Autonomous UAV Landing on a Moving Vessel: Localization Challenges and Implementation Framework

Carlos Castillo, Alexander Pyattaev, Jose Villa, Pavel Masek, Dmitri Moltchanov, and Aleksandr Ometov

aleksandr.ometov@tuni.fi

Abstract. The number of Unmanned Aerial Vehicle (UAV) applications is growing tremendously. The most critical ones are operations in use cases like natural disasters, and search and rescue activities. Many of these operations are performed on water scenarios. A standalone niche covering autonomous UAV operation is thus becoming increasingly important. One of the crucial parts of mentioned operations is a technology capable to land an autonomous UAV on a moving surface vessel. This approach could not be entirely possible without precise UAV positioning. However, conventional strategies that rely on satellite localization may not always be reliable, due to scenario specifics. Therefore, the development of an independent precise landing technology is essential. In this paper, we developed the localization and landing system based on Gauss-Newton's method, which allows to achieve the required localization accuracy.

Keywords: UAV · Positioning · Automatic Landing · Simulation.

1 Introduction

Unmanned Aerial Vehicle (UAV) operation is a topic that has been under careful research community attention for more than a decade [1], [2]. While its use has been a spreader, more applications have been found for the UAVs in life-rescuing and natural disaster scenarios [3], [4]. These involve border surveillance to rescue people in the water [5], where the performance of the UAVs has to be as perfect as possible [6]. However, new limitations appear with the new drone-based applications together with the need to overcome the UAV operation challenges. Commonly, UAVs are controlled by the operator having direct sight to the UAV [7], [8] [9]. In this case, the performance degradation may bring a mission failure when video transmission experience network delays, or if the UAV is not in the direct Line-of-sight (LOS). In order to prevent it, modern UAVs are equipped with Global Navigation Satellite System (GNSS) receivers that can estimate the position of the UAV and can trigger the UAV to "return home" mode in the emergency scenario, i.e., to return to the original position from which the UAV was launched or a preprogrammed location. However, the widely used Global Positioning System (GPS) trackers still face an error of approximately $1-10$ meters[1].

Work of the last author is supported by Nokia Foundation under a personal grant. The publication has been prepared with the support of the "RUDN University Program 5-100".

[1] See "GPS Accuracy" by United States Air Force, 2017: https://www.gps.gov/systems/gps/performance/accuracy/

GPS with less positioning error modules are also present on the market (or could be mitigated by utilizing multiple receivers [10]).

Autonomous and Collaborative Offshore Robotics (aColor) project[2] started in January 2018 in Tampere University of Technology, Finland. The core of this project is to achieve a shared intelligence between different offshore vehicles (Unmanned Surface Vehicle (USV), UAVs, and Autonomous Underwater Vehicle (AUV)), as well as the situational awareness of these subsystems. The ultimate aColor's goal is to build an autonomous and cooperative multicomponent robotic system, as well as to demonstrate it in a challenging open environment.

The aColor UAV will be used for water surveillance, tracking disruptions in the water surface, and also as a communications relay [11] if the distance between the vessel and the shore station is greater than the distance capability of a direct radio link. However, one essential key is missing, to be a fully autonomous system is needed a landing system for the UAV that can be performed on top of a moving surface without human aid. The aim of this paper is to introduce a safe method to land the UAV without any form of vision on a moving surface vessel not relying on GNSS. This goal is based on the desired outcome to transform the whole aColor concept into a fully autonomous system. The correct performance of the UAV has to be independent of weather conditions, as very dense fog, rain, snow or wind, which are especially common for next to the shore and maritime operation. These cases describe the drawback of having a ground operator, because of the lack of visual aid, the operator cannot anticipate the behavior of the UAV and prevent a crash.

This paper proposes to relay on antenna-anchors located on the vessel to perform the landing. The localization would be based on the real time processing of the received signal strength in order to approximate the distance from the antennas. Nonetheless, the reduction of the GNSS location error is required in the selected scenario. The main concept is shown in Fig. 1. This architecture is composed of four anchors forming a surface in which center the drone is supposed to land, implementing conventional IEEE 802.11n technology due to its broad market adoption [12] and an autonomous UAV.

This paper is organized as follows. In Section 2, the background information, and positioning strategy are briefed. The proposed solution is described in Section 3. Simulator and related numerical results are presented in Section 4. Finally, the last section concludes the paper.

2 Background Information

This section provides an overview of different autonomous landing approaches. In conventional aircraft, the landing is the most critical operation since passengers might get injured if the landing is not performed correctly. Today passenger aircraft is not yet unmanned, and a crew is controlling the flight on board and from the ground station. Over the years, significant improvements have been developed in this matter

[2] See "Autonomous and Collaborative Offshore Robotics (aCOLOR)" by Kari T. Koskinen, 2017: `https://techfinland100.fi/mita-rahoitamme/tutkimus/tulevaisuuden-tekijat/autonomous-and-collaborative-offshore-robotics-acolor/`

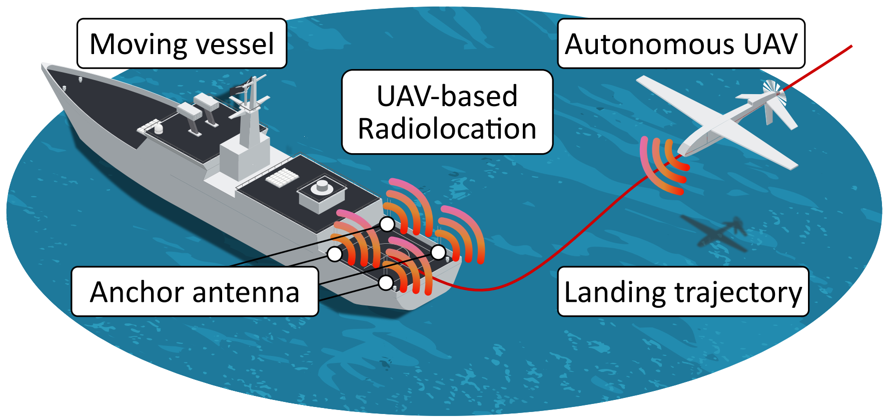

Fig. 1. Concept of the vessel-UAV landing.

to aid the pilots and the ground crew, creating an approach to a more autonomous landing system [13].

In UAVs, the autonomous landing capability has been studied and tested in more details, UAV presents an advantage due to the lack of direct risks. These techniques usually employ GNSS positioning and own UAV's autopilot to land on a steady base station [14]. However, in this approach, positioning error brought by the GNSS might be expected. In order to mitigate the landing accuracy error from GNSS, a visual analysis technique is commonly applied [15]. This hybrid landing system consists of taking the UAV to specific GNSS coordinates and, then, the UAV will recognize the visual pattern given in the landing point using its cameras and signal processing.

However, all these previous solutions have limitations in case of moving platforms. In this paper scenario, the landing points will have continually changing the coordinates compared to ones provided at the beginning of the mission. To overcome this situation, the UAV requires a stable communication link to the landing platform to receive the new coordinates, or another technique has to be employed. Visual aid provided by some given pattern in the landing platform can continue to be used to minimize the location error in the surface target position. In the scenario of interest, the moving platform is on the water surface, thus, creating a risk of damaging or losing the UAV. In order to land an UAV on a moving surface vessel, the use it's equipment to capture and retrieve should be applied.

Most approaches to autonomous UAV landing methods assume that the locations of the UAV and landing platform are known. The default localization system commonly used by many devices is the GNSS [16]. Due to these technologies, it is possible to locate any device that has a receiver in any part of the planet having LoS to the satellites. Moreover, GNSS positioning accuracy gets worse if multi-path propagation is present due to buildings, trees, bridges, etc., surrounding the receiver. Satellite-based localization requires the presence of four or more satellites. These satellites follow an orbit that it might imply that it is possible to have a "dead-zone" for some localization technologies. If the desired positioning error is in the magnitude of a few centimeters, then, satellite positioning technologies are not the best choice. Even though these technologies can reduce that error, the expense of a receiver increments the cost of the project greatly. For this purpose, it is necessary to find a technique that provides a better outdoors accuracy, and the cost is not very significant.

In contrast, high accuracy is more desired in indoor scenarios than outdoors because an error of few meters might mean that the object is on another floor. The most common approach for indoor positioning is the use of low range radio signals [17]. A transmitter acts as an anchor and the device that is meant to be located will measure the received signal estimating the distance to the anchor. If the indoor plan is known, the position estimation has an error of 0.5 meters measured in [18]. Works [19] and [20] have shown the possibility and related challenges to use not only RFID signals but IEEE 802.11 signals for indoor localization.

3 Localization Based on Modified Gauss-Newton's Method

In this paper, the indoor positioning-based method is proposed as an optimal solution for outdoor positioning. In the proposed scenario, the idea implies that the layout is not known beforehand and could dynamically be changed due to the mobility of the vessel and the effects of waves. Therefore, a method to calculate the position of an object in an unknown and potentially moving space is the problem statement. In this paper, a modification of the Gauss-Newton method for non-linear models is proposed to be used for localization. This method is iterative, meaning, the calculated intersection will be a better approximation to the root of the function than the original guess. This is why it is not known beforehand how many iterations are required to find the root of the function.

The calculation of the position of the UAV can be accomplished using the knowledge of Friis distances (applying Free Space Path Loss (FSPL)) from the anchor point to the UAV location. The position coordinates are non-linear, creating an extra difficulty to the UAV location calculation. One of the most studied methods to calculate non-linear regression by least squares is the use of the Gauss-Newton algorithm. This solution allows solving non-linear least square problems [21]. The following mathematical development modifying Gauss-Newton's method is shown to prove that the system is robust. The goal is to allow modeling a system by a non-linear function $y = f(x, a_1, a_2, \dots)$ composed by a set of parameters $a = [a_1, a_2, \dots]^T$ able to minimize the residual error between the actual location and the calculated position

$$\epsilon(a) = \sum_{i=1}^{N} r_i^2 = \sum_{i=1}^{N} [y_i - f(x_i, a)]^2 = \sum_{i=1}^{N} [y_i - f_i(a)]^2 \rightarrow min, \tag{1}$$

where a is the set of parameters that will define the system, $\epsilon(a)$ is the total residual error depending on the parameter set a, r_i is the residual error in every iteration, N is the number of data points $(x_i, y_i), (i = 1, ..., N)$, y_i is the real location of the UAV, and $f(x_i, a), (i = 1, ..., N)$ is the location calculated in every iteration. It has been defined $f_i(a)$ as $f(x_i, a)$.

The residual error is given by the cumulative sum of every iteration of the system. The minimization of this residual error is the ultimate goal. The residual error expressed in vector form to represent the general approach is as follows

$$r = \begin{pmatrix} r_1 \\ \dots \\ r_N \end{pmatrix} = \begin{pmatrix} y_1 - f_1(a) \\ \dots \\ y_N - f_N(a) \end{pmatrix} = \begin{pmatrix} y_1 \\ \dots \\ y_N \end{pmatrix} - \begin{pmatrix} f_1(a) \\ \dots \\ f_N(a) \end{pmatrix} = y - f(a), \tag{2}$$

where $y = [y_1, ..., y_N]^T$, $f(a) = [f_1(a), \dots, f_N(a)]^T$.

Therefore, the general equation in vector form is

$$\epsilon(a) = \sum_{i=1}^{N} r_i^2 = r^T r = ||r^2|| = ||y - f(a)^2||, \tag{3}$$

where the total residual error $\epsilon(a)$ is the absolute value obtained in the difference between the real and the calculated location of the UAV.

Once it is obtained the method to find the residual error, it is necessary to find a that minimizes $\epsilon(a)$. In order to do so, the equation where the gradient of the vector is equal to zero is used

$$\frac{\delta}{\delta a_j}\epsilon(a) = \frac{\delta}{\delta a_j}\sum_{i=1}^{N}[y_i - f_i(a)]^2 = -2\sum_{i=1}^{N}[y_i - f_i(a)]\frac{\delta f_i(a)}{\delta a_j} = -2\sum_{i=1}^{N}[y_i - f_i(a)]J_{ij} = 0, \quad (j = 1, \dots, M), \tag{4}$$

where J is the Jacobian matrix defined as

$$J_{ij} = \frac{\delta f_i(a)}{\delta a_j}, (i = 1, \dots, N, j = 1, \dots, M), \tag{5}$$

where the Jacobian is the first derivative with respect to the paramaters wanted to be minimized (a in this case), $i = 1, \dots, N$ defines the number of iterations, and $j = 1, \dots, M$ defines the number of parameters a.

However, it might happen that equation (5) does not have a closed solution for a. Finding the optimal parameters $a = [a_1, \dots, a_M]$ that will minimize the residual error $\epsilon(a)$ when the previous equations do not have a solution, can be done with the use of iteration$a_{n+1} = a_n + \Delta a$, where it is required to find $\Delta a = a_{n+1} - a_n = [\Delta a_1, \dots, \Delta a_M]^T$. If Taylor expansion is considered $f_i(a_{n+1})$ at a_n, then the following equation is found (in vector form)

$$f(a_{n+1}) \approx (a_n) + J\Delta a. \tag{6}$$

After substituting (6) in (4)

$$\sum_{i=1}^{N} J_{ij}\sum_{k=1}^{M} J_{ik}\Delta a_k = \sum_{i=1}^{N} J_{ij}[y_i - f_i(a_n)], (j = 1, \dots, M). \tag{7}$$

Adapting equation (7) to matrix form and solving for Δa

$$\begin{gathered} \Delta a = a_{n+1} - a_n = (J^T J)^{-1} J^T (y - f(a_n)) = J^-(y - f(a_n)), \\ a_{n+1} = a_n + \Delta a = a_n - J^-(f(a_n) - y), \end{gathered} \tag{8}$$

where $J^{-} = (J^T J)^{-1} J^T$ is the pseudoinverse, and is obtained the iteration

$$a_{n+1} = a_n + \Delta a = a_n - J^{-}(f(a_n) - y). \tag{9}$$

Finally, it is possible to see that the solution to the modeling problem is (by Newton's method for solving the multivariate non-linear equations)

$$f'(a) = f(a) - y = 0. \tag{10}$$

The situations may appear when the system may not converge at any iteration, this is why a parameter $0 < \gamma < 1$ is introduced to reduce the step size of the iteration. This parameter γ has to be calculated in order to maximize the performance of the system. This performance measures if the system has found the solution, and how long it has taken to find the solution.

The following would be further used to estimate the UAV position:

$$a_{n+1} = a_n + \gamma \Delta a, \tag{11}$$

where a_n in the first iteration is the initial guessed position, γ is the step parameter to smooth the step Δa obtaining a value a_{n+1} closer to the actual position of the UAV. The residual error is minimized at every iteration. In this paper, the initial guess position is analyzed and provided an optimal solution as well as the parameter γ.

4 Selected Numerical Results

This section provides the description of the scenario and the simulation with respect to the antenna spacing and elaborates the modified Gauss-Newton's algorithm to calculate the UAV coordinates.

In order to estimate the location of the UAV the following elements are needed: (i) Antennas that are acting as anchor points; (ii) The distance between anchors and UAV; (iii) Gauss-Newton's method estimation; (iv) Residual of the actual target location and estimated location. The anchors are antennas forming a surface in which center the UAV will land. The anchor-antennas are isotropic radiating in every direction as initially the location of the UAV is unknown. The antennas acting as the anchors form a flat surface. The center will be equidistant to every antenna, and the antennas will have the same distance between each other for the simplest case.

In order to find the distance between every antenna and the UAV, Friis distance formula was used. First, the Euclidean-Distance was calculated between every antenna and the UAV. Then, FSPL was obtained using as parameters the calculated distance and a frequency of 2.4 GHz. From the antenna specification, it is known that it has an error that follows a normal distribution of 1 dB, this error is also added to the path losses. Once the path loss is known, it is proceeded to calculate the Friis distance. For the simulation, it is necessary to randomize the initial location of the UAV. The UAV will appear in a volume of 1000 cubic meters (10 meters in each of the three coordinates). A vector of 5000 different UAV positions will be created in order to be able to check the performance of the system. Once the actual position of the UAV is obtained, as well as the knowledge on how to calculate the Friis distance to each antenna, the values will be submitted to customized Gauss-Newton's algorithm in order to estimate the UAV location. This algorithm is a variation of Gauss-Newton's method explained previously. It has been implemented manually to suit our purposes, no external library with this algorithm has been used. Here, the initial coordinate guess should be provided, i.e., the coordinates of the anchor-antennas are situated and the original Friss distance between the UAV actual position and the anchor.

The Gauss-Newton parameter γ defines if the system converges. It allows specifying the step to take if the coordinate has not yet found on every iteration. The error tolerance is used as the margin error between the calculated position using Newton's method and the measured position between the anchors and the UAV. If the error tolerance is not fulfilled, then a variation in the guessed position of the UAV will be applied depending on the direction of the vector connecting the anchor and the UAV. Providing the initial position guess, the Friis-distance from every anchor to the real UAV position, and the anchors' coordinates are input parameters. After the allowed error of the calculated and real distances is met, the new position is returned as well as the number of iterations required to find it. Once the UAV location has been found, the landing procedure should be executed. The landing surface might be moving, which makes the requirement of fast calculation of a trajectory from the current position to the landing point a must. To perform a soft landing, an algorithm should be able to be executed fast enough to estimate the new position taking into account bad weather conditions. The best solution that fulfills all the criteria is to have a parabolic trajectory between the UAV and the anchor-antennas. In this approach, the center of the anchors will act as one of the points of the parabola and the calculated position of the UAV will act as the vertex of the parabola $y = a(x - h)^2 + k$, where a is to be found, $[h, k]$ is the vertex coordinates, in this case the UAV coordinates, and $[y, x]$ are the coordinates of the center of the anchors.

In this paper, the error tolerance with value 0.1 m was used aiming to achieve the smallest error when calculating the position of the UAV. In order for the system to be able to converge, the error between the calculated distance and the measured distance must be smaller or equal to the error tolerance. At the same time, the spacing between the anchors will be taken into consideration, which influences the spatial diversity of the antenna, and together with the path loss, the error performance of the system will vary. During the first calculation, the idea was to represent the maximum positioning error, from the calculated position to the actual location of the UAV, that was calculated by the simulation tool. Every case has been run 1000 times with different UAV location every time. The maximum positioning error was defined as it is the most representative value that will affect directly proposed system. On every simulation step, the number of iterations needed for convergence was estimated when calculating the UAV coordinates. Convergence rate can be improved by allowing to have a higher positioning error between the calculated position and the actual location of the UAV. This might mean that a trade-off between convergence and positioning error should be considered.

4.1 Number and Spacing Between Anchors

The Newton parameter γ is set to 0.4. Together with the number of anchors, the spacing between the anchors was evaluated in order to get the optimal environment solution. In this experiment, the performance of the system using a different set of antennas and spacing between them is shown. For Fig. 2, the mean of errors at every distance to the center were calculated and then the overall mean was also obtained. The mean error is lower than 20 cm in every case, asserting that the proposed system is reliable. In case of *three antennas*, a significant improvement in the mean error when the spacing between the antennas is 50 cm compared to two antennas can be observed. With *four antennas*, there is an improvement compared to three antennas, but it is not that significant as the previous improvement. Since the goal is to have an accurate landing as possible, thus, the positioning error should be minimal when the UAV is close to the center of the anchors. The system that best fulfills this criterion is the one with four anchors. Therefore, it is proposed that the system should utilize *four anchors* with a distance of 1 m between them.

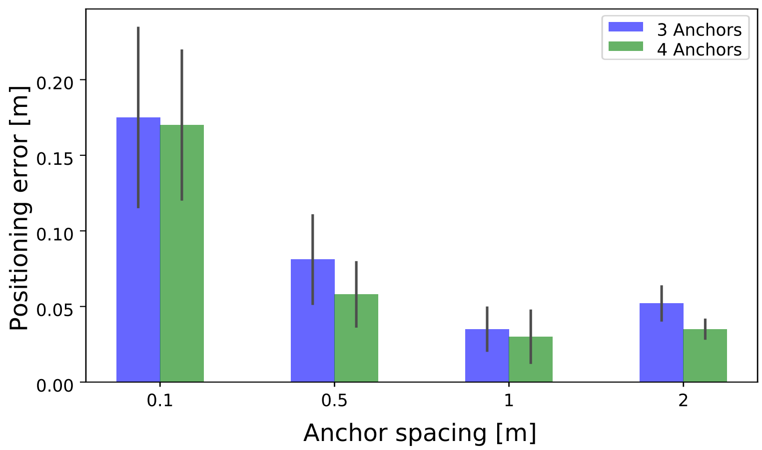

Fig. 2. Mean positioning error.

4.2 Influence of Newton's Method Parameter

Since error tolerance and path-loss are not variables, but the convergence must be improved. The Gauss-Newton's method parameter, γ, in equation (11) should improve reaching a solution with a minimized residual error. Antenna spacing is further set to 1 meter. Fig. 3 shows the influence of the parameter γ on positioning error and the number of iterations to achieve convergence. Parameter γ determines what will be the next movement of the drone in every iteration. If γ is too big, the calculated position of the drone will be far from the actual location, and if γ is too small, then the system will take longer to calculate the drone position with an error distance of 10 cm, causing the system to not converge (meaning that the position was not calculated). It is evident that the best overall performance is given when it is chosen γ value between 0.3 and 0.5. In all the simulations γ of 0.4 was used to maximize the performance of the system. The relationship between the number of iterations to achieve convergence of the system and the positioning error is also provided in this figure on top of every bar representing the positioning error for the analyzed γ value. With lower positioning error the system converges steadily. However, when γ takes values 0.3 and 0.4 a similar positioning accuracy can be achieved, except the convergence of the system is 30% faster for the case when γ is 0.4. A final analysis is that the needed number of iterations to converge is not directly related to the positioning error, but to the chosen γ value.

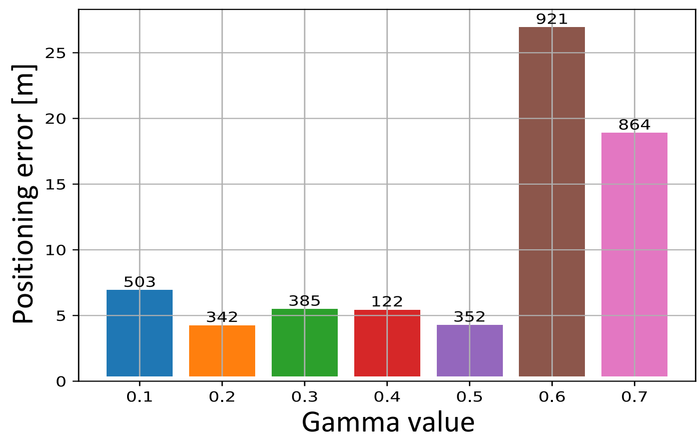

Fig. 3. System performance due to Newton's γ.

4.3 System Performance Depending on the Error Tolerance

During the evaluation, we faced low system convergence (the number of times the UAV was found, satisfying the permitted error calculation) of around 60% in most of the cases. It could be explained as a trade-off for having a low positioning error. According to the results given in Table 1, the performance of the system related to the mean and the maximum values shows that a chosen error tolerance of 10 cm improves the accuracy but a number of iterations to achieve convergence is very high. On the other hand, the accuracy of the system for error tolerance of 30 cm degrades in less than 10 cm in the mean calculation and around half a meter in the maximum accuracy error (with less number of iterations to reach convergence). Even though the overall performance of the system is similar for both cases (error tolerance has values of 10 or 30 cm), the convergence is faster for all cases when error tolerance is 30 cm. This analysis does not affect the previously obtained system performance results if an error tolerance of 10 cm was used. However, it was decided to study both cases for implementation of the system in a real-life scenario.

4.4 Unmanned Aerial Vehicle Landing

The results of applying the optimized parameters from Sections 4.2 and 4.3 for two different landing trajectories are detailed in this subsection.

This work aims to propose a solution to create an accurate landing system for the aColor project that will utilize two different UAVs being fixed-wing (landing according to parabola) and multi-rotor (landing vertically) ones. The velocity is shown as a number of points that the UAV has to overcome in order to move from its initial position to the center of anchors. The performance of the system can be improved by

Error Tolerance [m]	Init Position	Spacing [m]	Mean [m]	Max [m]	Convergence [Num iterations]
0.1	[0,0,0]	0.1	0.32	8.95	498
		1	0.273	8.98	501
	[5,5,5]	0.1	0.31	16.8	914
		1	0.04	4.13	254
	[10,10,10]	0.1	0.28	16.25	683
		1	0.05	4.5	525
0.3	[0,0,0]	0.1	0.25	8.65	251
		1	0.31	8.99	232
	[5,5,5]	0.1	0.3	17.5	487
		1	0.1	4.87	186
	[10,10,10]	0.1	0.3	16.73	330
		1	0.11	4.51	101

Table 1. Comparison between two error tolerance values.

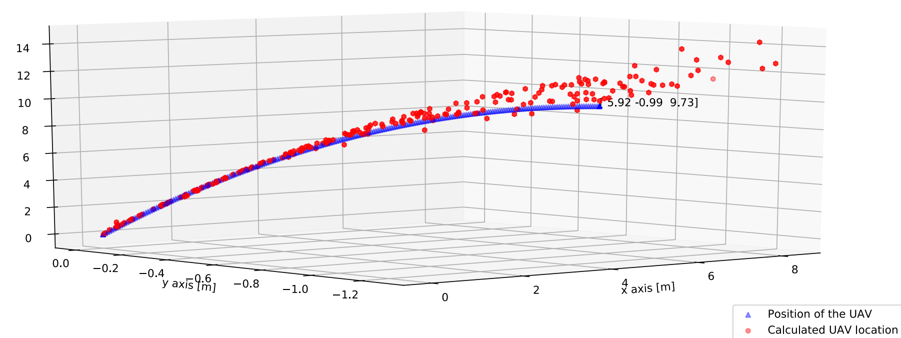

Fig. 4. Example fixed-wing UAV landing trajectory.

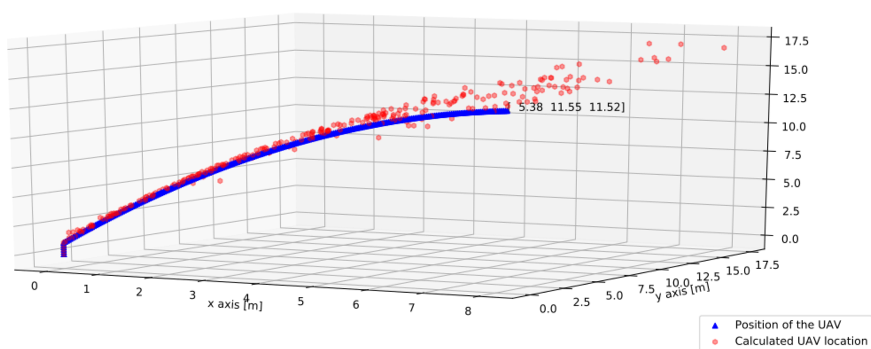

Fig. 5. Example multi-rotor UAV landing trajectory.

controlling the UAV velocity. If the drone travels too fast to the center of the anchors, the system might not converge in time for all the steps that the drone takes. Two examples represented in Figs. 4 and 5, are the simulation proofs that the system can be utilized in real life. When this solution gets applied to the real scenario, a series of tests will need to be done to maximize the performance of the system. It is possible to see that when the UAV is far away from the anchor points the calculated position does not coincide with the position of the UAV, but as soon as the Euclidean distance gets reduced the calculated position matches the actual position of the UAV, being almost perfect in the last meters to the landing point. The simulation of the system has proven to be almost perfect for the critical points of the different descent methods for both types of UAVs.

5 Conclusion and Future Work

The number of UAV applications is growing daily. A crucial niche of UAV development is related to the automated UAVs where positioning plays a significant role, especially during landing on moving objects, e.g., vehicles or vessels. In this work, a system for automatic landing support was developed. The paper focuses on the relationship between positioning errors and system configurations, aiming and keeping the landing surface as small as possible. The moving platform may change its coordinates over time, thus, a pre-decided location cannot be reliable. Moreover, a stable communication link between moving objects and UAV cannot be constantly assumed as there might be some disturbances in the radio link due to environmental and radio factors. A modified Newton-Gauss's method was selected to enable the localization of the UAV. The system designed in this paper could be proposed as a possible solution to achieve a fully automated UAV because of the accomplishment of a landing system with a high positioning accuracy. Currently, W.I.N.T.E.R and aColor teams are in the final phase of developing a full-scale prototype aiming at testing the developed system in the real-life case.

References

1. A. Trotta, M. Di Felice, F. Montori, K. R. Chowdhury, and L. Bononi, "Joint Coverage, Connectivity, and Charging Strategies for Distributed UAV Networks," *IEEE Transactions on Robotics*, vol. 34, no. 4, pp. 883–900, 2018.
2. A. Orsino, A. Ometov, G. Fodor, D. Moltchanov, L. Militano, S. Andreev, O. N. Yilmaz, T. Tirronen, J. Torsner, G. Araniti, *et al.*, "Effects of Heterogeneous Mobility on D2D- and Drone-Assisted Mission-Critical MTC in 5G," *IEEE Communications Magazine*, vol. 55, no. 2, pp. 79–87, 2017.
3. A. Merwaday and I. Guvenc, "UAV assisted heterogeneous networks for public safety communications," in *Proc. of IEEE Wireless Communications and Networking Conference Workshops (WCNCW)*, pp. 329–334, IEEE, 2015.
4. M. Erdelj, M. Król, and E. Natalizio, "Wireless Sensor Networks and Multi-UAV Systems for Natural Disaster Management," *Computer Networks*, vol. 124, pp. 72–86, 2017.
5. M. Erdelj and E. Natalizio, "Drones, Smartphones and Sensors to Face Natural Disasters," in *Proc. of 4th ACM Workshop on Micro Aerial Vehicle Networks, Systems, and Applications*, pp. 75–86, ACM, 2018.
6. S. G. Gupta, M. M. Ghonge, and P. Jawandhiya, "Review of unmanned aircraft system (UAS)," *International Journal of Advanced Research in Computer Engineering & Technology (IJARCET)*, vol. 2, no. 4, pp. 1646–1658, 2013.
7. W. Kong, D. Zhou, D. Zhang, and J. Zhang, "Vision-based autonomous landing system for unmanned aerial vehicle: A survey," in *Proc. of International Conference on Multisensor Fusion and Information Integration for Intelligent Systems (MFI)*, pp. 1–8, IEEE, 2014.

8. J. Pokorny, A. Ometov, P. Pascual, C. Baquero, P. Masek, A. Pyattaev, A. Garcia, C. Castillo, S. Andreev, J. Hosek, *et al.*, "Concept Design and Performance Evaluation of UAV-based Backhaul Link With Antenna Steering," *Journal of Communications and Networks*, vol. 20, no. 5, pp. 473–483, 2018.
9. A. Pyattaev, D. Solomitckii, and A. Ometov, "3D Folded Loop UAV Antenna Design," in *Proc. of International Conference on Wired/Wireless Internet Communication*, pp. 269–281, Springer, 2018.
10. M. Gowda, J. Manweiler, A. Dhekne, R. R. Choudhury, and J. D. Weisz, "Tracking drone orientation with multiple GPS receivers," in *Proc. of 22nd Annual International Conference on Mobile Computing and Networking*, pp. 280–293, ACM, 2016.
11. R. Kovalchukov, D. Moltchanov, A. Samuylov, A. Ometov, S. Andreev, Y. Koucheryavy, and K. Samouylov, "Analyzing Effects of Directionality and Random Heights in Drone-based mmWave Communication," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 10, pp. 10064–10069, 2018.
12. E. Vattapparamban, İ. Güvenç, A. İ. Yurekli, K. Akkaya, and S. Uluağaç, "Drones for smart cities: Issues in cybersecurity, privacy, and public safety," in *Proc. of International Wireless Communications and Mobile Computing Conference (IWCMC)*, pp. 216–221, IEEE, 2016.
13. A. A. Gharapurkar, A. F. Jahromi, R. B. Bhat, and W. Xie, "Semi-active control of aircraft landing gear system using H-infinity control approach," in *Proc. of International Conference on Connected Vehicles and Expo (ICCVE)*, pp. 679–686, Dec 2013.
14. R. Clarke, "Autonomous multi-rotor aerial vehicle with landing and charging system." US Patent 2017/0139409 A1, May 2017.
15. H. Chae, J. Park, H. Song, Y. Kim, and H. Jeong, "The IoT based automate landing system of a drone for the round-the-clock surveillance solution," in *Proc. of IEEE International Conference on Advanced Intelligent Mechatronics (AIM)*, pp. 1575–1580, July 2015.
16. E. S. Lohan, A. Alén-Savikko, L. Chen, K. Järvinen, H. Leppäkoski, H. Kuusniemi, and P. Korpisaari, "5G Positioning: Security and Privacy Aspects," *A Comprehensive Guide to 5G Security*, pp. 281–320, 2018.
17. H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, pp. 1067–1080, 2007.
18. E. S. Lohan, J. Talvitie, P. Figueiredo e Silva, H. Nurminen, S. Ali-Löytty, and R. Piché, "Received signal strength models for WLAN and BLE-based indoor positioning in multi-floor buildings," in *Proc. of International Conference on Location and GNSS (ICL-GNSS)*, pp. 1–6, June 2015.
19. E. S. Lohan, K. Koski, J. Talvitie, and L. Ukkonen, "WLAN and RFID Propagation channels for hybrid indoor positioning," in *Proc. of International Conference on Localization and GNSS 2014 (ICL-GNSS 2014)*, pp. 1–6, June 2014.
20. A. Basiri, E. S. Lohan, T. Moore, A. Winstanley, P. Peltola, C. Hill, P. Amirian, and P. F. e Silva, "Indoor location based services challenges, requirements and usability of current solutions," *Computer Science Review*, vol. 24, pp. 1–12, 2017.
21. J. Yan, C. Tiberius, G. Bellusci, and G. Janssen, "Feasibility of Gauss-Newton method for indoor positioning," in *Proc. of IEEE/ION Position, Location and Navigation Symposium*, pp. 660–670, May 2008.