Evaluation of Different Static Trajectories for the Localization of Users in a Mixed Indoor-Outdoor Scenario Using a Real Unmanned Aerial Vehicle

Oleksandr Artemenko, Alina Rubina, Tobias Simon,
and Andreas Mitschele-Thiel

Integrated Communication Systems Group, Technische Universität Ilmenau,
98693 Ilmenau, Germany
{Oleksandr.Artemenko,Alina.Rubina,Tobias.Simon,Mitsch}@tu-ilmenau.de

Abstract. This paper focuses on the experimental exploration of static trajectories applied for the localization of wireless nodes using unmanned aerial vehicles. Furthermore, a unique scenario is investigated that includes both indoor and outdoor areas. While moving around a building, an unmanned aerial vehicle localizes wireless nodes that are positioned inside that building.

First, a classification of up-to-date static trajectories is provided. Later on, an adaptation of several state-of-the-art static trajectories is presented. The latter include the so called Triangle and Circle trajectories which are investigated in real-world experiments using a single unmanned aerial vehicle serving as a mobile anchor. The experimental data is used to validate the trajectories. Experimental results show that Triangle is better suited for our unique indoor-outdoor scenario.

Keywords: Localization, Static trajectories, Mobile beacon, Disaster, Unmanned aerial vehicle, Experiment.

1 Introduction

Location information can be used for many purposes including rescue, coverage, routing, navigation and target tracking [6]. Localization in Wireless Networks (WNs) is a very challenging task and can be implemented in many different ways. A straightforward approach would be to use the Global Positioning System (GPS). However, equipping every node with a GPS-receiver is not practical because of high cost, limited precision and high power consumption. Moreover, GPS fails in indoor environments or under the ground [17]. Another approach named Mobility-Assisted Localization (MAL) uses only one or a few mobile anchor nodes that are equipped with a GPS module. Generally, an *anchor* represents a reference data set collected during the localization [14]. The main idea of MAL is to use a mobile anchor which traverses the network and periodically

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receives beacon messages coming from unknown nodes. A beacon is a short message, containing information specified by the used standard, e.g. IEEE 802.11x standard family.

Recently, considerable attention has been paid to the problem of *anchor placement* – methods to design a trajectory for a mobile anchor. It has been proven in the literature that a well-planned mobile anchor trajectory increases the speed and accuracy of the localization [14].

A very challenging scenario is considered – a disaster relief. Suppose, an unmanned aerial vehicle (UAV) is flying over an urban area, which suffers from a disaster. The purpose of a UAV is to localize 'survived' devices, enabled with Wi-Fi module. The obtained information will help to accelerate the rescue process of people who are stuck inside a building. Here, we consider the IEEE 802.11x standard family for the communication among nodes. In the literature, numerous trajectories have been proposed for steering a UAV. However, none of them fits to our scenario. Let us take a closer look at the scenario.

We consider a mixture of indoor and outdoor areas. We assume multiple wireless nodes, e.g. personal mobile devices like smartphones, tablets or notebooks, that are placed in an indoor area, e.g. a building of the university campus, and a UAV that can move outside this building. The mobile devices are periodically transmitting beacons (for this, the so called ad hoc mode is being applied). After collecting these beacons, the UAV will estimate the distance from its current location to the emitters and after some time will be able to calculate their positions. What is the challenge here?

The list of open issues includes, among many others, an accurate sensing strategy, distance calculation techniques, reference data selection approaches, and efficient trajectory planing algorithms. The latter will be in focus of this work. Moreover, in this paper, we present the results for the experimental evaluations of the trajectories that are represented by an adaptation of several state-of-the-art approaches.

The rest of the paper is organized as follows. In Section 2, a classification of the anchor placement algorithms will be given. Section 3 introduces an adaptation of the selected trajectories. Then, Section 4 describes our experiment setup. Section 5 presents an extensive analysis of the obtained results according to different metrics. In Section 6, conclusions are given.

2 Related Work in Anchor Placement

Current classifications of anchor placement algorithms found in [20,10,21] lack some of the most recently developed static trajectories. Moreover, a separation into two-dimensional (2D) and three-dimensional (3D) algorithms is missing. As a consequence, Fig. 1 presents the classification of the most important approaches.

In this regard, all anchor placement algorithms can be roughly divided into random and planned. The latter can be further subdivided into static and dynamic. Next, we present the details of every category.

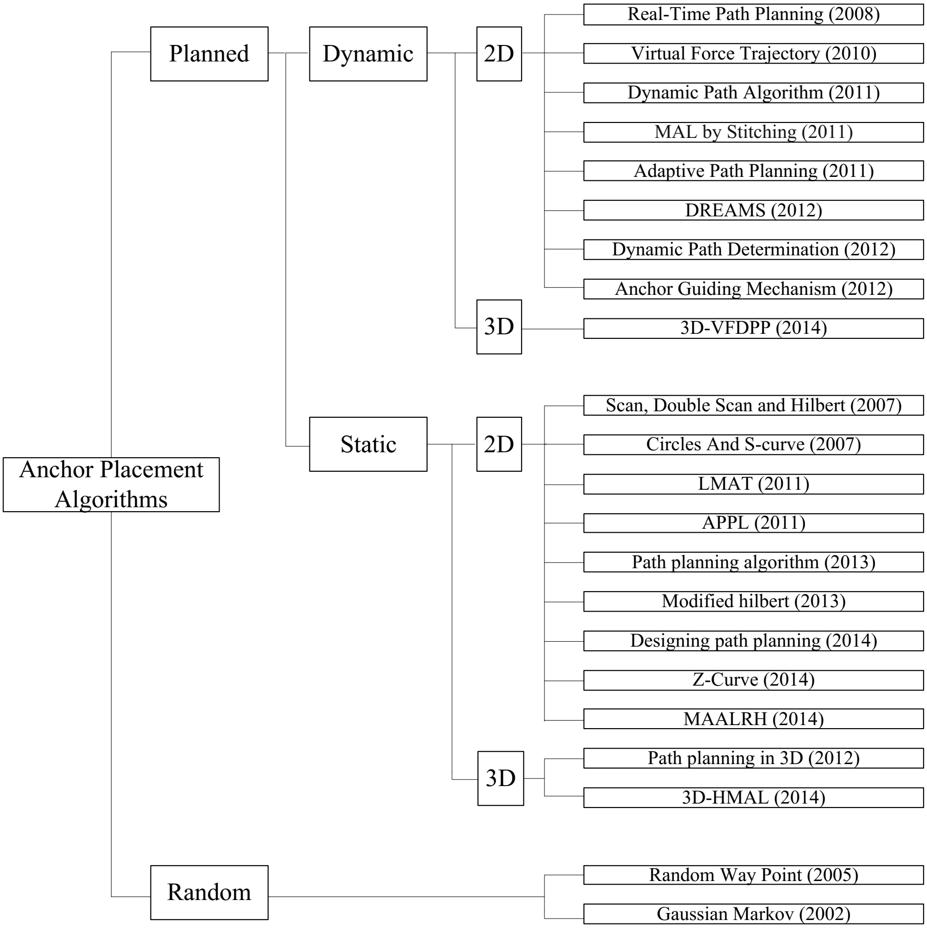


Fig. 1. Classification of different anchor placement algorithms

Random/Probabilistic Trajectories. If a trajectory does not follow a certain pattern or is based on a probabilistic scheme, we can classify it as random. Algorithms based on Random Way Point and Gauss-Markov Mobility models are the most common examples here [4]. These approaches are simple in their execution and provide non-uniform and unpredictable coverage of the area. If there is no information about the explore area random trajectories can be the best choice. Otherwise, according to [19], planned trajectories result in higher localization accuracy in comparison to random movements.

Dynamic Trajectories. With a little more information about the area (e.g., distribution of nodes, size of the area, nodes density), dynamic trajectories can be applied. These trajectories are not fully planned in advance. Instead, they are adapted based on the obtained information while the anchor is in motion. One of the drawbacks of those algorithms is the message overhead between the mobile anchor and unknown nodes. Furthermore, it is not possible to predict the moving time of the anchor as well as the path distance in advance. Under the time restrictions, as for example in disaster scenarios, it can be unsafe to apply such trajectories. Nevertheless, the literature on dynamic trajectories shows a variety of approaches as in [13,16,5].

Static Trajectories. One of the first examples of static trajectories is proposed by Koutsonikolas et al. in [15]. Three trajectories have been developed, particularly – SCAN, DOUBLE SCAN and HILBERT. CIRCLES and S-CURVES were proposed in [11] and were designed to reduce the collinearity problem of SCAN and DOUBLE SCAN.

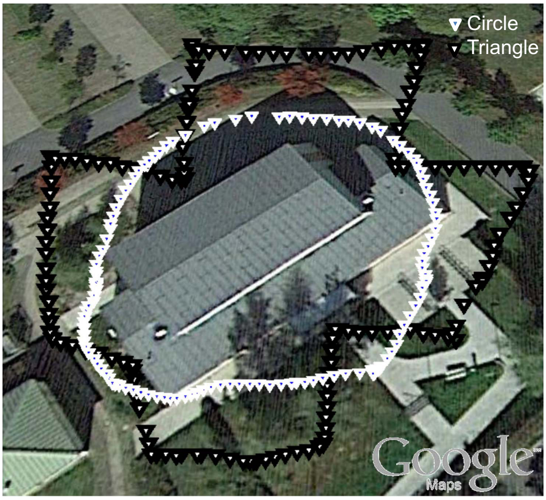
A so-called LMAT (**L**ocalization with a **M**obile **A**nchor node based on **T**rilateration in Wireless Sensor Networks) trajectory was proposed in [12]. It was proven that if a trajectory consists of equilateral triangles, it ensures the best node coverage and leads to the increased degree of the non-collinearity [12]. LMAT has demonstrated an average localization error of up to 0.7 m in the deployment area of 100×100 m^2. This trajectory indeed shows good performance and was already experimentally validated in an outdoor scenario in [1].

Benkhelifa et al. proposed three new modifications – SQUARES, ARCHIMEDEAN SPIRAL and WAVES in [3]. Farmani et al. in [9] defined a Modified-Hilbert approach. It is an improved version of the Hilbert trajectory. Another algorithm based on the *hexagonal* pattern was proposed by Kaushik et al. in [18]. The Z-curve was introduced by Rezazadeh et al. in [21]. The main element of the trajectory is build using the shape of the letter Z. Based on the simulation results, the Z-curve just slightly outperforms the LMAT and HILBERT trajectories. Here, a log-normal signal propagation model was included in the performed simulations. One further algorithm is proposed in [10] – MAALRH (**M**obile **A**nchor **A**ssisted localization algorithm based on **R**egular Hexagon).

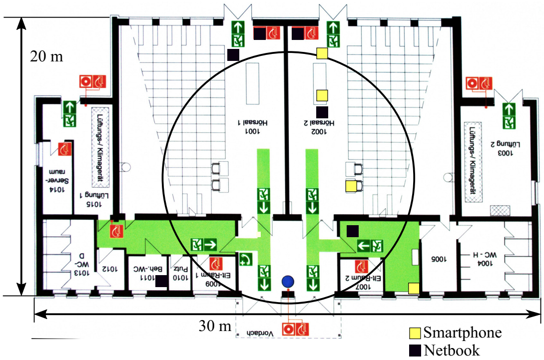
All approaches, mentioned above, have been designed to explore a simple outdoor scenario. They do not take into account any obstacles like buildings that must be avoided. One such algorithm has been proposed by Chia-Ho et al. in [19]. It ensures the location estimation of all unknown nodes and reduces the localization error. For this, a new position estimation algorithm based on the chord method is used along with the adopted SCAN trajectory. The designed trajectory can be also applied in case of obstacles. The size of obstacles is considered to be 10×30 m^2 or 30×10 m^2. However, the algorithm does not consider the exploration of obstacles and only implements a strategy to avoid them.

The same disadvantage is present in novel 3D path planning algorithms from recent research works. Here, such trajectories like five 3D curves, Layered-Scan, Layered-Curve, Triple-Scan, Triple-Curve and 3D-Hilbert can be mentioned [7].

In summary, static trajectories like LMAT, Z-curve, HILBERT and MAALRH have demonstrated the best performance in terms of the localization accuracy, length, difficulty and non-collinearity. Nevertheless, these trajectories fail in our considered scenario, because they are not suited for areas which include buildings. Z-curve and Improved Scan while considering obstacles present simple



(a) The top view of the building with the positions of the UAV obtained experimentally (© Google Maps ™).



(b) The floor-plan of the chosen building. Positions of the smartphones and netbooks are marked accordingly.

Fig. 2. The working area of the experiment

obstacle avoidance strategy. None of the present trajectories consider the unknown nodes to be located inside buildings. The unknown nodes are always assumed to be located randomly in a region of interest. As a consequence, new building-aware trajectories are required.

3 Design of New Trajectories

It is a well-known fact that a trajectory consisting of equilateral triangles leads to a better localization accuracy [12]. The triangular shape ensures at least three non-collinear anchors to every unknown node. The LMAT trajectory, being one

Table 1. Weather and experiment setup

Parameter	Value/Name
Air temperature	$7^\circ\ C$
Humidity	75, %
Speed of wind	5, m/s
Air pressure	1008, mb
Building size	30×20 m^2
Number of unknown nodes	10
Experiment repetitions	6
Number of trajectories	2
Data Acquisition Algorithm	RSS
Anchor Selection technique	SS
Distance Calculation	$d = 10^{\frac{P_{r_0} - P_r + W}{10\alpha}}$
Position Calculation Algorithm	Multilateration, Centroid, Min-Max

Table 2. Technical parameters of the UAV

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

of the most efficient approaches presented in the literature, follows the triangular pattern. In this regard, an isosceles triangle was chosen as a pattern for the first trajectory called *Triangle*.

The next trajectory, called *Circle*, follows a circular shape which is another popular pattern used in the literature to design a path for a mobile anchor. Circle represents a path that is simple and short.

Both trajectories can be observed in Fig. 2(a) that shows positions of a UAV which was flying around a building in our experiments. Next, the experiment setup and the detailed analysis of the results are presented.

4 Experiment Setup

The experiment was conducted at the Ilmenau University of Technology in Germany. One of the campus buildings, named Leonardo da Vinci Bau, was chosen for the experiment. The size of the building was 30×20 m^2. The experiment

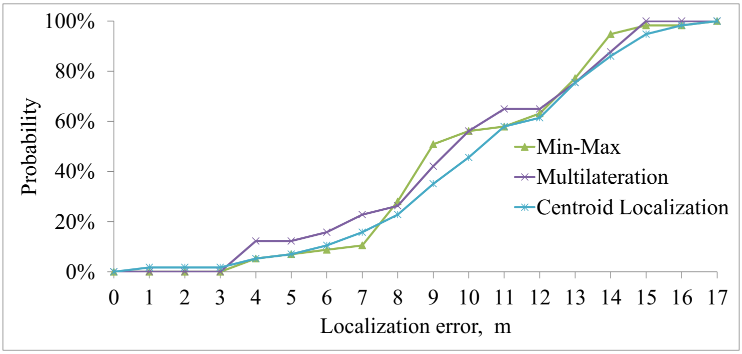
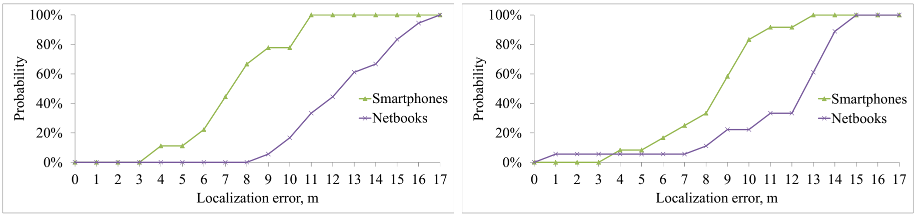
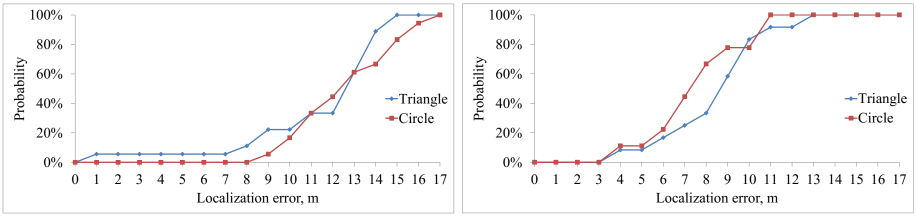


Fig. 3. Localization error CDF. Performance of different position estimation techniques.



(a) Flying along the Circle. (b) Flying along the Triangle.



(c) Netbooks. (d) Smartphones.

Fig. 4. Difference in localizing smartphones and netbooks

setup and the weather conditions at the time of the experiment are summarized in Table 1.

During the experiment, a UAV, represented by a quadrocopter with the parameters shown in Table 2, was flying around the building along the two chosen trajectories and receiving beacons once per second from unknown wireless nodes that were placed inside the building. For every beacon, a received signal strength (RSS) estimate has been obtained and stored along with the corresponding GPS position of the UAV representing an anchor. The GPS-position itself was Kalman-filtered, using acceleration and attitude data from a CHR-6DM attitude and heading reference system. The accuracy of the GPS module has been evaluated. For that, we kept the UAV in 15 different positions around the building for 3 minutes measuring a new GPS estimate every second. The average error for the GPS positioning was less than 0.9 m with a standard deviation of less than 0.5 m. Since the error introduced by the GPS positioning was much smaller that the error of the distance estimation, we consider GPS to be a ground truth for our experiments. To calculate the distance between the UAV and a corresponding wireless node, the received signal strength (RSS) method has been used along with a log-distance path loss model from [8]. This model considers wireless communication among nodes in a mixed outdoor-indoor environment. The model predicts a received signal strength $P_r(d)$ at a distance d as follows:

$$P_r(d) = P_r(d_0) - 10\alpha \log_{10}(d/d_0) + X_\sigma - W \ [dBm], \tag{1}$$

where $P_r(d_0)$ is a signal strength at the reference distance d_0; α is the path loss exponent; and W is the wall attenuation factor. In [8], the following values have been proposed: $P_r(d_0) = -40$ dBm, $\alpha = 3.32$, $W = 4.8$ dBm.

The building along with the trajectories can be seen in Fig. 2(a). Inside the building, 10 unknown nodes were randomly located. A floor plan of the building as well as the positions of the unknown nodes can be observed in Fig. 2(b).

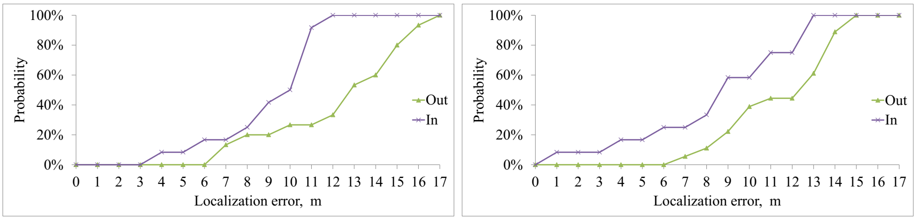
In the performed experiment, five netbooks ASUS Eee PC Seashell series and five smartphones Samsung Galaxy S were used. Netbooks were equipped with Wi-Fi IEEE 802.11 b/g modules, running in an ad hoc mode. Smartphones were launched in Wi-Fi IEEE 802.11 access point mode. The UAV was operated manually and experiment was repeated six times – three times for every trajectory. The average speed of the UAV, while moving along Circle and Triangle, was 0.8 m/s and 1.2 m/s accordingly. In one of the experiments, speed of the UAV was increased to 4.4 m/s, while moving along the Triangle. All results are presented in the form of a cumulative distribution function (CDF).

5 Results Analysis

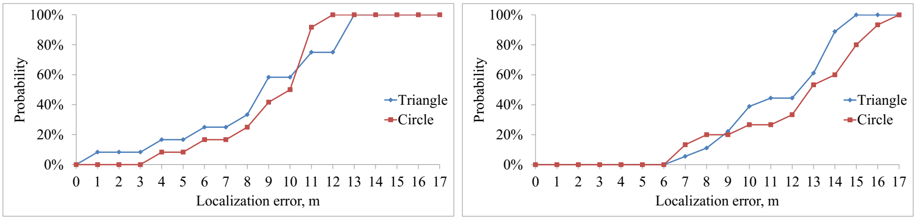
To obtain the accuracy of the localization, an average localization error was calculated. As follows, different metrics will be used to evaluate the performance of both trajectories.

The Type of the Position Calculation Method: Fig. 3 shows the localization error CDF for the three different position calculation methods – classical Centroid localization, Multilateration and Min-Max from [2]. All methods demonstrate a similar behavior. In case of small errors (less than 3 m), Centroid Localization demonstrates the best performance. In the range of average and big errors, Multilateration is the best. This is due to the fact that the multilateration minimizes the mean square distance error of the reference points to the unknown target position. Min-Max demonstrates quite an unstable behavior. Since Centroid Localization has demonstrated the highest probability of small errors, we used this method for the further analysis.

The Type of the Device to Be Localized: The performance of smartphones and netbooks was also compared. The key observation is, that smartphones are localized better than netbooks as shown in Fig. 4(a) and Fig. 4(b). Here, the



(a) Circle (b) Triangle



(c) In (d) Out

Fig. 5. Performance of the nodes, located closer to the center (In) or to the edges (Out) of the building in case of the Triangle and Circle

difference between smartphones and netbooks reaches up to 60% in the case of the Circle and Triangle. It can be explained as follows: Smartphones usually produce weaker RSS readings at the receiver with a smaller standard deviation as compared to the netbooks. As a consequence, when applying a signal model, a smaller uncertainty factor is reached. In addition, we have investigated whether there is a relation between trajectories and a device type. Fig. 4(c) and Fig. 4(d) show the performance of netbooks and smartphones in the case of two different trajectories. It can be observed that the Triangle is better suited for the localization of netbooks and smartphones tend to be localized better when using Circle trajectory. The last can be explained as follows: Smartphones were located mostly in the right plane of the building. As a result, the strongest RSS readings were produced at this side. Since, the Circle trajectory approached building closer than the Triangle, this could have resulted in a higher localization precision for the smartphones.

Positions of Nodes: Here, the relation between a node‘s position and a localization accuracy was investigated. We have related the position of a node to the center of the building. To determine which nodes were located closer or farther from the center, a circle was drawn. Radius of the circle was equal to the half of the buildings width. As a result, six nodes were located outside of the circle and four of them inside, as shown in Fig. 2(b). The obtained results are seen in Fig. 5(a) and Fig. 5(b). Nodes, located closer to the center of the building are localized better, than the nodes located closer to the walls of the building. This was the case for both of the trajectories. It can be explained as follows. Nodes which were inside the circle produced more uniform RSS readings from all four sides of the building, this resulted in a better performance of the position estimation techniques. As opposite, nodes outside the circle had strong RSS readings only on one side of the building. As a result, this led to a poorer localization.

In overall, the Triangle trajectory demonstrated a better performance for all the nodes.

6 Conclusion

In this paper, location estimation strategies have been explored in a unique indoor-outdoor scenario. We showed that the current research does not provide us with the building-aware static trajectories. As a result, two modifications of the state-of-the-art trajectories were introduced – Triangle and Circle. We can conclude that the Triangle performs better than Circle in terms of the localization error. The Triangle trajectory has achieved an average error of about 9 m, while Circle demonstrated only 11 m. Different metrics have been applied for the analysis of the experimentally obtained data. The main observations are:

- Three different position estimation algorithms were applied. The Centroid localization algorithm performed best in case of small localization errors.
- The obtained results indicate that smartphones are localized better than netbooks. This could have resulted due to a weaker RSS readings with a smaller standard deviation than that of the netbooks.
- Nodes, located closer to the center of the building are localized better, than the nodes located closer to the walls of the building. Nodes which were inside the circle produced more uniform RSS readings from all four sides of the building. As a consequence, this resulted in a better performance of the position estimation techniques.

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