Enabling Self-defense in Small Drones

Nakul Garg, Nirupam Roy
University of Maryland College Park
{nakul, nirupam}@cs.umd.edu

ABSTRACT

Drones are breaking away from their role as recreational toys and are emerging as trusted delivery systems and tools for law enforcement. This new role makes them targets of midair attacks for profit and vandalism. Despite tremendous advancement in robotic navigation and control, drones are still vulnerable to collisions with dynamic objects. While projectile detection and direction-of-arrival estimation techniques are mature in theory and fully functional in modern aircrafts' defense systems, these solutions could not make their ways to these resource-constrained flying robots. We envision to develop an ecosystem of lightweight and low-power defense modules for small drones. This paper explores the viability of this vision and as a proof of concept, develops a single microphone-based acoustic sensing mechanism capable of identifying the direction of approaching projectiles thrown at the drone. Experiments on the developed prototype of the sensing systems show perfect accuracy for detecting cases where a dynamic object is about to hit the drone. The low latency of our system detects an approaching object around 100 ms before the event giving sufficient time for the drone to dodge it. Despite being far from a complete defense solution, our prototype bolsters the possibility of developing sensing-inferencing modules for extreme resource-constrained scenarios.

CCS CONCEPTS

• **Computer systems organization** → **Embedded and cyber-physical systems**; **Sensors and actuators**;

KEYWORDS

Low-power acoustic sensing; Projectile intention detection

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1 INTRODUCTION

Drones are now trusted with serious responsibilities. It has emerged as a solution for the time-critical deliveries to the remote and unreachable location. Twenty percent of the medical deliveries in Rwanda, Central Africa is now carried out by drones [4]. Fast air delivery of packages to the doorsteps through drones [8, 12] is just around the corner. Unfortunately, important and valuable cargos make these unmanned vehicles vulnerable to en-route attacks by criminals and thieves. On the other hand, neighborhood surveillance police drones [11, 16] and recreational drones are potential targets of vandalism [3, 5]. Despite their important usages, drones are still defenseless even against thrown objects. The slightest midair collision can disrupt its stability leading to a crash. This paper envisions an ecosystem of defense mechanism for these resource constrained systems.

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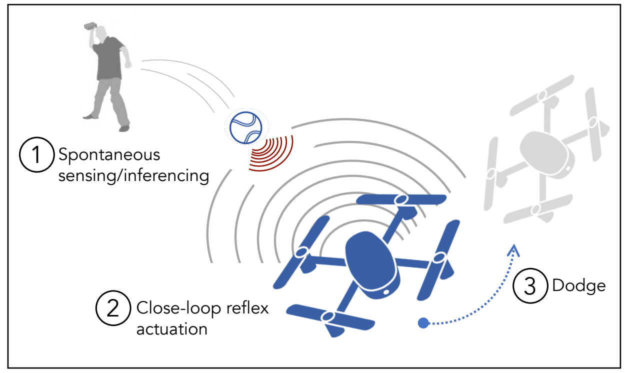

Figure 1: A lightweight, low-power self-defense system for small drones and other robotic vehicles.

An extensive set of techniques have been developed over the past five decades to prevent attacks on aircrafts. Advanced radar systems, Directed Infrared Countermeasure (DIRCM) systems, and various other situational awareness technologies are perfected to detect projectile attacks on commercial and military planes and helicopters. However, their smaller counterparts, the drones, are mostly defenseless. The best situational awareness system a commercial drone is equipped with today is the proximity sensor that can only detect large obstacles for flight safety and cannot detect speeding objects directed toward it. The primary reasons that prevent drones from adapting the existing defense technologies are the limited energy source, low weight carrying capacity, and low onboard computational power. Unlike some other drone-based applications, the self-defense mechanism cannot depend on offloading the data to a cloud server for computation. Self-defense system will require extremely low latency which is difficult to achieve through cloud-based computation. As shown in the Figure 1, we aim to develop onboard sensor-actuator modules and small-footprint inferencing algorithms for a defense system for drones.

This project is our first step toward a long-term research commitment focused around developing low-latency sensing-inferencing mechanism to defend autonomous systems against high-speed dynamic obstacles and projectile objects. We particularly target miniature robots and drones. Developing motion detection techniques for such devices are challenging because of three major reasons: (a) small form factor and low weight carrying capacity limits size of the sensor, (b) limited onboard processing power makes computationally expensive sensing techniques, including vision based approaches, infeasible, and (b) limited energy source discourages the use multi-sensor object detection techniques.

An acoustic signal changes its frequency when it is reflected off a moving object – a phenomenon known as Doppler shift. The core idea of this paper lies in the observation that the Doppler shift observed by a microphone depends on the object's direction of motion. We explore this idea further to find that it is possible to infer whether the object is about to collide by simply tracking the Doppler frequency on only one microphone. Unlike acoustic arrays or radar, our system does not attempt to find the direction of arrival of the object or its speed, it rather reports a one-bit information about whether a nearby moving object is about to hit the sensor. So, an acoustic sensing module mounted on a drone can instantly detect if an object is approaching and whether it is a threat or not. We develop our proof of concept prototype for low-power and low-latency sensing system to prevent a projectile attack on drones. While our primary application space is situational awareness in drone while operating in hostile environments, these techniques are equally capable in other robotic vehicles.

Needless to say, this paper is an explorative early attempt toward a broader vision and has many limitations at this point. It sidesteps the question of attacks from highly specialized systems like DroneGun [6] or trained birds [2]. While the projectile sensing prototype is operational as a standalone module for testing, we are yet to incorporate it on a flying drone. However, in this paper, we attempt to identify the key challenges, develop independent solutions for them, and most importantly assess the feasibility of enabling self-defense techniques on tiny robotic vehicles. Overall, we explore a new vision for sensing-inferencing research and share our early findings with the community.

2 SYSTEM OVERVIEW

The primary module of the system is a low-power sensing technique that detects if there is a dynamic object approaching the drone and gives a binary output classifying the intention of the projectile – meaning detecting whether or not the object will hit the drone. We develop a low-power, low-complexity sensing technique to detect this one-bit "hit" or "miss" information using a wave property, called the Doppler effect. Next, we describe the details of this 'projectile intention detection' approach, starting with a brief tutorial on the Doppler effect.

2.1 Doppler Effect: Primer

Sound wave is a function of both time and space. Therefore, the observed properties of a sound source, like the frequency, phase, and amplitude, depends on the time of the observation and also the relative location of the sound source and the observer (or the microphone). When the source or the microphone move relative to each other, the observed frequency appears different from the original frequency of the sound source. This change in observed frequency depends on their relative speed and is called the Doppler effect. The difference in frequency is referred as Doppler shift. The observed frequency can be calculated using the following equation, where f_o and f_s are the observed and source frequency values, and v_o, v_s, and v_{sound} are the velocities of the observer, source, and sound respectively. The velocities v_o and v_s are considered positive when the source and/or the observer moves closer to the other.

$$f_o = f_s \frac{v_{sound} + v_s}{v_{sound} - v_o} \tag{1}$$

However, as shown in Figure 2, despite the static sound source and microphone setup, the microphone can observe Doppler shift due to nearby moving objects that reflect the signal. The reflector behaves like a source of signal and the frequency is shifted twice, once while traveling from the sound source to the moving reflector and then while traveling from the reflector to the microphone.

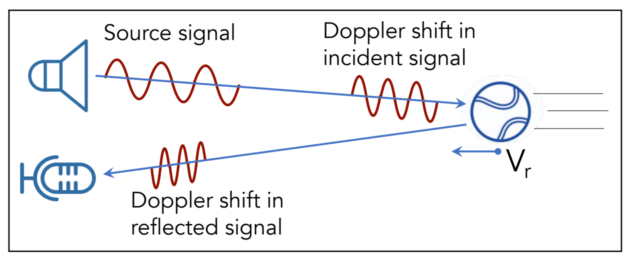

Figure 2: Doppler frequency shift due to moving reflector with static speaker-microphone setup.

The total Doppler shift (Δf) is shown by the following equation. Here, v_r is the velocity of the reflector which is the moving object in this case.

$$\Delta f = f_s \frac{2v_r}{v_{sound} - v_r} \approx f_s \frac{2v_r}{v_{sound}} \qquad [as\ v_r << v_{sound}] \tag{2}$$

We use a similar static transmitter-receiver setup to detect the doppler shift due to the approaching projectile.

2.2 Core Intuition: Motion angle from Doppler

The Doppler shift shown in Equation 2 considers the radial velocity of the projectile object. It is often ignored in literature that the shift in frequency also depends on the direction of the velocity. For instance, if the path of the moving object makes an angle θ with the straight line joining the object and the microphone, the observed doppler shift will be affected by only the radial component of the velocity, i.e., $v_r cos(\theta)$, as in the following equation.

$$\Delta f = f_s \frac{2v_r cos(\theta)}{v_{sound}} \tag{3}$$

Observe that the radial angle is zero when the object is moving straight toward the microphone, while for any other case this angle increases exponentially. Figure 3 explains this observation. Interestingly, the trend in this radial angle of a moving object can be estimated by tracking Doppler shift in only one microphone. For a constant projectile velocity, which is an assumption we relaxed later, the Doppler frequency shift is inversely proportional to the radial angle. As the angle increases the component of the velocity toward the microphone, $v_r cos(\theta)$, decreases and so does the Doppler frequency. When the object moves directly at the microphone, the radial velocity is maximum as the angle is zero. Therefore, when the projectile collides with the drone, we call a *Hit*, the Doppler frequency remains constant over a time. On the other hand, in a *Miss* case the frequency drops exponentially. A system that observes the trend in the Doppler shift can identify an imminent collision well ahead in time giving it an opportunity to react.

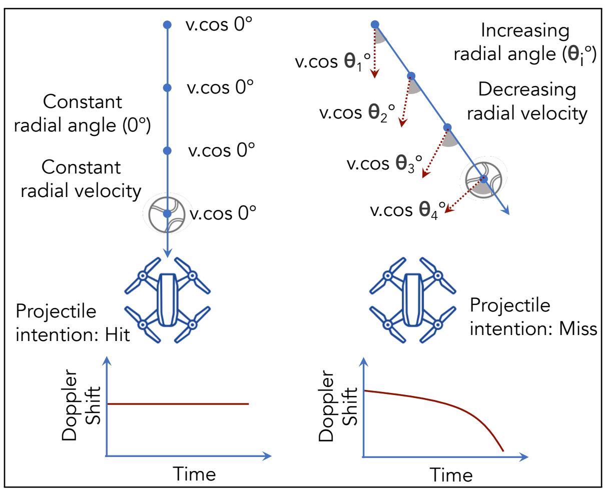

Figure 3: The different trends in the radial velocities and the Doppler frequencies when the projectile hits and misses the target.

We ran an experiment to verify our intuition with a collocated speaker-microphone setup as a Doppler sensor while throwing objects of various sizes at them. Figure 4 shows the trend in the Doppler shift for a *Hit* and a *Miss* case when a toy bullet [10] was shot at the sensor. Note that the strength of the received signal depends on the cross-section of the reflecting surface, i.e., the size of the moving object. However, due to low noise at the inaudible frequency bands, the plot shows prominent doppler shift even for the small cross-section of the toy bullet (0.91 cm-square) in our experiment.

We build on this core observation to develop a simple sensing system that can detect if a projectile is going to hit the drone or not. Obviously, key idea is to observe the Doppler frequency and estimate the trend in radial angle from it, but it is challenging to do so with minimum latency.

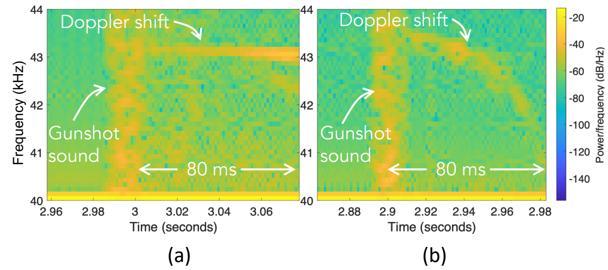

Figure 4: Spectrograms showing the doppler frequencies for two cases when a toy bullet is shot. (a) In the first case, the bullet hits the sensor, and (b) in the second case, it misses the sensor by twenty centimeters.

2.3 The Basic Solution

Along with the radial angle, the other factor in the Doppler frequency shift is the projectile's velocity and in practice the velocity changes (decreases) during the motion due to the environmental drag [27]. Variable velocity makes it difficult to estimate the radial angle from the Doppler shift. As a solution, we divide the flight time in a series of consecutive time segments. If time difference between two adjacent segments is Δt, then the Doppler shift in these segments can be written as:

$$\begin{aligned}\Delta f(t) &= f_s \frac{2v_r(t)cos(\theta(t))}{v_{sound}} \\ \Delta f(t+\Delta t) &= f_s \frac{2v_r(t+\Delta t)cos(\theta(t+\Delta t))}{v_{sound}}\end{aligned} \tag{4}$$

In the above equation, we select Δt such that the change in the object's speed is negligible. Then the ratio of the Doppler shifts in these segments gives the ratio of the radial angles as shown in Equation 5.

$$\frac{\Delta f(t+\Delta t)}{\Delta f(t)} \approx \frac{cos(\theta(t+\Delta t))}{cos(\theta(t))} \tag{5}$$

This ratio of angle is basically the rate of change in radial angle, we call this metric the *radial drift*. Clearly, a constant one value for the *radial drift* over multiple segment pairs indicates a *Hit* case. Ideally, any other value of this metric indicates a *Miss*. Although, in practice it won't strictly follow these values because of noise, but *Hit* and *Miss* cases will have a separation in their *radial drifts* providing a classification opportunity.

As a proof of concept, we develop a Short-Term-Fourier-Transform (STFT) based algorithm that applies Fast Fourier Transform (FFT) to estimates the frequency spectrum of each segment. It then locates Doppler frequency in them and calculates the *radial drifts*. Figure 5 shows the difference in the output *radial drifts* for a set of *Hit* and *Miss* projectile intentions from our experiments.

2.4 Challenge: Latency

Continuous detection of projectile will require continuous frequency estimation of the incoming signal that leads to hundreds of FFT operations per second. FFT is an expensive operation. Apart from super-linear computation complexity, its memory requirement

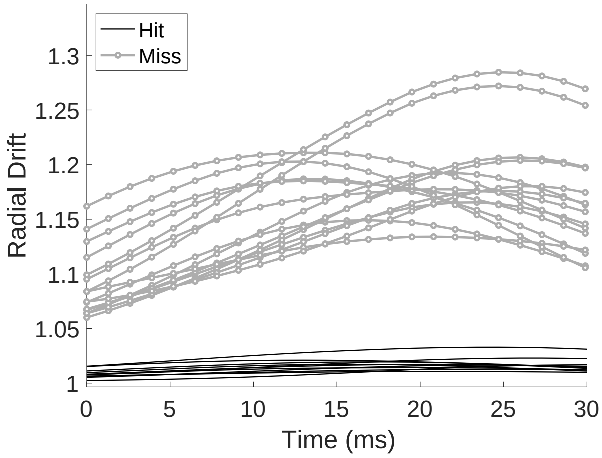

Figure 5: The estimated radial drift metric using FFT-based Doppler frequency tracking.

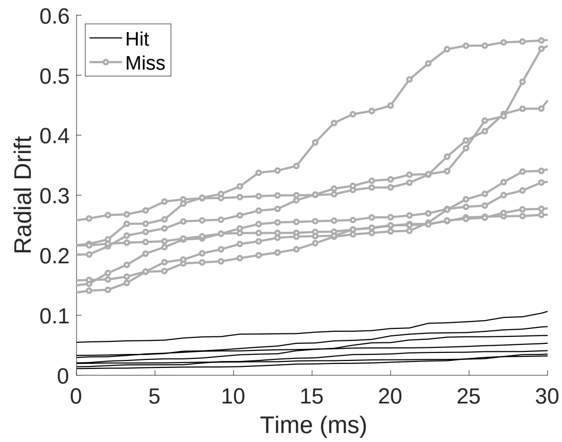

Figure 6: The estimated radial drift metric using DopplerDodge's frequency translation algorithm.

leads to frequent cache misses and page swaps increasing the latency even further for small micro-controllers. In our design, we attempt to reduce the computational complexity of the operations by replacing the FFT-based frequency tracking problem with our frequency translation-based approach.

2.5 Frequency translation

Imagine that the received signal is organized in consecutive windows of buffers, and *Buf_A* and *Buf_B* are two of such adjacent buffers. The Doppler frequencies of the signals in these buffers are f_A and f_B respectively. The signals *Buf_A* and *Buf_B* are shown below.

$$Buf\_A = sin(2\pi f_A t), \quad Buf\_B = sin(2\pi f_B t) \tag{6}$$

Following fundamental trigonometric rules, the time domain multiplication of these two signals will result in a signal with frequency components $(f_A + f_B)$ and $(f_A - f_B)$. We use the following formula to get an intermediate signal in *Buf_C*.

$$\begin{aligned} Buf\_C &= (Buf\_A \times Buf\_B) \\ &= sin(2\pi f_A t) \times sin(2\pi f_B t) \\ &= 0.5cos(2\pi(f_A - f_B)t) - 0.5cos(2\pi(f_A + f_B)t) \end{aligned} \tag{7}$$

Buf_C contains a fraction of the wavelength of the low frequency $(f_A - f_B)$ within its short buffer length. This makes the time domain signal in the buffer asymmetric around zero and therefore the sum of all sample values in *Buf_C* gives a non-zero output. Actually, in case of a *Miss*, the difference frequency $(f_A - f_B)$ changes over time and therefore the sample sum of *Buf_C* also varies. On the other hand, in a *Hit* case, the doppler frequency remains constant (i.e., $f_A = f_B$), which makes $(f_A - f_B)$ a non-oscillating DC component. This results in a symmetric time-domain signal around a constant DC bias in *Buf_C* and the sample sum gives a constant value. We track the change in the sample sum of *Buf_C* to separate a *Hit* projectile intention from a *Miss*. To capture this change in a metric, we first estimate the absolute difference in the sample sums over time. A cumulative sum of the outputs increases over time for a *Miss*, but remain close to zero for a *Hit*, as shown in Figure 6. This an alternative representation of the radial drift with a different span of values.

3 EVALUATION

Our evaluations focus on assessing the performance of the projectile intention detection module. We develop a stand-alone prototype of this sensing-inferencing module and collected data for different design parameters.

Implementation

The hardware frontend of our prototype consists of a speaker set and a microphone for generating the carrier frequency and recording the Doppler frequency. We tested the performance for two different types of carrier frequencies (f_s) – near-ultrasound 18 kHz and ultrasound 40 kHz. The 18 kHz frequency can be generated from regular speakers and we used piezo-electric ultrasound transducers for the 40 kHz tone. Although designed for applications with audible sounds, ADMP-401 MEMS microphones [1] have response over a wide range of frequencies (from 0 to 90 kHz) as observed in our past research [21–23]. Therefore, we used this microphone for experiments with both the carrier frequencies. We sample the pre-amplified analog output of this microphone using Keysight U2331A Data Acquisition System [9] and process the signal on a laptop.

Experimental setup

During the data experiments, we throw objects of various sizes, and shapes from 4 meters of distance toward the DopplerDodge sensor from different angles and at different speeds. In the *Hit* cases, the object either hits the sensor or lands within 10 cm from the microphone. For the *Miss* cases, we throw the objects such that it misses the sensor by a specified distance – we call 'missed-by distance'. Next we report our performance for each of these scenarios.

Performance: Detection accuracy

We plot the classification performance of the system using our low-computation frequency translation algorithm in Figure 7. Figure 8 show the performance with the FFT-based frequency tracking algorithm for comparison. As desired, both the algorithms perfectly identify all true cases of *Hits*. However, when the projectile misses the sensor by closer distances, they show some misclassification errors and falsely identify it as a *Hit*. This is because we tuned the system to avoid any false negatives for the *Hit* cases, which is a more expensive error compared to the reverse.

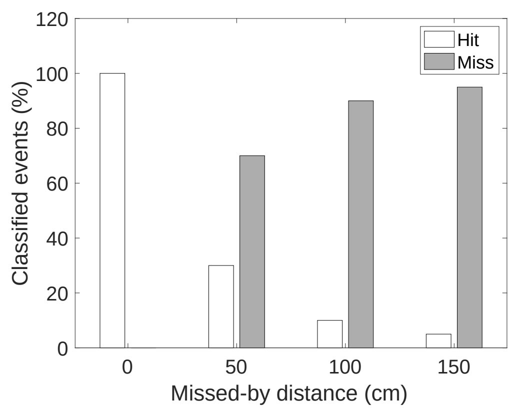

Figure 7: The performance of the projectile intention classification using DopplerDodge's frequency translation algorithm.

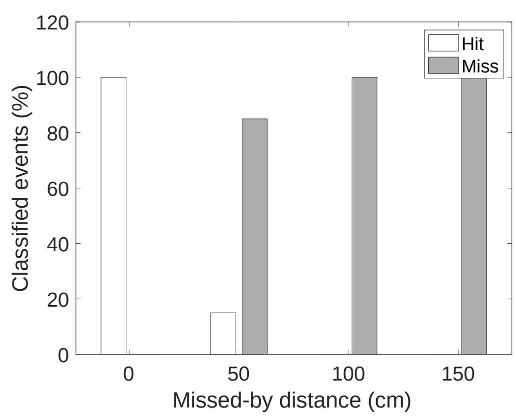

Figure 8: The performance of the projectile intention classification using FFT-based Doppler frequency tracking algorithm.

Performance: Computational latency

The FFT-based algorithm shows better accuracy at the expense of more computation, while our algorithm detects the event faster leaving time for the drone to move. Figure 9 compares the latency of these two algorithms for different buffer length. Our frequency translation algorithm completes the computation around 50% faster. The absolute value for the latency may differ when the algorithms run on a small micro-controller, but in that case frequency translation technique likely to work even better for its low space complexity. Note that the bigger buffer length gives faster processing but leads to a poor time resolution. The system waits longer to fill in the buffer wasting time when the projectile is in flight. Therefore, an implementation of the proposed system should find the optimal buffer length for its target application.

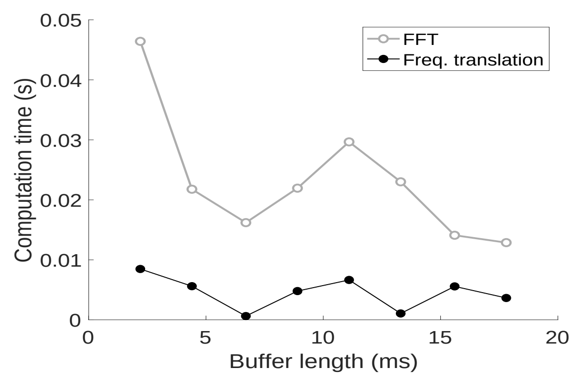

Figure 9: The computational latency for different buffer lengths in (a)FFT-based Doppler frequency tracking, and (b)DopplerDodge's frequency translation algorithm.

4 RELATED WORK

The fundamentals of moving object detection and projectile tracking system are deeply rooted into the rich literature of the wave theory [28], radar technology [25, 26], and acoustics [14, 17]. Applications of these ideas in robotic navigation is also not new [13, 18, 29]. Many recent works in mobile computing and cyber-physical systems have also adapted these core principles in various forms. For instance, WiSee [20] exploits doppler in OFDM signals to recognize human gestures. Soundwave [15] and FingerIO [19] uses microphone and speakers to detect hand and finger gestures. DopplerDodge explores a unique direction to develop an ecosystem of sensing and control techniques for situational awareness and defense in resource-constrained robotic vehicles. Probably the closest to our work is *EVDodge* [24], that develops a deep learning-based solution for dynamic obstacle avoidance using event cameras on a quadrotor. Apart from the strict lighting constraints and power requirement of the camera, processing each the multidimensional image frame through the neural-network algorithms takes significant portion of the onboard processing cycles. While targets the same problem as DopplerDodge, clearly this camera-based solution differs from our motivation of developing low-power, low-computation, and lightweight solution for drone's self-defense.

5 DISCUSSIONS

This paper is an initial step towards a broader vision. A substantial amount of work is part of our ongoing and future research plans. We discuss a few significant points here.

Adversarial attacks: DopplerDodge is based on acoustic sensing techniques and therefore susceptible to jamming attacks. Moreover, an equipped adversary can send modulated signal to spoof projectile attacks for disrupting the drone's normal flight path. We are set to explore a pseudo-random frequency hopping technique and a jamming detection logic to deal with such adversarial attacks.

High-speed projectiles: Dynamic obstacle detection systems, including the camera-based solutions and DopplerDodge, cannot detect very high-speed projectiles (e.g., bullets of firearms). Acoustic sensing-based techniques face additional challenges as the speed of such projectiles can be comparable to that of sound waves. However, in the state-of-the-art defense systems for drones the primary bottleneck is the computation latency. Despite the slow speed of sound, DopplerDodge shows the possibility to have better lookahead time than the camera-based systems. Of course, the core principle of its projectile intention detection technique can be used with RF signals, which are significantly faster than sound.

Detection range: The maximum range of a signal reflection-based technique depends on the attenuation factors of the signal. Our prototype is evaluated to detect thrown objects from a distance of four meters, allowing small drones sufficient lookahead time to maneuver. Commercial low-cost ultrasound devices are known to function from a distance of over 30 meters for reflected signals [7]. We believe a professional implementation of our technique can offer a longer detection range.

Estimating optimal motion path: Detecting *Hit* and *Miss* cases are sufficient for small and agile drones that can quickly move in a random direction to avoid the collision. However, bigger drones have higher inertia and take longer to move. Once the attacking projectile is detected, bigger drones will need to estimate an optimal motion path to utilize available time for a successful dodge. For the motion planning, the drone needs to know the direction of the incoming object. While a one-microphone system can detect the projectiles' intention, it cannot find the spatial direction of arrival of the object. We plan to build on the current system to explore low-power sensing techniques to address this problem.

6 CONCLUSION

This paper explores the vision of developing low-power sensing-inferencing modules to enable a way of self-defense in resource-constrained robotic vehicles and drones. As a proof of concept, we designed a low-power acoustic system to detect thrown objects at the drone. While there are many scopes for improvement, evaluation of our prototype shows promise. We believe that this research direction can mature to a complete defense solution to such lightweight unmanned aerial systems.

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REFERENCES

[1] 2012. ADMP401 MEMS microphone. https://www.analog.com/media/en/technical-documentation/obsolete-data-sheets/ADMP401.pdf. Last accessed January 19, 2020.

[2] 2016. Intercepting drones with trained birds. https://www.youtube.com/watch?time_continue=1&v=Vd00zh4NGcc. Last accessed January 19, 2020.

[3] 2017. Attacks on drones. https://www.schneier.com/blog/archives/2015/09/drone_self-defe.html. Last accessed January 19, 2020.

[4] 2017. Zipline drone blood delivery. https://www.ted.com/talks/keller_rinaudo_how_we_re_using_drones_to_deliver_blood_and_save_lives/transcript?language=en. Last accessed January 19, 2020.

[5] 2018. The future of drone and counter-drone technology. https://www.defenceiq.com/defence-technology/news/new-drone-and-counter-drone-technology. Last accessed January 19, 2020.

[6] 2019. DroneGun. https://www.droneshield.com/dronegun-tactical. Last accessed January 19, 2020.

[7] 2019. Ultrasonic Sensor FAQs. https://www.senix.com/ultrasonic-sensor-faqs/. Last accessed January 19, 2020.

[8] 2020. Amazon Prime Air. https://www.amazon.com/Amazon-Prime-Air/b?ie=UTF8&node=8037720011. Last accessed January 19, 2020.

[9] 2020. Keysight DAQ system. https://www.keysight.com/en/pd-824376-pn-U2331A/64-channel-1msa-s-usb-modular-multifunction-data-acquisition?cc=US&lc=eng. Last accessed January 19, 2020.

[10] 2020. Nerf N-Strike Elite Jolt Blaster. https://nerf.hasbro.com/en-us/product/nerf-n-strike-elite-jolt-blaster-green:EA2DED09-5056-9047-F5F1-8CBE583309F0. Last accessed January 19, 2020.

[11] 2020. Police drones. https://www.policechiefmagazine.org/remote-drone-dispatch/. Last accessed January 19, 2020.

[12] 2020. UPS drone delivery. https://www.cnbc.com/2019/10/21/ups-partners-with-cvs-to-develop-drone-delivery-service-for-prescriptions.html. Last accessed January 19, 2020.

[13] Hanafi Anis, Ahmad Haris Indra Fadhillah, Surya Darma, and Santoso Soekirno. 2018. Automatic Quadcopter Control Avoiding Obstacle Using Camera with Integrated Ultrasonic Sensor. In *Journal of Physics: Conference Series*, Vol. 1011. IOP Publishing, 012046.

[14] F Alton Everest. 2001. Master handbook of acoustics.

[15] Sidhant Gupta, Daniel Morris, Shwetak Patel, and Desney Tan. 2012. Soundwave: using the doppler effect to sense gestures. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 1911–1914.

[16] Philip J Hiltner. 2013. The drones are coming: Use of unmanned aerial vehicles for police surveillance and its fourth amendment implications. *Wake Forest JL & Pol'y* 3 (2013), 397.

[17] Lawrence E Kinsler, Austin R Frey, Alan B Coppens, and James V Sanders. 1999. Fundamentals of acoustics. *Fundamentals of Acoustics, 4th Edition, by Lawrence E. Kinsler, Austin R. Frey, Alan B. Coppens, James V. Sanders, pp. 560. ISBN 0-471-84789-5. Wiley-VCH, December 1999.* (1999), 560.

[18] Tomoyuki Mori and Sebastian Scherer. 2013. First results in detecting and avoiding frontal obstacles from a monocular camera for micro unmanned aerial vehicles. In *2013 IEEE International Conference on Robotics and Automation*. IEEE, 1750–1757.

[19] Rajalakshmi Nandakumar, Vikram Iyer, Desney Tan, and Shyamnath Gollakota. 2016. Fingerio: Using active sonar for fine-grained finger tracking. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, 1515–1525.

[20] Qifan Pu, Sidhant Gupta, Shyamnath Gollakota, and Shwetak Patel. 2013. Whole-home gesture recognition using wireless signals. In *Proceedings of the 19th annual international conference on Mobile computing & networking*. ACM, 27–38.

[21] Nirupam Roy. 2018. *Inaudible acoustics: techniques and applications*. Ph.D. Dissertation. University of Illinois at Urbana-Champaign.

[22] Nirupam Roy, Haitham Hassanieh, and Romit Roy Choudhury. 2017. Backdoor: Making microphones hear inaudible sounds. In *Proceedings of the 15th Annual International Conference on Mobile Systems, Applications, and Services*. ACM, 2–14.

[23] Nirupam Roy, Sheng Shen, Haitham Hassanieh, and Romit Roy Choudhury. 2018. Inaudible voice commands: The long-range attack and defense. In *15th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 18)*. 547–560.

[24] Nitin J Sanket, Chethan M Parameshwara, Chahat Deep Singh, Ashwin V Kuruttukulam, Cornelia Fermüller, Davide Scaramuzza, and Yiannis Aloimonos. 2019. EVDodge: Embodied AI For High-Speed Dodging On A Quadrotor Using Event Cameras. *arXiv preprint arXiv:1906.02919* (2019).

[25] Merrill Ivan Skolnik. 1970. Radar handbook. (1970).

[26] Merrill Ivan Skolnik. 1980. Introduction to radar systems. *New York, McGraw Hill Book Co., 1980. 590 p.* (1980).

[27] Gino Sovran. 2012. *Aerodynamic drag mechanisms of bluff bodies and road vehicles*. Springer Science & Business Media.

[28] Leung Tsang, Jin Au Kong, and Robert T Shin. 1985. Theory of microwave remote sensing. (1985).

[29] Qing Hua Wang, Teodor Ivanov, and Parham Aarabi. 2004. Acoustic robot navigation using distributed microphone arrays. *Information Fusion* 5, 2 (2004).