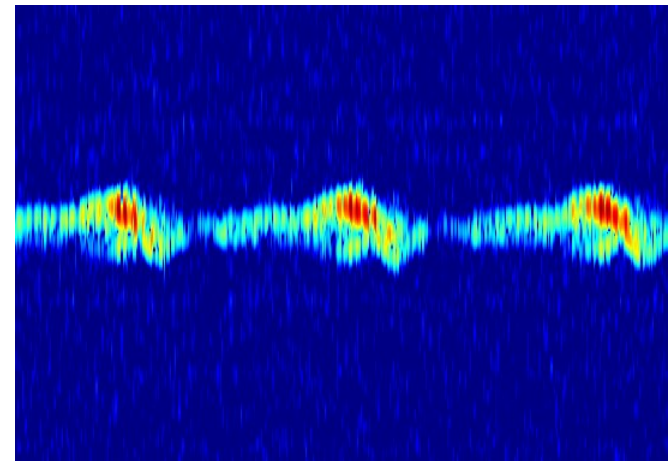
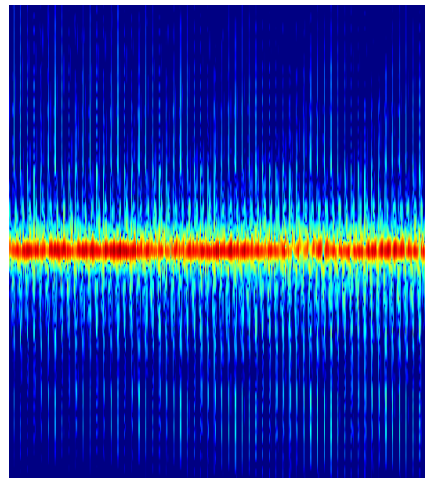




Time-Frequency Analysis of Millimeter-Wave Radar Micro-Doppler Data from Small UAVs



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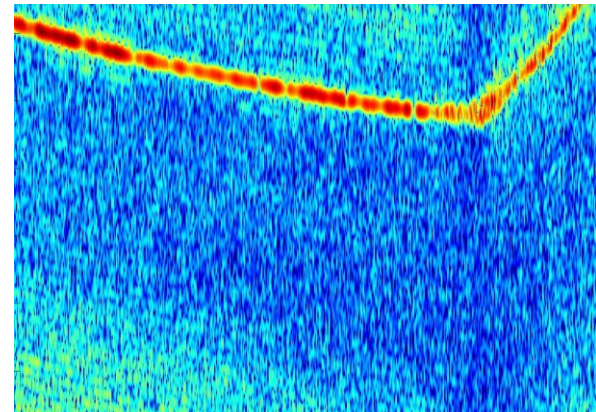
{sr206, dar}@st-andrews.ac.uk

<http://www.st-andrews.ac.uk/~mmwave>



Overview

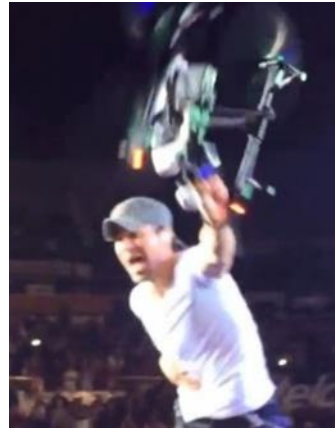
- Need for small UAV detection and classification system in defence sector
- Radar micro-Doppler signature analysis of sUAVs by STFT
- Wavelet Transform
 - *Continuous Wavelet Transform*
 - *Discrete Wavelet Transform*
 - *Wavelet transform for sUAV data analysis*
- Experimental results (Drone and Bionic Bird)
 - *CW radar*
 - *FMCW radar*
- Conclusions



Need for small UAV detection and classification system in defence sector



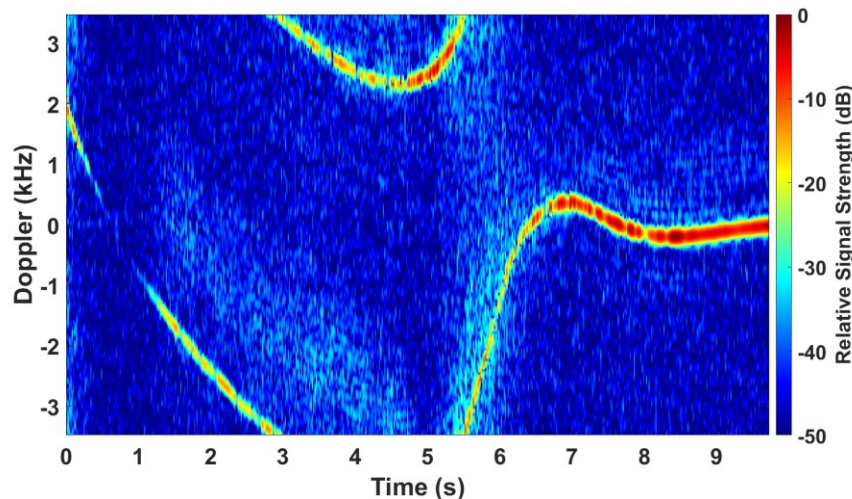
- Consumer drones have become readily available to the general public
- A user with malicious intent can use it for dropping/transferring explosives or contraband, illegal video recording etc.
- A novice user can create problems unintentionally which may disrupt a citizen's privacy/safety or create damage to an important facility
- There is a need for reliable, compact and low cost drone detection and classification system in the market



Radar micro-Doppler signature analysis of sUAVs by STFT



- Joint time-frequency analysis methods are mainly used for analysing micro-Doppler signals
- The most widely used technique is the linear analysis method, named the Short-Time Fourier Transform (STFT)
- Very intuitive, illustrates the variation in signal frequency content over time
- Millimeter-wave radar can produce high fidelity micro-Doppler returns from a sUAV due to the very fast rotating propeller blades

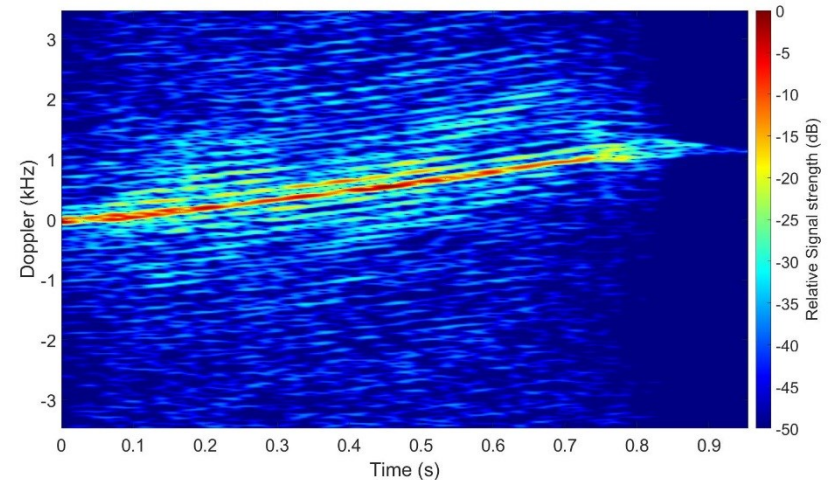
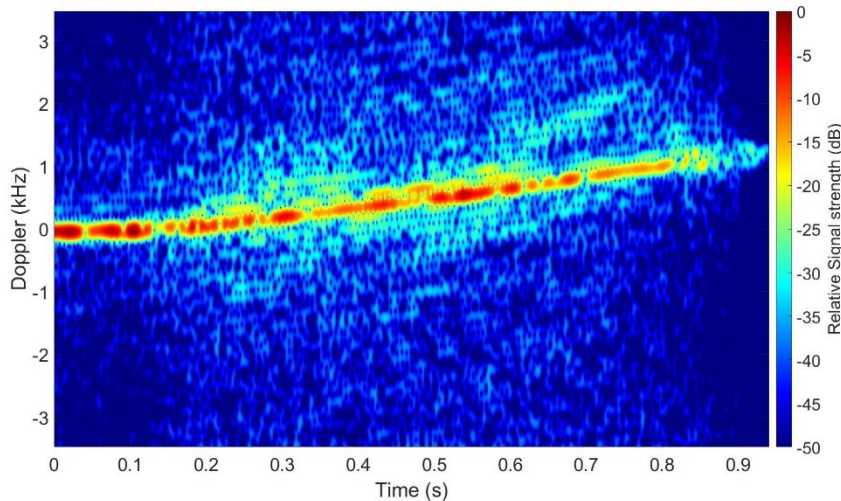


Spectrogram
of a flying
UAV

Radar micro-Doppler signature analysis of sUAVs by STFT



- In STFT, there is a trade-off between time and frequency resolution
- Different window lengths used in the STFT reveal different features



Spectrograms obtained by using different STFT window length revealing different features (HERM lines, blade flashes)

** Using different window lengths for feature extraction can increase computational load*

Wavelet transform



- Uses wavelets instead of sines/cosines as the basis function
- Wavelets are localized both in time and frequency
- The localization is achieved by means of scaling or dilation (frequency localization) and shifting or translation (time localization)
- The resultant analysis is represented by a scalogram, which shows the energy distribution of the signal in different scales (revealing different frequency components) over time
- Capability to extract Doppler signatures of fast moving objects (i.e. sUAV propeller blades)

Wavelet transform



Continuous Wavelet Transform (CWT)

$$CWT(a, b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} x(t) \psi^* \left(\frac{t-b}{a} \right) dt$$

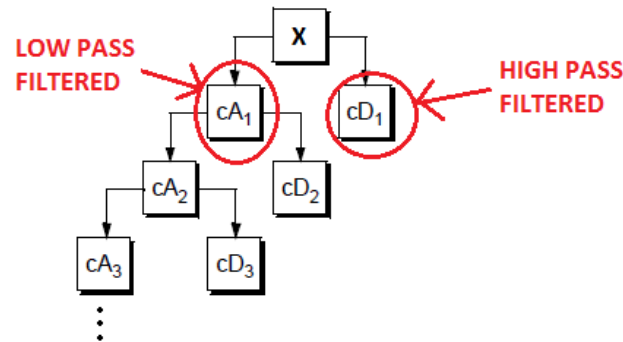
- a and b are the scaling and shifting parameters respectively
- ψ^* is the complex conjugate of the mother wavelet
- $x(t)$ is correlated with the different scaled versions of the wavelet function as well as the wavelet being shifted along the time axis
- The Haar (or Daubechies 1, 'db1') wavelet has been used to analyse data here

Wavelet transform



Discrete Wavelet Transform (DWT)

- The discretization is done in terms of integer powers of 2 ($2^j, j=1, 2, 3, \dots$)
- By performing multi-level DWTs, the original signal can be decomposed into various components corresponding to different frequencies



- The high-pass outputs are defined as the detailed coefficients and the final low-pass output defines the approximation coefficients
- A 5-level wavelet decomposition process,

$$x = cd_1 + cd_2 + cd_3 + cd_4 + cd_5 + ca_5$$

(The first five components correspond to detailed coefficients and the last one corresponds to approximate coefficients)

Wavelet transform



Wavelet Transform for sUAV data analysis

- Combination of CWT and DWT have been used to analyze the micro-Doppler signatures of the millimeter-wave radar data (in 3 steps)

Step 1- Perform wavelet decomposition (4-6 levels) on the phase coherent radar return signal.

Step 2- Select cd1 and/or cd2 and performing CWT to attain micro-Doppler feature.

Step 3- Select the final low-pass output and perform CWT to get bulk Doppler feature.



Millimeter-wave radars used for micro-Doppler measurements

94 GHz FMCW/CW radar 'T-220'

- 94GHz FMCW / CW
- +18 dBm
- B up to 1.8GHz
- Dual antenna fan beam
- $0.92^\circ \text{Az} \times 3.00^\circ \text{El}$ (40.5dBi)
- CP only (odd bounce)
- $NF \sim 6\text{dB}$
- 70dB Tx-Rx isolation
- Staring or slow pan
- Very low phase noise
- DDS chirps



94 GHz FMCW radar 'NIRAD'

- 94GHz FMCW
- +20 dBm
- B up to 600 MHz
- Single antenna pencil beam
- $0.74^\circ \text{Az} \times 0.87^\circ \text{El}$ (42.5dBi)
- CP, V, H or 45° (co- and x-pol)
- $NF_{\text{eff}} \sim 26.5\text{ dB}$ (Tx-Rx leakage)
- R^3 filter
- 10 Hz PPI rate or Staring
- Low phase noise
- DDS chirps



sUAVs used for data collection



- DJI Phantom 3 Standard

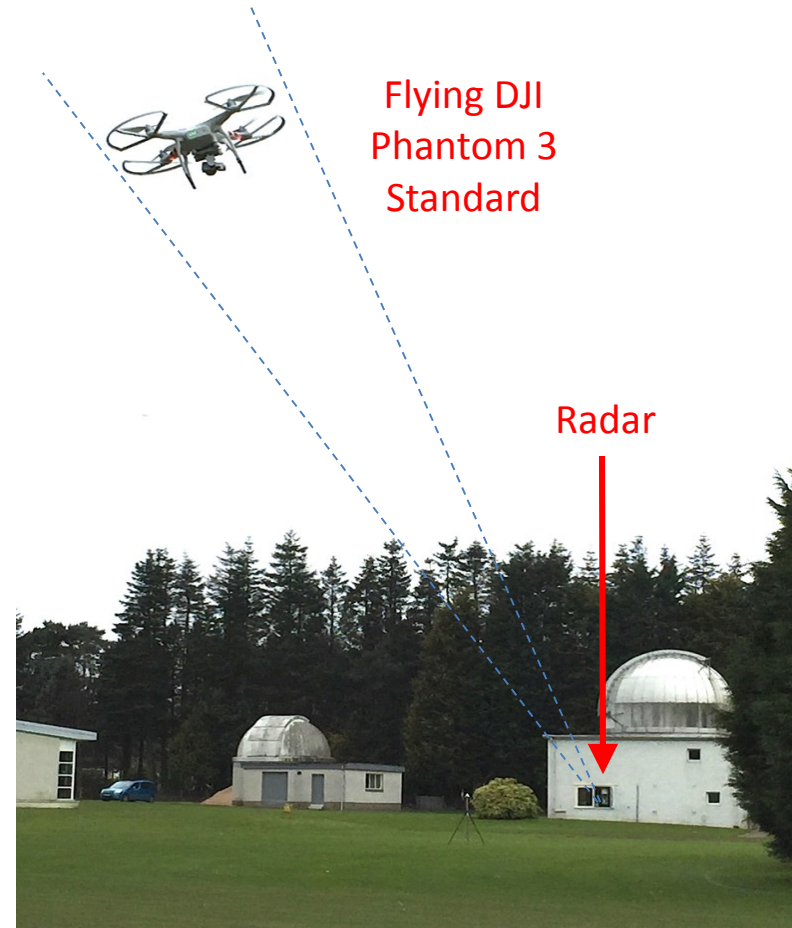


<https://www.dji.com/phantom-3-standard>

- Bionic bird biomimetic drone



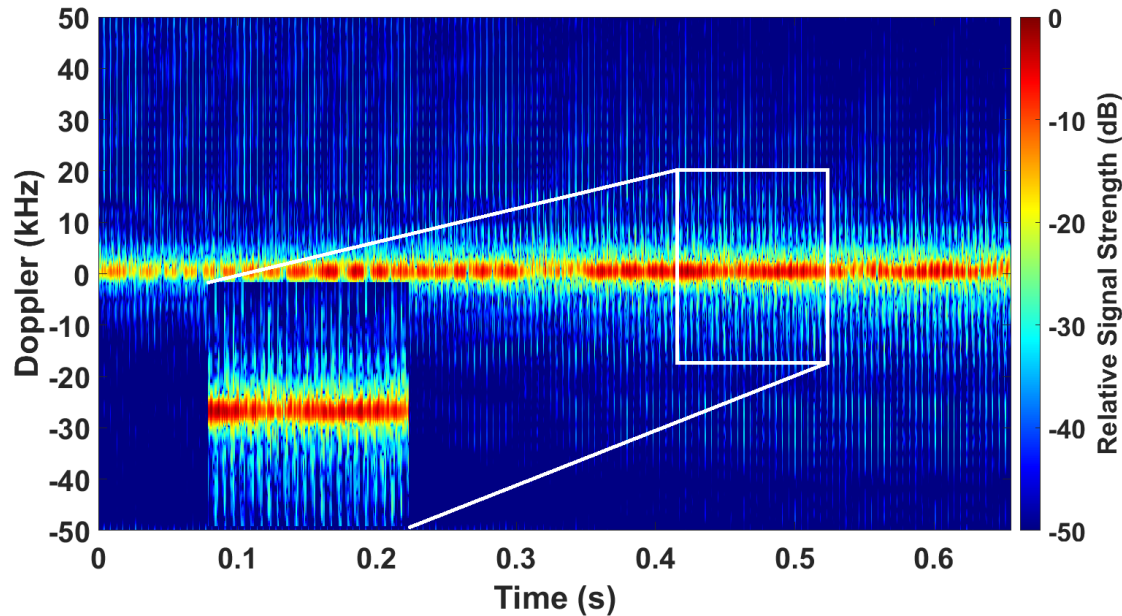
<http://www.mybionicbird.com/?lang=en>



Flying DJI
Phantom 3
Standard

Radar

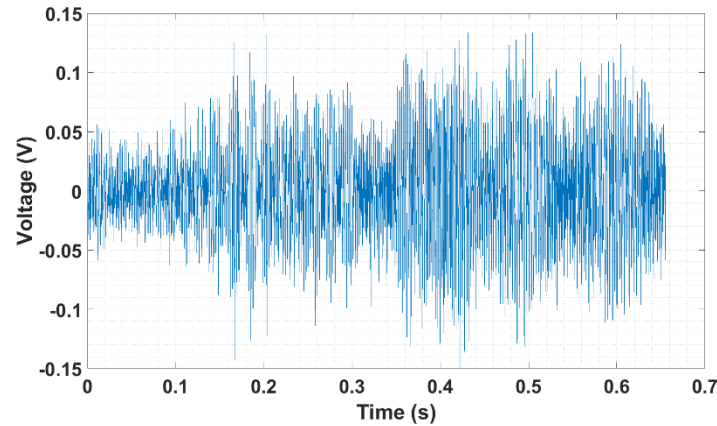
CW radar data (DJI Phantom 3 Standard)- Spectrogram



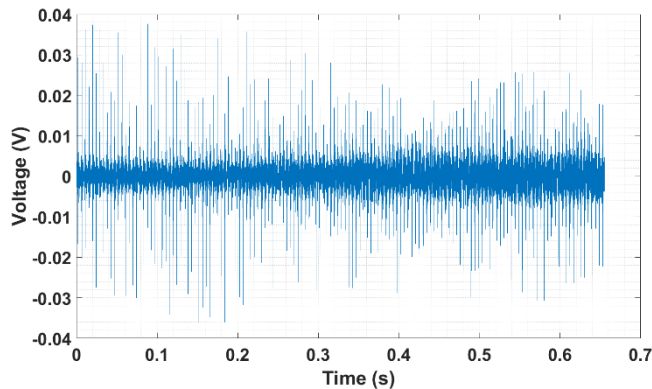
Spectrogram of hovering DJI phantom with blades attached to only one rotor

- Conventional STFT with Gaussian windowing is used
- The Phantom was ~ 20 m away from the radar

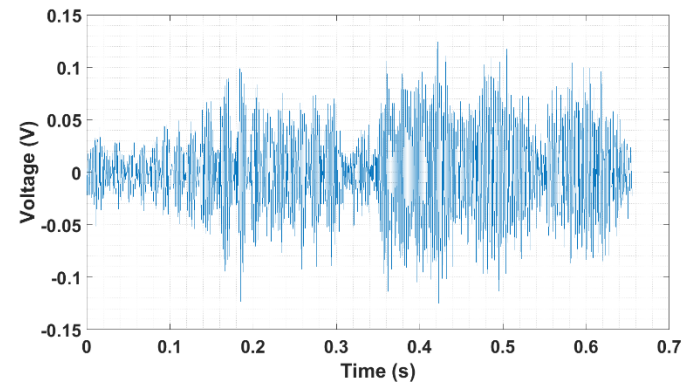
CW radar data (DJI Phantom 3 Standard)- 6-level wavelet decomposition



Real part



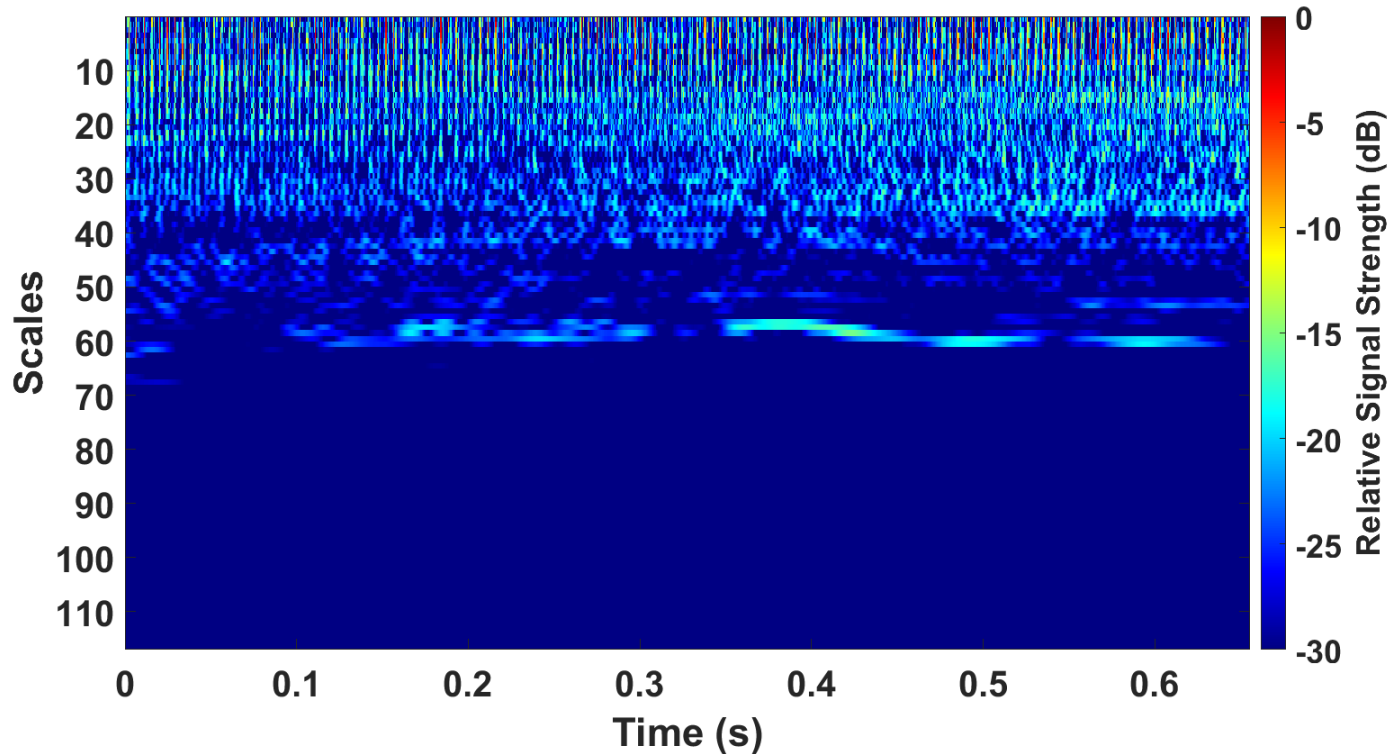
High Frequency component, cd_1



Low frequency component, ca_6

- Most of the signal energy is concentrated in bulk velocity component

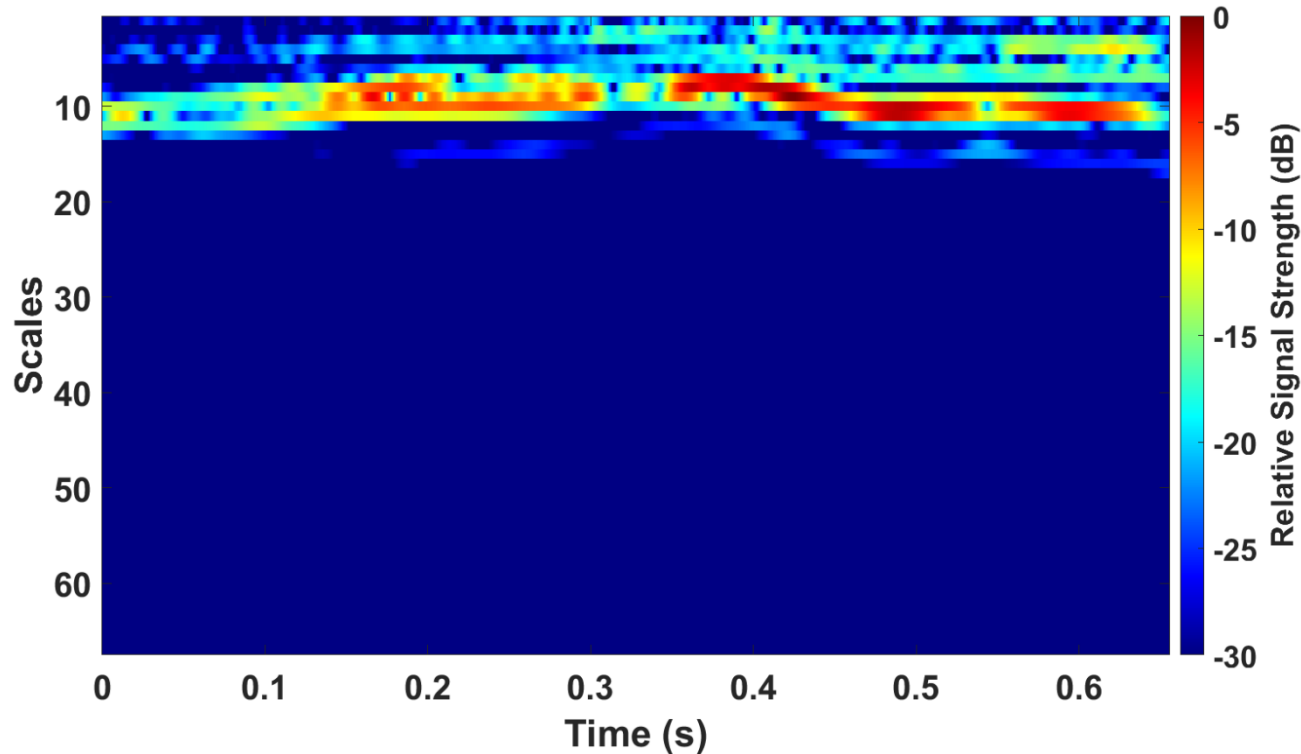
CW radar data (DJI Phantom 3 Standard)- Scalogram, high frequency component



Scalogram of the high frequency component, cd_1 . The blade flashes are observed

** The scaling parameter is discretized in terms of $2^{1/v}$. Here, v is greater than 1, hence the scale factor is always positive*

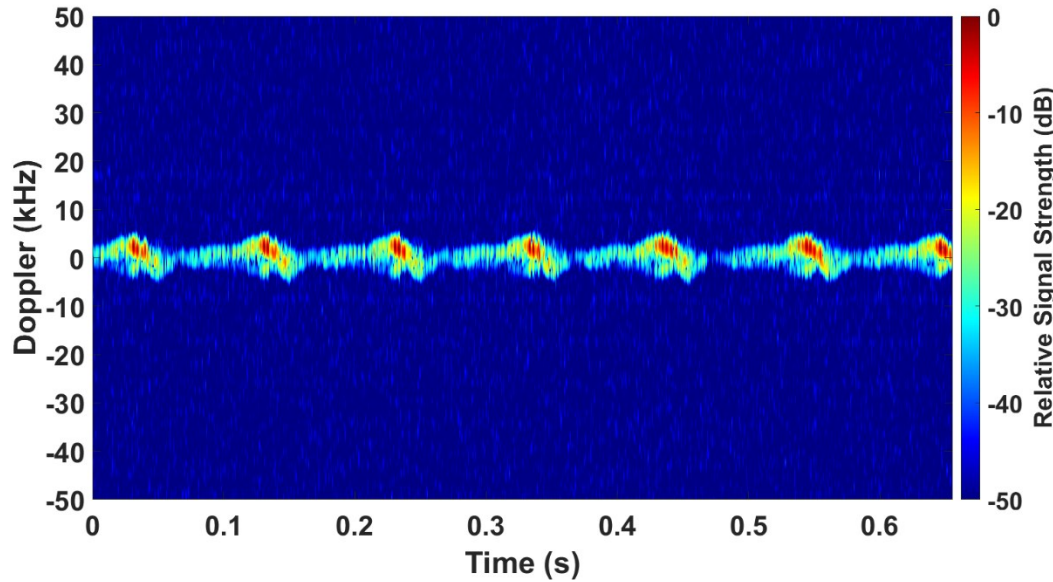
CW radar data (DJI Phantom 3 Standard)- Scalogram, low frequency component



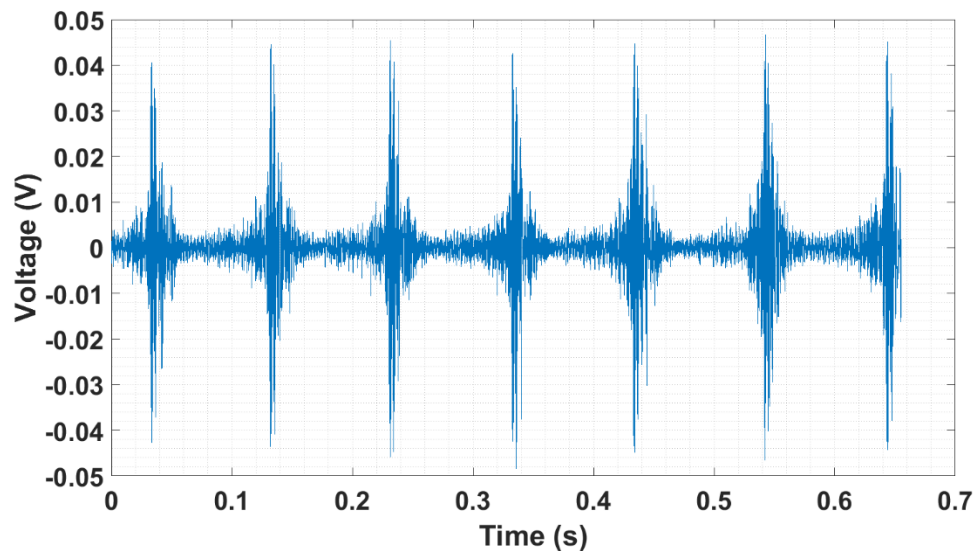
Scalogram of the low frequency component, ca_6 . Zero Doppler components are observed

** The bulk-Doppler and micro-Doppler (due to propeller blade rotation) components are hence separated*

CW radar data (Bionic bird)- Spectrogram

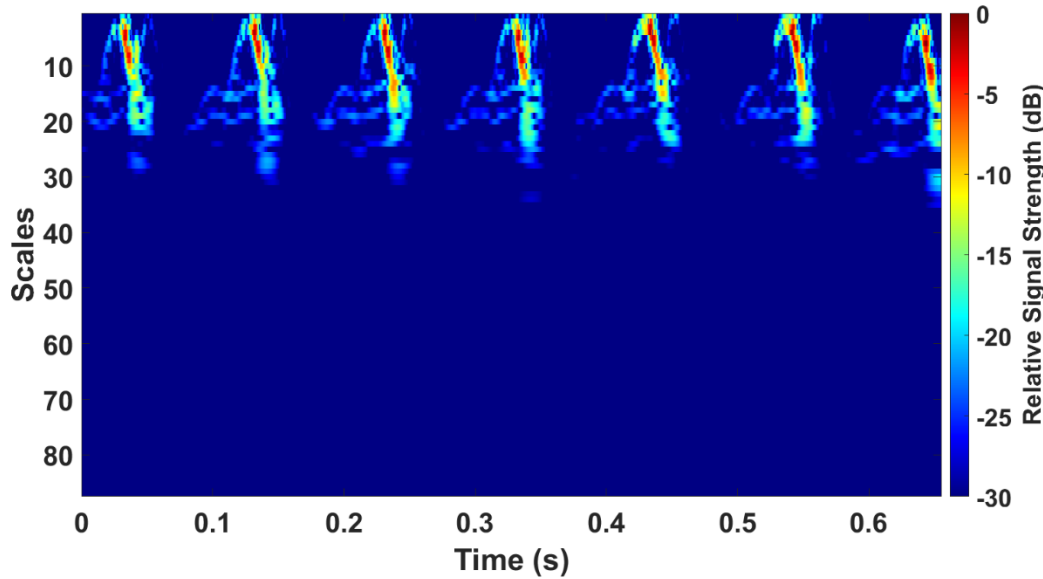


- Spectrogram of the Bionic Bird flapping wings. The periodic motion of the wing beats is clearly observed

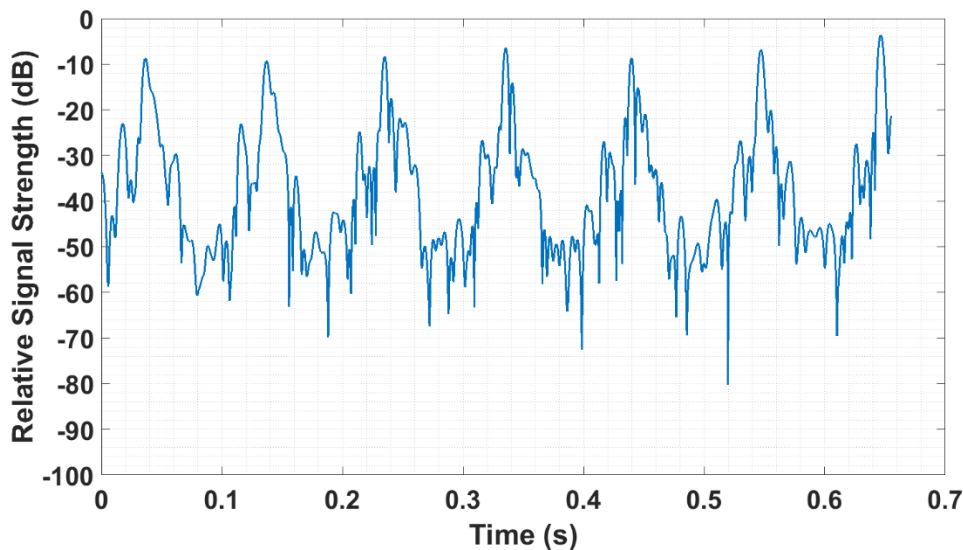


- the real part of the corresponding time-domain signal. Negligible bulk Doppler

CW radar data (Bionic bird)- Scalogram

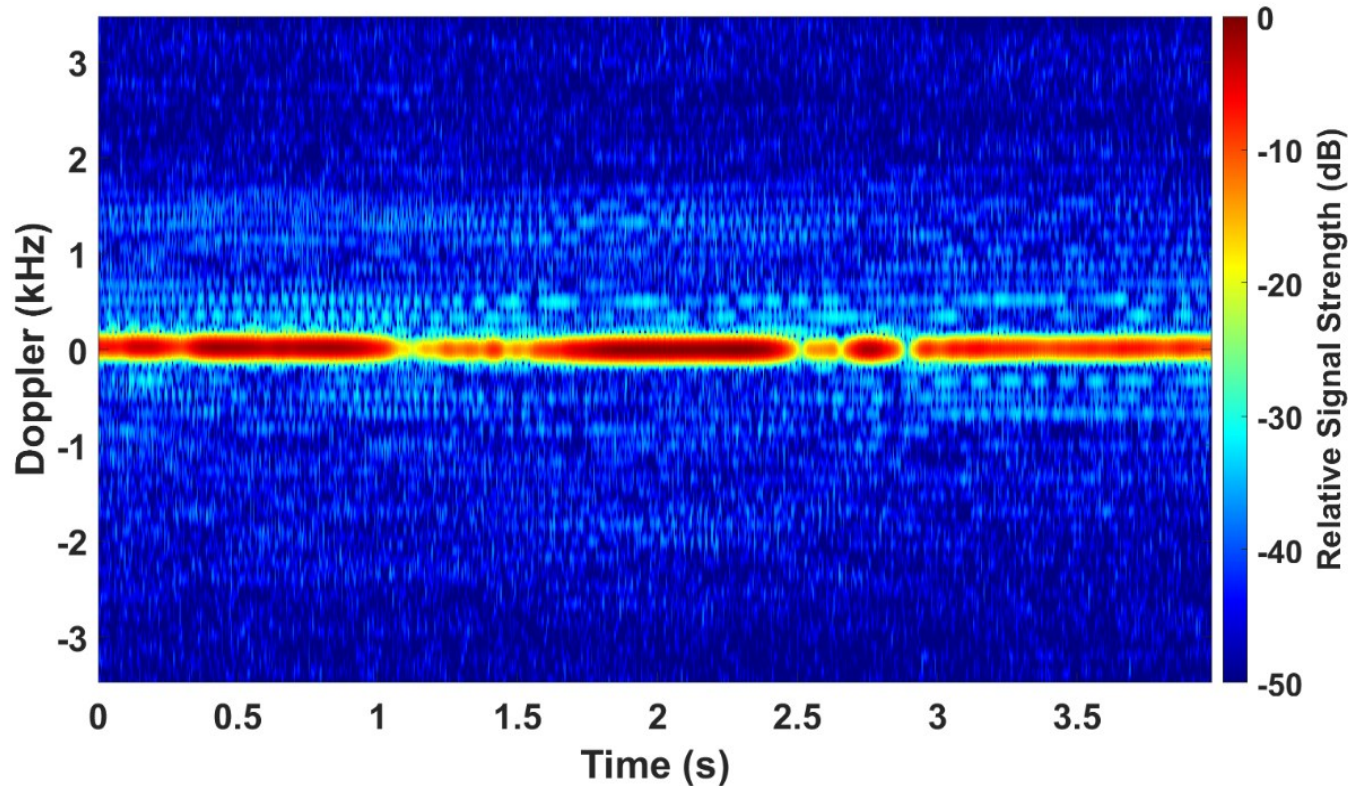


- Scalogram of the same data showing wing beats. 4-level wavelet decomposition is performed



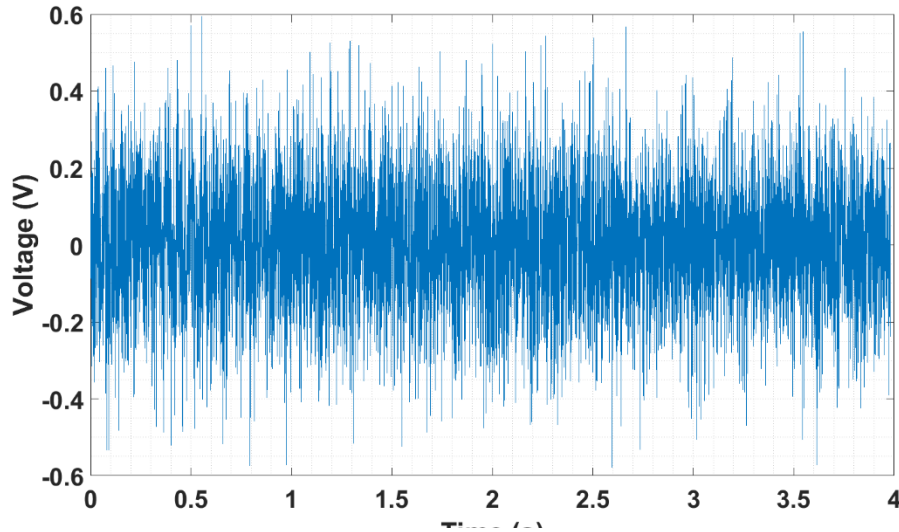
- Time slice of the 10th scale

FMCW radar data (DJI Phantom 3 Standard)- Spectrogram

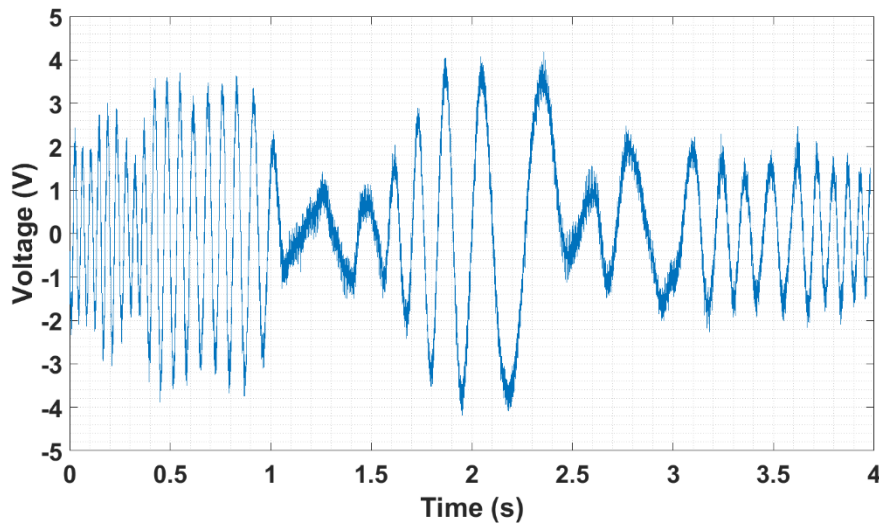


- All 4 rotor blades rotating
- Both micro-Doppler and bulk Doppler signatures are observed, but neither is fully resolved

FMCW radar data (DJI Phantom 3 Standard)- 6-level wavelet decomposition

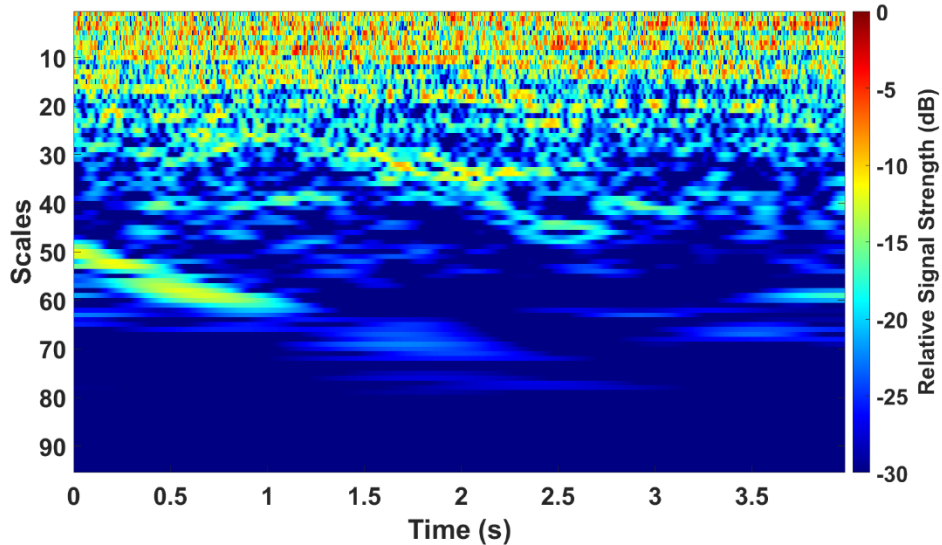


- Real part of the deramped signal of the sUAV return. 6-level wavelet decomposition performed

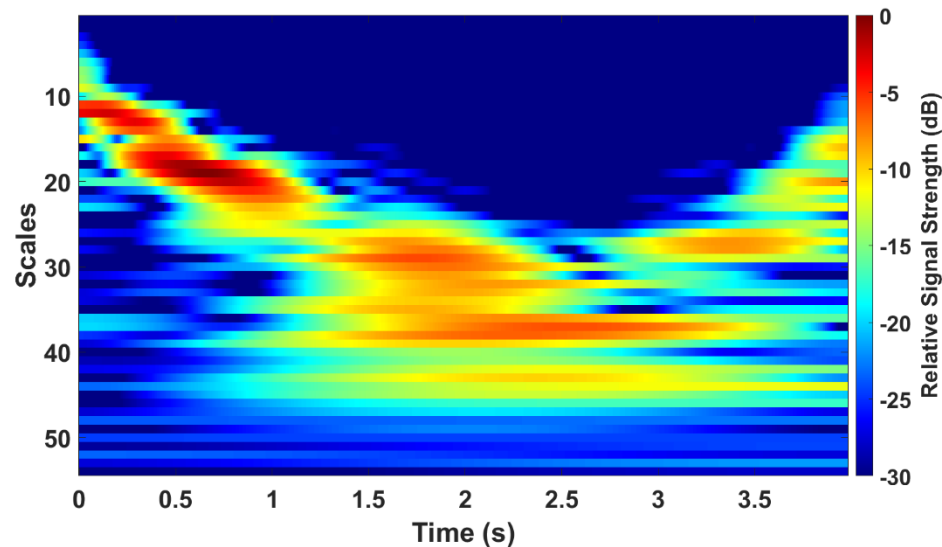


- High frequency component, cd_2 , first iteration did not suppress the low frequency part entirely, hence cd_2 is chosen

FMCW radar data (DJI Phantom 3 Standard)- Scalogram



- Scalogram of the high frequency component (top), cd_2 , showing the micro-Doppler features of the sUAV



- Scalogram of the low frequency component (bottom), ca_6 . Micro-Doppler features are filtered out in this case

Conclusions

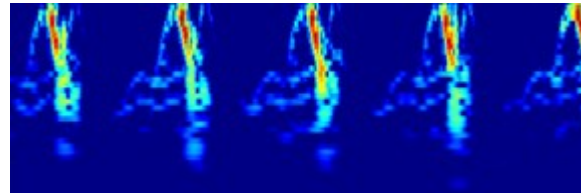


- Spectrograms provide very good visualization of the micro-Doppler features
- Combination of wavelet decomposition and scalograms obtained by CWTs can be used for separating the micro-Doppler information
- The wavelet transform method can be used to feed a classifier with unique sUAV micro-Doppler characteristic
- The computational complexity
 - Fast wavelet transform $O(n)$
 - Fast Fourier transform $O(n \cdot \log_2(n))$
- For real-time sUAV detection operation, the proposed method has the potential to be more efficient in terms of false alarm rate and computational load



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Thank you! Any questions?

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