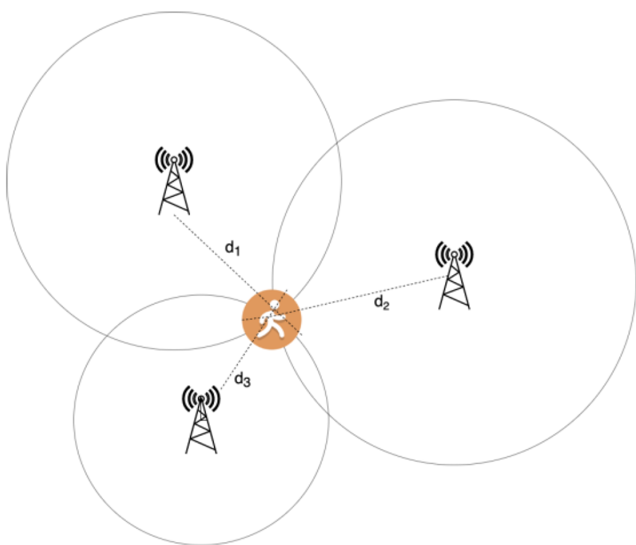

FIGURE 2 Geolocation based on trilateration

The solution proposed in this paper uses multiple links that a LoRaWAN node establishes with surrounding GWs. All established GWs in our area receiving a packet from a LoRaWAN IoT device and forward it to the network server. This leads the network server to have multiple copies of the same package. The next step is to filter the duplicate copies and send a sole copy to the application service. The above data can be extracted through the application service by developing a simple API. In this scenario, MQTT used to receive the above information. It is a lightweight messaging protocol being used for small sensors and IoT modules, optimized for high-latency or unreliable networks improving the data communication. The basic concept is the deployment of a broker, publishers/subscribers, and topic creation. A JSON file containing all the data and various details about the data channels and GWs is being created.

The locations of GWs to be installed and their total number depend on the context in which localization is to be predicted. A paradigm is available on Figure 3. The setup of the LoRaWAN GWs has to be done into consideration of factors like the surface we want to cover, the number of devices that can be scanned and any buildings that may be inside.[16,17]

3.2.3 | Multilateration through TDoA

Multilateration refers on the time difference in the arrival of message signals to base stations. Through the literature on positioning systems, this technique is being used in indoor and outdoor confined regions. For this reason, we extend our previous research about trilateration by integration multilateration in a SAR system. The popular positioning methodology known as time difference of arrival (TDoA) uses multilateration in which the base stations (LoRa GWs) need to be synchronized. In this method, the end-nodes (people in need) send out data packets with their information that are received by the established GWs. The time difference between the GWs is the basis of the distance calculation and the location of the object. The idea behind multilateration is similar to trilateration, except that there's no circle or sphere in this case; TDoA is known as one of the most accurate and power-optimized technique for localization. This method does not require the exact distance from an end-node to each GW but only the differences in distance from each gateway to the end-device. The difference between the distances can be identified with the TDoA of a signal from a device to the GWs. For this reason, many times it is referred as TDoA localization.

TDoA is a well-known technique for localization as it does not require the receivers to be synchronized with the transmitter. This is because TDoA only requires the variations between transmissions. Let us give a SAR scenario where we have to locate an end-node (person in need) in a unknown distance from our established GWs. When a LoRa signal is transmitted from a device, it is received by one or more gateways (where n is the number of established GWs).

TDoA uses the difference in time in order to estimate the position; there is a measurement for each possible pair of GWs. The total number of possible pairs is a binomial coefficient: $\binom{n}{2}$. For each GW pairs, the TDoA can be presented

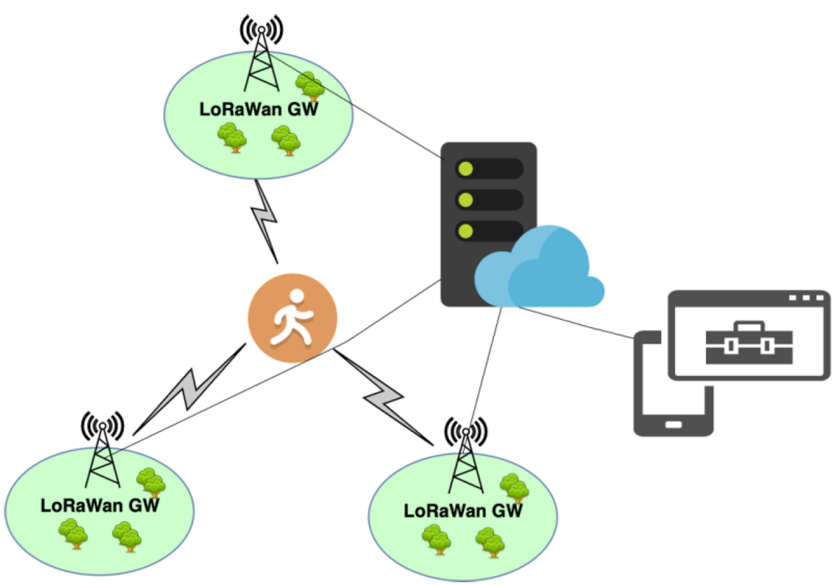

FIGURE 3 The architecture of the proposed system

by $\Delta t_{i,j} = t_j - t_i$, where $1 \leq i < j \leq n$ and t_i and t_j are the timestamps of the GWs. By using the time difference from all the possible gateway pairs, we can calculate the position of the transmitter if the signal was received by at least three GWs. The time differences can be referred as the TDoA measurement and the distance as TDoA distance. The distance is extracted from the mathematical formula below: $\Delta d_{i,j} = c\Delta t_{i,j}$, where c is the speed of light through air. By using TDoA for distance calculation, we can create a hyperbola consisting of all the possible points of where the end-node (person in need) could be. The equation for localization calculation using TOA is

TOA: $st_i = [(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2]^{1/2}$. From the other hand, the equation for the TDOA case is given as below:

$$\text{TDOA:} \quad \begin{aligned} s\Delta t_{ij} &= \left[(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2\right]^{1/2} \\ &- \left[(x-x_j)^2 + \left(y-y_j\right)^2 + \left(z-z_j\right)^2\right]^{1/2}, \\ i,j &= 1,\ldots,N \end{aligned}$$

where s is the signal propagation velocity, t_i is the signal traveling time from the source to GW, and Δ_{ij} the time difference as described above. The terms x, y, z are the coordinates for the position of the person in need in the SAR system. The possible location of the person in a SAR system is generated using a hyperbolic line of position (LOP). In this LOP, the focal points of the hyperbola consist the position of the two receivers that will be used in the TDOA computation. Because TOA and TDoA have measurements errors, the location of a person in need in a SAR scenario may be estimated by propagating the errors through the computation. In the 3-D case, where we build our simulation, a hyperboloid is defined by each TDoA, and at least three TDoAs need to intersect at a unique point to identify a person in SAR system. Intersection of LOPs, a geometric construct is an ideal candidate for position estimation.[18]

4 | SIMULATIONS

In this section, we thoroughly present the simulation of trilateration and multilateration using simulations. As for the geographical area, the experiments took place near the area of University of Patras where three FiPy modules were acting as GWs and Sipy Modules act as end-nodes. Due to the fact that we had a theoretical study in previous sections, we start by installing the GWs on specific positions and with ability to catch the RSSI from end-nodes as a way exploit the mechanism of trilateration.

4.1 | Trilateration

LoRa is capable to be used on low power IoT devices in long range communications. The selection of SF affects the whole communication protocol. Table 1 refers our metrics being used in our simulation. A LoRaWAN network makes use of SF to set the data transfer rate The network server gear the data in form of JSON file with various information about data channels and the GWs where the packet came from.

TABLE 1 Simulation settings

Parameter	Value
Spectrum	Un—licensed
Modulation	Chirp spread spectrum (CSS)
BW	From 125 to 500 kHz
Device capacity	GW configured
SF	7–12
NoG (number of gateways)	3 FiPy modules
End-nodes	2 SiPy modules

Example of metadata format in JSON


```
{
    "modulation": LoRa,
    "code_rate": "4/5",
    "data_rate": "SF7BW125",
    "frequency": 868.1,
    "GWS": [
    {
    "channel": 1,
    "id": eui-fipy2,
    "latitude": 38.316520
    "longitude": 21.788365,
    "rssi": -94,
    "snr": 11
    "time": "2019-12-12T12:20:42"
    },...
}
```


Our approach includes devices which act as end-devices (for example wearable IoT devices) and GWs. The end-points are associated with whatever the vulnerable people are required to be located. The main advantages of these devices are small size and low-energy consumption. The roles of these devices are the periodically broadcast of the selected data. Frequency of this functionality varies according to network availability as well as power consumption in the specific time. This also is varying through the degree of the mobility of the user wearing the IoT device. For example, an IoT device may stream the data in 3 to 7 min, while other may stream in some seconds. Duty cycle is one of the major factors of LoRaWAN standard and so much be considered. For this reason, and use and deployment of low cost modules is required. In this project Pycom modules (by Pycom LTD) is used including: FiPy modules together with PySense sensor shield, track PyTrack sensors shield and SiPy modules. In our case, GWs (FiPy modules) can be single channel devices that do not require additional software to operate them. All GWs must be directed to the central network server and must be configured to be part of the same "application." The code running on both GWs and end-devices is Micropython.

4.1.1 | Geolocation algorithm

In this phase, the geolocation algorithm is being proposed. The basic characteristic of the algorithm is that it uses the generated JSON file as proposed. The LoRaWAN architecture supply information about the GWs coming from the wearable device and the strength of the signal (RSSI) with which it was received. Using these data, we can apply the algorithm. As already proposed, the algorithm is based on trilateration. The same logic is used by the already known GPS. With three LoRaWAN GWs, the real position can be provided as the central point where all three circles intersect. In our case, the GWs that receive the broadcasted message from the wearable device act like the satellite on the GPS use case, and the RSSI value for each GW perceived by the client is used to determine an estimate of the distance. The received RSSI values from the three GWs are the starting point for the estimation of the distance. This process is already known in the literature through various models.[19] So it can be defined as:

$$P_r(d) = \frac{P_t}{d^n}, \tag{1}$$

where n is the called distance-power gradient. In the ideal case, $n = 2$. Interval of value n is[2,6]

$$d = 10^{\frac{RSSI}{10*n}}. \tag{2}$$

Supposing the use of the RSSI value from three different LoRaWAN GWs, g1, g2, g3 that are located at coordinates of type (x, y).[20] If we indicate the computed distances as d1, d2, d3, we have the following equations:

$$
\begin{aligned}
(x-x_{g1})^2+\left(y-y_{g1}\right)^2&={d_1}^2\\
(x-x_{g2})^2+\left(y-y_{g2}\right)^2&={d_2}^2\\
(x-x_{g3})^2+\left(y-y_{g3}\right)^2&={d_3}^2.
\end{aligned}
\tag{3}
$$

After expanding the squares and subtracting the equations:

$$
\begin{aligned}
Ax+By&=C\\
Dx+Ey&=F,
\end{aligned}
\tag{4}
$$

which finally give us:

$$
\begin{aligned}
x&=\frac{CE-FB}{E-BD}\\
y&=\frac{CD-AE}{BD-AE},
\end{aligned}
\tag{5}
$$

where

$$
\begin{aligned}
&A=\left(-2x_{g1}+2x_{g2}\right),\\
&B=\left(-2y_{g1}+2y_{g2}\right),\\
&C={d_1}^2-{d_2}^2-x_{g1}^2+x_{g2}^2-{y_{g1}}^2+{y_{g2}}^2,\\
&D=\left(-2x_{g2}+2x_{g3}\right),\\
&E=\left(-2y_{g2}+2y_{g3}\right),\text{ and } F={d_2}^2-{d_3}^2-x_{g2}^2+x_{g3}^2-y_{g2}^2+y_{g3}^2.
\end{aligned}
$$

This is clearly a 2-D plane.

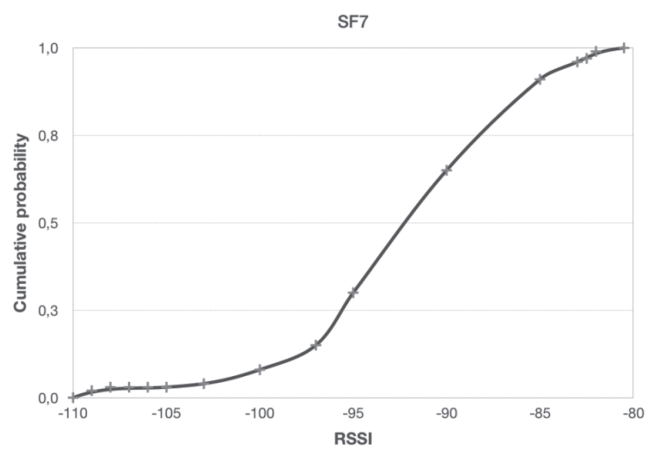

FIGURE 4 Cumulative distribution of the RSSI for SF7 at 150 m

Python Algorithm Implementation

```
#Trilateration formulas to return intersection point of three circles

def trackIoTWearable(x1,y1,r1,x2,y2,r2,x3,y3,r3):
  A = 2*x2 - 2*x1
  B = 2*y2 - 2*y1
  C = r1**2 - r2**2 - x1**2 + x2**2 - y1**2 + y2**2
  D = 2*x3 - 2*x2
  E = 2*y3 - 2*y2
  F = r2**2 - r3**2 - x2**2 + x3**2 - y2**2 + y3**2
  x = (C*E - F*B) / (E*A - B*D)
  y = (C*D - A*F) / (B*D - A*E)
  return x,y

#Generate and represent data to be used by the trilateration algorithm

x1 = randint(-150,-80)
y1 = randint(-150,150)
x2 = randint(80,150)
y2 = randint(20,150)
x3 = randint(80,150)
y3 = randint(-150,-20)
x  = randint(-60,60)
y  = randint(-60,60)
r1 = ((x-x1)**2 + (y-y1)**2)**0.5
r2 = ((x-x2)**2 + (y-y2)**2)**0.5
r3 = ((x-x3)**2 + (y-y3)**2)**0.5

x,y = trackIoTWearable(x1,y1,r1,x2,y2,r2,x3,y3,r3)

#Output IoT location - coordinates
```

4.1.2 | Simulation performance

This section includes the results as extracted from out experiments. We run our experiments in area of Rion of Patras (Greece). The GWs were distributed around the area in distance about 100–200 m. In addition, although the area was not Urban, the study scenarios involved both LoS and nLOS cases in which buildings and objects exist between end-node and GWs that may not be conducive to communication with the terminal device. The hardware used for the experiments were three FiPy modules acting as GWs and 2 SiPy modules acting like clients. The networks servers were provided through the things network (TTN) for simplicity reasons.

Our goal in this study is the calculation of the distance as extracted from the RSSI information.[21,22] The spreading factor (SF) indicates number of chips used to represent a symbol. Since in our scenario the end-node acting like a wearable device at vulnerable people only needs to broadcast the latitude, longitude as well as their id. BER is not a factor that is major.

On about 200 m with SF12, the packet loss rate we could achieve was about 0, with SF10 the packet loss was about 25% higher and on SF7 packet loss rate was higher than 47% of initial value Figure 4. This can also be viewed from the figures below:

The cumulative distribution as metric describes the chance that a given variable will fall between or within a specific range. Using Equation 2, we have $n = \frac{|RSSI|}{10*\log_{10}(d)}$ with $n = 3.9$, $d = 150$ m and $|\mathrm{RSSI}| = 82$. This value may be different in other cases where the topology is different and RSSI signal is vary. Values of n at interval[4,6] seem to be ideal in our scenario using three GWs for trilateration.

Figure 5 displays the distribution on the position estimation of IoT modules. Using geometric dilution of precision (GDOP), we can report the error caused by the relevant position of the devices; In essence, the more signals a LoRaWAN receiver can "see," the more precise it can be. From another aspect, if the GWs are spread apart in the locations, then we could have a better GDOP, as we can see from Figure 6.[23]

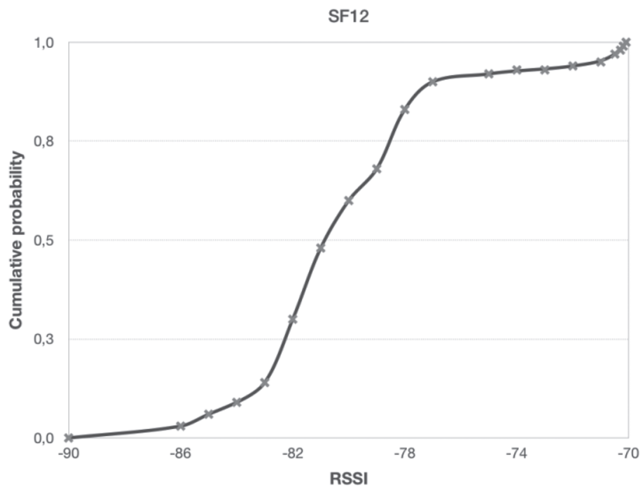

FIGURE 5 Cumulative distribution of the RSSI for SF12 at 150 m

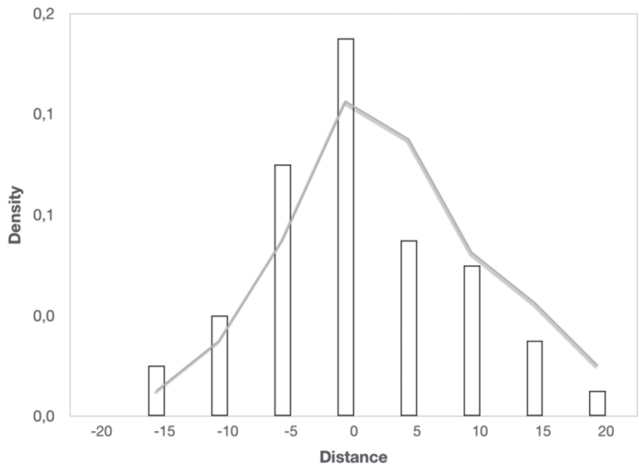

FIGURE 6 Variation of the precision of the localization

4.2 | Multilateration

3-D localization and tracking of people in a SAR system needs at least four different GWs to form the required nonlinear localization equations. From TDoA equation described above, the precision of the estimation of a person can be estimated as a mathematical equation of the errors in the measurements of GWs locations, TDoA, and signal velocity. In our research on the above algorithms, we start by configure four different LoRa GWs in a specific area of Western Greece Figure 7, (view positions in Table 2). The position of the person in SAR scenario was in the area of University of Patras at (38.282200, 21.787980). We will try to assess the position of a person inside the area depicted in Figure 7.

The technique used in our research uses TDoA data measured at four synchronized GWs with known locations. The position and architecture of the GWs and LoRa network server has been studied following authors in Zhou et al.[24] The architecture GWs, LoRa network server and end-nodes have been installed based on streaming data for the interconnectivity between modules and GWs, so as to ensure flexibility and scalability and inside the area. Using the above algorithms, we start by studying the positioning accuracy and error as it emerged from the simulations in Python.[25]

4.2.1 | Positioning accuracy

Table 4 includes the prediction of position estimation using the algorithms from Table 3. For the whole simulation, the position of the GWs is fixed using values of Table 2. Using the mathematical model of each algorithm, we are tried to estimate the position of an IoT device in SAR use case.

Via the Friedlander algorithm the calculated position of the person in need in the SAR use case as we can see is (38.282424, 21.788484). The calculated position seems to be very close to the actual position. The other algorithms seem

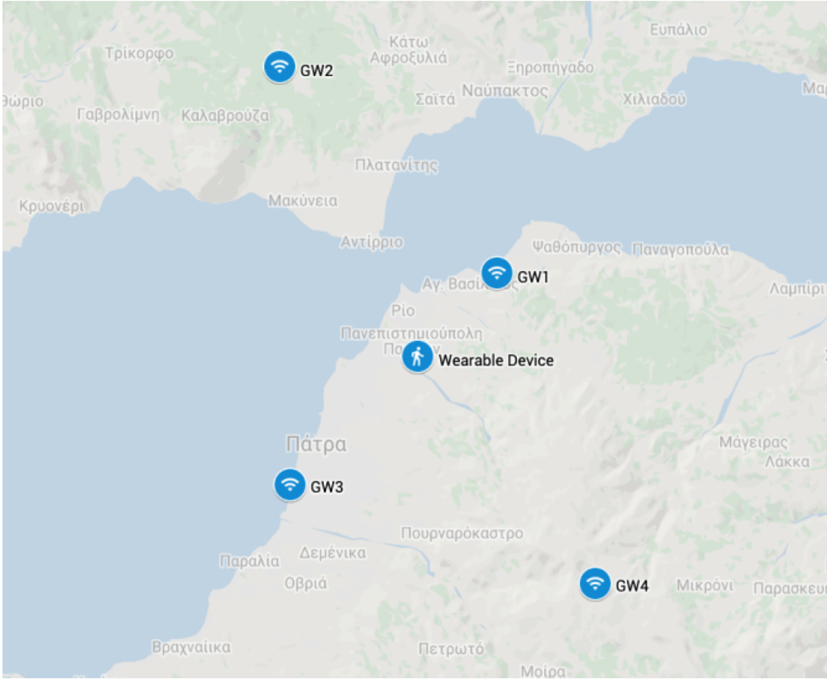

FIGURE 7 Actual position of GWs and wearable in SAR scenario

TABLE 2 Actual location position of gateways

GW	Actual position in 3-D area
#1	(38.31685, 21.82320)
#2	(38.36312, 21.6529)
#3	(38.21386, 21.74062)
#4	(38.2005, 21.92099)

TABLE 3 Summary of TDoA localization algorithms in LoS condition

Author, year	Algorithm	Advantages/disadvantages
Schmidt, 1972	LOCA: Location on the conic axis. Straight line in two dimensions and a plane in three dimensions of people position in SAR system	The GWs appear on the conic and thus the person's location appears at foci rather than on a hyperbola.
Friedlander, 1987	Weighted LS method	Produce a linearization algorithm for estimating a person's speed by TDOA.
S. Robinson, 1987	Spherical intersection (SX) method	Requires an initial solution for the actual position range.
Foy, 1976	Taylor-series, an Gauss-Newton method, giving LS solution	In need of an initial guess, prior the application begins. Is computationally expensive. Effective in multiple measurements

to compute the position of the IoT device with a deviation from the actual position Figure 8. The worst accuracy with the biggest deviation from the actual position is the prediction of the schauAndRobinson3 algorithm (38.18953, 21.86329).

The natural significance of the above results is that the method of calculating the position using multilateration in the case of the friedlander3 and taylorSeries calculates the position of a person more accurately. The location of base

TABLE 4 Results of algorithms estimation about the position of person in SAR system

Algorithm	Calculated longitude	Calculated longitude
Actual position	38.28220	21.78798
schauAndRobinson3	38.18953	21.86329
schauAndRobinson	38.32114	21.74945
friedlander3	38.26205	21.79862
friedlander	38.28242	21.78848
taylorSeries	38.27241	21.78800
schmidt	38.26232	21.78856

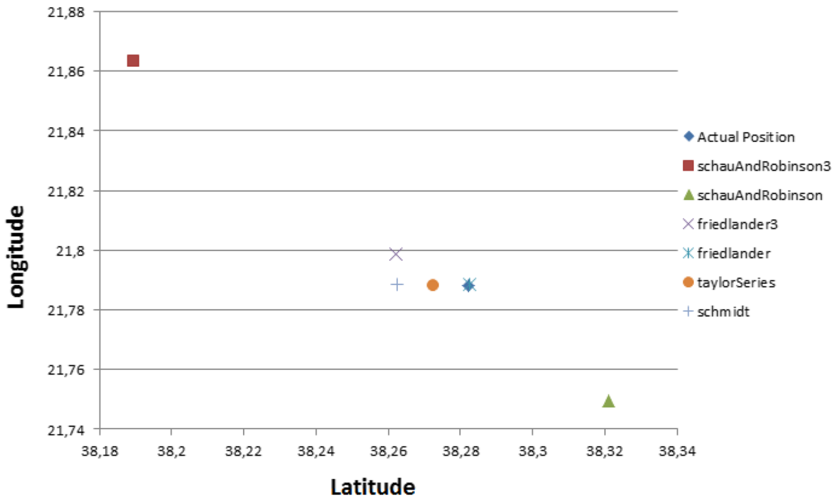

FIGURE 8 Position estimation based on algorithms

stations or better GWs must be fixed in order to be accurate. Upon improving accuracy in location estimation, LoRa shields have great efficiency in energy factors. These benefits make them an ideal choice for transmitters that can continuously operate without usage of continuously power supply. This is very useful in emergencies like people with high probability to get lost as the accuracy of the position should be as high as possible.[26]

4.2.2 | Positioning error

Figure 9 depicts the distance error as calculated in our simulation using the algorithms from Table 2. The results in this research vary based on factors used such as initial guesses and base stations positions. As we can see from the diagram below, the distance error of friedlander is some meters from the actual position of the IoT device (50.6 meters). Next, taylorSeries estimation had a distance error of ~200 m, while friedlander3 and schmidt approached the error on about 1 km relative to the actual position. The worst cases seem to be schauAndRobinson3, schauAndRobinson where the distance error is increasing to 6 and 7 km.

As we mentioned in the case of position accuracy, our goal here is to reduce the margin of error in calculating the position of a person or an IoT device. Figure 10 shows the percent distance error in each different algorithm. As we can see, friedlander calculates the distance with the minimum error in comparison with schauAndRobinson and friedlander3 whose error percent is about 95%–99%. This is very important in SAR cases while the accuracy of the position must be a few meters, for familiar but also police or emergency services, fire brigades which must be immediately called to the site.

The above research is based on mathematical models and algorithms, so a practical study with real time information could be also beneficial for our next steps. Some improvements on GWs positions, interferences from close devices or improvements at transmission power, and improved path-loss model with similar LOS could lead to better results. The above solutions could achieve even better localization accuracy as well as reduce the distance error.

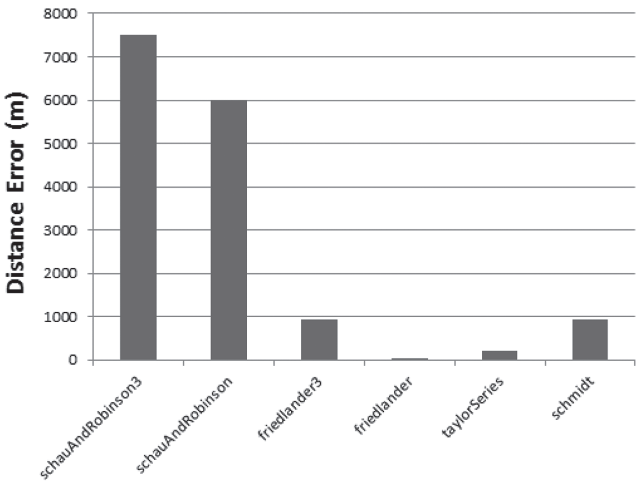

FIGURE 9 Distance statistical error on meters

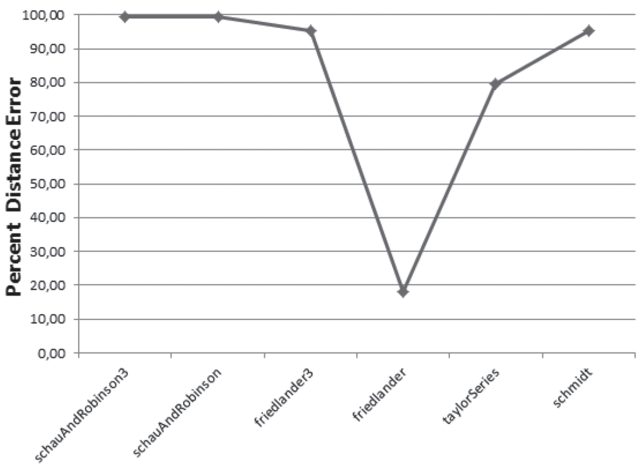

FIGURE 10 Percent distance error

5 | CONCLUSIONS

This section concludes our study on LoRaWAN distance estimation through trilateration algorithm. We described a solution which is based on IoT modules and the integration-deployment of various LoRaWAN GWs to provide localization of vulnerable people use cases. Some improvements must be implemented in order to make this system work as a real-time tracking system. Through calculation using trilateration, the localization of the person can be obtained within 40–60 m range. This approach is based on the usage of the RSSI by various GWs. In this study we focus on the RSSI meaning value, together with the SF selection for the distance estimation. We consider that the above solution could be a research study for indoors areas such as shopping malls, universities campus, or even playgrounds where we could locate people wearing just a wearable device. The main advantage of the use case of trilateration is that it is low cost as the modules cost a few dollars and as a mechanism can give better results even indoors.

Compared to other signal source localization approaches and triangulation and trilateration, TDoA is suitable for applications that require high accuracy. For this reason, we focused on the simulation and research study of some of the most known algorithms. We came to the result that many factors can affect the performance of localization algorithms in specific applications like SAR. These include the GWs positions, the number of people in need, IoT limitations (lost connection to GWs, synchronization, channel structure, battery life), mobility in network, environmental conditions, and uncertainties in propagations (e.g., non-line of sight [NLOS], multipath, and sound speed variation). Despite that companies and research studies focus on the development and improvements on both software and hardware, the challenges on location estimation still exist as they try to achieve high performance and accuracy with economical solutions on both hardware and software.

6 | FUTURE WORK

Future work in this study could be the improvement of the above hypotheses and experiments through GW factors modification or ED's factors such as power of data transmission. These modifications could be made in order to work as a real-time tracking system. Technologies like machine learning, decision tree, naive Bayes, or support vector machine could be applied to RSSI different datasets of measurements improving accuracy of positioning. There are many research studies that focus on the improvement of power consumption by using neural networks coming from machine learning.

Also, next steps could be the integration of the above algorithms on the development of the hardware running on the SAR end-node so as to verify our research in practical experiments. To extend the above study, our goal is the study of the power management and machine learning techniques integration as described in related work in the hardware and software level while using one or more of the above location algorithms proposed in this study.

One more add-on in our research study could be the development of a beta web application together with a mobile app that could be used to monitor and track in real time people in need wearing an IoT device. In addition to real-time monitoring, this application could also include alerts sent by the IoT device via LoRa to the network server. These alerts could be triggered in case this person needs help and could also be part of a general SAR solution.

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