# A Novel Hybrid Path Planning Algorithm for Localization in Wireless Networks

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## ABSTRACT

In this paper, we consider the problem of designing an efficient hybrid path planning algorithm to maximize the localization accuracy and to minimize the energy cost represented by the length of the trajectory taken by an Unmanned Aerial Vehicle (UAV).

Our developed hybrid trajectories were compared with the state-of-the-art algorithms through extensive simulations. The obtained results indicate that for the same assumptions, the proposed Hybrid G trajectory reduces the path length in average by 42 %, with the increase of relative localization error only by 6 %, when compared to the best performing Double-Scan trajectory. Moreover, it ensures 99 % of localized nodes in the area of size 160000 $\mathrm{m}^2$.

## Keywords

UAV; path planning; mobile anchor; localization; wireless network; disaster scenario

## 1. INTRODUCTION

An important application of mobile ad-hoc networks is to aid the emergency rescue and reconnaissance operations over a disaster-affected region. 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 victims. Here, we consider the IEEE 802.11x standard family for the communication among nodes.

The path or trajectory taken by the UAV, aka the mobile anchor (MA), can be very critical in determining the efficiency in terms of energy consumption, mission time and accuracy of the localization process. Through a rational path planning, mission time can be minimized and more unknown nodes can be localized effectively.

Typically, there are two classes of path planning algorithms – static and dynamic. A static path is a pre-planned deterministic trajectory, which does not consider the distribution and density of the nodes, whereas a dynamic path is decided on the fly based on the demands of the scenario. Our initial observations show that the static path planning is not efficient in case if nodes, which need to be localized, are distributed non-uniformly in the search area [1]. Moreover, UAV always covers the entire region of investigation uniformly, including those parts where there are no nodes. This will unnecessarily increase trajectory length [2]. However, as was also showed in [1], static trajectories ensure high localization accuracy, especially Double-Scan and Triangle trajectories (which later are compared with our developed algorithm). On the contrary, the dynamic path planning can avoid unpopulated regions focusing on dense areas instead, in this way minimizing the path length. This leads to the main research question of this work – *Can a combination of static and dynamic path planning algorithms (further called hybrid trajectory) provide better results in terms of both – the localization accuracy and the trajectory length?* This demands a strong incentive to dynamically adjust the path (altering between dynamic and static trajectories) during the localization procedure.

The rest of the paper is organized as follows: Section II presents the related work in the field of dynamic path planning. In Section III, the novel hybrid path planning algorithms are presented. Section IV discusses the simulations and the analysis of results. Finally, we summarize the paper in Section V.

## 2. RELATED WORK

In this chapter we present a summary of dynamic path planning approaches, as only they have the same adaptive nature as our proposed approach.

In [3], a Grid Benefit concept is introduced and an anchor-guiding mechanism based on this concept. Here, nodes already have a rectangular area of its position estimate. Experimental study reveals that the proposed anchor-guiding mechanism effectively guides the mobile anchor to move along an efficient path, thereby saving the time required for improving or balancing the location inaccuracies of all sensor nodes. However, this research assumes that previously range-free localization algorithms have been executed for a period of time.

The authors in [2, 4, 5] use a concept of Virtual Force (VF) on MA that is exerted by unknown nodes. Though the results seem to be promising, VF computation uses directional reception antennas to determine the direction of beacons from nodes and hence the coverage rate is reduced.



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Furthermore, in [4] and [5], the sensors are moved to new locations during the second sensor relocation phase representing a very specific scenario.

In [6], a wireless sensor network is treated as a connected uni-directed graph and path planning is solved as a traversal of the graph. The paper proposes Breadth-First (BRF) and Backtracking Greedy (BTG) algorithms for Spanning Tree and provides robust localization of nodes which are randomly distributed obtaining high localization precision in the simulations and real experiments. But, the main drawback is that it requires precedented topology information.

The developed algorithms in [7, 8] are lightweight in computation, economical in energy utility, and have been proved to be effective using simulations. Here, the number of neighbors for every node is used to compute the weights, but all neighbors are treated as equally effective. The key drawback is that some nodes, being localized by a MA, are used as references for the localization of neighbors, which can lead to a propagation of errors into the system.

# 3. NOVEL HYBRID PATH PLANNING ALGORITHM

The proposed algorithm combines the best qualities of the static and dynamic path planning algorithms. On the one hand, it adapts to the distribution of nodes, applying a so called Weighted Random Walk (WRW), and on the other hand, after identifying a group of nodes, it applies chosen static shapes – Circle and G-shape. The WRW is a modified version of a Random Walk (RW) [9]. In our developed algorithm, the MA starts moving randomly choosing the direction distributed in the range $[0,\ 2\pi]$. When it detects nodes and estimates their location, it chooses the node with the highest number of the unlocalized neighbors (further $\alpha$-node). It is assumed that nodes in one group exchange certain information such as their status (localized, unlocalized) and number of unlocalized neighbors. Then, the MA flies towards the estimated position of the $\alpha$-node and applies earlier mentioned static shape to successfully and accurately localize the unlocalized neighbors. The static shape ensures non-collinear points for all the nodes in the group and this improves the localization accuracy.

## 3.1 Hybrid Circle Trajectory

As known from our previous work, Circle static trajectory ensures high localization accuracy, as round shape provides good degree of non-collinearity. Here, the size of radius is equal to an $R$ (resolution). The resolution can be defined as a distance between two consecutive beacon points. To ensure a localization of all nodes inside a circle, the maximum radius must be smaller than the transmission range of the used wireless communication interface. From this, the UAV must ensure the following minimal number of measurement locations on a circle trajectory:

$$N = \frac{D_{\min}}{R} = \frac{2 \times \pi \times R}{R} \approx 6.28 \tag{1}$$

We chose N=7 as the next possible integer.

## 3.2 Hybrid G Trajectory

We chose G letter as the second static shape, because it provides the shortest path taken by the UAV to localize nodes in a square area, ensuring good localization accuracy when using centroid localization algorithm. If a point A is the estimated position of an $\alpha$-node, the goal is to localize its neighbors in the area defined by a square BCDE. The shortest distance the UAV should take to reach the corners of square from the center A is:

$$D_{\min} = \frac{R}{\sqrt{2}} + 3 \times R \tag{2}$$

So, if we want to localize any unknown node inside the square BCDE, using centroid localization, we will always ensure at least four non-collinear points (e.g., ABCD, BCDE).

Both shapes provide non-collinear beacons. For a given resolution $R$, Circle presents a 40 % longer path covering a larger area than G-shape. For that purpose, both of the algorithms will be evaluated via simulations.

## 3.3 Route Length Optimization

In order to further optimize the route length, we need to ensure that the static part is not repeated several times over the same region, if the nodes there have already been localized. For that, we apply the following steps: 1. Virtually divide the total area of interest into squares of sides equal to the communication range. 2. Calculate the mid-points of each square and create a database with these points. Each mid-point corresponds to a square. 3. If a UAV has traveled to the square, it is then removed from the database, in this way we avoid repeating the static figure in that square. 4. In case a UAV visits the square second time, it computes the distance from its current location to the remaining mid–points in the database. Then, it travels to the square with the smallest distance to form a static trajectory there.

# 4. PERFORMANCE EVALUATION

To evaluate our approach we run extensive simulations and compare it to several state-of-the-art approaches including the Localization with a Mobile Anchor node based on Trilateration in wireless sensor networks (LMAT) [10] (further called Triangle), Double-Scan [11] and WRW trajectories. Moreover, as localization accuracy depends on the applied position calculation technique, we have used two techniques - centroid and weighted centroid algorithms. More information on these techniques can be find in [13].

*Simulation Setup*: One UAV traverses the region of size $400 \times 400$ m$^2$ in order to localize unknown nodes. A total of 100 sensor nodes are distributed randomly over an area and grouped in four groups. As it is more likely that in the disaster affected area people are trapped under collapsed structures. To keep the scenario realistic, four groups represent four campus buildings of the Technical University Ilmenau.

To calculate the distance between the UAV and a corresponding wireless node, the received signal strength (RSSI) method has been used along with a log-distance path loss model from [12] seen in Table 1. It considers wireless communication among nodes in a mixed outdoor-indoor environment. This model together with chosen propagation parameters was already validated in our previous work and has shown accurate RSSI to distance mapping.

The simulations were repeated 500 times to obtain a reliable probability distribution. One simulation run ended when 99 % of nodes were localized. Further simulation parameters are found in Table 1.

*Simulation Results and Analysis*: In the most applications, it is desired to have accurate and fast localization results.

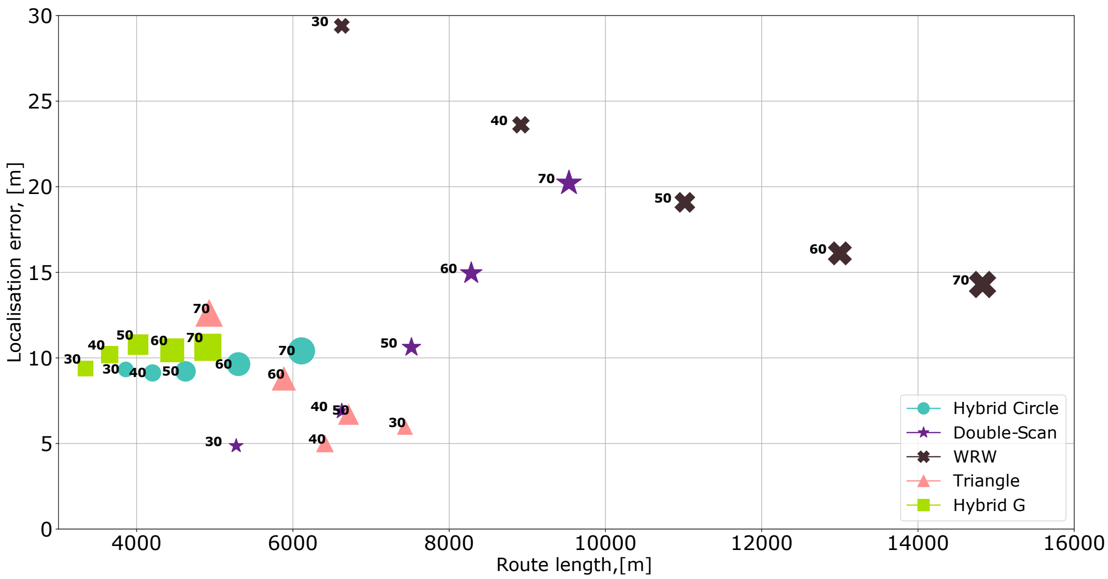


**Figure 1: Localization error vs route length for simulated trajectories. Number near a marker indicates the corresponding resolution factor.**

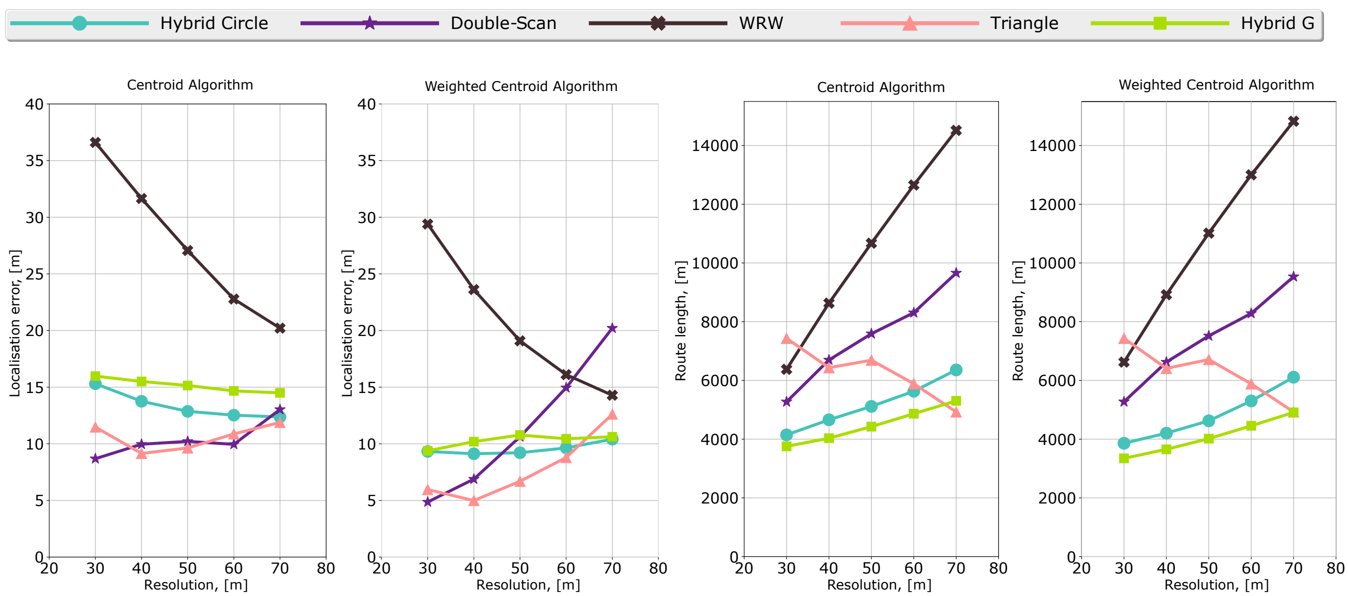


**Figure 2: Comparison of localization accuracy and route length for centroid and weighted position calculation algorithms.**

For that, we analyzed both – the localization error (LE) and the route length (represents the mission time). The results are shown in Fig. 1 for the better performing weighted centroid algorithm. Comparison between these two algorithms is shown in Fig. 2.

From Fig. 1, it is observed that Hybrid Circle and Hybrid G ensure the fastest localization – they have the smallest route length ($R$=[30, 50] m), also their LE slightly varies between 9 and 11 m. For the $R$=30 m, Hybrid G shows a reduction in route length by around 42 % when compared to the Double-Scan, 55 % compared to the Triangle and 50 % compared to the WRW. This also means reduced energy consumption and mission time. Hybrid Circle performs similarly presenting a slightly better LE. However, in terms of the path length, Hybrid G clearly outperforms Hybrid Circle.

WRW shows the worst performance presenting the highest LE in the range from 15 m to 30 m. For Double-Scan with $R$=30 m, the LE is the smallest and is only 5 m. However with the increase of $R$, performance drops significantly. When $R$=70 m, the LE is already 20 m and route length increases almost twice. Triangle trajectory shows unstable behavior, for $R$=[30, 50] m it has accurate localization, but higher route length. When $R$ increases, route length decreases and the LE becomes smaller.

This analysis of the results helps to identify a combina-

| Parameter | Value |
|---|---|
| Area size | $400 \times 400$ m$^2$ |
| Number of unknown nodes | 100 |
| Simulation runs | 500 |
| Resolution ($R$) | [30, 70] m |
| $\mathrm{P}_{\text{threshold}}$ | -100 dB |
| Data Assessment Algorithm | RSSI |
| Wireless Propagation Model | $P_r(d) = \mathrm{P}_{r_o} - 10\alpha\log(d) - \mathrm{W} + X_\sigma$ [dBm] [12] |
| Applied Propagation Parameters | $\mathrm{P}_{r_o}$ = - 40 dBm, $\alpha = 3.32$, W = 4.8 dBm, $\sigma = 3.1$ dB |

**Table 1: Main simulation parameters.**

tion of the trajectory and resolution for different scenario requirements. For example, if the most precise localization is required (in order to locate victims), the best fit is the Double-Scan trajectory with $R$=30 m. However, if we want to ensure the fastest localization (when using UAV the battery life time is limited), Hybrid G with $R$=30 m must be used, though a slight decrease in the LE is present then.

In Fig. 2, it is shown how the LE and route length depend on the resolution for different trajectories and are affected by two position calculation algorithms. First of all, weighted centroid algorithm shows the best results – the LE never goes beyond 30 m. For both algorithms, we clearly see that the LE of WRW decreases with the increase of $R$. Hybrid trajectories, on the other hand, have quite stable behavior and the LE does not depend much on the resolution. Static trajectories perform well in case of the centroid algorithm, but in the case of the weighted centroid their LE raises with the resolution. In terms of the route length, WRW has the longest route length that increases with the resolution, as it frequently covers the same area over and over. Also, it can cover the area without any nodes.

# 5. CONCLUSION

Current literature research and our own previous work state that static trajectories ensure high localization accuracy, but are only feasible for uniform distribution of nodes. As opposite, the dynamic trajectories adapt to the distribution of nodes, in such a way reducing the total path length, but not ensuring the best localization accuracy.

In this paper, we combined both types of trajectories and created novel algorithms - Hybrid G and Hybrid Circle trajectories. The simulation results clearly indicate that our proposed trajectories outperform the state-of-the-art approaches in terms of the path length, ensuring the fastest localization by reducing the average path length by 42 % when compared to the best performing Double-Scan. Furthermore, developed trajectories ensure accurate localization with the average relative accuracy of 14 % (in relation to the $R_{\max}$) and ensure 99 % of nodes to be localized.

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