Development of Real-Time Control System based on Deep Learning for UAV's Object Detection, Tracking and Safe-Landing

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Abstract—**In the current work, an approach to implement AI-based techniques in real-time focusing mainly on the detection, tracking, and landing on the target object is presented. For an object detection, CNN algorithm is utilized. For object tracking and stabilizing, a novel algorithm is developed that can execute along with object detection via sequential stream data. For landing, a vision-based algorithm is used to estimate the distance between the UAV and the detected object. For UAV control, a Fuzzy-PID controller is designed to steer the UAV by a continuously manipulation of the actuators based on the stream data from the tracking unit and dynamics of the UAV. For UAV landing, a new type of fuzzy logic controller is developed to compensate for the nonlinear ground effect that affects the safe landing of the UAV. All the developed algorithms are executed on an NVIDIA Jetson TX2 embedded artificial intelligence device, and an ARM Cortex M4. Experimental results show that the tracking algorithm responds faster than conventionally used approaches, and the safe landing algorithm minimized the landing time of the UAV and provided the safety assurance as compared to conventional controllers. Furthermore, a farming monitoring and automated wireless charging is considered as an application example.**

I. Introduction

Autonomous multicopter robots are among the most promising research activities due to the special characteristics of these robots such as mechanical simplicity, small size, and easy to control. Among these multicopter robots are the Quadcopters. Quadcopter is a type of Unmanned Aerial Vehicles (UAV), which is lifted and propelled by four rotors [1]. The Quadcopter has been increasingly used in education and research area due to its low cost, and high maneuverability. Furthermore, a quadcopter is capable of handling complex tasks in cramped and crowded environments, cable of taking-off and landing in cramped areas [2], as well as it has a simple control mechanism compared to the other types of UAVs [2].

Object-detection, tracking and safe-landing process is one of the most important pre-functions in the UAVs, as it can be used in different separate applications, e.g., surveillance [3] and safe-landing for battery charging [4], or drone delivery service [5]. Also, drones offer a potential solution for agri-environmental monitoring application including crop health monitoring, landscape assessment, livestock health monitoring and overall biodiversity assessment of rural areas [6].

There have been several methods focusing on object tracking and based on making use of different sensors [7]. Vision-based object detection is one of the cheapest and convenient method by which the obtained information from vision sensors, e.g., RGB camera, can be used in other tasks simultaneously, e.g., odometry and navigation [8] [9].

The main drawback of vision-based object tracking methods is the high computation cost of executing their algorithms w.r.t. the performance, energy, and accuracy [10]. Using cloud servers for object detection is not possible since the communication cost between the drone and cloud enormously prolongs response time in real-time stream data processing of object tracking; Cloud computing systems are internet-based, and service outages are always possible and can occur for various reason. Furthermore, using wireless communication for streaming data is not practical due to its limited coverage area and high latency which lead to significant degrade in performance. Moreover, detecting objects in run-time basically faces noisy and low-resolution images accompanied by the background motion that negatively affects the accuracy of the detection outcome. Therefore, application execution on this platform requires appropriate system architecture and adopted algorithms to improve the system constraints as much as possible while meeting the strict requirements.

In this paper, our aim is to provide an adaptable fuzzy control mechanism for the Quadcopter that is able to manipulate its actuators, i.e., throttle adjustment and the roll and pitch of the drone, in different environments. Two separate fuzzy controllers are proposed, 1) a fuzzy controller to adjust the drone's throttle based on two inputs of speed and distance from the ground, 2) a fuzzy mechanism to *adjust* the parameters of the PID controller based on two observations of position of the drone and speed. The former controller is responsible to adjust the throttle of the drone to provide fast and smooth navigation movement while the latter controller manipulates the roll and pitch of the drone for efficient tracking in different environmental conditions.

II. Implemented real-time control algorithms

In this work, a real-time feedback-based object detection, tracking and landing algorithm is developed that can be adapted to be executed on the presented system architecture. Fig. 1 shows the feedback-based algorithm for the devel-

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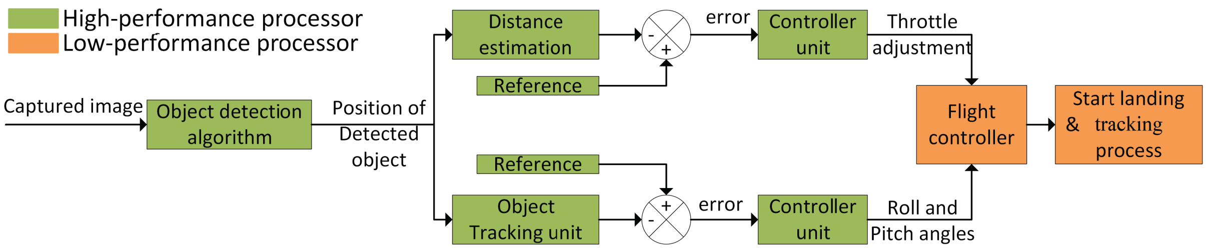

Fig. 1. Block diagram of the developed system

oped algorithm. The proposed system is divided into three main algorithms:

- Object detection algorithm.
- Distance estimation.
- Object tracking algorithm.

The high-performance processor receives the visionary data from the camera and fed it into the object detection algorithm to detect the target object for tracking and landing. Once the target is detected in the camera scene, the CNN returns the image with a boundary box around the detected object, and its position in the frame. Afterwards, the position of the detected target is passed to the object tracking and landing algorithms simultaneously and is subtracted from a reference, which is the center of the frame to give out the error. The controller units is utilized based on the error of each algorithm to output the suitable throttle adjustment required for controlling the Quadcopter landing and the roll/pitch angles responsible for stabilizing the Quadcopter above the detected target, and thereby, the actuation parameters to each motor will be adjusted.

A. Object detection algorithm

After receiving the captured image from the camera, a CNN algorithm is applied. In this work, a pretrained Single Shot Multibox (SSD) with the MobileNet detector is used for object detection [11]. After applying the SSD model, a boundary box will be drawn around the detected object. The location data of the detected object is extracted and used as an input to the object tracking and landing algorithms.

B. Distance estimation algorithm

Once the object is detected and the position of the detected object is extracted, this information is fed to the distance estimation algorithm to control the landing of the Quadcopter. In this work, a pinhole camera model [12] is utilized to calculate the distance between the Quadcopter and the detected object. Once the distance is estimated and filtered, the vertical speed of the Quadcopter is obtained and is passed to the controller unit as shown in Fig. 1 to give out the suitable throttle adjustment value that is required to land the Quadcopter safely on the detected object.

To account for the *ground effect* that exists near the ground while the Quadcopter is descending, a fuzzy logic controller (FLC) is utilized to control the Quadcopter landing. Ground effect refers to the increased upward force to the multicopter frame near the ground, in relation to high altitude flight conditions. The FLC proposed in this paper has been developed and explained in our previous articles [13] [14].

C. Object tracking algorithm

In Figure 1, once the object is detected, its position is given to the object tracking unit to start the tracking process. In this work, a Fuzzy-PID controller is utilized to overcome the instability of the Quadcopter, especially under external disturbances such as wind. Two inputs are given to the Fuzzy-PID, position of the detected object (pos) and its change of position ($\triangle pos$), and three outputs are acquired, K_{pf}, K_{if} and K_{df} which are determined by a set of fuzzy rules that are used to adapt the K_p, K_i and K_d gains of the PID controller as in Equation 1-3, where G is a gain value that can be used to for tuning the output of the Fuzzy-PID, P is the sum of the proportional gain K_p and the K_{pf} gain, I is the sum of the integral gain K_i and the K_{if} gain, and D is the sum of the derivative gain K_d and the K_{df} gain. The output of the Fuzzy-PID is described in Equation 4, where the error $e(t) = pos$ represnts the current position of the detected object, and $y(t)$ is the the required angle needed for tracking the object. Figure 2 depicts the basic structure of the Fuzzy-PID controller. The Fuzzy-PID developed in this work is based on [7].

$$P = (G \times K_{pf}) + K_p \quad (1)$$
$$I = (G \times K_{if}) + K_i \quad (2)$$
$$D = (G \times K_{df}) + K_d \quad (3)$$

$$y(t) = (P \times e(t)) + (I \times \int_0^t e(\tau)d(\tau)) + (D \times \frac{de(t)}{dt}) \quad (4)$$

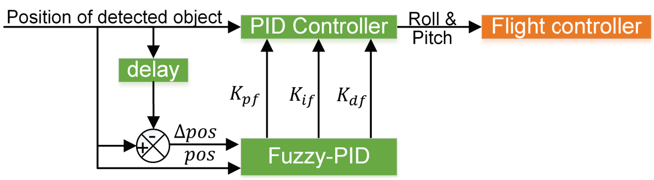

Fig. 2. Fuzzy-PID basic structure

III. Experimental studies and results

A. Object detection

The CNN algorithm used for detecting the objects is a SSD_mobilenet_v1 which is optimized to run on embedded platforms in real-time. The SSD_mobilenet_v1 is implemented on a low power-consumption Nvidia Jetson TX2 in the Python programming language. The object detector is trained to detect two objects, a circular and a rectangular object as shown in Figure 3. The average frame rate (fps) achieved by SSD_mobilenet_v1 is 25fps with 90% accuracy which make it more suitable for real-time applications.

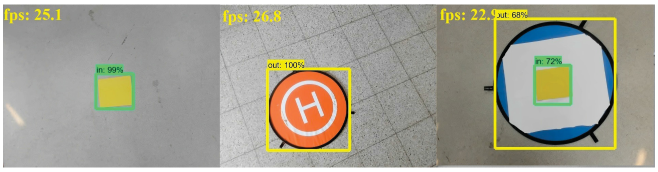

Fig. 3. Object detection algorithm output

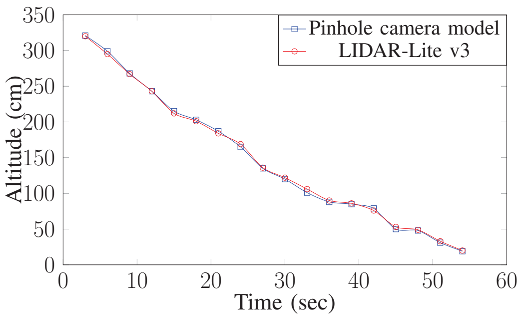

Fig. 4. Distance estimation output comparison

Fig. 5. Quadcopter experimental setup

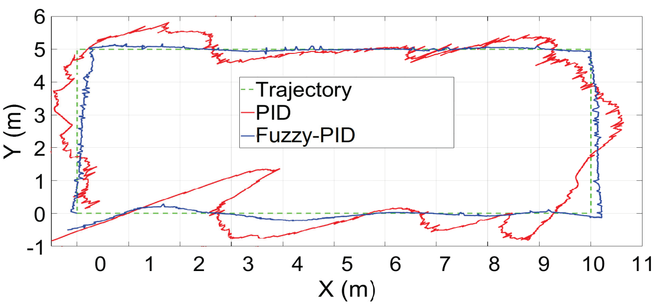

Fig. 6. Controller result in a rectangular trajectory

B. Distance estimation

Initially, the Quadcopter is hovering at the 3 meters altitude. Once the object is detected in the scene, a pinhole camera model is applied to estimate the distance between the Quadcopter and the detected objects. Later, the estimated distance is passed to the FLC to calculate the throttle adjustment required for safely landing the Quadcopter on the detected object. The drawback of detecting one object is that this objects needs to have a big size to be able to be detected in high altitude. However, while the Quadcopter is approaching the ground specifically under 1m, it will become impossible to estimate the distance due to the insufficient size of the big detected object. For this, a smaller object has been placed on the bigger one, so when the Quadcopter approaches the 100cm it will estimate the distance based on the information of the smaller objects.

Figure 4 shows the output values of the pinhole camera model while the Quadcopter was landing compared to a laser-based optical ranging sensor (LIDAR-Lite v3). The mean error of the pinhole camera model is 2.4% which makes it suitable for such applications where we have a known width of the detected object.

C. Object tracking

To verify the feasibility of the developed algorithm, several experiments were performed outdoor under environment effects, e.g., windy weather, to obtain the optimal values for the parameters gains that is used for object-tracking algorithm. The experimental setup shown in Figure 5, is composed of Quadcopter frame with a flight controller connected to a Jetson TX2 through UART communication. Initially the Quadcopter is flying at the altitude of 3 meters, and is tracking an RC car in a rectangular trajectory, to test the response of the proposed controller. Once the RC car is detected, real-time object detection is triggered, and a boundary box is drawn around the moving RC car based on our developed object detector. The object tracking algorithm will then proceed.

The experimental target is moving in a rectangular path under various speed. Figure 6 show the results of the performed trials using our object tracking algorithm and is compared to a PID controller that was developed in our previous work to follow a human based on CNN detection [15].

According to the previous evaluation of the experimental results, the Fuzzy-PID controller has proven that it has better response, and shorter settling time compared to the typical PID controller.

IV. Autonomous Navigation of a UAV and Wireless Automated Charging for Farm Monitoring

We now introduce a potential practical application of the real-time control system presented in the previous sections, namely autonomous navigation and wireless charging for farm monitoring. It consists of three main parts: A ground station system, an autonomous navigation system, and a wireless charging station. The ground station system is responsible of sending the required path to be followed to the UAV. Also, its responsible for acquiring the locations of the drone wireless stations around the planned path. The autonomous navigation system consists of a flight controller that regulates the drone attitude and measures the drone battery voltage in real-time, and an AI embedded platform which oversees calculating the required drone attitude for autonomous navigation. The AI

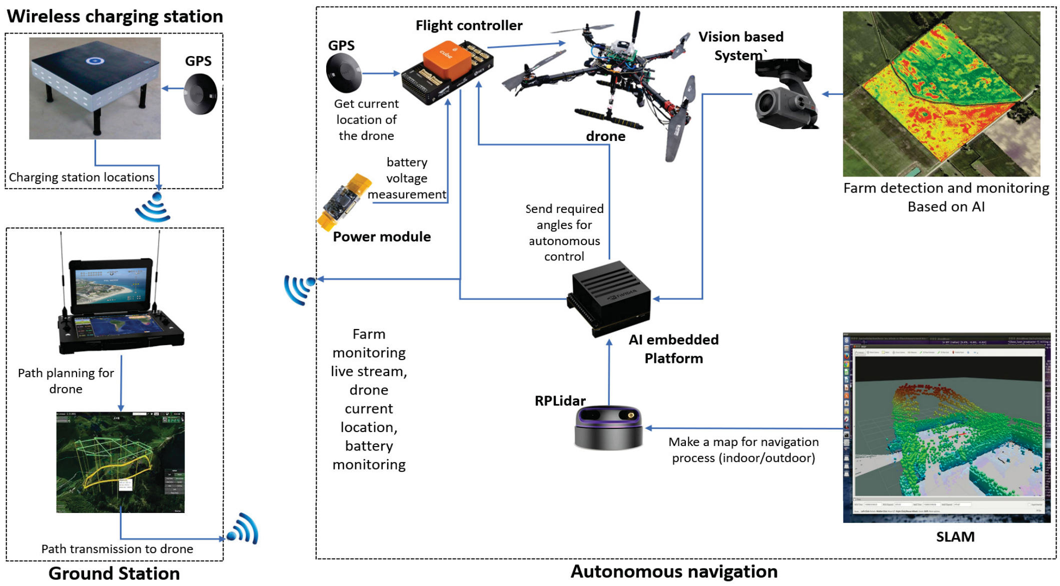

Fig. 7. Schematic diagram of the proposed example application

embedded platform is connected to a vision-based system that is used in farm monitoring based on AI, and a LiDAR that is used to create a detailed 3D map to aid the drone in the navigation process by creating a path planning, especially in the controlled-environment agriculture (CEA). Based on the output of the vision-based system and the LiDAR, the drone will be able to adjust its attitude as the geography varies to avoid collisions by utilizing the tracking algorithm. Finally, a live data stream (e.g. farm monitoring images, drone location, battery voltage etc.) is sent back to the ground station. If the measured battery voltage reached a specific lower threshold, the ground station would send the location of the nearest wireless charging station to the drone to interrupt its ongoing task and move to charge its battery. To ensure a smooth and safe landing to the wireless charging station, the proposed object detection and distance estimation is used to detect the charging station based on a vision-based system and control the speed and position of the drone while landing. The diagram of the proposed solution is depicted in Figure 7

V. Conclusion

In the current study, an approach for real-time implementation of CNN-based object detection, tracking and landing for a Quadcopter is presented. The current research provides a major contribution in UAV automation system. The developed system provides an efficient way for using a CNN to detect an object in real-time, extract its position, and use this data to ensure a safe, fast and stable tracking, stabilizing and landing process without the need of using any additional sensors. The presented system can be used in many applications such as search-and-rescue, tracking a specific object, landing for battery charging, drone delivery service, and agriculture applications. The developed system provides an efficient way for using a CNN to detect an object in real-time, extract its position, and use this data to ensure a safe, fast and stable tracking, and landing process without the need of using any additional sensors.

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