Maritime Rapid Enviromental Assessment Conference
Quantifying, Predicting, Exploiting Uncertainties in Maritime Environments

Adaptive selection of the background estimation procedure for target detection IR systems in naval surveillance applications

A. Rossi[1], N. Acito[2], M. Diani[1] and G. Corsini[1]

[1] Università di Pisa, Dipartimento di Ingegneria dell'Informazione, Pisa, Italy

[2] Accademia Navale di Livorno, Livorno, Italy

October 22nd, 2010
Villa Marigola, Lerici, Italy

Outline

- Introduction
  - Problem description
  - Signal model
  - Formalization of the background removal step
- Proposed technique
  - Automatic setting of the background estimation algorithm (BEA) parameters
  - Extension to automatic BEA selection
- Experimental results
  - Sea-sky scenario
  - Initialization
  - Visualization of the residual frames
  - Validation of the results
    - Visualization of the frames
    - Ex-ROC
- Conclusions

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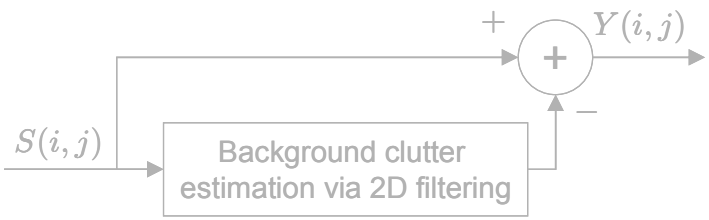
- Detection of dim targets in IR systems.

- Characteristics of the operating scenario:
  - highly structured clutter (i.e., clouds in the analyzed maritime scenario);
  - non-stationary clutter.

- Detection scheme:
  - step #1: background removal;
  - step #2: target detection.



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- Original contribution of the work → a criterion to select the background estimation technique:
  - based on simulation of dim targets;
  - selects the best performing BEA technique in its best performing parameters setting.

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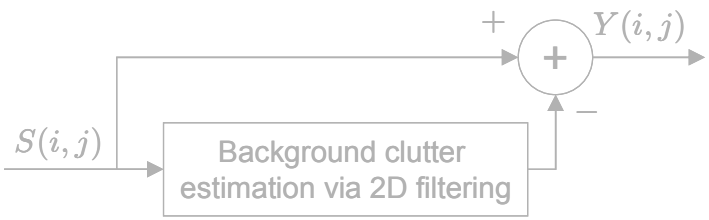

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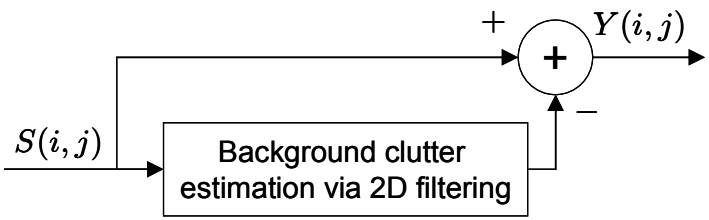

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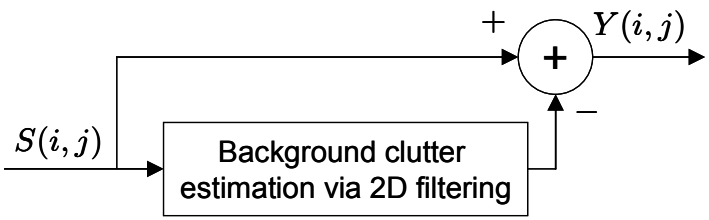

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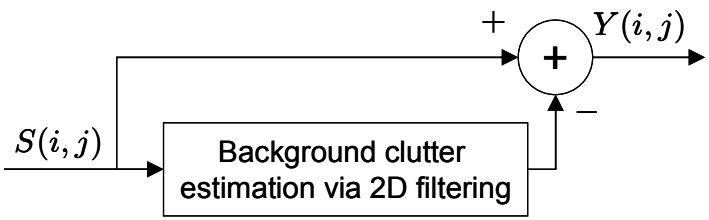

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Signal model

$$S(i,j) = \underbrace{t(i,j)}_{\text{Target signal}} + \underbrace{b(i,j)}_{\text{Background signal}} + \underbrace{N(i,j)}_{\text{Instrumental noise}}$$

Model of the acquired signal

$$E\{N(i,j)\} = 0$$

$$t(i,j) = \underbrace{A_T}_{\text{Target peak value}} \cdot \underbrace{s_T(i - i_0, j - j_0)}_{\text{Amplitude normalized target signal centered in } (i_0,\, j_0)}$$

Model of the target signal

$$SCR = \frac{(A_T - \eta_b)^2}{\sigma^2_{b+n}}$$

Signal-to-clutter ratio

Local statistics of the background-plus-noise signal

Overview of the detection system

$$\begin{cases} \mathrm{H}_0 : S(i,j) = b(i,j) + N(i,j) \\ \mathrm{H}_1 : S(i,j) = t(i,j) + b(i,j) + N(i,j) \end{cases}$$

Binary decision problem

$$Y(i,j) = S(i,j) - \hat{B}(i,j) = t(i,j) + \underbrace{R(i,j) + N(i,j)}$$

Background removal step

$G(i,j)$ **(residual signal – zero mean signal)**

$$\begin{cases} \mathrm{H}_0 : Y(i,j) = G(i,j) \\ \mathrm{H}_1 : Y(i,j) = t(i,j) + G(i,j) \end{cases}$$

Binary decision problem (in terms of *G(i,j)*)

$$T[Y(i,j)] \underset{H_1}{\overset{H_0}{\lessgtr}} \lambda$$

Detection rule

Probability of detection $P_D(\theta,\lambda) = Pr\left\{T[Y(i,j,\theta)] > \lambda | H_1\right\}$

Probability of false alarms $P_F(\theta,\lambda) = Pr\left\{T[Y(i,j,\theta)] > \lambda | H_0\right\}$

Performance analysis

Automatic setting of the parameters

Problem optimization

$$\begin{cases} \theta_{opt} = \underset{\theta \in \Theta}{\operatorname{argmin}} \{P_F(\theta, \lambda^*)\} \\ P_D(\theta, \lambda^*) = P_D^* \end{cases}$$

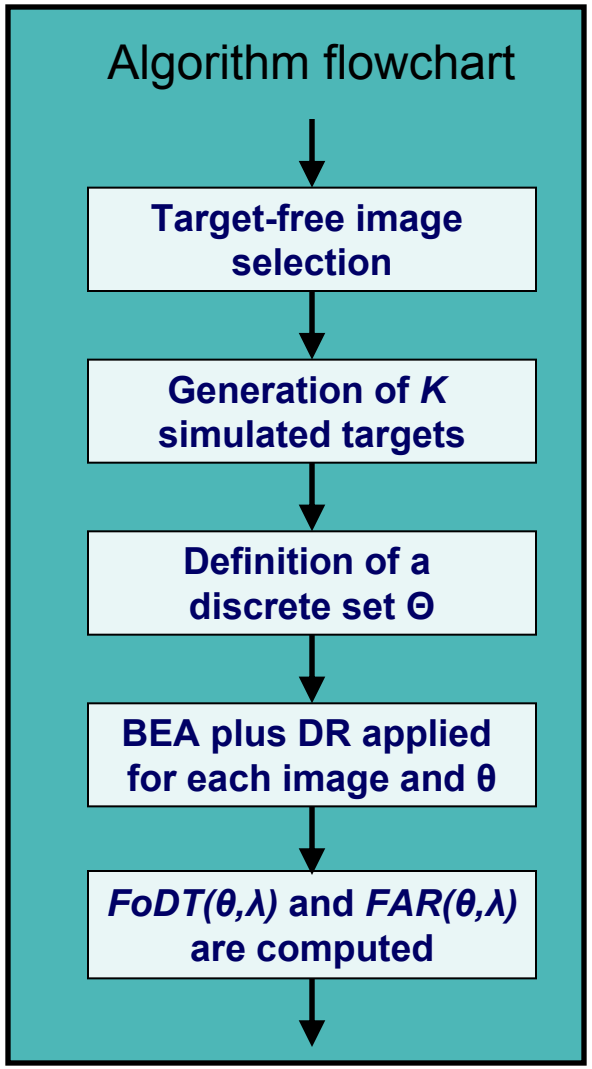
Numerical approximation

$$\begin{cases} \tilde{\theta}_{opt} = \underset{\theta \in \Theta}{\operatorname{argmin}} \{FAR(\theta, \lambda^*(\theta))\} \\ \lambda^* : \quad FoDT(\theta, \lambda^*(\theta)) \geqslant P_D^* \end{cases}$$

$$\tilde{\theta}_{opt} \to \theta_{opt}$$

$$\begin{cases} FoDT(\theta, \lambda) \to P_D(\theta, \lambda) \quad K \to +\infty \\ FAR(\theta, \lambda) \to P_F(\theta, \lambda) \quad M \cdot N \to +\infty \end{cases}$$

K **= # of simulated targets**
M, N **= dimensions of the image**



Extension to BEA selection

- To improve the performance of the whole detection system, the user has to choose not only the design parameters but also the best BEA.

- The proposed procedure is extended to the case where different BEAs are available.

$\{BEA_1, BEA_2, ..., BEA_P\} \longrightarrow$ set of P available BEAs, each of them characterized by an array $\theta^{(p)}$

$$\begin{cases} BEA_{opt} = BEA_{p_opt} \\ p_opt = \underset{p=1,2,...,P}{\operatorname{argmin}} \left\{ FAR^{(p)}(\tilde{\theta}_{opt}^{(p)}, \lambda^*(\tilde{\theta}_{opt}^{(p)})) \right\} \\ \tilde{\theta}_{opt} = \tilde{\theta}_{opt}^{(p_opt)} \end{cases}$$

$\tilde{\theta}_{opt}^{(p)} \rightarrow$ **Optimum parameter vector for the *p*-th BEA**

$FAR^{(p)}(\cdot) \rightarrow$ **False alarm rate achieved employing the *p*-th BEA in the detection scheme**

Practical issues

- Off-line procedure.
- Tailored to applications where the overall appearance of the background varies slowly in time.
- Periodical updating according to the frequency of the global changes of the scenario.
- Spatial coordinates of the targets randomly generated in the regions of edges.
- If the optimization problem has not a unique solution, one could prefer the one computationally more efficient.

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Experimental results

- Analyzed BEAs and related parameter setting
  - 2-D MA $\theta \equiv \{(D_r, D_c) : D_r \in [1:2:21]; D_c \in [1:2:21]$
  - MEDIAN $\theta \equiv \{(D_r, D_c) : D_r \in [1:2:21]; D_c \in [1:2:21]$
  - BILATERAL FILTER $\theta \equiv \{(D_r, \sigma_r) : D \in [3:2:21]; \sigma_r \in [0.01:0.01:1]$
- Test statistic:

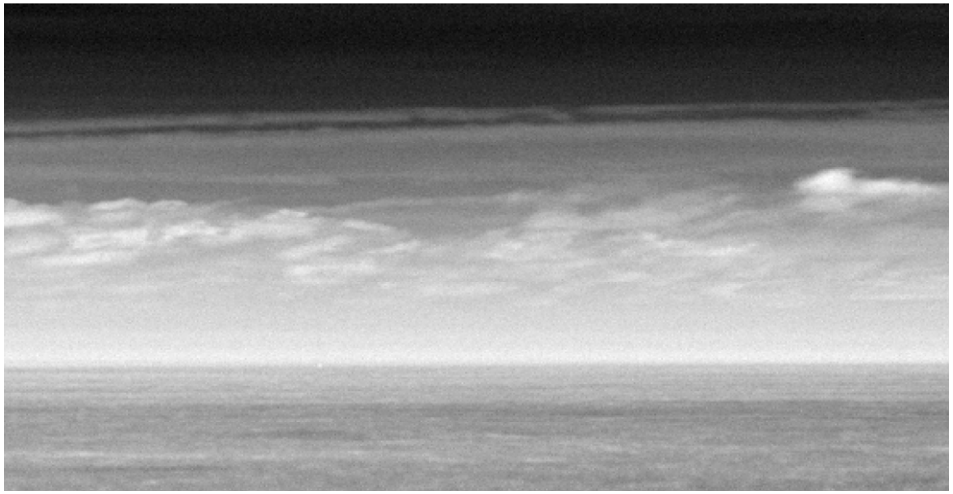
$$T[Y(i,j,\theta)] = \frac{Y(i,j,\theta)}{\hat{\sigma}} \underset{H_1}{\overset{H_0}{\lessgtr}} \lambda$$

- Data Set:
  - Sea-sky scenario
  - MWIR camera
- Simulation setup

K=100

SCR=8 dB ← DIM TARGET

$P_D^* = 0.9$



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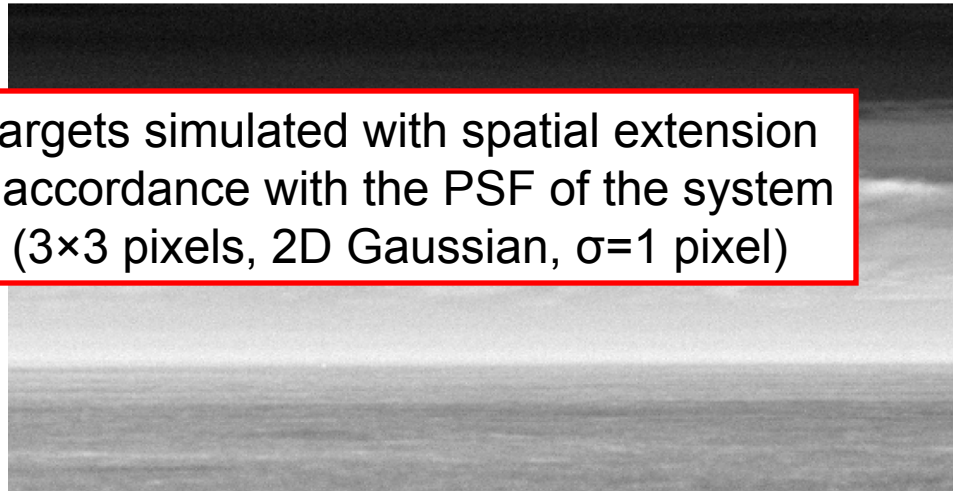
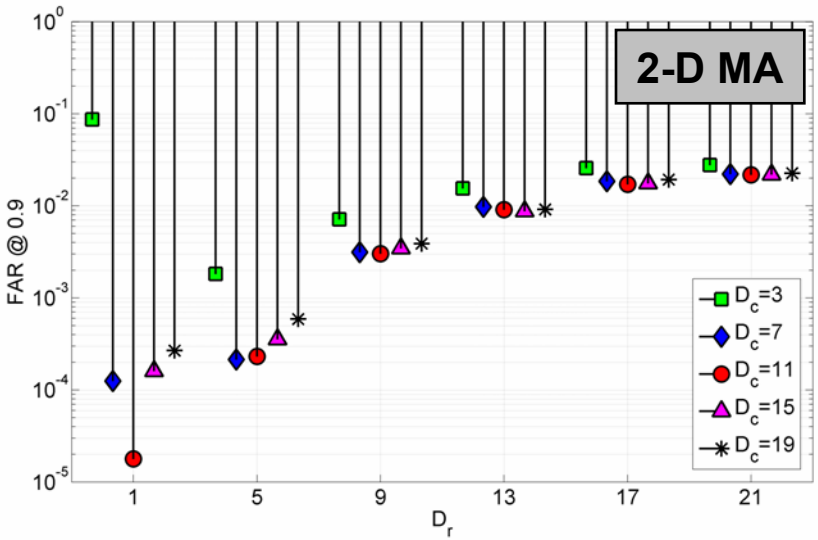
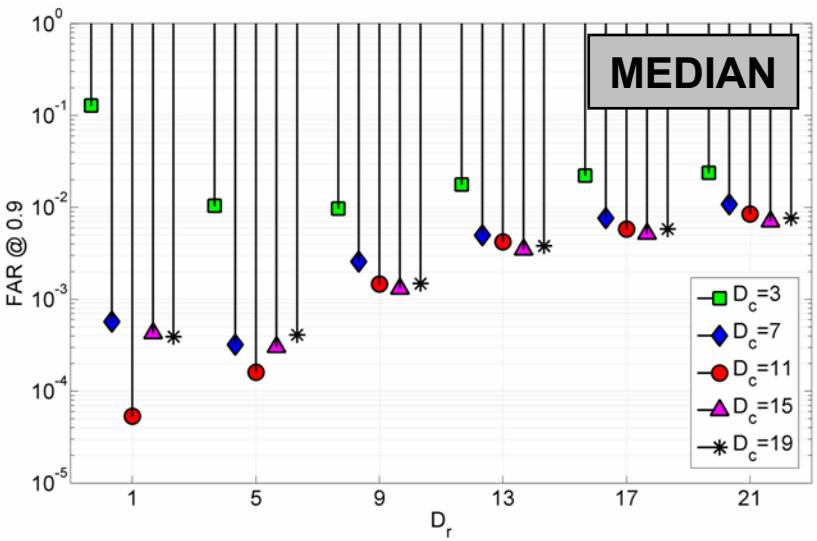
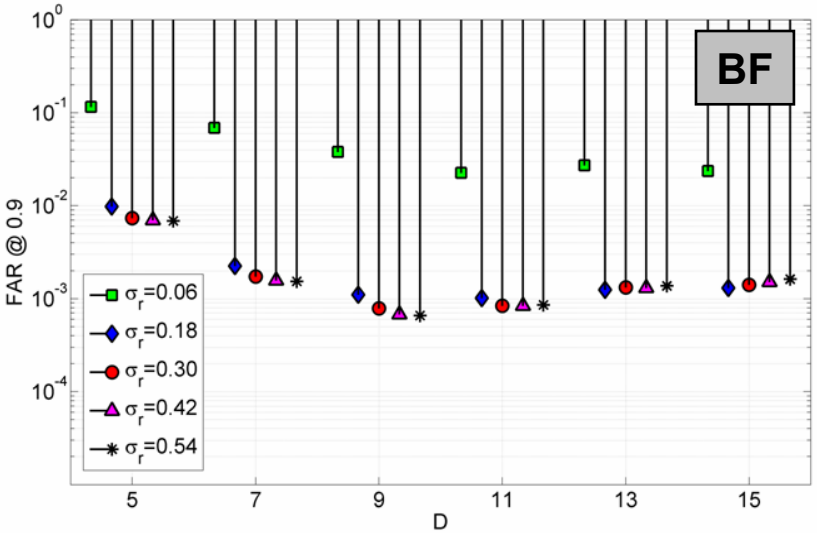


Targets simulated with spatial extension in accordance with the PSF of the system (3×3 pixels, 2D Gaussian, σ=1 pixel)

Initialization

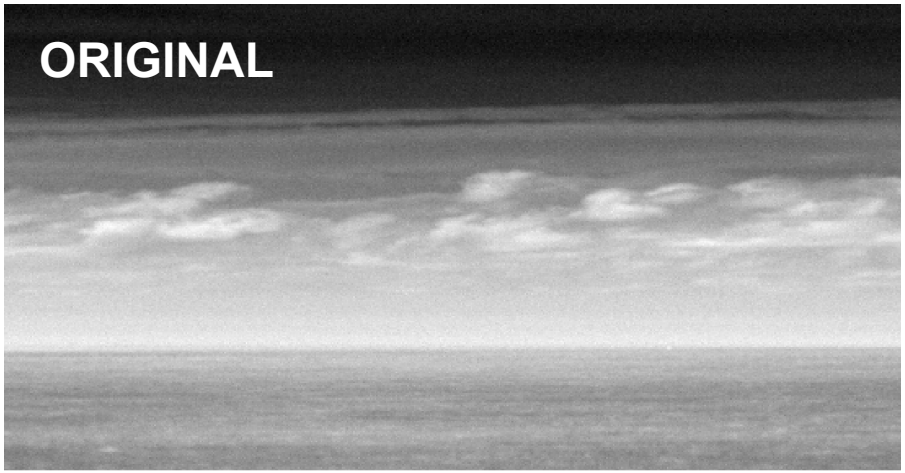


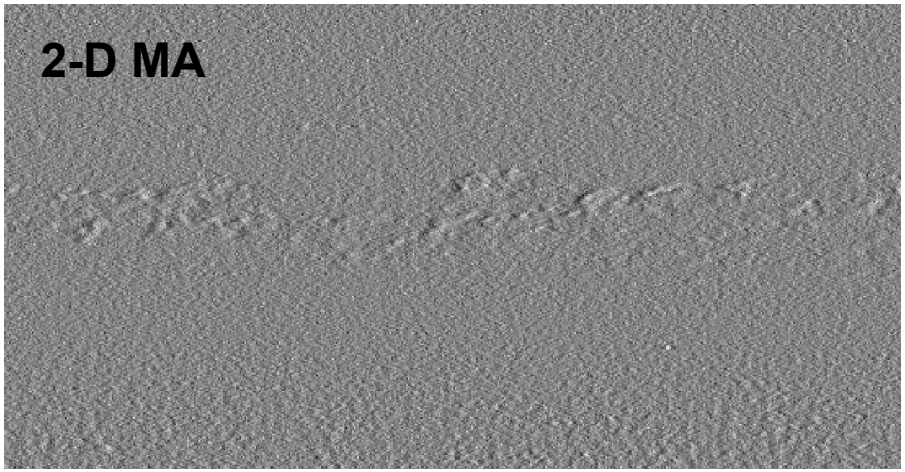


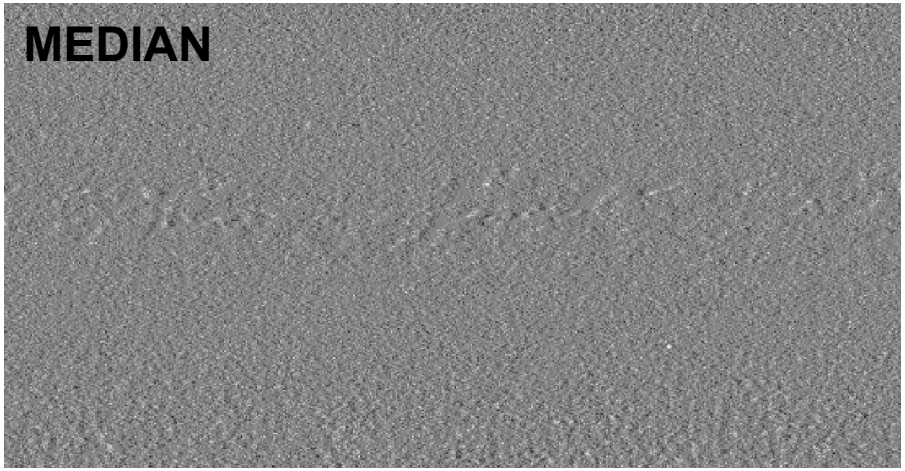


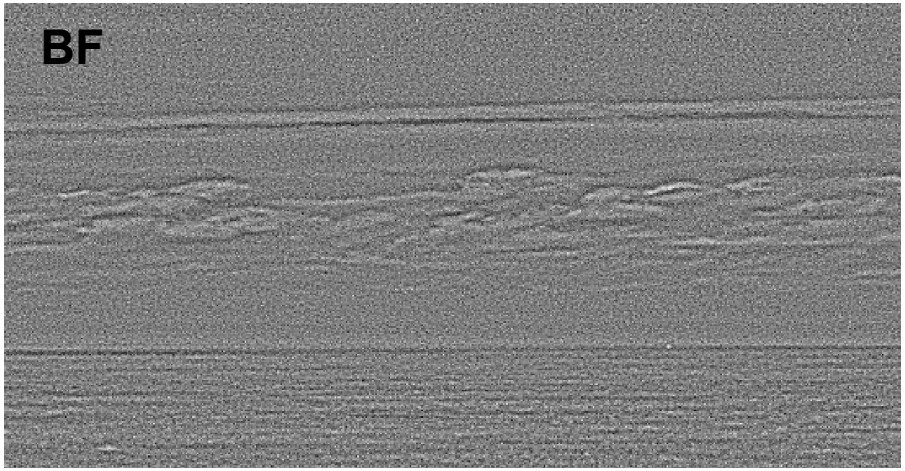
- The best results were obtained by the 2-D MA and MEDIAN BEAs with one-dimensional masks, in accordance with the characteristics of the scenario.
- The worst performace was obtained by the BILATERAL FILTER-based BEA. It provided *FAR@0.9* of about one order of magnitude higher than the other BEAs.

Frames after background removal









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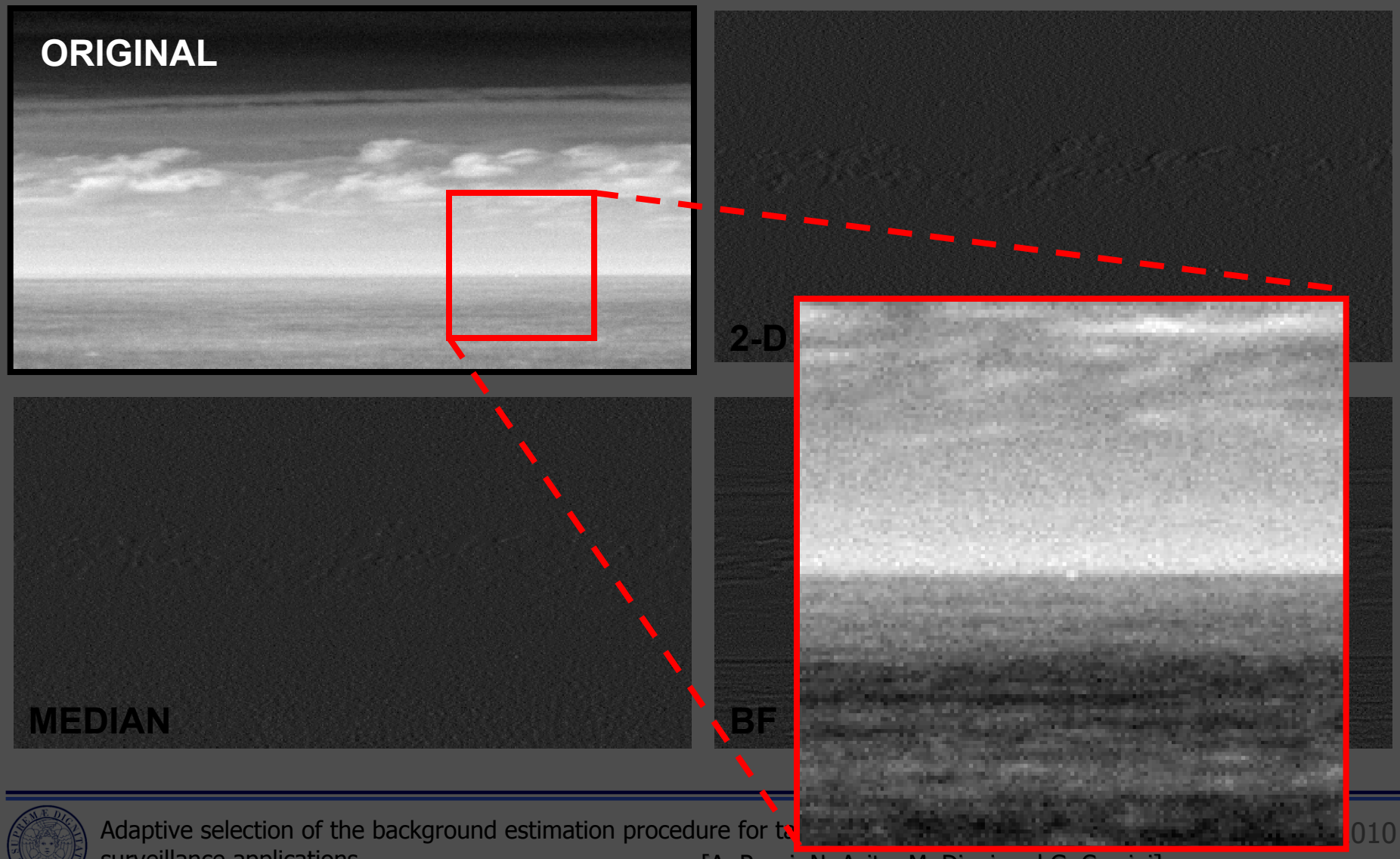

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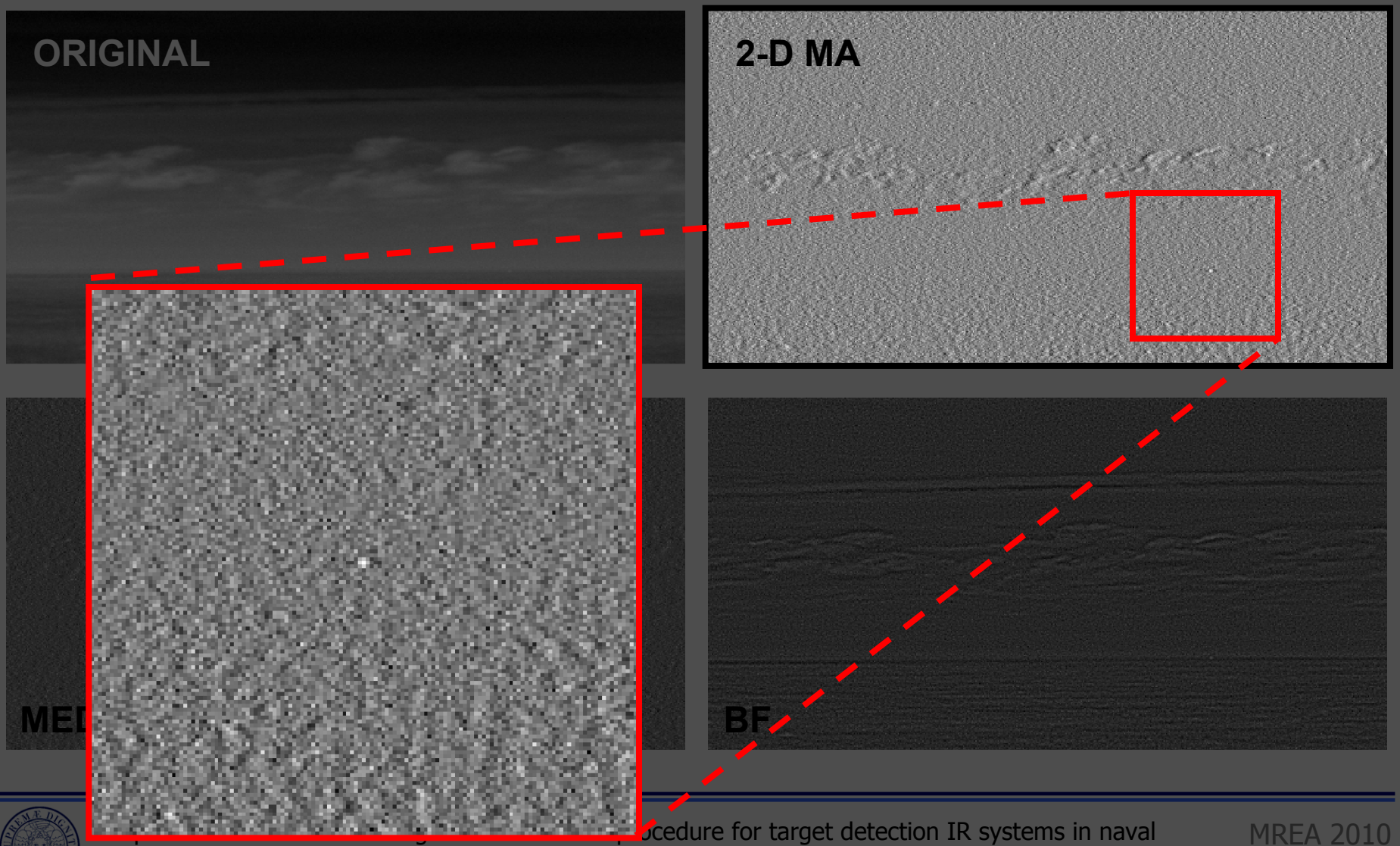

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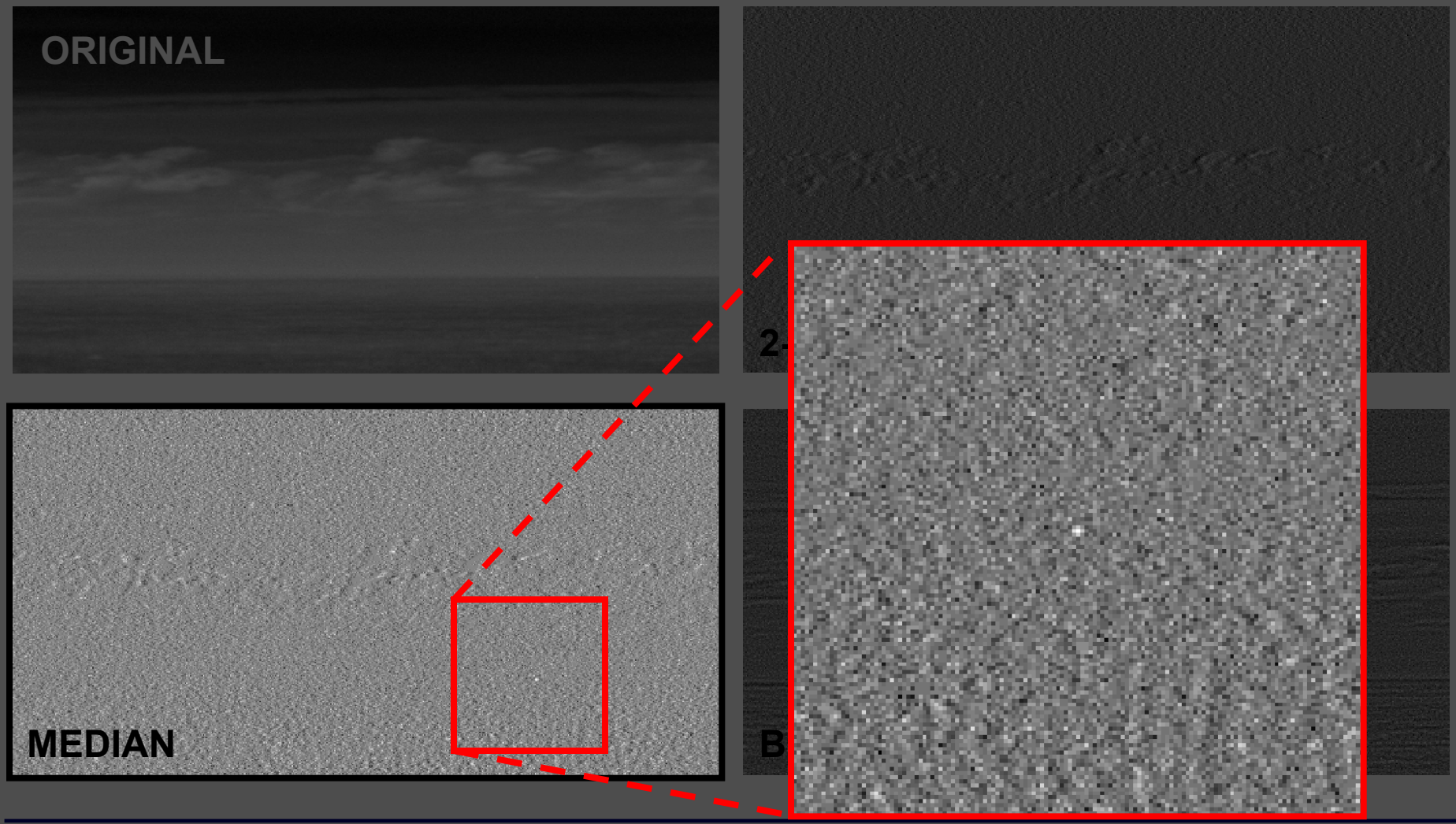

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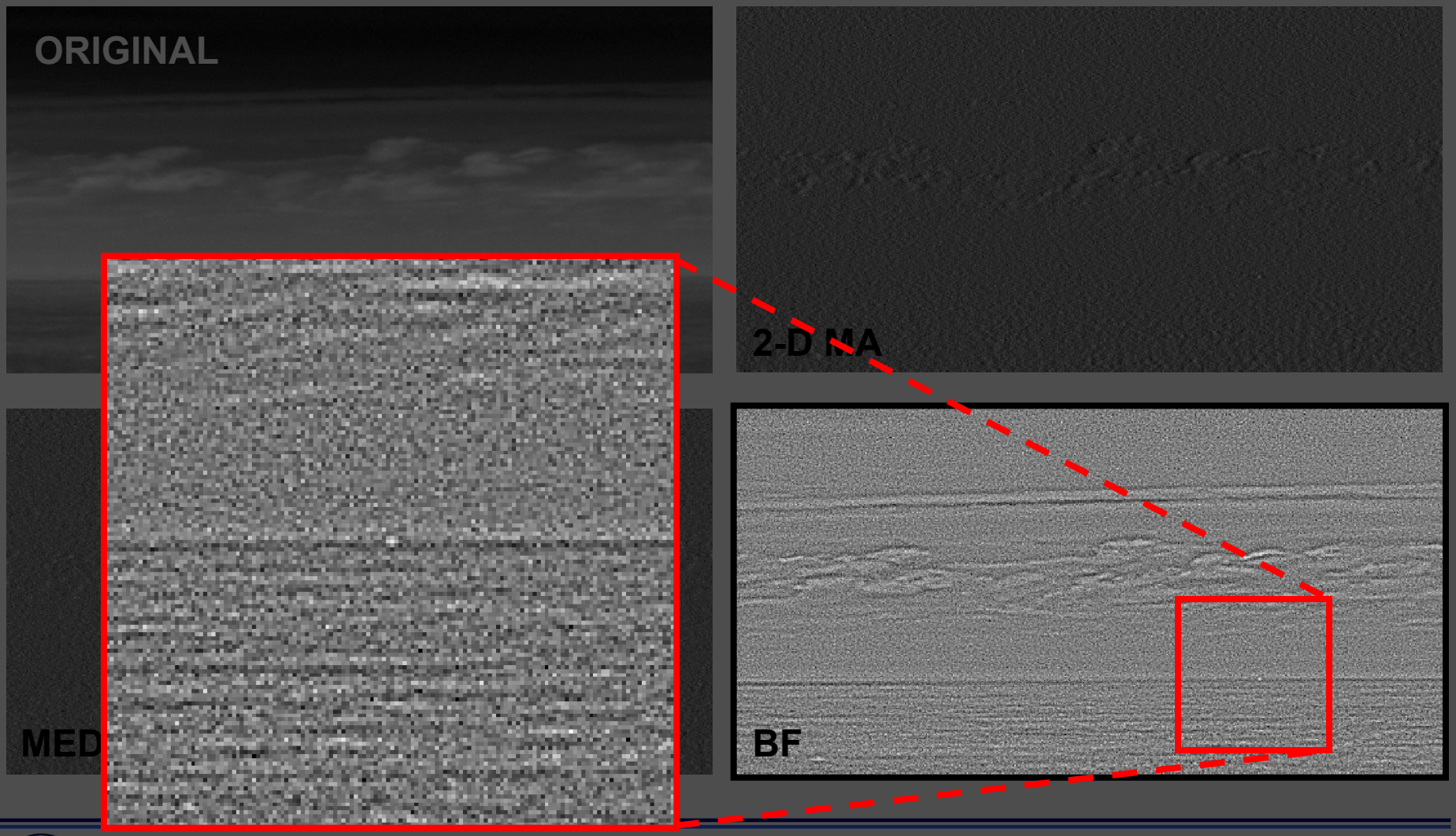
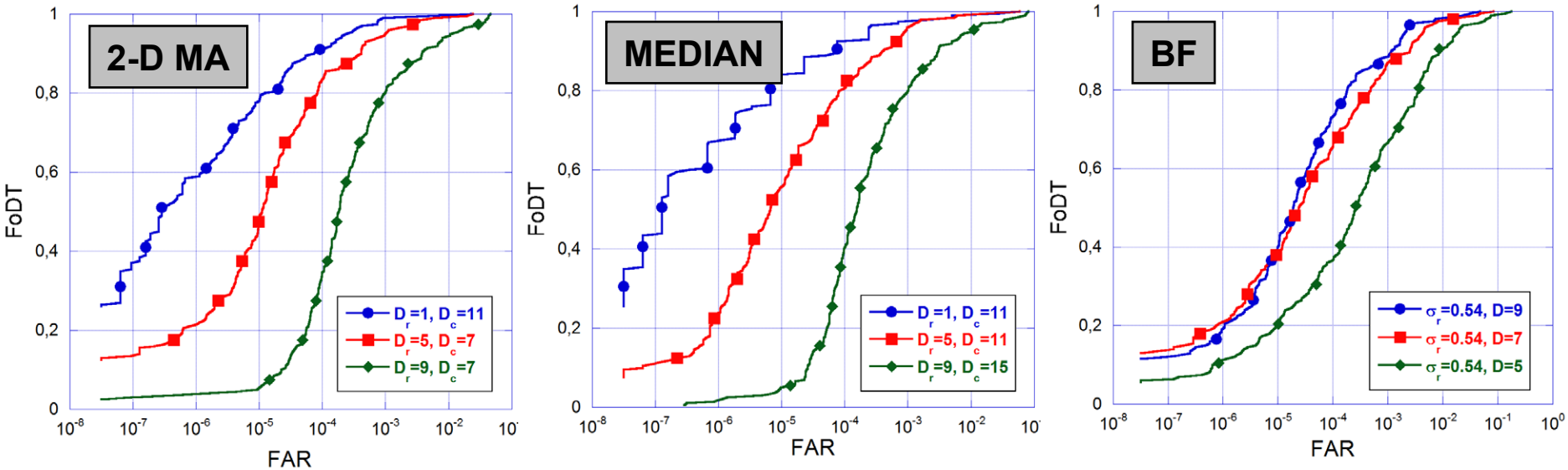
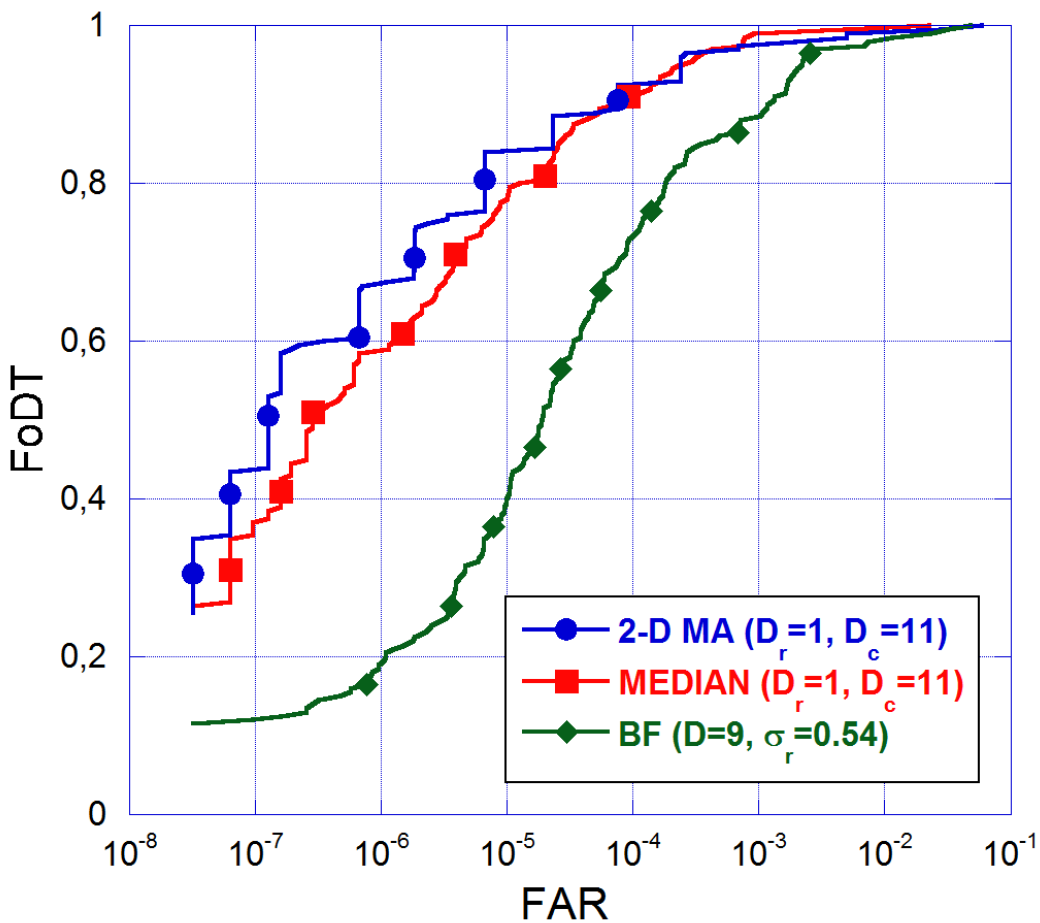


Validation of the results: Ex-ROC (i)



- Ex-ROC curves: FoDT vs. FAR computed over the entire sequence of frames with simulated targets.
- For each BEA, the comparison of the Ex-ROC curves is made in correspondence of these parameter setting configurations:
  - "optimum";
  - FAR@0.9 one order of magnitude higher;
  - FAR@0.9 two order of magnitude higher.

Validation of the results: Ex-ROC (ii)



- Ex-ROCs obtained by the three considered BEAs using the "optimum" parameters setting suggested by the proposed procedure.
- The worst performance is obtained by the BILATERAL FILTER, in accordance with the proposed procedure.
- 2-D MA and MEDIAN provide very similar results in terms of Ex-ROC.

Conclusions

- We have proposed a novel procedure for the choice of the most performing background estimation algorithm in IR systems.
- The proposed technique is based on the simulation of dim targets on a target-free image representing the scenario of interest.
- The most performing BEA has been chosen evaluating the FAR for several parameter configurations of the analyzed BEAs.
- An experimental IR sequence representing a typical naval scenario has been used in order to test the novel procedure.
- The effectiveness of the technique has been demonstrated by applying the detection algorithm over the IR sequence with simulated target for several configurations of the BEAs parameters.
- The results support the validity of the novel procedure. In fact, the optimum parameter setting is in complete accordance with the characteristics of the scene.