Robot Self-Localization Based on Sensor Fusion of GPS and iBeacons Measurements

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Abstract. Autonomous robots must be able to navigate on a given unknown environment, which implies awareness of the environment and self-localization. Although the Global Position System (GPS) is widely used for localization, the position provided is not free of deviations, which increases when the environment conditions block the signal. Robots used for crop monitoring and harvesting require robust and accurate localization systems in order to navigate on harsh and challenging environment conditions. This work explored the use of artificial landmarks to increase the accuracy of a robot localization based on GPS data. Distance estimations were done using Received Strength Signal Indicator (RSSI) based approaches. By comparing the Empirical and Analytical models for wave propagation, it's expected to observe a better distance estimation for the Analytical model, because the Empirical one does not considered signal attenuation. Regarding the robot pose estimation, it's expected to be more accurate when fusing the GPS data and the estimated distances, instead of using only the GPS data.

Keywords: Outdoor Mobile Robot Localization · SLAM · Sensor Fusion · iBeacons · Wave Propagation · Path Loss Model

1 Introduction

Robot navigation is a key problem when developing autonomous robots. In order to be truly autonomous, the robot must be able to navigate freely on an unknown environment. For this to be true, the robot must be aware of the world around him and be capable to self-locate in that environment. Self-awareness and self-localization capabilities rely greatly on environment perceptions, which is possible due to the usage of sensors. These capabilities are challenging, because sensors aren't perfect and noisy sensor data leads to errors on the world representation and in bad position estimations. Moreover, inferring the robot position must be done by integrating sensor data from multiple sensors over time, using sensor fusion techniques [6, 9, 27], since one sensor is usually insufficient to do a good estimation. The problem becomes even more complex if the environment is highly dynamic or if the robot needs to represent a 3D world instead of a 2D.

Nowadays, the American Global Position System (GPS) [7, 11, 12] is widely used for outdoor localization, since the service is globally available, providing a good quality

3D position and the GPS receivers are relatively cheap. This system is limited to outdoor environments due to the signal blockage that occur when the receiver hasn't a clear sight of the satellites. But, even outdoor environments present challenges to the development of robot localization and mapping capabilities using only GPS signal. These may occur due to signal blockage, harsh atmospheric conditions or even tall buildings or mountains that cause multi-path interference, compromising the GPS accuracy and signal availability.

This work intends to improve robot outdoor self-location capabilities, when GPS data is compromised. It's expected to improve robot position estimation, by fusion GPS data and other sensor data, such as Odometry, distance observations to artificial beacons and beacon's mapping, by means of a Particle filter. Regarding the distance observations to the artificial beacons, RSSI methodologies were used to estimate the distances. A comparison between an Empirical and Analytical wave propagation models is performed, which is expected to obtain a better distance estimation using the Analytical model, because the Empirical one does not considered signal attenuation.

The paper is organized in four more sections. Section 2 gives an overview of what mobile robot localization is, describing how GPS works and its main limitations and the top challenges of wave propagation analysis. Section 3 describes the methodology of this work. Session 4 describes the tests performed and results. Session 5 finalizes the paper with conclusions and future work.

2 Mobile Robot Localization Strategies

There are no universal best solution regarding localization approaches. Each approach is fitted to a specific environment, such as indoor or outdoor spaces and the conditions in each environment, such as urban areas, forests, underwater, etc. Also, since the localization task depends greatly on sensor data, the sensors used on the robot for localization are chosen accordingly to the specific environment conditions. These sensors can be classified by how the interaction is made with the environment and what is the origin of the sensor data [18].

Known approaches for self-localization, without relying on external components, are the Dead Reckoning systems, which calculates one's current position using a previous know position, such as Odometry and Inertial Measurement Unit (IMU) [2]. These systems are based on the distance, orientation and speed of the robot motion by using accelerometers (motion sensors), gyroscopes (rotation sensors) and encoders connected to the motor or wheels. Accuracy may be compromised in this systems. A small deviation in the beginning will result on a big deviation after some iterations, invalidating the use of these techniques over a large period of time. For this reason, in order to avoid internal state cumulative errors, sensors must also measure the state of the environment.

The world around the robot can be measured using landmarks (both natural and artificial), which consists on specific spots in the worlds with known location. With these approaches, the robot must use sensors to detect the landmark in the environment and calculate its position related to the known position of the landmark, using triangulation and trilateration techniques [5, 15]. Natural landmarks [19], such as walls, doors or trees can be detected using Light Detection and Ranging (LIDAR) sensors [10, 26] and Radio Detection and Ranging (RADAR) [1]. LIDAR and RADAR use respectively a laser scanner or radio waves to measure the distance to the landmark, calculated by the signal Time of Flight (TOF) [21], i.e., the time duration between signal emission and eco reception. Other wide used sensors are the optical sensors, which are based on vision systems such as RGB-D [29] and monocular/stereo vision algorithms [30].

Artificial landmarks can be passive, such as laser reflectors and computer vision patterns, or active, such as Radio Frequency (RF) beacons, Radio Frequency Identification (RFID) tags and WiFi/cellphone relays. There are several methods [15] to estimate the distance between the robot and a beacon, based on the RF signal time travel between beacon and robot or signal angle of arrival in the robot. Some of these methods are the previously mentioned TOF, Time Difference of Arrival (TDOA) [20] and Angle of Arrival (AOA) [14, 16]. Another method is the RSSI [1, 20, 25], which estimates the distance based on the strength of the RF signal received on the robot. In comparison with other methods, the RSSI method has the advantage of no extra hardware is required, other than a simple RF antenna. The disadvantage is the lower precision of measurements when signal noise and interference exist.

All the previous solutions are suitable (but not limited) to use on indoor environments, since first, there are controlled conditions regarding indoor environments and, second, on outdoor environments Global Navigation Satellite Systems (GNSS) [11] are widely used, in particular the GPS.

2.1 Global Position System

The GPS [7, 11, 12] was the first and still by far the most commonly used advanced satellite navigation system in the world. GPS is globally fully operational and it's assured to be free of cost to all users. The tremendous growth of GPS is driven by the enormous number of applications of this system, which are far beyond what was originally designed to be strictly U.S. military system. GPS is widely used on aviation, marine, space and vehicle navigation, mapping, locating and tracking of objects and people, for medical purposes and disaster management.

Restrictions. If the distance between the satellites and the receiver is known, together with the speed of light, the receivers can determine its location. The speed of light is approximately 300000 Km/s in vacuum, but the signal has to propagate through Earth's atmosphere, ionosphere and troposphere, which bend and slow the signal, causing position errors on the ground by making the satellites appear farther than they are. Although being the largest source of error, several other factors affect the accuracy of the GPS, such as accuracy of satellite and receiver clocks, position error on the satellites, atmospheric errors, multi-path interference in the signal and receiver internal errors (when computing the location).

GPS Alternatives. Currently, several countries launched or are developing their own navigation satellite systems, which are used regionally or globally. GPS is the American system, currently the world's most utilized satellite navigation system. The Russian Global Navigation Satellite System[1] (Glonass) also operates globally. The Chinese Beidou Navigation Satellite System[2] (BDS) and the Indian Regional Navigation Satellite System[3] (INRSS) operate regionally, with the possibility of expand their operation globally in the future. The Galileo[4] is European navigation system, currently being developed and with no predictions of being operational before 2020.

Systems based on Differential GPS (D-GPS) and Augmented GPS (A-GPS) currently exist in order to improve the quality and reliability of GNSS, by mitigating signal path distortions and satellite errors. Wide Area Augmentation System (WAAS) provides real time and continental augmentation, operating in North America and extended coverage into South America, the Atlantic and Pacific Oceans. Several other similar international systems exist, such as the Russian System for Differential Corrections and Monitoring (SDCM), the Indian GPS And Geo-Augmented Navigation (GAGAN), the Japanese Multi-functional Transport Satellite (MTSAT)-based Satellite augmentation System (MSAS) and the European EGNOS[5].

2.2 Robot Localization based on RSSI

As mentioned previously, RF devices can be used as artificial landmarks. By receiving and extracting the RSSI value of the RF signal emitted by those devices, the robot is able to estimate the distance between them, using a wave propagation model.

A RF signal is an electromagnetic wave that propagates in every direction through space in a straight line. In the presence of obstacles, both direction of the wave propagation and its amplitude are modified, which represent deviations on signal reception.

Wave Propagation. It's very complex to characterize a wave propagation's behavior, because behavior changes are caused by random events. According to Alencar [3], several phenomenon affect negatively the wave propagation [13], such as reflection, refraction, dispersion (shown on Fig. 1), diffraction and fading. There are advanced techniques, shown by He [28] that try to simulate the complex signal attenuation by having a 3D model of the world and simulating the reflections / refractions that a signal would be subject to before arriving to the receiver.

1 Available in https://www.glonass-iac.ru/en/
2 Available in http://en.beidou.gov.cn/
3 Available in http://www.isro.gov.in/irnss-programme
4 Available in http://www.gsa.europa.eu/galileo/why-galileo
5 Available in http://egnos-portal.gsa.europa.eu/

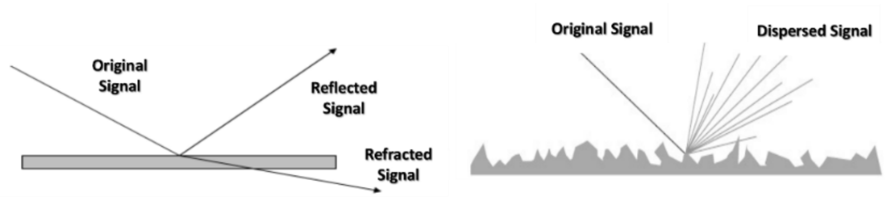

Fig. 1. Reflection, Refraction and Dispersion phenomenon on signal propagation

When a RF signal travels through an object with different density (often occurs on atmospheric variations), a part of the signal is refracted and another one is reflected, which is the number one cause for problems regarding multipath transmission. Dispersion/Spreading is a phenomenon that occurs when the RF signal reaches a rough surface object, dividing the signal into multiple one with different intensity and direction.

Propagation Models. Wave propagation models [13] try to estimate the RSSI at a given distance. Several models exist for different environment conditions, but they are all based on the Free Space propagation model [8, 22], which uses the Friis formula [24] to characterize the signal propagation when no obstacles are blocking the path between transmitter and receiver. Friis formula is valid only in situations where d (distance between the transmitter and the receiver) is at a minimum distance of the transmitter antenna, called the Fraunhofer distance d_f, represented on Eq. (1), where λ is the wave length of the RF signal.

$$d_f = \frac{2d^2}{\lambda}, \quad d_f \gg d \wedge d_f \gg \lambda \tag{1}$$

Since the Fraunhofer distance is not defined for $D = 0$, the model uses a reference distance d_0, represented by Eq. (2), where $P_r(d_0)$ is the received signal strength of reference.

$$P_r(d)_{dBm} = P_r(d_0)_{dBm} + 20 \times \log(\frac{d_0}{d}), \quad d \geq d_0 \geq d_f \tag{2}$$

Outdoor Path Loss Model. Because there is no perfect conditions, the RF signal is normally attenuated due to the phenomenon described earlier, leading to deviations on the calculations [3, 13]. Signal noise and deviations are considered on Eq. (3), where η is the path loss coefficient, X_θ is a normal random variable used to modulate and A is the signal attenuation. The path loss coefficient depends on the propagation environment and must be calculated according to the context (on outdoor the usual value is 2). By knowing η, is possible to linearize the relation between the RSSI ($P_r(d)$) and the distance between the signal emitter and receiver ($d_{i,j}$), represented on Eq. (4). The calculated distance is always associated with an ambiguity factor represented by a Gaussian distribution.

$$P_r(d)_{dB} = P_r(d_0)_{dB} + \mathrm{A} - 10\eta \times \log\left(\frac{d_0}{d}\right) + X_\theta \tag{3}$$

$$d_{i,j} = d_0 \times 10^{\frac{P_r(d_0) - P_r(d)}{10\eta}} \tag{4}$$

Dual-Slope Model. While the Path Loss model considers only the original wave that travels between the emitter and receiver, the Dual-Slope model considers also the resulting waves of reflection that reaches the receiver. The model is characterized by Eq. (5), where h_t and h_r are the highs of the transmitter and receiver related to the ground.

$$P_r(d) = P_t \times G_t \times G_r \frac{{h_t}^2 \times {h_r}^2}{d^4}, \quad d > \frac{4h_t h_r}{\lambda} \tag{5}$$

3 Methodology

Sensor fusion was used to improve the quality of a mobile robot (AGROB V14 platform [19]) localization. A Simultaneous Localization And Mapping (SLAM) technique was implemented, where GPS and RSSI data (from artificial RF beacons) were used to locate the robot and map the world. The robot location was improved by GPS data fusion with Odometry velocity, the beacons distance observations and the beacon's mapping.

Localization systems based on RSSI have three main components: distance estimation between the RF signal emitter and receiver, position calculation based on the distance estimations and localization algorithm.

3.1 Beacons Distance Observation

iBeacons[6] are small Bluetooth devices used as artificial landmarks in the environment. The RF signals emitted were received by an Android mobile device connected to the robot, which used the RSSI value to estimate the distance to the beacon. The distance was first estimated by means of an empirical model that is described, in the Android Beacon Library[7], by Eq. (6), where d is the estimated distance in meters, $RSSI$ is the value received in the Android phone from one iBeacon, $RefPower$ is the reference of the RSSI value (at a distance of 1 meter) and A, B and C are constants to be adjusted according to the environment conditions where the iBeacons are being used. After several field tests, A, B and C were derived from power regression against a table of distance/RSSI values (provided by the referred library), resulting on Eq. (7).

$$d = A \times \left(\frac{RSSI}{RefPower}\right)^B + C \tag{6}$$

$$d = 0.3534536 \times \left(\frac{RSSI}{RefPower}\right)^{14.8393466} + 0.7566785 \tag{7}$$

The empirical analysis has the advantage to consider every factor that influence the radio wave propagation on a given context. On the other hand, the equation obtained from regression may not work correctly on environments different from the one used

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6 Available in https://developer.apple.com/ibeacon/

7 Available in http://altbeacon.github.io/android-beacon-library/distance-calculations.html

to collect data in the first place. Moreover, Eq. (6) may itself be source of deviations and noise. Also, the regression process is very dependent on the Android device used to obtain the data. The simple fact of using devices with different characteristics may lead to deviations and noise. For these reasons, analytical models, namely the outdoor path loss and dual-slope models mentioned before, for wave propagation were used in order to calculate the distance based on the RSSI values.

3.2 Robot Position Calculation

For a 2D position estimation, the robot needs at least three distance measurements to different beacons with known locations. Because the beacon's mapping is unknown and the robot location is estimated based on noisy GPS data, a SLAM approach is implemented, where the beacons are mapped at the same time as the robot position is calculated.

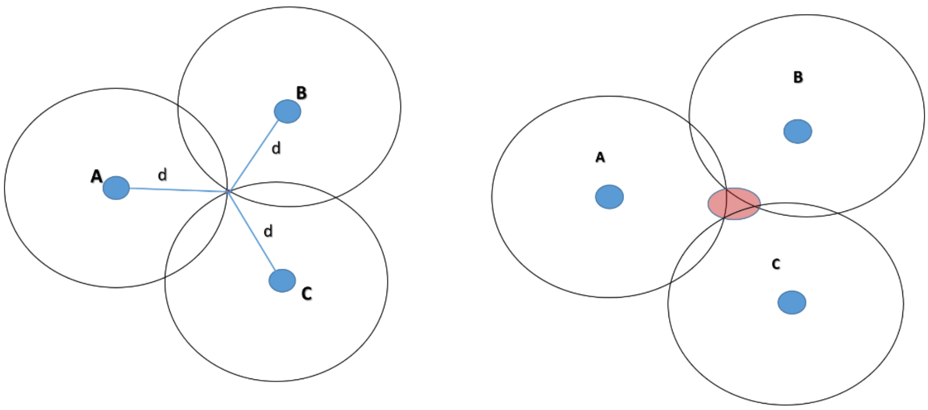

Fig. 2. Both theoretical and real triangulation results

Mapping the iBeacons is accomplished by estimating the beacons location in relation to the robot. By knowing the robot location and the distance between the robot and beacons, one can calculate the beacon position by using the trilateration method. Because only flat terrains were considered so far, the localization problem can be simplified to a 2D format, instead of 3D. At least three robot locations are represented graphically by circumferences, where the radius is the distance to the beacon. The resulting interception point of the three circumferences is the position of the beacon, as shown on Fig. 2 on the left.

3.3 Localization Algorithm

The uncertainties associated to the distances calculated and robot position, shown on Fig.3 on the right, motivated the appearance of probabilistic approaches [17]. Instead of resulting in just one point, the interception of the circumferences, when using the trilateration, results on a set of points, each one associated with a probability that represents the actual position of the beacon. These approaches are associated with filters [23], such as Kalman, Histogram and Particle filters, which increase the quality of the positioning process by decreasing the deviations of samples.

In this case, because robot localization is a highly nonlinear problem, the beacon mapping procedure developed on work [4] was used, which implements both a Particle and a Histogram filter. For a better estimation on the robot location, the Particle filter was used to fuse the GPS data, Odometry and beacon's distance estimation. The Histogram filter was applied to the robot location and distance estimation between robot and beacons (based on RSSI data), in order to map the beacons.

The Particle filter consists in spreading random points through space and associate to each one a probability of being in the actual beacon position. Every time a new GPS message arrives, the probability of each point is updated and the cloud of points gets concentrated, because points with lower probability are deleted and new points are generated close to the most likely ones.

$$P_t(x,y) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(d-z_t)^2 / 2\sigma^2} \tag{8}$$

The Histogram filter consists on a discretization of a 2D space into a grid of cells (likelihood grid map), where the center of the grid is the robot location estimation. The goal is to calculate the grid's occupancy by assigning to each cell a probability of the beacon being located on that cell. The cell probability at time t ($P_t(x,y)$) depends of the beacon distance (d) and robot position (z_t) estimation, as shown on Eq. (8), where σ is the deviation (on a normal distribution) that represents the sum of all uncertainties associated with the robot position and beacon distance estimation.

4 Tests and Results

Beacon distance estimation was tested by comparing the use of an empirical and analytical models for wave propagation. The algorithm for beacon mapping on [4] was tested, using data provided by the iBeacons Kontakt[8].

4.1 Distance Estimation

Distance estimation based on RSSI techniques rely on modeling the beacons RF signal propagation. The empirical model identified on Eq. (6) and Eq. (7) is compared with the Outdoor Path Loss model, identified on Eq. (3) and Eq. (4). Because data is being post-processed and the ground true is unknown, the comparison in relatively to each approach and not absolute. RSSI values were collected and used on both models to calculate the distance to the corresponding beacon. Results are shown on Fig. 3.

[8] Available in https://www.kontakt.io

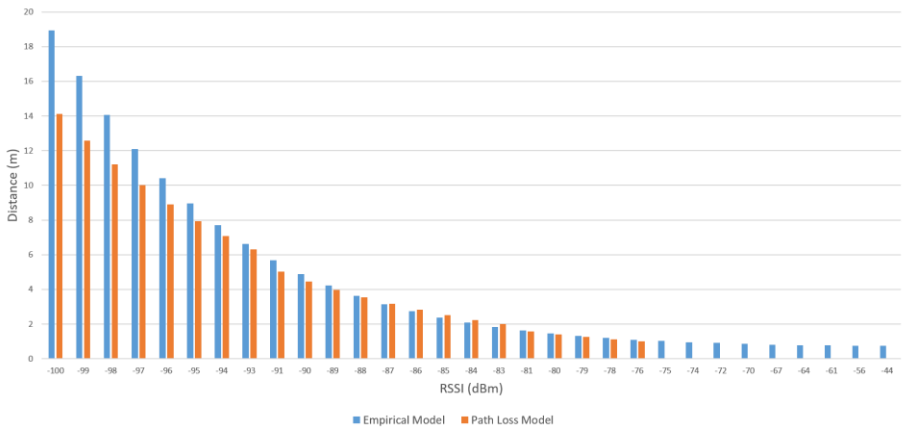

Fig. 3. Distance comparison between the Empirical Model and Path Loss Model approaches

The curve for the empirical model behaves exponentially, while the Path Loss model fits the empirical one (differences are lower than 1m) only between -95dBm and -75dBm, which corresponds closely to 8m and 1m of distance.

For RSSI values higher than -75dBm, the empirical model is more accurate, because 1m is the reference distance used in the Path Loss model. As said before, the reference distance is the minimum defined distance in this model, so results lower than 1m don't make any sense. On the other hand, the empirical model follows its exponential behavior until it reaches a distance very close to 0 on high RSSI values.

For RSSI values lower than -95dBm, a major difference is found between the Path Loss and the Empirical models. On the 8m distance mark, the RF probably suffers deviations, such as reflection and refractions, which weren't considered on the empirical model. Although being theoretically considered on the Path Loss model, the model lacks calibration regarding some parameters, such as signal attenuation and path loss coefficient, which may lead to less accurate modulation of the wave propagation. The static values considered of path loss coefficient is 2 (value defined for outdoor environments) and the signal attenuation is simplified to 1, but, for better accuracy on calculations, these variables should be dynamically calculated over each iteration. Still, 8m is already a big distance to be estimated, considering the problem context and the noise associated to signal propagation at this kind of distances. The accuracy will improve if distances higher then 8m are not considered for calculations.

4.2 Algorithm for beacon mapping

As shown by Duarte [4], the beacons and robot position estimation have improved significantly when fusing the GPS data and the beacon's distance observation, by using a particle filter.

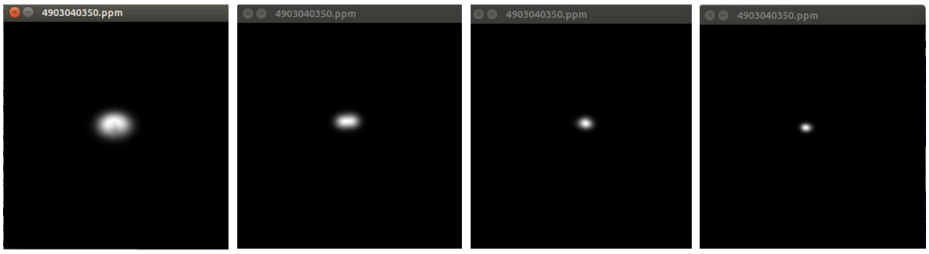

Fig. 4. Evolution of an iBeacon (id = 4903040350) Grid Map with 0.25meters/pixel resolution

In Fig. 4 is shown the obtained likehood grid map for one beacon at four different time instances (0, 70, 200 and 330 seconds), on a test duration of 560. The grid map resolution is 0.25meters/pixel. The possible beacon position starts with a large circle, evolving to two small regions on stage two, which becomes one small region and ends with a very small spot.

4.3 Robot Position

Google maps API was used for illustrating the robot estimated positions on different time instances. By using the particle filter, robot estimation was obtained from the fusion of GPS and odometry, considering the mapped beacons and beacons distance observation.

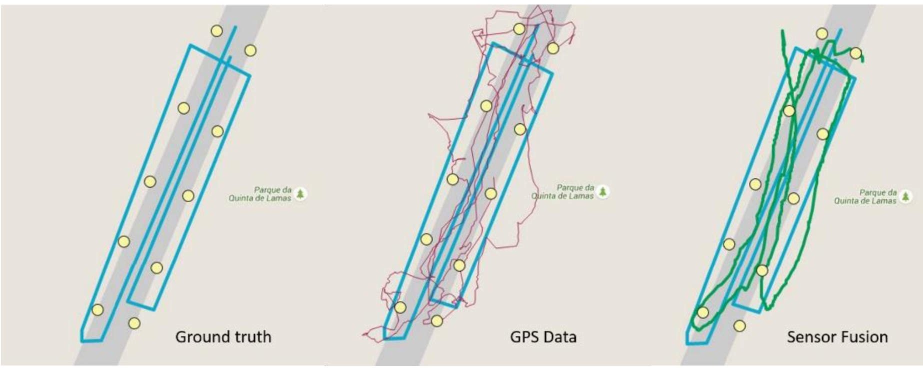

Fig. 5. Planned and estimated robot trajectory

Fig. 5 represents the tests performed for evaluating the robot position, by identifying the robot planned trajectory (on the left), which is considered to be the ground truth for comparison, the estimated trajectory using only GPS data (in the middle) and the estimated trajectory using the results from the sensor fusion described, considering the beacons mapping and distance to beacons (on the right).

5 Conclusions

The main goal of this work is to improve the robot self-localization capability by performing sensor fusion techniques on data from different sensors built in AGROB V14. It was proven in the previous work [4] that the robot location improves by fusing beacons distance information and mapping with GPS data.

The problem of improving the robot location may be approached on two levels: the first is to clean and improve individual noisy sensor data already used to estimate the robot location. The second is to add new (still noisy) sensor data to the sensor fusion approach, in order to get a better estimative of the robot location. The current work approaches the problem by improving the noisy data of the beacons distance observations before fusing it with GPS data. Empirical and analytical models for wave propagation (on RF signals) were considered and compared. Also, by fusing beacon's distance estimation calculated on the models and GPS data, is possible to correct the robot position.

For future work, noisy GPS data can be corrected, by using GPS Augmentation approaches. Regarding sensor fusion, the AGROB V14 is equipped with other important sensors that can be used for localization, such as a RADAR, IMU and a camera, which weren't used in the current work. These sensors' data can also be fused to the GPS data. Also, since several robot locations are required to estimate a beacon position, this work can be expanded by using multi-robot scenarios.

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