LoRaquatica: Studying Range and Location Estimation using LoRa and IoT in Aquatic Sensing

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***Abstract*—While ubiquitous computing remains vastly applied in urban environments, their applications in ocean environment remain scarce due to the limitations in range and cost of current radio technology. This hinders environmental telemetry in the oceans and other remote areas. In this study, we explore the usage of IoT and Long Range Radio Communication (LoRa) in ocean environments. We study the maximum distance for LoRa and a potential location estimation based on the same technology using the passive RSSI analysis. Using three coastal based nodes and a node mounted on a sea vessel, we report a maximum range of 83.6km. We also achieve a location error within a radius of 3.4km (4% of maximum distance) in the sea. These results support marine biologist expeditions, allowing them to use low-cost, long-lasting and easy to deploy solutions for tracking marine objects and species in open ocean, providing them data in near-real-time. We discuss the findings from used models, outlining limitations, and providing a scenario for future ubiquitous IoT applications for tracking sea objects.**

***Index Terms*—location services, sensor networks, embedded systems, LoRa, IoT, sea Vessels, environmental telemetry**

I. Introduction

Interest for ocean exploration has been growing evermore during the last years, both in terms of natural resource scavenging, as well as in its protection and conservation. While most of the oceans remain greatly unexplored, current applications of technology in aquatic settings allow sea vessels to accomplish numerous tasks. For instance, present tools on market such as sonars[1] facilitate the detection of fish and other marine taxa using sound waves and Wi-Fi for communication to a mobile application. Moreover, emergency position indicating radio beacons [Joo, Lee, Lee, Sin, Lee, and KimJoo et al.2008] (EPIRB) using 406 MHz radio in combination with GPS, facilitate the rescue of those in need. Nevertheless, marine biologists are of crucial importance regarding oceanic studies. As they explore marine species, they focus on understanding the impact of human activities on their natural habitat. However, they often find themselves limited by the high costs of current existing technologies. These existing devices indeed, can collect valuable parameters which are crucial for studying the marine flora and fauna, their habitats and ecosystems. However, all of these technologies have a high cost, facing challenges and risks when applied in harsh ocean settings. These challenges include dealing with poor signal propagation, salt corrosion, water and pressure proofing, battery autonomy, etc, even though some devices can use renewable energies, such as solar panels, wind turbines, or Wave Energy Converters (WEC). [Rynne and Von EllenriederRynne and Von Ellenrieder2008]. Another big challenge is obtaining the geolocation of the collected data. Traditionally, geolocation is acquired using satellite-based systems, which is then stored locally with other relevant data. However, satellite-based location systems are both expensive and energy consuming, and the data can only be retrieved later, when marine biologists recapture the taxa [Cermeño, Quílez-Badia, Ospina-Alvarez, and BlockCermeño et al.2015].

A. Application Scenario

In most cases, marine biologists study species by gathering data from animal tags either by: (i) physically recovering the tag, or by (ii) using radio (usually VHF) and satellite communication (typically GPS). The former solution is long with repetitive tasks which require the recapture of the animals taking months or even years to locate again. As opposed to land animals, marine animals do not have as many physical constraints, and the ability to dive makes it very difficult to relocate them, increasing fuel costs. On other hand, the latter solution is an improvement, using radio signals for the tag recovery, providing a rough estimate of direction and range from a receiving antenna. It still requires the tags to be physically recovered to obtain back the data. Satellites also provide both remote data recovery and accurate geolocation, however, by using the GPS, the battery autonomy of bio loggers is short and the data transfer fees are high (e.g. ARGUS). Our study explores LoRa as a low-cost and long range solution for real-time remote environmental telemetry and location

[1] https://deepersonar.com

estimation for future scientists, while also studying the longest LoRa range.

B. Research Questions and Contributions

While other studies focus on small distances, or city environments, this study, explores the issues of using long range radio (LoRa) in ocean environments, focusing on low altitudes for data collection using sea vessels, where the curvature of the Earth makes a great impact on communications range [P. M. HallP. M. Hall1980]. We explore LoRa as a mean for oceanic environmental telemetry as well as to approximate location without the usage of high energy devices. To achieve this, we focus on the following research questions:

[RQ1]. Which is the maximum LoRa distance in ocean environments? We explore the maximum range of LoRa signal, emitted from the sea vessel reaching the coastal nodes.

[RQ2]. How does the RSSI-based distance and location estimation behaves in ocean setting? Using several distances obtained from land and the nodes, we explore the feasibility of a generic model to estimate the distance from sender to receiver, applied in ocean setting.

The contribution of this study is therefore the maximum range in ocean environments and location estimation techniques using LoRa and low-cost Internet of Things (IoT).

II. Related Work

In this IoT era, sensing and communicating is becoming inexpensive, and is a favorable occasion to explore low-cost sensing and location estimation. This opens an opportunity to obtain geotagged environment data and empower regular citizens to use these technologies, previously only available to corporations or researchers. The areas of previous work that primarily drive this research are: (1) long range radio data communication; and (2) location estimation techniques without satellite-assisted systems.

A following experiment, conducted by [Gogendeau, Murad, Bernard, Kerzerho, and BonhommeauGogendeau et al.2018], explored the different configurations of LoRa (spreading factor, bandwidth, coding rate) in sea environments. Trying to obtain the location of endpoints (using RSSI) which were fixed in 8 coastal locations. They claim a maximum location error of 100m at a maximum distance of 1.6km. Our study, builds upon these findings, focusing in expanding the range much further.

A. Long Range Radio Communication

Most modern communication systems use either electricity or electromagnetism as a way to carry information. Several technologies exist with ranges that go from a few meters (Infra-Red Transmitters, Bluetooth, Wi-Fi) to thousands of km (Satellite), passing through those with a range of a few km (Mobile Phones, TV and Radio). Usually, the longer the range, the more restricted and expensive it becomes, greatly limiting its usage in IoT low-cost solutions.

Many studies have used LoRa or similar technologies in urban and other land environments [Fargas and PetersenFargas and Petersen2017] where it behaves significantly different than in the ocean environments [Guegan, Murad, Lebreton, and BonhommeauGuegan et al.2017], [Gogendeau, Murad, Bernard, Kerzerho, and BonhommeauGogendeau et al.2018] which are the focus of our study. Furthermore, they only focus on small distances (under 10 km), where in this paper, we focus on large open areas. When dealing with geolocation estimation, the Lora Alliance can provide solutions using LoRa transceivers [CommitteeCommittee[n. d.]]. Their solutions can use two different technologies to achieve the geolocation: (i) One using the Received Signal Strength Indication (RSSI) for a coarser geolocation (1 - 2 km) and; (ii) the other which uses Time Difference of Arrival (TDoA) for a finer (20 - 200 m) geolocation.

SmartParks[2] is an example of an initiative which uses LoRaWAN geolocation technology to help with nature study and conservation. In a presentation[3] during the The Things Network (TTN) 2017 conference, Tim Van Dam[4], explained the usage of their system to cover, track and protect endangered species in natural parks. Their biggest example is the Akagera National Park with an area of 1 122 km^2. Even though they managed to keep their costs relatively low, the solution is still based on large stationary gateways using additional expensive hardware. There are several projects run by SmartParks that use a similar system to protect wildlife, one of which tries to protect the black rhinos from poachers in Tanzania.

Recent studies use low-cost controllers to detect and classify cetacean vocal calls [Radeta, Nunes, Vasconcelos, and NisiRadeta et al.2018]. Also, Nikita and colleges used Raspberry Pi and Arduino UNO to build a simple ROV prototype for a surveillance application [Pinjare, Chaitra, Shraavan, Naveen, et al.Pinjare et al.2017]. The Parrticle Photon, an Arduino based integrated IoT platform, has been successfully used in biodiversity monitoring, and simple signal processing [Vasconcelos, Nunes, Ribeiro, Prandi, and RogersVasconcelos et al.2019].

B. Location Estimation Techniques without satellite-assistance

In general, several techniques can be used to estimate the position of ubiquitous devices. These techniques commonly use what has become a standard of GPS. However, GPS cannot be used in some applications due to hardware, power or location (e.g. indoor) constraints.

Distance Estimation based on RSSI - Several research has been done by using the signal strength in the form of RSSI [Elnahrawy, Li, and MartinElnahrawy et al.2004]. RSSI represents the relationship between a transmited and a received power, used to calculate the distance between a transmitter and a receiver when most of the signal propagates in a line-of-sight. It has the disadvantage of depending on the transmitted power, thus not being applied to all hardware, however, it has the advantage of being less costly and not requiring additional hardware.

[2]https://www.smartparks.org/

[3]TimVanDam$_{protectingWildLifeWithLoRaWAN}$

[4]https://www.wildlabs.net/users/tim-van-dam/

III. Methodology

We deployed 5 coastal based nodes (2 failed) and 2 sea vessel nodes on the same vessel, for the duration of 3 days, allowing us to test the range and location of the sea vessel.

A. System Apparatus

The system apparatus was based on 3 coastal nodes and 1 sea vessel node. Each node used a LoPy microcontroller, which was placed into a casing. These LoPys were equipped with the PySense expansion board granting us access to several sensors. Three coastal nodes were deployed within an average distance of 30km, at static locations facing the south of the Madeira island, Portugal. Each node has been placed on top of a 3m pole at an altitude higher than 50m from the sea level. Finally, one node was mounted on top of the sea vessel, capturing the GPS location using a PyTrack. We used the following settings for LoRa: *Region*: EU868; *Transmitted power*: 14 dBm; *Bandwidth*: 125 KHz *Spreading Factor*: 7.

B. Sensory Input

From this apparatus, we gathered a total of 4 366 data points starting at 18:00 hours and the following 40 hours, spanning to 3 days, including a vessel stationary period between the hour 14 to 24.

C. Location Estimation

We explored a basic location estimation using the RSSI. Since the RSSI is in a logarithmic scale, we can either derive the linear equation for the data by: 1) turning the RSSI into a linear scale or 2) turning the distance into a logarithmic scale. We used the first approach, using a common formula (eq. 1) [Al AlawiAl Alawi2011] for calculating the RSSI:

$$RSSI = -(10 \times n) log_{10}(d) - A \tag{1}$$

and reversing it to get the distance: $d = 10^{RSSI/10}$

These equations use the *RSSI* in dBm, and the distance d in meters and have tunning parameters such as n, the signal propagation constant and A being a reference received signal strength in dBm (the RSSI value measured at 1m distance). Figure 1 shows this geometrically, and the solution points are defined as the following [Cota-Ruiz, Rosiles, Sifuentes, and Rivas-PereaCota-Ruiz et al.2012]:

- $d > r_0 + r_1 \rightarrow$ no solutions - circles are separated.
- $d < |r_0 - r_1| \rightarrow$ no solutions - one circle is contained within the other.
- $d = 0$ and $r_0 = r_1 \rightarrow$ the circles are coincident and there are an infinite number of solutions.

Figure 1 (left) shows this geometrically, and the solution points are defined as the following: $a^2 + h^2 = r_0^2$ and $b^2 + h^2 = r_1^2$ Using $d = a + b$ we can solve for a, and it can be readily shown that this reduces to r_0 when the two circles touch at one point, i.e.: $d = r_0 r_1$.

Solving for h by replacing a into the first equation, we get $h^2 = r_0^2 - a^2$. Thus,

$$P_2 = \frac{P_0 + a(P_1 - P_0)}{d} \tag{2}$$

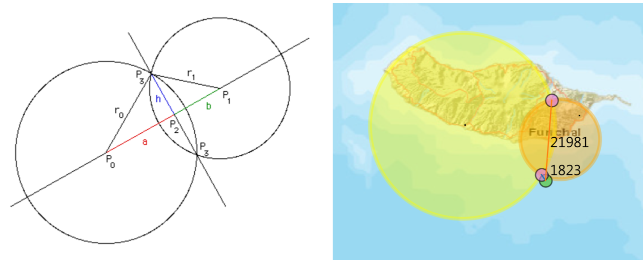

Figure 1. Left: Bilateration theory [Cota-Ruiz, Rosiles, Sifuentes, and Rivas-PereaCota-Ruiz et al.2012]; Right: Bilateration example with the two solutions, and an error of 1823 (excluding the solution located on land).

And finally, $P_3 = (x_3, y_3)$ in terms of $P_0 = (x_0, y_0), P_1 = (x_1, y_1)$ and $P_2 = (x_2, y_2)$, is:

$$\begin{aligned} x_3 &= x_2 + -h(y_1 - y_0)/d \\ y_3 &= y_2 - +h(x_1 - x_0)/d \end{aligned} \tag{3}$$

When the two circles do not intercept, we only know that the solution is along the line perpendicular to P0P1 with its center in the point P2. A relaxation can be made, to estimate that the solutions satisfy the $R_i j = q_j - q_k - R_i k$. Then averaging those two solutions, a single solution would fall in the equivalent of P2 when the circles do not intersect. The same principle applies when one circle is contained inside the other.

Although a higher degree multilateration would usually result in better solutions, in this case bilateration was chosen for 2 reasons: 1) the land-nodes are aligned in an almost straight line with a small curvature in-land. This causes the multilateration equations to near a singularity where it is highly unstable and also tends to give false results inland. 2) the nodes' RSSI values are unstable and don't provide coherent values throughout time, which translates in oscillating calculated radius from each node. Issue 2) further exaggerates issue 1) leading to the usage of a more stable, although less accurate solution: bilateration.

IV. Results

In this section, we present our results, namely the maximum range obtained when sensing data from the sea (subsection 4.1), the distance estimation based on RSSI error using the different data sources (subsection 4.2), location calculation and errors from the bilateration (subsection 4.3), as well as the environmental telemetry (subsection 4.4).

A. LoRa maximum distance

The maximum sustained distance captured by all 3 nodes was of 54.9km away from the shore with a minimum RSSI of -127. And the peak distance was captured by node Green with a distance of 83.6km and an RSSI of -126. These results were captured when the vessel was going away from the coast in a straight line.

B. Distance Estimation from RSSI

We modeled the data using both the raw logarithmic RSSI and distance values and applying the linear regression to them, and we also transformed the RSSI into a linear scale.

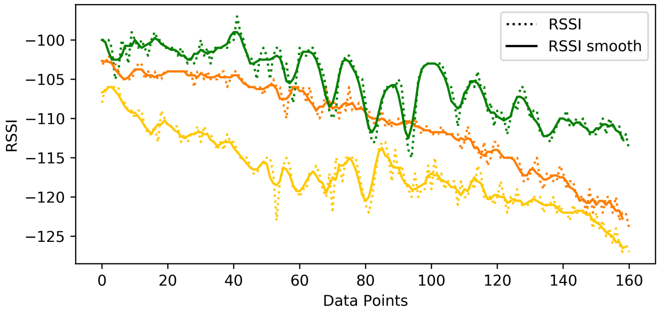

Figure 2. RSSI evolution of the 3 receivers by colors over the trip different distances for the same data point. Original RSSI as a dashed line and the moving average as a solid line.

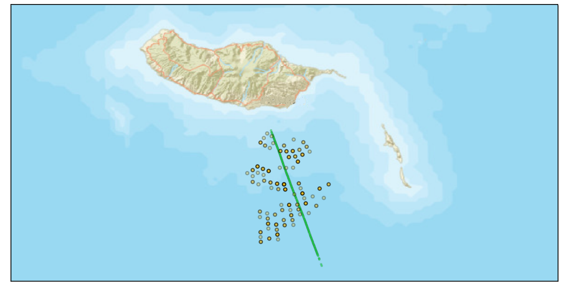

Figure 3. Location estimation from RSSI: GPS ground truth (green); location estimation (yellow - the darker, the more overlapped points).

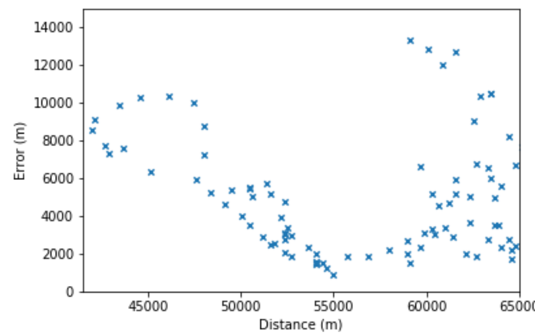

Figure 4. Estimated location errors (in meters) along the distance (as the vessel got further away)

Due the presence of outliers we use the RANSAC (RANdom SAmple Consensus) method [DerpanisDerpanis2010] iteratively using the minimum number of observations and generating candidate solutions where the maximum residual/threshold for a data sample to be classified as an inlier was the MAD (Median Absolute Deviation). This threshold is a robust measure of how spread out a dataset is. It uses the variance and standard deviation, also measuring spread, however they are more affected by extremely high or low values and non normality. [Leys, Ley, Klein, Bernard, and LicataLeys et al.2013].

In figure 2 we can see the variations of the different RSSI signals corresponding to the same vessel location at the different distances that the land nodes were located. While we can observe a steady progression for the orange line, we also notice many oscillations in the green and yellow even in the smoothed signal, which affect modeling. These oscillations are possibly resultant from the placement of the land nodesdue to some mountains and land nearby hindering the line of sight and the capture of the first signals.

Table I shows the residual errors comparison for the different combinations of datasets and models created, combining them in pairs for the different models. We observe that the oscillations from the Green and Yellow receivers (figure 2) influence the inter-dataset data modeling, as the errors increase. In the LoRa context and this oceanic setting, the mean errors have a relatively low impact on the system if we look at them as a percentage of the maximum range of 83.6km and 54.9 km, the average of the combined Orange && Yellow for instance (Orange=1 578 m; Yellow=3 997 m; μ=2 788 m) represents only 3.3% and 5% respectively of the maximum distances.

C. Modeling Location Estimation from IoT input

For the bilateration, we needed to choose two of the receivers, and, as we noted in the previous section, the green receiver has a large error which influences its model and any other model that pairs with it. Hence, we decided to perform the bilateration using only the estimated distance from the receivers Orange and Yellow. The location estimation was modeled using bilateration with an average RSSI of 4 points. The data in figure 3 shows the estimation errors. Due to the low resolution of RSSI, it creates an aliasing effect which results in a grid-like pattern of the location estimation with some estimations overlap (represented by the transparency).

The location estimation resulted in the errors presented in table II. We can observe that the minimal errors come from the Orange and Orange and Yellow using the LS method, followed by the Yellow. As expected from the previous section, any combinations that involved the green receiver, resulted in large errors, due to its model and noise.

Seeing the error in a relative perspective of the maximum distance observed in section IV-A, when comparing to 83.6km and 54.9km, for instance the Orange and Yellow models have average error (Orange=5 657; Yellow=6 207, μ=5 932), which represents 7% and 10.8% respectively of the maximum distances possible we achieve.

Figure 3 shows the estimated locations in comparison to the GPS ground truth. While many points are very close to the GPS line, we can also see the deviations that occur along the way, due to the inconsistency of the Yellow, in comparison to the Orange. In figure 4 we can see the progression of the error over the data points, where with the bigger the distance, the bigger the error becomes. This comes from oscillations in the lower end of the RSSI range, which being logarithmic, small oscillations produce larges distance in the estimation. This error could be diminished by obtaining more points for each location, instead of just the four used in the moving average due to the sea vessel being in constant movement.

V. Discussion

A. Research Findings

1) Maximum Distance using LoRa: During this study, we achieved a maximum range of 83.6km while using LoRa overseas. This range linked a land endpoint (at an altitude of 281m) to a boat's endpoint in the middle of the ocean. This is above the manufacturers' range of 10 to 40 km but bellow a record that used a helium balloon to rise the endpoint up to 38 km of altitude before transmitting a packet to 702 km away with a transmit power similar to ours[5]. The maximum simultaneous range from all the land endpoints to the boat endpoint was of 54.9 km (at altitudes ranging from 57 m to 281 m), within predicted ranges, achieved using LoPy devices coupled with a 1/4 length 868MHz LoRa monopoles. No high-end and expensive gateways or antennas were used in the setup. We can all but speculate that the achieved higher ranges were due to any combination of the bellow as well as any other unforeseen factor:

- Having perfect line-of-sight without obstacles or reflections. The land points were mounted facing the sea, with no obstacles;
- The altitude of the land endpoint vs the ocean endpoint. The longest range was achieved from the highest endpoint (83.6km range from 281m high) and there is a trend of declining range with the altitude (63.8km range from 185m high and 54.9 km range from 57m high). At 281 m high, the distance to the equator, in direct line of sight, is about 60km, which is the majority of whole range, meaning that the signal still has to travel 23km over the horizon to get to the 83.6km range.
- An improved build quality that was achieved over time. The LoRa technology was patented in 2008 and has had time to mature and improve since then.

2) Distance Estimation with LoRa: One of our focus on this study was to use a low tech, low energy solution to find location. This ruled out the power hungry satellite based technology and the expensive ToF based technologies. We were left out with multilateration or multiangulation based technologies. We do not have a low-cost way to find the angle, but do for range, we used multilateration with RSSI values, to find the distance between the nodes. Since the RSSI is inherently sensitive to the environment, even after post-processing, some noise remained, as can be seen in figure 2. Despite that, our results show an average distance error (compared to the GPS ground truth) for the individual models that ranges from 1 359m (with a standard deviation of 1 183 m) up to 5 749 m (with a standard deviation of 4 754 m) which represents 3.5% to 7% of the maximum range measured. The results also show individual errors points with a minimum error of 1 m (that are very close to the estimated regression line) and a maximum error of 25 070 m from a very noisy endpoint. Excluding this endpoint, the maximum error is less than 10km. By combining the dataset from two endpoints, we managed to slightly improve the worst endpoint range estimation at the cost of the other endpoints. This evidentiates how sensitive the model is to noise, but it also suggests that solutions such as a higher number of endpoints or a moving average, do reduce the error.

3) Location Estimation using Bilateration: In our case we were forced to use bilateration. As we explained in chapter 3, the two reasons are: 1) the land endpoints are aligned in an almost straight line with a small curvature in-land. And 2) the nodes' RSSI values are unstable and don't provide coherent values through the time, resulting in different estimated distances for each node. We can fix 1) in the future by better placing or adding more nodes making a better geometry. As for 2), would require a more expensive setup or better hardware. Using the post processed RSSI range values and bilateration from two land endpoints, we calculated the boat endpoint's location. We then compared those values to GPS derived values to understand the accuracy and quality of our results as seen in figure II. The geolocation error ranges from an average of 5 657m for the model that uses just the orange endpoint to an average geolocation error of 21 531 when using the very noisy green model. For individual points in the dataset, the results have a minimum geolocation error of 218 m and a maximum geolocation error of 33 461m, again, for the green model. If we exclude the green model, the maximum error

[5]https://www.thethingsnetwork.org/article/ground-breaking-world-record-lorawan-packet-received-at-702-km-436-miles-distance

Table I
Error comparison (in meters) for the different models used after linearizing the RSSI

Modeled Data Sources	Dataset	Nr samples	Error LS				Error RANSAC			
			μ	σ	min	max	μ	σ	min	max
Individual Model	Orange	251	1 359	1 183	1	7 156	1 359	1 183	1	7 156
	Yellow	221	3 595	2 135	115	9 542	3 616	2 591	7	10 635
	Green	363	5 749	4 754	3	25 070	5 718	4 861	61	25 820
Orange & Yellow	Orange	251	1 578	1 361	6	7 635	1 578	1 361	6	7 635
	Yellow	221	3 997	2 553	25	11 300	3 997	2 553	25	11 300
Yellow & Green	Yellow	251	9 722	4 218	2 023	19 526	14 566	5 633	110	25 247
	Green	363	8 979	4 785	8	19 718	7 143	5 110	25	23 876
Orange & Green	Orange	251	7 793	4 660	151	19 703	9 169	6 270	39	24 258
	Green	363	7 288	3 937	76	16 963	6 514	4 935	8	23 106

Table II
COMPARISON OF LOCATION ESTIMATION ERRORS (IN METERS) FOR THE DIFFERENT MODELS USED FOR BILATERATION

	LS		RANSAC	
	μ	σ	μ	σ
Ora.	3 432	2 013	3 432	2 013
Yel.	6 213	3 696	7 513	4 356
Green	21 313	3 812	22 046	3 848
Orange && Yellow	4 067	2 170	4 067	2 170
Yellow && Green	12 324	2 422	20 279	2 422
Orange && Green	16 343	3 724	21 650	5 989
Orange && Yellow && Green	10 631	2 399	4 550	1 206

is around 15km. Since our bilateration derives, directly, from the distance estimated using RSSI, all the improvements and pitfalls are shared. Although in absolute values these may seem large, in open ocean, with an average error of around 3.4km, it is possible to locate objects with the naked eye, thus this location estimation proving to be useful in such scenarios. Improvements may be done to remove the outliers from the dataset when testing against the models, reducing the error in 30-40%, however, as in real scenarios, we would not know in advance which values were outliers.

B. Contributions

We contribute with nearly 84km of LoRa maximum distance and a location error of 3.4km (4 % of maximum distance) for the long range tests. Nevertheless, other short range studies (max 2km) claim an accuracy of 100m (5% of distance) [Guegan, Murad, Lebreton, and BonhommeauGuegan et al.2017]. When using the real-time location of marine species, 3.4km is adequate when studying migration flows. Our main focus in this study was to use an IoT low cost and energy efficient LoRa solution that could be used in sea environments, to aid the research and conservation of marine life. We explored LoRa, how it behaves over the ocean and the extraction of geolocation of nodes using the RSSI that comes at no cost in any kind of radio communication. We delivered LoRa packets at a maximum distance of 83.6km, much more than the manufacturer claimed range (40km for Pycom LoPy4) as well as most literature.

We also modeled a bilateration and RSSI based geolocation that, even though is far from the accuracy of the modern satellite based technology, is low-cost both in terms of hardware/software as in terms of energy usage. The geolocation had an average error of approximately 5% of the maximum range, or, about 3.4 km. This error is adequate for study of migration patterns, the general location of animals and other situations where a pin-point location is not needed.

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