A Real-time Autonomous Flight Navigation Trajectory Assessment for Unmanned Aerial Vehicles

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***Abstract*— In the recent years, different indoor local positioning techniques are proposed for robotics or UAV systems. This is due to the new research and industrial applications that they can cover. Assessing the performance and autonomous manoeuvring capability of the UAV in a dynamic and interactive indoor environment is challenging. To this end, this paper proposes a Performance Visualized Assessment (PVA) model to assess the performance quality of an autonomous UAV system in indoor environments. The PVA model includes Chi-square Inference (CSI) module and Visualized Mission Grid (VMG) map. The CSI has an optical flow indoor trajectory tracking and localization technique. It estimates the UAV flying positioning indoor without the GPS service. The VMG map has a visualized domain knowledge of the environment and the navigation mission scenario. The PVA model checks and visualizes the trajectory and the behaviour of the UAV when operating navigation missions. The PVA model is applied to track and assess the performance of a quadrotor UAV in real-time search missions. The results show the ability of the model to estimate and visualize the performance quality of the search missions with convenient accuracy. It narrows down the needed parameters of a critical assessment and reduces a human supervisor workload while monitoring the system's performance.**

Keywords*— *unmanned aerial vehicle, trajectory tracking technique, autonomous system, performance-based assessment.

I. INTRODUCTION

Autonomous Unmanned Aerial Vehicle (UAV) systems incorporate advance aeronautical, mechatronic and software technologies. Recently, micro UAVs such as quadcopters have become primary and popular research area due to the achieved progress in this technology [1], [2]. The micro UAVs have the advantages of small size, low cost, manoeuvrability, high accessibility and multiple purposes. Many applications have been developed with micro UAVs including aerial surveillance, data collection, remote sensing, monitoring, search and rescue, and remote control [3]. However, a large part of the applications are manually controlled by a human or needs a human supervisor [4]. The work on autonomous UAVs is growing increasingly. In the near feature, autonomous micro UAVs will play important roles in both military and civilian domains [5].

Currently, the navigation of UAVs is critically dependent on the localization service provided by the Global Positioning System (GPS), which suffers from the multipath effect and blockage of line-of-sight, and fails to work in an indoor, forest or urban environment [3]. Many potential applications to the Micro UAVs are in indoor environments for monitoring, investigation, surveillance, photographing and remote control tasks such as in police work, airports, sports courts, factories or storages. The indoor autonomous flight in a GPS denied environment entails advanced positioning and trajectory tracking techniques [6].

The existing indoor UAV systems consider positioning techniques of propagation distance minimization, statistical, Trajectory Tracking [7]. These techniques estimate the UAV position, motion and trajectory. They are considered inconsistent, especially for the long term of run [8]. Hence, different position estimation and trajectory tracking techniques and methods are proposed in the literature. Superlative UAV positioning entails a system that provides complete details of the environment which is complex and costly [9].

Performance-based assessment is a well-known and widely used technique in autonomous systems literature [10], [11]. Usually, this technique is implemented independently to avoid interference with a system's functionalities. The technique aims to study the appropriateness of the autonomous system performance in real-time scenarios [12]. An issue with this technique is that highly accurate results do not guarantee optimal performance or the consistency of optimal performance due to the dynamics of the environment and hardware constraints [13]. This paper proposes a Performance Visualized Assessment (PVA) model to assess the performance quality of an autonomous UAV system in indoor environments. The PVA includes an optical flow as a low-cost indoor trajectory tracking and localization technique. It estimates the UAV positioning and performance quality indoor without the GPS service.

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The rest of the paper is organized in five sections. Section II presents the related work in indoor navigation trajectory tracking of UAV systems. Section III illustrates the research methods and materials including the experimental quadcopter, the trajectory technique and the experimental testing environment. Section IV presents the theoretical model, demonstrate the implementation and discusses the obtained results. Section V concludes the work and suggests future work.

II. Related Work

The literature reports the need for advanced research in deploying UAVs in indoor environments. There is a variety of utilization to the trajectory tracking technique for the UAV in the literature. Some examples are UAV localization, e.g., [11], navigation control e.g., [8] and [14], and autonomous missions, e.g., [1], [2] and [6]. This section review some of these examples in the following.

Gariepy [8] propose an image processing algorithm to improves the performance of trajectory tracking technique when performing with low-quality images. The algorithm combines a Random Sample Consensus (RANSAC) with Extended Kalman Filter (EKF) and feature selection technique. The RANSAC is used to remove outliers from the images, the EKF is used to improve the visual measurement and the overall positioning estimation and the feature extraction technique is used to reduce the computational cost of image processing. The algorithm is applied in an AR.Drone quadcopter to estimate its position in an indoor environment from the 2D plane. The algorithm improves the speed and quality of the trajectory tracking technique (40 cm). Figure 1 shows the controlling architecture of the trajectory tracking technique. The outcomes of this work verify the possibility of trajectory tracking of the UAV to be used as a visual input to the UAV navigation of autonomous missions.

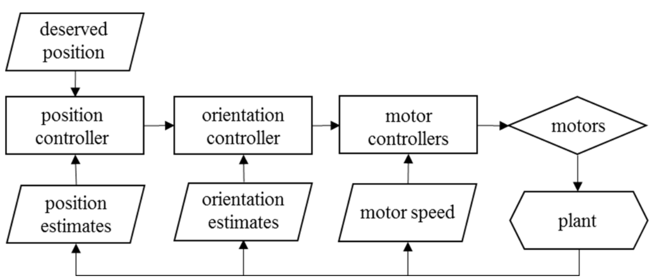

Fig. 1. The nested control loop of the quadcopter [8].

Cheng et al [11] propose a mini-UAV localization module to localize mini UAV in an indoor environment of a Wireless Sensor Network (WSN). The environment is non-line of sight (NLOS) that contains obstacles blocks direct paths of signals from the beacon to the target of the WSN. The module uses Received Signal Strength (RSS) and a Sequential Probability Ratio (SPR) test to estimate the range of the WSN and overcome the fluctuations of the signal. The test results show that the module improves the localization accuracy in such NLOS environments.

Khosiawan and Nielsen [6] report the need for an advance research in deploying UAVs in indoor environments for monitoring and surveillance tasks such as in a manufacturing environment. They propose a UAV scheduling operations framework that operates a UAV system in an indoor application. The framework divides the UAV tasks to UAV operation tasks and domain application tasks. The execution of these tasks enables the UAV to perform autonomous missions. The UAV control system has an indoor radio-based positioning software that contributes to the possible trajectories of performing particular tasks. The framework provides a systematic scheduling abstraction of long surveillance missions according to three sources of data: task data, UAV data and map data.

Fowowe [5] propose a cooperative framework between a UAV (AR.Drone) and UGV for simultaneous localization and mapping. The UGV and UAV cooperative to perform autonomous surveillance tasks in an unknown environment. The mission scenario is that the UGV uses the UAV to reach inaccessible areas, calculate possible navigation paths and avoid obstacles. The cooperative system operates depending on onboard gyroscopes and altimeter sensors and visual navigation which are used to estimate the position of the UAV and UGV during runtime. The visual navigation depends on trajectory tracking technique and EKF. Figure 2 shows a schematic representation of the control loop in the cooperative system. The quality of the system performance and autonomous control is assessed by mission success and time parameters.

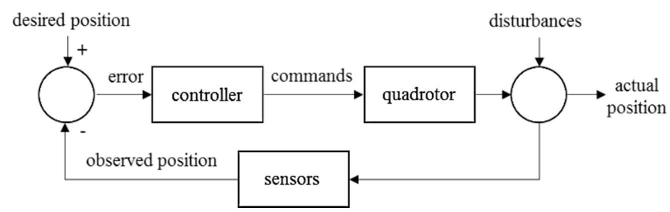

Fig. 2. The control loop [5].

Gesbert [7] explore the ability to use a UAV system as a flying wireless relay in wireless networking. The aim of the work is providing the capacity boost of connectivity to users in urban topology. The work entails an automated UAV positioning mechanism in order to distribute the wireless networking services in which the accuracy of the UAV position affects the performance of the network's end-to-end throughput. Chen & Gesbert propose a local positioning model that consists of search and propagation algorithms. The algorithms work according to the length of the search trajectory and a signal strength map. The model shows positioning accuracy results near the commercial Line-of-Sight (LOS) statistical model.

III. Research Methods

The research methods include an Unmanned Aerial Vehicle (UAV) or drone system of AR. Drone 2.0. The drone is operated by an adjustable autonomous multi-agent system [1], [13]. A human supervisor monitors and provides a global control over the system [4].

A AR. Drone

The AR. Drone is a quad-rotor helicopter fixed with four rotor fans that spin rapidly to provide lifts to the main body of the helicopter and other payloads [3]. We study the drone characteristics and specifications to determine the settings of the autonomy applications that the drone performs. Figure 3 shows the AR.Drone 2.0 in (a) outdoor and (b) indoor forms.

Fig. 3. The AR. Drone 2.0.

The original drone comes with remote control software, downloadable from the supplier's website, for an operator to control its flight. However, there is no autonomy given to the drone, i.e., other than basic controls, it needs to be programmed to serve other purposes [3], [5]. We incorporate an autonomous drone software that sends remote control signals to the drone from a laptop to autonomously perform basic manoeuvrability and flight functions. The overall system is named a Dynamic Adjustable Autonomous Drone (DAAD). A comprehensive description of the system is presented in [1], [4] and [13].

The drone's DAAD autonomous software complete with auxiliary software is set up in the laptop for testing. They emit output Wi-Fi signals from the laptop to implement remote autonomous functions for the drone. The drone is preliminarily tested in a predetermined environment to check its autonomous functions. Figure 4 shows the experimental drone system general operations.

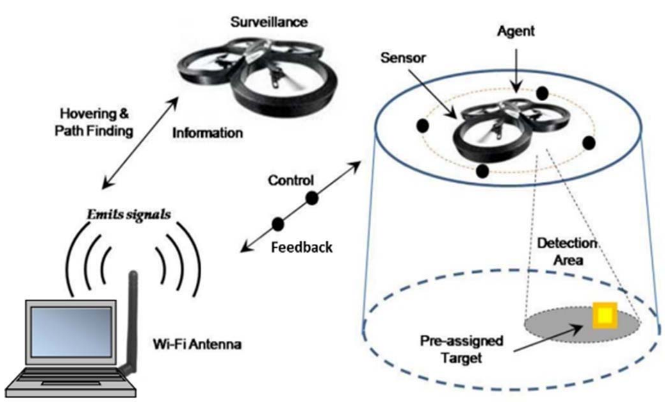

Fig. 4. The experimental drone system.

B Trajectory Tracking Technique

The main challenge of this work is to dynamically estimate the drone's position for indoor autonomous flight. This challenge is essential for the drone from the perspective of control since the work is in a GPS denied environment [8], [11]. The onboard localization (odometer) sensors of the drone are accelerometers and gyroscopes. The odometer's readings manifest uncertainty for drone position estimation and ultimately for autonomous navigation.

The trajectory tracking or the optical flow is a low-cost indoor localization technique that provides reasonably accurate results [14]. The technique uses the onboard downward-facing camera of the drone for its localization. The camera continuously captures a stream of low-quality images. The trajectory tracking technique includes an image processing algorithm for extracting the positioning data from the images and position estimation algorithm to map the image positioning data with drone positioning data to estimate the drone positioning in the environment or the world. Figure 5 shows a general model for the trajectory tracking technique.

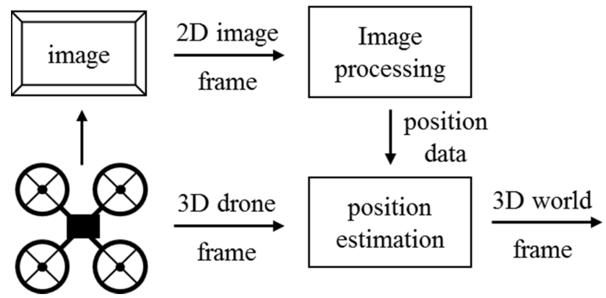

Fig. 5. An overview of the trajectory tracking technique.

The position estimation algorithm involves coordinating the drone 3D frame with the image 2D frame to project the world 3D frame [8]. Figure 6 shows the coordinates of the three frames.

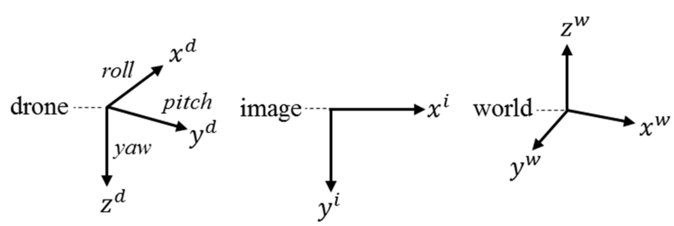

Fig. 6. The coordinates of the frames.

This coordination allows a point to be related to the world frame as in Equation (1):

$$\begin{bmatrix} x_i^w \\ y_i^w \end{bmatrix} = \begin{bmatrix} x^w + \frac{r_i^1}{s^s} + \frac{r_i^2}{s^y} \\ y_i^w + \frac{r_i^3}{s^y} + \frac{r_i^4}{s^s} \end{bmatrix} \tag{1}$$

where $r_i^1 = z_i^w \cos(8 + yaw)(y_i^d - y_i^i)$, $r_i^2 = z_i^w \sin(8 + yaw)(x_i^d - x_i^i)$, $r_i^3 = z_i^w \cos(8 + yaw)(x_i^d - x_i^i)$, $r_i^4 = z_i^w \sin(8 + yaw)(y_i^d - y_i^i)$, s^s and s^y are the scaling ratios of an image and 8 is the angular offset between the image frame and the drone frame.

The image processing algorithm continuously processes pairs of low-quality images. The projection to the difference between points of two images at t and $t + \Delta t$ times infers the position data of the images. The first image provides an initial reference and the second image offsets the difference of the drone movement between the two images. The following formula shows the basic mechanism of a 2D optical flow technique.

$$P(x, y, t) = x + \Delta x, y + \Delta y, t + \Delta t \tag{2}$$

where P is a point of two coordinates x and y in time t. Δ is the difference between the measurement of two points.

Then the position estimation algorithm estimates the horizontal and vertical motions of the drone based on the series of the generated points [8], [14]. However, this technique works well in grounds with polished surfaces and clear patterns.

C Experimental Environment

The experimental scenario is a *search* mission in which the drone manoeuvres and looks for a number of tags in a predefined environment. The design of the *search* demonstrates different behaviours in order to create a suitable test plan and ensure significant results. The *search* mission has some behaviours with high complexity as it entails tasks and actions that are proactively configured. The challenge of the experimental scenario design is to create a mission that can comprehensively test the system with a lesser number of trials. Consequently, the system can successfully perform the mission regardless of the hardware constraints. The *search* mission is designed for an indoor testing arena of 30 x 25 x 20 meters (*m*) dimensions. The arena has four pillars, surrounded by walls on its four sides and a closed roof. Figure 7 shows a top view of the testing arena.

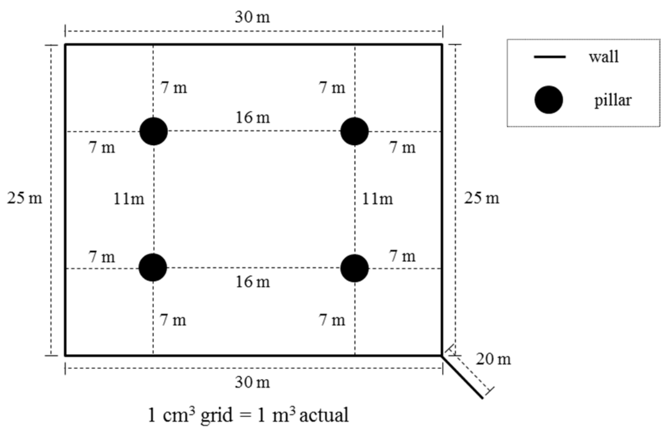

Fig. 7. The blueprint of the testing arena.

IV. The Performance Visualized Assessment Model

The Performance Visualized Assessment (PVA) model provides a global view of the DAAD system performance. It checks the ability of the DAAD system when performing the *search* mission in dynamic environments. The PVA model concerns with tracking the drone movement to visualizes and evaluate the system's responses in the environment. The visualization reveals the misfits between the actual attainments and the intended performance.

The PVA model basically consists of a Chi-square Inference (CSI) algorithm and Visualized Mission Grid (VMG) map. The CSI algorithm has a Chi-square and trajectory tracking algorithms. The VMG map has a domain knowledge of the arena and the scenario. The domain knowledge is the drone required path and the locations of the objects in the arena.

The CSI algorithm plots the positioning and trajectory tracking data with the VMG map to estimate and generate the performance assessment results. The CSI interacts with the VMG for every 65 milliseconds to update the drone's positioning in the VMG map. The VMG draws the implemented route of the drone and highlights the milestones that the DAAD system achieves. The CSI validates the behaviour of the system by comparing the implemented route with the expected or planned route and the detected objects with the surrounding active objects. Figure 8 shows the PVA model

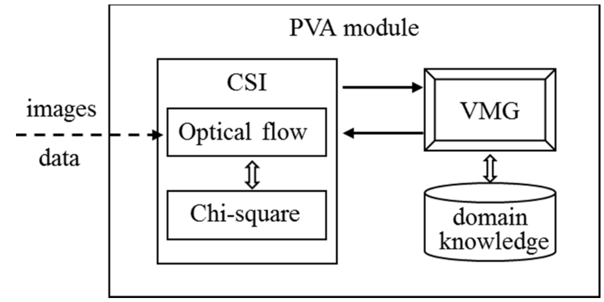

Fig. 8. The PVA model.

The CSI uses a Chi-square formula to show the similarity or the differences between multiple points of the expected route coordinates and the traversed route coordinates. The coordinates of the two are represented in a two-dimensional array of expected, R^E, and traversed, R^T routes along with the time T. The R^E is configured after a number of attempts and considered as the best successful tests accordingly to form the VMG map of a domain knowledge. The Chi-square similarity or accuracy matching formula is defined as:

$$S_t = \sum_{i=0}^{r} \frac{(v1_i - v2_i)^2 * (t1_i - t2_i)^2}{(v1_i + v2_i) * (t1_i + t2_i)} \tag{3}$$

where S is the similarity matching result in a time index t, v1 is the coordinate value of the expected route in the expected time t1 and v2 is the coordinate value of the traversed route in the traversed time t2 and r is the number of coordinates that are produced by the optical flow algorithm in the overall t.

Formula (3) is applied for X, and Y, coordinates separately and the results of which are S^s and S^y. The S value represents the quality of the performed test. If the S for each of the S^s and S^y has a small value, it indicates that there is a high similarity between the expected route and the traversed route and, hence, high-performance accuracy. Contrarily, if the S for each of the S^s and S^y has a big value, it indicates that there is a low similarity and, hence, low-performance accuracy. Additionally, human observation to the VMG after each test including the traversed rout and the detected objects detriments the quality of the overall performance.

V. Implementation and Results

The PVA model implementation platform is Java and the agent platform is the Java Agent DEvelopment (JADE). The implementation also includes utilizing a number of open source libraries. The PVA model depicts the drone activities by means of the CSI and other DAAD system parameters for every 65 ms and updates the VMG. The model has a test mechanism to manually visualize and trace the expected activities based on the

VMG copies. The VMG represents each of its copies in an image of 700x500 pixels. The VMG implementation includes image processing algorithms and a grid. The grid is a two-dimensional area of pixels in which a pixel represents the grid's measurement unit. The grid is scaled such that an actual 1x1x1cubic meter (1 m3) equals 20x20 pixels (i.e., 1 pixel equals 5CN^{2}). The VMG neglects the altitude for convenience.

The DAAD system operates the *search* scenario for four successful attempts. A test is considered as successful when it goes as expected and without disturbance. A test is considered as unsuccessful when an unexpected incident occurs during the test that is beyond the system's control such as hardware failure or dramatic change in the environment. The diagnosis of the test success is based on a human supervisor's observation of the system and the recorded data. The PVA visualizes and assesses the performance of the system to the four search missions. The trajectory plot of the VMG to the drone movement for the four tests is shown in Figure 9.

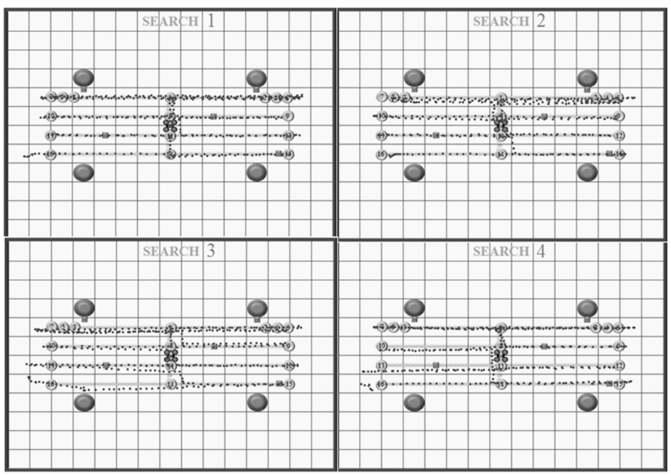

Fig. 9. The VMG results from the *search* scenario.

The distance measurement between the expected route and the traversed route shows high to medium similarity and accuracy performance. The first and the fourth tests show the highest accuracy performance. The second test shows intermediate accuracy performance and the third test shows the lowest accuracy performance. Table 1 shows the performance accuracy results of the DAAD according to the PVA model.

TABLE 1: THE PERFORMANCE ASSESSMENT RESULTS OF THE DAAD

test	time	S_t^x	S_t^y	accuracy
1	4.05	0.8158	0.6141	0.5009
2	4.00	0.9537	1.0294	0.9817
3	4.22	0.8621	1.2231	1.05443
4	4.03	0.7793	0.5891	0.45908

The average time to complete the search mission is 4.08 minutes. The overall result of the four tests shows that the DAAD system consistently and adequately performs the *search* mission. Comparing with human observation to the drone performance and the VMG results, the PVA model represents a promising method for assessing the manoeuvrability quality of autonomous drone systems in the indoor environment. Additionally, the assessment data can be feed to the system to improve its performance. The current system uses an autonomous agent to control the drone [1], [15], [16], [17]. Advance technologies of human behaviour context [18] and norm [19] identification and assimilation [20] by drone agents are some possible new research contributions.

VI. CONCLUSION AND FUTURE WORK

This work investigates a real-time autonomous flight navigation trajectory assessment for UAVs flying indoor without the GPS service. Subsequently, this paper proposes a Performance Visualized Assessment (PVA) model to assess the performance quality of an autonomous quadcopter UAV or drone system in indoor environments. The PVA model consists of Chi-square Inference (CSI) module and Visualized Mission Grid (VMG) map that performs a visualized trajectory tracking and localization to the UAV missions. The PVA gives a complete view of the UAV navigation trajectory and the behaviour of the UAV when operating search missions. The test results show that the PVA model implementation narrows down the needed parameters of a critical assessment and reduces a human supervisor workload while monitoring the system's performance. The recorded accuracies of the performed search missions are considered high. The future work deliberates testing the UAV system in different circumstances and with different missions.

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