Combination of Radar and Audio Sensors for Identification of Rotor-type Unmanned Aerial Vehicles (UAVs)

Seongha Park, Sangmi Shin, Yongho Kim and Eric T. Matson
M2M Laboratory, Computer and Information Technology
Purdue University
West Lafayette, Indiana, USA
{park708, shin180, kim1681, ematson}@purdue.edu

Kyuhwan Lee
Institute for Information & communications Technology Promotion
Daejeon, South Korea
berg76@iitp.kr

Joseph C. Slater, Matthew Scherreik, Monica Sam and John C. Gallagher
Wright State University
Dayton, Ohio, USA
{joseph.slater, matthew.scherreik, sam.6, john.gallagher}@wright.edu

Paul J. Kolodzy
Kolodzy Consulting
Falls Church, Virginia, USA
pkolodzy@kolodzy.com

Benjamin R. Fox and Michael Hopmeier
Unconventional Concepts, Inc.
Mary Esther, Florida, USA
fenbox@vt.edu and hopmeier@unconventional-inc.com

Abstract—Rotor-type small size Unmanned Aerial Vehicles (UAVs) for recreational purposes have threatened people in public area by flying over them and crashing accidently without any safe mechanisms. In order to offset such threats, we investigated various types of sensors to detect airborne objects and propose a combination of radar and acoustic sensors. The proposed combination is able not only to detect an object, but also to identify whether the object is a threat or an uninterested object (e.g., birds). Moreover, we used inexpensive COTS components to reduce the cost of a system that uses the sensors. Preliminary experiments show an initial configuration of the system and the results that the sensors are able to identify a pre-profiled UAVs flying over the surveillance area.

Keywords—Sensor combination; Radar; Acoustic Sensor Array; Detection and Identification; Rotor-type Unmanned Aerial Vehicles

I. INTRODUCTION

Recreational purpose rotor-type UAVs, which fall into Micro or Mini classifications [1], have gained popularity from people due to low-cost and ease of use. At the same time, threats caused by flying UAVs in public places have recently escalated. Since rotor-type UAV has higher maneuverability than fixed-wings UAVs meaning that rotor-type UAV flies to all directions, it is hard to predict the trajectory of UAV's movement. This makes other people hard to avoid themselves from crash of the UAVs. To offset this threat, such UAVs flying in public areas should be detected and identified.

Various types of sensors such as sonar, vision, radar, acoustic and laser range finder can be used in order to detect and identify airborne object. However, most of sensors limit their capabilities by its characteristics. For instance, light sensor is capable of sensing distance from the reflected object, but it is vulnerable to noise such as ultraviolet and infrared. In addition to the example, using only light sensor cannot provide identification information of the object. Such fact reveals an importance of sensor fusion approach and thus makes researchers combine different types of sensors not only to enhance the functionality of their system, but also to complementarily compensate the sensors' weaknesses in their problem domain [2-4].

We propose a sensor combination of two types of sensors: radar, which is one of the well-known technologies that enables us to detect an object with high accuracy and fast response time, and acoustic, which recognizes signals at low frequency band typically spread in 2 – 20 KHz. Using radio frequency allows us to have a robust detector, which is not vulnerable to noisy environments (e.g., raining, night, etc.).

We target a scenario in which a UAV haphazardly appears and flies in a public place, where people exist. A certain number of the proposed sensor combination is deployed in the area to detect airborne objects. In order to cover larger surveillance area with a limited budget, the authors of this paper have preliminary investigated best configurations of sensor deployment using Agent Based Modeling (ABM) simulation [5]. In this paper, we will focus more on how to detect and identify UAVs, which are potential threat, using the proposed combination of sensors.

To construct a system with the selected sensors, we use a modified version of handmade radar, which is called 'Cantenna', introduced by MIT Lincoln Laboratory [6] to

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detect any moving objects in a target area. Once the radar locates any moving object in the area, an acoustic sensor array determines whether the moving object is a UAV or an object of no interest (e.g., birds) using profile information, which contains frequency band that a specific commercial rotor-type UAV generates to fly. The proposed approach is not only cost-efficient, but also relatively simpler in terms of complexity of system comparing with aforementioned sensor fusion approaches [2-3] for detection and identification of UAVs.

II. MULTI-SENSOR COMBINATION

A. *FMCW radar sensor*

We used Frequency-Modulated Continuous Wave (FMCW) to get information of an object sitting in front of the radar. Fig. 1 shows a prototype of our Cantenna. We used two coffee cans for transmission and reception of signals. The radar sensor emits a ramp-shape frequency between 2.3 GHz and 2.4 GHz to the field of view of its antenna and receives a modified frequency reflected from an object. The sensor costs only about 350 U.S. dollars, even it can detect an object that is at least 100 m away from the sensor. This allows us to deploy a significant number of the sensor to the surveillance area with a little budget. Note that most of existing radar sensors such as [3] have over-performance (e.g., detection range of several kilometers with about a hundred meters resolution or less) for our problem domain and are expensive.

Fig. 2 shows an initial test of the radar sensor at short range. A human walked back and forth at the Field Of View (FOV) of the sensor in order to measure the minimum distance and resolution. As a result, the minimum distance is about 12 cm and the resolution is about 2-3 cm.

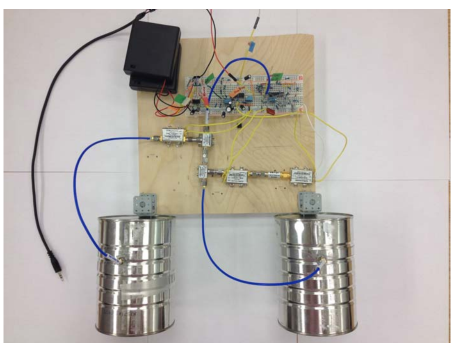

Fig. 1. Hardware setup of radar sensor. It consist of two antennas, modulator, RF compoenets, amplifier, and band-pass filter.

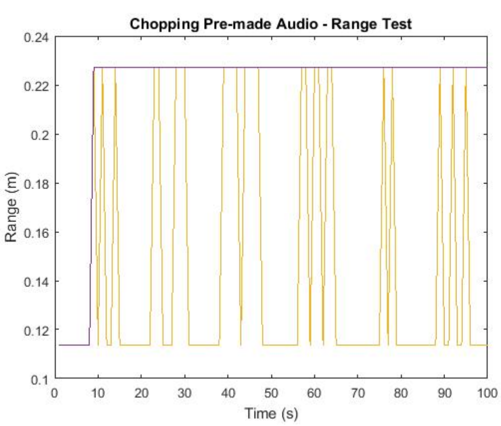

Fig. 2. Range test of radar sensor in short distance. An object walked back and forth in front of the sensor.

B. *Acoustic sensor array*

Acoustic systems are used not only for detection of an object entering a particular space or coming over a barrier, or such as a prison wall [7-8], but also for localization of a robot [9]. As part of the multi-sensor approach explored in this paper, we constructed a prototype audio sensor with the intent to both discriminate UAV targets of interest from other birds or other sources of distraction in the environment. In this preliminary work, we focused on feasibility of detection and discrimination using inexpensive COTS equipment. Especially considering the low-expense of the hardware involved, expansion to the tasks of spatial localization and determination of velocity are also possible and will be discussed.

Although many types of audio sensor placements and use cases are possible, for the initial work we decided to employ small collections of directional, “upward looking” microphones placed in a tripwire configuration. The initial idea was that lines or grids of point detectors could be used as a “zone defense” to ID specific threats as they moved around the area of interest. Fusing this information with radar traces could enable one to tag radar-identified targets, on which we would already have location and velocity information, with an estimate of threat condition type. A primary consideration in the trial effort was to limit cost of the equipment. This means we opted for inexpensive COTS sensors and commodity computational hardware as opposed to task specific, optimized, devices. Our detectors were single electret condenser mics with integrated FET amplifiers installed into tin mint cases as shown in Fig. 3 (Right). The estimated cost of each of these microphone assemblies can be conservatively estimated at 10 U.S. dollars each. Each of these microphones was mounted at the approximate focal point of off-the-shelf plastic salad bowls and the bowls mounted to the ground facing directly upwards shown in Fig. 3 (Left). Each microphone and dish assembly was connected to a commodity laptop computer. We used the laptops’ built-in consumer grade stereo inputs with 44.1 kHz sampling rate to collect audio. Required processing such as FFTs, pattern-recognition, etc. were accomplished on board the

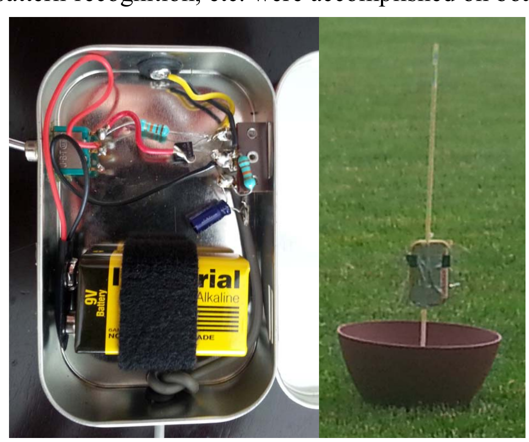

Fig. 3. (Right) an acoustic sensor, (Left) the acoustic sensor mounted on the structure.

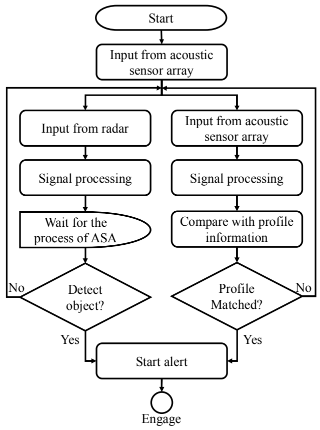

Fig. 4. Sequential flow of the system.

local laptops and event information/id tags were passed into the fusion engine via Ethernet.

C. An detection system with the combination of sensors

In order to integrate the two sensors, main computer to judge whether there is a profiled UAV flying over people is considered. Fig. 4 shows the sequence flow of the system. The radar-side task awaits until the acoustic sensor side task in order for them to synchronize. Profile information is defined by measuring the frequency band of a commercial UAV under various conditions (e.g., hovering, carrying an object, etc.). The data from two sensors will be transferred to the main computer in order to generate identification information of the UAV.

III. PREMILINARY EXPERIMENTS

A. The radar sensor experiments

We performed ranging tests of the sensor in an indoor/outdoor environment. Power emission of the sensor was about 10 mW. A structure with an aluminum foil reflector was used as an object. We gathered preprocessed signals and performed a FFT with the signals. As shown in Fig. 5, the radar sensor successfully showed a track of the object in time domain. Note that the reason why signal strength at closer distance is stronger is that the object reflects more transmitted signals back to the receiver. Although there are noises widely spread in the figure, we can discriminate them from the interesting signal by its signal strength.

B. The acoustic sensor array experiments

For our initial testing, we were primarily interested in detection and discriminating among the following target types: DJI Phantom I, DJI Phantom II without payload, and DJI Phantom II carrying 0.5 kg of modeling clay as a simulant of a potentially dangerous payload. Since we presumed that the Phantom would be controlled by a human within line-of-site of the vehicle, we targeted an effective Target-To-Sensor (TSR) range of about 50 meters. We chose this distance because, beyond it, it becomes difficult for a pilot to maintain visual contact with the vehicle.

Extensive data collection at multiple TSRs was conducted for each of the three target cases using the equipment shown in Fig. 3. Extensive background and ambient data with no targets present was also conducted. Ambient collection was done in the test environment all collections include road noise, freeway noise, train noise, distant construction equipment noise, human conversation, and wind gusts. Initial spectrogram analysis indicated that DJI phantoms contained strong power content at least in ranges around 2.5 kHz, 4 kHz, and 8 kHz. Sustained power in those ranges from background noise seemed relatively rare, being mostly constrained to ranges below 1.0 kHz. This suggested that, although drawing specific conclusions about target type and/or load might not be completely straightforward, there was at least audio power content that correlated well to the presence of a DJI phantom.

As a first attempt, it was decided to window incoming audio samples, compute a FFT, and compute the total audio power in a number of power ranges defined in Fig. 6. The raw power in each of these ranges, some of which purposely overlap with others, was computed for windows of data collected under the conditions of DJI 1 in area, DJI 2 unloaded in area, DJI 2 loaded in area, and ambient. This pre-precomputed, windowed, power data was used to train, as classifiers, a variety of feed-forward perceptron-style artificial neural networks. Among the candidate architectures of artificial neural networks, the best classifier we have found was a collection of three non-linear classifiers each with symmetric sigmoidal transfer neurons, fifty hidden layer neurons, and a single output neuron that was trained to return a value of 1.0 under the conditions of "P1", "unloaded P2", and "loaded P2" respectively. These three classifiers were trained with the field collected data appropriate the classifiers purpose with an output target of 1 when a triggering condition was present and -1 when exposed to a random sample from the large database of

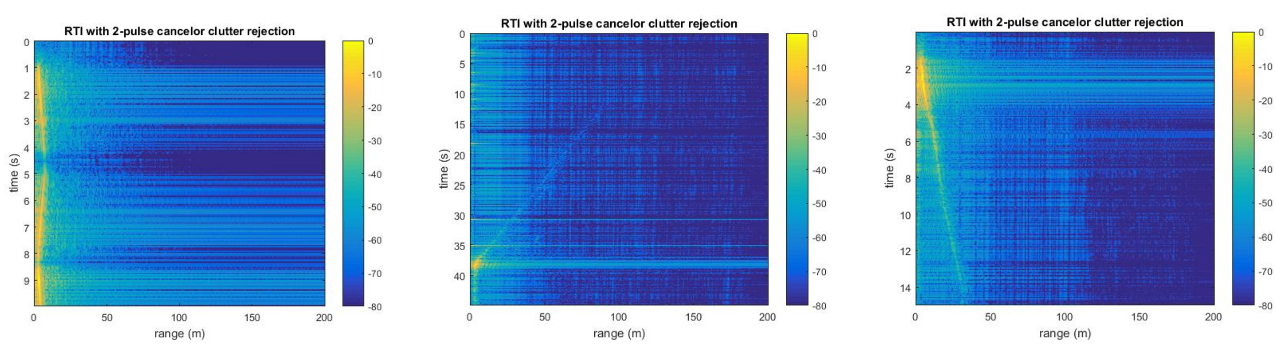

Fig. 5. Ranging tests of the radar sensor. The legend shows strength of received signal in dBm. (Left) an object moved back and forth with having. (Middle) an object coming from 100 m away from the sensor. (Right) an object is gradually moving away from the sensor.

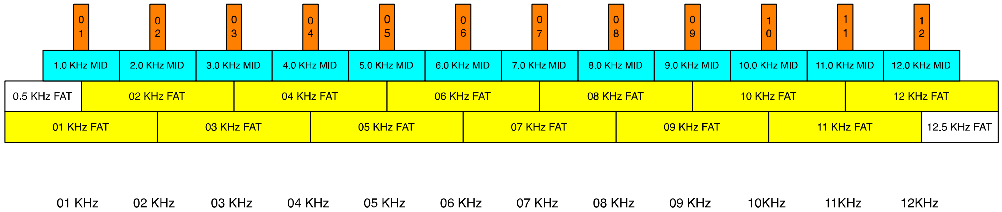

Fig. 6. Precomputed Spectral Power Bins and Input Features to Classifier.

ambient noises. The three classifiers, once trained, were embedded in a simple listener application that listened to 1 second segments of microphone input, then used each classifier to produce a vote. Votes were accumulated over time and a ratio of yes to no votes was used as an estimator of confidence that the particular vehicle was in hearing range. Testing from both recorded and field data revealed that this system could correctly detect all the three cases with no observed false negatives and only few, and transient, false positives. By conducting flyover tests, we estimate the effective detection range to be at least 50 meters TSR when flying above a 10 meter radius circle around the microphone.

IV. DISCUSSIONS

Although it is confirmed that the sensor combination can be used to detect and identify UAVs with a low installation cost, we have encountered several issues that we need to consider in order to improve the system.

The radar sensor we implemented was a fixed-point, non-rotating radar. Thus, it is only able to detect objects moving in z-axis in a Cartesian coordination, where XY plain is perpendicular to the aperture; side movements from the sensor's view cannot be recognizable. To be able to detect such side movements, the sensor should be either rotating or moving itself or having multiple receivers. Obviously, modifying Synthetic Aperture Radar (SAR) to fit in our problem domain would be one of the solutions.

The acoustic sensor array work was an attempt to understand the problem space by making a fast, and sometimes reckless, drive toward the goal with the understanding that we would debrief the results to better inform a future cycle of development. From that perspective, we have learned inexpensive sensors and even a fairly arbitrary choices of classifier and input feature generation could lead to effective classification and diagnosis of a small class of rotor-type aircraft. Naturally, there is a number of elaborations that can and should be considered. The classifier architectures we used so far are extremely simplistic. We are not, but should, take advantage of statefull computational units, which would be of obvious benefit in a system that could better reject transients that mimic the sustained spectral content of real targets. On the sensor side, one could without significantly raising overall expense, use two microphones per listening station to improve input signal gain. If one were to relax the cost constraints, multi-microphone beam forming could arguably enable determination of vehicle angle of attack and position [10] along with determination of vehicle type and load.

V. CONCLUSIONS AND FUTURE WORKS

We propose a system that uses a combination of radar and acoustic sensors in order to detect and track identifiable rotor-type UAVs, which fly in public places and thus are potential threats. As an initial attempt, we have confirmed that the approach of combining the sensors allows us to have a cheap and reliable solution to resolve the problem. We are trying to improve performance of the system by attempting several works. First, since we used the two sensors individually in the experiments, we will physically and electrically merge them into a platform such that we would easily deploy a number of the platform to the target area. In addition, we will work on building an embedded signal processor that takes care of FFT, signal conversion so that it provides faster response time against the threats.

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