Improving correlation based detection, tracking and classification of passive acoustic signatures with modern signal processing

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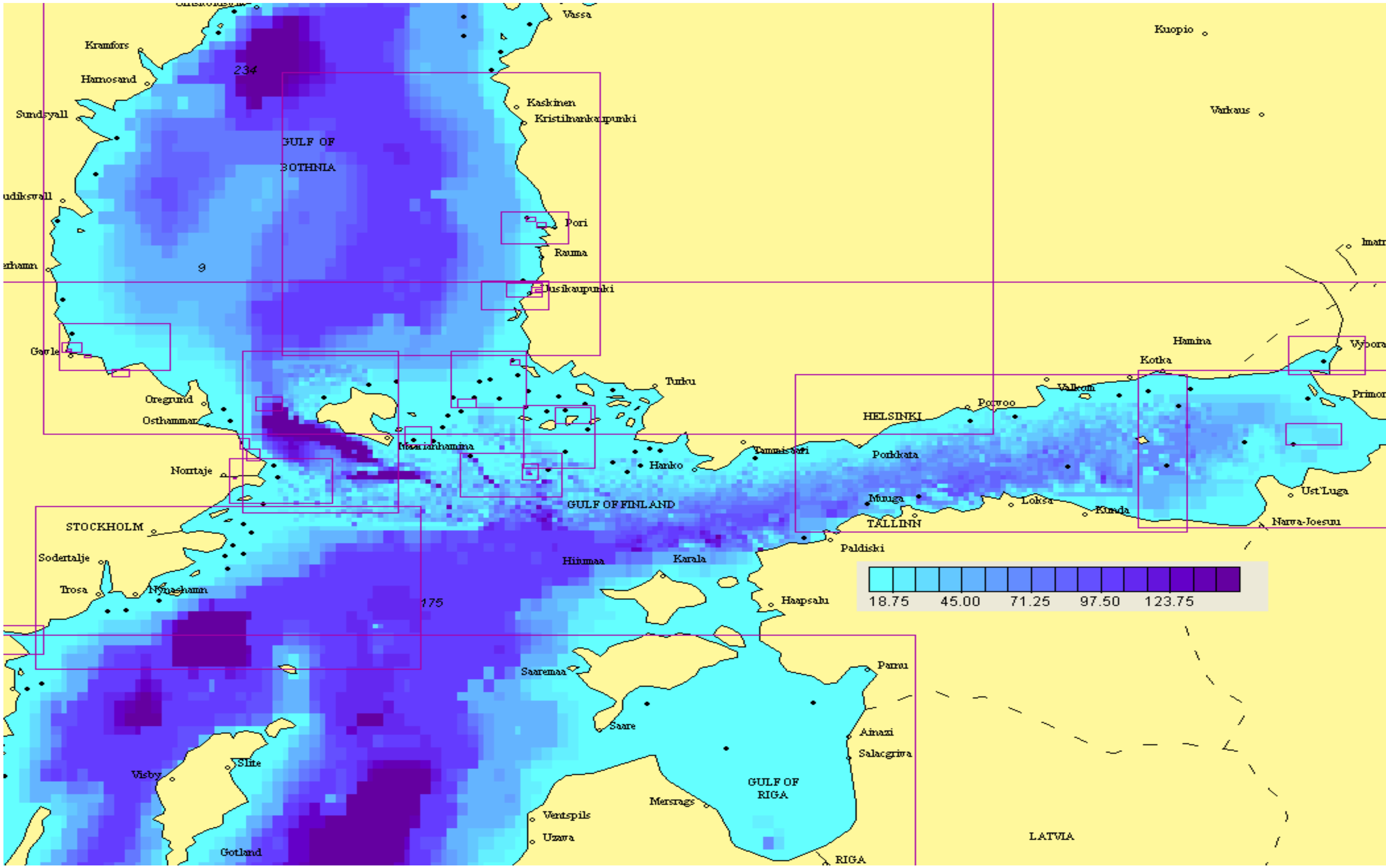
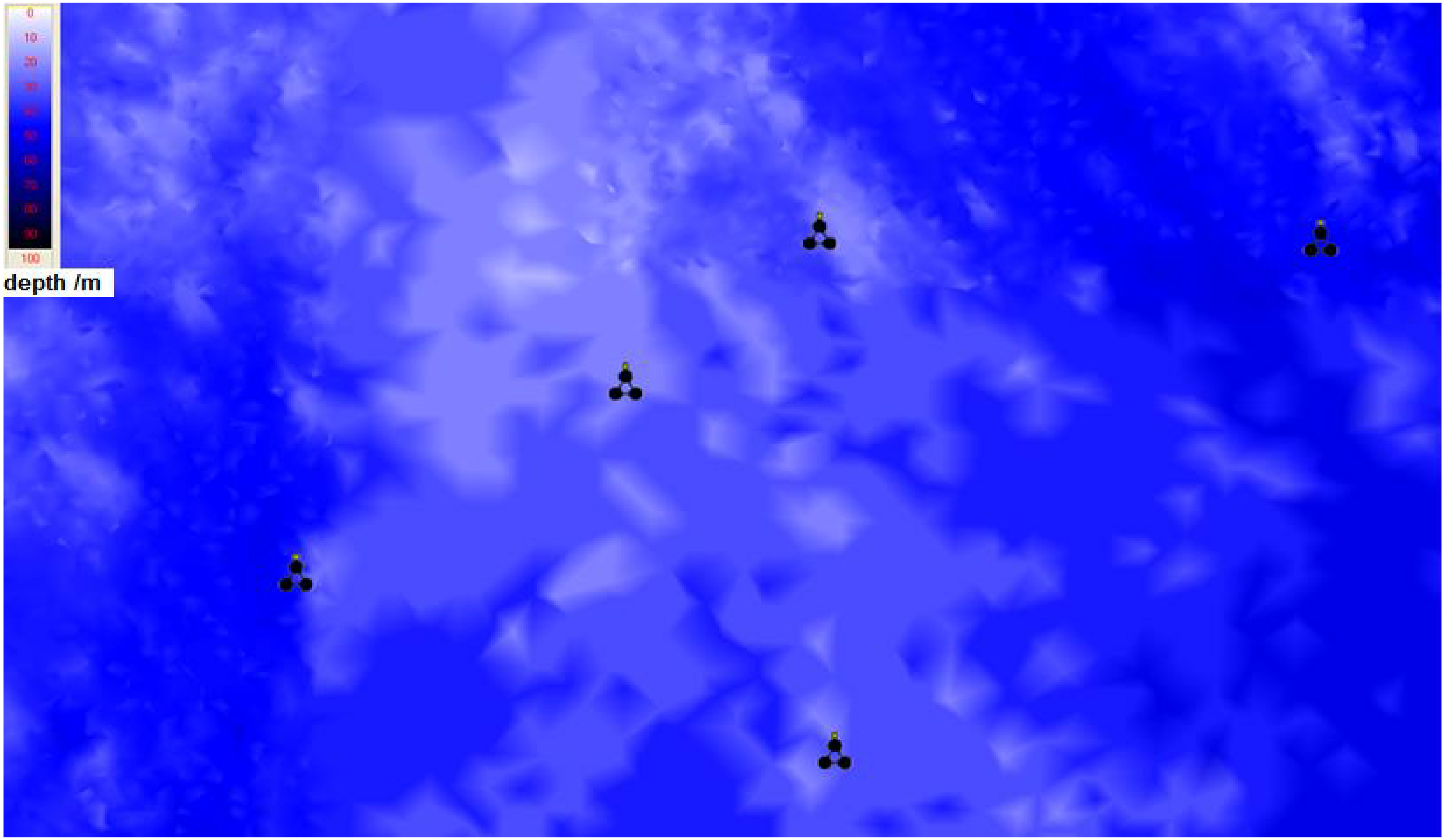
1. Introduction

- Average depth of the surveillance area in Northern Baltic and the Gulf of Finland is less than 50 meters
- Interference and reverberation are major sonar performance limiting factors.
- The original sensor system was designed a couple of years ago and we have found a need to improve particularly the bearing of targets, multi target tracking and operator aided classification.
- The passive prototype surveillance sensor field consists of several sensor units with digital optical sea cables to enhance data bandwidth and quality (avoiding analog cable attenuation).
- The purpose is to improve the performance of an existing underwater acoustic surveillance system in challenging shallow water environment.

1. Introduction – Northern Baltic depths



1. Introduction – Example of simulated sensor locations and depth – distributed sensor field



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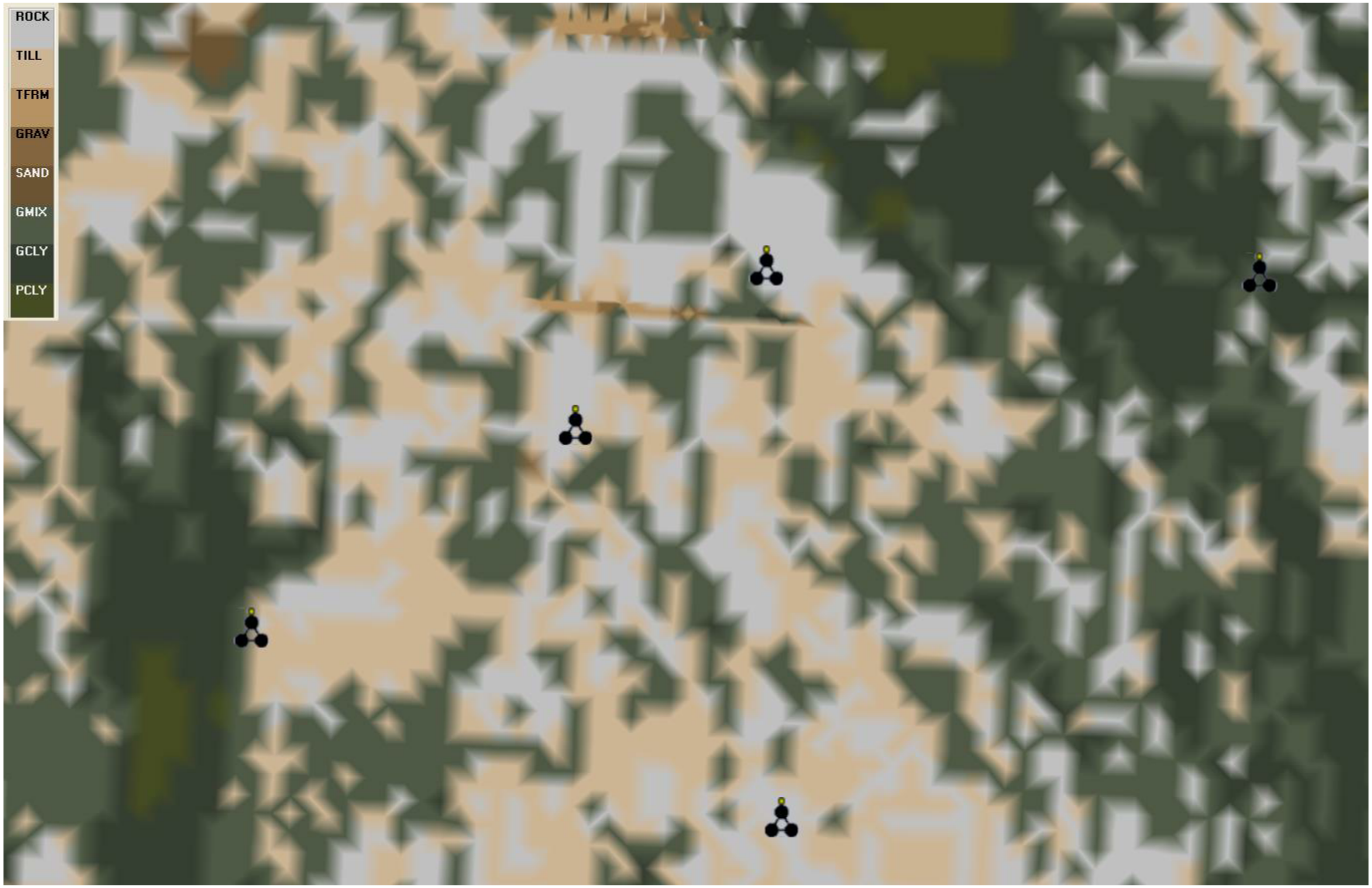
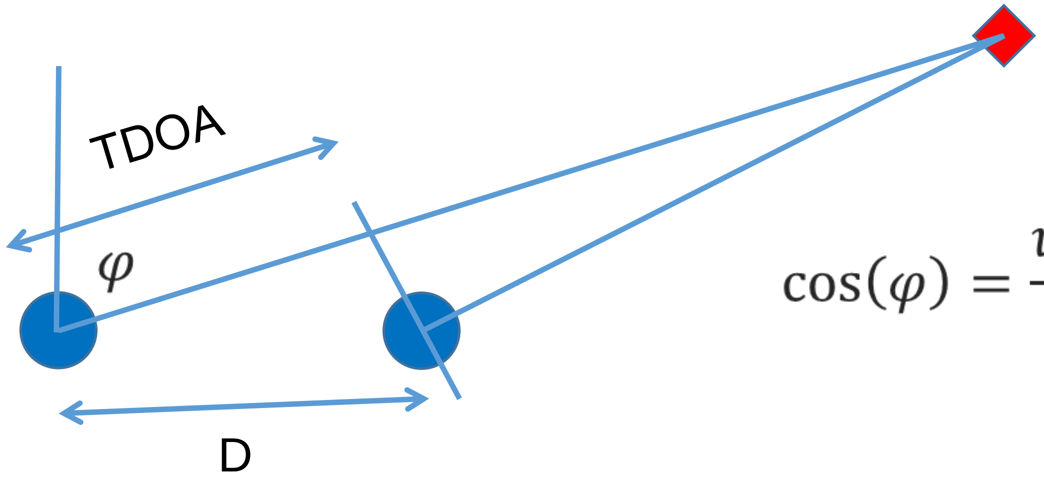
1. Introduction – example of simulated sensor locations and sea bottom type



2. Tracking - Introduction

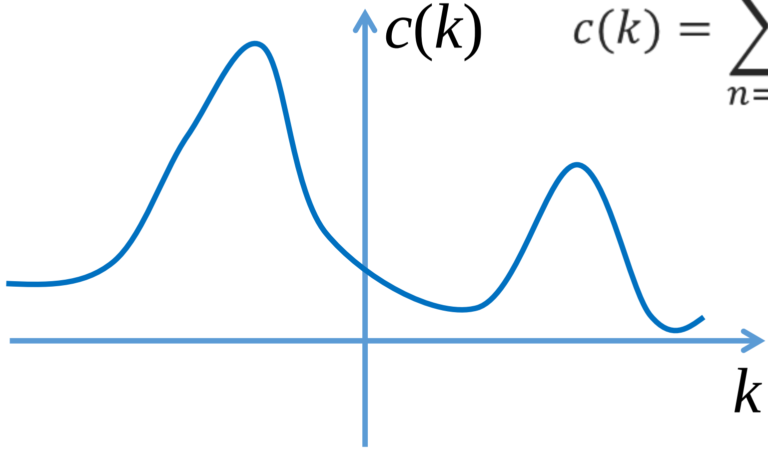
- Direction of an audio source can be estimated from time difference of arrival between two or more sensors.
- The difference is shown in the phase difference between the two received signals.



$$\cos(\varphi) = \frac{v \cdot TDOA}{D}$$

2. Tracking – Correlation

- Measure of similarity between two signals
- Assuming zero mean signals x and y
- Time delay estimation compares relative magnitude of correlation



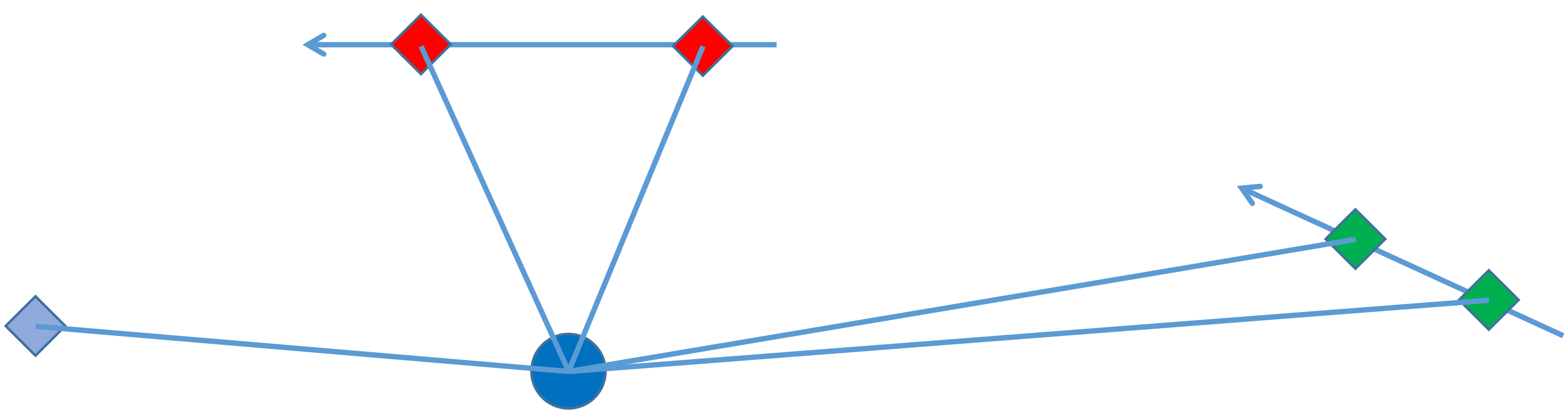
$$c(k) = \sum_{n=0}^{N-1} x_n \cdot y_{n-k}$$

2. Tracking – Frequency Domain Correlation

- Computationally efficient: $N\log(N)$ vs. N^2
- Allows spectral transforms
  - Frequency shift
  - Phase extraction
- Simple filtering
  - Band pass
  - Band stop
- More accurate time delay estimation through spectrum phase comparison

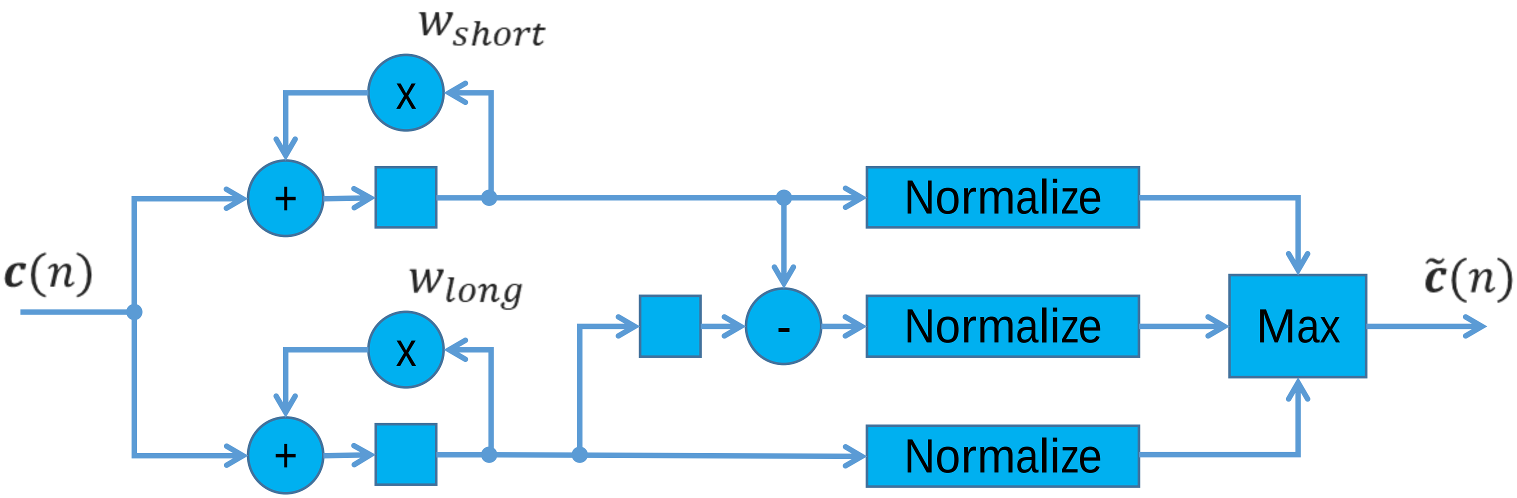
2. Tracking – Combining Correlation Lengths

- Problems:
  - Distant and weak targets need long correlation
  - Fast targets need short correlation
  - Static background must be cancelled



2. Tracking – Combining Correlation Lengths

- Using two correlation lengths
  - Long for static and weak signals
  - Short for fast moving targets
- Using long correlation as background estimate

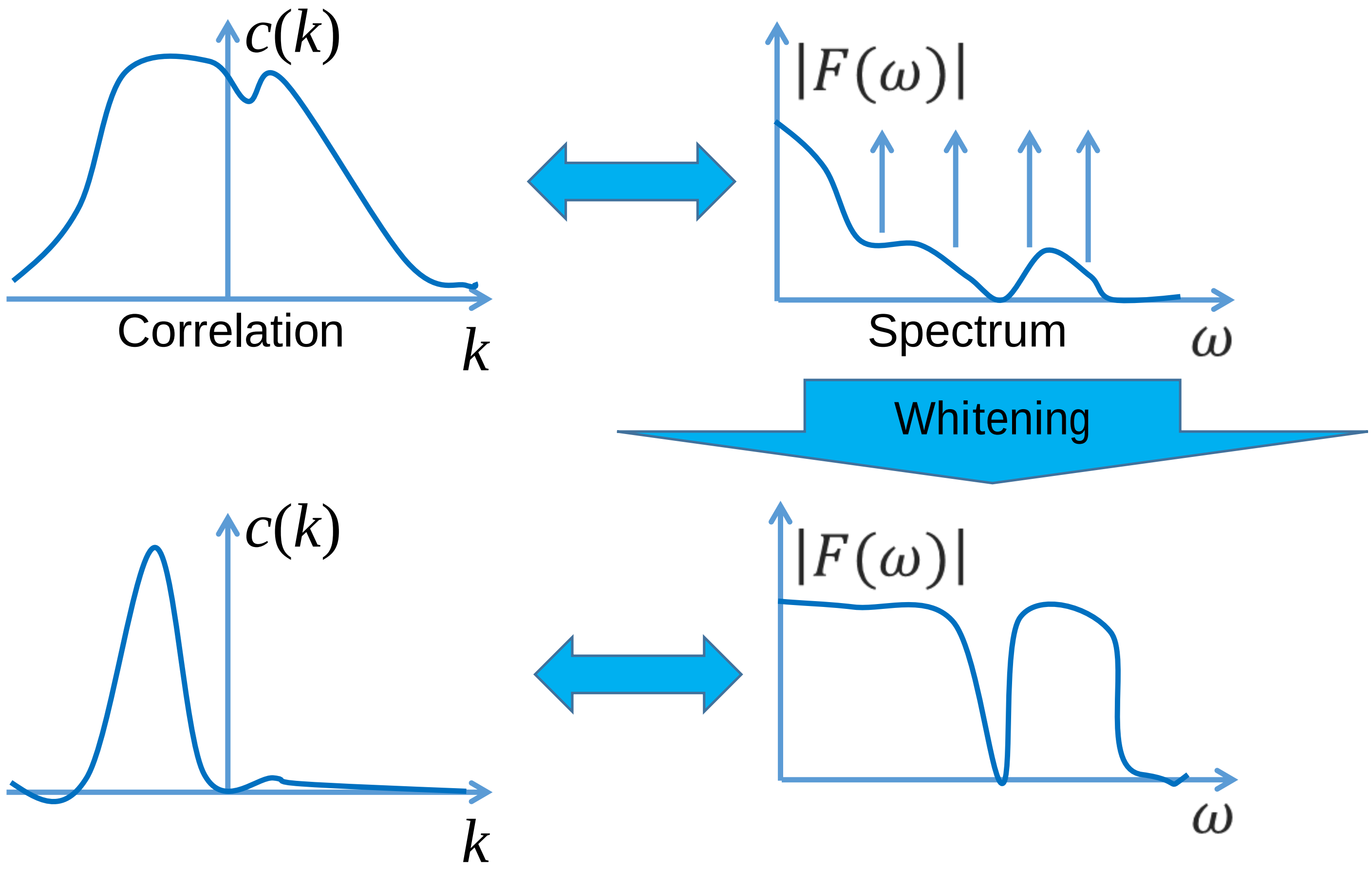


2. Tracking – Blind Channel Equalization

- Problem:
  - Multipaths in the propagation channel blur the correlation and create additional peaks
  - Source signal is unknown
  - The channel is unknown
- Solution:
  - Removing autocorrelation from the received signal

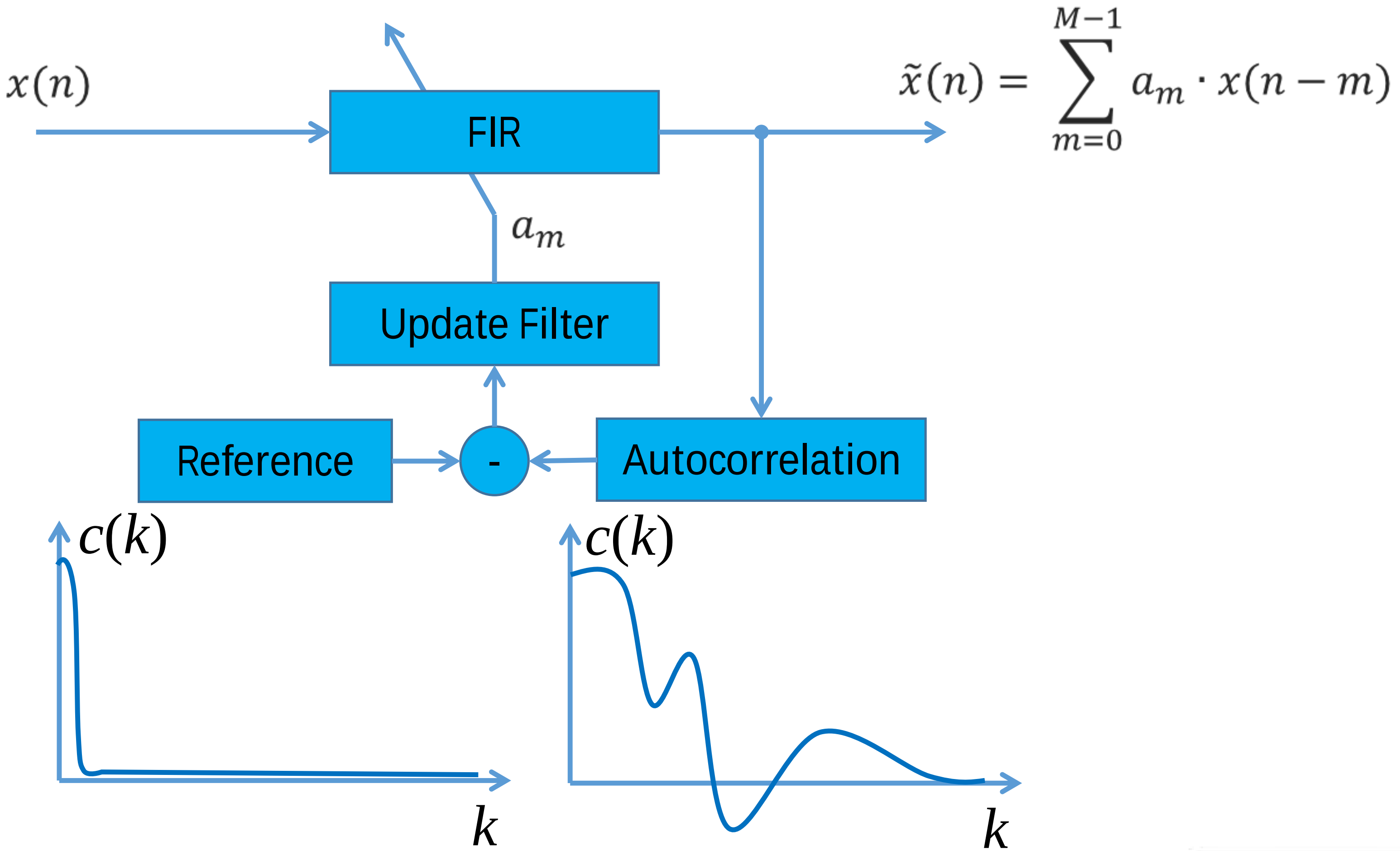
2. Tracking – Blind Channel Equalization

- Option 1: Spectral whitening



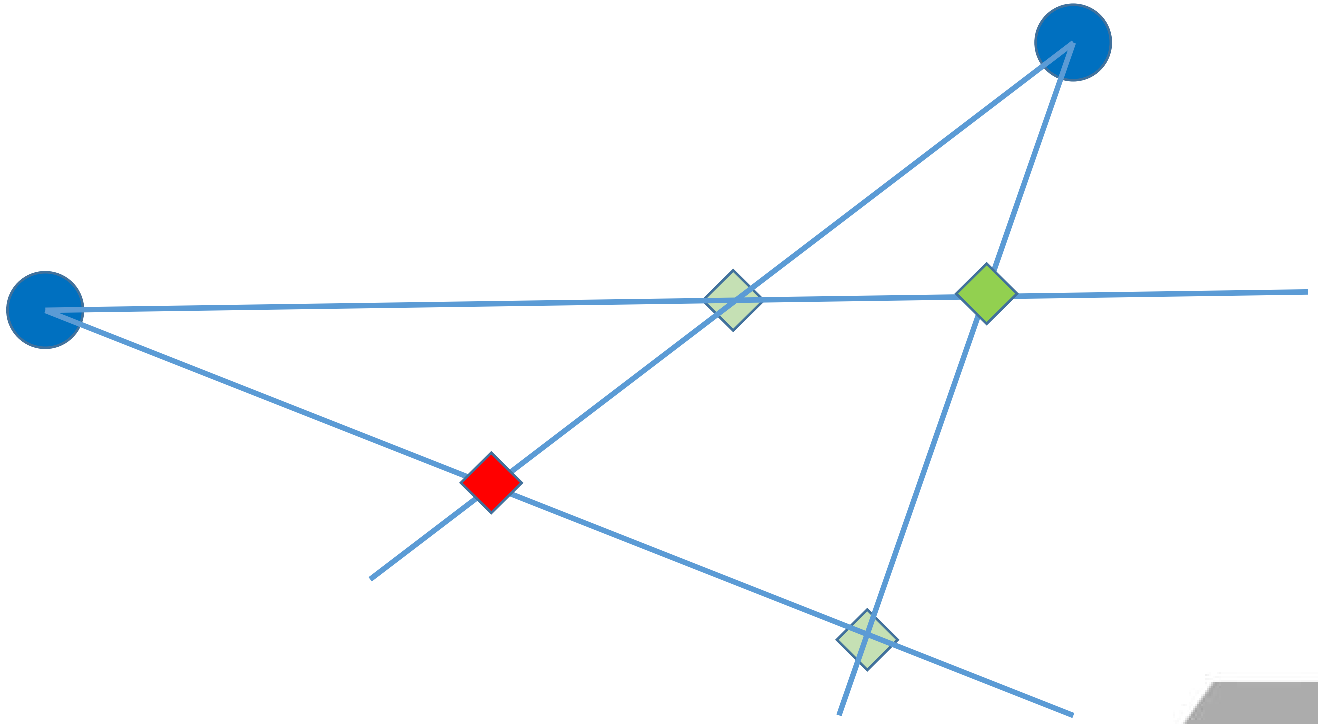
2. Tracking – Blind Channel Equalization

- Option 2: Adaptive FIR filtering



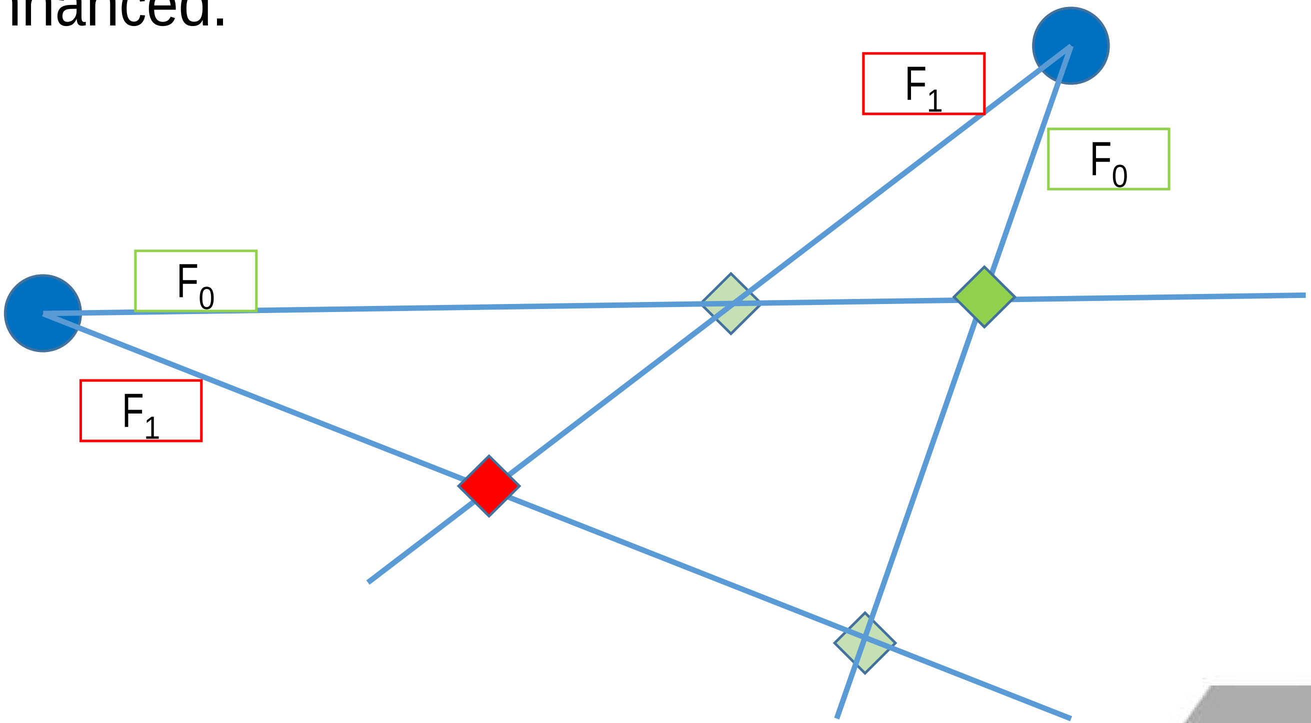
2. Tracking – Spectral Profile Detection

- Problem:
  - Multiple targets
  - Crossing bearings between targets
  - Ghost targets are produced



2. Tracking – Spectral Profile Detection

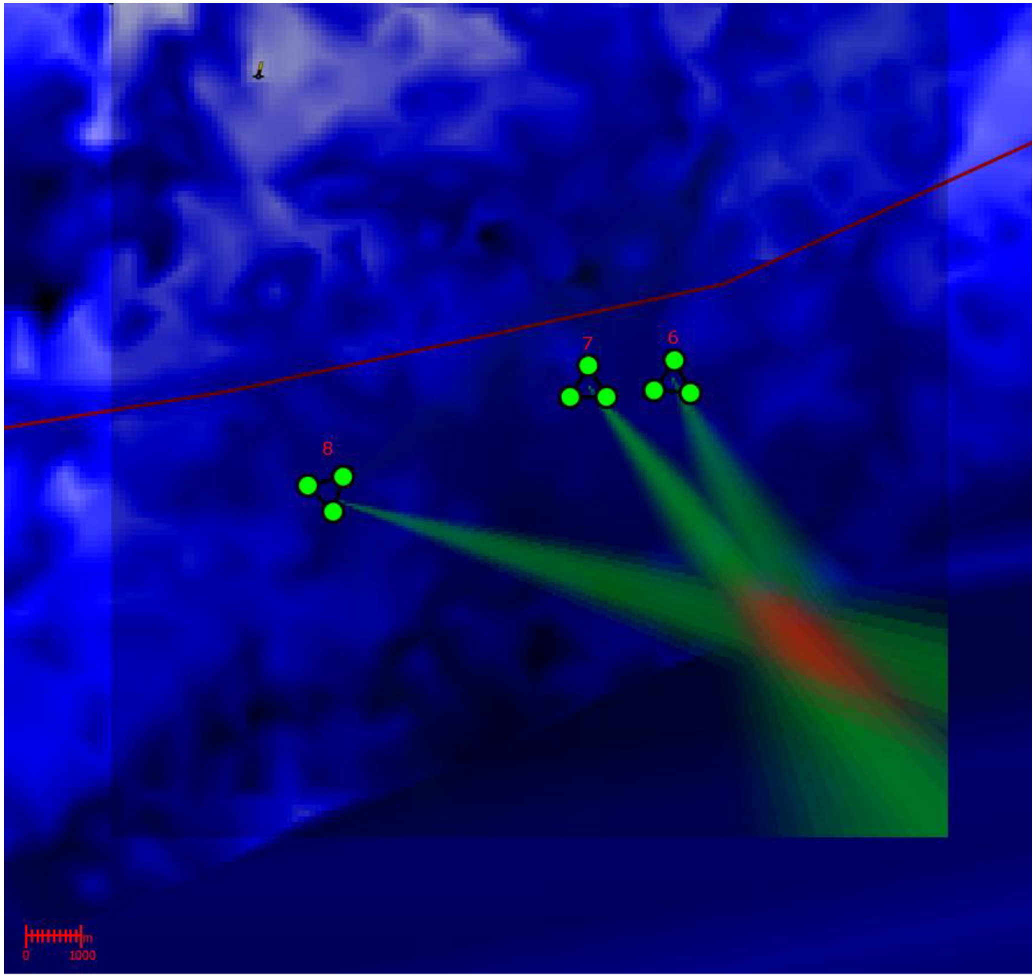
- Each sensor unit computes spectral features for the strong bearings
- The bearing-feature pairs are matched so that the ghost targets are removed and the true targets are enhanced.



2. Tracking – Sensor Fusion

- Problem:
  - Multiple overlapping detection sources
  - Discriminate ambiguous bearings without interfering with true bearings
- Combining normalized detection probabilities
- Mixing functions compute display intensities
- Spectral feature comparison enhances targets
- Local result normalization balances areas with different acoustic activity

2. Tracking – Results



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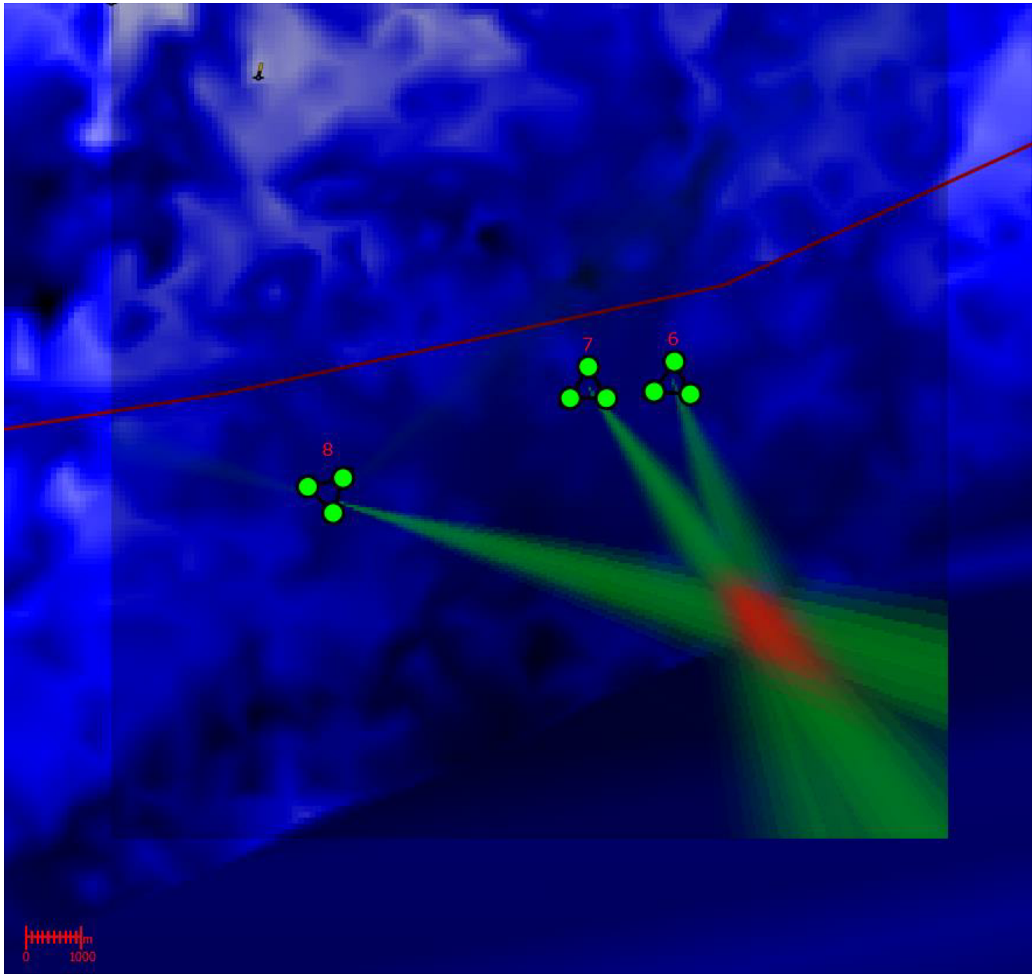

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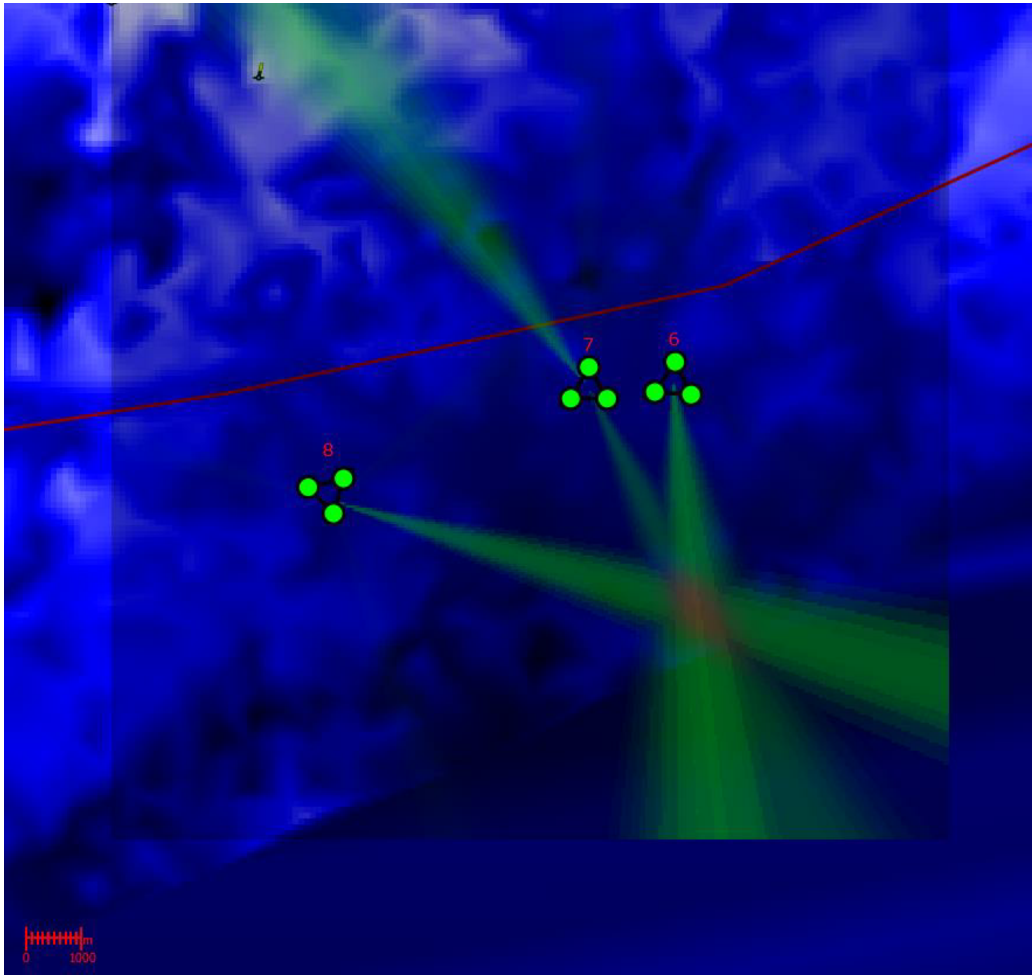

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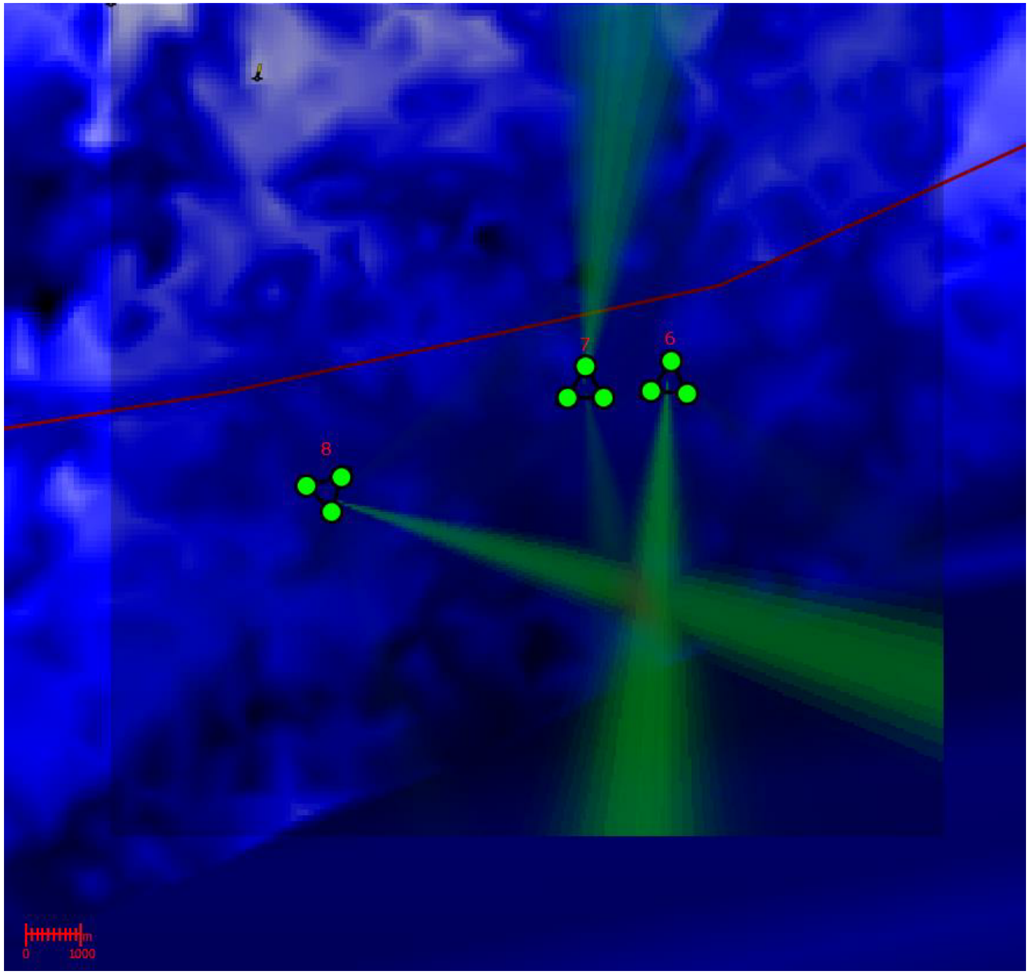
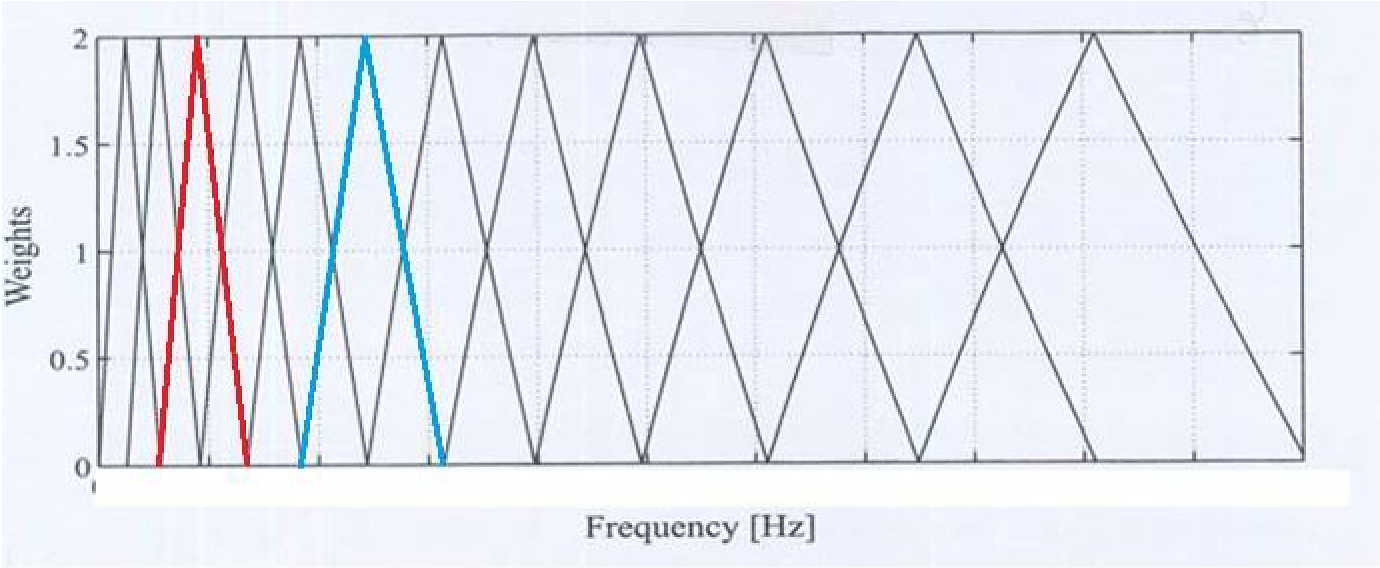


3. Operator aided acoustic target classification

- The need for automatic acoustic target classification comes from a huge surveillance human operator load
- On the other hand there exists the necessity to replace or complement the performance of surface surveillance (radar surveillance can be missing)
- This presentation handles classification of surface targets

3. Operator aided acoustic target classification

- Used features are based on MEL –frequency cepstrum, which is a representation of short –term power spectrum of the acoustic sample, based on a linear cosine transform of a log power spectrum on a nonlinear MEL scale of frequency:



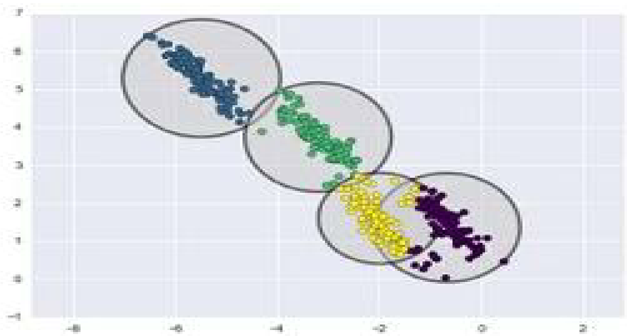
- Figure. A MEL –feature bank of 12 step filters.

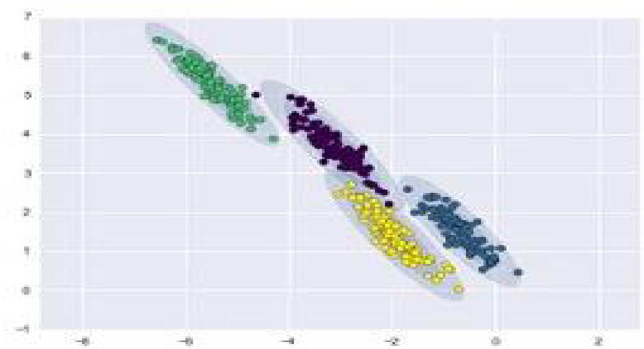
3. Operator aided acoustic target classification

- A hybrid feature vector is formed by linking some operator aided parameters to the MFCC (MEL frequency cepstral coefficient) vector
- These features can be SR, BR, TPK, number of harmonics in LOFAR band
- Learning algorithm (supervised learning): Expectation maximization (EM), iterative
- EM is an iterative method in statistics to find maximum likelihood estimates of parameters in statistical models, where the model depends on unobserved latent variables

3. Operator aided acoustic target classification

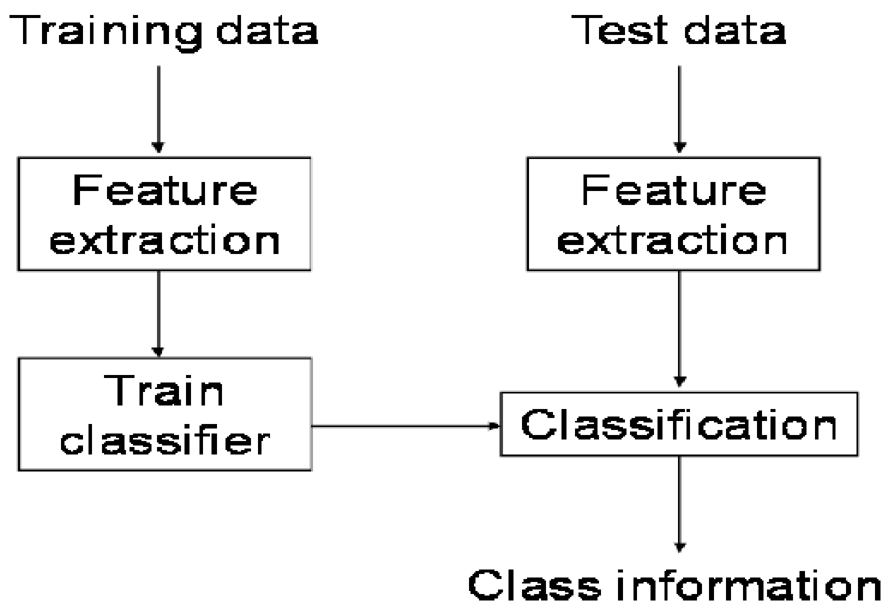
- Classification algorithm is GMM (Gaussian mixture model):
- GMM is a statistical classification method, which models the probability density of the feature vectors utilizing weighted Gaussian distributions (a "soft weighting" compared to K-means clustering)
- Target speed is estimated before classification (acoustically by Doppler shift or roughly by other means), in simulations by radar track.





- K-means "hard" clustering GMM "soft" clustering

3. Operator aided acoustic target classification



3. Operator aided acoustic target classification

- The training data set can include samples of a single target type using several speeds or engine RPM:s
- The variation in engine revolutions has a remarkable effect to cepstral MFCC features
- That is why we try to "normalize" the effect of revolution changes by stretching or shrinking the spectrum of the sample before estimation of MFCC:s depending on the target speed.
- Merchant and military ships with a fixed pitch propeller (FPP) and a displacement hull have normally a linear dependence between speed and engine revolutions until a limit (so called Froude number), and above this limit another linear dependence, which we try to utilize when shrinking the spectrum (see next figure).

3. Operator aided acoustic target classification- principle of dependence of SR and target speed

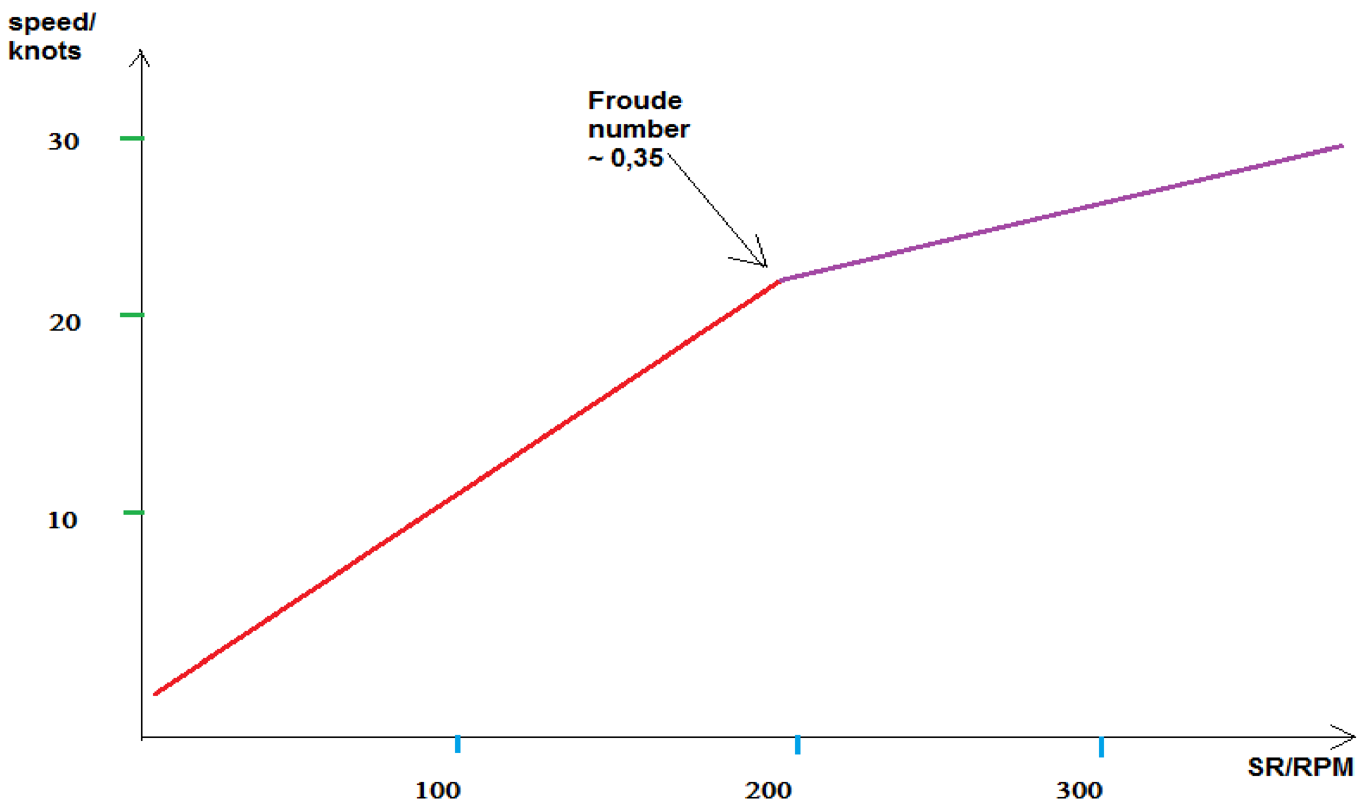


Fig. The dependence of SR revolutions and speed of ships with displacement hull and FPP propeller type

3. Operator aided acoustic target classification

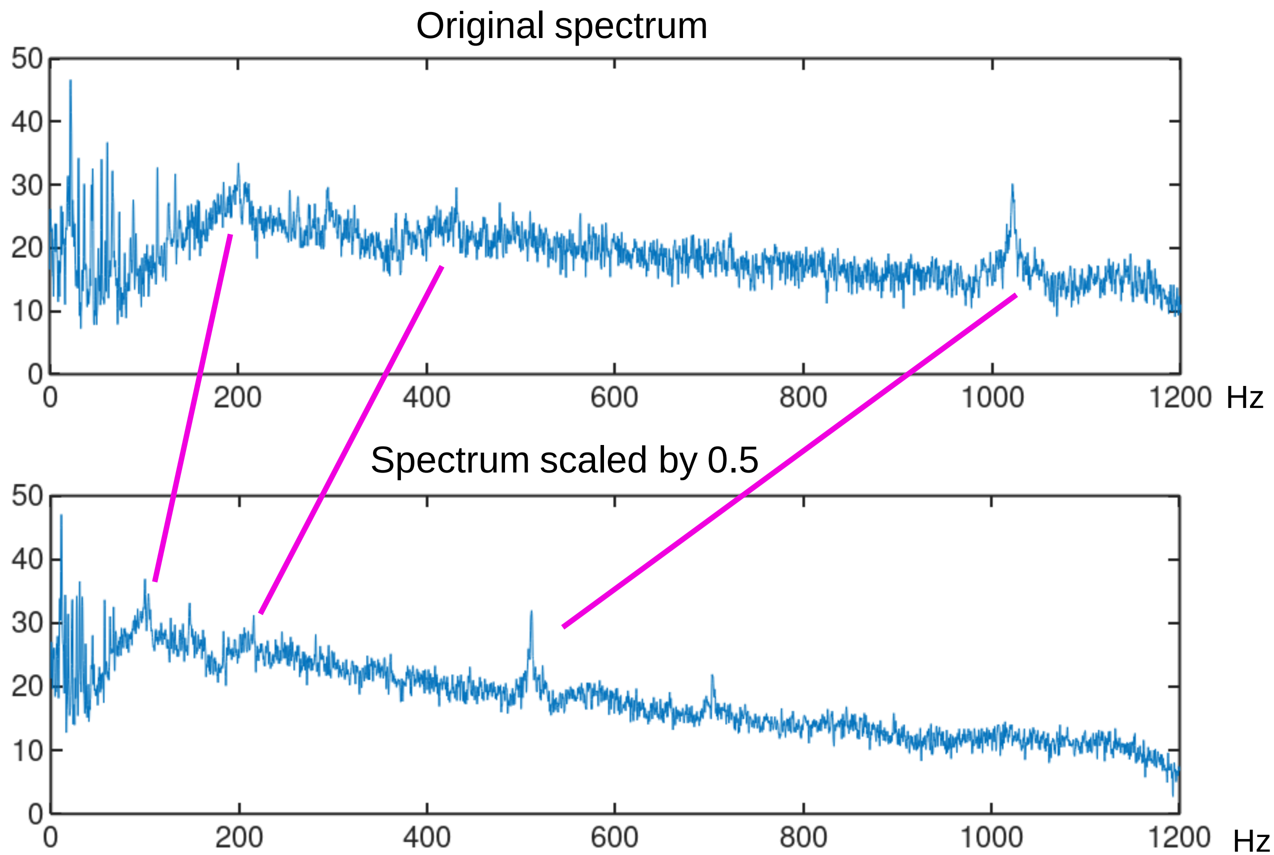


Figure. Example of spectrum shrinking before forming MFCCs.

3. Operator aided acoustic target classification

Results:

Training:

Used 488 samples in training, 310 merchant and 178 military ship signatures with good or moderate SNR

Number of targets 70 merchant, 41 military

Classifying:

Promising results in classifying military /merchant (80-90 %)

Subclass division under testing presently

Classification performance strongly target range (SNR) dependent

4. Conclusion and future plans

- New signal processing algorithms are applied to frquency domain cross correlation and they improve detection and tracking of acoustic targets in shallow water environment including strong interferences
- Operator aided classification of passive surface ship targets is developed and tested using MFCC coeffients with operator parameters as features, EM learning algorithm and GMM classification
- Varying engine revolutions are normalized by shrinking and stretching target spectra depending on target speed, which has to be measured before classification
- Target track should be included as one extra classification feature in the future ("Track before classify"- principle)