Multiparametric Sea State Fields from Synthetic Aperture Radar using Method combining CWAVE Approach and Machine Learning

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Abstract

This study presents the algorithm SAR-SeaStaR (SAR Sea State Retrieval) for estimating series of integrated sea state parameters from satellite-borne synthetic aperture radar (SAR): total significant wave height H_s, dominant and secondary swell and windsea wave heights, first and second moment wave periods, mean wave period and period of wind sea. SAR-SeaStaR applies a combination of classical approach using linear regression with machine learning. It comprises the complete processing chain with a series of steps each needed to reach high accuracy: denoising, filtering image artefacts, SAR features estimation and control, model functions (linear regression and machine learning models) for estimation of sea state parameters and control of results using filtering procedures. SAR-SeaStaR is applied to C-band Sentinel-1 (S1) Interferometric Wide Swath Mode (IW), Extra Wide (EW) and Wave Mode (WM) Level-1 (L1) and to X-band TerraSAR-X (TS-X) StripMap (SM) products. The wide scenes are processed in raster format, resulting in continuous sea state fields. For each S1 WV 20 km × 20 km imagette, averaged values of each sea state parameter are derived. Validated with worldwide data the reached RMSE for H_s is 0.25 m for S1 WV, ~0.35 m for TS-X SM, ~0,50 m for the coarser S1 IW and ~0.60 m for S1 EW. The method was realized in Sea State Processor (SSP) software using modular architecture and allowing processing SAR-data from different satellites and modes in near real time (NRT).
In scope of ESA's SARWave study **[1]** the S1 IW archive was processed for 2020 with a raster of 5 km (ca. 1,600 subscenes/image). The validation with MFWAM (CMEMS, **[2]**) model results in an RMSE=0.51 m for significant wave height (H_s) and 0.78 s for crossing zero wave period (T_{m2}).

1. Methodology

The ongoing development of space-borne SAR sensors together with corresponding data transfer and data processing infrastructures has made a series of oceanographic applications possible in near real time (NRT), e.g. **[3,4,5]**. Also, in the past few years, machine learning techniques have taken a leading position in science, as their results are superior to those of analytical and simple empirical solutions when sufficiently large databases are available. Even though a few years ago, these applications did not noticeably provide more accurate solutions than the classical approaches, today they already exceed them. For example, in 2017, the accuracy of H_s obtained by applying neural networks (NN) in comparison to a traditional CWAVE **[6]** method had not improved significantly (RMSE of ca. 0.50 m for H_s) **[7]**, whereas by using a deep learning technique in 2020 the accuracy had significantly been improved to an RMSE of around 0.30 m **[8]**. In last year, the accuracy of ca. 0.25 m was reached **[9]**.

When comparing the application of the empirical approaches based on linear regression (LR) models and machine learning (ML) models, the following can be noted: the advantage of the LR is that an analytical solution exists. The coefficients can be obtained comparatively quickly, extensive machine learning training is not necessary. Although the linear solution is inferior in accuracy to that obtained by adding ML, this solution is already stable with around 1/10 samples needed for ML by a normal distribution of data used for tuning. In addition, as practice shows, LR extrapolates much more successfully, if the modelled conditions are outside the training data conditions while the ML models can give an error with outliers significantly exceeding three times the RMSE.

Further, in addition to ML training (can take months), the developed ML model is many orders of magnitude larger (takes Gigabytes) than the list of coefficients for the LR model (takes Kilobytes). LR outperforms ML in terms of parsing speed of the model, which is important for NRT services. This point is important, as a migration of the sea state processing for direct installation on a satellite for on-board-processing has been developed **[10]**. In this case, no huge amount of SAR raw data will be transferred from satellite to earth, before the processing can be done, but only already derived sea state parameters. This technology will significantly simplify the data transfer and reduce the delay.

Based on all these reasons, the proposed SAR-SeaStaR algorithm combines both: LR (based on CWAVE approach **[6]** extended by series of additional features **[9]**) and ML model (using support vector machine (SVM) technique) for sea state processing. The solution of LR model (H_s) is used as first guess value for ML (additional feature) and also is applied for control of results.

2. Algorithm basic parameters

In a classic way, the estimation of sea state parameters is based on a normalized radar cross-section (NRCS) analysis of subscenes. One of the basic variables represents the SAR image spectrum obtained using fast Fourier transformation FFT applied to the ground range detected, radiometrically calibrated, filtered, denoised land-masked and normalised subscenes with a size of 1,024×1,024 pixels in wave number domain as introduced in **[5]**. SAR features estimated from a subscene are of five different types:

- NRCS and NRCS statistics (variance, skewness, kurtosis, etc.).
- Geophysical parameters (wind speed using CMOD-5 algorithms for C-band **[11]** and XMOD-2 for X-Band **[11]**).
- Grey Level Cooccurrence Matrix (GLCM) parameters (entropy, correlation, homogeneity, contrast, dissimilarity, energy, etc.).
- Spectral parameters, based on image spectrum integration of different wavelength domains (0-30 m, 30-100 m, 100-400 m, etc.) and spectral width parameters (Longuet-Higgins, Goda).
- Spectral parameters using products of normalized image spectrum with orthonormal functions (CWAVE approach) and cutoff wavelength estimated using autocorrelation function (ACF).

3. Sea state processor (SSP)

SSP was designed in a modular architecture for S1 IW, EW, WV and TS-X SM/SL modes. The DLR Ground Station “Neustrelitz” applies the SSP as part of a near real-time demonstrator service that involves a fully automated daily provision of surface wind and sea state parameters estimated from S1 IW images of the North and Baltic Sea. Due to implemented parallelization, a fine raster can be processed. For example, S1 IW image with coverage of 200 km × 250 km can be processed using a raster with 1 km sized grid cells (~50,000 subscenes) during minutes. Each of maritime information products, i.e. sea state retrieval, wind speed retrieval, ship detection and AIS defines each one independent data layer. The data layers are combined for processor-internal information exchange and presentation to the operator **[9]**.

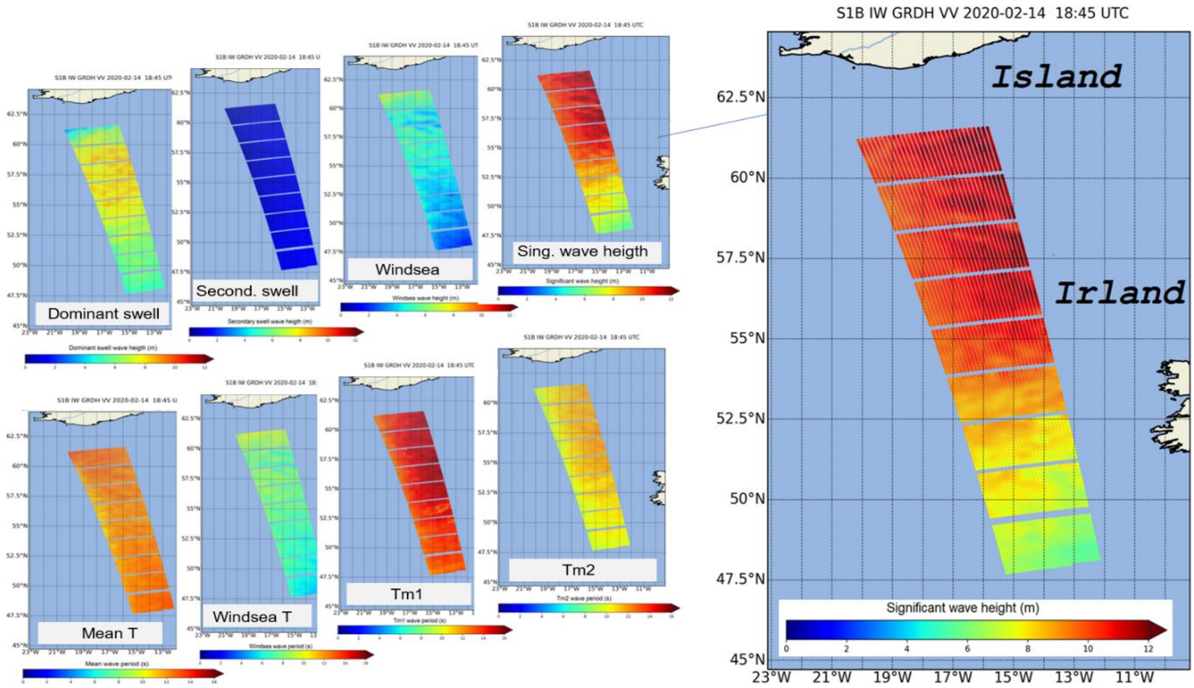

Figure 1: *Example of eight sea state fields processed from S-1 IW scene with ~1600 km by ~200 km coverage acquired during a storm in North Atlantic with H_s reaching ~14 m*

Using the SSP, the complete archive of S1 WV data from December 2014 until February 2021 with around 60 overflights/day, each including around 120 imagettes, was processed. The validation using the WFWAM/CMEMS **[2]** model resulted in an RMSE of 0.245/0.273 m for wv1/wv2 imagettes, respectively. Comparisons to 61 NDBC buoys **[13]**, collocated at distances shorter than 50 km to worldwide S1 WV imagettes, result into an RMSE of 0.41 m. The data is available to the public within the scope of ESA's climate change initiative CCI **[14]**.

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