ABSTRACT

The European Space Agency (ESA) recently supported research studies and development activities on the potentiality to generate sea surface wind and waves level-2 (L2) products from ENVISAT ASAR Image mode, Wide Swath mode and Alternate Polarization mode products. The objective of this project was to define, develop and validate prototypes to generate Synthetic Aperture Radar (SAR) Ocean Wind and Waves L2 products. In parallel, the potentiality of the Doppler analysis of complex products to retrieve sea surface currents was explored. The characteristics of the improved wind retrieval prototype are presented in this paper. Validation results obtained from an unprecedented comparison between wind fields retrieved from ENVISAT Wide Swath images and more than 1000 in situ buoy measurements are also discussed.

1 INTRODUCTION

Following the recommendations expressed during last workshops on marine and coastal applications of SAR imagery (Svalbard 2003 and SEASAR 2006), research studies have been undertaken to widely extend and enhance the application uses of high resolution ocean SAR scenes. Under the initiative of ESA, advanced wind and waves’ retrieval methods were thoroughly investigated by a consortium of well-experienced companies (see acknowledgements). A number of new methods has been developed, optimized, intensively validated and documented. The most performing methods were eventually selected. This intensive work has led to the definition and implementation of prototype algorithms to generate ENVISAT ASAR level-2 wind and wave products. The outcomes of this project concerning wind retrieval using SAR imagery are presented in this paper.

Traditionally, the sea surface wind field is measured using wind scatterometer based on empirically derived radar cross section models. The main weakness of the scatterometer is the relatively coarse spatial resolution (typically 25 x 25 km) which limits the use of scatterometer data in coastal areas. In contrast to the scatterometer, the SAR image can provide estimates of radar cross section at much higher spatial resolution opening the way to the generation of high resolution wind fields at a resolution scale ranging from the order of tens of kilometres down to less than 1 km. As a matter of fact, SAR sensors behave like high resolutions scatterometers. As the wind blows over the sea surface, it generates surface roughness generally aligned with the wind. Consequently the radar backscatter from this roughened surface is related to the wind speed and direction. Unlike multi-antenna or rotating scatterometers, the SAR instrument points at a single direction. Hence, for a given normalised radar cross section (NRCS) and incidence angle, a large number of wind speed and direction pairs may be solution of any chosen backscattering model function, leading to an ambiguous set of solutions - in fact one couple (speed, direction) for each direction.

In general, this ambiguous problem is solved in obtaining information on the wind direction at the wind cells location. The most common approach consists in using wind direction given by ancillary source of information from numerical weather prediction (NWP) models [1], in-situ observations [2] or other remote sensing instrument such as scatterometer [3]. Taking wind directions given by NWP models is considered today as the most practical and “classical” approach.

A more satisfying approach consists in retrieving the wind direction on the SAR image itself whenever this is possible. As an example, visible wind shadowing or wind acceleration effect due to coastal relief generate typical features on the SAR intensity which provide very clear indication on the local sea surface wind direction. Furthermore, SAR signatures of atmospheric boundary layer rolls or wind streaks have revealed to give valuable information on the local wind direction [4]. When present, these are generally characterized by typical streak-like texture on the SAR image, the wavelength usually ranges between 1.25 and 2.5 km [5].

Investigations on the wind retrieval were essentially targeted at addressing two key issues. To what extend can the wind direction be estimated on the SAR image? How can the wind vector estimation be optimized given an a priori knowledge of wind characteristics at sea?

2 RETRIEVAL OF THE WIND DIRECTION

At early stage, a review of most of the wind retrieval methods from SAR imagery known from the state of the art was made to assess their characteristics, range of
validity, performance and eventually their potential. In particular, a great attention was paid to investigate the capacity of SAR measurements to provide information on the wind direction at sea surface. This would help to reduce, whenever is possible, the necessity to use external information to solve the intrinsic ambiguity in the “classical” wind retrieval scheme.

The performance of the Phase Plane method, which consists in assigning the wind direction to the orientation of a tilted plane approximation of the non-linear part of the phase spectrum [6], revealed to be highly dependent on the wind speed, performing best at high wind speed [7]. The phase plane method is not precise enough as a stand-alone method, but has a potential in a statistical combination with other estimators for removing the 180 propagation ambiguity.

Alternatively, methods that consist in estimating the wind directions from the SAR signatures of the linear features associated to marine atmospheric boundary layer rolls (ABL) were also studied. Due to the linear and periodic properties of such SAR signatures, two specific image processing tools naturally come to mind to detect and identify the presence of wind streaks: The Fast Fourier Transform (FFT) and the projection in the Radon domain. These two approaches have been developed and tested to assess their performances. The FFT-based algorithm, which eventually revealed to perform better in terms of performance and at much lower computation time, is briefly presented below:

First, the SAR level-1 product must be sub-tiled to produce sub-imagettes the size of which enables to detect wavelengths ranging between 1 and 2.5 kilometers in the Fourier domain. Typical size should range between 10 and 20 km. Each imagette is then high-pass filtered to remove most of the spectral signature associated to oceanic and atmospheric phenomena not related to wind streaks (e.g. atmospheric gravity waves). The resulting power spectrum of each imagette is given below:

$$P_{i}(k_{x},k_{y}) = |HP(k,k_{low})|^2 |FFT(f_{i}(x,y),-1)|^2$$ (1)

Where $k = \sqrt{k_{x}^2 + k_{y}^2}$, $FFT(\ast,-1)$ represents the discrete Fourier Transform from spatial domain to spectral domain and $HP(k,k_{low})$ figures a Butterworth omni-directional high-pass filter having a cut-off wave-number at $k_{low}$:

$$HP(k,k_{low}) = \frac{1 - 1 / (1+(k/k_{low})^{2n})}{2}$$ (2)

Where $1/k_{low} = 2500m$ and $n = 5$.

Then, a directional filter $D_{\phi}(k,\phi)$ oriented along the direction $\phi$ will be applied to $P(k,\theta)$ and the resulting spectral energy will be computed as follows:

$$P_{\phi}(k_{x},k_{y}) = \int P_{i}(k_{x},k_{y}) \cdot D_{\phi}(k_{x},k_{y}) dk_{x}dk_{y}$$

$$D_{\phi}(k_{x},k_{y}) = \exp\left\{-\left(\frac{k}{\sigma_{k}}\right)^2\right\}\exp\left\{-\frac{1}{2}\left(\frac{\phi-\alpha}{\sigma_{\phi}}\right)^2\right\}$$ (3)

with, $\phi = \arctan(k_{y}/k_{x})$, $\sigma_{k} = (1/1200) m^{-1}$, $\sigma_{\phi} = 15^\circ$.

This operation is repeated for direction $\alpha$ ranging between 0 and 180° in order to get a set of values $\{P_{\phi}\}_{0\leq\phi<\pi}$ such as shown on Figure 1(c).

Figure 1: (a) Portion of ENVISAT ASAR Wide Swath image showing typical wind streaks signature. (b) Low wave-number spectral domain showing wind streaks spectral signature and the shape of directional filter. (c) Profile of $\{P_{\phi}\}_{0\leq\phi<\pi}$ for directions ranging between 0 and 180°.
The direction \( \alpha_0 \) is the direction value which gives the highest value of \( \{ P_{\alpha i} \}_{0 \leq \alpha < \pi} \):

\[
(\alpha_0) = \arg \max_{0 \leq \alpha < \pi} \{ P_{\alpha i} \}
\]  

(4)

3 THE INVERSION PROBLEM

3.1 Principles of the inversion problem

Let \( \sigma^0 \) be a noisy observation of the normalized radar cross section NRCS defined as:

\[
\text{NRCS} = \text{GMF}(u, \theta) = \text{GMF}(U, \phi, \theta)
\]  

(5)

In the case of ENVISAT ASAR C-band data, the Geophysical Model Function (GMF) can be represented by any empirical CMOD scattering model (e.g. [8]) weighted by a polarization ratio in case of HH-polarized acquisition. The parameter \( \theta \) is the value of the incidence angle and the vector \( u \) represents the wind vector to be estimated. The latter is defined by its modulus \( U \) and the direction \( \phi \) relative to radar look direction. Thus, it is implicitly assumed in the following that the observation is only generated by the wind. In other words, there are no other scattering contributions caused by oceanic or atmospheric phenomena.

The SAR wind retrieval issue can be formulated as an estimation problem that consists in estimating the sea surface wind vector \( u \) that has led to the observation \( \sigma^0 \). Without any other a priori information, the problem is underdetermined as it is known that there is a number of solution pairs \( u = (U, \phi) \) for a given \( \sigma^0 \). Hence, a priori information is required to solve this estimation problem.

3.2 Classical approach

In the classical scatterometry approach, only the direction of the wind, such as given by independent ancillary wind source like NWP models, is considered as a priori information. It is assumed as well the estimate of the observation \( \sigma^0 \) is noise-free. Finally, the estimator reduces a simple Least Square (LS) estimator:

\[
\hat{U}_{LS} = \arg \min_u \left( \| \sigma^0 - \text{GMF}(U, \phi_{\text{AP}}, \theta) \| \right)
\]  

(6)

As a result, the wind inversion process must be treated as a zero-crossing problem. This approach is illustrated on Figure 2. As can be observed, the output wind direction \( \phi \) of the SAR-retrieved wind field will be exactly the same than the direction that is given by the ancillary source information \( \phi_{\text{AP}} \).

In other words, this approach leaves very little flexibility to capture any departure from the a priori wind information which may arise when the spatial resolution of the a priori external wind information source is too coarse to feature small-scale spatial variations of wind, when the atmospheric situation has significantly evolved between the acquisition time of the SAR scene and the time of the a priori ancillary wind product or when the a priori ancillary wind information is simply not correct.

![Figure 2: Wind speed retrieval using the conventional scatterometry approach for a given observation \( \sigma^0 \) and priori information on wind direction \( \phi \).](image)

3.3 Bayesian approach

The classical inversion method is very basic from the point of view of the decision theory. A very limited and somehow inappropriate use is actually made of the global a priori knowledge we have about the wind situation at sea.

Let us suppose that the sea surface wind vector \( u \) can be modeled as a random vector, the probability density function (pdf) \( f_u(u) \) of which models the prior knowledge of having that wind vector.

Assuming that the distribution \( f(\sigma^0 | u, \theta) \) is known; the Maximum A Posteriori (MAP) estimator can then be defined by:

\[
\hat{U}_{\text{MAP}} = \arg \max_u f(\sigma^0 | u, \theta) f_u(u)
\]  

(7)

Portabella et al. [9] indeed proposed a sub-optimal resolution method which consisted in looking for the wind vector solution in a limited vicinity of the a priori wind vector. The proposed implementation was unfortunately very time-consuming in terms of computational time without really ensuring the capacity to find the optimal wind vector solution. It is will be shown in the following that most of the technical and practical limitations of Portabella’s method can easily be circumvented.
If it is assumed that the estimate of the NRCS value $\sigma^0$ is not noisy, $f(\sigma^0|\mathbf{u}, \theta)$ can then be written as follows:

$$f(\sigma^0|\mathbf{u}, \theta) = \delta_{\mathrm{GMF}(U, \theta, \theta^r)}(\sigma^0)$$

(8)

In other words, this means that the probability density function of the $\sigma^0$ variable at incidence angle $\theta$ is featured by an elliptic shape-like closed curve on which the wind vector solution is to be found (Figure 2). This assumption holds as long as the NRCS value is estimated on enough pixels [10].

From a practical point of view, the elliptic shape-like solution curve must be computed at low computation cost. Indeed, all the possible wind directions need to be considered to find the most likely wind vector solution. This precludes the zero-crossing approach of eq. (6) and appeals for the derivation of an inverse GMF function providing directly the wind speed value $U$ as an analytic function of the triplet $(\sigma^0, \phi, \theta)$:

$$U = \mathrm{GMF}^{-1}(\sigma^0, \phi, \theta)$$

(9)

The derivation of such function is feasible using neural network approach [11].

3.3.1 A simple Gaussian formulation

In the following, it will be further supposed that the $a$ priori distribution $f_u(\mathbf{u})$ of the wind vector can be written as the separable product of the probability density functions of wind speed and wind direction, both being modeled as Gaussian distributions:

$$f_u(\mathbf{u}) = N_U(U_{\text{AP}}, \sigma_{U_{\text{AP}}}^2) \times N_\phi(\phi_{\text{AP}}, \sigma_{\phi_{\text{AP}}}^2)$$

(10)

Thus, the MAP estimator is given by:

$$\hat{\mathbf{u}}_{\text{MAP}} = \arg \min_{\mathbf{u} \in \mathbb{C}^{(U, \phi, \theta)}} \left\{ \frac{(U - U_{\text{AP}})^2}{2\sigma_{U_{\text{AP}}}^2} + \frac{(\phi - \phi_{\text{AP}})^2}{2\sigma_{\phi_{\text{AP}}}^2} \right\}$$

(11)

The authors are fully aware that such statistical description of wind vector parameters is far too simple and may easily be improved in the future. However, it will be shown that even such simplistic model outperforms the classical wind retrieval algorithm (which uses fixed wind direction provided by a priori wind information). It is interesting to note that the “classical” wind retrieval approach is just a particular case of this simple Bayesian formalism $\sigma_{\phi_{\text{AP}}} = 0^\circ$.

3.3.2 Implementation requirements

A priori knowledge of the statistical information of the wind stands as a major pre-requisite of the Bayesian approach. As an example, wind vector parameters given by an NWP model and root mean square (RMS) errors of the model may be sufficient if one assumes that the wind vector can be fully statically described by the first two order moments.

From a computation point of view, it must be stressed that the implementation of such a method is possible using an analytical expression of the inverse geophysical function of eq.(9).

4 VALIDATION RESULTS

4.1 Description of the validation dataset

588 ENVISAT ASAR level-1 products (including 467 Wide Swath complex products and 121 IMM products) all in VV polarization have been used to assess the performance of the FFT-based retrieval method of the wind direction a sea (see 2). The performance of the “classical” algorithm (see 3.2) and the Bayesian approach (see 3.3) were also compared.

The results were checked against 1035 buoys wind measurements (part of US NDBC and the French METEO-FRANCE network). 6 of the available in-situ measurements are located near US coasts, while the 12 others are close to European coast. It is important to note that a correction factor is applied to buoy measurements to (partially) compensate the difference between the height of in-situ measurements and the 10-m equivalent SAR-derived wind vector.

4.2 FFT-based wind direction retrieval

The validation of the FFT- based detection algorithm of SAR wind streaks signature gives relatively good results such as shown in Figure 4. Approximately 50% of estimated wind directions agree with buoys wind directions (with an RMS error of 25°). In general, successful estimates are obtained at higher winds.
4.3 The Bayesian wind vector inversion

The wind fields, retrieved using the Bayesian estimator of eq. (11), were compared to 1035 in-situ measurements. These validation results were also compared to the traditional inversion scheme (taking wind direction as granted from a priori wind information) such as expressed in eq. (6). ECMWF 6-hourly wind predictions 0.5° x 0.5° were used as a priori wind information in either case. To model the statistical knowledge of a priori wind source, the standard deviation of wind speed (resp. direction) was set to $\sigma_{U, a} = 2 \text{m/s}$ (resp. $\sigma_{\phi, a} = 20^\circ$).

Figure 5(a) reveals that the Bayesian inversion provides better estimates of wind speeds at all range of winds speeds. Best performances are obtained at average wind speeds (i.e. ~7 m/s) where the root mean square (RMS) error in wind speed decreases down to 1.6 m/s, showing a gain of nearly 19% compared to the “classical” method.

The improvement of Bayesian scheme versus “classical” inversion increases with increasing incidence angle (Figure 5(b)). The gain is about 12% at low incidence angle (around 20°) to 27% at large incidence angle (around 40°) i.e. when sensitivity to directivity effects increases.

The use of CMOD-IFR2 in the Bayesian inversion allows improving significantly with respect to traditional inversion scheme (17%) while the use of CMOD4 only brings a gain of 6%.

As observed, the implementation of Bayesian inversion scheme brings significant gain in situations where the sensitivity to directional effects increases (cross and diagonal winds, large incidence angles) or when the directionality is well modeled (as CMOD-IFR2 does much better than CMOD4).

Figure 5: Wind retrieval validation results as a function of ranges of (a) wind speeds and (b) incidence angles.

The quality of the obtained validations results not only validates the concept of using Bayesian inversion in the future, it also demonstrates that the neural network implementation of inverse scattering model was good enough not to add significant error estimate.

5 SUMMARY

The most recent and innovative wind retrieval methods have been reviewed to assess their potential performance, their domain of application and validity range. They have been implemented, validated and documented with a particular focus on technical requirements and implications in terms of implementation. The most promising methods were selected to form wind retrieval prototype software.

Remarkable progress has been achieved for the wind retrieval since a gain of nearly 20% in the wind speed estimation was obtained using a Bayesian wind vector estimation method compared to the “state of the art” approach. It was also shown that the FFT-based wind streaks detection method has demonstrated a great potential.

Although this was not mentioned in the core of the paper, the use of a wind-dependant modelling of the polarization ratio [12] was also investigated to address the issue of the processing of HH-polarized data. Unfortunately the very recent scheduling of VV and HH-pol Wave Mode acquisitions at larger incidence angle (IS4) did not allow to complete the assessment.

Thanks to an intensive validation against not less than 1000 in situ wind buoys measurements, it has been demonstrated that wind vector retrieval is operationally feasible on ENVISAT ASAR Wide Swath and Image
mode products providing recommendations are followed (use of well documented a priori wind with know uncertainties, need for an accurate radiometric calibration, keep a low noise level, speckle correction and wind cells averaging).

Obviously, the retrieval of high resolution wind fields over coastal areas using Wide Swath model products stands as the most promising and interesting issue. It provides a unique opportunity to capture the finer details of small scale up to meso-scale wind circulation over the largest area with comparable performance in terms of speed and direction estimations at acceptable spatial resolutions (between 500 and 1000 meters).

Such developments will have a significant impact on the ocean and coastal community only if they benefit from a large visibility and accessibility to a wide number of potential end-users. To address this issue, a number of recommendations are proposed to promote the use of SAR winds and stimulate end-users interests:

In the short term, it is recommended to setup a rapid demonstration of the potentiality of SAR wind/waves level-2 products using ESA rolling archive. Near real-time availability of such products systematically generated over European seas will help potential users (met offices, offshore, harbour authorities, coastal management, civil engineering, ship routing operators, etc) to get accustomed to them and to assess their usefulness. Such demonstration should also not fail to anticipate the increased usage of SAR-derived high resolution wind and waves fields (such as expressed by EMSA for the coming oil spill detection services). It will also prepare the upcoming generation of Sentinel SAR satellites for operational oceanography in the context of GMES.

Eventually, such demonstration must generate database large enough to investigate the potentiality of level-3 products (e.g. seasonal mean products, risk maps, etc).

There is today an increasing demand, from worldwide research and academic organisations, for a simple, efficient and very low-cost analysis software oriented towards SAR marine applications (and particularly for wind retrieval). Such interest is often expressed by scientists who are willing to extract simple marine information from SAR products ordered within the frame of experimental campaigns, research programs or other ESA Category I activities. Other scientists just wish they could illustrate the potential of SAR imagery as part of their teaching activities. The development of such freeware or shareware must be supported by space agencies. This support will not fail to consolidate and increase the panel of scientists using SAR products and to stimulate discussions and feedback on the potentiality of SAR.

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7 REFERENCES