# ADVANCED PHASE-BASED ALGORITHMS IN SAR DATA FOR MARITIME SURVEILLANCE

A. Radius ICEYE Oy, Maarintie 6, 02150 Espoo, Finland
L. Lamentowski ICEYE Oy, Maarintie 6, 02150 Espoo, Finland
R. Vehmas ICEYE Oy, Maarintie 6, 02150 Espoo, Finland
O. Dogan ICEYE Oy, Maarintie 6, 02150 Espoo, Finland
V. Ignatenko ICEYE Oy, Maarintie 6, 02150 Espoo, Finland
D. Muff ICEYE Oy, Maarintie 6, 02150 Espoo, Finland
P. Leprovost ICEYE Oy, Maarintie 6, 02150 Espoo, Finland
M. Nottingham ICEYE Oy, Maarintie 6, 02150 Espoo, Finland
P. Vilja ICEYE Oy, Maarintie 6, 02150 Espoo, Finland
T. Seilonen ICEYE Oy, Maarintie 6, 02150 Espoo, Finland

## 1 INTRODUCTION

The Synthetic Aperture Radar (SAR) plays a very important role in the maritime surveillance, providing important information in commercial, surveillance and strategic contexts. For the growing constellation of ICEYE satellites we are constantly exploring new methods of data exploitation to facilitate capabilities not available to the general public before the SAR microsatellites data entered the commercial market. One such capability offered by the increasing number of SAR systems of the new SAR satellite constellations is the global ocean monitoring, thanks to the high area coverage and revisit frequency maritime surveillance. The main requirements for the operational maritime surveillance are the detection sensitivity, the low false alarms and a low computational time required to compile a ship detection report. Moreover, additional information about the detected targets is strongly preferred, enabling classification or tracking of movement. In this paper we will focus on the target detection as well as discrimination between moving and stationary ships but we intentionally leave non-cooperative target recognition outside our field of interest.

The paper firstly proposes a theoretical analysis of the phase exploitation, then exhaustively describes what information we can extract for the target analysis through the generation of additional informative layers. Finally, an algorithm to generate dedicated maps for ship detection and classification will be described and tested on ICEYE Spotlight data.

## 2 MARITIME SURVEILLANCE ALGORITHMS

### 2.1 State of the art

Many algorithms have been proposed for ship detection, most of them based on the amplitude exploitation[1,2,3,4]. The major limitations of these algorithms are currently due to the false alarms occurrence in some conditions, as with strong sea clutter due to the wind and the sea state and in the presence of artifacts, as the range and azimuth ambiguities. Moreover, the amplitude data only allow to estimate the velocity when the wake is visible. Other algorithms work on the complex data, allowing to detect the ships and retrieve their motion parameters[5,6,7]. The major limit is represented by an heavier computational load of the algorithms, that could require a long processing time. In case of the ocean monitoring the phase information plays a fundamental role of increasing the informative content of the detected targets, decreasing the false alarm occurrence and improving the classification capabilities. This paper focuses the attention to the importance of the phase for maritime surveillance, proposing algorithms for the ship detection and classification improvement. The proposed methods that will be presented and explored are based on analyzing azimuth subapertures, phase derivative and dedicated gradient filters.

## 2.2 Phase exploitation

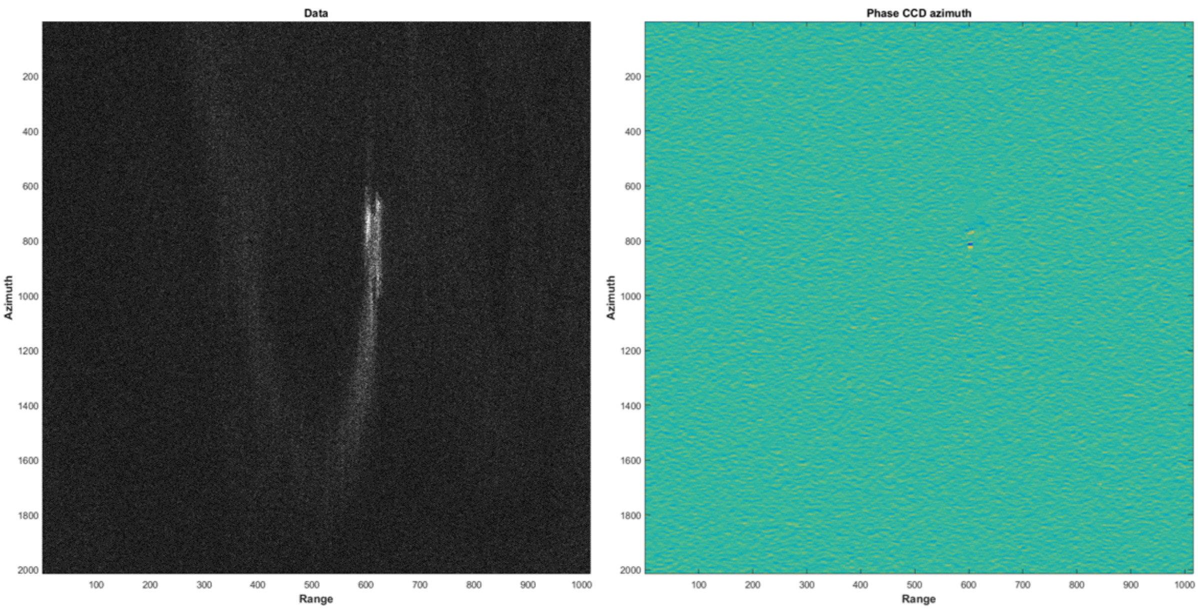
The sea environment monitoring is really complex because the surface is continuously moulded by many features, such as surface waves, mesoscale circulation structures as eddies and currents, oil slicks and surface manifestations of ocean dynamics under the surface, as internal waves and currents flowing over shallow shoals. The SAR signal is sensitive to the surface roughness at the scale of the radar wavelength, that is influenced by all of the aforementioned ocean features. However, the main contribution to the surface roughness is the wind that blows over the sea. Ships and boats navigate on a surface that continuously moves, and their radar echo could be masked by some strong feature that increases the sea backscattering. The phase information that the radar provides is the key to increase the ship detection performance and is fundamental to discriminate moving and stationary targets.

### 2.2.1 Coherent Change Detection on Azimuth Subapertures

The first principle that can increase the detection performances is the coherence, that measures the correlation between two images. In fact, the ships are coherent targets constituted by complex structures that move in a non coherent surface, as is the ocean[6]. The use of azimuth subapertures can be useful to discriminate coherent targets from the incoherent sea surface.

From two symmetrical azimuth subapertures $\zeta_1$ and $\zeta_2$ it is possible to perform the Coherent Change Detection (CCD), that is used to filter out what is not coherent. On the sea, coherent targets can be detected using the phase information of azimuth subapertures also in strong meteorological conditions.

$$CCD_{Az} = \angle \overline{\zeta_1(s,t) * conj(\zeta_2(s,t))} \tag{1}$$




(a) Image with maneuvering ship

(b) Coherent Change Detection

Figure 1: Example of CCD applied on ICEYE Spotlight data.

The CCD on azimuth subapertures calculates the coherence of the targets during the integration time. The informative content of this parameter is proportionally dependent on the integration time, meaning that in stripmap images the informative content is lower than in spotlight images.

Note that the phase needs overlapped looks, otherwise the phase is completely incoherent. Figure 1 shows the interesting case of a fast maneuvering ship that generates a long turbulent wake. It is difficult to detect the exact position of the ship due to the sea clutter. The coherence image allows to detect the position of the ship with strong clutter.

### 2.2.2 Phase Derivative in Azimuth

More advanced techniques to classify moving targets require an higher exploitation level of the phase. As the motion introduces a signal modulation, the phase derivative results are very useful. The phase derivative in azimuth and range provide useful information about the moving targets; however, the phase derivative in the range direction is sensitive to signals with strong dependency on range, as the azimuth ambiguities or very fast targets moving in the range direction. As the motion of the target modulates the signal in azimuth, we only use the phase derivative in azimuth. The signal of a stationary target after compression is:

$$\zeta(s,t) = p_{rg}(t)p_{az}(s)e^{-j\frac{4\pi}{\lambda}R_0}e^{j2\pi f_{dc}s} \tag{2}$$

where $p_{rg}$ and $p_{az}$ are the sinc-like amplitudes of the impulse response function in range and azimuth, $s$ and $t$ are respectively the azimuth and the range time, $R_0$ is the slant range at the zero Doppler, $\lambda$ is the wavelength and $f_{dc}$ is the Doppler centroid. The phase of $\zeta$ is composed by a linear term, that represents the residual phase due to the non-zero Doppler centroid, and by a constant phase due to the target position.

$$\angle\zeta(s,t) = 2\pi f_{dc}s - \frac{4\pi}{\lambda}R_0 \tag{3}$$

In many cases an additional phase term $\Phi$ appears in the equation:

$$\angle\zeta_{MT}(s,t) = 2\pi f_{dc}s - \frac{4\pi}{\lambda}R_0 + \Phi(s,t) \tag{4}$$

The phase is sensitive to many contributions, and the phase $\Phi$ can be generated by:

1. Moving targets. The motion modifies the hyperbolic equation used for the slant range calculation. The range and azimuth velocities and acceleration are responsible for this contribution. When the motion is only in the azimuth direction, the phase contribution only depends on the azimuth time.
2. Azimuth ambiguities. The contribution is really strong due to the high sensitivity of the phase factor to the modulation impressed by the ambiguity. The phase contribution depends on the azimuth and range time.
3. Range ambiguities. The phase contribution depends only on the azimuth time.
4. Multiple bound reflections. This phenomenon appears especially in the urban environment with high buildings, but also in the harbours.

5. Sidelobes of very bright targets. The sidelobes of strong targets have the same phase and contribute to the phase term.

6. Surfaces with a local incidence angle and complex geometries. Complex targets could present a phase contribution due to their geometry, as roughs with a local incidence angle.

The derivative of the phase in azimuth and range is respectively:

$$\angle\zeta_{MT}(s,t) : \begin{cases} \frac{\partial\angle\zeta_{MT}(s,t)}{\partial s} = 2\pi f_{dc} + \frac{\partial\Phi(s,t)}{\partial s} \\ \frac{\partial\angle\zeta_{MT}(s,t)}{\partial t} = \frac{\partial\Phi(s,t)}{\partial t} \end{cases} \tag{5}$$

and is measured in radians.

The phase derivative in range is negligible compared to the phase derivative in azimuth in case of moving targets, unless the moving targets move very fast in the range direction. In fact, the range derivative phase is sensitive to signals with a strong dependence on the range, and can be particularly useful for the azimuth ambiguity detection[8]. For this reason we focus our attention on the phase derivative in azimuth, trying to discriminate the motion from the other contributions that generate the phase term $\Phi$.
The azimuth phase derivative is composed of two terms. The first term represents a constant phase that represents the residual phase due to the non-zero Doppler centroid. Note that this term can be removed by shifting the data spectrum to the Doppler centroid.

To discriminate the different contributions from the target motion, we can apply dedicated techniques to filter out some contributions.

1. Azimuth ambiguities: the azimuth ambiguities can be reduced by applying dedicated azimuth ambiguity suppression techniques, as the SDFS algorithm proposed in[9].

2. Range ambiguities: the range ambiguities can be mitigated by using waveform diversity as in[10].

3. Sidelobes of very bright targets: the sidelobes of strong targets can be reduced by applying some windowing as Hamming or Kaiser.

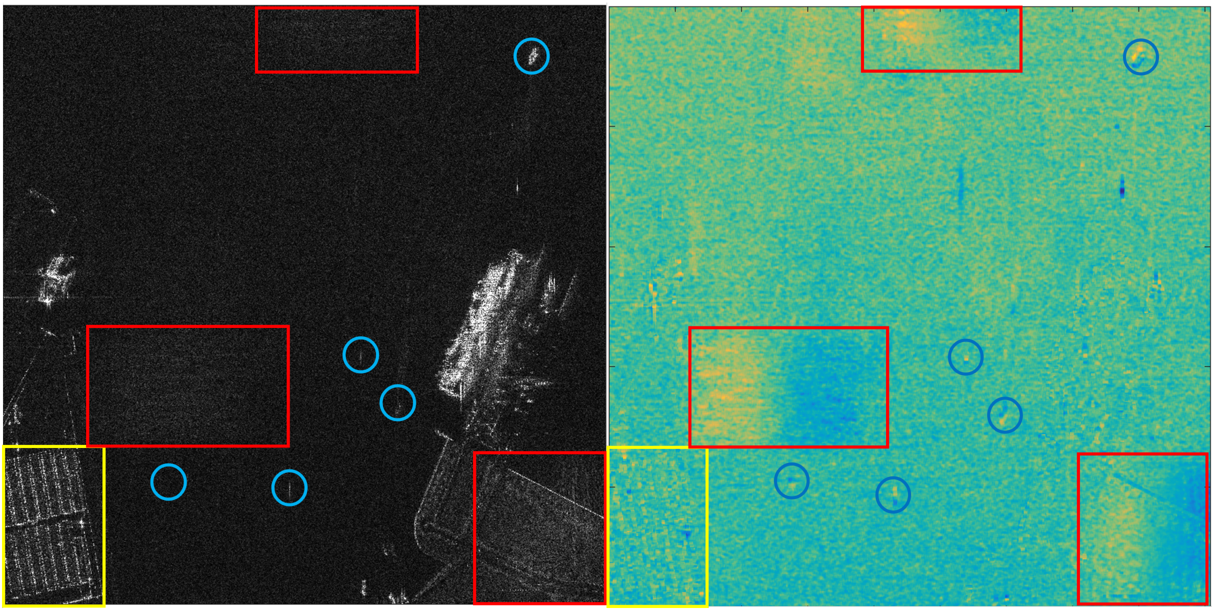
The application of the aforementioned techniques decreases some phase contributions but does not solve the problem of the complex targets. The key to discriminate moving targets from the other contributions is the phase distribution. In fact, every contribution generates a different phase distribution, as shown in Figure 2:

1. Azimuth ambiguities: the phase derivative has a gradient in the range direction.

2. Range ambiguities: the phase derivative has a large gradient in the azimuth direction.

3. Moving targets: the phase derivative has a gradient in the azimuth direction.

4. Target with a complex geometry and multiple bound reflections: the phase derivative is different from 0 but does not present gradients.



(a) Image

(b) Phase Derivative in azimuth

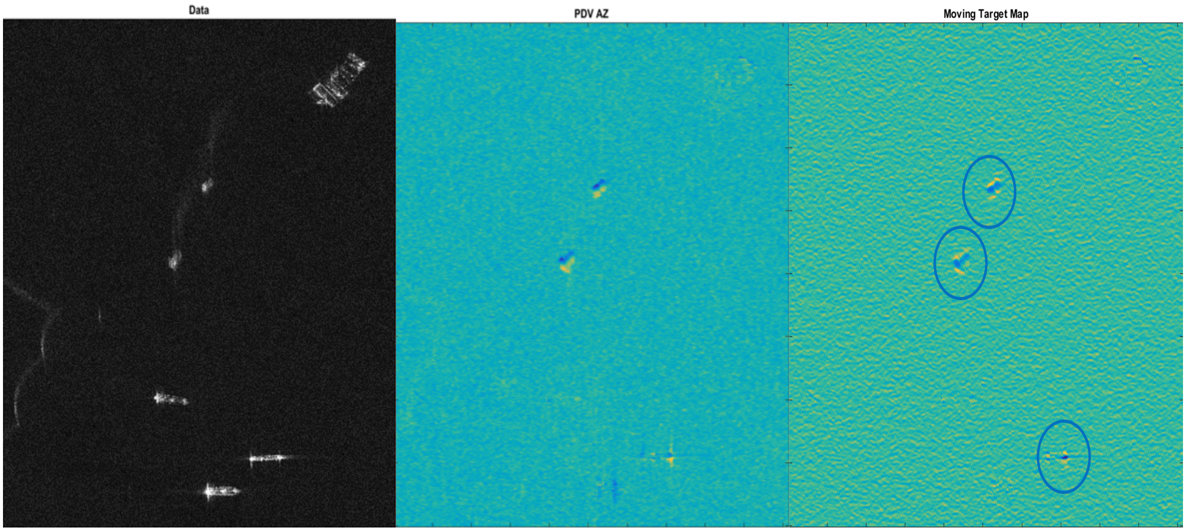
Figure 2: Phase derivative in azimuth applied on ICEYE Spotlight data. In red there are the azimuth ambiguities, in yellow the stationary complex targets and in blue the moving targets

# 3 MOVING TARGET DETECTION MAP

It has been shown in the previous section that the phase distribution of the phase derivative in azimuth allows to discriminate the different phase contributions depending on the gradient direction.
We developed an algorithm that generates moving target maps by using the phase information. The algorithm steps are:

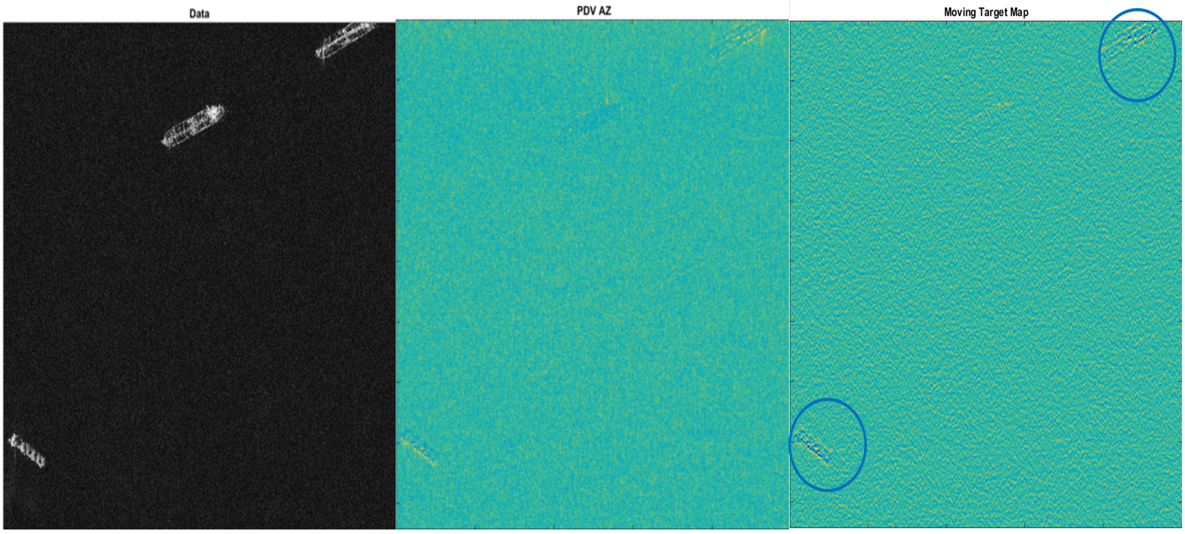
1. The SDFS algorithm is run to suppress the azimuth ambiguities and the windowing of the image is applied to reduce the sidelobes of the strong targets.
2. The Phase Derivative Map is calculated in the azimuth direction.
3. The CCD could be optionally applied on azimuth subapertures to discriminate the coherent targets. The coherence is used to weight the image, decreasing the noise from the sea.
4. The azimuth columns of the Phase Derivative Map in azimuth are correlated with a sinusoidal kernel. The use of a sinusoidal kernel is useful to detect azimuth gradients of the phase when the phase has an inversion of sign, that occurs in presence of moving targets.

In the next figures the generation of the moving target map from the phase derivative is shown on ICEYE spotlight images.




(a) Image (b) Phase Derivative in azimuth (c) Moving Target Map

Figure 3: First example of Moving Target Map generation. The targets circled in blue are the moving ships




(a) Image (b) Phase Derivative in azimuth (c) Moving Target Map

Figure 4: Second example of Moving Target Map generation. The targets circled in blue are the moving ships

# 4 CONCLUSIONS

The paper describes some techniques for the phase exploitation to increase the data informative content for maritime surveillance. We presented a new algorithm for MTI purposes, able to discriminate the moving ships from the stationary targets.

The implemented algorithm discriminates the moving targets with a computational efficient technique. However, when extended to the urban areas, the algorithm can generate false alarms due to the phase noise due to the buildings.

In the future the following algorithm improvements are foreseen:

1. Dedicated prefiltering step to further decrease the contributions non related with the motion;
2. Use of an adaptive specific correlation kernel to increase the classification performances;
3. Velocity estimation from the phase distribution.

# 5 REFERENCES

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