Use a UAV System to Enhance Port Security in Unconstrained Environment

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Abstract. Ensuring maritime port security—a rapidly increasing concern in a post-9/11 world—presents certain operational challenges. As batteries and electric motors grow increasingly lighter and more powerful, unmanned aerial vehicles (UAVs) have been shown to be capable of enhancing a surveillance system's capabilities and mitigating its vulnerabilities. In this paper, we looked at the current role unmanned systems are playing in port security and proposed an image-based method to enhance port security. The proposed method uses UAV real-time videos to detect and identify humans via human body detection and facial recognition. Experiments evaluated the system in real-time under differing environmental, daylight, and weather conditions. Three parameters were used to test feasibility: distance, height and angle. The findings suggest UAVs as an affordable, effective tool that may greatly enhance port safety and security.

Keywords: Port security · Unmanned aerial vehicles · Human body detection · Human facial recognition

1 Introduction

Port security, a specific area of maritime security, refers to the safety and law enforcement measures that fall within the port and maritime domain and includes the protection and inspection of cargo transported through the ports from unlawful activities. Port security is crucial to national security, as maritime transport serves as a primary means of international trade and transport of goods. Proper monitoring and inspection are essential to preventing the inappropriate use of cargo containers. Port security discussions often revolve around prevalent maritime threats, such as terrorism, organized crime, smuggling, piracy, and even accidental spills and other cargo release events. For example, since October 1st, 2019, Homeland Security and its partners have recorded more than 100 smuggling attempts along the coast, according to CBP [1].

Before the September 2001 terrorism incidents, the most significant port security threats were organized crime and drug smuggling. However, since then, terrorist attacks

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have become a major issue in port-related security risks. The need for improved maritime port security has increased in recent years, since terrorists and pirates have begun using sea routes to cause greater levels of damage to society.

As the need for enhanced maritime and port security has intensified, technology developers have responded, producing next-generation security control systems with enhanced video surveillance, alarm monitoring, and other features. More recently, unmanned aerial vehicle (UAV) technology has evolved to address certain operational challenges, as standard port surveillance systems must operate in a complex environment with a high volume of merchant and fishing vessel traffic. Drones can be remotely controlled by radio/infrared communication, eliminating the need for pilots and increasing human safety. UAVs can also mitigate the inherent vulnerabilities of ground radar systems: fixed radar cannot cover "blind zones." In addition, drones possess the range and ability to deliver accurate real-time images to ground staff who can make informed, timely decisions based on that intelligence. As their batteries and electric motors grow increasingly lighter and more powerful, UAVs have been shown to be capable of enhancing a surveillance system's capabilities and mitigating its vulnerabilities. Integrating one or two UAVs into a traditional surveillance system can enhance the detection efficiency and make it possible to continuously monitor enemy and neutral targets. Exigent examples abound of this new drone technology in action. Japan's Sky Remote Company has developed Kite UAV, which is being used for land, coastline, and ocean surveying in China [2]. Abu Dhabi Ports Company (ADPC) has reported that two remote-controlled flying drones are patrolling Abu Dhabi's ports to strengthen maritime security [3].

This paper focused primarily on enhancing port security using UAV (drone) systems. The study tested the feasibility of a collaborative UAV system in an unconstrained environment through the deep learning method. Human body detection and facial recognition algorithms were used to identify humans in UAV real-time videos.

2 Methodology

The proposed system consists of three major steps: (1) system setup; (2) human body detection; and (3) human facial detection and recognition. The methodologies for these steps are explained in the following three sections.

2.1 System Setup

To detect suspicious targets, an Android application called DJI Go 4 was used to receive and transmit UAV camera data. The transmission of data from an Android device and reception of the data on the laptop PC was achieved using nginx Real-Time Messaging Protocol (RTMP). The UAV remote controller and the Android device were connected via USB cable, and the Android device was connected to the computer through the laptop's hotspot local network. The IP address of the computer from which to send the data was assigned in the Android application. The PC acted as a server and received data from the Android device.

Figure 1 illustrates the UAV-based real-time human detection and facial recognition system. The UAV was set by the DJI GO 4 App to fly through several preset waypoints at a high altitude to monitor the situation of a designated area. The video captured by the UAV onboard camera was transmitted to the Android device on the remote controller. This video was then streamed by Android device to the PC using local wireless network. Once a suspicious person was detected, a second drone flew to the area where the person was detected. This drone was controlled manually and flew at a closer range for the purpose of human facial detection and recognition. The same streaming system was applied so that the real-time video could be transferred to a PC where a facial detection and recognition program was running.

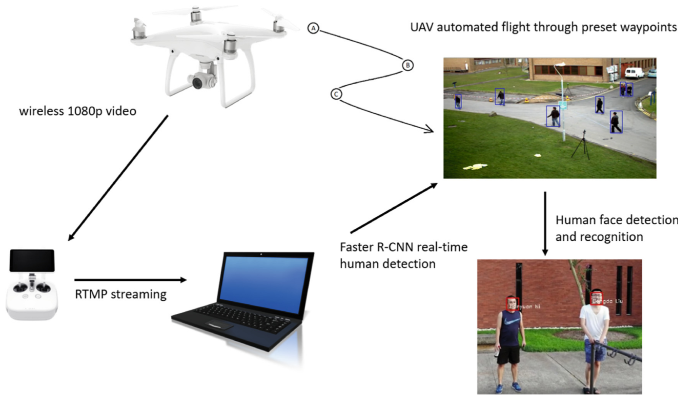

Fig. 1. UAV-based human detection and facial recognition system

2.2 Human Body Detection

Based on the experiments, deep learning-based approaches perform significantly better than traditional histograms of oriented gradients (HOG) [4] and Haar [5, 6] approaches for human detection. Among those, the Faster RCN Inception V2 COCO Model gives a much better result. The Faster R-CNN method [7, 8] was applied to process video frames on the PC for human detection in the system.

Compared with traditional image feature-based approaches [9, 10], deep neural network-based approaches provide more accurate results at cost of more computations. Most problems in early human detection methods are solved, and these fixes are introduced at the cost of more computations. However, in the presence of GPU acceleration, modern machine learning libraries can provide these improved results with comparable frame rates. The Faster RCN Inception V2 COCO Model gives a fair trade-off between accuracy and speed for GPU accelerated environments. It also provides a tight, consistent boundary around a detected person (see Fig. 2).

2.3 Human Facial Recognition

After the human body has been detected, facial recognition will be performed to match the suspicious target in the database. In this case, a deep learning-based facial recognition

Fig. 2. Deep learning-based human detection

algorithm was used to detect and recognize human faces (see Fig. 3). It is a powerful open-source recognition project built using Dlib's state-of-the-art facial recognition technique. The algorithm will detect a face in the streaming video sent back by the drone and compare it with faces in the datasets to decide whether it belongs to a stranger.

Fig. 3. Deep learning-based facial recognition

The facial recognition pipeline consisted of the following 4 steps:

(1) Detecting the face. HOG was used to locate faces in an image. To find a face in HOG image, we found the part of the image that looked most like the known HOG pattern extracted from other training faces.

(2) Determining the post of the face. In some cases, a face may turn in different directions and look completely different to a computer. To solve this problem, a face landmark estimation algorithm [11] was used to locate 68 landmarks on every face.

Once we knew where the eyes and mouth were, we simply rotated and scaled the image so that the eyes and mouth were centered as best as possible.

(3) Encoding faces. In order to tell faces apart, a convolutional neural network (CNN) was trained to generate 128 measurements for each face.

(4) Matching the person's name. A simple linear SVM classifier was trained to take measurements from new test images and tell which known person was closest to the match.

3 Experimental Results

Using the computer system (Microsoft Windows 10 PC with a i7-6700HQ CPU, 2.60 GHz per CPU core, 24 GB of memory and a NVIDA GTX 970M video card) with a DJI Mavic Air model drone, the process for one frame with resolution of 640 × 360 pixels took approximately 0.22 s (with resolution of 3840 × 2160 pixels, this took approximately 4.8 s).

3.1 Clear Environment

When the drone kept a horizontal distance from the experimenter, the face could be detected and recognized within 2.95 m. If the drone moved further away, it was unable to recognize the face.

If the drone and the candidate maintained a horizontal distance of 2.95 m, when the candidate turned his/her face to one side (left or right) no more than 45°, the face could be recognized. If the candidate turned his/her face at a larger angle, the face could not be recognized. Also, according to the tests, this angle was independent of the distance between the drone and the face. That is, even if the drone moved in the direction of the face so that the distance between them was closer, the maximum angle did not increase.

At the same distance, if the candidate faced the drone, the maximum height at which the drone recognized his/her face was 1.28 m. If the drone moved to a higher altitude, the face was not recognized. Also, it had an impact on the angle. At this height, the maximum angle at which the drone recognized a human face was 31°. If the angle became larger, the face was not recognized.

3.2 Cloudy

When the drone kept a horizontal distance from the candidate, the maximum distance at which the drone detected and recognized the face was 3 m. If the drone moved further away, it was unable to recognize the face as well.

Since the distance has no particular impact on the angle, we directly tested height in other weather conditions. The maximum height at which the drone recognized a face was 0.8 m. At this height, the maximum angle at which the drone recognized a face was 41°. Similar to sunny days, if the angle became larger, the face was not recognized.

3.3 Sunset

When the drone kept a horizontal distance from the candidate, the maximum distance at which the drone detected and recognized the face was 2.9 m. Also, the maximum height at which the drone recognized a face was 1.71 m. At this height, the maximum angle at which the drone recognized a face was 39°. Similar to other conditions, if the angle became larger, the face was not recognized.

3.4 Dark Conditions with Artificial Light

When the drone kept a horizontal distance from the candidate, the maximum distance at which the drone detected and recognized the face was 2.9 m. Also, the maximum height at which the drone recognized a face was 1.41 m. At this height, the maximum angle at which the drone recognized a human face was 32°. Similar to other conditions, if the angle became larger, the face was not recognized.

3.5 Experimental Summary and Discussions

Table 1 shows the experimental measurements in different conditions: clear environment, cloudy, sunset, and dark under artificial light. Different resolutions were tried during each process. High resolution achieved longer detection distance but resulted in longer processing time. Compared with high resolution, low resolution can achieve faster processing, but it will shorten the detection distance. To achieve real time processing, the resolution was set at 640 * 360.

Table 1. Experimental measurements

	Distance	Height	Angle
Clear environment	2.95 m	1.28 m	31°
Cloudy	3 m	0.8 m	41°
Sunset	2.9 m	1.71 m	39°
Dark conditions with artificial light	2.9 m	1.41 m	32°

4 Conclusions

Today port operations security and property safety have become an important issue of global concern. Many security control systems have been used, such as video surveillance and alarm monitoring, but modern security needs require evolved technology. This research developed a collaborative UAV for surveillance in an unconstrained environment using human facial detection and recognition methods. Based on experimental measurements, the results show that these body detection and facial recognition algorithms perform well under established conditions. Further research will focus on performance improvement, such as extending the ranges of facial recognition within various environments under different conditions.

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References

1. Border Patrol Arrests 123 Men on Smuggling Boats. https://fox5sandiego.com/2019/05/30/border-patrol-arrests-13-men-on-smuggling-boats/
2. Nonami, K., Kendoul, F., Suzuki, S., Wang, W., Nakazawa, D.: Autonomous Flying Robots: Unmanned Aerial Vehicles and Micro Aerial Vehicles. Springer, Tokyo (2010)
3. Eye in the Sky: Abu Dhabi's Ports Now Protected by Drones. https://www.thenational.ae/business/eye-in-the-sky-abu-dhabi-s-ports-now-protected-by-drones-1.595388
4. Dalal, N., Triggs, B.: Histograms of oriented gradients for human detection. In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR, San Diego, vol. 1, pp. 886–893 (2005)
5. Viola, P., Jones, M.: Rapid object detection using a boosted cascade of simple features. In: Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition, CVPR, Kauai (2001)
6. Kruppa, H., Santana, M.C., Schiele, B.: Fast and Robust Face Finding via Local Context. IEEE Computer Society, Mantua (2003)
7. Jiang, H., Learned-Miller, E.: Face detection with the faster R-CNN. In: 12th IEEE International Conference on Automatic Face and Gesture Recognition, FG, Washington, D.C., pp. 650–657 (2017)
8. Bootstrapping Face Detection with Hard Negative Examples. https://arxiv.org/pdf/1608.02236.pdf
9. Gaszczak, A., Breckon, T., Han, J.: Real-time people and vehicle detection from UAV imagery. In: Proceeding SPIE, vol. 7878 (2011)
10. Rudol, P., Doherty, P.: Human body detection and geolocalization for UAV search and rescue missions using color and thermal imagery. In: IEEE Aerospace Conference, Big Sky, pp. 1–8 (2008)
11. Kazemi, V., Sullivan, J.: One millisecond face alignment with an ensemble of regression trees. In: IEEE Conference on Computer Vision and Pattern Recognition, CVPR, pp. 1867–1874 (2014)