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Exploring Use of CFD Based Simulated Audio Signatures to develop Machine Learning Model for Drone Identification and Classification (A Review Study)

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Abstract

Quadcopters or drones are the emerging technology of today and are quickly finding their effectivity in every field of life. While their generalized use has brought ease, the possibility of their proliferation and illegal used by certain rogue elements and lone wolves also pose a serious security threat. With a lot of research directed towards ensuring the safe usage of these technologically advanced platforms, this publication review discusses various available techniques for drone detection and identification. The simplicity and effectiveness of audio-based designs for drone identification and localization is the primary focus of study. These available methods primarily rely on experimentally obtained drone data to build a machine learning model requiring physical setups and are mostly limited by the availability of model geometries and audio recording sessions. Towards the end of this technical review an effort is being made to lay the foundation for proposed utilization of Computational Fluid Dynamics (CFD) simulated audio data of different drone / quadcopter geometries. Same predicted data can in-turn be augmented with available experimental drone sounds and commercially available noise data to develop a drone identification machine learning (ML) model.

1.1 Applications of Drone Technology

The dawn of the present century has witnessed rapid technological advancement and growth in different areas. A large share of this progress is related to the use of smart systems and automation, to minimize human physical effort. A direct beneficiary of these developments is the field of autonomous aerial vehicles. Recent estimates suggest that more than 10,000 drones will be operational for commercial use by 2024. The primary reason being low costs and budgets when compared with commercial helicopters and easy manipulation tools [1].These drones, varying in size from few inches to multiples of feet, are seen in common use today in diverse range of fields including surveillance, targeting, delivery applications, journalism, asset management, search and rescue, healthcare, sports coverage and scores of others.

1.2 Military Usages- Latest Development and Occurrences

Besides numerous commercial applications, unmanned aerial systems (UAS) have been the perfect choice for military use, specially the counter-insurgency and terrorism operations. The military UAV systems are being employed for persistent close air support, precision shelling, aerial surveillance and reconnaissance, unmanned air strikes, underwater surveillance and target assassination and killing. Most of these high value target killings are generally executed by drone strikes, with platforms such as Global Hawk, Predator, Reaper and Protector RG Mk1 drones been used extensively in the past to eliminate key terrorist figures [2]. The explosive-laden drone class of these UAS may also employ killer drones, kamikaze drones or loitering munitions for targeting purpose. This specific concept has been materialized by Israeli K1-UAV or Loitering Munitions such as Israeli Aerospace Industries (IAI) Harpi and IAI Mini-Harpi. Loitering munitions such as Harop and Orbiter 1K were used effectively by Azerbaijan Defense Forces (ADF) during Nagorno-Karabakh conflict in 2020 [3]. Due to their effectivity and low operational cost, the list of countries manufacturing drones and especially the loitering munitions continue to grow.

1.3 Use by Terrorists / Extremist Elements

With the flexibility in use, low budgetary requirements, high effectivity and diversity in operations, the proliferations of drones has resulted in serious threats and challenges. They are being employed by terrorist entities, rogue elements, militant organizations, armed wings and lone wolves for targeted operations and sophisticated attacks. The use of UAVs by different non-state actors dates back to 2004 when the Lebanese militant group Hezbollah flew MIRSAD-1, a small Iranian built military-grade drone, over Israeli airspace. Similary, UAVs and drones both were used by ISIS for reconnaissance and to drop bombs in conflict zones, targeting Iraqi and Syrian military personnel [4]. Over the past decade, these low cost drones have been employed in all recent conflicts. Drones were used by Moscow backed rebels in Eastern Ukraine to destroy Ukraine's arm's depot in 2017. The Syrian and Yemen wars have also witnessed the use of Iranian-origin drone technology with military grade Shahed-129 and Qasef-1 drones been employed against US-led Special Operation force and Saudi-led coalition by the rebels [5].

Since the availability of consumer drones to public at an affordable price, nefarious actors have begun experimenting to use them for malicious purposes. While established terrorist organizations are experimenting with expensive models or larger captured drones for their specific goals, the widely available consumer drones offer tools to bypass traditional security measures to small organizations and lone wolves, at an affordable price. On August 4th, 2018, two-drones wrapped with explosives were used in an attempt to assassinate the Venezuelan president [6]. Multiple instances have taken place in which consumer drones have been used to target high profile figures. In 2013, a member of the opposition party crashed a Parrot quadcopter near the feet of German chancellor Angela Merkel at a campaign rally [7]. The aim was solely political but the incident highlighted the need for additional security protocols. Likewise, in January 2015, a government employee accidently crashed a DJI Phantom quadcopter into the White House lawn, raising questions on existing security measures in place. Later that year, another incident took place in which a drone carrying a bottle of radioactive sand was landed on the roof of the Japanese Prime Minister's Tokyo office [8]. Globally dozens of similar occurrences related to uncontrolled use of drones have taken places, leading to speculations that these drones in the wrong hands can lead to serious consequences.

2.1 Need for Protective and Preventive Counter-Measures

The wide range of readily available commercial drones offer an easily accessible and low cost capability to the public, especially the lone wolf terrorists and rogue elements, who may obtain explosives, procure a consumer drone and independently conduct an attack. The probability of these attacks is high and they can have devastating effects. The production of these consumer drones has multiplied over the past few years with FAA estimating more than 30,000 drones in US airspace only, in 2020 [9]. The gravity of risks posed by uncontrolled drone usage also increases each year, with growing number and advancement in technology. Therefore, keeping in view the probability for potential misuse of the drone technology, it becomes imperative that identification systems be developed to detect, classify, track and neutralize potentially hostile entities as quickly as possible.

2.2 Present Available Tools

With growing drone industry, a lot of research is also being directed towards facilitating safe usage of these drones. The primary requirement being correct and quick drone detection and identification, over the past few years multiple studies have been undertaken to demonstrate the feasibility of various techniques based on video data, thermal imaging, radar based systems, RF emissions and acoustic signatures. Many of these technologies are still nascent with each having certain advantages and limitations for use.

2.2.1 Use of Video Data

Using visual data (either image or video) to detect an incoming drone seems to be the simplest solution to our problem. An easier approach is to use a handcrafted feature based method involving image processing and motion detection for controlling movement and drone detection while employing a suitable machine learning algorithm. A further refined approach involves the use of faster R-CNN drone detection module to detect and localize the drone from available static images and later use the processed data to predict exact location of drone in next frame [10]. Vision-based methods can achieve high accuracy with high-resolution cameras under strict line-of-sight. However, this would require very large amount of data sets along with use of advanced technology. Nonetheless, such hardware is expensive, and vision-based methods are likely to operate poorly at night time and limited visibility conditions, and may fail drastically in adverse weather conditions such as rain, dust, mist or fog [11].

2.2.2 Thermal imaging

Thermal imaging is a very specific source of information with its data interpretation greatly dependent on the properties of visualized object, especially in the presence of strong, local intensity background. It serves as the primary element of an infrared scanner for detection of small objects flying at low altitude. The quality of thermal imaging can be improved by employing a suitable algorithm to remove local image disturbances using a median filter and later applying contrast enhancement to the imagery obtained from infrared scanner [12]. The effect of a strong and structured background such as trees or buildings while identifying / targeting an object can be further dampened by employing a range-gated imaging system. The gate, if thin enough and positioned at the appropriate distance, can suppress the unnecessary foreground and the background around the object [13]. The EO/IR systems are able to detect small UAVs from few under clean environment. However, the performance of these systems can become degraded due to various noise factors like fixed patterns, dead or bad pixels and complex background conditions such as saturated images or foggy environments.

2.2.3 Use of Radar Technology

Radar has been associated with the aviation industry since 1930s, finding its effective role in navigation, control, air defense and targeting. Radars based methods use reflected radar signatures to detect and classify drones, just like normal aircraft. The only difference is that due to slow speed, smaller size, use of special materials and geometry profile the radar cross section of drones is way less than conventional UAS or aircrafts. With these limitations in view, micro-doppler radars serve as the best available tool to detect drones. An automatic and robust classification scheme was applied to X-band radar data monitoring a target scene, to differentiate between a UAV and non-UAV targets. The normalized log spectrum was developed using the available phase information and time frequency transformations for feature extraction prior to feeding the same to machine learning algorithm [14]. LiDAR is an acronym for Light Detection and Ranging which uses electromagnetic radiation of optical and infrared wavelengths. Like a radar, it has an active sensor that emits electromagnetic waves and receives reflected waves, only at much higher frequencies of range 200-400 THz. Evaluation of LiDAR for detection of a drone resulted in achieving about 90% of detection rate with a range of up to 200 m [15]. Radar-based methods have the advantage of being less influenced by environmental conditions and they do not require line-of-sight, thus they can assist in drone detection and localization. However, they may have limited use when it comes to drones with smaller surface area or operating at low altitudes [16].

2.2.4 RF-Based Systems

Radio frequency (RF) sensors work on a passive approach, which sense the wireless transmission between a malicious drone and the remote pilot's radio control and subsequently detect and identify drones accordingly. RF detection techniques may involve use of a known protocol or recognition of the communication spectral pattern. The RF fingerprint of the radio controller can also be recognized and the classification of the drone can be carried out using Machine learning algorithm [17]. This however, will not be effective, if the communication scheme is customized or the MAC address database is not updated. An easier approach is to localize the RF signal, in which direction of arrival (DoA) estimation is carried out using the received signal strength (RSS) or spectral analysis. A simple architecture based on an array of four antennas and a software defined radio (SDR) platform for processing employed the same scheme, in which a precision varying between 1.9° to 6° was achieved over a coverage range for 120° arc [18]; the results however, were improved further by using a commercial SDR, enhancing ability to localize drones for a range of 75 m. Since, RF signature-based detection methods require active communication between the drone and its controller, they offer less effectivity for autonomous drones. Moreover, the performance deteriorates over long distances and due to signal interference from other RF transmissions, especially for unlicensed frequency bands used by commercial and recreational drones.

2.2.5 Use of Acoustic Sensors

Besides above stated techniques, studies have been undertaken to exploit drone acoustic signature for detection and identification. The engine, motor and propellers of the drones generate acoustic waves in human audible frequency range which can be recorded by employing single or an array of high fidelity microphones. This acquired signal can in-turn be compared with library of available acoustic signatures to distinguish a drone from other objects. Sound generated by drone's propellers and motor was used to develop a sound based drone detection and identification (DDI) setup. A support vector machine (SVM) classifier was used as a Machine learning (ML) framework to identify a flying object as a drone or otherwise, based on features exhibited by their sounds [19]. With increased number of microphones and arranging the same in an array, the azimuth and elevation of one or more targets can be estimated using DoA. An identification success rate of around 80% was obtained using an acoustic circular microphone array while employing Hidden Markov Model (HMM) for classification and Recursive Least Square (RLS) beamforming for tracking [20]. For each identification setup, the drone detection range varies with size and quality of microphones, characteristics of the array and the type of processing

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being performed. Results in literature, therefore seem to lie in a wide range, from 5 m to 600 m. A small tetrahedron microphone arrangement was used to measure acoustic signature of a Class-1 UAS with detection algorithm implemented using an adaptive Kalman filtering for input from a beamforming algorithm. The setup rendered a success rate of 99.5 percent with a detection range of up to 600 m [21].

3.1 Audio Characteristics of Drones

UAS including multiple types of drones and commercially available quadcopters are inherently noisy in nature. Drone structure including its propellers, motor and engine have peculiar acoustic signatures which differ from other sounds in the surroundings. Over the past few years, several audio-based drone detection methods have been proposed which make use of concise parametric representation i.e. acoustic features, to detect a drone audio. These acoustic features capture the unique drone acoustic fingerprints and are more discriminative and reliable for detection as compared to the original drone audio. Depending upon the scheme being employed, these features can either be manually engineering like Mel-Frequency Cepstral Coefficients (MFCC) and Linear prediction Coding [22] or they can be obtained directly using Deep learning Algorithms like Recurrent Neural Networks (RNN) or Convolution Neural networks (CNN) [23].

3.2 Aerodynamics of Drone Rotors

Acoustic signature of a drone consists of aeroacoustics noise produced by rotor blades, drone motor noise, mechanical vibrations, noise from electric components, and noise from aero elastic effects. The primary source being the rotor blades, it is imperative to understand the rotor aerodynamics and aeroacoustics. Aerodynamics and aeroacoustics are the two topics that go hand-in-hand. That is the reason why better aerodynamic performance, either in terms of power loading or figure of merit, is generally accompanied by better acoustic performance as well. Here power loading is defined as the ratio of thrust to power while figure of merit is the ratio of ideal power required to actual power. In terms of aerodynamic performance, the changes caused by simple rotor design parameters such as rotor planform shape, twist, taper, airfoil geometry and certain other factors have been investigated by many authors. A comprehensive parametric study [24] revealed that airfoil shape had the largest effect on power loading and figure of merit. While thinner airfoils with thickness to chord ratio between 0.02 and 0.06 were found to give optimum performance; likewise, airfoils with moderate camber ranging from 4.5 to 6.5 percent had better performance. Similarly, it was also concluded that increasing the rotor chord and the number of blades also had large impacts on the amount of thrust produced [25].

Since the Reynolds number associated with airflow for small scale quadcopters or rotors is low, therefore, the drag component for these platforms is primarily due to flow separation over the airfoil. Reynolds number represents ratio of viscous forces to inertial forces, therefore low Reynolds number flows in-turn, are dominated by viscous fluid action. Another important aspect is to study the wake structure produced by small-scale rotors and their effect on performance values such power loading and figure of merit. It was shown through smoke visualization [26] that the small scale rotors produced a poor wake contraction ratio with tip vortices that were large as compared to the rotor size. In short, a requisite reduction in size of the tip vortices and thickness of the wake sheet could be achieved then the aerodynamic performance would be improved.

3.3 Drone Rotor Aeroacoustics

Drone noise is affected by many factors including size and number of motors, propeller diameter, rotational speed and operating environment. This drone noise generated by different sources can been broadly categorized as tonal or deterministic noise and broadband noise. Tonal noise also referred to as harmonic noise is characterized by high amplitude spikes which appear at discrete frequencies directly related to the rotor motion i.e. the blade pass frequency and its harmonics [27]. Mostly spikes in these cases tend to appear at lower frequencies and serve as the most dominant source of rotor noise. At other instances, however, the noise sources do not have a particular frequency at which they occur, such as steady rotor loading or rotor thickness, since these sources are always present. Another important characteristics of this kind of noise is directivity, as the sources in this case are highly directive in nature. The theoretical prediction of this harmonic noise produced by rotating blades, in particular by propellers, is governed by the Ffowcs-Williams/Hawkings (FW-H) acoustic analogy. [28]

As previously discussed, steady rotor loading results in noise propagation above and below the rotor plane, while the rotor thickness also causes increased noise in the plane of the rotor. Apart from these two contributors, an additional phenomenon is unsteady loading which gives rise to tonal noise. Unsteady loading can occur at multiple instances including blade-airframe interaction, blade-wake interaction, blade-turbulence interaction and blade-vortex interaction (BVI). It is important to note that these tonal spikes appear because of the unsteady loading and not the actual flow phenomenon itself, such as vortex shedding. An example of such unsteady loading is the BVI noise, a highly directive noise appearing at mid to high frequencies in the spectrum and is caused once the shed tip vortex is impacted upon by a rotor blade [29].

The broadband noise meanwhile, is not characterized by amplitude peaks at specific frequencies but appear as a continuous signal, even at frequencies where tonal noise is not present. A broadband noise source may appear due to conditions such as turbulent inflow, turbulent up-flow and rotor self-noise sources such as boundary layers, flow separation, rotor wakes, and vortex shedding [30]. At most instances, broadband noise is usually a small contributor towards the overall noise spectrum, but it becomes of increased significance in low speed flow conditions such as small scale quadcopters or micro-rotors [31]. Unlike the full scale rotors on helicopters, the micro-rotors installed on small drones or quadcopters typically operate at Reynold Number between 10^4 and 10^5. Subsequently, these platforms fall in the regime of flow transition from laminar to turbulent and see more broadband noise contribution as compared to the full scale rotors.

4.1 Use of Computational Fluid Dynamics for Prediction of Drones Noise

Computational Fluid Dynamics (CFD) is an evolving field, which over the years has gained attention in development of modern UAVs, simulating diverse range of conditions for operational feasibility. Recently number of researches have also been undertaken on design of quadcopters, and the characterization of flow generated by its propellers. A simplified version of DJI Phantom-3 was simulated in ANSYS 17.1 using Realizable k-epsilon model and employing the moving reference frame (MRF) and sliding mesh techniques to reproduce the flow generated by the propellers. These steady state simulations gave results in agreement with classical theoretical models, for entire range of heights [32]. CAA of a quadcopter was carried out using a combined frame work of CFD with unsteady Reynold-Averaged Navier-Stokes (RANS) and FW-H acoustic model. The rotor’s virtual blade model (VBM) was used to obtain the momentum sources as the first approximation and the model was applied to simulate both hovering and forward flight conditions. The aero acoustic footprints were analyzed and the predicted octave band sound levels were found to be in good agreement with the experimental data [33]. An effective tool to capture minutest turbulences and eddies, while ensuring smooth transition from one flow state to another is the use of scale resolving Simulations (SRS). Using the same with the FW-H acoustic analogy, the SRS scheme had been used to accurately predict the acoustic signature for NACA 0012 airfoil, and the results including location and amplitude of the main tone frequencies were found in good agreement with numerical and experimental data [34]. Another study proposed a combined CFD, CAA and machine learning methodology to predict drone noise given the uncertainties of rotational speed values. CFD simulation of the LHI-QAV250 quadcopter (a low cost model) was performed using scFLOW v2021. The pressure-based incompressible LES solver with WALE (Wall-Adapting Local Eddy-Viscosity) sub-grid scale turbulence model was used, with solution of a steady RANS calculation set as initial condition for the simulation. The acoustic solution was later computed using ACTRAN 2021 by solving the FEM formulation of Lighthill's analogy in the frequency domain. The acoustic results were then provided as input data to train the selected machine learning regressor model. The predictions reconstructed with the regression algorithm were found to match well the experimental data, especially for peak's amplitudes. Some divergences were observed for broadband noise, primarily attributed to limited data recorded using CFD/CAA setup [35].

4.2 Present Available Tools for CFD Generated Sound

The acoustic module of CFD solvers like ANSYS FLUENT have been previously brought in use to primary calculate and analyze Sound Pressure Levels (SPLs) of multiple acoustic sources at different receivers' locations. The generic methodology generally employs FW-H Acoustic Analogy Model to compute sound generated because of source surfaces at different user defined locations to analyze sound characteristics around the area of interest. These results were generally restricted to discrete Sound parameters available in time and frequency domain with additional tools for Power Spectral density and Sound Energy content for later post processing of generated signals. The real part however, would have been to listen to the same and compare it with realistic sound obtained using experimental setups. This problem has been addressed with the introduction of ANSYS VRXPERIENCE Sound / ANSY Sound which enables the user to listen, analyze and design sound sources based on CFD acoustic simulation results. The software offers an innovative post-processing tool to predict and assess noise via human hearing, in early stages of virtual product modeling or using the available dataset [36]. The same information can in-turn be augmented with a suitable design like driving or flight simulator or any other relevant virtual reality platform.

The acoustic workflow available in ANSYS software release, 2021 R1, can be used to couple ANSYS Fluent CFD simulations to ANSYS VRXPERIENCE Sound, which enables advanced acoustics analysis techniques for analysis of acoustic pressure signals computed by CFD. The Setup gives the provision to use CFD-generated sound pressure signals to provide psychoacoustics indictors and simulate resultant human perceived sound using different metrics such as loudness, tonality, sharpness, and articulation index. Using the same setup at ANSYS, traditional spectral plots were turned into real audio *.wav files with ANSYS VRXPERIENCE Sound Acoustic tool and study the impact of these predicted sounds on observers in close proximity to the drone's flight path [37].

The use of ANSYS VRXPERIENCE Sound analysis tool was used effectively to compute 12 psychoacoustic indicators using different sound recordings and the results were found consistent with literature data. The setup appreciated the use of this virtual reality setup to predict interior train background noise annoyance perceived by the user [38]. Likewise in order to analyze the correlation between the sound pressure level (SPL) and engine power, ANSYS Sound module was utilized whereby engine order components were separated from the overall interior noise in case of an electric vehicle (EV) design. The measurement data was imported into the software such that the Fast Fourier Transform (FFT) spectrum of the interior noise cold be analyzed. Based on certain important factors in hand, a sound sample was generated in ASD Module of the ANSYS VRXPERIENCE Sound and overall sound pressure level (OASPL) and FFT spectrums were obtained [39]. The software proposes the use of dynamic sound synthesis that can be interfaced with a simulator to evaluate different sound designs. The software is compatible with several 3D-sound, multichannel playback systems and allows realistic rendering of the active sound together with other sound sources such as engine sound, aerodynamic noise, rolling noise, traffic noise, and weather effects. ANSYS VRXPERIENCE Sound offers a dedicated solution making it possible to test, compare, and finely tune different sound design candidates which was also employed by RENAULT to observe the difference between the expected sound and the sound perceived in vehicle [40].

5. Proposed Futuristic Direction

Recently, a lot of research has been direction towards identification and classification of quadcopters / drones, based on their recorded peculiar acoustic signatures. While all these studies have employed physical acoustic measurement aids coupled with Machine learning algorithm setups, an effort may be been made to use available CFD solvers for predicting noise levels of selected drone geometries. The study may involve use of CFD-based simple alternative solution to physical setups which are presently in use, for recording and predicting acoustics signatures for diverse range of flight conditions and multirotor geometries. Aerodynamics and Aeroacoustics analysis of few drones have already been carried out successfully vide researches mentioned in earlier sections. Using latest CFD Acoustic interfaces like ANSYS VRXPERIENCE Sound, the acoustic data obtained for multiple quadcopter geometries after post processing of CFD data may be utilized to obtain audio files for each modeled receiver. Same in-turn can be used to develop consolidated audio library for selected drones along with commercially recorded drones and environmental sounds. This extensive data can be augmented with Machine Learning setups to obtain specific audio characteristics and help develop a refined ML model for subsequent drone identification and classification.

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