





## MSG-SET-183 - DETECTION AND CHARACTERIZATION OF A UAS RF FHSS COMMUNICATION LINK VINCENT VAN DER KNAAP, MILLAD MOURI, PETER ZWAMBORN, DANIELA DEIANA

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# **BACKGROUND** MOTIVATION AND PROBLEM DESCRIPTION

### **MOTIVATION**

- Capabilities of Unmanned Aerial Systems (UAS), in both military and civilian applications, are growing rapidly
- ) UAS hardware has become ubiquitous
- Reliable detection techniques to enable appropriate counter measures is becoming crucial

### **PROBLEM DESCRIPTION**

Detection and characterization of a RF uplink using FHSS modulation used for drone communications





# **SIGNAL PROCESSING CHAIN** OVERVIEW

Received FHSS signal

**Detection and Coarse Parameter Estimation** 

#### **Fine Parameter Estimation**

#### **RECEIVED SIGNAL**

 In this study, Frequency Hopping Spread Spectrum (FHSS) is identified as one of the main communication techniques in use by UAS.

### DETECTION

 Detecting UAS through characterization of their communication link is very promising as it directly provides information useful for possible counter measures, such as smart jamming.

### PARAMETER ESTIMATION

 An algorithm based on the combination of Wavelet Transform and Sparse Learning is investigated.



### **FHSS WAVEFORM PARAMETERS**

) Carrier frequency and bandwidth  $f_c$ , B;



![](_page_4_Picture_4.jpeg)

### **FHSS WAVEFORM PARAMETERS**

) Carrier frequency and bandwidth  $f_c$ , B;

> hopping pattern with 16 hops (96 ms);

![](_page_5_Figure_4.jpeg)

![](_page_5_Picture_5.jpeg)

### **FHSS WAVEFORM PARAMETERS**

) Carrier frequency and bandwidth  $f_c$ , B;

> hopping pattern with 16 hops (96 ms);

![](_page_6_Figure_4.jpeg)

![](_page_6_Picture_5.jpeg)

### **FHSS WAVEFORM PARAMETERS**

) Carrier frequency and bandwidth  $f_c$ , B;

> hopping pattern with 16 hops (96 ms);

![](_page_7_Figure_4.jpeg)

![](_page_7_Picture_5.jpeg)

### **FHSS WAVEFORM PARAMETERS**

Carrier frequency and bandwidth f<sub>c</sub>, B;
hopping pattern with 16 hops (96 ms);
Dwell-Time T<sub>d</sub> = 6 ms (167 hops/s);
Duty cycle D = 0.1

![](_page_8_Figure_3.jpeg)

### **FHSS WAVEFORM PARAMETERS**

- ) Carrier frequency and bandwidth  $f_c$ , B;
- > hopping pattern with 16 hops (96 ms);
- ) Dwell-Time  $T_d = 6$  ms;
- ) Duty cycle D = 0.1

## **ASSUMPTIONS**

- )  $f_c$  and B are known and constant
- ) Fixed hopping pattern
- A single FHSS signal is presented at each time

![](_page_9_Figure_10.jpeg)

![](_page_9_Picture_11.jpeg)

# **RF LINK DETECTION AND CHARACTERIZATION** PARAMETRIC AND NON-PARAMETRIC METHODS

![](_page_10_Figure_1.jpeg)

### **CWT-BASED DETECTION**

- Detection of FHSS signal performed based on CWT
- A rough estimate of the hop time, dwell time, duty cycle and hopping pattern duration are provided

![](_page_10_Picture_5.jpeg)

## **CWT-BASED FHSS DETECTION** CONTINUOUS WAVELET TRANSFORM

## **DETECTION PROBLEM**

) Detect if an FHSS signal is present

 $\mathcal{H}_0$ : noise only  $\mathcal{H}_1$ : signal and noise

## **CONTINUOUS WAVELET TRANSFORM**

 Captures both the slowly varying changes (hopping pattern) as the abrupt changes (single hops)

### **DETECTION PROCEDURE**

Detect peaks indicating hopping pattern, not individual hops.

![](_page_11_Figure_8.jpeg)

![](_page_11_Picture_10.jpeg)

## **DETECTION PROBLEM**

- ) Detect if an FHSS signal is present
  - $\mathcal{H}_0$ : noise only  $\mathcal{H}_1$ : signal and noise

### **CONTINUOUS WAVELET TRANSFORM**

 Captures both the slowly varying changes (hopping pattern) as the abrupt changes (single hops)

### **DETECTION PROCEDURE**

Detect peaks indicating hopping pattern, not individual hops.

## Mean of wavelet coefficients

![](_page_12_Figure_9.jpeg)

![](_page_12_Picture_11.jpeg)

## **CWT-BASED FHSS DETECTION** CONTINUOUS WAVELET TRANSFORM

## **DETECTION PROBLEM**

- > Detect if an FHSS signal is present
  - $\mathcal{H}_0$ : noise only  $\mathcal{H}_1$ : signal and noise

### **CONTINUOUS WAVELET TRANSFORM**

 Captures both the slowly varying changes (hopping pattern) as the abrupt changes (single hops)

### **DETECTION PROCEDURE**

Detect peaks indicating hopping pattern, not individual hops.

## Mean of Fourier coefficients

![](_page_13_Figure_9.jpeg)

![](_page_13_Picture_11.jpeg)

## **CWT-BASED FHSS DETECTION** CONTINUOUS WAVELET TRANSFORM

## **DETECTION PROBLEM**

) Detect if an FHSS signal is present

 $\mathcal{H}_0$ : noise only  $\mathcal{H}_1$ : signal and noise

### **CONTINUOUS WAVELET TRANSFORM**

 Captures both the slowly varying changes (hopping pattern) as the abrupt changes (single hops)

### **DETECTION PROCEDURE**

Detect peaks indicating hopping pattern, not individual hops.

## Mean of wavelet coefficients: two hops

![](_page_14_Figure_9.jpeg)

![](_page_14_Picture_11.jpeg)

# **CWT-BASED FHSS DETECTION** RESULTS

## **SCENARIO**

- ) Single FHSS signal in AWGN
- ) Range of SNR regimes
- > Single snapshot (two hopping sequences)

### **MULTIPLE SNAPSHOTS**

- Single snapshot, relatively low integration time
- Realistic observation time is larger

Single Snapshot Detection Results T SNR = 6 dB0.8 SNR = 3 dB – SNR = 0 dB0.6---SNR = -3 dB- $P_D$ 0.40.20 0.20.6 0.80.40 FAR

![](_page_15_Picture_9.jpeg)

# **CWT-BASED FHSS DETECTION** SUMMARY

## **CWT-BASED DETECTION**

- Captures both the slowly varying changes (hopping pattern) as the abrupt changes (single hops)
- Enables detection of FHSS signals

### LIMITATIONS

- ) Differentiate between FHSS and other signal types
- ) Practical problem of multiple signals present at the same time

### **POSSIBLE SOLUTIONS**

- ) ML approach; performs both detection and classifications.
- ) i.e. known with high probability if the received signal is indeed FHSS modulated.

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![](_page_16_Picture_11.jpeg)

## **RELATIONSHIP BETWEEN CWT AND SLR** NON – PARAMETRIC AND PARAMETRIC

![](_page_17_Figure_1.jpeg)

### **CWT-BASED DETECTION**

- Detection of FHSS signal performed based on CWT
- A rough estimate of the hop time, dwell time, duty cycle and hopping pattern duration are provided

### **SLR-BASED RF LINK CHARACTERIZATION**

- Initialize using coarse bandwidth CWT estimate
- **)** Fine estimation of signal parameters

![](_page_17_Picture_8.jpeg)

## **SLR-BASED FHSS PARAMETER ESTIMATION** SPARSE LINEAR REGRESSION

### **SPARSE LINEAR REGRESSION\***

- A sparse representation of Time-Frequency distribution (TFD) is estimated from the time samples
- )  $\theta$  represents samples of the TFD of the signal
- ) First term is a standard data matching least squares

$$\widehat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \|\mathbf{Y}_{K} - \mathbf{M}\boldsymbol{\theta}\|_{F} - \lambda_{1} \|\boldsymbol{\theta}\|_{1} - \lambda_{2} \|\mathbf{D}\boldsymbol{\theta}\|_{1}$$

\* D. Angelosante, G. B. Giannakis and N. D. Sidiropoulos, "Estimating multiple frequency-hopping signal parameters via sparse linear regression," *IEEE Trans. Signal Process.*, vol. 58, no. 10, pp. 5044-5056 (2010).

![](_page_18_Picture_8.jpeg)

## **SLR-BASED FHSS PARAMETER ESTIMATION** SPARSE LINEAR REGRESSION

## **SPARSE LINEAR REGRESSION\***

- A sparse representation of TFD is estimated from the time samples
- **θ** represents samples of the Time-Frequency distribution (TFD) of the signal
- ) First term is a standard data matching least squares
- ) Sparsity in frequency is controlled by  $\lambda_1$

$$\widehat{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \|\boldsymbol{Y}_{K} - \boldsymbol{M}\boldsymbol{\theta}\|_{F} - \lambda_{1} \|\boldsymbol{\theta}\|_{1} - \lambda_{2} \|\boldsymbol{D}\boldsymbol{\theta}\|_{1}$$

![](_page_19_Figure_7.jpeg)

\* D. Angelosante, G. B. Giannakis and N. D. Sidiropoulos, "Estimating multiple frequency-hopping signal parameters via sparse linear regression," *IEEE Trans. Signal Process.*, vol. 58, no. 10, pp. 5044-5056 (2010).

![](_page_19_Picture_9.jpeg)

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## **SLR-BASED FHSS PARAMETER ESTIMATION** SPARSE LINEAR REGRESSION

## **SPARSE LINEAR REGRESSION\***

- A sparse representation of TFD is estimated from the time samples
- θ represents samples of the Time-Frequency distribution (TFD) of the signal
- ) First term is a standard data matching least squares
- ) Sparsity in frequency is controlled by  $\lambda_1$
- ) Sparsity (of transitions) in time is controlled by  $\lambda_2$

$$\widehat{\mathbf{\Theta}} = \arg\min_{\mathbf{\Theta}} \|\mathbf{Y}_{K} - \mathbf{M}\mathbf{\Theta}\|_{F} - \lambda_{1} \|\mathbf{\Theta}\|_{1} - \lambda_{2} \|\mathbf{D}\mathbf{\Theta}\|_{1}$$

![](_page_20_Figure_8.jpeg)

\* D. Angelosante, G. B. Giannakis and N. D. Sidiropoulos, "Estimating multiple frequency-hopping signal parameters via sparse linear regression," *IEEE Trans. Signal Process.*, vol. 58, no. 10, pp. 5044-5056 (2010).

![](_page_20_Picture_10.jpeg)

**TNO** innovation 21

# **SLR-BASED FHSS PARAMETER ESTIMATION** RESULTS

## **SCENARIO**

- ) Single hop from FHSS sequence
- ) SNR 20 dB

## DISCUSSION

- Super resolution time-frequency estimate can be obtained based on SLR
- > Resolution vs processing trade-off

![](_page_21_Figure_7.jpeg)

![](_page_21_Picture_8.jpeg)

# **SLR-BASED FHSS PARAMETER ESTIMATION** RESULTS

## **SCENARIO**

- ) Single hop from FHSS sequence
- ) SNR 20 dB

## DISCUSSION

- Super resolution time-frequency estimate can be obtained based on SLR
- > Resolution vs processing trade-off

![](_page_22_Figure_7.jpeg)

![](_page_22_Picture_8.jpeg)

# **CHALLENGES IMPLEMENTING SLR** BIG DATA VOLUME

### **SPARSE LINEAR REGRESSION**

- ) The data matrix  $\mathbf{Y}_{K}$  is constructed by full over-segmentation of the data
  - The sampling rate is relatively high (hundreds of MHz)
  - Large system of equations must be solved (at each iteration)
- ) Both the mixing matrix **M**, and the unknown vector  $\boldsymbol{\theta}$  are (block) sparse
  - MinresQLP as a candidate Krylov subspace based solver is used
  - Operations involving the matrices M and D are implemented as subroutines (to avoid large memory requirements)
- Results from detection methods are used to reduce data volume

Processing time ~10 minutes for N = 13000 samples on a typical laptop (e.g. Pentium i7 with 12GB memory).

![](_page_23_Figure_10.jpeg)

![](_page_23_Picture_12.jpeg)

## **SUMMARY** DETECTION AND FHSS PARAMETER ESTIMATION

![](_page_24_Figure_1.jpeg)

![](_page_24_Picture_2.jpeg)

![](_page_24_Picture_3.jpeg)

![](_page_24_Figure_4.jpeg)

![](_page_24_Picture_5.jpeg)

![](_page_24_Picture_6.jpeg)

- Detection and classification
  - Demonstrate machine Learning based detection and classification of multiple signal types in simulation environment
- ) Counter Measures
  - Jamming selective in time and frequency with low transmit power
  - > Demonstrate feasibility and effectiveness of selective jamming in lab environment
- ) Multiple targets and harsh transmission environments
  - > Exploiting spectral diversity
  - Source separation (e.g. based on direction finding)

# ACKNOWLEDGEMENTS

) Joint counter UAS knowledge build-up program financed by the Netherlands Ministry of Defence and the National Police

![](_page_26_Picture_2.jpeg)

Ministerie van Defensie

![](_page_26_Picture_4.jpeg)

![](_page_26_Picture_5.jpeg)