

A Framework for a Cooperative UAV-UGV System for Path Discovery and Planning

Abderrahmane Lakas*, Boumediene Belkhouche*,
Omar Benkraouda†, Amin Shuaib†, and Hussain Jaffar Alasmawi‡

* College of IT, UAE University

† Students at College of Engineering, UAE University

‡ Student at College of Science, UAE University

United Arab Emirates University, PO Box 15551, Al Ain, UAE

{alakas, b.belkhouche}@uaeu.ac.ae

Abstract—We describe a new framework for computer vision-based cooperative uav-assisted path planning for autonomous ground vehicles. In recent years, unmanned aerial vehicles (UAVs) have proved to be beneficial in many applications and services including path planning for autonomous vehicles. Most of the path planning applications assumes the availability of a digital map that allows a vehicle, be it ground or aerial, to navigate through landmarks and obstacles. However, in the scenario of unavailable maps especially during a natural disaster or a in war zone, it becomes extremely handy to have a drone that serves as an *eye in the sky* that explores the surrounding environment, and generates in real-time a trajectory guiding the vehicles on the ground around obstacles and obstructions. In this research, the UAV, serving as the *eye in the sky* is equipped with a camera that collects images of the surroundings and assists the ground vehicle in planning its path towards its final destination. Our approach includes the use of a vision-based algorithm which recognizes roads, pathways and obstacles, and calculates a path around them towards the destination. Simultaneously, the UAV keeps track of the ground vehicle progress towards the destination by monitoring and tracking its movement. The generation of the trajectory is based on an enhanced version of the *A** algorithm. The experimental setup includes a robot and a drone, and an ultra-wide band (UWB) indoor positioning system which allows the vehicles to know their current location.

Keywords—UAV-UGV cooperation, path planning, vision-based obstacle detection, tracking.

I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) or drones, as commonly referred to, are expected to swarm over the national air space in the very near future. Along with other types of unmanned transportation vehicles, UAVs will play an important role in the deployment of new sophisticated services and applications for delivering goods, monitoring, surveying, target detection, search and rescue, surveillance, etc., for both urban and rural areas. As it is envisioned in many civilian and military applications, UAVs operate in cooperation with other unmanned vehicles, either aerial, ground and possibly marine vehicles. For mission-based applications, UAVs tightly cooperate and communicate with other autonomous ground vehicles with the common objective to execute a specific mission that may require distributed and coordinated tasks. In such applications, UAVs, equipped with cameras and other sensing capabilities are viewed as the *eyes in the sky* for the vehicles on the ground. That is, to the vehicles in the ground, UAVs can be seen as an

expansion of their degree of freedom. Search and rescue (S&R) and mission-based field operations are the typical examples of applications that are in most need for the support of UAV to the ground vehicles. Indeed, in the case of search and rescue operations, ground vehicles often find it extremely difficult to progress normally in an unknown environment especially in disaster or post-catastrophe areas. The use of one or several UAVs flying above the unmanned ground vehicle (UGV) and overseeing its surroundings can help provide guidance and assistance.

In this paper we address the case of a UGV assisted by a UAV for path planning while in progress towards accomplishing application-specific tasks. The remainder of this paper is organized as follows: in the next section, we present and review the main research on vision-based techniques for the detection and identification of obstacles and obstructions using aerial images provided by drones. In Section II, we present the design of our system and explain its main components. Section III provides the performance results of our system along with an analysis. We conclude our paper in Section IV.

A. Related Work

Various research studies have addressed the problem of UAV-UGV cooperation for path planning and obstacle avoidance. In [1], the authors presents an architecture developed on a webGIS platform, which allows cooperation of a UAV and a ground robot. The UAV autonomously follows the ground robot while feeding it with a trajectory that the UAV computes using an image processing algorithm.

The idea of UAV-UGV is extended to assist multiple robots on the ground. In [2], the authors present a decentralized multi-robot aerial-ground cooperation scheme for objects transportation. In this scheme, a group of ground mobile robots destined for the transportation of objects are guided by a drone, allowing the group to move in a predefined formation. The path is constantly computed by the drone and transmitted to the leader of the group in the ground. The rest of the group follows the leader by using a predictive vision-based target tracking mechanism to maintain the formation around the leader.

In [3], the authors developed a switched cooperative control scheme for locating moving targets using a group of coordinating ground and aerial vehicles. Similarly to the work above, the scheme consists of maintaining the ground group in

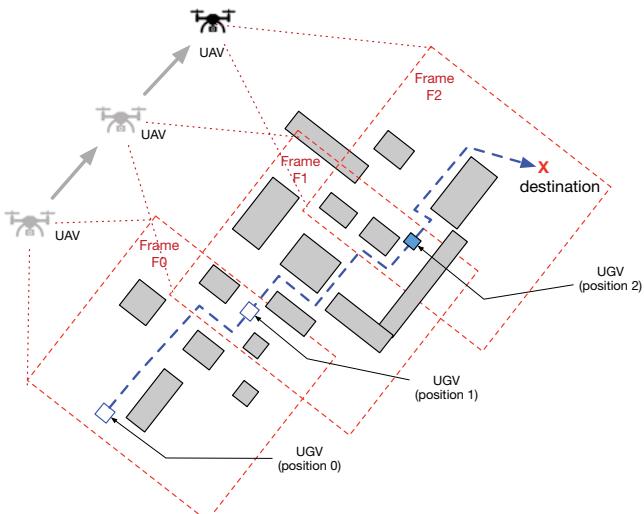


Fig. 1: Eye in the sky

while following and tracking the target based on a trajectory computed by the group of UAVs flying over the area. The main idea of this work is in combining decentralized flocking algorithms with navigation functions for obstacle avoidance.

More recently, the authors of [4] presented a technique for automatic map building and path planning using a UAV-UGV cooperative system. In this technique the UAV regularly captures a ground image and processes it through a series of transformations like denoising, image correction, and pattern matching to detect obstacles. The generated map is then transmitted to the UGV for path planning using an optimal path planning based on genetic algorithms.

UAV-UGV cooperative systems have been used for monitoring and tracking crowds. In this context, the authors of [5] presented a vision-based target detection and localization system of a group of UAVs and multiple UGV for tracking crowds based on a motion detection algorithm. The UAVs are equipped with a localization algorithm that uses the images taken by the UAV and estimates the geographic locations of the detected individuals.

Thanks to increased computer power and improvements to the automated image processing, camera-equipped UAVs have spawned many research studies on the analysis of aerial images. One of the interesting aspects of these studies is the image analysis at the semantic level for its potential benefits to many industrial and consumer applications. Indeed, many of the computer vision algorithms developed recently for the automatic recognition and matching of roads, buildings, landmarks and intersections are presented in [6].

The authors of [7] have developed a road detection and tracking framework using UAV-captured videos. Their work proposes a graph-cut based detection approach for the extraction of a road map from a specific region using a fast homography-based road-tracking scheme.

Several studies have focused on surveying the latest computer-vision techniques for pattern matching and object

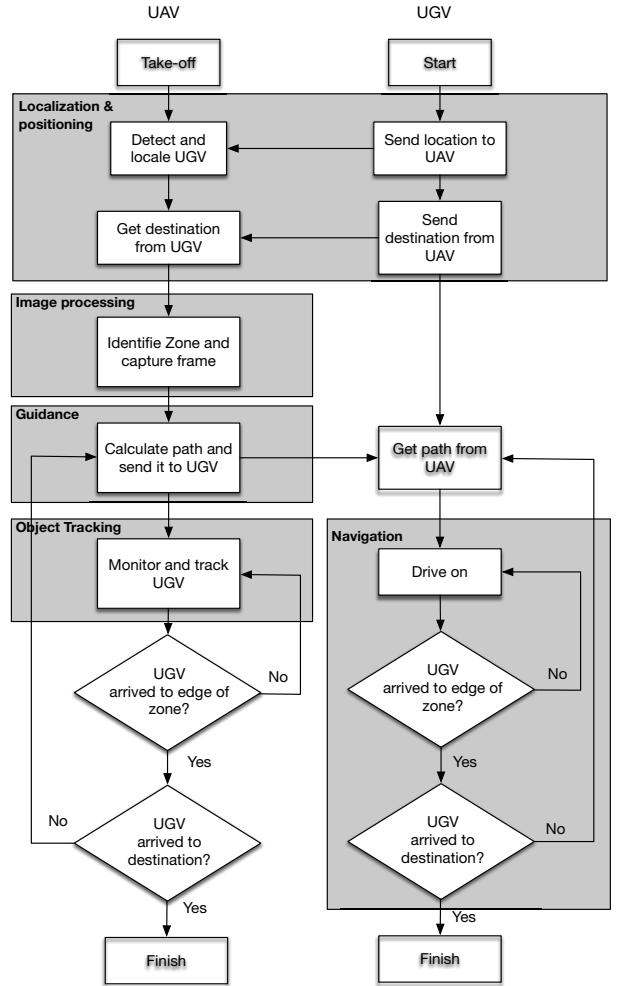


Fig. 2: Eye in the sky

detection using aerial images. A survey on computer-vision techniques for images produced by UAVs is provided in [8].

II. SYSTEM DESIGN

In this paper, we address the problem of mapping an unknown environment by recognizing road and obstruction features in aerial images generated by a flying UAV. The purpose is to assist ground vehicles and cooperatively plan for appropriate trajectories for reaching their destination. That is, we consider a typical disaster-rescue application, where the main goal is to navigate through an unknown environment by building in real-time a ground map that allows rescuers and their vehicles to reach the victims location in optimal times. Building and streaming a map on-the-fly allows rescuers to plan an efficient and feasible path for the rescue operations. The main contributions of this paper are as follows.

- 1) Using the UAV, we can obtain an aerial image and process it to extract indications of obstacles. This can be done through simple algorithms like image de-noising, image correction, and pattern recognition techniques. Most existing works do not use image

correction, which will affect obstacle recognition. Here, we add image correction to help the UGV improve the recognition accuracy of obstacles. Subsequently, the obstacles can be avoided and a more feasible path can be obtained.

- 2) The complexity of detecting obstacles of various nature and planning a path around them is extended to the one of keeping track of the vehicle on the ground. After all, the path is generated for the UGV and none of this can be done if for some reason, the UGV is no longer within the vision fields of the UAV's camera. That is, our work includes an algorithm that efficiently allows the UAV to constantly track and follow the UGV while performing the other tasks. The tracking method used is based on the use of a DESP (double exponential smoothing prediction) technique which allows the UAV to predict the next moves of the UGV and therefore to reposition appropriately itself even when the UGV disappears from the UAV's field of vision for a moment.
- 3) Based on the map information, we propose a hybrid path planning algorithm allowing the UGV to progress further towards the destination. We use an optimized version of A* algorithm. Path planning for search and rescue applications are usually *exploratory* of nature and the destinations that we plan for are often of temporary nature. Therefore, our planning algorithm allows for the alteration of a current path by inputting a new destination on-the-fly.
- 4) In this research, we present performance results that are lab-based experiments to test our system. We performed several scenarios to test the accuracy and the efficiency of our system.

A. Obstacle Detection Algorithm

The process of detecting obstacles in an image frame follows a series of image transformations using image processing algorithms illustrated in the following main steps:

- 1) *Image denoising*: This step consists of removing Gaussian noise from the image by applying Gaussian filtering.
- 2) *Extracting contours*: This step consists of finding the contours of the obstacles by first transforming the image into a binary image (black and white), then we use canny edge detection algorithm to find the contours of the obstacles (see Figure 3b).

3) *Size estimation*: After finding the contours and identifying the obstacles, we estimate the size of each obstacles by considering it as a box. This step is useful later in the process for the positioning and localization of the detected obstacles (see Figure 3c).

B. Tracking

Tracking a moving target using UAV on the ground is an important application like surveillance, reconnaissance, and monitoring. Tracking has been studied extensively recently and many tracking strategies have been proposed. In our case

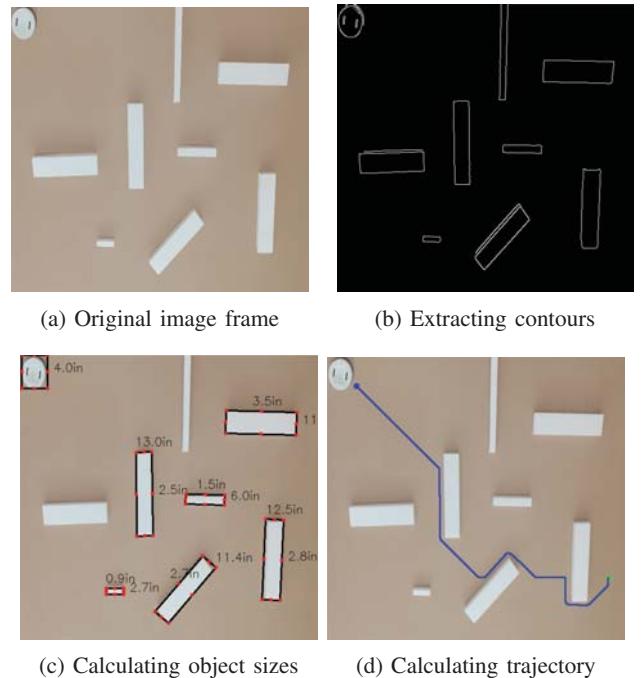


Fig. 3: Image transformations

tracking a UGV requires the UAV to perform certain tasks such as continuously acquiring the position of the UGV through various means and hover over its position. For our system, we propose two strategies. The first one is used in the case of available support for positioning and localization system such as GPS. Here we rely on the UGV informing the UAV with its current position when needed, thus allowing the UAV to position itself over the UGV.

The second strategy consists of using vision-based technique using the camera on board the UAV, and allowing it to position itself so as to maintain the UGV within the frame. For this strategy, the optical flow technique is a commonly used technique for feature tracking using video frames. One of the most widely used algorithms of optical flow is the Lucas-Kanade optical flow algorithm. This technique consists of measuring the distance a pixel has moved from one frame to another in a video. The distances traveled by a set of pixels between subsequent frames can then be used to determine the velocity of the target within the video.

Using the available functionality within openCV for optical flow, the overall process of tracking a vehicle in the ground can summarized by the following steps:

- 1) *Salient points identification*: a set of good features is required in order to do the tracking and is determined using openCV to get a set of Shi-Tomasi good features [9].
- 2) *Lucas-Kanade method*: taking the features extracted from the previous step, we use the Lucas-Kanade algorithm [10] to calculate the optical flow.
- 3) *Velocity calculation*: This step consists of calculating the moving average velocity of all the good features deter-

mined. This is needed to determine the UAV's motion model and decide where its next position will be.

C. UGV Trajectory Prediction

Even though target detection methods are usually accurate enough, detecting false alarms or mis-detections may occur especially when the target leaves the vision scope of the UAV. Therefore, these mis-detections can be corrected by applying prediction techniques to re-enforce the detection and tracking process. Kalman filters (KF) are considered the most common methods for object tracking. However, given the latency introduced by these methods for such real-time applications as target tracking, we opted for the use of the double exponential smoothing-based prediction (DESP) algorithm, which is considered a much faster prediction method [11]. In effect, exponential smoothing is a low-pass filter that aims to remove noise. The DESP algorithm can predict a vehicle's pose (position plus direction of the vehicle) few steps into the future. That is, DESP operation can be formulated by the following equations:

$$S'_t = \alpha x_t + (1 - \alpha) S'_{t-1} \quad t > 0 \quad (1)$$

$$S''_t = \alpha y_t + (1 - \alpha) (S''_{t-1} + b_{t-1}) \quad 0 \leq \alpha \leq 1 \quad (2)$$

$$b_t = \beta (S_t - S'_{t-1}) + (1 - \beta) b_{t-1} \quad 0 \leq \beta \leq 1, t > 0 \quad (3)$$

where α is a constant referred to as the *smoothing factor*, and β as the *trend smoothing factor* where $0 \leq \alpha \leq 1$ and $0 \leq \beta \leq 1$. In the equation above, the estimation of the state S at time t is made in two rounds represented in the first equation by S' , and in the second equation by S'' . Table I contains an example of the actual path waypoints of the ground vehicle, and the estimated position obtained using DESP method at each step. Fig. 4 illustrates the actual and the estimated path obtained from the data in Table I.

D. Path Generation Algorithm

This algorithm consists of finding the best path for the ground vehicle to take from its current position to the target destination. The A* algorithm [12] is one of the best known path planning algorithm. A* is applied to a grid-based configuration space. This algorithm is defined as a best-first search algorithm where each cell in the configuration space is assigned a value based on the following equation:

$$f(v) = h(v) + g(v)$$

Where $h(v)$ is a heuristic distance (i.e, Manhattan, Euclidean, Chebyshev, etc.) of the cell to the destination cell, and $g(v)$ is the length of the path from the initial cell to the destination cell through the selected sequence of cells.

III. EXPERIMENTS AND SETUP

Our system is intended for operation outdoors, and therefore the use of an outdoor position system such as GPS or similar is assumed. However and for the purpose of experimentation in an indoor lab, we have opted for the use of Ultra-Wideband (UWB) based positioning system, which shares many architectural similarities to GPS. The main characteristics of UWB is that unlike other radio frequency signals, it transmits its signal over multiple frequency bands simultaneously (3.1 to 10.6 GHz), therefore featuring a bandwidth

Actual		Estimated	
x	y	x	y
0.5	3	0.78	2.25
1	2	1.34	3.31
1.5	3	1.28	2.25
2	3	1.70	2.92
2.5	2.5	2.25	3.11
3	4	2.83	2.63
3.5	4.5	3.39	3.98
4	4	3.93	4.82
4.5	3.5	4.46	4.45
5	3.5	4.98	3.75
5.5	2	5.49	3.51
6	1.5	5.99	1.95
6.5	1.5	6.50	1.07
7	1	7.00	0.96

TABLE I: Actual and estimated position.

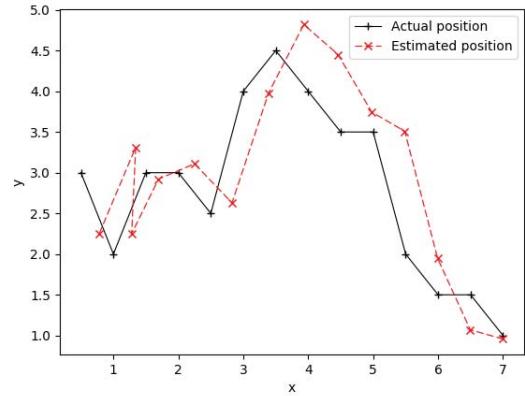


Fig. 4: UGV's position estimation using DESP ($\alpha = 0.5, \beta = 0.5$) with an error $\epsilon = 0.2632$

over 500MHz. For the self-localization of indoor objects, UWB has a potentially high positioning accuracy. This positioning system enables both the UAV and the UGV to self-localize based on the reception of UWB radio signals from fixed-position [13].

For the experiments, we used the bitcraze [14] loco position anchors and tags (see Figure 5) which are intended for use with drones, but we extended their use to the robots as well. The base stations in this case are represented by anchors placed at known locations in the lab, which periodically transmit signals that are received by the vehicles. Anchors have the capacity of operating in either mode: TOA or TDOA.

IV. CONCLUSION

In this paper we presented a framework for a cooperative mission-based application where a UAV and a UGV work in tandem in the process of completing a rescue task. In this context the UAV flying over the UGV collects images of the environment surrounding the UGV, and through the processing of a series of computer-vision algorithms, the UAV detects obstacles for the UGV to avoid. The system also includes a tracking algorithm based on a double exponential smoothing technique which predicts the next moves of the UGV allowing the UAV to keep it within the vision field of its onboard camera. For the positioning and self-localization of the

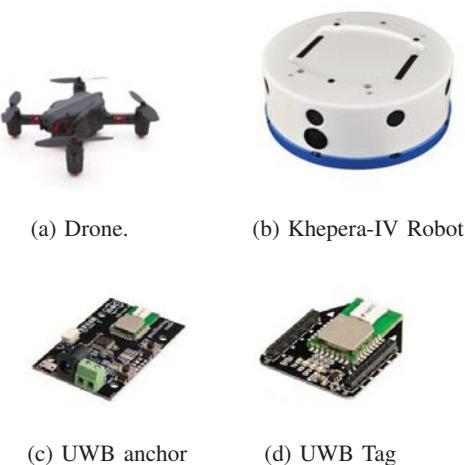


Fig. 5: Equipment used in the experiments.

UAV and the UGV, we used an 8-anchor UWB-based indoor positioning system. The path planning is based on a modified version of the popular A* algorithm allowing the UGV to operate in the exploratory mode where the final destination is dynamically changing. We plan to pursue further thus research by undertaking more experimentation tests and improve further the various algorithms in place.

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