

Thesis review

High performance satellite AIS and Radar data fusion for maritime surveillance

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**TESA / ISAE / ENSEEIHT
THALES ALENIA SPACE / OMNISYS**

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Agenda

- Introduction
 - Overview
 - Generalities AIS
 - Generalities BFR radar
 - Motivation
 - Thesis subject
- The four research topics
 - Simulator description
 - Description of 1st research topic
 - Description of 2nd research topic
- Conclusions
- Next steps

Introduction

□ Why maritime surveillance?

- Safety and security of navigation in general
- Application of regulation to protect the marine environment
- Fishery control
- Fight against trafficking and illegal immigration

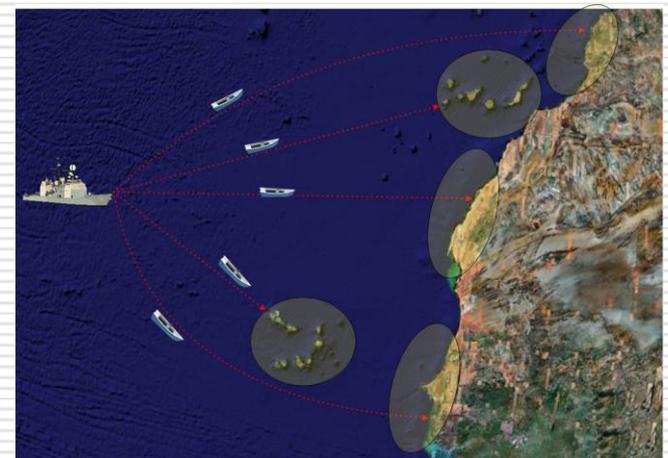
Sea safety



Pollution



Illicit traffic

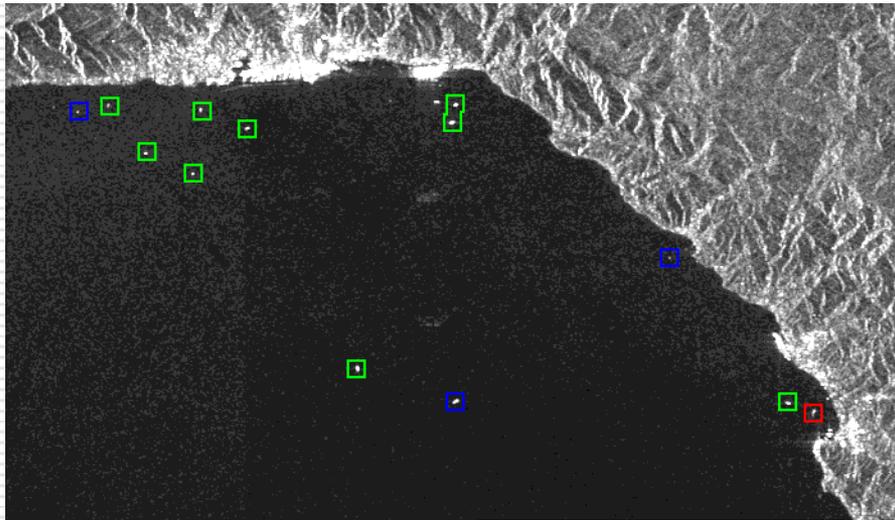


Illegal Fishing



Introduction

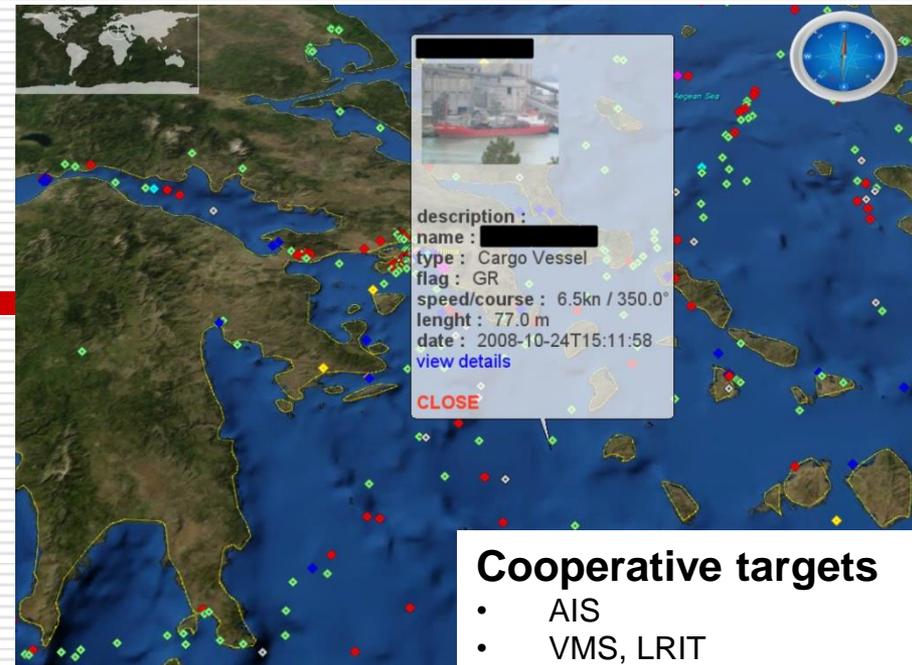
- Desirable characteristics
 - It must deal with the surveillance scenario diversity



Thales Alenia Space

Non-cooperative targets

- Coastal / Boat / Airborne Radar
- Spaceborne Radar & Optical
- Vessel RF emission detection



Cooperative targets

- AIS
- VMS, LRIT
- ARGOS

- Cover both cooperative and non-cooperative targets
- High availability
- Global coverage

Overview

- A constellation of satellites with embedded vessel detection sensors was proposed to monitor ship activity on sea
- Two sensors
 - AIS – Automatic Identification System
 - SAR - Synthetic Aperture Radar

AIS receiver

- ❑ Decodes AIS transmissions containing ID, position, heading, size, speed, etc.
- ❑ Vessels cooperatively broadcast AIS messages at regular times following the AIS protocol specification
- ❑ Covers large areas
- ❑ Susceptible to message errors and intentional deception

SAR sensors

- Characteristics of Synthetic Aperture Radar (SAR) sensors
 - Operational duty cycle limited to 10/20%
 - Limited swath and accessibility
 - Not dedicated to perform ship detection mission in maritime surveillance
- Poor operational availability and limited area coverage regarding maritime surveillance needs

BFR radar

- ❑ The BFR radar is a SAR at a high incidence angle and a low PRF - pulse repetition frequency
- ❑ Broadens the radar coverage at the expense of adding ambiguities

Ambiguities

- Problematic for radar imaging
- Can be managed when image quality is not a constraint (detection)

Low grazing angle

- Less radar clutter from sea
- Better ship cross section (RCS) due to the low grazing angle

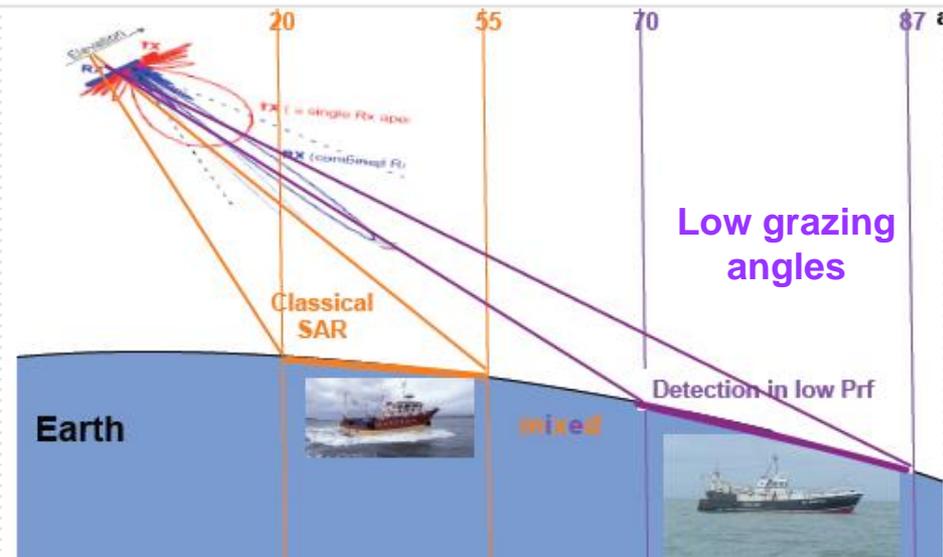
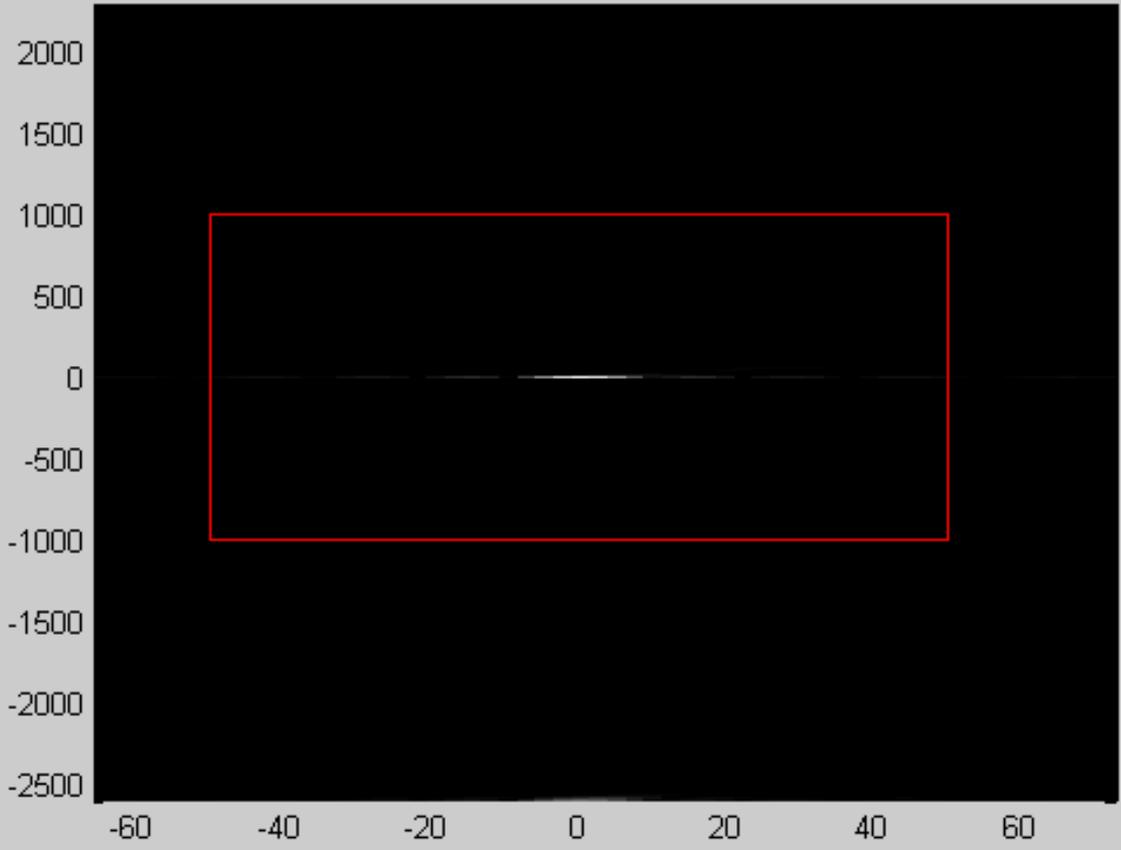


Figure 2: SAR RANGE-DOPPLER MAP

File Edit View Insert Tools Desktop Window Help



SAR unambiguous

SAR simulator

Fc	9.65	GHz
Tp	1	us
B0	20	MHz
La	3	meters
Theta	50	Degrees
dY	1000	meters
dX	50	meters
yTarget	0	meters
xTarget	0	meters
RCS	900000	meters ²

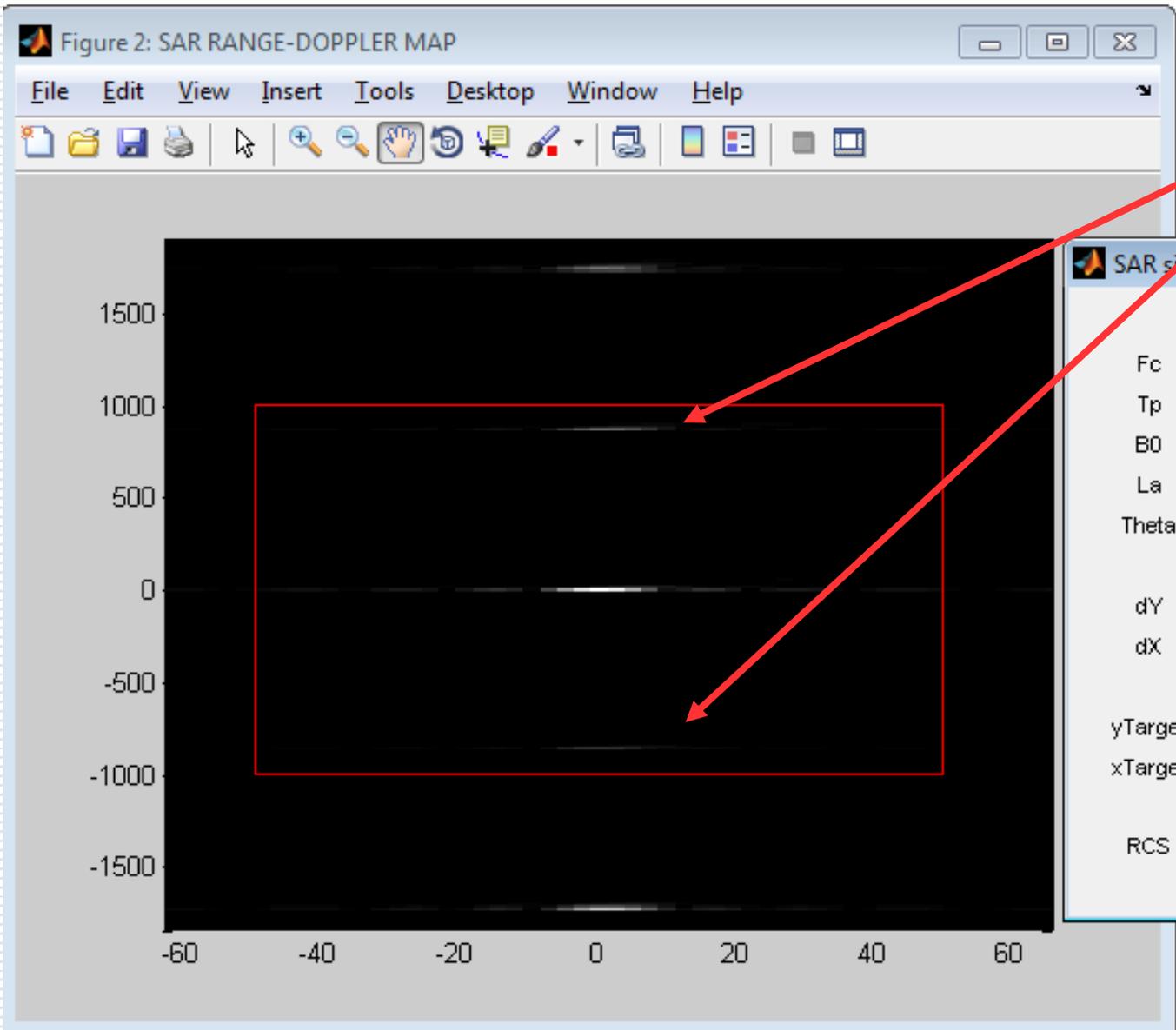
Reset Clear

Start

Range compression
 Range-doppler processing
 MAP RANGE/A
 src x smb0
 Debug Window

k_Fs 4 Fasttime s

PRF 1643.5 Hz



SAR ambiguous
(low PRF)

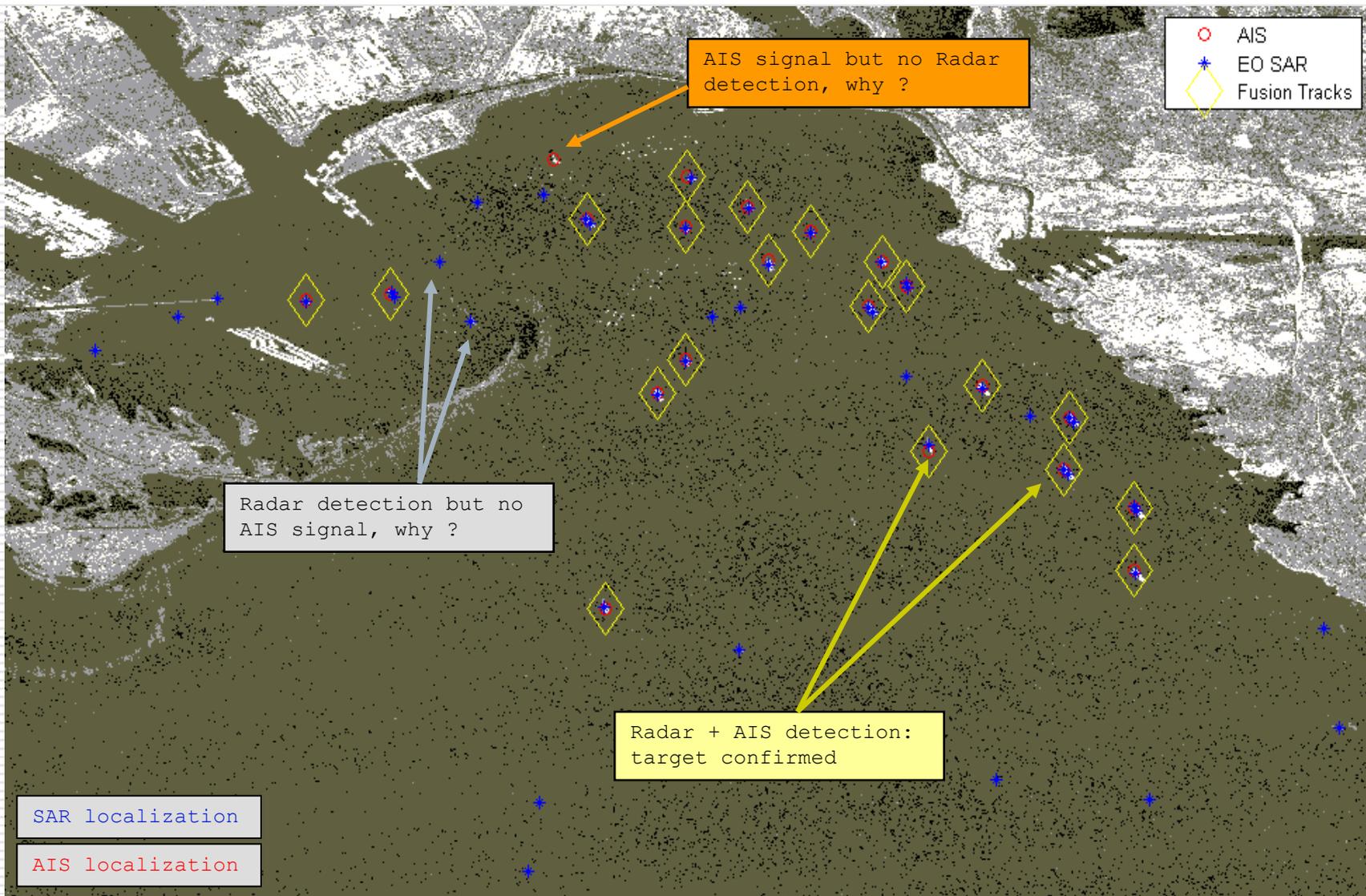
SAR simulator

Fc	9.65	GHz
Tp	1	us
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La	3	meters
Theta	50	Degrees
dY	1000	meters
dX	50	meters
yTarget	0	meters
xTarget	0	meters
RCS	900000	meters ²
k_Fs	4	Fasttime s
PRF	0543.5	Hz

Buttons: Reset, Clear, Start

Checkboxes: Range compre, Range-doppler, MAP RANGE/A, src x smb0, Debug Window

The PRF parameter is circled in red.



Motivation

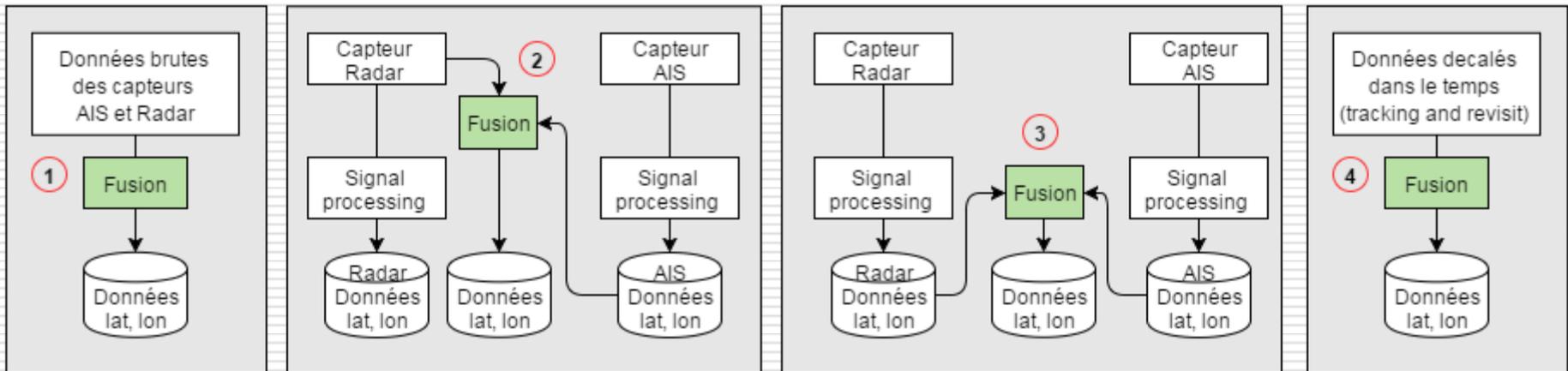
- ❑ Deal with the diversity of maritime surveillance scenarios including cooperative and non-cooperative ships
- ❑ A natural solution is to integrate different sources of information
- ❑ Today's methods are based on merging sensor post-processed data
- ❑ The main objective is to search for improved sensor data fusion techniques to obtain high performance maritime surveillance

Thesis subject

- Fusion of satellite AIS and low PRF radar data for high performance maritime surveillance
- Explore the diversity of both low PRF radar and AIS sensors to
 - Improve small vessel detection
 - Identify ships
 - Track non-uncooperative ships

The four research topics

- ❑ We proposed some research topics to improve target detection using sensor data fusion
- ❑ Four levels of sensor data fusion were identified



The four research topics

1. Explore the diversity of raw sensor signals

- Considers data before any signal processing

2. Explore AIS processed data to improve radar detection

- Use extra information from AIS message (e.g., speed, position, time) to improve the radar detection

3. Explore AIS and radar processed data to improve detection

- In this case, both AIS and radar processed data provide separate lists of detections that need to be merged

4. Slow time integration

- Integrate slow time data from satellite scene revisit for tracking

Fundamentals

- Satellite orbit simulator
 - Auxiliary to the study
 - Simulate satellite parameters (speed / Doppler, altitude, look angle, elevation, heading, position, etc.)
 - Transformation of coordinates
- Low PRF SAR model
 - Generate raw signatures targets
 - At specific configuration of radar, ship and satellite (altitude, power, speed, view angle, frequency, resolution, etc.)
 - Radar equation (model the target RCS (radar cross section) and SNR)
- Low PRF SAR imaging simulator
 - Generates a radar image of punctual targets
 - Range-Doppler algorithm
- AIS signal simulator
 - Generates raw AIS signatures
 - Referenced on satellite and ship dynamics

Fundamentals

- Maximum likelihood estimation (MLE)
 - MLE algorithm to estimate unknown parameters of the AIS signal model
 - Estimate ship coordinates (Lat/Lon) from AIS and radar raw signatures
- Detection using the generalized likelihood ratio test (GLRT)
 - Simpler model with added constraints
- Performance evaluation
 - Statistical model and Receiver Operational Characteristics (ROC) curves.

The four research topics

1. Explore the diversity of raw sensor signals

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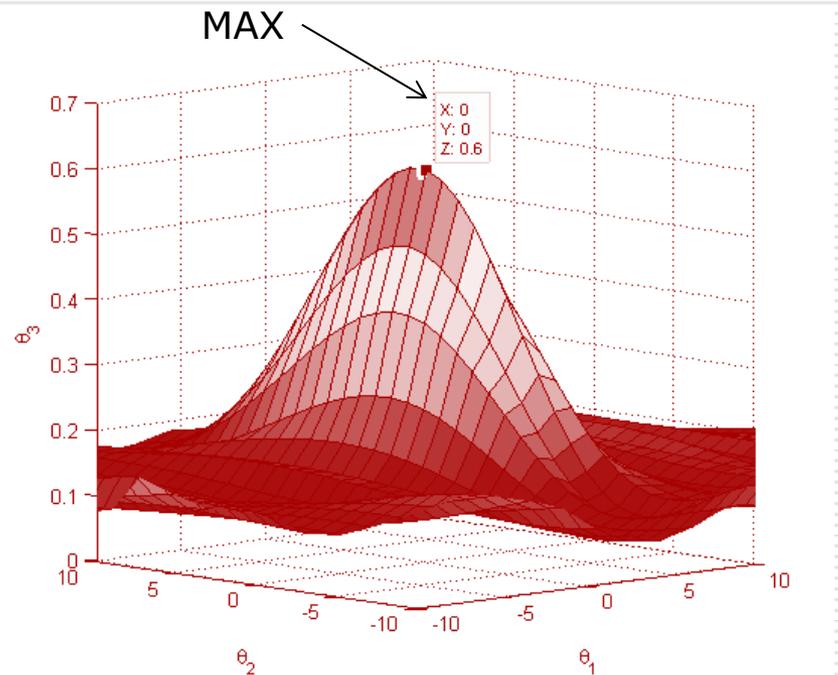
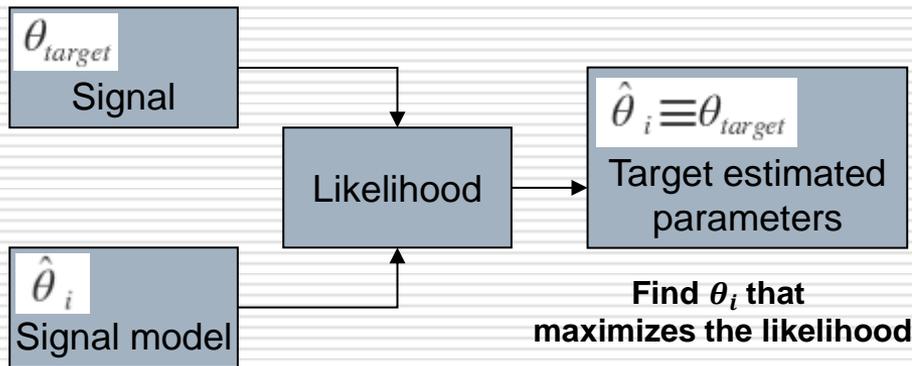
1st topic : Explore the diversity of raw sensor signals

MLE - Maximum likelihood estimator

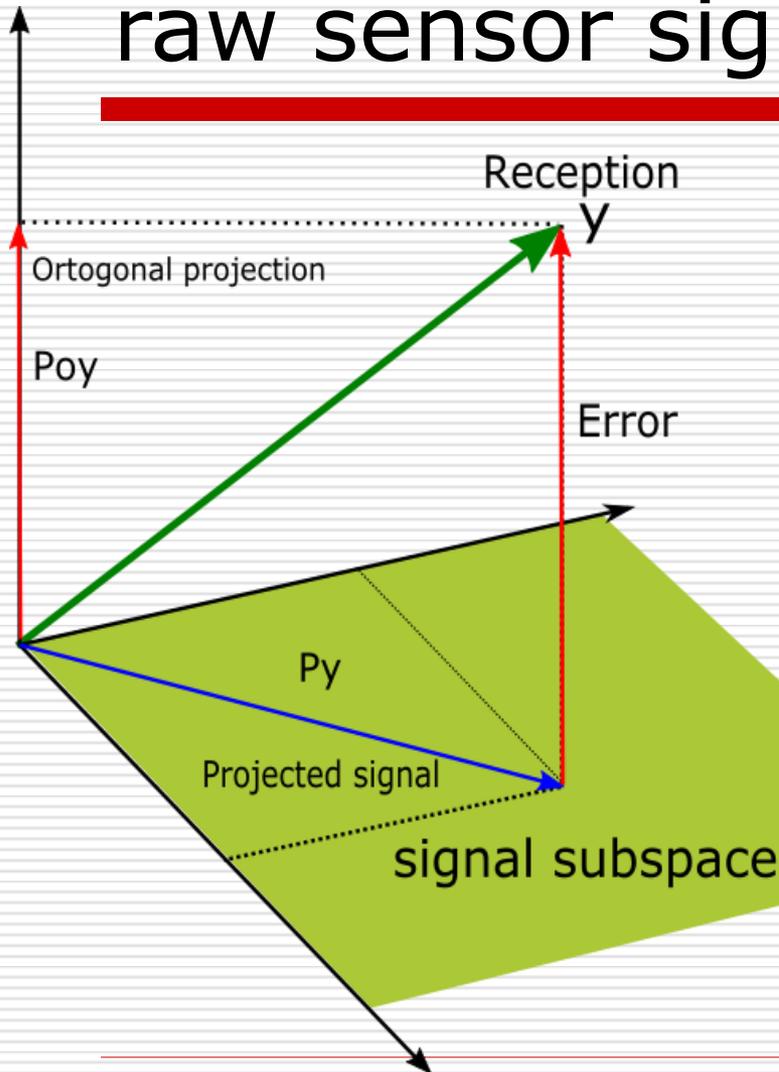
- ❑ The idea is to estimate some information from target signatures associated with AIS and radar sensors
- ❑ The target signatures are for the raw sensor data after complex quadrature demodulation
- ❑ The information is contained into the unknown parameters of the signal model that we need to estimate (e.g., lat/lon);
- ❑ The MLE determines the parameters that maximize the likelihood function

1st topic : Explore the diversity of raw sensor signals

- Maximizing the likelihood corresponds to finding the vector of parameters θ_i that is the most likely with respect to the measurements y



1st topic : Explore the diversity of raw sensor signals



Geometric representation

- The received message is a composition of information (signal) and some error (noise)
- The signal subspace is a subset of the total space of all possible signals in C^N
- The signal subspace is characterized by the signal model (where the reception (target signal) is a linear span of a set of vectors from the model)
- The reception can be split into components that represent the signal subspace and the orthogonal subspace (error)
- In short, we separate signal from error with the orthogonal projection operation

1st topic : Explore the diversity of raw sensor signals

□ Equations

Signal representation $\begin{cases} y_{radar} = A(\theta)\alpha + n_{radar} \\ y_{ais} = B(\theta)\beta + n_{ais} \end{cases}$

Signature = y
Models = $A; B$
Parameter vector = θ
Noise = n

Note:
 θ = Lat/Lon for AIS
 θ = X,Y Coords in radar

MLE - Maximum likelihood estimator

Case 1:
known noise power

$$\theta = \text{ArgMax} \left[\frac{y_{radar}^H P_A(\theta) y_{radar}}{\sigma_{radar}^2} + \frac{y_{ais}^H P_B(\theta) y_{ais}}{\sigma_{ais}^2} \right]$$

Case 2:
unknown noise power

$$\theta = \text{ArgMin} \left([y_{radar}^H (I - P_A(\theta)) y_{radar}]^{N_{radar}} [y_{ais}^H (I - P_B(\theta)) y_{ais}]^{N_{ais}} \right)$$

where

$$P_A(\theta) = A[A^H A]^{-1} A^H$$

$$P_B(\theta) = B[B^H B]^{-1} B^H$$

1st topic : Explore the diversity of raw sensor signals

- The MLE provide the optimal solution (no information is discarded)
- The research of the maximum is conducted into a $(2 + K)M$ dimensional space
 - M is the number of ships in the scene (and need to be estimated)
 - K is the number of unknown parameters to estimate for each ship (identification, speed, frequency, delay, among others)
- This solution is not implementable unless for a very small area with few ships
- An alternative is to exchange the estimation approach into a detection problem

1st topic : Explore the diversity of raw sensor signals

Detection using the GLRT - Generalized Likelihood Ratio Test

- The problem is now to test a single position for the two classical hypotheses in detection
 - H_0 : There is a ship **AND** AIS detection ($\alpha = \beta = 0$)
 - H_1 : There is **no** ship **AND no** AIS detection ($\alpha \neq 0, \beta \neq 0$)

Signal model	$\begin{cases} y_{\text{radar}} = A(\theta)\alpha + n_{\text{radar}} \\ y_{\text{ais}} = B(\theta)\beta + n_{\text{ais}} \end{cases}$	Likelihood ratio	$\frac{p(y_{\text{radar}}, y_{\text{ais}}/H_1, \widehat{\theta}_1)}{p(y_{\text{radar}}, y_{\text{ais}}/H_0, \widehat{\theta}_1)} > T$
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Case 1: known noise power

$$\left(\frac{y_{\text{radar}}^H P_a(\theta) y_{\text{radar}}}{\sigma_{\text{radar}}^2} + \frac{y_{\text{ais}}^H P_b(\theta) y_{\text{ais}}}{\sigma_{\text{ais}}^2} \right) > T$$

$$H_0 \begin{cases} y_{\text{radar}} = n_{\text{radar}} \\ y_{\text{ais}} = n_{\text{ais}} \end{cases}$$

$$H_1 \begin{cases} y_{\text{radar}} = a(\theta)\alpha + n_{\text{radar}} \\ y_{\text{ais}} = b(\theta)\beta + n_{\text{ais}} \end{cases}$$

Case 2: unknown noise power

$$\left(\left[1 + \frac{y_{\text{radar}}^H P_a(\theta) y_{\text{radar}}}{y_{\text{radar}}^H (I - P_a(\theta)) y_{\text{radar}}} \right]^{N_{\text{radar}}} \left[1 + \frac{y_{\text{ais}}^H P_b(\theta) y_{\text{ais}}}{y_{\text{ais}}^H (I - P_b(\theta)) y_{\text{ais}}} \right]^{N_{\text{ais}}} \right) > T$$

Results

- Using AIS, radar and to AIS and radar
- Comparison of the MLE algorithm with SAR range-Doppler image processing
- Constraints are used to ease the signal modelling (no collision in AIS messages, bit stuffing disabled, no false AIS, maximum of one ship at a single position, etc.)

Note: The measurements are simulated signals with additive white Gaussian noise

AIS signal

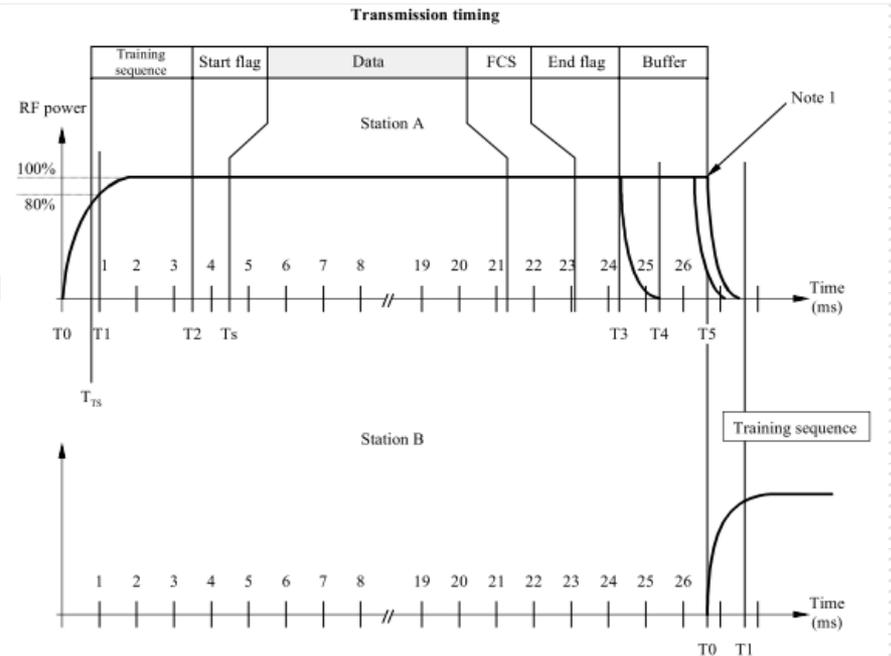


Bit Order	M---L--	M-----	-----	-----	--LML000
Symbol	TTTTTTDI	MMMMMMMM	MMMMMMMM	MMMMMMMM	MMMN000
Byte Order	1	2	3	4	5

Output order to VHF data link (bit-stuffing is disregarded in the example):

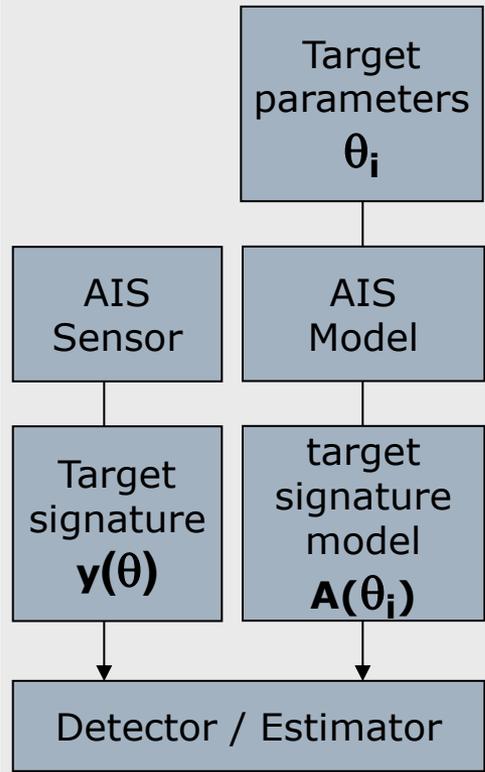
Bit Order	--L---M	-----M	-----	-----	000LML--
Symbol	IDTTTTTT	MMMMMMMM	MMMMMMMM	MMMMMMMM	000NNMMM
Byte Order	1	2	3	4	5

Ramp up	8 bits	T0 to T1 in Figure 6
Training sequence	24 bits	Necessary for synchronization
Start flag	8 bits	In accordance with HDLC (7E _h)
Data	168 bits	Default
CRC	16 bits	In accordance with HDLC
End flag	8 bits	In accordance with HDLC (7E _h)
Buffering	24 bits	Bit stuffing distance delays, repeater delay and jitter
Total	256 bits	



- Bit-stuffing
- Flip-bits
- Delta between ship and satellite frequencies
- Time offset of the signal in the reception window
- Initial phase of the signal

MLE AIS

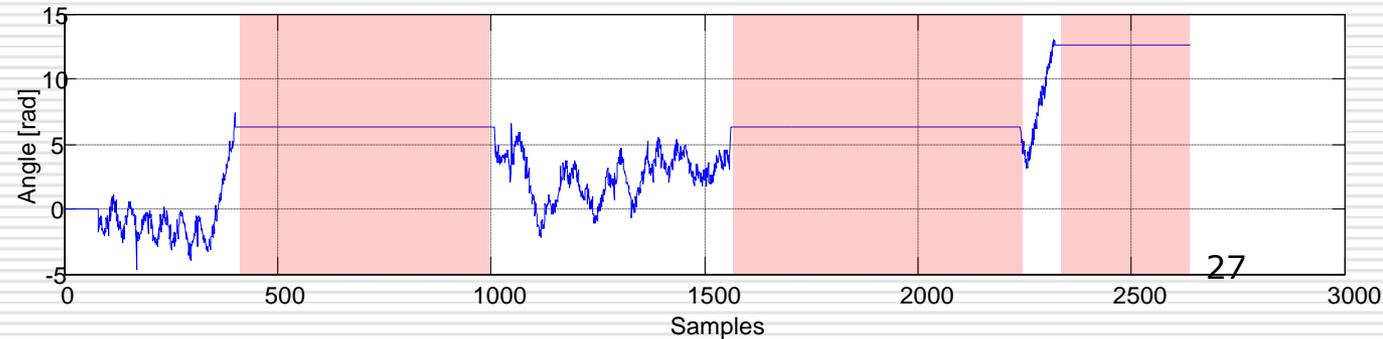
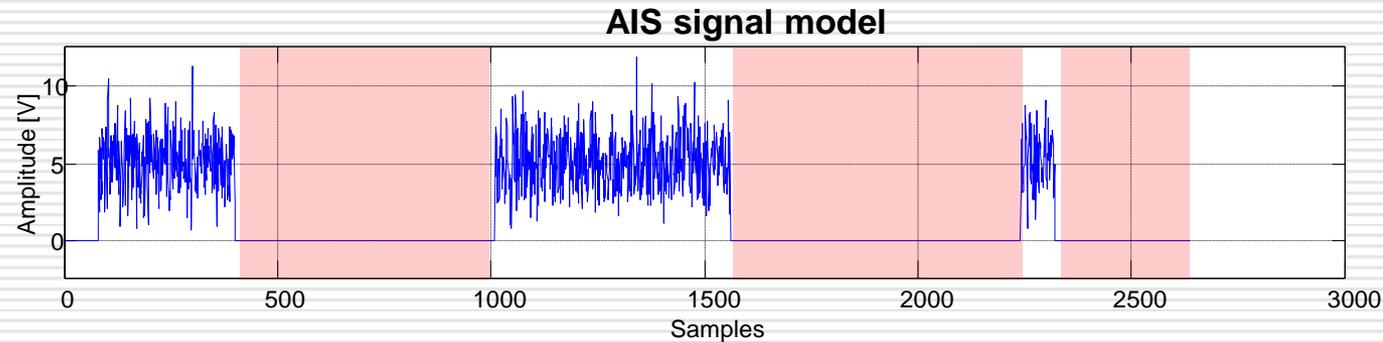
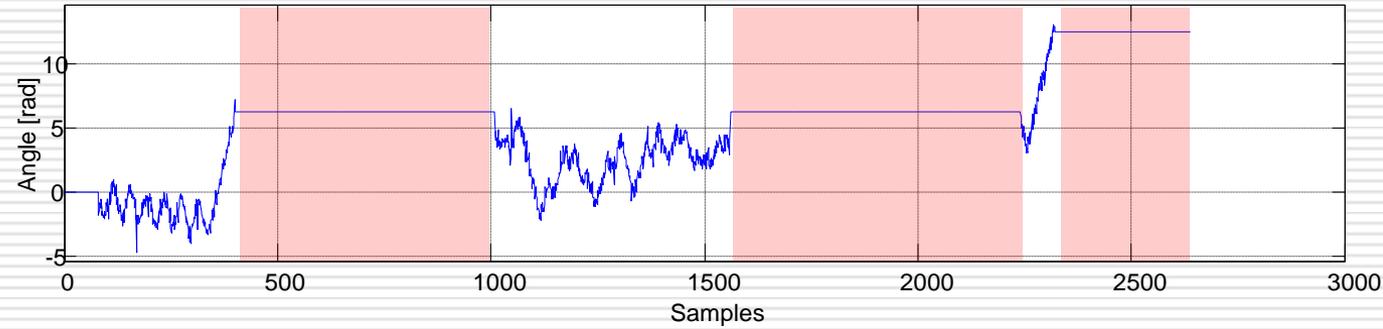
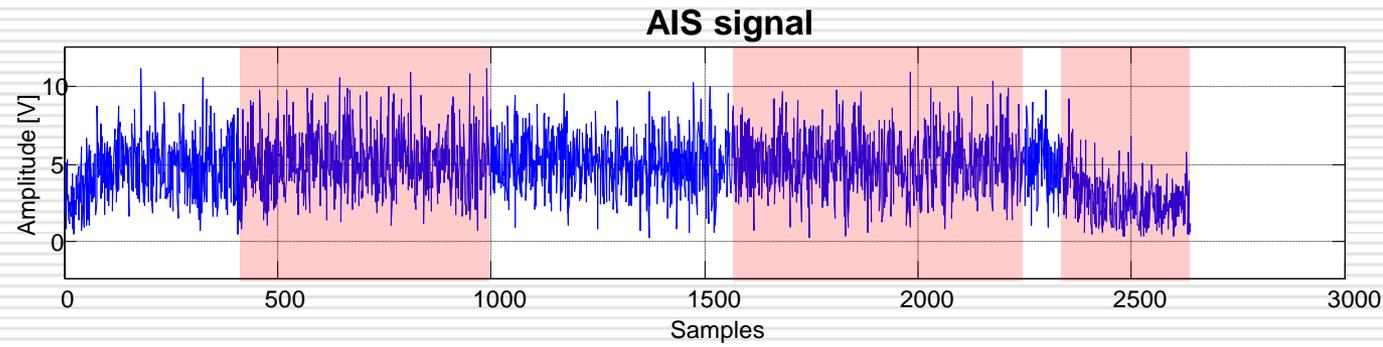


$$\hat{\theta} = \text{ArgMin} \left(\frac{y_{AIS}^H P_A(\theta_i) y_{AIS}}{\sigma_{AIS}^2} \right)$$

$$T_{AIS} = \frac{y_{AIS}^H P_A(\theta_i) y_{AIS}}{\sigma_{AIS}^2}$$

NOTES:

- In red the data that are unknown (replaced by zeros);
- θ_i = sample theta;
- θ = real theta(to be found);

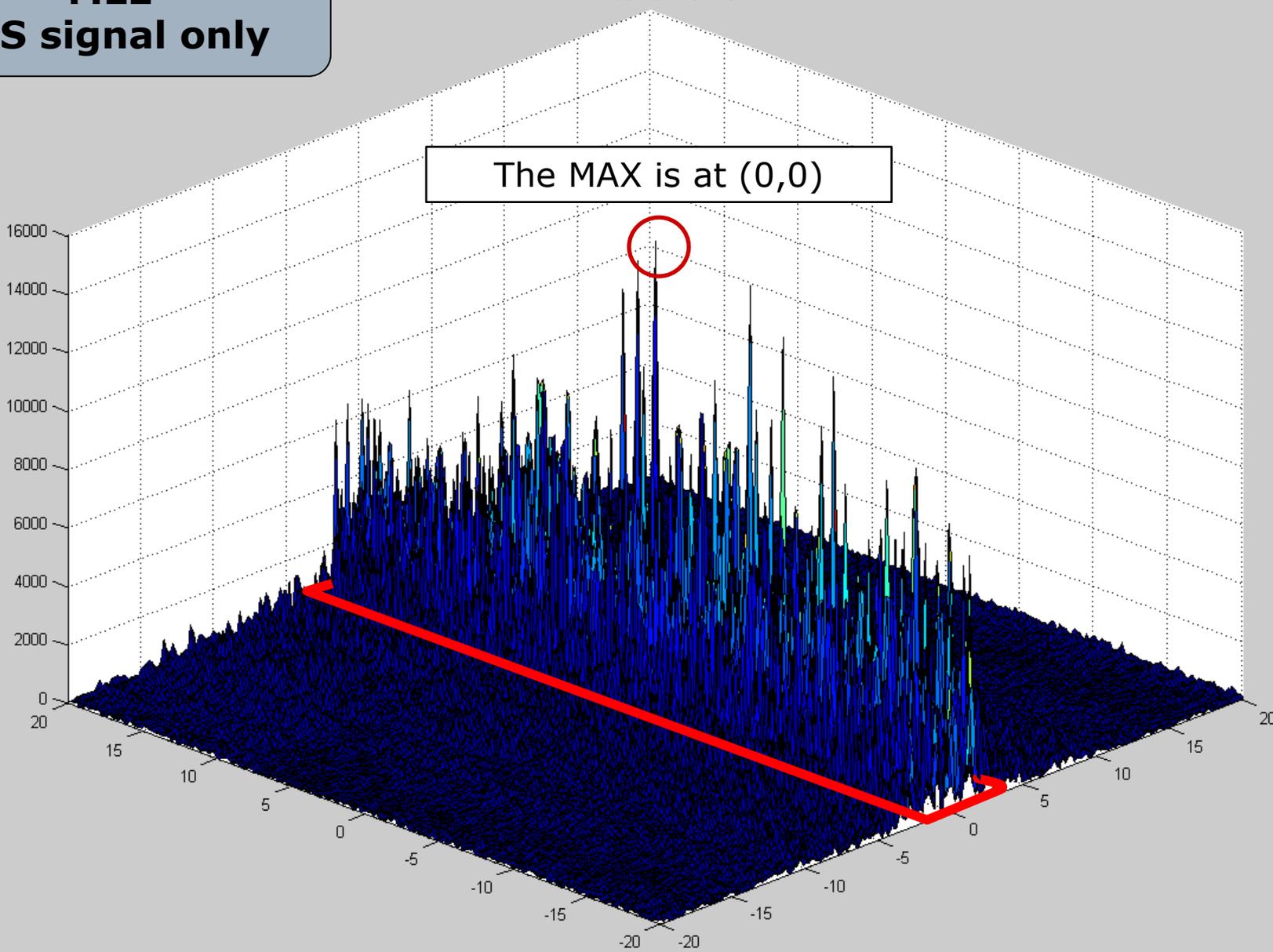


MLE
AIS signal only

$$y^T P(\theta) y$$

Def: $P(\theta) = A(A^T A)^{-1} A^T$

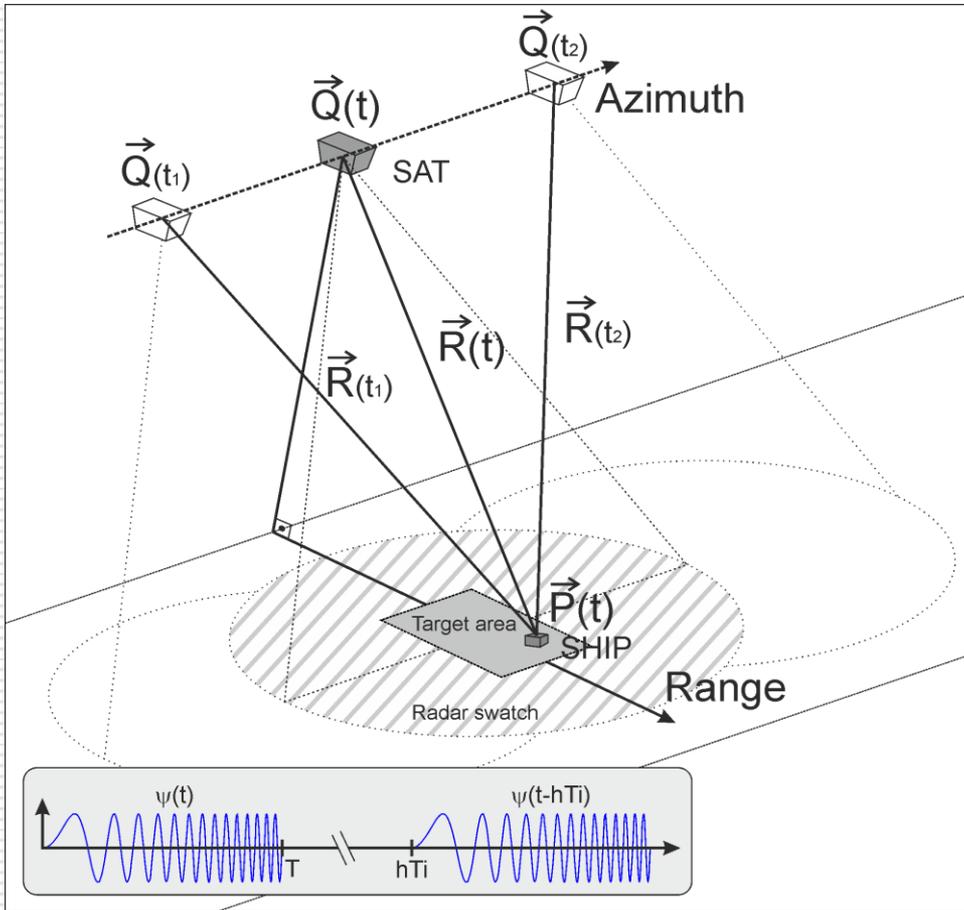
The MAX is at (0,0)



Y axis in meters

X axis in meters

Radar signal



$$\psi(t) = 1_T(t)e^{j\gamma t^2}$$

$$s(t) = \sum_{h=1}^{N_P} \psi(t - hT_i)e^{j2\pi f_0 t}$$

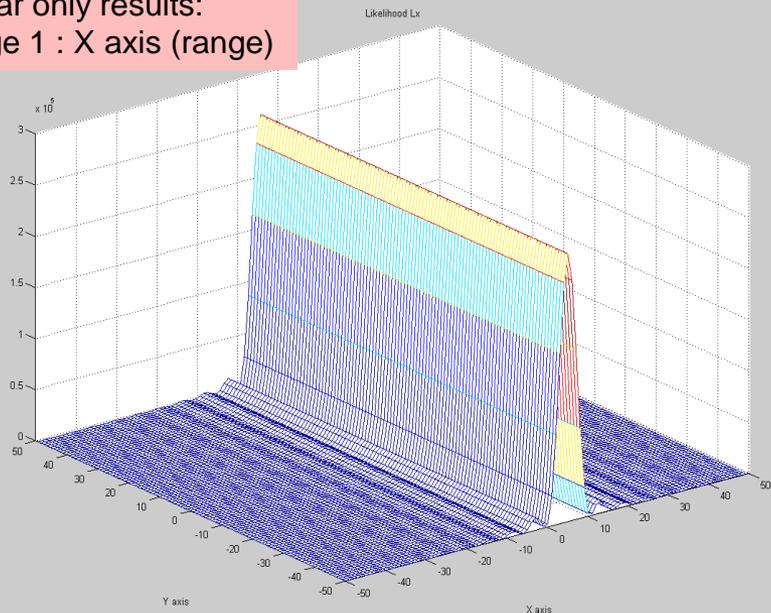
$$A_r(t) = A_s(t - \tau_\theta(t))$$

$$\tau_\theta(t) = 2R_\theta(t)/c$$

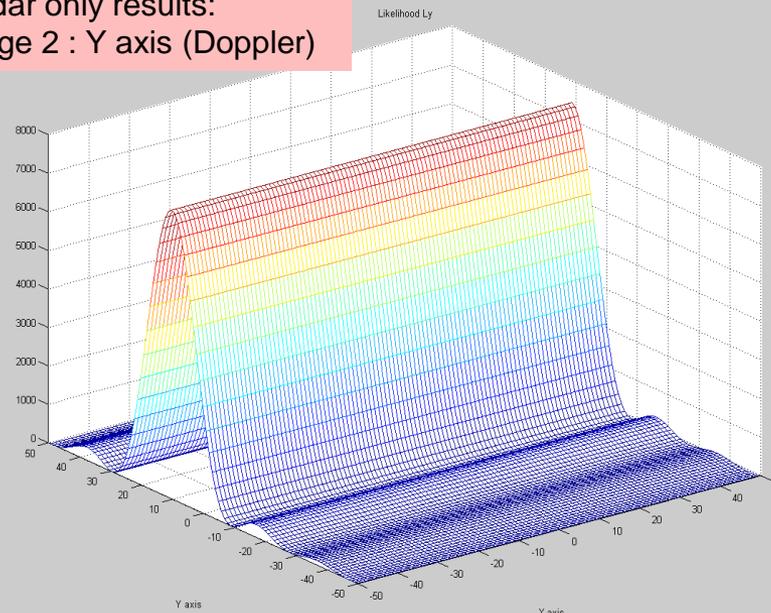
$$R_\theta(t) = \left\| \vec{P}(t) - \vec{Q}(t) \right\|$$

- Range-Doppler process uses matched filter for imaging
- MLE correlation outputs an image

Radars only results:
Stage 1 : X axis (range)



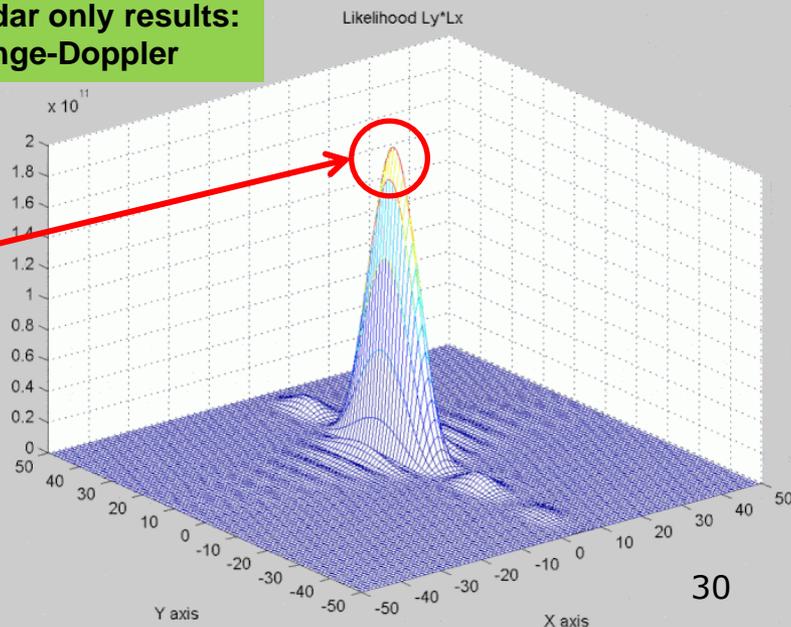
Radars only results:
Stage 2 : Y axis (Doppler)



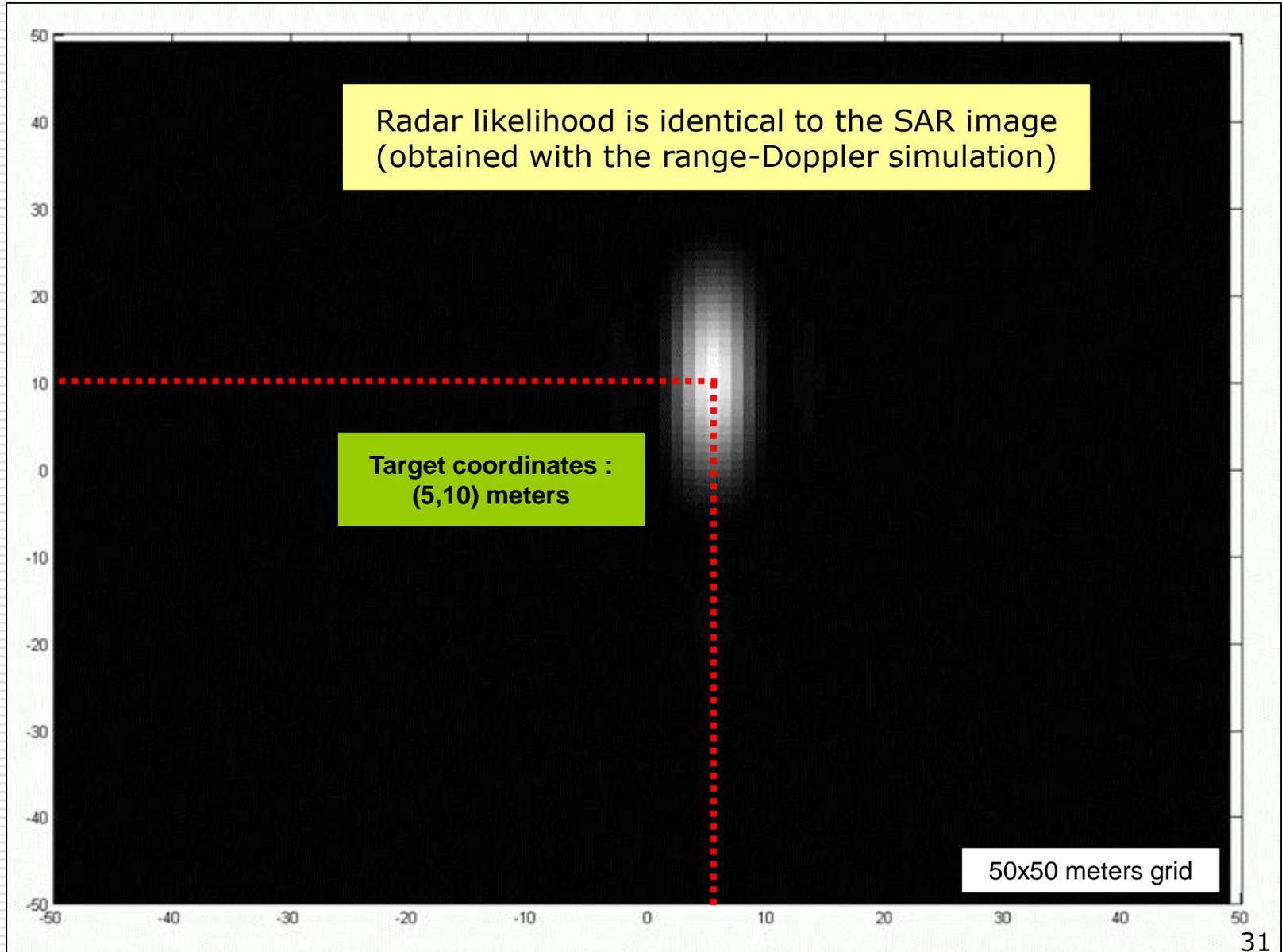
**MLE
Radar signal only**

**Target coordinates:
(5,10) meters**

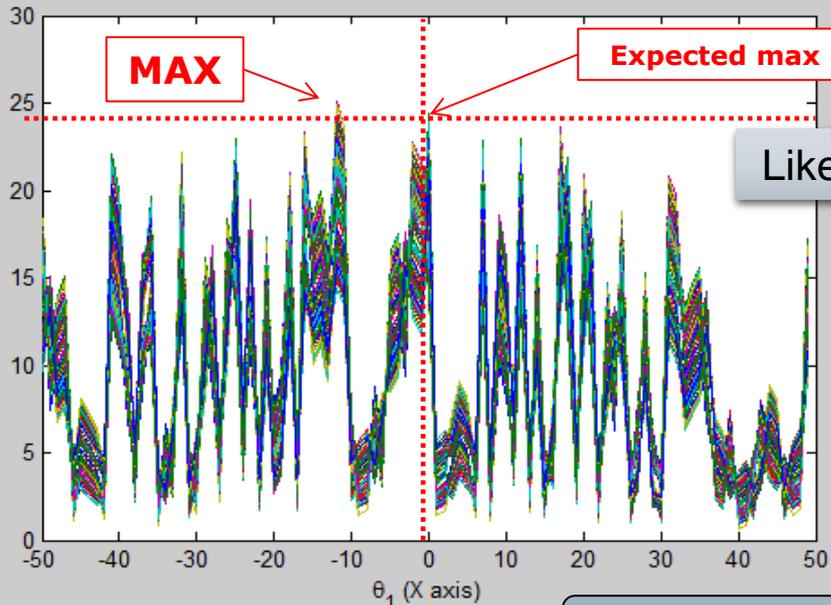
Radars only results:
Range-Doppler



SAR range-Doppler image

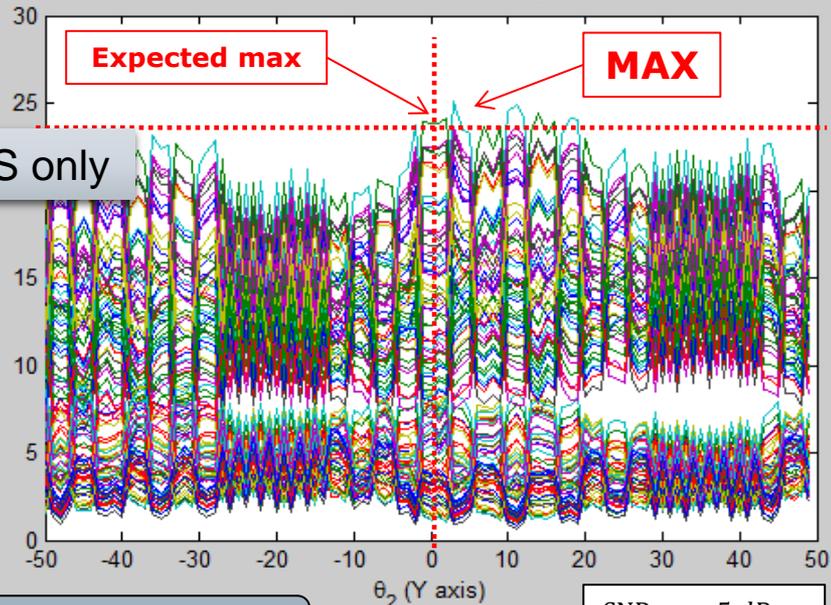


$$\text{AIS} = \|\text{Pb.y}_{\text{AIS}}\|^2 / \sigma_{\text{AIS}}^2$$



Likelihood AIS only

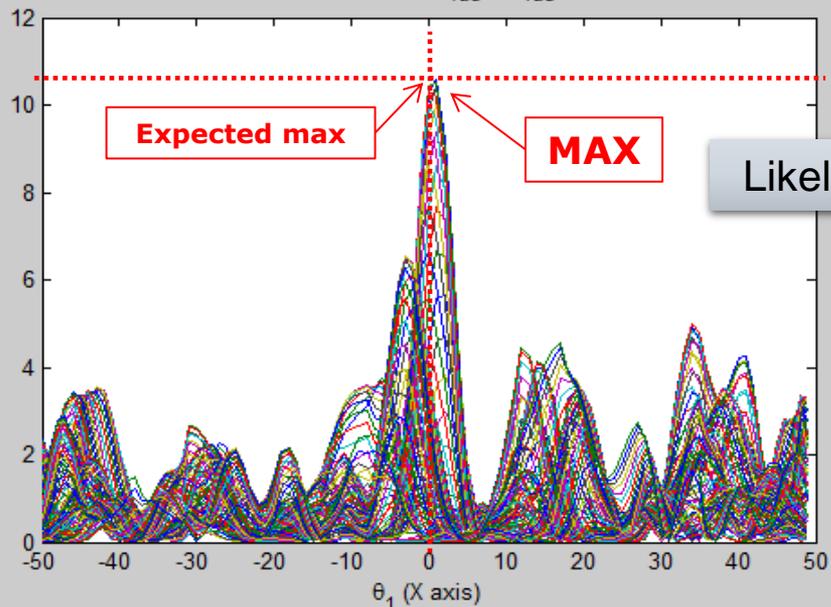
$$\text{AIS} = \|\text{Pb.y}_{\text{AIS}}\|^2 / \sigma_{\text{AIS}}^2$$



Radar and AIS likelihoods

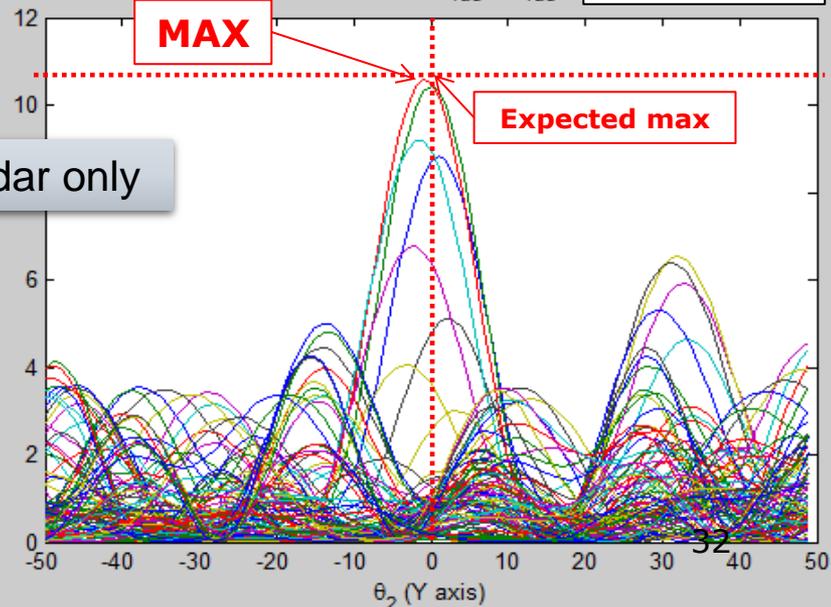
SNR_{AIS}: -5 dB
 SNR_{rad}: -30 dB
 N_{AIS}: 95
 N_{rad}: 17487

$$\text{Radar} = \|\text{Pa.y}_{\text{rad}}\|^2 / \sigma_{\text{rad}}^2$$

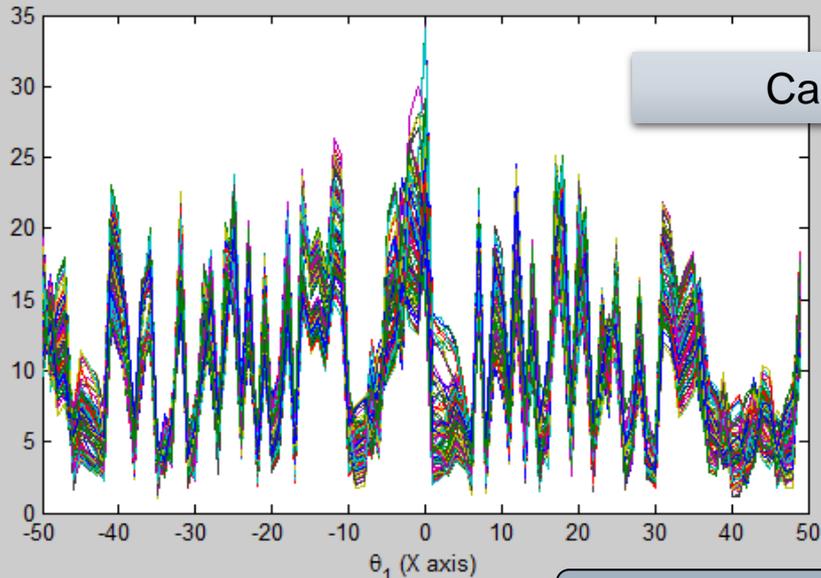


Likelihood Radar only

$$\text{Radar} = \|\text{Pa.y}_{\text{rad}}\|^2 / \sigma_{\text{rad}}^2$$

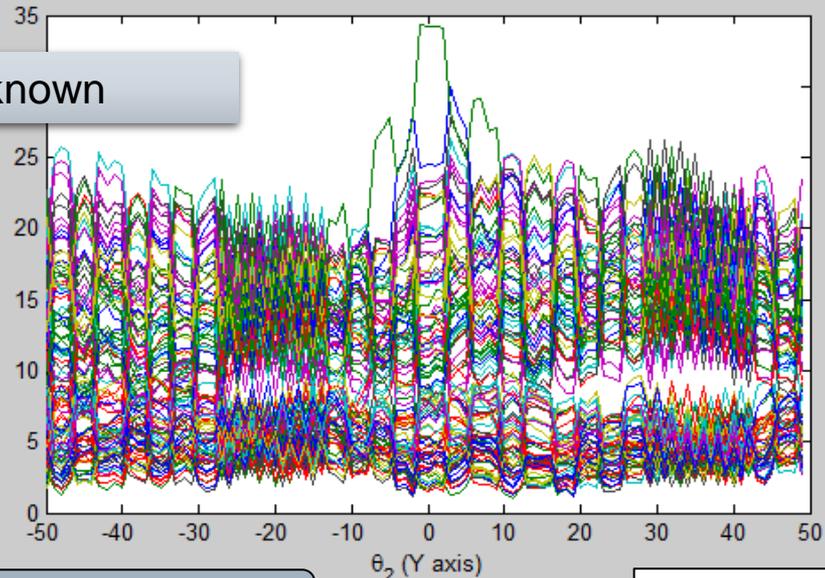


FUSION 1: log-GLRT
 $\|Pa.y_{ais}\|^2/\sigma_{ais}^2 + \|Pb.y_{rad}\|^2/\sigma_{rad}^2$



Case 1: σ^2 known

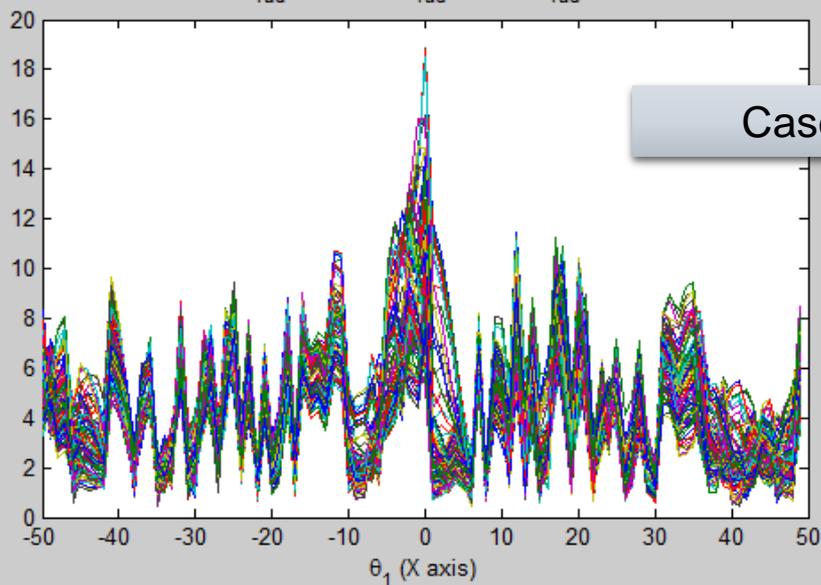
FUSION 1: log-GLRT
 $\|Pa.y_{ais}\|^2/\sigma_{ais}^2 + \|Pb.y_{rad}\|^2/\sigma_{rad}^2$



Fusion of Radar and AIS

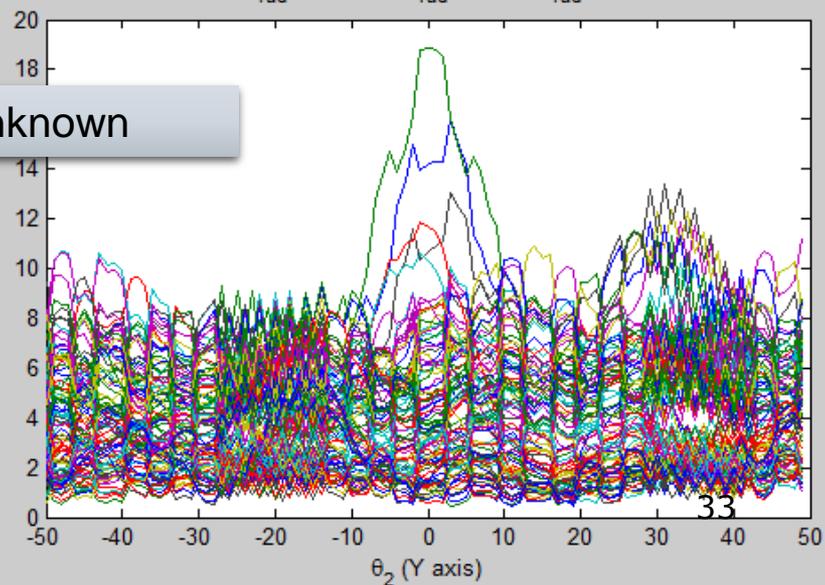
$SNR_{AIS}: -5 \text{ dB}$
 $SNR_{rad}: -30 \text{ dB}$
 $N_{AIS}: 95$
 $N_{rad}: 17487$

FUSION 2: log-GLRT
 $N_{ais} * \log(1 + \|Pa.y_{ais}\|^2 / \|POa.y_{ais}\|^2) +$
 $N_{rad} * \log(1 + \|Pb.y_{rad}\|^2 / \|POb.y_{rad}\|^2)$



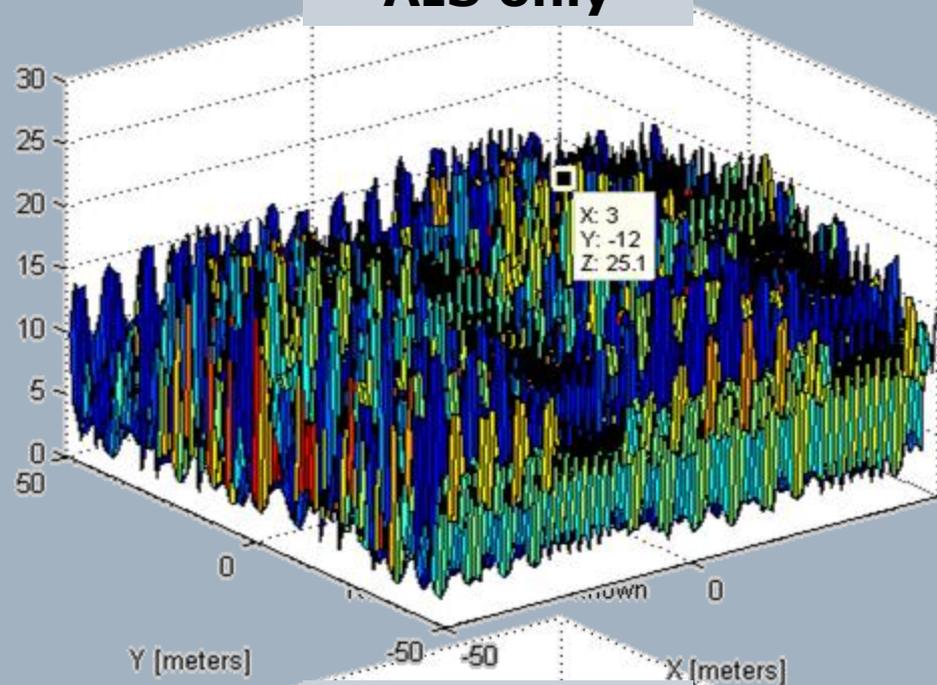
Case 2: σ^2 unknown

FUSION 2: log-GLRT
 $N_{ais} * \log(1 + \|Pa.y_{ais}\|^2 / \|POa.y_{ais}\|^2) +$
 $N_{rad} * \log(1 + \|Pb.y_{rad}\|^2 / \|POb.y_{rad}\|^2)$



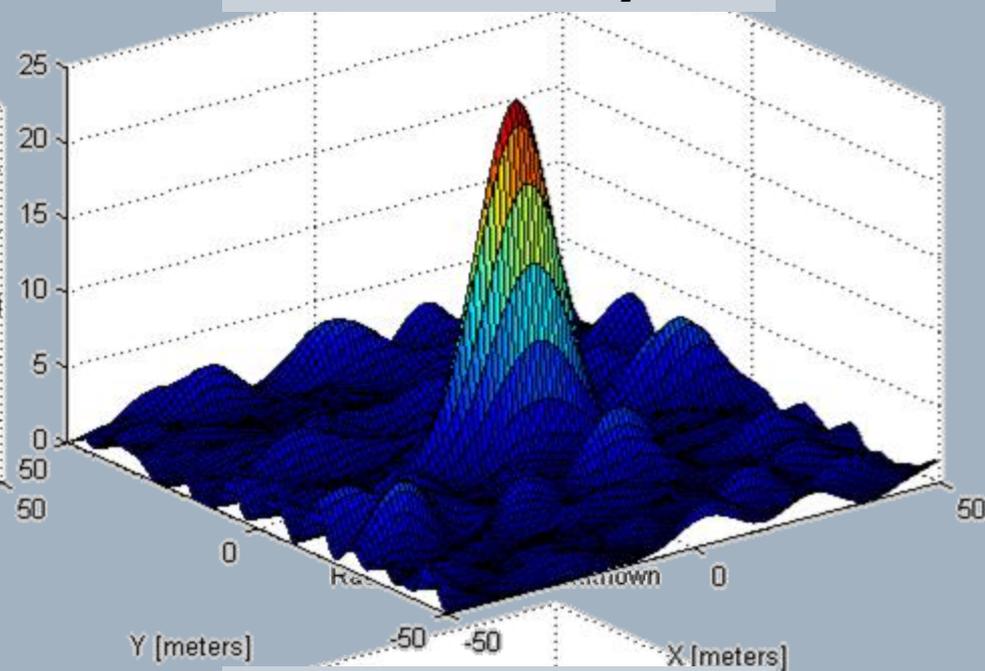
AIS only

AIS only

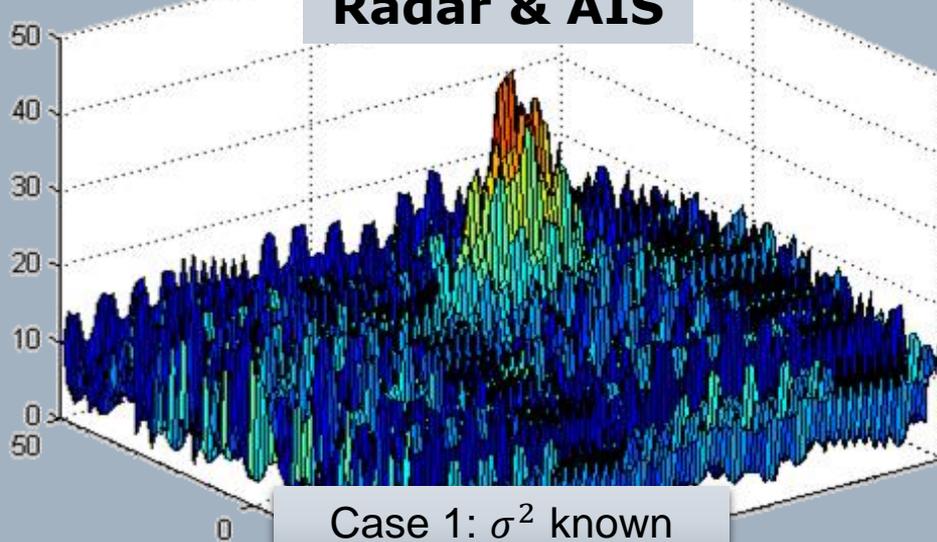


Radar only

Radar only

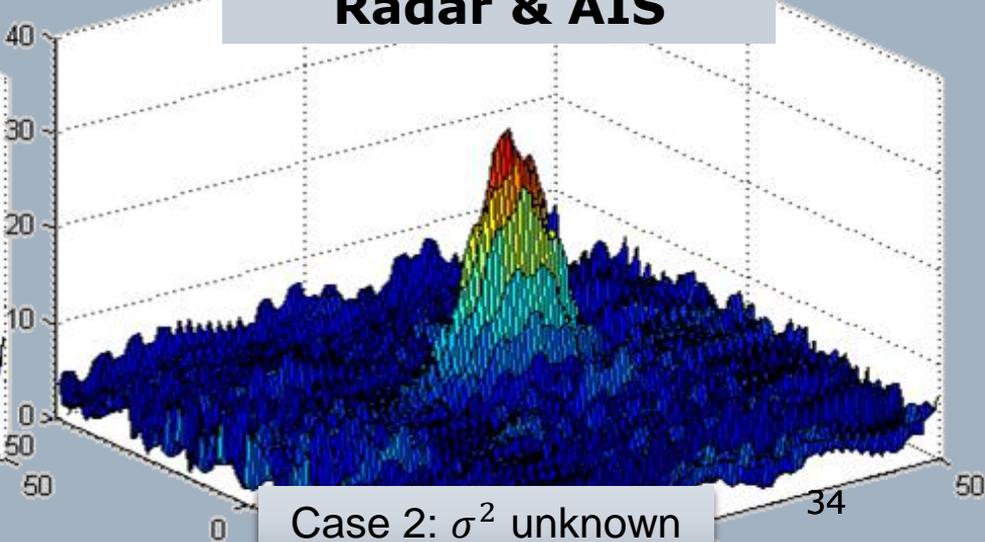


Radar & AIS



Case 1: σ^2 known

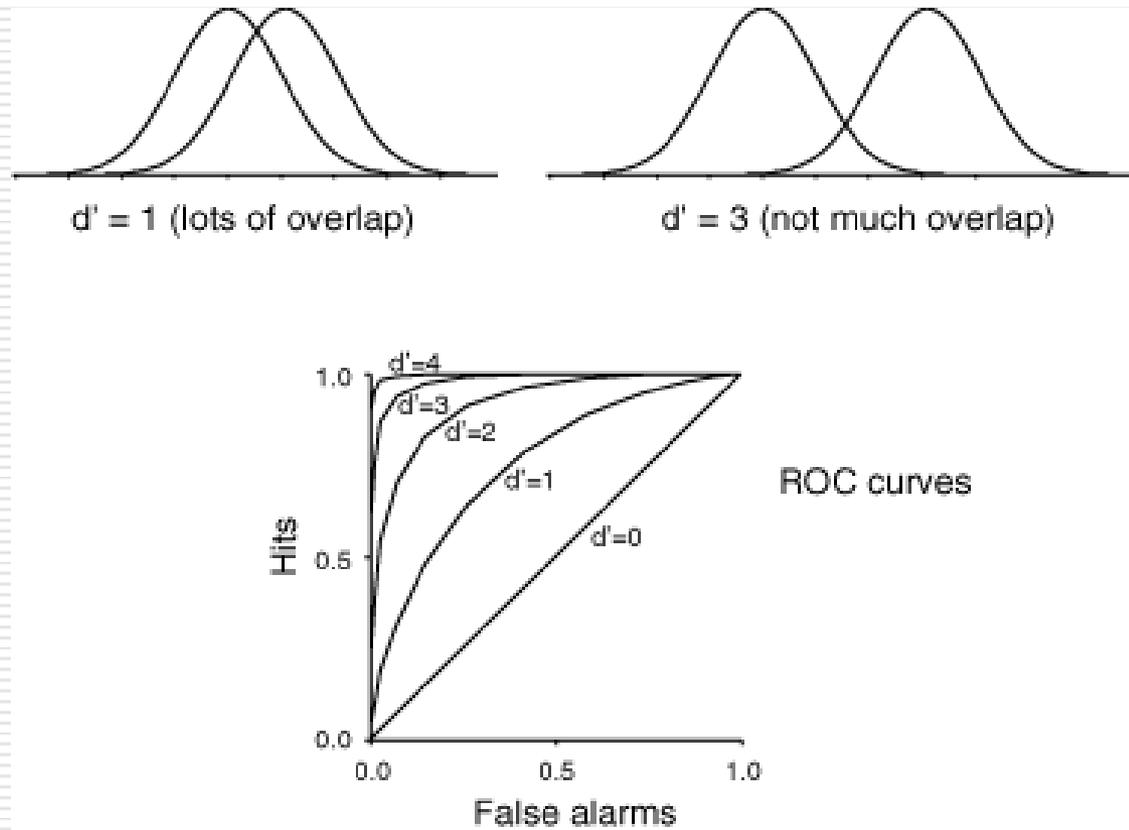
Radar & AIS



Case 2: σ^2 unknown

1st topic : Performance analysis

□ We can trace the PFA versus the detection probability to compare the different detectors with the receiver operating characteristics (ROC curves)



1st topic : Performance analysis

- Determine the distribution of the test statistics under both hypotheses for all detectors
- The statistics of the detectors are

$$T_f \sim \begin{cases} \frac{1}{2}\chi_4^2(0) & \text{under } H_0 \\ \frac{1}{2}\chi_4^2(\lambda_{\text{AIS}} + \lambda_{\text{rad}}) & \text{under } H_1 \end{cases}$$

$$T_{\text{rad}} \sim \begin{cases} \frac{1}{2}\chi_2^2(0) & \text{under } H_0 \\ \frac{1}{2}\chi_2^2(\lambda_{\text{rad}}) & \text{under } H_1 \end{cases}$$

$$\lambda_{\text{rad}} = 2N_{\text{rad}} \text{SNR}_{\text{rad}} = 2 \text{SNR}_{O_{\text{rad}}}$$

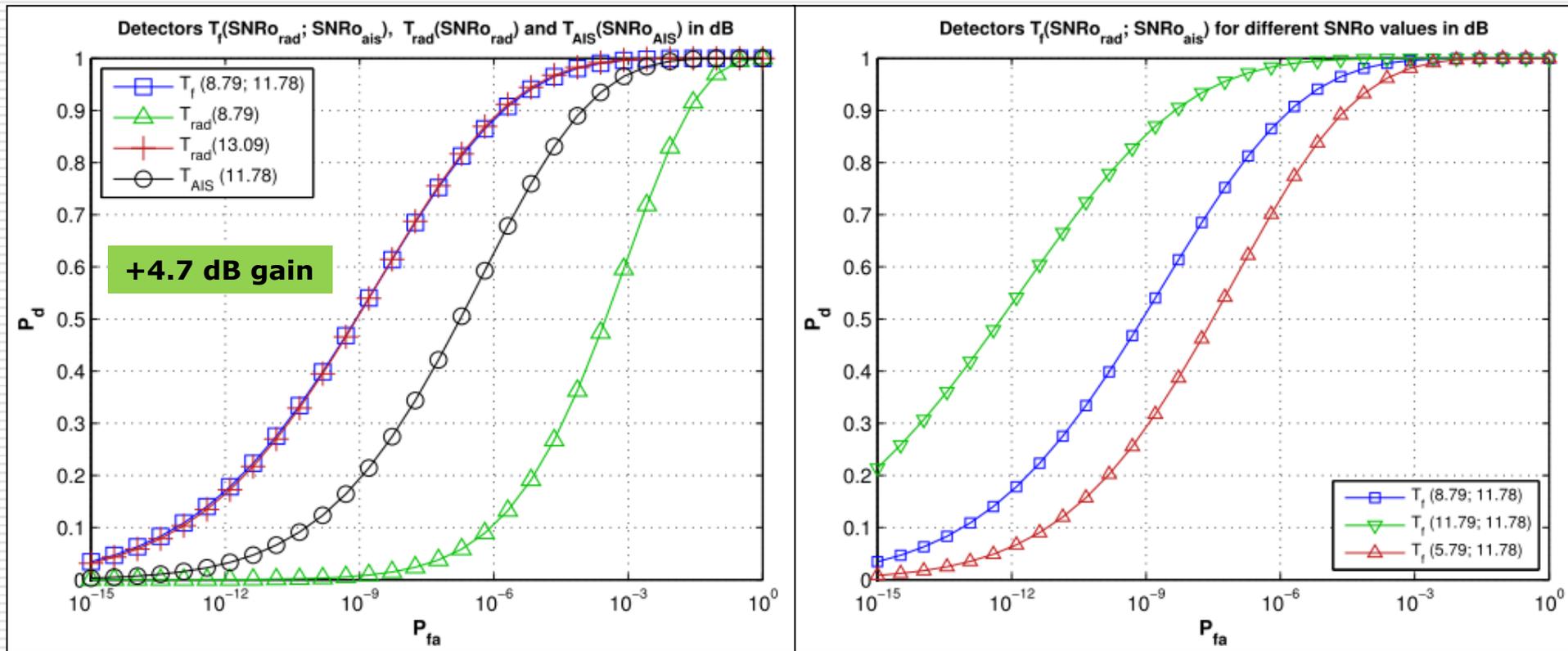
$$\lambda_{\text{AIS}} = 2N_{\text{AIS}} \text{SNR}_{\text{AIS}} = 2 \text{SNR}_{O_{\text{AIS}}}$$

Signal representation: $\mathbf{y}_{\text{rad}} = \alpha \mathbf{a}(\theta) + \mathbf{n}_{\text{rad}}$
 $\mathbf{y}_{\text{AIS}} = \beta \mathbf{b}(\theta) + \mathbf{n}_{\text{AIS}}$

Modeling assumptions

- Both radar and AIS signals are synchronous with respect to the ship position
- There is a maximum of one single ship per test position
- Bit stuffing is disabled
- The signal model only depends on the position θ (the other parameters are known)

1st topic : Performance analysis



Parameters:

SNR input : $\text{SNR}_{\text{rad}} = -33\text{dB}$, $\text{SNR}_{\text{AIS}} = -8\text{dB}$

For correct AIS demodulation $\text{SNR}_{\text{AIS}} > +10\text{dB}$ is needed

1st topic : Results

- ❑ We cannot infer about detection performance of the detector only by looking at the likelihoods
- ❑ The ROC curves show a considerable gain by integrating both sources of data
- ❑ Model constraints are very restrictive
- ❑ Estimation of AIS parameters is time-consuming
 - ❑ Significant computational power is necessary to allow the practical implementation of the method
- ❑ **We decided to advance to the second method which could provide interesting results with reduced computational complexity**

The four research topics

1. Explore the diversity of raw sensor signals

- Considers data before any signal processing

2. Explore AIS processed data to improve radar detection

- Use extra information from AIS message (e.g., speed, position, time) to improve the radar detection

3. Explore AIS and radar processed data to improve detection

- In this case, both AIS and radar processed data provide separate lists of detections that need to be merged

4. Slow time integration

- Integrate slow time data from satellite scene revisit for tracking

2nd topic : Explore AIS processed data to improve radar detection

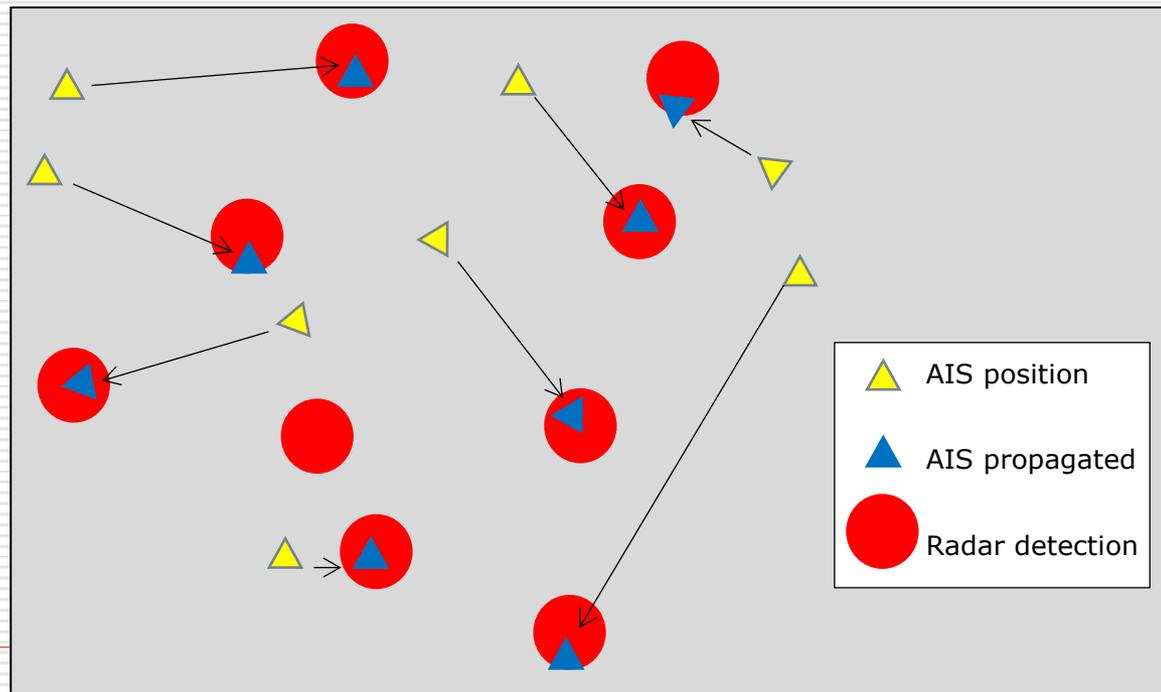
□ ***Main idea***

The knowledge of the existence of a ship at some position due to AIS information can be consolidated by radar data to improve detection

- Target signatures are now only the radar raw signals
- The AIS is a list of target positions with timestamps

2nd topic : Explore AIS processed data to improve radar detection

- The AIS list is propagated to their expected positions at the instant of the radar measurement



2nd topic : Explore AIS processed data to improve radar detection

□ Formulation

Signal representation :

$$y_{radar} = A(\theta_{ais_pro})\alpha + a(\theta_i)\beta + n_{radar}$$

Signal = y
Radar signature = A, a
Parameter vector = θ
Noise = n

Note:
 $\theta = x, y$ coords in radar

Where:

θ_i is the parameter vector of the test case i

$a(\theta_i)$ is the radar signature for θ_i

θ_{ais_pro} is the parameter vector of AIS targets propagated into the radar scene

$A(\theta_{ais_pro})$ is the radar signature for θ_{ais_pro}

Formulation on a two hypotheses test

$H_0: \{y = A(\theta_{ais_pro})\alpha + n ; \beta = 0$ (no radar echoes, only noise)

$H_1: \{y = A(\theta_{ais_pro})\alpha + a(\theta_i)\beta + n ; \beta \neq 0$ (signal and noise)

2nd topic : Explore AIS processed data to improve radar detection

Signal model

Model for unknown signal amplitude and noise power

Hypothesis H_0 : $y = A(\theta_{ais_pro})\alpha + n, \beta = 0$

Estimator for the signal amplitude : $\hat{\alpha}_0 = (A^H A)^{-1} A^H y$

Estimator for noise power : $\hat{\sigma}_0^2 = (y - A\alpha)^H (y - A\alpha) / N$

Likelihood : $L_0 = K_0 (y^H P_A^\perp y)^{-N} = K_0 \|P_A^\perp y\|^{-2N}$

$$K_0 = \left(\frac{\pi}{N} e\right)^{-N}$$

2nd topic : Explore AIS processed data to improve radar detection

Hypothesis H1 : $y = A(\theta_{ais_pro})\alpha + a(\theta_i)\beta + n, \beta \neq 0$

Model for unknown signal amplitude and noise power

Estimator for noise power: $\hat{\sigma}_1^2 = (y - A\alpha - a\beta)^H (y - A\alpha - a\beta) / N$

Estimator for signal amplitudes : $\hat{\alpha}_1 = (A^H A)^{-1} A^H (y - a\beta)$
 $\hat{\beta}_1 = (a^H P_A^\perp a)^{-1} P_A^\perp a^H y$

Likelihood : $L_1 = K_0 \left(y^H P_A^\perp y - \frac{y^H P_A^\perp a a^H P_A^\perp y}{a^H P_A^\perp a} \right)^{-N}$ $K_0 = \left(\frac{\pi}{N} e \right)^{-N}$

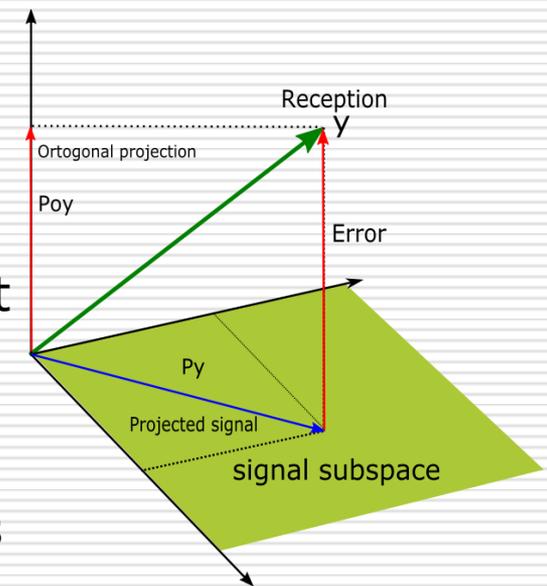
GLRT – Generalized Likelihood ratio test

$$T = \frac{H_1}{H_0}; \hat{T} = \frac{\|a'^H y'\|^2}{\|a'\|^2 \|y'\|^2} = \cos^2 \theta \quad \theta \text{ is the angle between } a' \text{ and } y'$$

2nd topic : Explore AIS processed data to improve radar detection

The proposed detector explores the knowledge about the (possible) existence of a target at θ and detects the signal amplitude that is outside the subspace $\langle A \rangle$ (the AIS list)

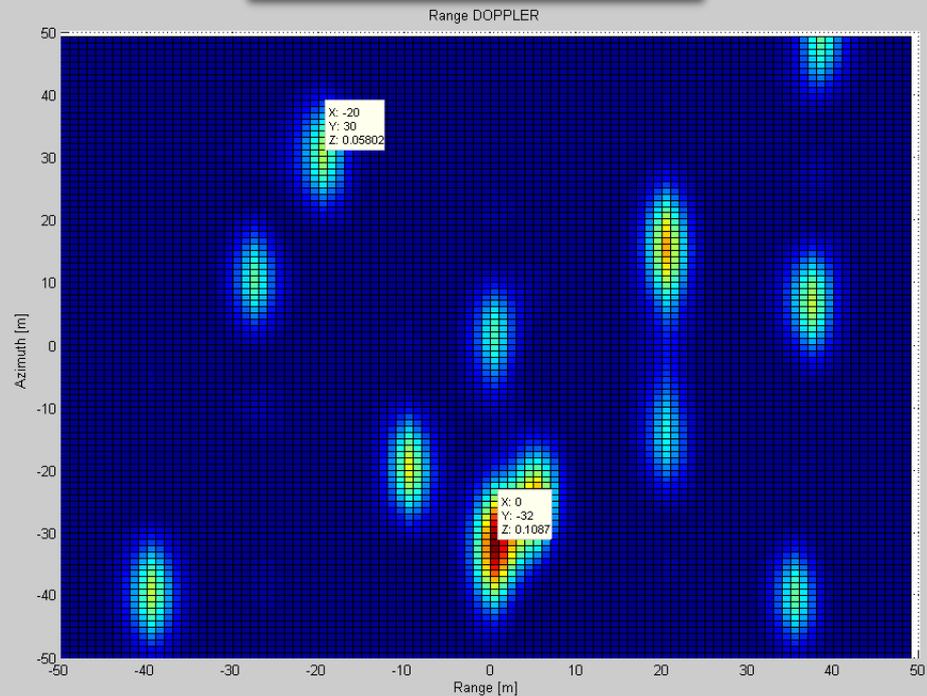
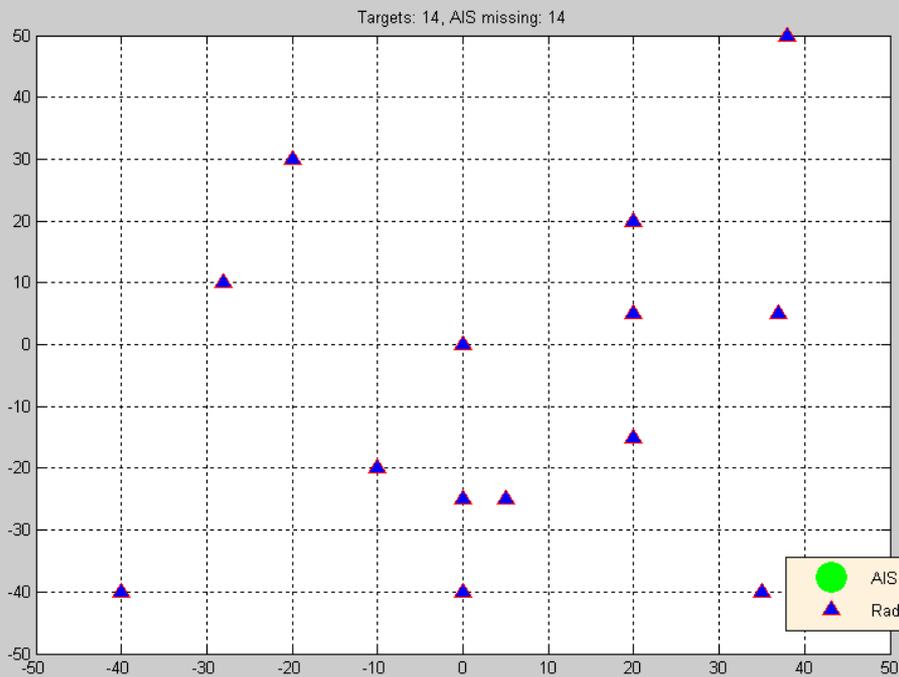
- $A(\theta)\alpha$ is the amplitude of a signal at θ
- $a(\theta)\beta$ is the amplitude measured at θ that is not present inside $\langle A \rangle$ subspace
- n is the measurement noise
- In H_0 , there is no radar signal (measurement is outside $\langle a \rangle$ and $\langle a \rangle \subset \langle A_{\perp} \rangle$)
- In H_1 , the measurement at θ can be partially inside $\langle A \rangle$ and inside $\langle a \rangle \subset \langle A_{\perp} \rangle$



2nd topic : Study case

- Consider a scenario with 14 identical ships at a scene
- Some are not separable with the radar detector

Radar detector



2nd topic : Study case

- Considering the AIS information of targets propagated to the current radar scene

AIS and radar targets

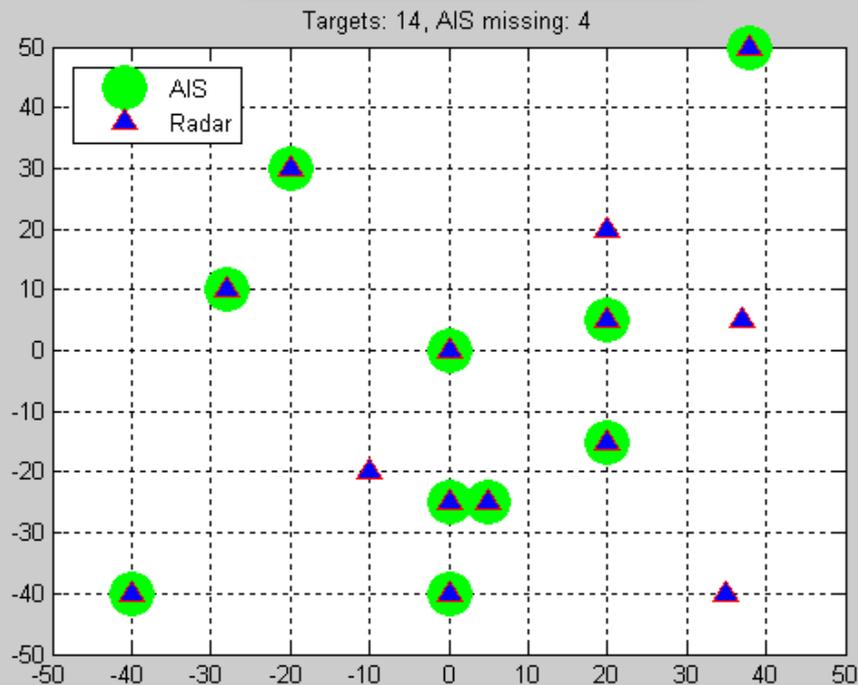
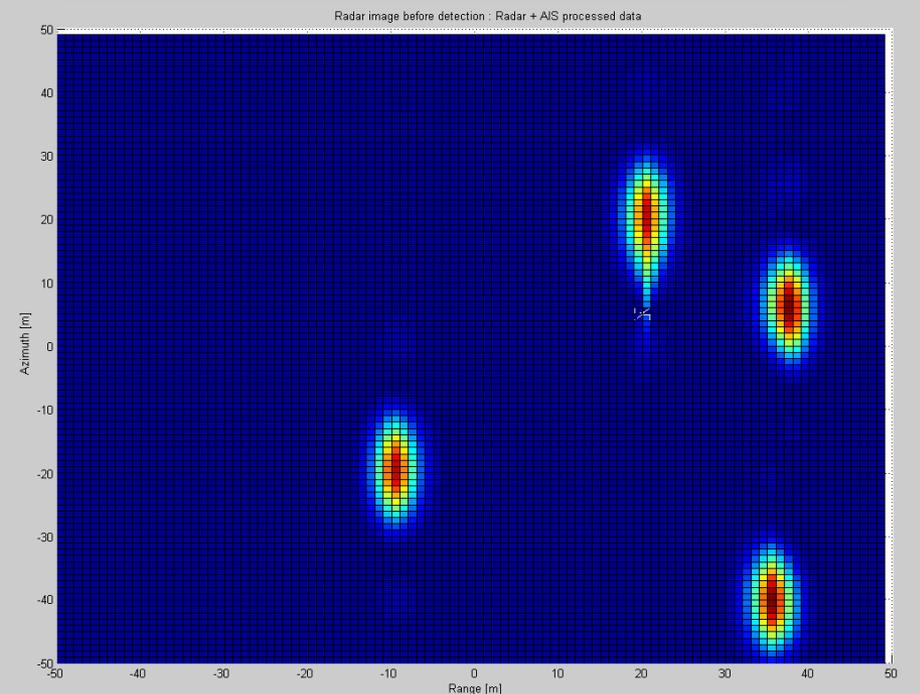
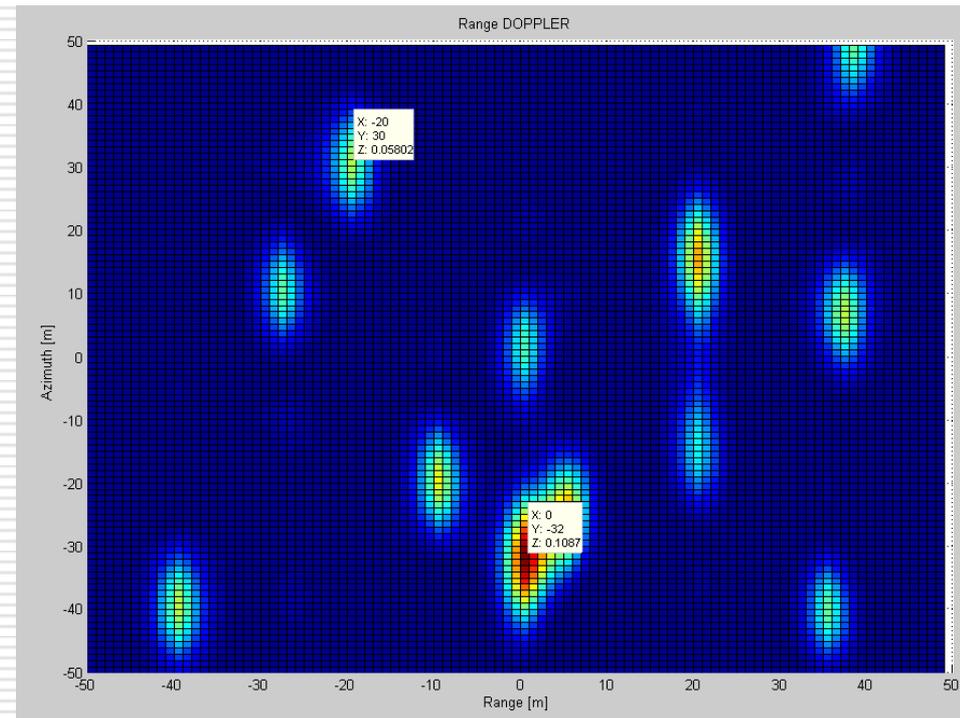
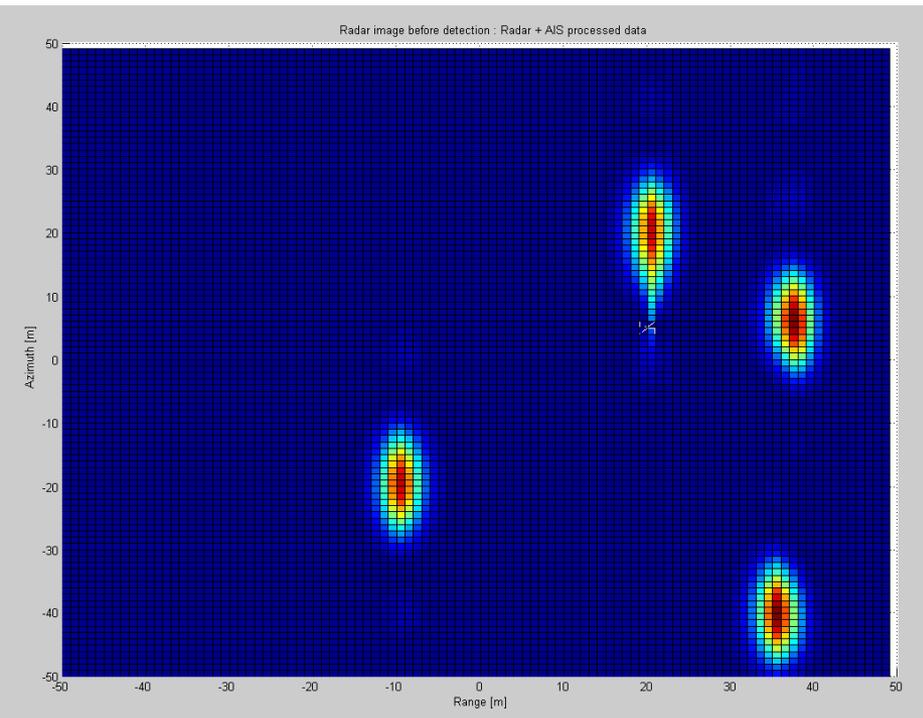


Image with the proposed detector

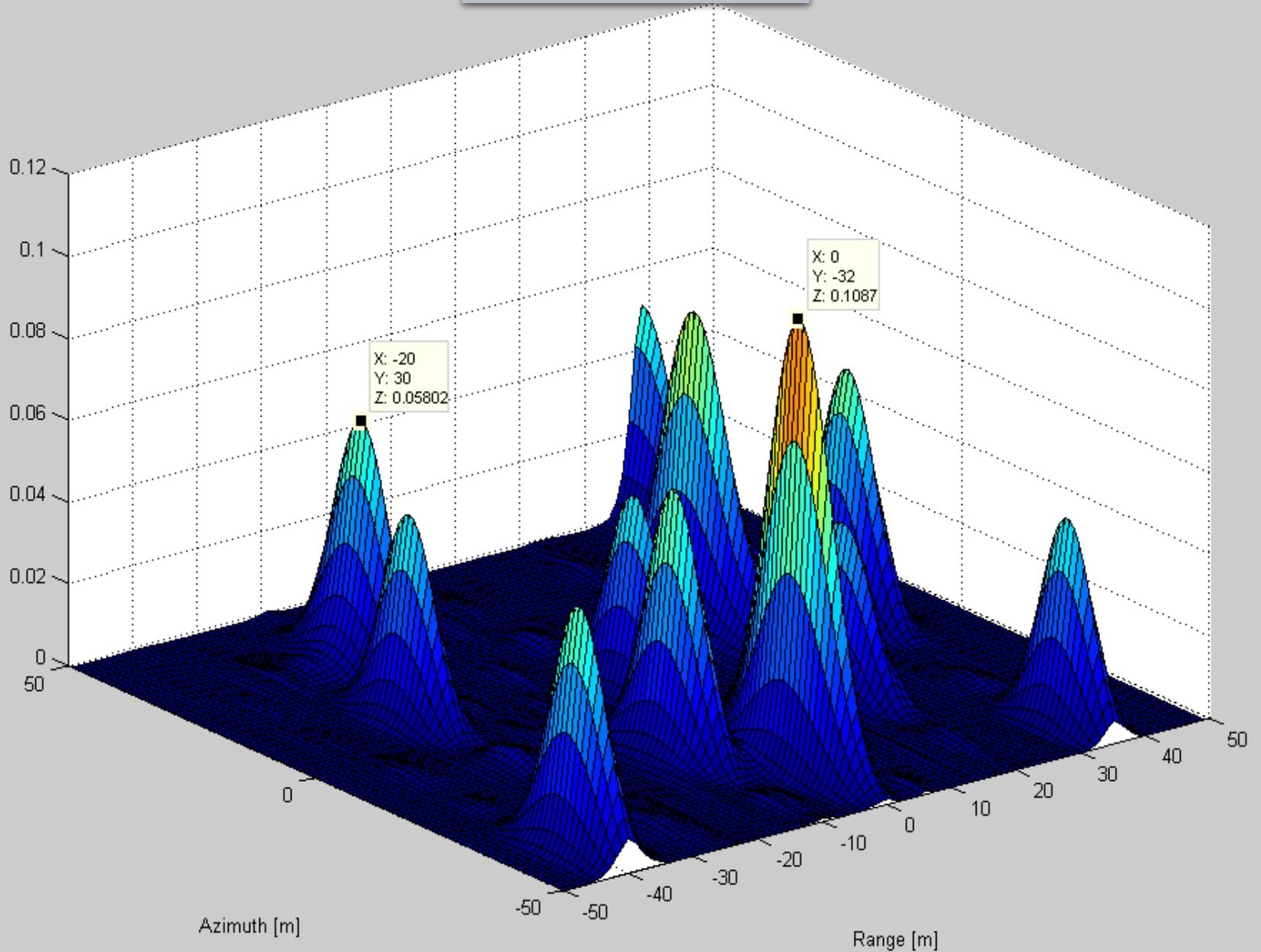


2nd topic : Study case

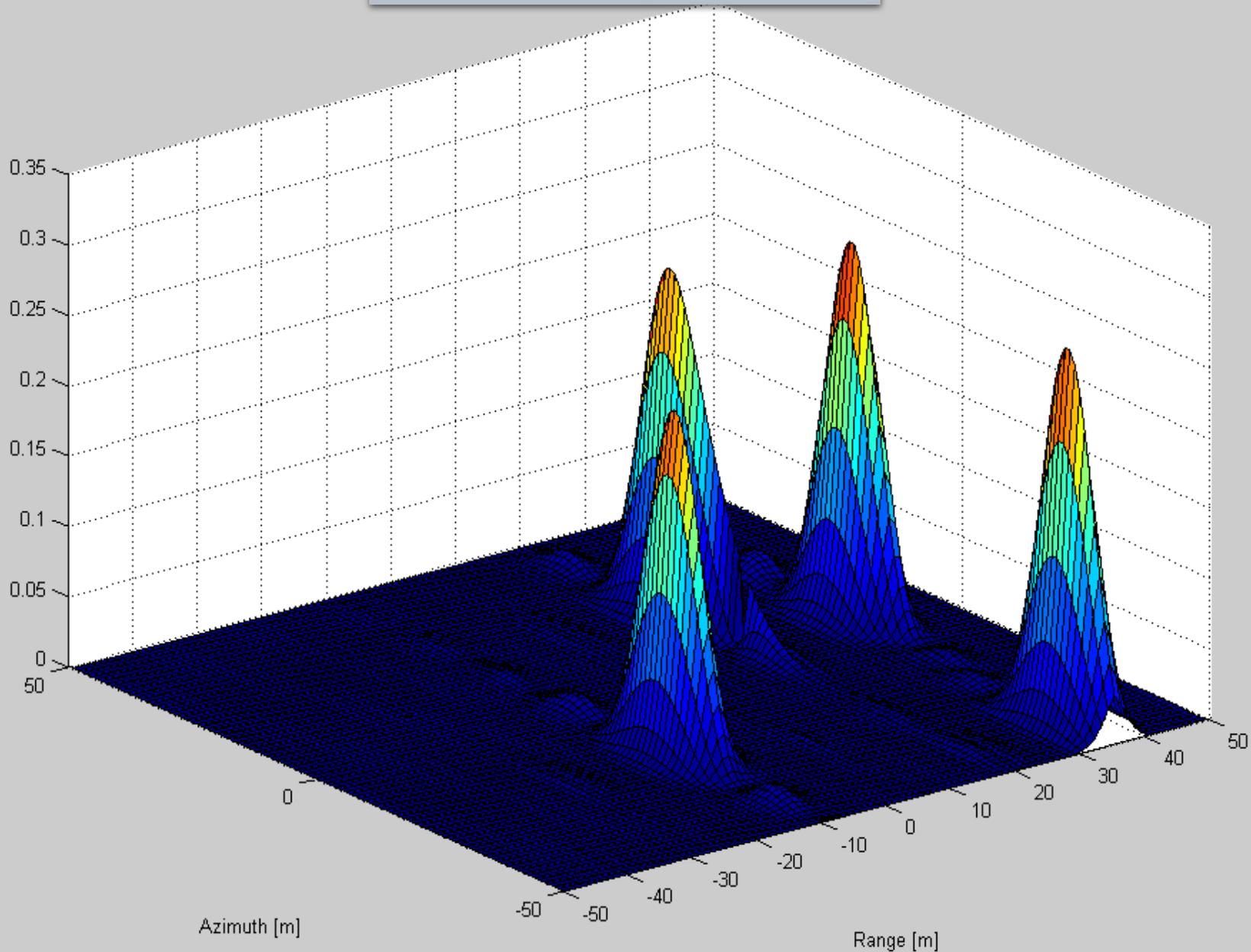
- ❑ Comparing both detectors
- ❑ Targets are now separable if AIS information is present



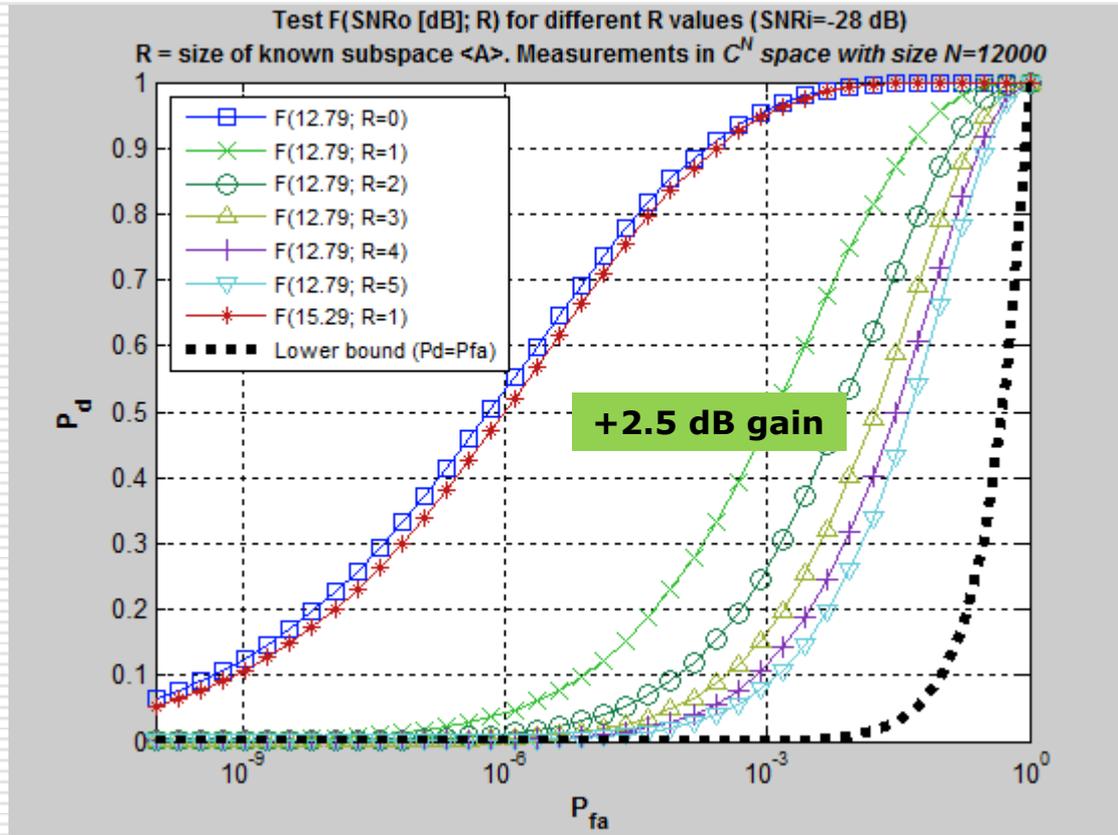
Radar detector



Detection using the AIS list



2nd topic : Performance analysis



Parameters:

SNR input : $SNR_{rad} = -33\text{dB}$, $SNR_{AIS} = -8\text{dB}$

For correct AIS demodulation $SNR_{AIS} > +10\text{dB}$ is needed

2nd topic : Explore AIS processed data to improve radar detection

- AIS positions may have errors
 - GPS error, propagation error, false data

Scenarios:

1. Small errors in AIS position (error < rad. resolution)

- Errors are acceptable, but AIS positions may be false
- A solution is to test the AIS list to remove the wrong data vectors

2. Important errors in AIS position (error > rad. resolution)

- The detector needs to consider positioning errors
- Approaches
 - A. Errors are obtained by secondary data
 - B. Errors are formalized by Bayesian approach

2nd topic : Explore AIS processed data to improve radar detection

2. Important errors in AIS position (error > rad. resolution)

A. Use of secondary data

- We include the uncertainty of the ship position in the detector model

$$\begin{cases} y_{radar} = A(\theta_r)\alpha + a(\theta_a)\beta + n_r \\ \theta_a = \theta_r + n_a \end{cases}$$

- Sources of information to deal with position noise power
 - GPS precision data
 - Ship history data about heading and speed
 - Those can lead to a good estimation of σ_a^2

Conclusions

- In the first method AIS raw signals improved radar detection performance in a conditioned scenario
 - Without decoding the AIS message
 - Even when the AIS signal-to-noise ratio (SNR) is not sufficient to decode the AIS message
 - The gain with the first method is the theoretical limit (optimal detector)
 - Reference for other detectors based on processed data
- In the second method, the AIS decoded message provided information for a detector that uses radar raw data to improve ship detection
 - It separates the signals that are related to the AIS positions from new detections
- Second method is less computer intensive than first method
 - It does not need to model the AIS signal
 - It is more prone to be implemented in practice

Next steps

- ❑ Continue the performance evaluation of the second method
- ❑ Compare performance of different methods
- ❑ Evaluate special scenarios and practical problems
 - Multiples hypotheses in both first and second methods
 - AIS deception and message collisions
 - Low PRF SAR ambiguities
- ❑ Implement the model with positioning errors
- ❑ Use the Bayes approach to deal with positioning errors
- ❑ Advance to evaluate the third and forth fusion methods
 - Data association using processed data from sensors
 - Tracking and long term integration
- ❑ Explore other AIS information (e.g. identification, ship size)
 - Ship discrimination, estimation of other parameters and errors