Validation and Evaluation of the Chosen Path Planning Algorithm for Localization of Nodes Using an Unmanned Aerial Vehicle in Disaster Scenarios

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Abstract. In this paper, a so-called LMAT (**L**ocalization algorithm with a **M**obile **A**nchor node based on **T**rilateration) path planning algorithm is being validated using simulations and evaluated in experiments using a real unmanned aerial vehicle (UAV). Our focus is to find out if the flying path used for our unique scenario, represented by a disastrous event, fulfills the required accuracy. In our scenario, we consider an UAV that moves around buildings and localizes "survived" devices inside a building. This can help to detect victims and to accelerate the rescue process. For this, fast and accurate localization is essential.

Keywords: Localization · Path planing algorithm · Mobile beacon · Disaster · Unmanned aerial vehicle · Simulation · Experiment

1 Introduction

With a rapid deployment of technology and usage of mobile devices, the role of object localization is increasing. Localization of wireless devices in wireless networks is an important and challenging task for many applications, such as healthcare monitoring, personnel and asset tracking, emergency rescue and recovery [2]. One very challenging scenario, that requires fast and accurate location estimation, is represented by the localization during or after a disastrous event. We assume a well-known Wi-Fi technology (IEEE 802.11 standard family) for the communication among nodes in this work. Furthermore, a scenario is considered in which unmanned aerial vehicle (UAV) is flying over an urban area that suffers from a disaster and measures received signal strength of 802.11 beacon frames, coming from nodes that need to be localized. The purpose of the UAV is to localize all survived devices that are Wi-Fi-enabled and can be represented by user mobile phones, notebooks, gadgets. Thus, this information might be very beneficial to accelerate the rescue process.

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In our work, we concentrate on the anchor-based localization algorithms, i.e. there exists an external reference node which knows its position. The latter is represented by an UAV collecting the information for the position estimation process. Furthermore, this work focuses on a range-based localization approach that uses signal strength readings to calculate distances between nodes. Signal strength-based localization is very attractive despite its lower location accuracy in comparison to other methods. Its main benefits are low-complexity and no need in any additional hardware installations.

The related work in the field of anchor-based localization with moving beacons deals mainly with two problems: anchor placement (aka path planning) and anchor selection. Many anchor selection algorithms have been already investigated in our previous work [4]. This paper instead focuses on the validation and evaluation of a path planning algorithm which is represented by LMAT (**L**ocalization algorithm with a **M**obile **A**nchor node based on **T**rilateration) trajectory from [8]. The authors have shown that the LMAT trajectory outperforms many other trajectories in terms of localization accuracy. The goal of this paper is to confirm that the LMAT trajectory can be also applied to a new scenario represented by disasters. The main contribution of this paper is threefold: (1) a validation of the trajectory is being provided with simulations using a signal propagation model that reflects disaster conditions, (2) an experimental evaluation using real hardware equipment that includes an UAV, smartphones and netbooks, (3) a detailed analysis and comparison of results obtained by simulations and experiments.

The rest of the paper is organized as follows. In Section 2, the overview on the anchor placement algorithms will be given. In Section 3, the simulation environment and results are presented. Then, the description of the experimental evaluation follows in Section 4. Section 5 presents a detailed analysis and comparison of the results obtained in simulations and experiments. In Section 6, conclusions are given.

2 Related Work

This work considers methods that fall into the category of localization algorithms using static nodes that need to be localized and mobile beacons (aka mobile landmarks). The latter are represented by UAVs in our scenario. Furthermore, we use geometrical relationships between a mobile beacon and static nodes in order to determine the coordinates of the latter. It has been shown in [8] that the trajectory of the mobile landmark can be crucial and has direct impact on the localization precision. For this, different path planning algorithms have been developed [5–10,13].

The idea of the path planning localization algorithms can be explained as follows. A landmark moves along some specific trajectory and broadcasts information about its position. The problem here is to find an optimal path in terms of localization accuracy and required time to complete the selected trajectory.

In [7], authors proposed three trajectories named SCAN, DOUBLE SCAN and HILBERT. It has been shown that the static trajectories help to improve localization accuracy in comparison to the random movements. Also, it was observed that SCAN performs better than HILBERT achieving a higher resolution defined as a relation between the average distance to anchors and the trajectory length. The smallest localization error was obtained using DOUBLE SCAN trajectory. However, the distance traveled must have been doubled as compared to SCAN.

In [5] and [6], authors suggest spiral-shaped and S-shaped (aka S-CURVE) trajectories. It has been shown with simulations that S-CURVE is shorter and the energy consumption is lower compared with other trajectories like CIRCLES, SCAN and HILBERT. However, due to difficult signal propagation, S-CURVE trajectory showed poor results in scenarios when unknown nodes are located close to the edges of the area of interest.

Another work in [8] compared the existing trajectories SPIRAL, SCAN, DOUBLE SCAN, and HILBERT to the so-called LMAT method (**L**ocalization algorithm with a **M**obile **A**nchor node based on **T**rilateration) which was introduced by Jiang et al. The LMAT trajectory consists out of triangles that cover the whole area of interest. This guarantees that all nodes will receive beacons required for the localization process. The results show that LMAT outperforms the existing algorithms in terms of localization accuracy. Also, it has been proven that the localization error is the smallest when the triangles are equilateral.

Han et al. in [9] investigate the performance of already mentioned trajectories (LMAT, SCAN, DOUBLE SCAN, HILBERT, and SPIRAL) using a mobile anchor node. However, the authors do not use any signal propagation model. Instead, they add a noise variance to the distances between nodes being simulated during the localization process. This is not realistic since the relation between distance and estimated signal parameters is not directly proportional. It is not described explicitly how the range of the noise variance is chosen. The length of LMAT trajectory is assumed to be over 400 m. In our simulations, we consider a shorter trajectory length and much slower flying speed of an UAV to reduce negative effects of high speed movements that would destructively affect the localization results. Instead, we collect a bigger number of readings and apply a sophisticated algorithm to select the most beneficial constellation of these measurements. This results in saving energy of an UAV battery and increase of the localization accuracy. Also in our simulations, we apply an appropriate signal model that reflects a difficult signal propagation environment in case of a disaster scenario.

In [10], a pseudo formation control based trajectory algorithm is presented to determine an optimal trajectory of a moving beacon. Although authors are assuming a similar scenario as in our paper, simulations are performed using a free-space signal propagation model. For our scenario, this would result in higher localization uncertainty. A difficult signal propagation environment, that includes wall penetration, must be considered. In [10], the obtained trajectory has an adaptive character, while we are concentrating on a static path planning. Deterministic trajectories help to save energy as well as to keep the reconnaissance time predictable and as short as possible.

A so-called Z-curve path planning mechanism has been proposed in [13]. It has been proven that a Z-shaped trajectory ensures three consecutive non-collinear messages through the shortest possible path. Motivated by the need to build a path that avoids obstacles, authors developed a mechanism that uses known positions of obstacles and constructs a path with a high number of turns. However in our scenario, a lot of points, in which an UAV has to rotate changing the direction, would introduce a considerable overhead resulting in unnecessary time delays and energy waste. Furthermore, in disaster scenarios, it is not realistic to assume that there is a map of obstacles available before the reconnaissance.

Based on the above overview of the state-of-the-art path planning approaches as well as their strong and weak aspects, we have chosen LMAT trajectory for the validation and further experimental evaluations. According to the results in [13], the best efficiency with minor variations is presented by LMAT and Z-curve mechanisms. However for our scenario, Z-curve is considered to be unrealistic.

The effectiveness of the chosen path planning algorithm has to be validated. For this, simulations were performed in advance of experimental evaluation to confirm the correct choice. Next, we introduce the simulation setup.

3 Simulation Setup and Results

We assumed the following scenario: an UAV is flying over the 10x10 m area along the LMAT (see Fig.1). The trajectory consists of 500 points in which the UAV takes RSS (Received Signal Strength) measurements of signals coming from nodes to be localized. Location estimation is performed after every new measurement, building 500 intermediate results. In order to make simulations as close as possible to the reality, a state-of-the-art signal propagation model was included.

3.1 Signal Propagation Model

For our disaster scenario, it is important to consider a wireless communication between the outdoor and indoor devices. A similar scenario was investigated in [11] where RSS readings have been measured by an access point inside a building of signals emitted by a wireless device that was outside. The result of this campaign was a signal propagation model that additionally considers a wall attenuation factor:

$$P_r(d) = P_{r_o} - 10\alpha log(d) - W + X_\sigma \ [dBm], \tag{1}$$

where P_{r_o} is the path loss on a distance 1 m from a transmitter, α is the path loss exponent, W is a wall attenuation factor. X_σ represents shadowing, which is modeled as Gaussian random variable with zero mean and standard deviation σ dB [11]. This model has been applied to the experimental results obtained in our previous work [4], where a similar scenario has been investigated. It was found that the best fit is represented by the following parameters:

$P_{r_o} = -40$ dBm, $\alpha = 3.32$, $W = 4.8$ dBm, $\sigma = 3.1$ dB.

These parameters together with eq. (1) have been used in the simulation to generate RSS readings and to calculate distances according to these readings.

3.2 Anchor Selection Technique

The main idea of anchor selection is to choose the most effective constellation of the reference data sets from redundant data available for the location estimation. In our simulations, a Joint Clustering (JC) method has been used. It has been proven in our previous work in [4] that JC shows better results in terms of localization accuracy and complexity compared to other anchor selection algorithms.

The Joint Clustering method was first introduced by Youssed et al. [12]. The main idea of this method is to choose k anchors from the m strongest signal strength levels among a set of available anchors to perform a location estimation. Authors proposed to choose three measurements each from the three strongest RSS levels. In our simulation however, we extended the number k to ten in order to increase the localization precision.

Furthermore, a multilateration technique from [4] was used for the calculation of nodes' coordinates using location information of up to ten anchors and the estimated distances to these anchors. In our studies, multilateration is referred to as an algorithm that incorporates multiple reference points by minimizing the mean square distance error of these points to the unknown target position.

3.3 Simulation Results

Massive simulations were performed. For the LMAT trajectory, simulations have been repeated 1000 times, each time changing the position of the target node randomly using uniform distribution inside the area of interest. In this way, we excluded any co-dependencies. Furthermore, the simulation process was repeated twice, each time resulting in the same statistical interpretation. The simulation results in form of the Cumulative Distribution Functions (CDFs) are given in Fig. 4(a) and (b) where simulation results are presented with dashed lines. While the plot in Fig. 4(a) represents all intermediate results (500 localizations for every from 1000 repetitions), the plot in Fig. 4(b) is only based on the 500th iteration.

We observed that the average localization error less than 1 m obtained in our simulations corresponds to the order of magnitude of the localization error obtained in other works [9,10,13]. With this, we confirm that the LMAT trajectory can also be used for our scenario. For that reason, we applied LMAT trajectory to our real time experiment which is described in the next section.

4 Experimental Evaluation

There is a lot of theoretical work about path planning algorithms, but to the best of our knowledge, there are very few of them that present evaluation using experiments. For our experiments, we used a four-rotor quadrocopter (QC) that will be described below.

4.1 Experimental Setup

The experiment was conducted at the Ilmenau University of Technology, Germany. The chosen trajectory was mapped to the area of 10x10 m, according to Fig. 1.

Weather conditions at the time of the experiments are summarized in Table 1.

Table 1. Environmental conditions at the time of the experiments

Atmospheric conditions	Index
Air temperature	17.9 °C
Humidity	38,7 %
Speed of wind	5 m/s
Strength of sunlight	362,4 W/ m^2
Air pressure	985,5 hPa

During the real-time experiments a QC was flying around the area of interest according to the LMAT trajectory. Both experimental (a snapshot of one trajectory that the QC flew) and theoretical trajectories are shown in Fig. 1. Five netbooks of model ASUS Eee PC Seashell series and five Samsung Galaxy S smartphones, running Android 4.2 were chosen for our experiment. Netbooks were equipped with Wi-Fi IEEE 802.11 b/g antennas, configured to run in an ad-hoc mode. Smartphones were launched in Wi-Fi IEEE 802.11 access point mode. We have chosen the location of the nodes, in a way that four of the nodes were positioned in the corners of the area of interest and the rest were spread randomly. In this way, obtained results will show how the position of nodes influences the localization precision. The detailed coordinates of all devices is presented in Table 2. The setup of our experiment is seen in Fig. 3.

Table 2. Positions of unlocalized nodes

Equipment	Coordinates (x,y)
Smartphones	(2.5,2.5); (2,8); (10,0); (5,5); (9.5,4)
Netbooks	(0,0); (10,10); (5,1); (2.5,5); (0,10)

The description of the main QC parameters can be found in Table 3. QC was operated remotely. The experiment was repeated six times.

Next, we present a detailed analysis and comparison of the results obtained with both simulations and experiments.

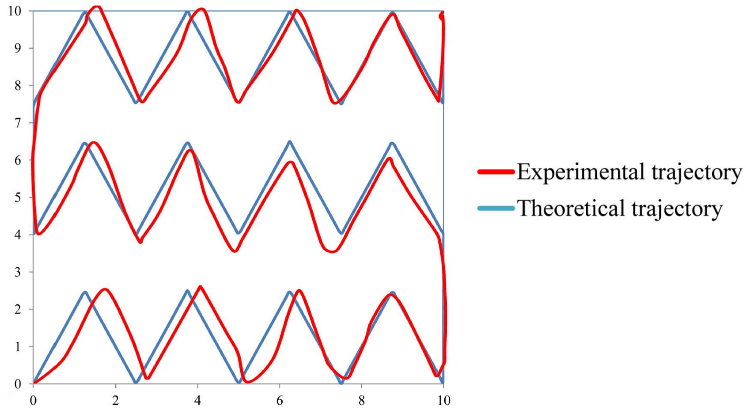


Fig. 1. Comparison of theoretical and experimental trajectories (red-colored: experimental, blue-colored: theoretical)

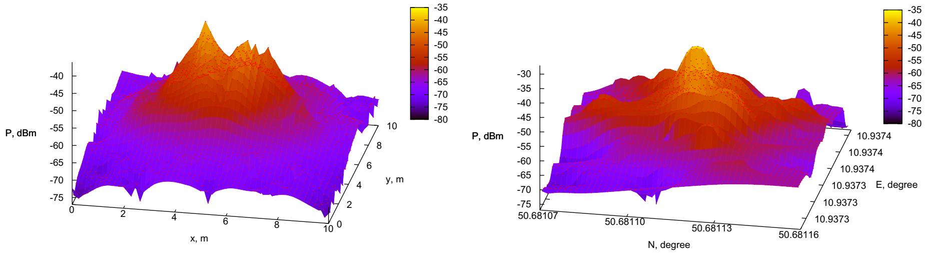
Table 3. Technical parameters of the quadrocopter

Technical Characteristic	Model or Parameter
Processor	600MHz Cortex A8
RAM	256MB
Gyroscope/Acceleration Sensor	MPU6050
Magnetic Field Sensor	HMC5883L
GPS Receiver	UBLOX6
Barometric Pressure Sensor	MS5611
Ultrasonic Sensor	MaxSonar I2CXL
Operating System	Gentoo Linux
Flight and Measurement Software	PengPilot (www.github.com/PenguPilot)

5 Detailed Analysis and Comparison of the Results

To evaluate the performance of the chosen trajectory and the signal propagation model used in both simulations and experiments, we have used several metrics. First, we compare the heat diagrams of the signal strength derived with simulations and experimental data. Next, we calculate an average localization error in meters, to obtain the accuracy of the localization. For the selection of anchors, we have applied three different anchor selection algorithms, which will also be reflected in the plots. Since both netbooks and smartphones were used in our experiments, we compare the location estimation accuracy between these two device types. Moreover, we observe a relationship between nodes' positions and localization error.

1. **Accuracy of the applied signal propagation model:** According to the data collected by QC, the heat diagram of the received signal strength was



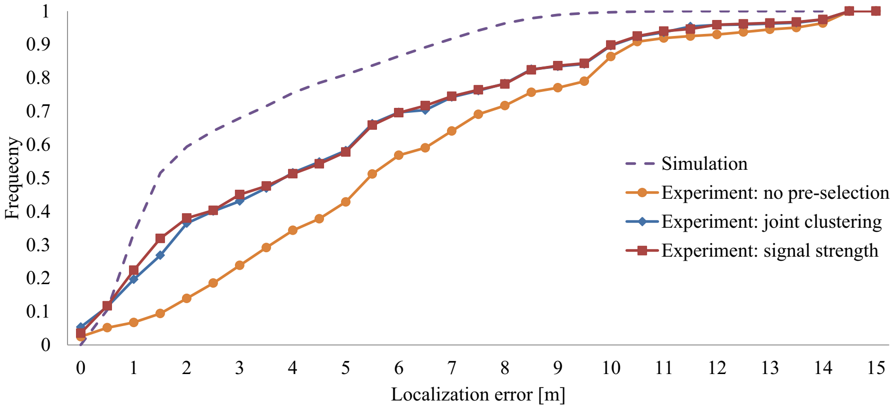
(a) Theoretical heat diagram (b) Experimentally obtained heat diagram

Fig. 2. Heat diagrams of the signal strength for the target node located at the coordinate (4.9 m, 6 m) in simulations and (5 m, 5 m) in experiments

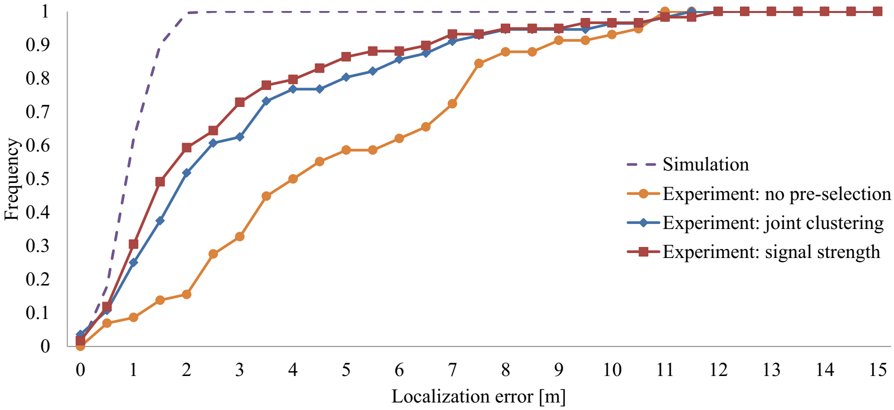
Fig. 3. The working area of the performed experiment. Size of the marked area is 10x10 m.

created. It can be observed in Fig. 2(b). In comparison to the heat diagram derived from our simulation results (Fig. 2(a)), the experimental one shows higher and more frequent fluctuations. The simulated signal strength is decaying more or less equally in all directions, which is different in Fig. 2(b). This happens due to the fact that in the simulation, shadowing is assumed to be normally distributed. In the reality this is not the case.
However, we can see that both have approximately the same received strength range, varying from -35 dBm to -70 dBm. This shows that implemented signal propagation model gives results which are close to the reality due to two factors. First of all, the wall attenuation factor was taken into account and secondly shadowing was modeled as a random Gaussian variable, the importance of which was discussed earlier. This shows that implemented signal propagation model can be applied to disaster scenarios.

2. **The type of anchor selection algorithm**: Fig. 4(a) and Fig. 4(b) show the cumulative distribution function of the localization error obtained from simulation and experimental data. While the plots in Fig. 4(a) represent all



(a) Localization error CDF for all intermediate results.



(b) Localization error CDF for the last iteration.

Fig. 4. Simulated and experimentally obtained localization error CDFs. Three different anchor selection algorithms were applied to the experimental data.

intermediate results, plots in Figure 4(b) are only based on the last iteration. Here, we also compare the performance of different anchor selection algorithms. In our simulation we used Joint Clustering (JC) method only which was explained in the previous chapter. For experimentally obtained data, besides JC, we applied further two methods from our previous work in [4]: (1) signal strength-based method (SS) and (2) algorithm which does not have any pre-selection criteria and incorporates all available data sets using multilateration method to calculate a corresponding coordinate. The key observations here are the following. The smallest localization error less than 2 m was obtained by the SS method. SS method chooses data sets with the strongest signal strength for calculating the distances, ensuring the accuracy of the localization. Those data sets can all contain the signals of the same level. The selection based on JC method cannot choose the strongest readings and just selects data sets with different signal strength levels. In the real world, this can lead to a collinear constellation of data sets selected because, as we have seen in the heat diagram (Fig. 2), the signal strength drops not uniformly in all directions.

The worst results in terms of the accuracy are presented by the method with no pre-selection criteria. Due to the obvious bias in the distribution of signal strength over the area of interest, the precision of this method will always depend on the overall picture of the signal strength distribution and not only on the data sets with strongest signals. The higher the bias of the overall signal distribution is, the higher the resulting localization error will be.

3. **Location of the nodes**: Here, we investigated how the position of nodes affects the localization precision. We placed four nodes in the corners of the area of interest and other six were located randomly inside the area. Figure 5 plots the difference between the CDFs for the nodes located inside the area and in the corners ($CDF_{difference} = CDF_{inside} - CDF_{incorners}$). It was observed that, basically, the devices which are inside the area are localized better than the nodes in the corners. For small localization errors (less than 2 m) difference is around 20 %. For JC and SS methods, difference varies in the range of 10-20 % also for medium errors (3-10 m). As a conclusion, both JC and SS approaches tolerate, to some extend (10-20 %), even such obviously difficult positions like the corners.

   For the multilateration with no pre-selection, we get the biggest difference in the localization precision depending on the location of nodes. As can be seen in Fig. 5, the difference reaches even 65 %. Obviously, this is due to the fact that the position estimation deals in such a case with a big number of data sets that all are located on one side of the node presenting a trend: the bigger the number of readings is, the bigger the localization error will be.

   Concluding, the trajectory has to be constructed considering an UAV going beyond the borders of the area where unlocalized nodes are expected to be found. This will ensure non-collinear data sets, even though it will increase the path length and flying time.
4. **The type of the device**: Analysis of the obtained data from experiments for smartphones and netbooks has shown that there is almost no obvious relationship in localization precision between these two types of devices. This can be seen in the Fig. 6. The difference varies in the range of 0-30 %. The overall difference is not significant. However, smartphones tend to be localized better than netbooks. This can be due to following reasons. The signals emitted by smartphones are generally weaker and show significantly bigger standard deviation in signal strength than the netbooks. As a result, obvious picks are constructed within the area of interest leading to a smaller uncertainty. It is expected that this effect will neglect if the area of interest will increase.

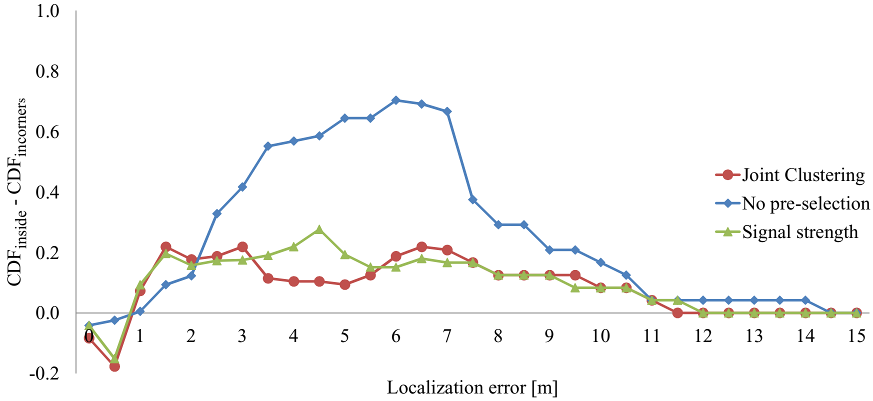


Fig. 5. Difference between localization error CDFs of nodes located inside the area of interest and in the corners as $CDF_{difference} = CDF_{inside} - CDF_{incorners}$

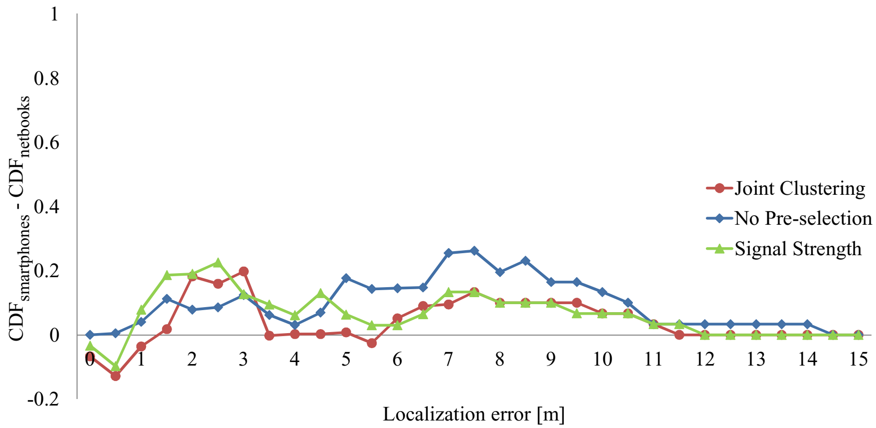


Fig. 6. Difference for localization error CDFs of smartphones and netbooks as $CDF_{difference} = CDF_{smartphones} - CDF_{netbooks}$

6 Conclusions

In this paper, the LMAT trajectory has been validated using simulations and evaluated using experiments with a flying UAV. It is to conclude that this path planning algorithm can be applied for disaster scenarios. Furthermore, our experimental evaluation has shown that implemented signal propagation model allows performing simulations which are very similar to the real world. In the experiments, the most accurate results have been obtained using a simple signal strength-based selection algorithm. This algorithm performs the best in tolerating signal strength readings highly biased by the environment.

Furthermore, we observed a clear relationship in localization error between nodes positioned inside the area of interest and in its corners. The nodes inside the area are localized significantly better than the nodes in the corners. Constructing a path, one has to consider an UAV going beyond the borders of the area where unlocalized nodes are expected to be found to ensure equal localization precision of all nodes.

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