

Environment Sensing and Landmarks Detection for Accurate Self-Localisation

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Abstract—In the future system, self-localization emerges as a critical approach to address various challenges, enhance accuracy, and alleviate network-side burdens by shifting computational load to terminal devices. Leveraging diverse sensing and machine learning capabilities becomes instrumental in facilitating self-localization, especially when terminals are equipped with sensors like Light Detection and Ranging (LiDAR) alongside limited computational resources. This paper introduces a self-localization method wherein terminals detect landmarks with known locations in the environment to estimate their own positions. Using LiDAR, terminals scan the surroundings and employ a pretrained machine learning model to detect landmarks. Subsequently, they estimate their positions by comparing the perceived locations of landmarks (derived from LiDAR measurements) with their actual positions. An experiment conducted in our laboratory utilized regular shapes to represent landmarks in any environment, such as doors, windows, and furniture. The results demonstrate accurate location estimation, with errors less than 10 cm when a single landmark is detected. The single-landmark localisation is particularly beneficial in dense environments (Line-of-Sight availability to landmarks is limited) or those with limited features. Additionally, performance significantly improves when multiple landmarks are detected, showcasing the robustness and effectiveness of the proposed approach. The results also show that performance is improved significantly and the error is less than 3 cm when multiple landmarks are detected.

Index Terms—Self-Localisation, 6G IoT Networks, Landmark Detection.

I. INTRODUCTION

Localisation is one of the most important aspects in the communication systems to support a number of applications such as Industry 4.0, self driving cars and Internet of Things (IoT) [1], [2]. It has been predicted that there will be 500 billion IoT devices by 2023 [3]. It is widely believed that each individual localisation method is unable to meet the future requirements by itself due to challenges regarding scalability, blockages and sensitivity to the environment [4], [6]. Therefore, multiple localisation methods and new approaches such as integrated sensing communication are essential to overcome the current challenges and meet the future requirements [5].

In addition to meeting the future requirements (e.g. centimetre accuracy), the localisation systems need to cope with the increasing number of IoT devices and their traffic. Although Multi-Access Edge Computing (MEC) is of vital importance to improve the system performance and reduce latency, it is believed that by enabling terminals to participate in the localization process, the computational burden on centralized systems or infrastructure can be reduced. Terminals can perform certain localization tasks locally (e.g. self-localisation), thus offloading the computational load from central servers or networks which is very desired and supports the system in meeting the future requirements.

Self-localisation in which the terminal is provided with some sensing equipment (e.g. Radio Detection and Ranging (RADAR) and Light Detection and Ranging (LiDAR)) to estimate her location, is considered to be an important strategy to boost scalability and free some of the high demanded resources at the MEC. Developing low-weight localisation algorithms powered by machine learning and compatible with limited computational resources at the terminal's side can minimize the burden on the system and bring further benefits such as providing an alternative localisation method, facilitating navigation and collision avoidance and, identifying and locating different objects and other unreachable IoT devices in the environment. Furthermore, self-localisation can facilitate a secure mutual localisation which is another strategy to ease some of the localisation challenges (e.g. limited LOS in the system) and boost the reliability [7].

It is of vital importance to emulate and further explore the sensing capabilities, in order to benefit from the current sensing equipment and help implement the integration of sensing and communication. We address the LiDAR sensor as it is considered as one of the important sensing equipment in the current systems. LiDAR is a remote sensing technology that uses laser light to measure distances and create highly detailed, three-dimensional maps of the surrounding environment. LiDAR sensors have received significant attention in

different applications such as self-driving cars and robots due to its high angular and depth resolutions, which can provide high measurement accuracy for the environments [8]. The point cloud registration is a common method in literature to align two or more different point clouds obtained from more than one LiDAR by estimating the relative transformation between them [9]. This method has been considered in different applications such as simultaneous localization and mapping (SLAM), localisation and locating objects. The point cloud registration has been addressed by two main methods, traditional point cloud registration [10] and learning point cloud registration [9], [11]. Although the learning method can achieve a centimetre-accuracy in comparison to the traditional method, the main drawback of the point cloud registration method is dealing with large data. This requires significant computational performance and storages. Furthermore, it may suffer from significant delays [12].

Data fusion, in which more than one sensor are used to estimate location, has also received significant attention in literature. Although this methodology can improve performance in terms of accuracy and reliability, in self-localisation, it requires more sensors which means more computational resources are needed and more power consumption is taking place at the terminal's side [13]. As a result, investing the full potential of self-localisation becomes more challenging.

[12] proposed a self-localization framework which included a normal distribution transform algorithm and a two-way information interaction mechanism to provide accurate estimations. Although this paper showed that this method could minimize the storage and computing time consumption required in comparison with other algorithms, e.g. KD-TREE-based nearest neighbour search (NNS) on point cloud, this method is based on multi-sensor fusion (data fusion). In [14], finite-impulse response filter is designed and incorporated into the localization scheme. The location of user is estimated by using the distances between the LiDAR and corner points. It was shown that this scheme provided better performance in term of robustness in comparison to the ones using Kalman filtering. The main challenges in the corner points-based strategies are detecting the correct corners and measurements not being always available especially in large and dense venues. [15] addressed the challenges and system performance degradation due to using one LiDAR. The authors proposed using multiple LiDARs to improve the system performance in self-localization and mapping. Furthermore, similar to [12], localisation in [14] and [15] are based on sensor fusion (LiDAR/Inertial Measurement Unit (IMU) or multiple LiDARs).

The main contribution of this paper is to emulate the 6G sensing system and propose a self-localisation strategy for indoor environment. In this strategy, the LiDAR data is converted into images to train convolutional neural network (CNN) model. This model is used to detect and identify the landmarks with fixed and known locations in the environment. Furthermore, the measurements obtained from the LiDAR (distances to the landmarks with known locations in the environment) are processed along with the other information from

the environment (the terminal is provided with the landmarks and their locations in the environment) to estimate the terminal's location. Note that the landmarks in the environments represent doors, windows, walls or furniture.

The contribution of this paper is summarized as follows:

- A strategy is proposed to enable self-localisation with high accuracy. In this strategy, landmarks with known locations in the environment (e.g. doors, windows, furniture) are detected, identified and located in order to estimate the terminal's location. This strategy invests presence of different landmarks with their unique features in the environment (e.g. shapes and locations) to use as references and estimate the terminal's location.
- This strategy includes a two-step algorithm with light-weight learning model to be used by the terminal with limited computational capabilities and storage.
- The proposed algorithm includes two stages. In the first stage, landmarks in the environment are detected and identified. The second stage is to estimate the terminal's location by processing the limited information obtained from stage one (identified landmarks and detection confidence) and the information about the landmarks such as the coordinates of actual locations in the environment.
- Furthermore, this algorithm can be used to estimate the terminal's location when the number of detected landmarks is as low as one with good accuracy. This supports different type of environments and scenarios such as a high density environment when the LOS availability is limited. The performance of this algorithm is improved significantly when the number of detected landmarks in the environment increases.
- The performance of this strategy is validated in our well-equipped laboratory. This laboratory is provided with different equipment to ensure accuracy such as an automated 3D plotter and laser range finder.

II. PROPOSED SYSTEM

One possible scenario to benefit from the newly emerged technologies and approaches such as sensing technologies and machine learning is that some of IoT devices can be equipped with some sensors (e.g. LiDAR) and suitable computational capabilities to perform some of the localisation tasks locally. In this way, the computational burden on centralized systems or infrastructure can be reduced and the system performance (e.g. localisation accuracy) can be improved. Fig. 1 shows that some of IoT devices (e.g. terminal A) are equipped with sensing capability (e.g. LiDAR) to sense the environment. It is assumed that terminal A is also equipped with suitable computational capabilities to process the sensor data locally (e.g. machine learning model). Terminal A can detect landmarks and objects in the environment which can be used to navigate safely and locate herself, other IoT devices and objects in the surrounding accurately. This information can be shared with the network and other IoT devices in the environment. For example, in Fig. 1, terminal B is can not be located accurately due to LOS links being blocked by the objects in the environment (note that the

number of LOS links are required for an accurate localisation, for instance, 4 anchors are required to achieve 3D localisation when using time difference of arrival [4]). Terminal A can assist in localising terminal B (and other objects in the surroundings) and share this information with the network and/or terminal B. Later in this section, a strategy of self-localisation includes an algorithm to estimate the terminal's location from at least one landmark. The LiDAR is triggered to scan the environment and the LiDAR data is processed by a pre-trained model to detect and classify landmarks in the environment and then estimate the terminal's location. Note that although the strategy proposed in this paper addresses the self-localisation aspect only, this strategy can be easily expanded to address other aspects such as localising other objects and terminals (or IoT devices) in the environment.

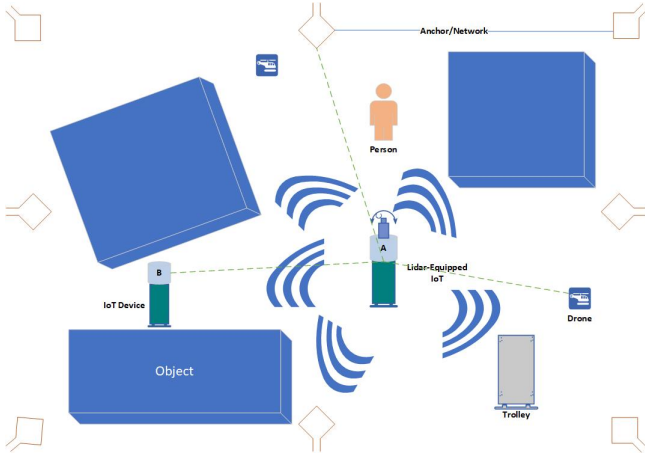


Fig. 1. System Model. The dashed green lines represents communication links between different IoT devices and the networks

A. Proposed Algorithm

In this experiment, we use Ouster LiDAR [16]. The LiDAR sensor data includes four layers for each pixel. These layers are Range, Signal, Near-IR, and Reflectivity as shown in Fig. 2. The Range layer is the distance between a point and the LiDAR, measured by using time of flight (TOF). The Signal layer is the strength of the light returned to the LiDAR. The Near-IR layer is the strength of sunlight collected for a given point. The Reflectivity layer is the reflectivity of the object or landmark in the environment that was detected by the LiDAR.

In the offline phase, some landmarks (different regular shapes such as square, circle, triangle, rectangular) are created and installed in the lab to mock a real environment with different-shaped landmarks in different locations (e.g. doors, windows, different-shaped furniture). And then, real LiDAR data (in form of pcap and json files) is obtained from our lab to extract and convert the Reflectivity layer of each pixel in to images, Fig. 2. These images are processed to train a CNN model. The trained model is used later to detect and identify the landmarks in the online phase as explained later. In this paper, a custom dataset (Reflectivity layer of each pixel) is trained with a modified Yolov5 model [17].



Fig. 2. LiDAR Sensor Data [16].

In the online phase, a proposed algorithm is used to detect and identify the installed landmarks in the environment for location estimation. The proposed algorithm includes two stages, the detection stage and the estimation stage:

1) *Detection Stage*: In the detection stage, the pre-trained model is used to detect and identify the landmarks in the surrounding Fig. 3. In this stage, the Reflectivity layer of each pixel is converted into images to detect and identify the landmarks by using the pre-trained model. Some of the information is obtained at this stage such as the number and shape of the detected landmarks, the confidence (the degree of certainty the model has in its predictions regarding the shape of the landmark) which takes a value between 0 and 1, and regions of interest. The regions of interest represent the locations of detected landmarks on the Reflectivity layer of the LiDAR data. These regions will be used later in the estimation stage to map to the relevant measurements (e.g. distances to the detected landmarks) on the Range layer.

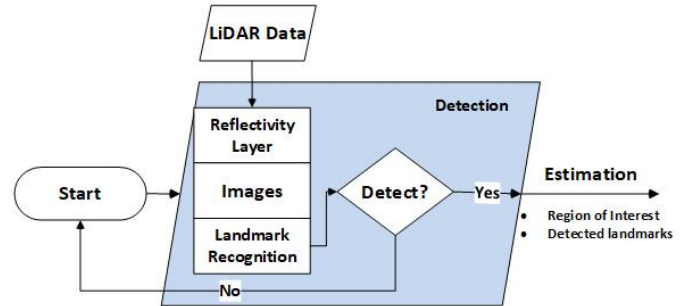


Fig. 3. Landmark Detection.

2) *Estimation Stage*: In the estimation stage, the information received from the detection stage (number and shapes of detected landmarks, confidence and regions of interest) and the actual locations of landmarks in the environment (the actual locations of landmarks in the environment are assumed to be available and known to the terminals) are processed to estimate the terminal's location Fig. 4. The detected landmarks are organized in a list where the landmark with highest confidence is on the top of this list (it is also marked as a reference landmark). This is to avoid any errors due to misidentifying landmarks during the detection stage. Next, the location of

detected landmark from the terminal perspective is measured on the Range layer by using the region of interest obtained from the detection stage. Finally, the location of the terminal is estimated by using the locations of landmarks on the Range layer and the actual locations of landmarks in the environment.

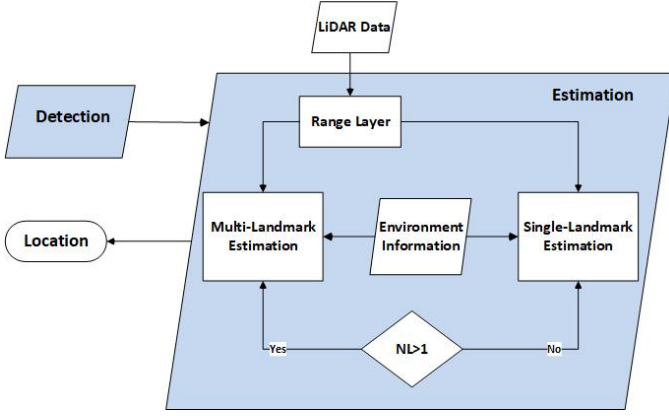


Fig. 4. Landmark Estimation.

B. Location Estimation

The model detects some of the landmarks with some confidences. For instance, different shapes are detected with some confidences similar to Fig. 5. The shapes (or landmarks) need to be chosen carefully as some shapes might be detected and classified as different shapes other than the original shapes. However, some shapes are mistakenly classified due to the scan angle. Assume there are N_L landmarks detected by the terminal where $N_L \geq 1$. The actual location of i th landmark in the environment (global location) is represented by $\mathbb{L}_i = [x_i, y_i, z_i]$ where $i = 1, \dots, N_L$. When the terminal is located at m th point $\mathbb{U}_m = [x_m, y_m, z_m]$ in the environment, the i th landmark is detected by the terminal at s th scan with some confidence. The information obtained from processing the LiDAR data is represented by:

$$\mathcal{I}_{i,m}^s = [\mathcal{L}_{i,m}^s, C_{i,m}^s] \quad (1)$$



Fig. 5. Detected landmarks (shapes) in environment (in our lab). The detected landmarks are classified with some confidence.

where $\mathcal{L}_{i,m}^s$ is estimated location of i th landmark from the terminal's perspective on s th scan when the terminal is located at $\mathbb{U}_m$ (the estimated location is known as LiDAR landmark location as it is obtained with an assumption of the terminal being located at the origin) and $C_{i,m}^s$ represents the confidence of i th landmark on s th scan when the terminal is located at

$\mathbb{U}_m$. The estimated distance between the terminal at $\mathbb{U}_m$ and the i th landmark can be obtained as:

$$\mathcal{D}_{i,m}^s = |\mathbb{U}_m - \mathcal{L}_{i,m}^s| \quad (2)$$

where $|\cdot|$ represents the Euclidean distance. In this strategy, one landmark is sufficient to estimate the terminal's location. Choosing the best landmark is important for accurate estimation. To avoid misleading information when errors occur during the object detection process, the reference landmark is chosen with the highest confidence:

$$\mathcal{R}_{0,m}^s = \mathcal{L}_{n,m}^s \quad \text{when } C_{n,m}^s = \max_{\forall i} C_{i,m}^s \quad (3)$$

Next, the terminal's location is estimated in two scenarios. The first scenario assumes that the terminal detects one landmark. In the second scenario, it is assumed that the terminal detects at least two landmarks.

1) *Location from single landmark*: Finding the location from a single landmark helps the system overcome the challenge regarding LOS availability in the environment. This normally happens in dense environments. In order to find the terminal's location with one landmark, pre-knowledge about the environment (e.g. coordinates of landmarks in the environment) is essential. Assume that we address the system shown in Fig. 6. In the LiDAR coordinates, the terminal is located at the origin and the reference landmark is located at $\mathcal{R}_{0,m}^s$. In order to find the location of terminal in the global coordinates, the locations of landmarks in the environment needs to be considered. The estimated global location of terminal can be found as:

$$\bar{\mathbb{U}}_m = \mathbb{L}_i - \mathcal{R}_{0,m}^s \quad (4)$$

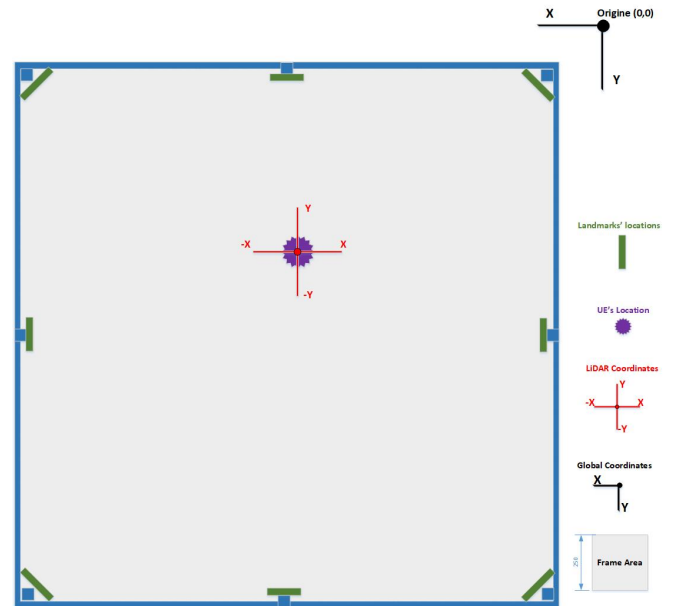


Fig. 6. System.

2) *Location from two landmarks*: The terminal's location in the environment can also be estimated by using multiple landmarks. Assume that the terminal detects at least two landmarks. There are two circles with centres at i th and $i + 1$ th landmarks. The location of the terminal is one of the intersection points of the two circles. The centres of the first with radius $\mathcal{D}_{i,m}^s$ and the second circles with radius of $\mathcal{D}_{i+1,m}^s$ are at $\mathcal{L}_{i,m}^s$ and $\mathcal{L}_{i+1,m}^s$ respectively. The questions of these circles can be expressed:

$$(x - x_{i,m})^2 + (y - y_{i,m})^2 = \mathcal{D}_{i,m}^{s^2} \quad (5)$$

$$(x - x_{i+1,m})^2 + (y - y_{i+1,m})^2 = \mathcal{D}_{i+1,m}^{s^2} \quad (6)$$

Since these circles are intersected, the equation of the line cut through the intersection can be expressed by:

$$y = ax + b \quad (7)$$

where $a = \frac{x_{i+1,m} - x_{i,m}}{y_{i,m} - y_{i+1,m}}$ and $b = \frac{x_{i,m}^2 + y_{i,m}^2 + \mathcal{D}_{i,m}^{s^2} - (x_{i+1,m}^2 + y_{i+1,m}^2 + \mathcal{D}_{i+1,m}^{s^2})}{2(y_{i,m} - y_{i+1,m})}$. If Eq. (7) is substituted in Eq. (5):

$$(1 + a^2)x^2 + (2a(b - y_{i,m}) - 2x_{i,m})x + (x_{i,m} + (b - y_{i,m})^2 - \mathcal{D}_{i,m}^{s^2}) = 0 \quad (8)$$

Eq. (8) can be solved by using quadratic formula:

$$x = \frac{-B \pm \sqrt{B^2 - 4AC}}{2A} \quad (9)$$

where $A = 1 + a^2$, $B = 2a(b - y_{i,m}) - 2x_{i,m}$ and $C = x_{i,m} + (b - y_{i,m})^2 - \mathcal{D}_{i,m}^{s^2}$. The values of y can be obtained by using Eq. (7). Note that the results include two points and one of them will be eliminated by using the prior knowledge on the environment and/or the reference landmark.

III. EXPERIMENT

Our lab is equipped with an aluminium frame (2.5m x 2.5m x 2.16m) and a 3D flatbed plotter. In order to measure the locations of the terminal and landmarks in the environment precisely, a millimetre resolution graph paper is laid on the floor and a Laster Range Finder is used, see Fig. 7. A remotely controlled flatbed plotter is located on the floor of the coverage area, whose head can be moved by voice commands to any required position within the plotter frame [18]. A fixture has been designed and 3D printed for the purpose of integrating the RPi, power bank and LiDAR. The LiDAR system consists of vertical resolution of 32 planes covering 45 degrees in the vertical direction and 512, 1024, 2048 configurable resolution in horizontal plane covering 360 degrees in horizontal direction with angular sampling accuracy in Vertical: $\pm 0.01^\circ$ / Horizontal: $\pm 0.01^\circ$, with 100m in depth performing 10 or 20 Hz (configurable) rotation rate. The resolution of the navigation parameters are: 0.01 m in position, 0.05 Km/h in speed, 0.03 deg in pitch/roll angle, 0.1 degree in heading angle and timestamp resolution $< 1 \mu s$, data latency < 10 ms. A number of landmarks (different shapes) are

created and placed at known locations in the environment as shown in Fig. 7. Note that the landmarks can be items of furniture, doors, windows or any other fixed landmarks in the environments. Each landmark is made of wood and is attached with unique features and information such as shape and location S_i, X_i . For bigger avenue, these landmarks can be reused in the same venue with a different sequence. In addition to the previous location information, this enables the terminal to estimate the location correctly in this venue.



Fig. 7. Lab setup.

IV. RESULTS

In Fig. (8), the locations of terminal are estimated in two scenarios by using the proposed strategy. In the first scenario, a single-landmark is used to estimate the terminal's locations in the environment. The second scenario considers two landmarks to estimate the terminal's locations in the environment. In this figure, the black rings represent the actual location in the environment and, the blue and red rings represent the estimated locations of terminal in the environment in the first and second scenarios respectively. The first scenario (blue rings) shows that this strategy can estimate the terminal location precisely when the number of landmarks detected by the terminal is as low as one landmark in the environment. This scenario simulates localisation in high dense environment where LOS availability to anchors and landmarks is very limited. The second scenario (red rings), in which the location of terminal is estimated when more than one landmark can be detected by terminal, shows that estimation accuracy is improved significantly.

Fig. (9) shows the localisation estimation error in the proposed strategy. It further shows a comparison between the aforementioned scenarios in terms of accuracy. This strategy can achieve an accuracy of less than 10 cm when one landmark is considered. Its accuracy improves to less than 3 cm when two landmarks are considered to estimate the terminal's locations.

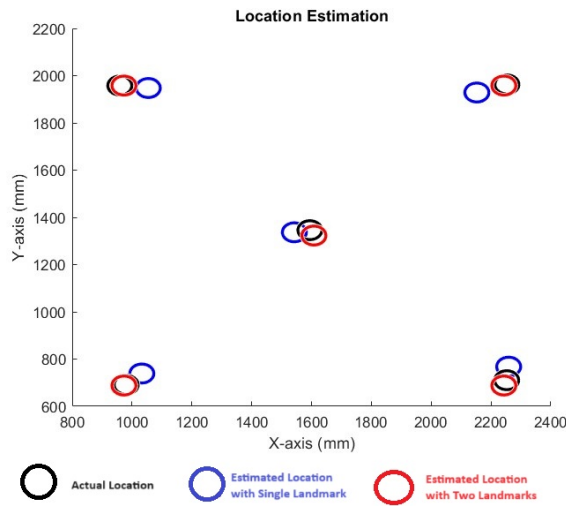


Fig. 8. Results. A comparison between the actual locations, locations estimated by single landmark and locations estimated by multiple landmarks.

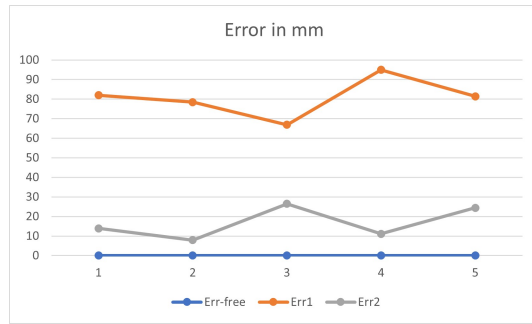


Fig. 9. Results. Errors in location estimation.

V. CONCLUSION

In this paper, some of the potential sensing capabilities powered by machine learning are further explored to support the effort of integrating sensing and communication which aims to enhance localization strategies and improve the overall efficiency of the system. This paper also presented a novel approach to self-localization using sensing equipment (LiDAR), landmarks and machine learning algorithms. The proposed self-localisation strategy suggests using the landmarks in the environment as references to estimate the terminal's location. This strategy includes an algorithm powered by machine learning to detect and localize the landmarks in the environment in order to estimate the terminal's location. Furthermore, this strategy takes into consideration the low computational capabilities at the terminals' side to enable self-localisation. The results show that this strategy can achieve a good accuracy when the number of detected landmarks is one. This demonstrates the localisation in a dense environment when the LOS availability is limited and the environment has limited features or landmarks. The results further show that the accuracy is improved significantly when the terminal detects multiple landmarks. The error is less than 3 cm when the

number of detected landmarks is two or more. As a future work, we consider expanding the strategy to localise other terminals and objects in the environment. We believe this can offer further improvement in terms of scalability and reliability.

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