Faculty of Engineering – Australian Center for Space Engineering Research

Blind Sea Clutter Suppression for Spaceborne GNSS-R Target Detection

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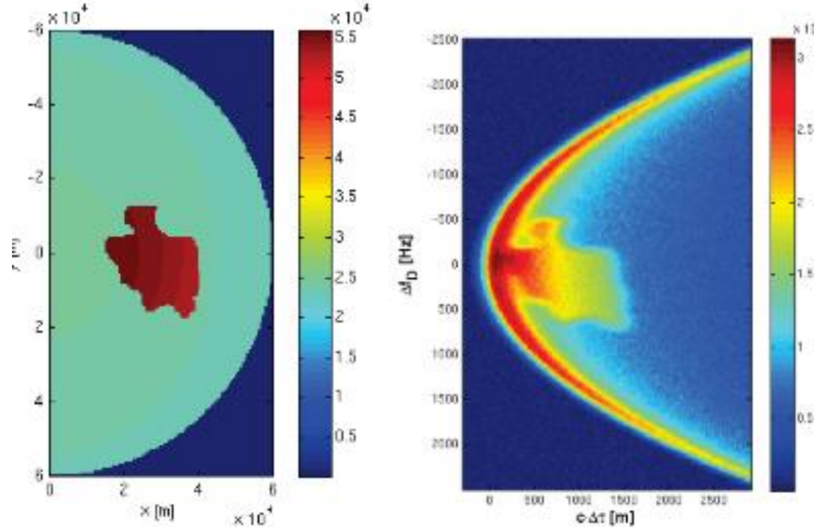
SNAP Lab

Problem Statement

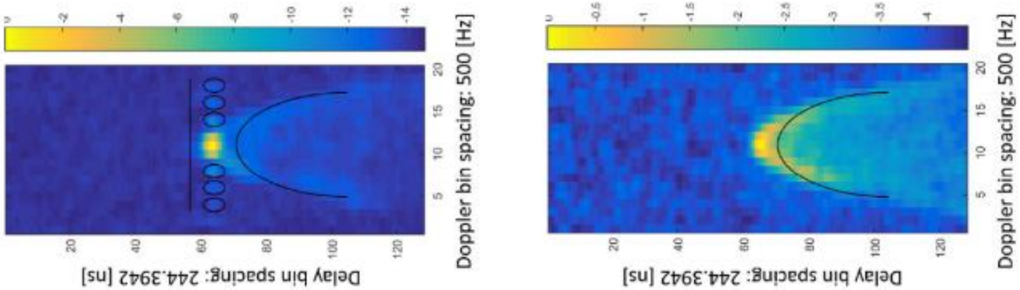
Aim

- We want to be able to detect fluctuations in the received signals via GNSS-R to identify sea targets such as
  - Ships
  - Oil Slick
  - Sea ice



Problem

- There is a very significant signal response from the sea clutter



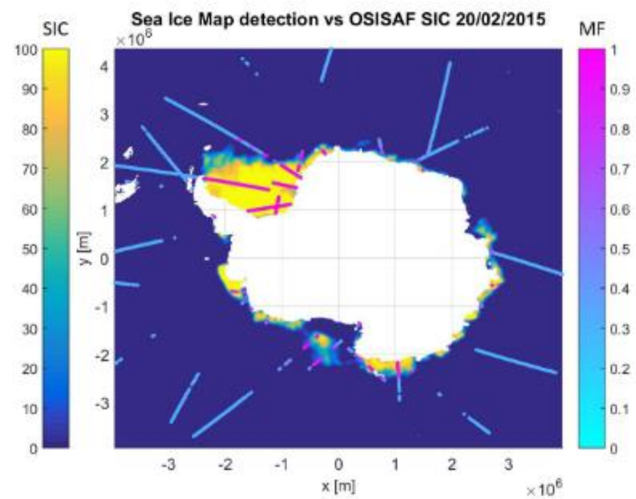


Image Credit: E. Valencia, A. Camps, H. Park, N. Rodriguez-Alvarez, X. Bosch-Lluis, and I. Ramos-Perez, “Oil slicks detection using GNSS-R,” Int. Geosci. Remote Sens. Symp., vol. 2, no. 1, pp. 4383–4386, 2011.

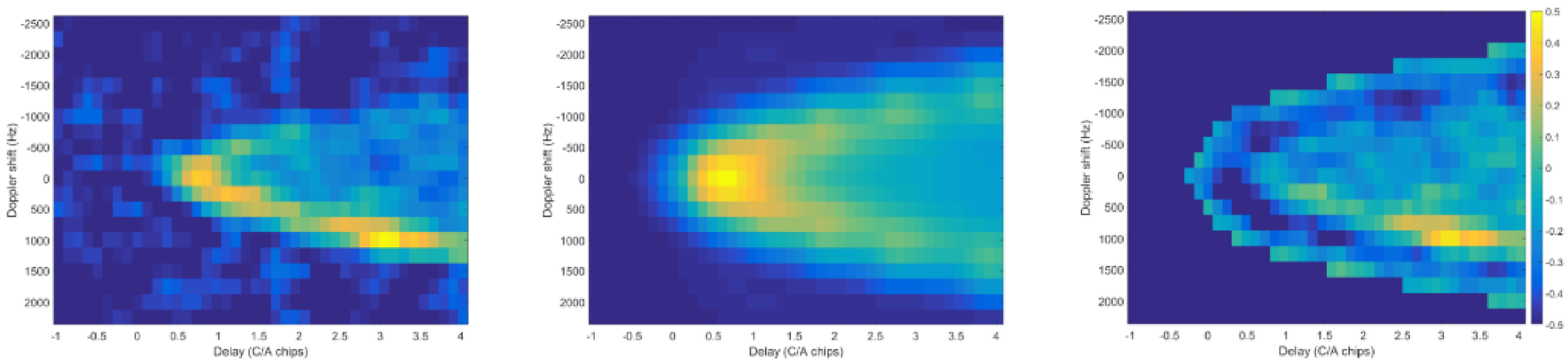
Image Credit: A. Alonso-arroyo, S. Member, V. U. Zavorotny, and A. Camps, “Sea Ice Detection Using U . K . TDS-1 GNSS-R Data,” vol. 55, no. 9, pp. 4989–5001, 2017.

Conventional Sea Clutter Modelling

Conventional sea clutter models uses the Zavorotny - Voronovich model *

$$\overline{|Y(\tau,\omega_D)|^2_{nc}} = \frac{P_{tr}}{4\pi} \int\int \frac{|D_{tr}(\vec{m}_\perp,\omega_0)D_{rec}(\vec{n}_\perp,\omega_0)|^2}{R_0^2 R^2} \times \langle|\chi(\delta\tau,\delta\omega,\beta)|^2\rangle \sigma_0(\vec{n}_\perp,\vec{m}_\perp;\omega_0)\,d\vec{\rho}.$$

- We can subtract the expected sea clutter DDM from received DDM the using ZV model
- Assumption: we have the true values of **sea wind speed** and **sea wind direction.** If this assumption is violated, unwanted artefacts will be embedded in the DDM
- A clean subtraction can reveal any component that are not due to sea clutter



* A. G. Voronovich and V. U. Zavorotny, "Bistatic radar equation for signals of opportunity revisited," IEEE Trans. Geosci. Remote Sens., vol. 56, no. 4, pp. 1959–1968, 2018

Image Credit: A. Di Simone, A. Iodice, D. Riccio, A. Camps, and H. Park, "GNSS-R: A useful tool for sea target detection in near real-Time," RTSI 2017 - IEEE 3rd Int. Forum Res. Technol. Soc. Ind. Conf. Proc., 2017.

Delay Doppler Map Dataset

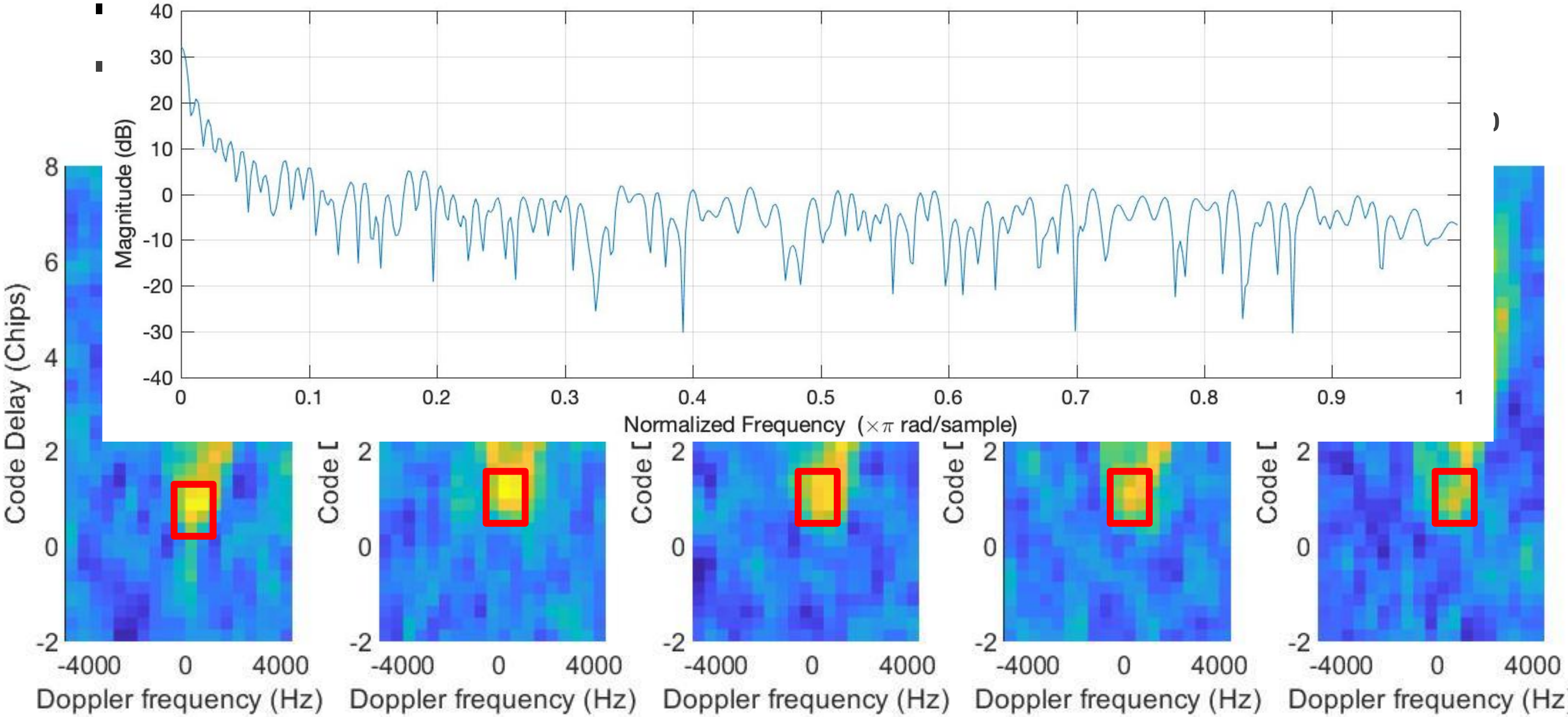
- DDM dataset: TDS-1 (3/12/2017) – H18 Group 35 indices 470 - 699
- DDMs normalisation

$$\zeta_{\bar{\tau},\bar{f}_D}[n] = \frac{\left|Y\left(\bar{\tau},\bar{f}_D,t\right)\right|^2_{t=nT}}{\tilde{P}_N} - 1$$

- AR analysis needs to have temporal detrending applied to the DDM dataset

Sea Clutter DDMs: A slow varying process

- The following time series of DDMs show how correlated the sea clutter components are to each other once we have properly normalised it.
  - First Fresnel Zone resp.: High Amplitude. Slow varying from epoch to epoch. Possible that signal DDM cells has temporal correlation



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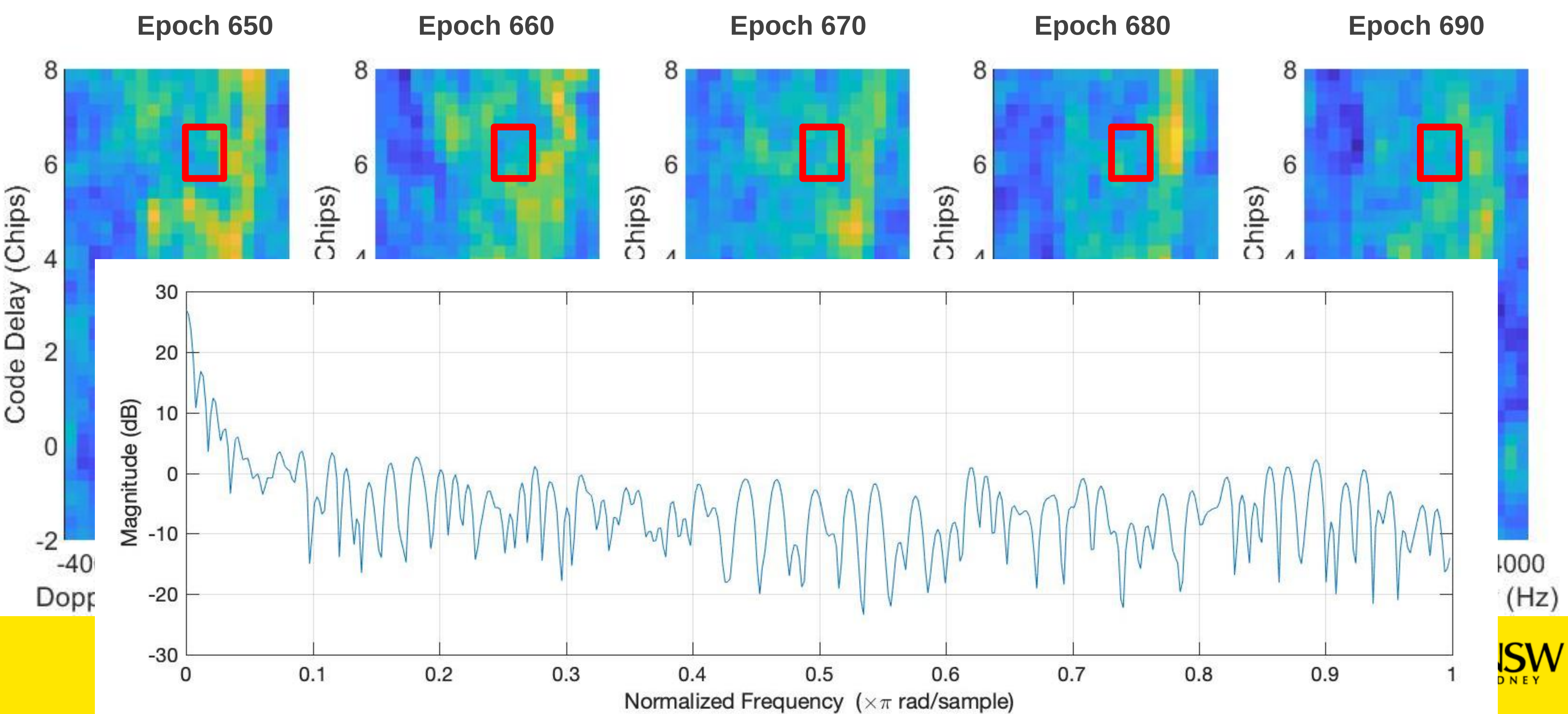
  - Large τ resp.: Lower Amplitude and faster varying.
  - Noise resp.: Low amplitude and fast varying.



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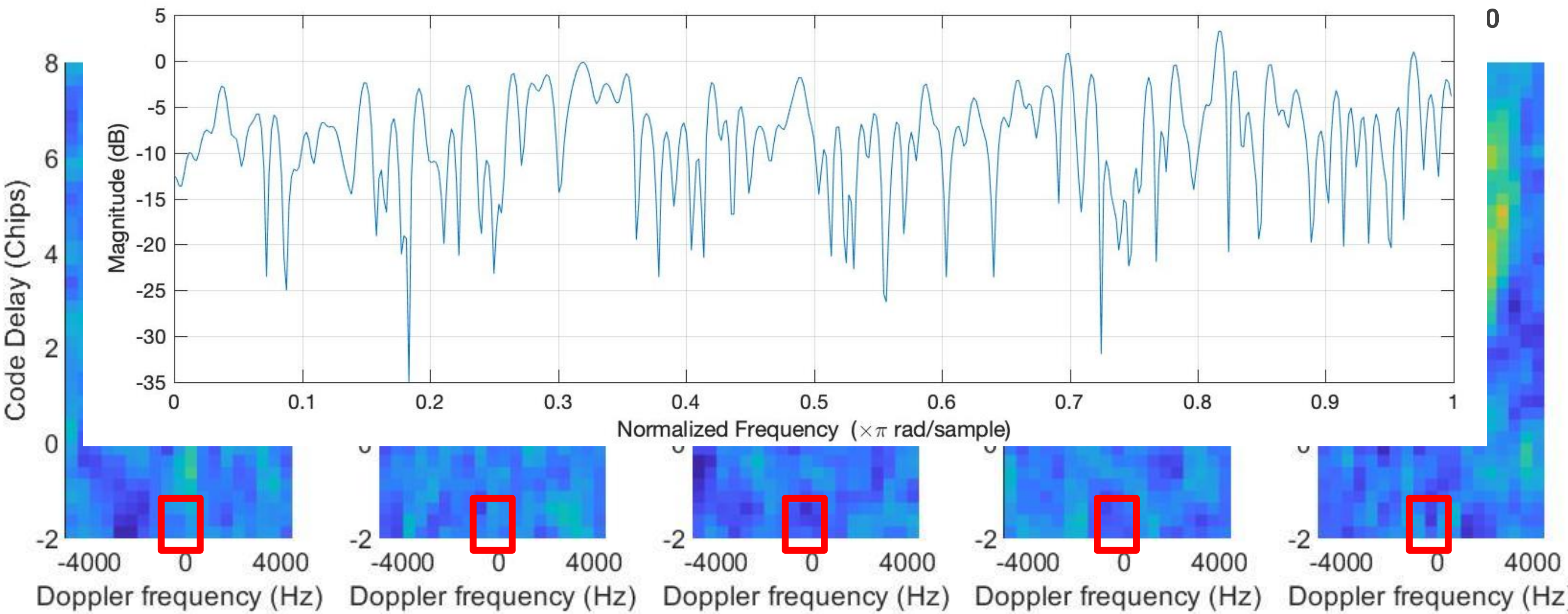
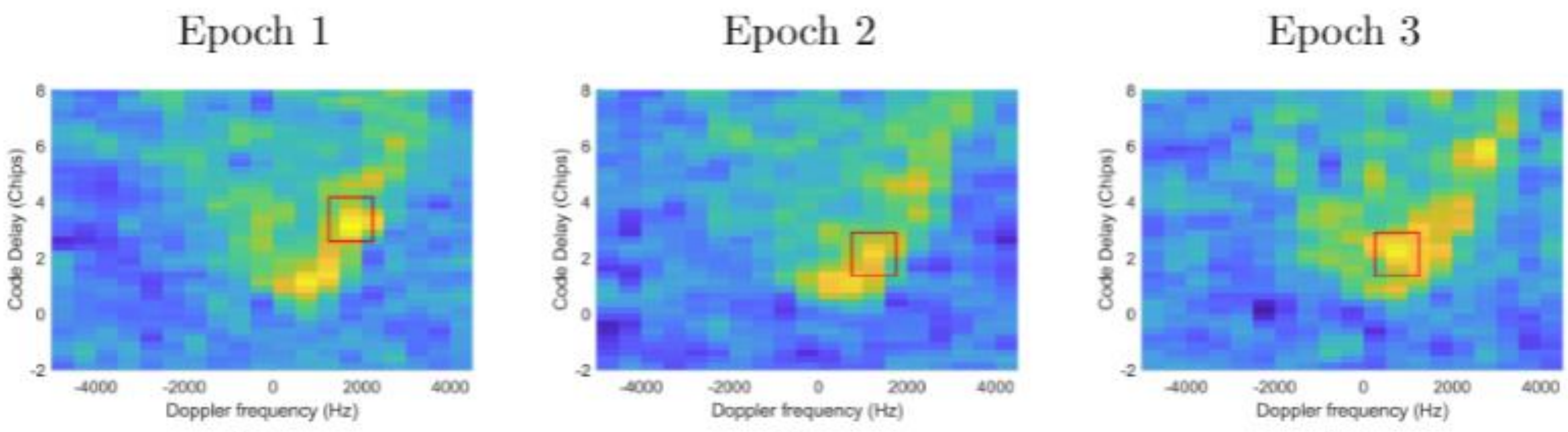
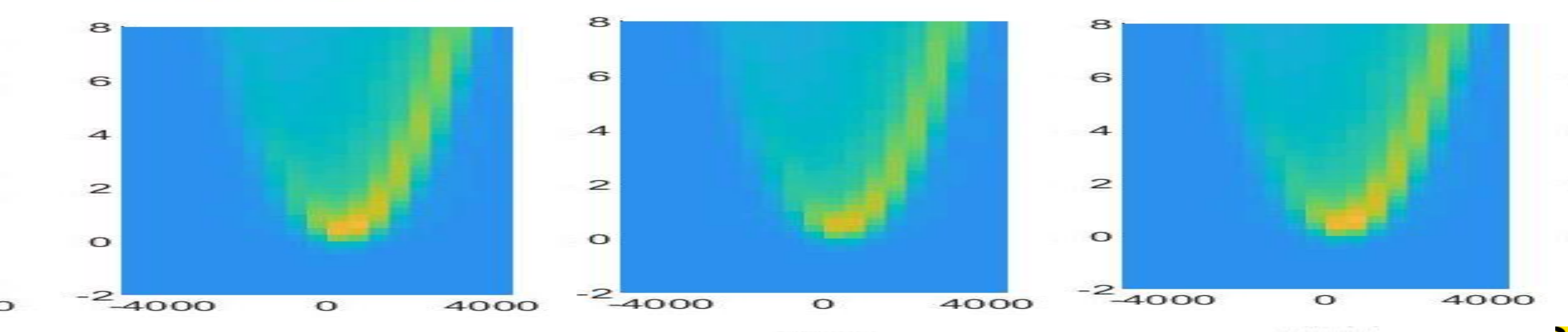


Conventional: Sea Clutter Model Subtraction

$$\overline{|Y(\tau,\omega_D)|^2_{nc}} = \frac{P_{\rm tr}}{4\pi}\int\int \frac{|D_{\rm tr}(\vec{m}_\perp,\omega_0)D_{\rm rec}(\vec{n}_\perp,\omega_0)|^2}{R_0^2R^2} \times\langle|\chi(\delta\tau,\delta\omega,\beta)|^2\rangle\sigma_0(\vec{n}_\perp,\vec{m}_\perp;\omega_0)d\vec{\rho}.$$



Raw DDM – Red box indicating a target entering the DDM from top right



Modelled Sea Clutter

Conventional: Sea Clutter Model Subtraction

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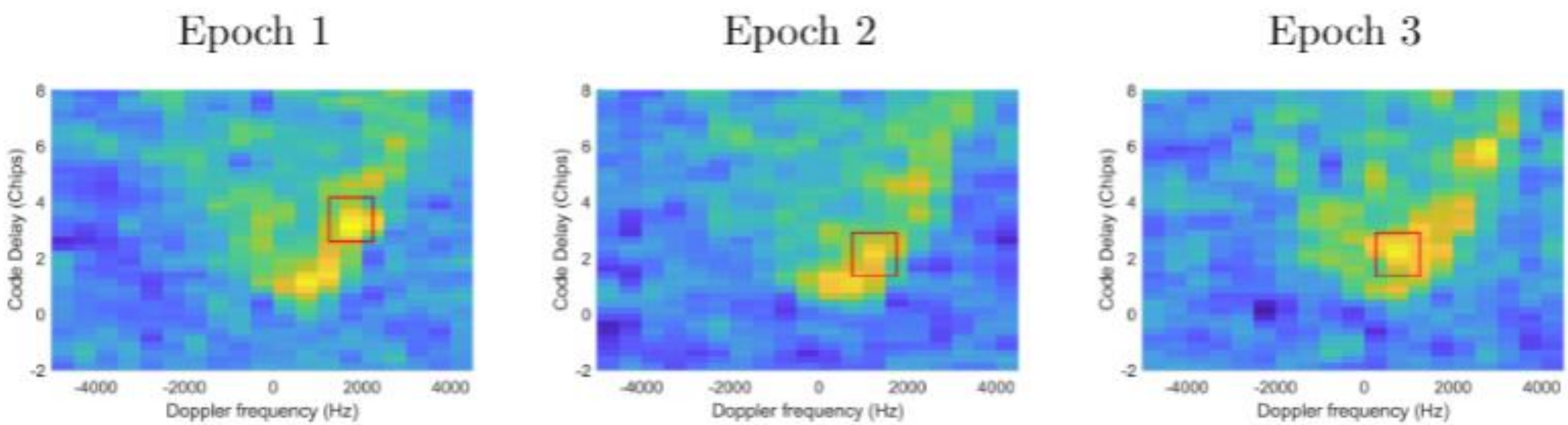
$$\times\langle|\chi(\delta\tau,\delta\omega,\beta)|^2\rangle\sigma_0(\vec{n}_\perp,\vec{m}_\perp;\omega_0)d\vec{\rho}.$$



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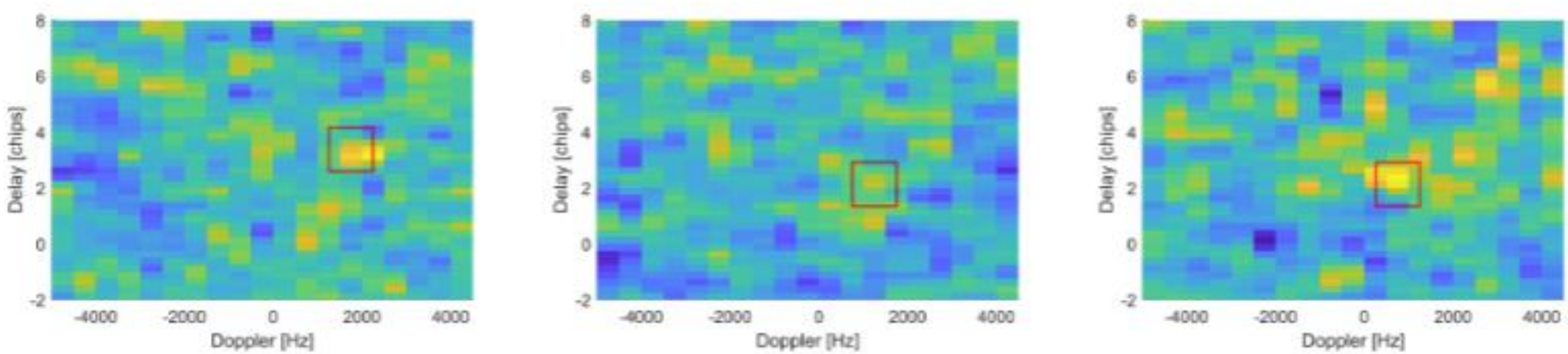
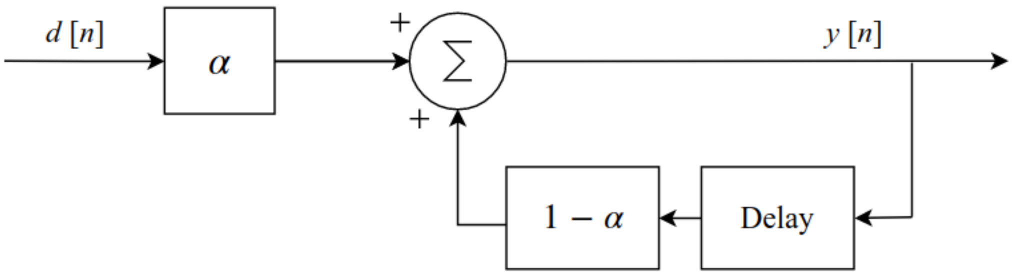
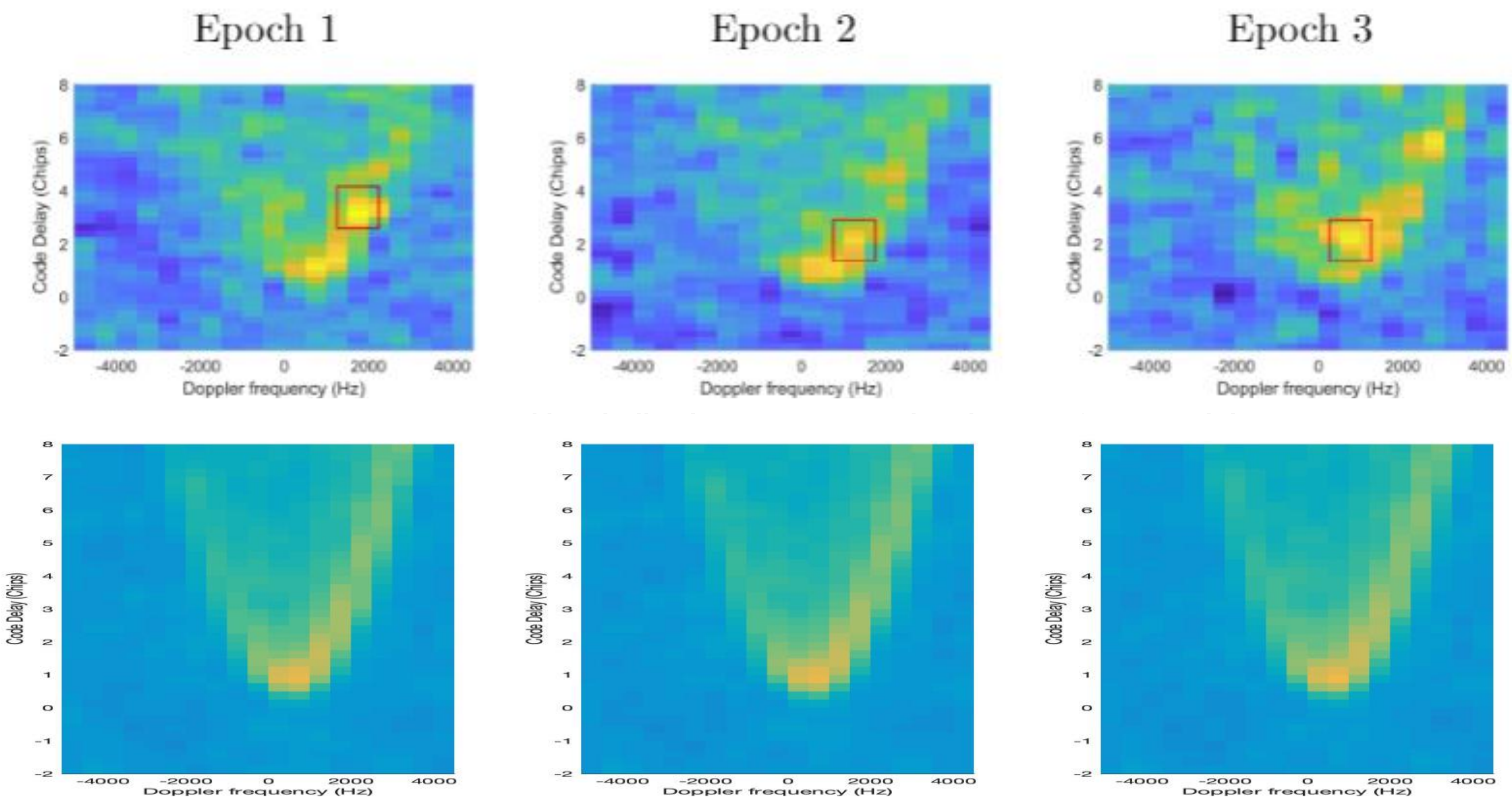


Sea Clutter Model Subtraction

Proposed:
Low Pass Filter

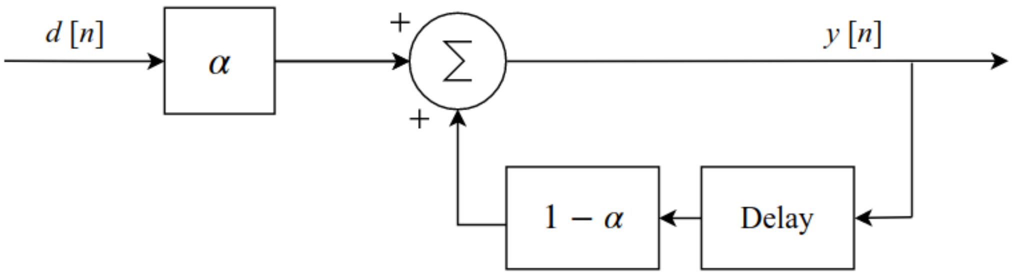


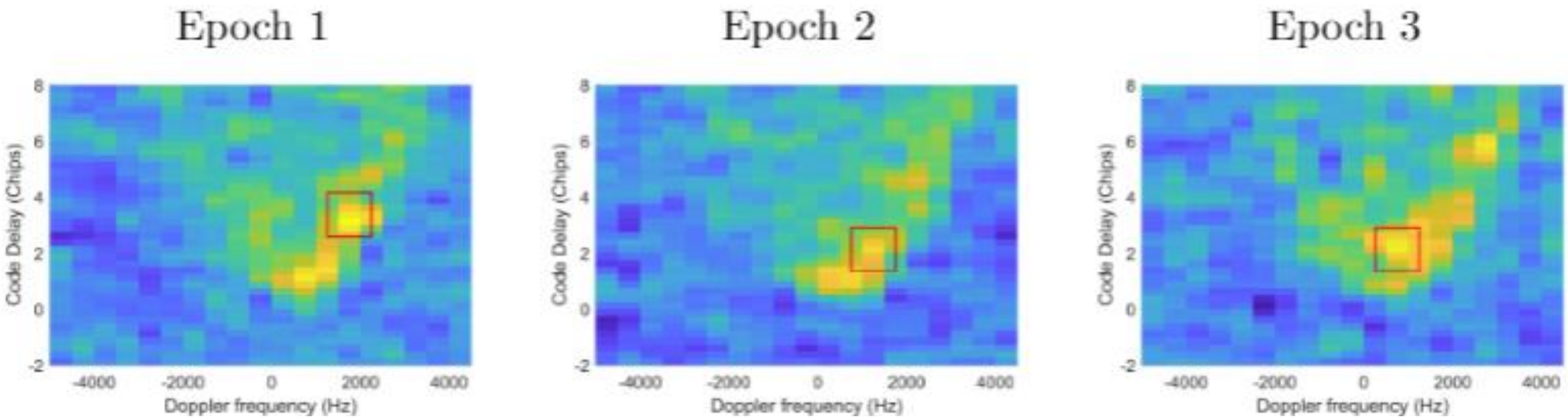


Modelled Sea Clutter using LPF using a = 0.05

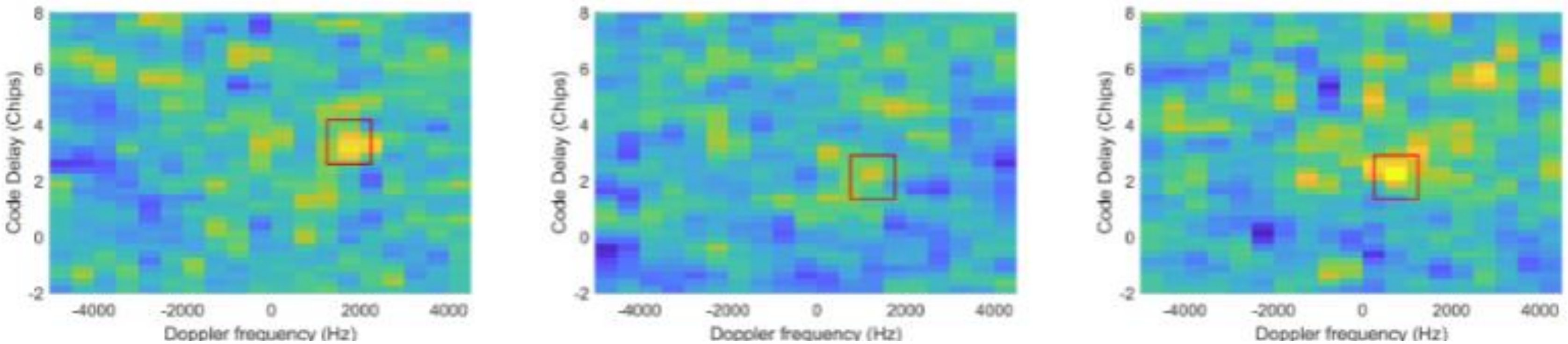
Credit: http://e-rokodelnica.si/A003/A003_EN.html

Proposed: Low Pass Filter





Raw DDM – Red box indicating a target entering the DDM from top right



Lowpass filtered using a = 0.05

AutoRegressive (AR) Analysis: Methodology

Autoregressive (AR) Model

- Signal at epoch *m* can be expressed as a linear combination of signals at previous epochs *m - k*

$$\gamma_m = \sum_{k=1}^{p} \varphi_k \gamma_{m-k}$$

Partial Auto-Correlation Function (PACF)

- PACF solves the Yule-Walker equations to obtain the AR coefficients φ_p for *p* ranging from *0* to L_{max}

$$\begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \vdots \\ \gamma_p \end{bmatrix} = \begin{bmatrix} \gamma_0 & \gamma_{-1} & \gamma_{-2} & \cdots \\ \gamma_1 & \gamma_0 & \gamma_{-1} & \cdots \\ \gamma_2 & \gamma_1 & \gamma_0 & \cdots \\ \vdots & \vdots & \vdots & \ddots \\ \gamma_{p-1} & \gamma_{p-2} & \gamma_{p-3} & \cdots \end{bmatrix} \begin{bmatrix} \varphi_1 \\ \varphi_2 \\ \varphi_3 \\ \vdots \\ \varphi_p \end{bmatrix}$$

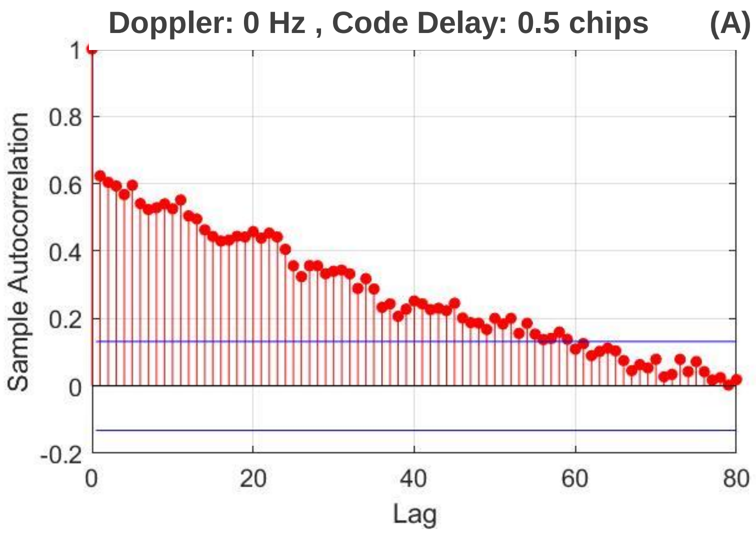
Auto-Correlation Function

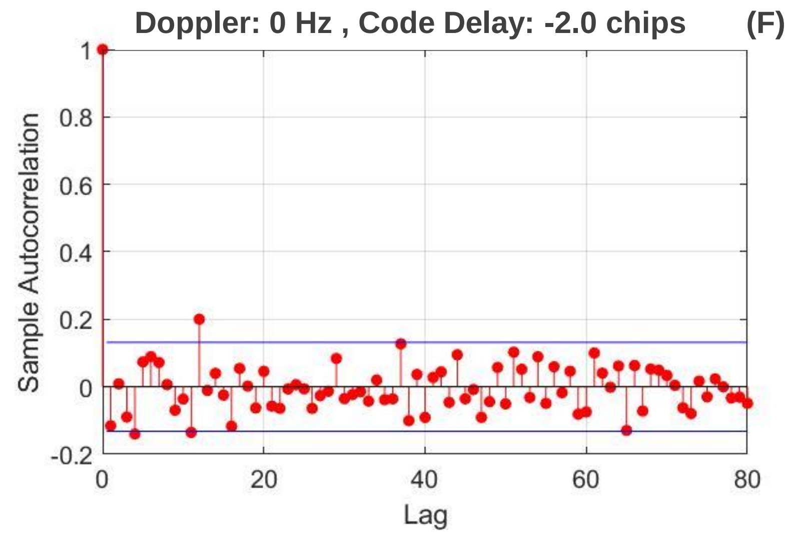
- ACF is the correlation of a signal with a delayed copy of itself
- It's a measure of similarity of γ_m with delayed versions of itself

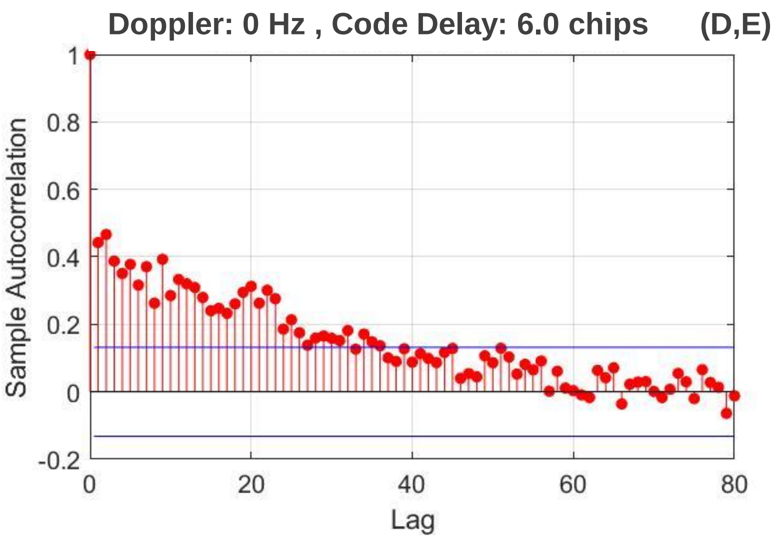
$$r_p = \sum_{k=0}^{N} \gamma_k \gamma_{k+p}^{*}$$

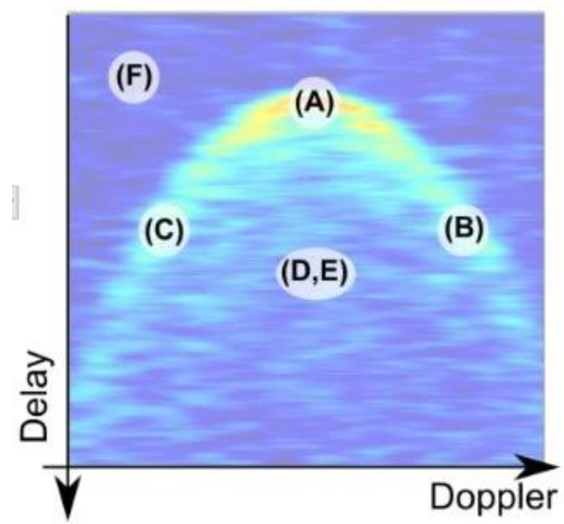
- If the PACF order (max. length) is much shorter than the ACF order (max. length), the process is considered highly autoregressive.

Auto Correlation Function (ACF)

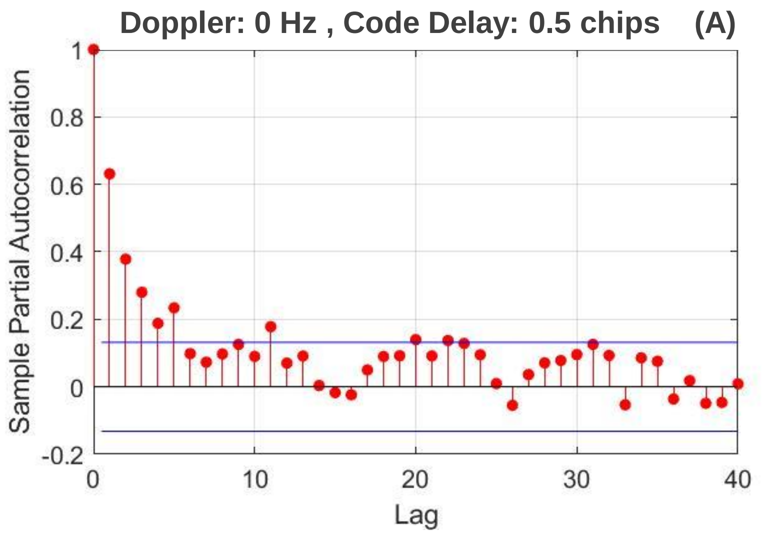


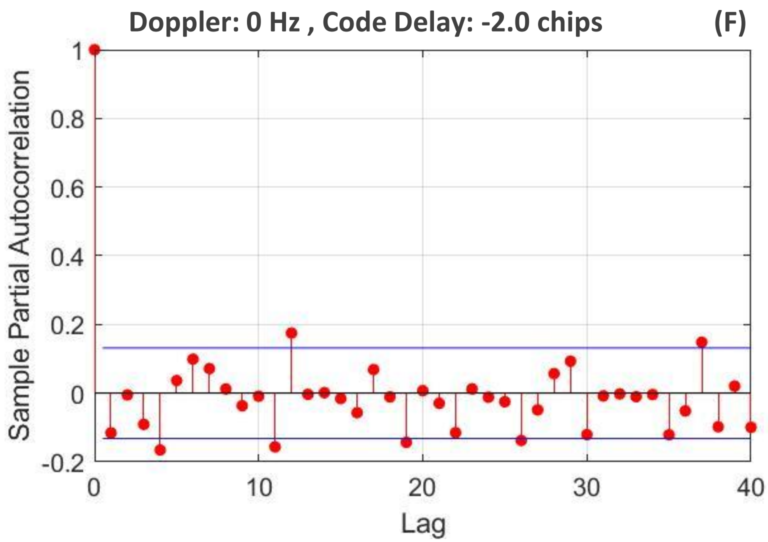


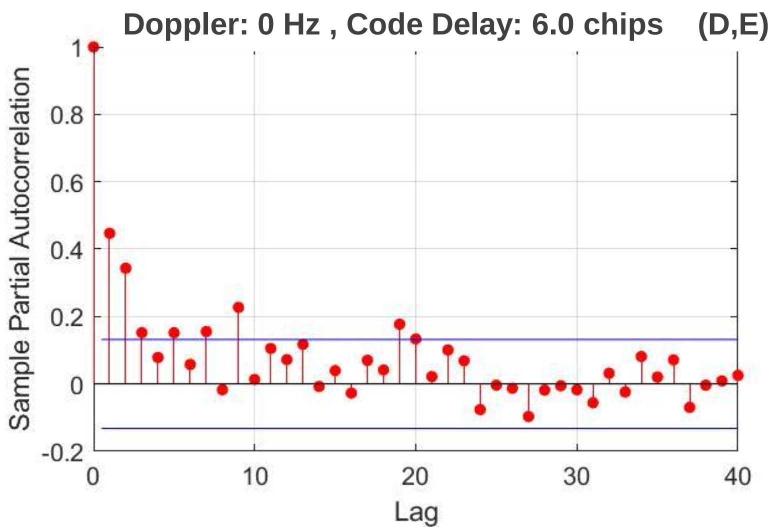


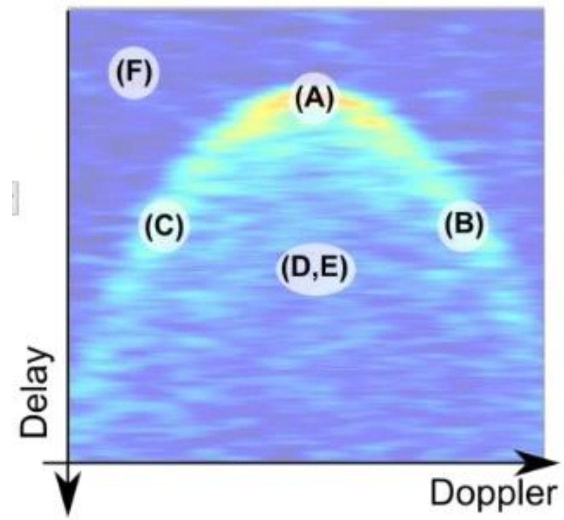


Partial Auto Correlation Function (PACF)



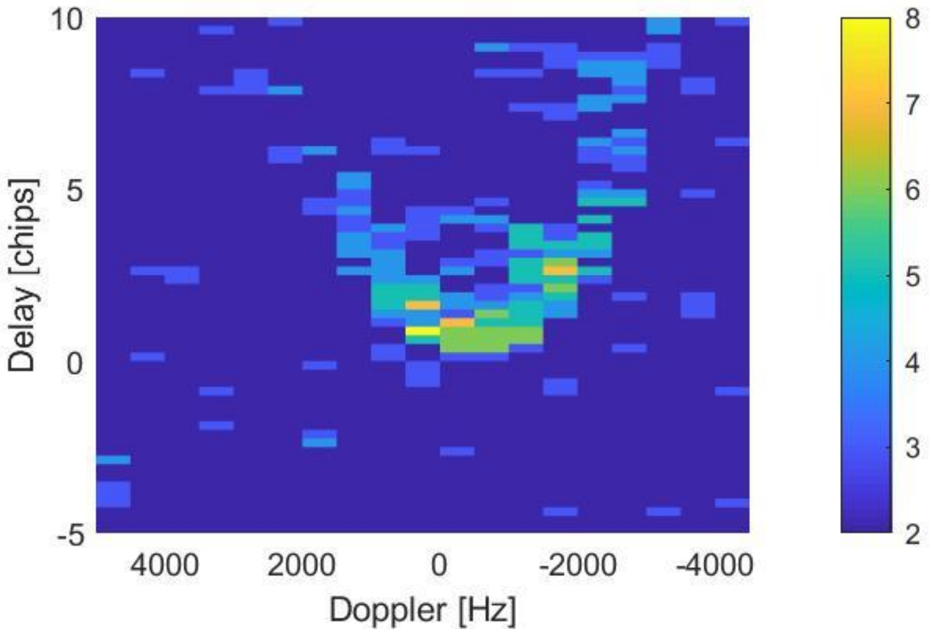


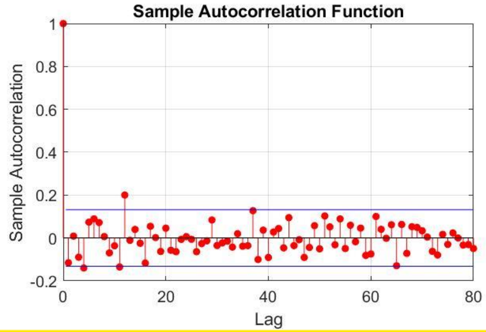




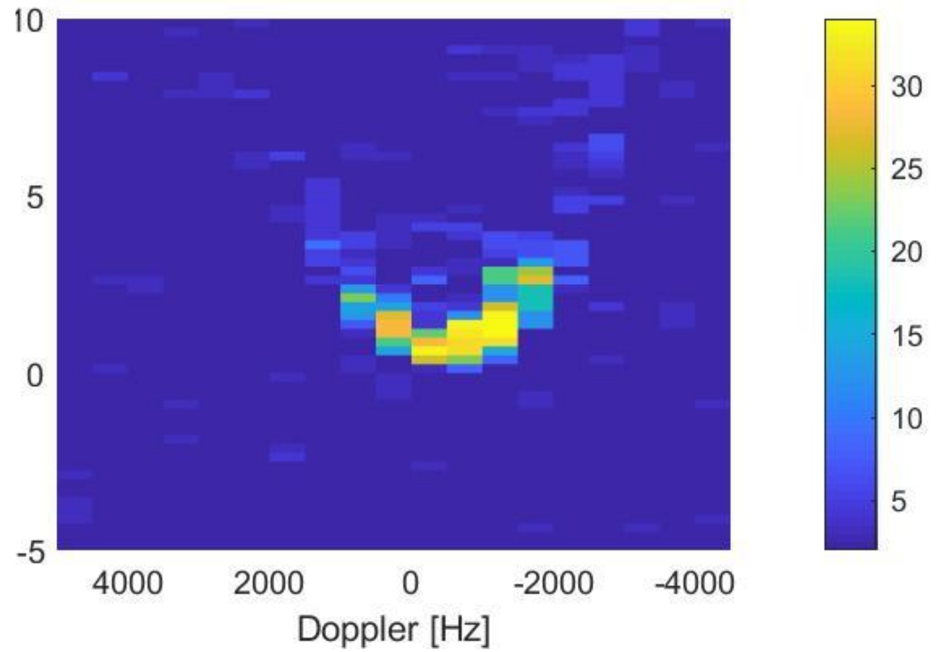
AutoRegressive (AR) Analysis: Max. Lag

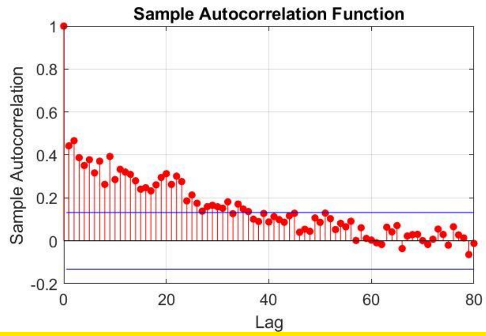
PACF



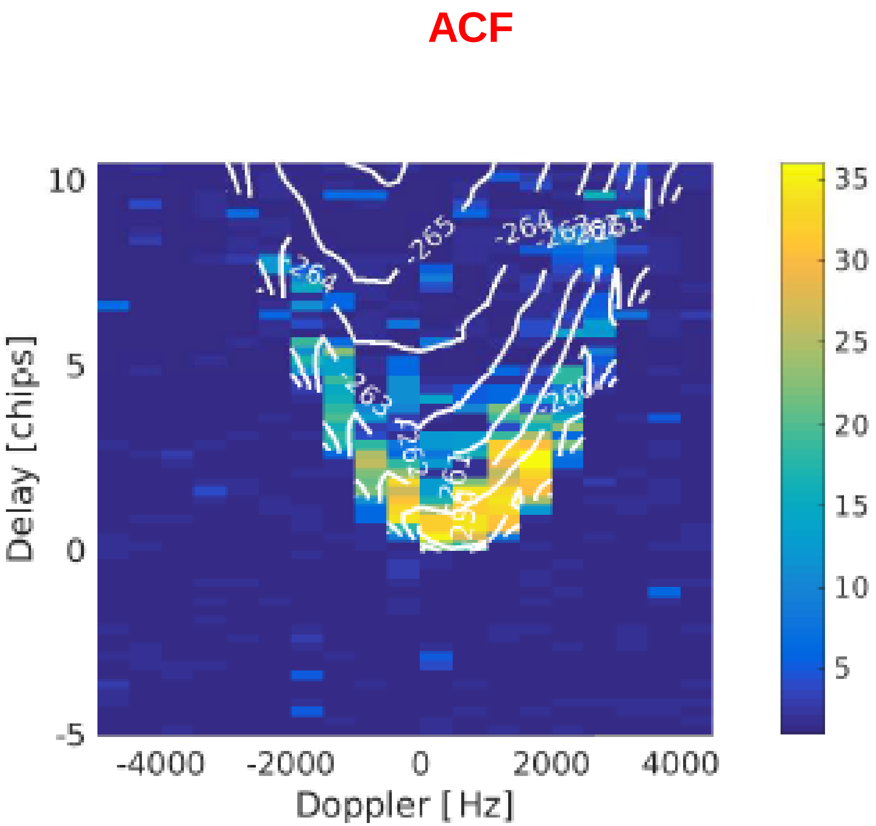


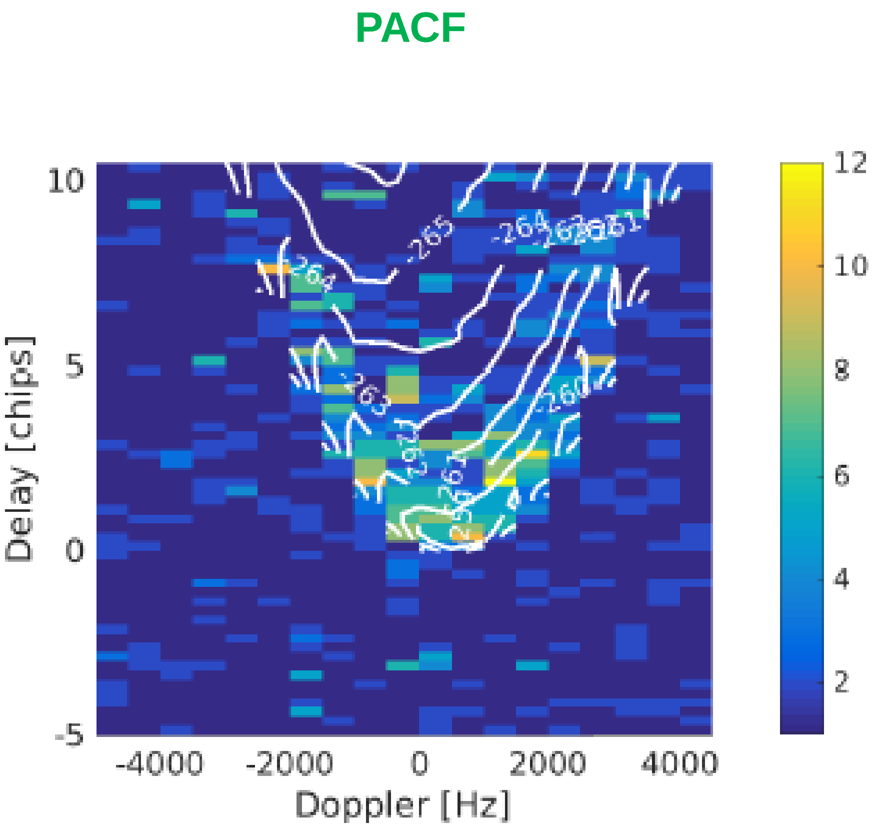
ACF





System Gain vs. Max. Lag





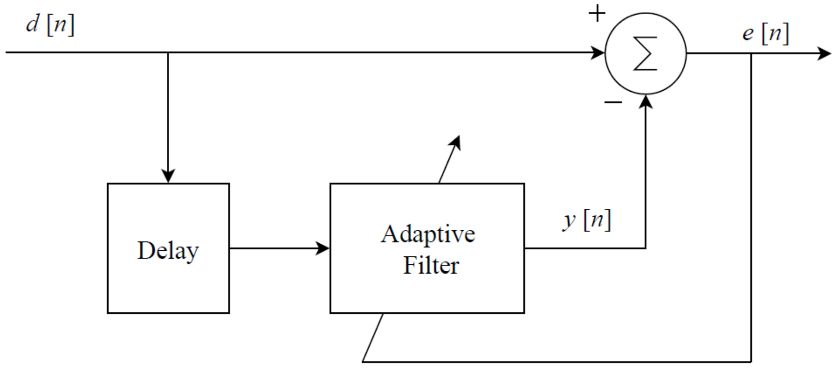
We need to have a <u>variable filter order</u> across the various Delay and Doppler bin for 'matched filtering'

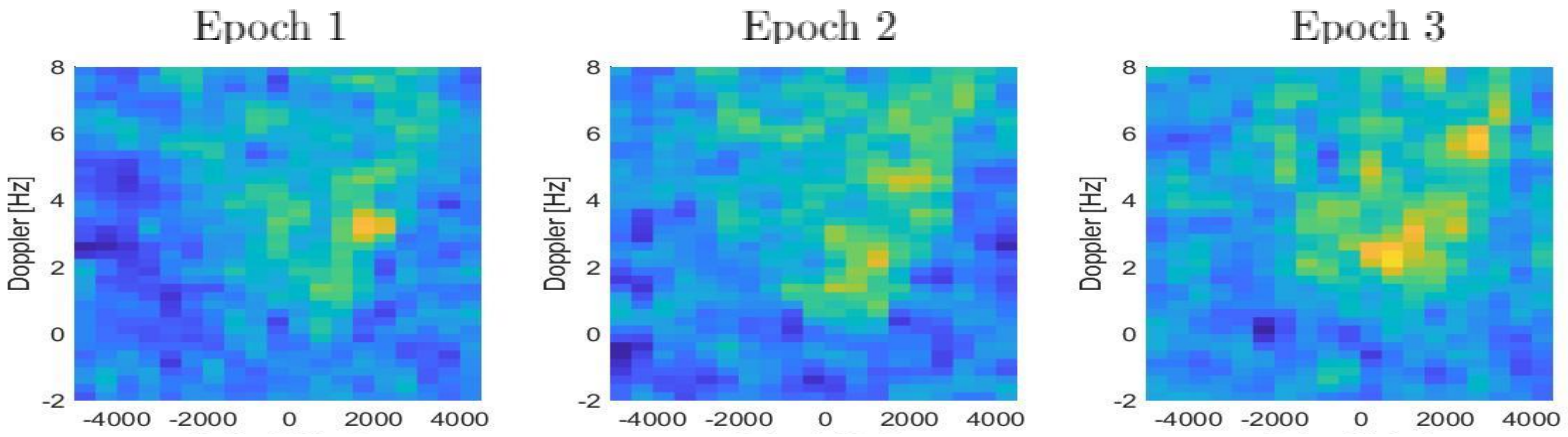
Whitening DDM using Adaptive Filters

$$y[n] = \sum_{k=1}^{M} w_k z^{-1} d[n-k]$$

$$\boldsymbol{W} = [w_1, w_2, \ldots w_M]^T$$

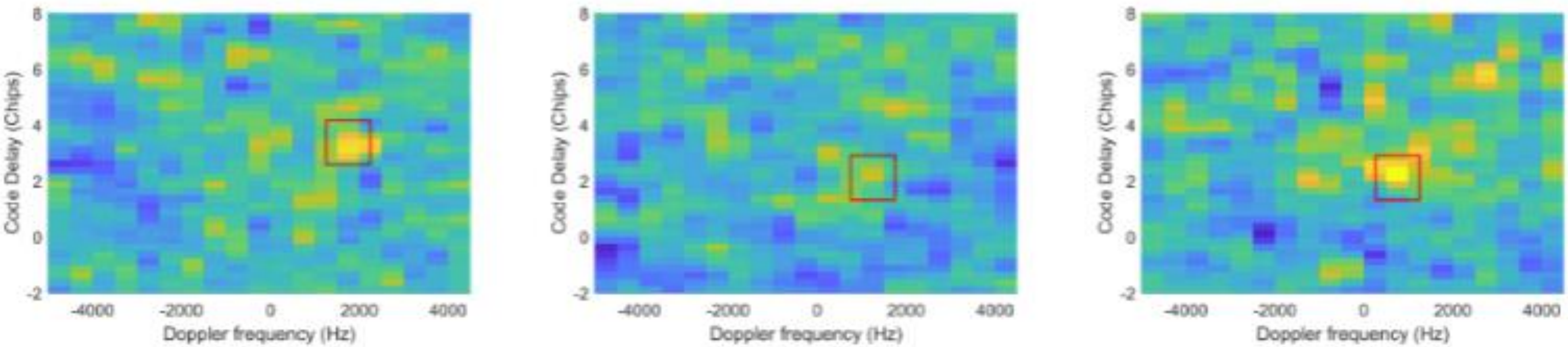
- Equations for updating ***W*** comes from solving the Yule-Walker equations via Least Mean Squares



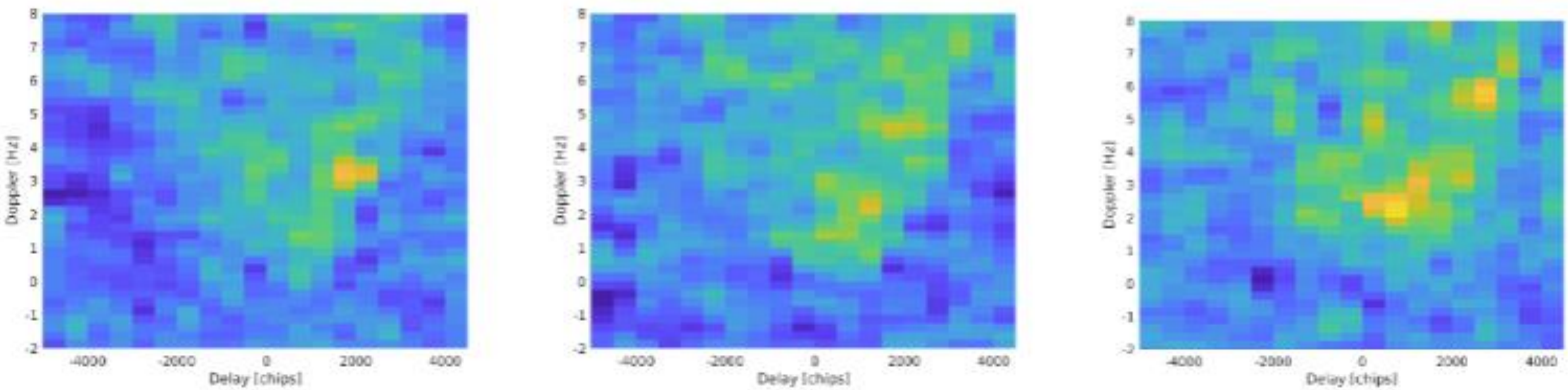


Adaptively Filtered DDMs – target is very visible

LPF vs. Adaptive Filtering: Improved Sea Clutter Suppression



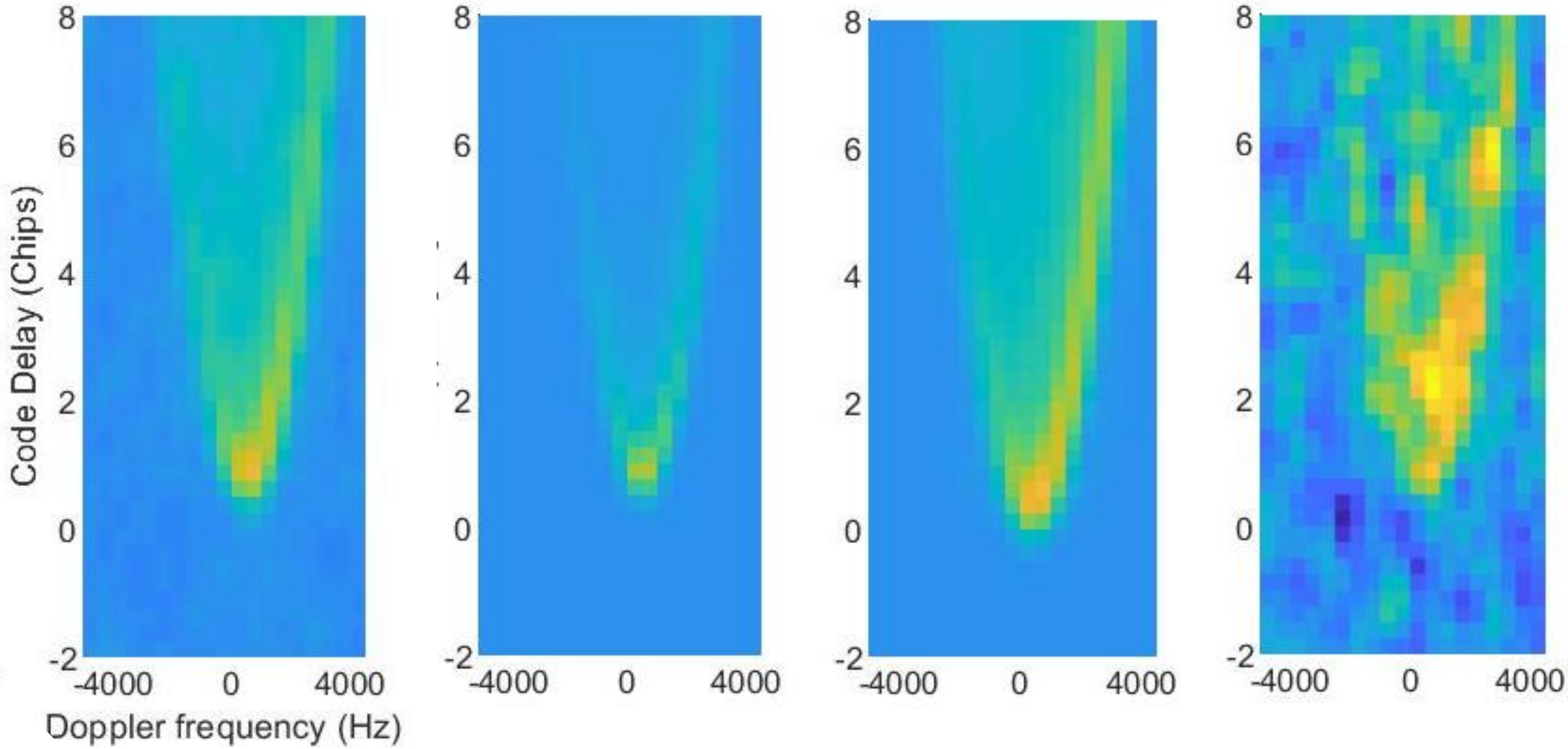
Low Pass Filtered DDMs – target in red boxes is less visible



Adaptively Filtered DDMs – target is much more visible

LPF vs. Adaptive Filtering: Improved Sea Clutter Model

Sea Clutter modelled from LPF | Sea Clutter Modelled from Adaptive Filter | Sea Clutter Modelled from ZV LS fit | Raw DDM



Conclusion

Method 1: **<u>Stationary Low Pass Filter</u>,** Method 2: **<u>Adaptive Filter</u>**

- We have shown empirical evidence from TDS-1 dataset that both methods work.
- We have shown that the adaptive filter is able to autonomously adjust its filter coefficients to minimise temporal correlation and be effective to suppress sea clutter
- Two sea clutter suppression methods employed in this paper are blind methods, hence the estimation or a priori knowledge of wind speed and wind direction is not required.
- No application of arbitrary morphological filters is needed for target detection
- The low computational effort for adaptive filter permits on-board processing. Can also be implemented using FPGAs.

Applications

- Enhanced Sensitivity to Target Detection
- Improved Sea State Estimation
- Findings useful for derivation of on-board DDM Compression for downlinking to the ground.