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Indoor Localization of Unmanned Aerial Vehicles Based on RSSI

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***Abstract*—Nowadays, finding the Unmanned Aerial Vehicle (UAV) position in the absence of GPS is attractive and challenging problem in the research community. In this paper, we present a novel algorithm for mini UAV indoor localization based on distance measurements between the UAV and the existing infrastructure consisting of WiFi Access Points. Our algorithm uses two well-known techniques from the literature: Multi-dimensional Scaling (MDS) and Weighted Centroid Localization (WCL). Through extensive simulations we have shown that our algorithm is very suitable for indoor localization of mini UAVs. For small radio-range error, our algorithm exhibits a small localization error of less than 5% of the radio range.**

Keywords—indoor localization; positioning; unmanned aerial vehicle; multidimensional scaling; weighted centroid

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) attracted tremendous interest among researchers due to their outstanding maneuverability, small size and low cost. Mini UAVs, also known as drones or quadrotors, have been used in many governmental and nongovernmental operations in the last decade, including disaster recovery operations and humanitarian actions after the Nepal earthquakes and Cyclone Pam in Vanuatu in 2015 [1].

UAVs commercial potential is yet to come. The Federal Aviation Administration (FAA) of USA [2], after launching compulsory drone registration in December 2015, recorded more than 450,000 hobbyist owners registered only in the first 6 months, a number that by far exceeded the overall total of approximately 300,000 manned aircrafts on the FAA's aircraft registry [3]. Therefore, drones are expected to be deployed in many civilian and commercial applications in the near future, ranging from service delivery, warehouse management, building surveillance, etc. [4][5]. Regarding smart city applications, UAVs have the potential to perform or be included in geo-spatial and surveying activities, traffic and crowd management, agriculture and environmental management, urban and civilian security, as well as natural disaster control and monitoring in situations like fires, floods, and earthquakes [6][7].

However, deploying UAVs for general commercial applications cannot be done before solving relevant issues, mainly related to ethics and privacy [8], cost, licensing and legislations, as well as business adoption. Technical challenges associated with efficient drone exploration include traffic management, collision avoidance, obstacle avoidance, routing, data collection and processing, etc. [5][9][10]. Among these, the issue of localization is one of the most challenging.

Most UAVs obtain the location information from satellite navigation systems, like the US Global Positioning System (GPS) or the Russian Global Navigation Satellite System (Glonass). However, these systems do not work in indoor environments. If the mini-UAV cannot obtain the location information, it will have difficulties to fly autonomously, therefore, indoor UAV localization requires designing new methods and techniques for localization, based on algorithmic approaches for sensor measurements' processing and exploration.

The problem of UAVs indoor localization has been investigated in the last couple of years. Based on the approach being used solutions proposed in the literature can be categorized into two groups: vision based and ultrasound signals based solutions.

Vision based solutions perform image processing on optical measurements such as digital charge-coupled device (CCD) cameras, which are standard equipment in modern mini UAVs. The most popular light detection and ranging LiDAR instrument usually has 40Hz scanning rate [11]. Therefore, these solutions are usually very slow, power consuming, and need appropriate pattern recognition algorithms.

Among other, received signal strength indicator (RSSI) is one of the cheapest and least invasive ways to measure the distance. It does not require additional hardware; however, it is not an accurate method. In [12], the authors combine RSSI with ultrasound waves to obtain accurate distances between the mini UAV and the referent (beacon) nodes. Using those distances, the final UAV position is obtained by swarm intelligence, i.e. particle swarm optimization. In [13], time difference of arrival is used to measure the distances between the UAV and four base stations placed at four corners of the room. The UAV state is estimated using Extended Kalman Filter (EKF).

Widely used RSSI fingerprinting solutions for indoor localization of smartphones are not adequate for drone localization. These solutions consist of two phases: offline phase of constructing a database (DB) with WiFi RSS fingerprints at each location, and online phase of comparing the currently observed fingerprint with those in the DB.

The offline phase, also known as radio mapping process, is very time consuming because in three-dimensional (3D) space it cannot be performed by crowdsensing/crowdsourcing based applications. Furthermore, in the online phase, RSS matching cannot be performed by the UAV, but instead at the central server, since the size of the RSS DB requires remote storage. Thus, communication latency will obstruct the real-time localization.

In [14] the authors propose HiQuadLoc system for Indoor Localization based on RSS Fingerprints collected from surrounding WiFi Access Points (APs), but under two assumptions, which are straight line indoor trajectory at high speeds and continues probability value for RSSs to appear at a given 3D position, thus reducing the offline phase.

In this paper, we developed a novel algorithm for mini UAV indoor localization based on distance measurements between the UAV and the existing infrastructure consisting of WiFi APs. In our solution, the UAV itself obtains its position. The main advantages of our algorithm are: it does not require site survey, it is performed locally by the UAV, it is lightweight and therefore the location can be obtained in real time. Moreover, the locations of the WiFi APs can be anywhere in the 3D space, without any restrictions. The rest of this paper is organized as follows. Section II presents the new algorithm for mini UAV localization. Section III provides results analysis considering different setup scenarios. The paper is concluded in Section IV.

II. Novel Algorithm for Indoor Localization of UAV based on **RSSI** (NIL-RSS)

Our algorithm for UAV indoor localization is based on distance measurements between the UAV and the anchor nodes with a-priory known location. These anchor nodes can be represented with any pre-installed infrastructure, existing in almost all indoor environments, like WiFi APs with locations that are known in advance, or can be easily obtained. NIL-RSS enables the UAV to find its own position with respect to the anchor nodes, via different ranging techniques, like RSSI, Time-of-Arrival (ToA) or Direction-of-Arrival (DoA) measurements. If the number of measurements is equal or greater than 4, than the location of the UAV can be easily obtained using some of the well-known techniques for localization. In NIL-RSS, we choose between two popular localization techniques from the literature, i.e. multidimensional scaling and weighted centroid localization.

For NIL-RSS, we made the following assumptions:

- The UAV flies indoor from an origin to a destination.
- Many WiFi APs, which are placed along the UAV's travel path, are used to assist the localization process. The WiFi APs are aware of their position a-priori.
- The UAV collects RSS from the WiFi APs in its near proximity and transforms these RSS measurements into distances.

The last assumption can be more general, i.e. the modern UAVs are equipped with different sensors, thus, any ranging technique that can obtain the distance between the UAV and a referent point can be applicable for this purpose (ToA, DoA, ultrasound, visible light communication [15], etc.).

The NIL-RSS algorithm for indoor UAV localization consists of the following phases:

- At each discrete computing time step t_i, the UAV collects the RSSI from the surrounding WiFi Access points. Only the first 10 strongest signals are considered. Then the UAV converts each RSSI into distance.
- WiFi APs periodically broadcast their location. Thus, the UAV will know the exact WiFi AP location even when that WiFi AP is not one of the 10 with the strongest signal. UAV stores the WiFi APs' locations internally.
- Based on the number of collected RSSI measurements, one of two different localization techniques can be applied. Namely, if the number of RSSI measurements is less than 4, WCL technique is applied. Otherwise, MDS technique is applied.
- The final phase is trajectory reconstruction, i.e. for all predicted locations, interpolation is performed and the trajectory of the UAV is constructed. This phase is application specific and is not always compulsory.

When the number of neighboring (surrounding) WiFi APs is small, WCL performs better than MDS. Therefore, in NIL-RSS algorithm, WCL is used when the number of nodes is less than 4.

Fig. 1 presents NIL-RSS algorithm in a more visual way.

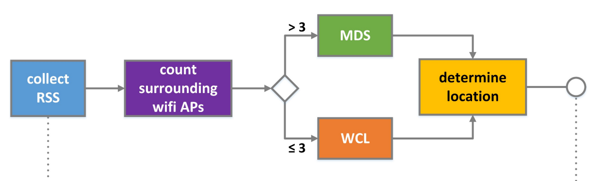


Fig. 1. NIL-RSS algorithm for mini UAV localization

A. *Multidimensional Scaling (MDS)*

Multidimensional scaling (MDS) is a very popular technique for visualization that shows hidden structures in the data. Variation of MDS known as MDS-MAP has been used for solving the localization problem in Wireless Senor Networks (WSN). MDS-MAP algorithm uses the distances between each pair of object as an input and generates 3D points as an output [16].

The MDS-MAP for 3D WSN consists of the following 3 steps [17]:

(1) Calculate the shortest distances between every pair of nodes (using either Dijkstra's or Floyd's all pairs shortest path algorithm) and construct the distance matrix [18].

(2) Apply classical multidimensional scaling technique to the distance matrix and use the first 3 largest eigenvalues and eigenvectors to produce a relative map with relative location for each node.

(3) Transform the relative map into absolute map using sufficient number of anchor nodes (at least 4). This process usually includes translation, rotation, and reflection.

In NIL-RSS, in step 1, the UAV collects the RSSs to at most 10 WiFi APs and transforms the RSSs into distances. The UAV also calculates the distances between the WiFi APs using their exact positions. Since only 10 WiFi APs are considered, there is no need of approximation with Dijkstra's or Floyd's algorithms. Step 2 and Step 3 are the same as in the original MDS-MAP.

B. Weighted Centroid Localization (WCL)

Weighted Centroid Localization is one of the oldest and the simplest technique for WSN localization [19]. In WCL, the position of the unknown node is calculated as centroid [20]. The weight represents how close are two nodes, and is inversely proportional with the distance between them, i.e. the weight w_{ij} between node i and node j is defined as:

$$w_{ij} = \frac{1}{d_{ij}} \tag{1}$$

where d_{ij} refers to the distance between them. The position of the unknown node is obtained as:

$$P_i(x, y, z) = \frac{\sum_{j=1}^{n}(w_{ij} P_j(x, y, z))}{\sum_{j=1}^{n} w_{ij}} \tag{2}$$

where P_i is the position of the unknown node, P_j is the position of node j, while n is total number of neighbors of node i.

C. Time Complexity of NIL-RSS algorithm

In MDS-MAP technique, step 1 requires $O(n^3)$, where n is the number of WiFi APs (maximum 10), step 2 requires $O(n^3)$ due to singular value decomposition and step 3 has constant complexity, which is equal to the transformation matrix with dimension 3 x 3 [17].

Since MDS-MAP has cube complexity, it is appropriate to select maximum 10 nearest WiFi APs, in order to optimize resources. This is important because MDS-MAP will be performed locally at the UAV, which has constraints regarding memory and processing capabilities.

WCL technique works in linear time, i.e. the time complexity for the drone to find its own unknown coordinates is $O(n)$.

Although MDS-MAP is more computationally expensive compared with MCL, it is still lightweight algorithm that can be performed locally by the mini UAV in real time.

III. Simulation Setup and Results

In order to simulate NIL-RSS algorithm, we developed a simulator in Matlab. Our simulation pipeline consists of the following steps:

```
1. Create random trajectory
2. Place the WiFi APs at random locations
3. Take current location
4. Calculate distances between the current location and the surrounding WiFi APs (maximum 10).
5. Check number of neighbors
If(#neighbors>3) then apply MDS
Else apply WCL
6. Take new location (goto 3)
```

A. Trajectory generation

We simulated randomly generated trajectories represented as curves in 3D space. On equidistant intervals, we selected a point from the trajectory and performed localization.

For trajectory generation, we used a recursive approach that generates points in 3D space. Fig. 2 shows an example of one trajectory.

In our experiments, each trajectory consisted of 33 points, which were further conidered for localization. The 33 points are represented with circles in Fig. 2. For plotting the trajectiry, the points are interpolated.

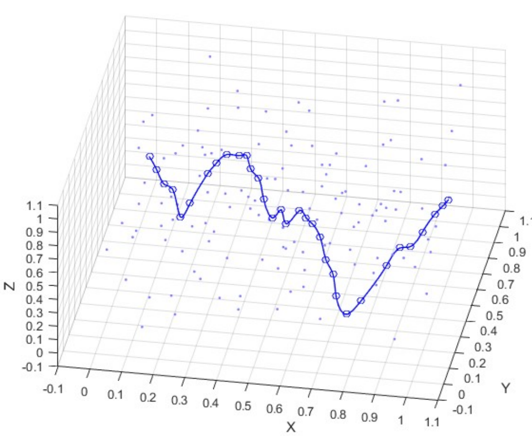


Fig. 2. AUV example trajectory

B. Simulation settings

We considered a cubic area r x r x r, where r is a unit length distance. The UAV can fly autonomously inside the cube. There are no obstacles inside the cube.

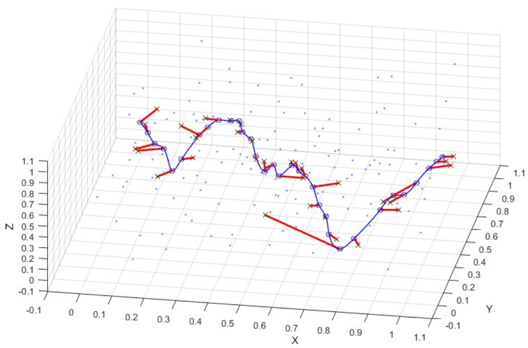


Fig. 3. Example of one simulation obtained for radio range R=0.25, connectivity 6.5, *AEE*=27.01%R, e_r=10%R

The cube is divided into 125 smaller cubes with edge k=0.2*r. Inside each small cube a WiFi AP is placed at random location. This simulation setting is very generic and allows for our algorithm to be easily adopted to more complex scenarios. For example, WiFi APs inside the cube can be replaced by other flying UAVs. As we expect heavier UAV traffic, these flying objects can cooperate with each other in the process of localization and exchange useful information regarding their location. If one UAV has already obtained its own location with small localization error, it can become an anchor node for the surrounding UAVs.

Our simulations were focused on exploring the effect of the average network connectivity and radio range error on the performance of the NIL-RSS. We considered the following:

i. Different radio range R which lead to different average connectivity (average number of surrounding WiFi APs).

ii. Different radio range error e_r, which is modeled as noise with normal distribution.

iii. Only the first 10 nearest WiFi APs are considered for the calculation.

The estimation error (*EE*), estimation error normalized by the radio range R (*NEE*) and the average estimation error *AEE* are given in (3), (4) and (5),

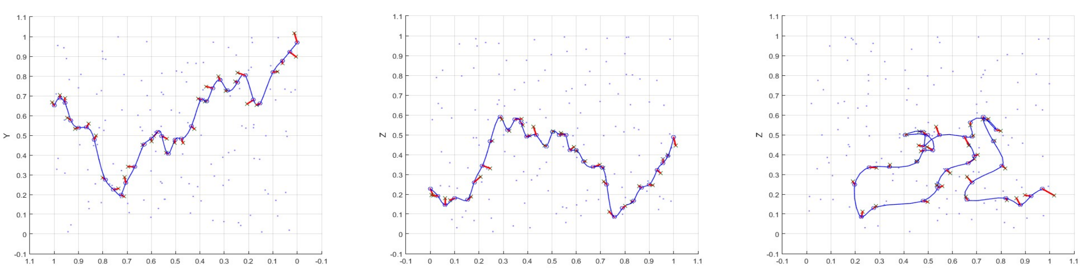
$$EE = \sqrt{(x_i - x_i')^2 + (y_i - y_i')^2 + (z_i - z_i')^2} \quad (3)$$

$$NEE = \frac{EE}{R} * 100\% \quad (4)$$

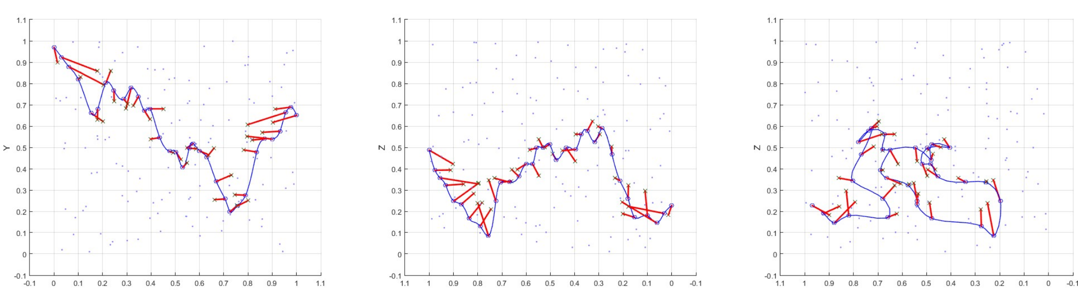
$$Error = AEE = \frac{1}{n}\sum_{i=1}^{n} NEE \quad (5)$$

where (x_i', y_i', z_i') is the estimated location and (x_i, y_i, z_i) is the true location of the i-th trajectory point from the UAV path. *AEE* represents an average over n trajectory points considered from the UAV path, in our case 33.

Fig. 3 shows the *EE* for all 33 points for one example trajectory. The *EE* is presented with red line, which is the difference between the real and the estimated position in 3D space. Two dimensional projection of the *EE* for two different simulation setups is given in Fig. 4.



a)



b)

Fig. 4. XY (left), XZ (middle) and YZ (right) projection of the *EE* for 33 points of a trajectory, obtained for: R=0.4, e_r= 10%R (a) and R=0.4, e_r= 40%R (b)

C. Results

Fig. 5 presents the relationship between the radio range error e_r and the average estimation error for four different connectivity levels.

For each of the 33 points on the trajectory, we investigated 51 different values for e_r (from 0 to 50% of R with step 1% of R) and 4 different values for R from Table I, which led to different connectivity. The connectivity parameter and the estimation error for each scenario represent an average over 10 trials. In total, 33x51x4x10=67320 simulations were performed on 51x4x10=2040 random generated topologies and trajectories.

TABLE I. RELATIONSHIP BETWEEN RADIO RANGE AND CONNECTIVITY

Radio range *R*	0.25	0.3	0.35	0.4
Connectivity	6.5	10.6	16	22.5

As expected, radio range error e_r significantly increases the *AEE*. Therefore, the performance of the algorithm mainly depends on the accuracy of the ranging technique. The connectivity has impact, especially for small connectivity levels. As connectivity increases, there is no difference. This is due to the fact that we consider only the first closest 10 WiFi APs, thus, the connectivity is kept constant artificially.

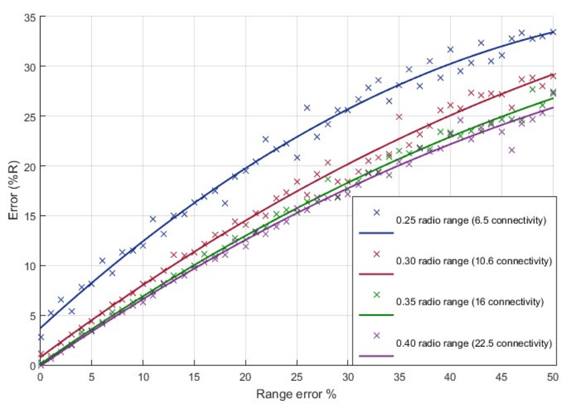


Fig. 5. Relationship between the radio range error and the average estimation error for different connectivity level

Fig. 6 shows the relationship between the radio range R and the average estimation error for four different radio range errors. Radio range R is in the interval [0.2,1] with step 0.01, while e_r has values of 10%, 20%, 30% and 40% of the radio range R. The 10 closest WiFi APs are considered. The estimation error for each scenario represents an average over 10 trials. In total, 33x81x4x10=106920 simulations were performed on 81x4x10=3240 random generated topologies and trajectories. From Fig. 6 we can conclude that greater radio range R ensures smaller *AEE*. Again, if R is large enough (above 0.35), and range error (noise) is small enough (bellow 30%R), the *AEE* is almost constant ragardless of R. For greater range error (30%R and 40%R), *AEE* continues to decrease for greater R.

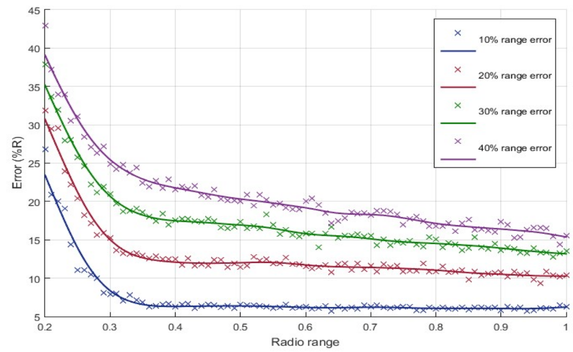


Fig. 6. Relationship between radio range and average estimation error for different radio range error

As mentioned earlier, the *AEE* is stable for greater values of R. In order to investigate whether this stability occurs as a result of the artificial limit of considering only 10 nearest WiFi APs, we repeated the simulation, considering all available WiFi APs within the radio range. The comparison of the results for both scenarios is given in Fig. 7. As can be seen, regardless of how accurate the ranging technique is, using more WiFi APs in the computation decreases the *AEE* of the algorithm.

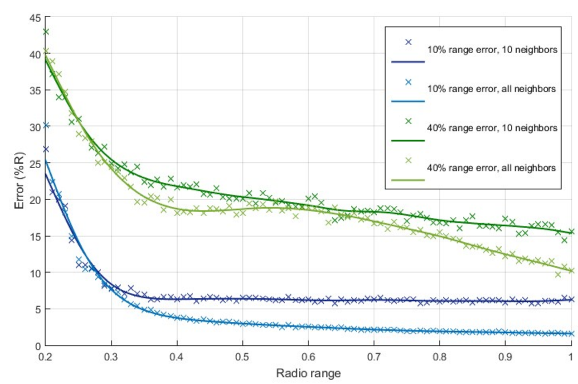


Fig. 7. *AEE* obtained when considering all available surrounding WiFi APs and considering only the 10 closest WiFi APs

The effect of using different number of surrounding WiFi APs is shown in Fig. 8, where distinct colors represent the *AEE* obtained when using different number of WiFi APs, i.e. 5, 10, 15, 20 and 25. The results are obtained for e_r=10%R. As can be seen from Fig. 8, increasing the number of APs from 5 to 10, or from 10 to 15, has positive effect on *AEE*. Further increasing of surrounding APs decreases the *AEE,* but not significantly.

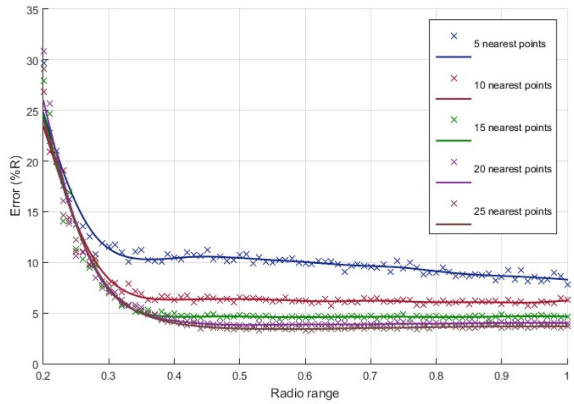


Fig. 8. *AEE* obtained for different number of surrounding WiFi APs

Therefore, choosing the number of surrounding WiFi APs to be considered in the algorithm is a tradeoff between the desired accuracy and the desired complexity of the algorithm.

IV. Conclusion

In this paper, we proposed NIL-RSS, a novel infrastructure based algorithm for UAV localization in indoor environments. NIL-RSS assumes infrastructure like WiFi access points, with a-priory known locations. The locations of the WiFi APs can be anywhere in the 3D space, without any restrictions. Our approach is based on two well-known techniques from the literature for solving the localization problem: multidimensional scaling (MDS) and weighted centroid localization (WCL). NIL-RSS is performed locally by the UAV. Because it is lightweight, the location of the UAV is obtained in real time. This approach is very generic and can be easily extended to more complex scenarios.

To the best of our knowledge, this is the first attempt to use MDS and WCL for AUV localization in indoor environment. We investigated the localization accuracy of NIL-RSS algorithm regarding different parameters, like radio range, radio range error, network topology and network density. Our results have shown that NIL-RSS can be a solid base for solving the localization problem, and can be also combined with other approaches to increase the localization accuracy.

Acknowledgment

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