



A multi-peak waveform retracker for coastal altimetry

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ABSTRACT

We present a retracker specially designed to process waveforms where the openocean, Brown-like model is modified by the presence of one or more peaks

main aim is the integration of Earth Observation data in storm surge modelling and forecasting) and builds on vital experience gained through the COASTALT Project.

The present retracking system is capable of modelling an arbitrary number of peaks superposed onto an arbitrary Brown-like retracker. It may be regarded as an evolution of COASTALT's mixed retracker and of the BAG (Brown +

its performance applied to ENVISAT data using the model of Halami, et al (1).

Finally, we present our plans for the immediate future of the retracker and discuss what needs to be done in order

Southampton University Waterfront Campus European Way, Southampton United Kingdom	normally associated with bright targets like those often encountered in coastal waters	The novel algorithms presented have been implemented in a modern C++ idiom and exploit generic-programming	Gaussian Peak) retracker developed within CNES' PISTACH project.	to make the software fit for operational deployment in the longer term.
ljw@noc.ac.uk +44 23 8059 6404	The retracker has been developed within the ESA-funded eSurge project (whose	and object-oriented techniques to manage the complexity expected to arise in an highly configurable retracker suite.	Although the retracker will be capable of processing data from multiple altimeter missions, here we present examples of	

THEORY

PRACTICE

Any realistic Brown retracker that supports thermal noise plus a number of well-described peaks will have a necessarily large number of parameters that need to be estimated.

Finding a global minimum in such a high dimensional space is not a trivial task. Black-box 'downhill' optimisers are notoriously inept at this task.

The following recipe, then, was adopted to estimate and adjust the parameters in an orderly sequence.

Firstly, the problem was represented as a linear sum of generally non-linear models, where u are the amplitudes of the component models, θ are the nonlinear parameters, and x is a proxy for time (gate-number, for example):

 $F(x;u,\theta) \equiv \sum u_i f_i(x;\theta)$

Here, thermal noise appears as just another non-linear model - albeit an highly degenerate one. Next, the goodness-of-fit metric, G, is assumed to be a weighted sum of squares:

To test our implementation it seems appropriate to choose the Halimi model (1) with a section of data from ENVISAT for our initial investigation. In future, the model used by Gomez-Enri (2) will be used.

Immediately it is apparent from the main figure that the Brown-like function has been distorted. The optimiser is working correctly, but the slope is clearly too flat and the amplitude is too high. This is because the routine is attempting to fit the peaks with the Brown model.

The addition of a peak changes the parameter set quite drastically. The slope is now better able to approximate the data in this region, as the peak model carries the burden of taking out the largest spike, but the addition of a second peak in this example does not _40 appear to affect the slope further. It does, however, have a dramatic effect on the amplitude of the fitted waveform.



CONCLUSIONS

It is now possible to obtain robust estimates for the parameters of a Brown-like model in the presence of an arbitrary number of peaks.

Furthermore, initial 'guessing' for the epochs and amplitude parameters is now redundant.

It is also clear that the addition of more than one peak can elicit information about the underlying model parameters.

The epoch parameter seems imune from peaks that are far down the tail of the waveform, but the amplitudes - which are easy to compute are very strongly affected by the presence of peak-models.

FURTHER WORK

Although the estimation of many parameters is now robust, the question of how many peaks ought to considered for a given waveform still needs to be investigated.

$$G(u;\theta) \equiv \sum_{k}^{n} w_{k} (y_{k} - F(x_{k};u,\theta))^{2}$$

Both LSQ and MLE, are represented in this manner simply by choosing appropriate weights, w. Here, y, is the data to be approximated.

Substitution the expression for *F* into *G* gives the following

$$G(u;\theta) \equiv \sum_{k}^{n} w_{k} \left(y_{k} - \sum_{i}^{m} u_{i} f_{i}(x_{k};\theta) \right)^{2}$$

A turning-point analysis of G w.r.t the θ 's yields a matrix equation of very low rank (typically less than five) which can be solved for the coefficients, *u*.

$$Au \equiv b$$

The elements of *A* involved only derivatives of the *f*'s w.r.t. The non-linear parameters, and may be computed numerically if need be.

The benefit of the above representation is that amplitude parameters may now 500 be calculated directly; they feature no longer in the global optimisation.



60

20

700

600



The fit may be better, but the physical description will be very poor, as the physical parameters all belong to the Brown-like model.



influence

The epoch in this right-hand section clearly benefits from the introduction of peak a first peak model, but the second does not enhance it.

This does not mean a second peak is not useful, only that it does not enhance the epoch parameter. The diagrams below shows that the addition of an additional peak improves the goodness of fit predominantly by adjusting the amplitude parameter.

Deciding whether a particular spike in a waveform is physical or statistical is not easy, and it may be that better estimates can be obtained when adjacent waveforms are taken together.

Also, if a waveform is a poor statistical match for the Brown model, it is possible the peak model will provide a better fit. This causes the optimiser to supplant the Brown model with the peak model giving inphysical value for all parameters.

It may be possible to limit this behaviour by enforcing a cap on the width of a peak, or by analysing the quality of the Goodness of fit.

Another problem that must be overcome if these methods are ever to achieve operational success is the computing issue.

At present, 1 second of data takes a few seconds to process, which is of limited, at best, for prediction.

It is easy to suggest that tomorrows computers will solve this problem, but tomorrow's instruments will likely produce larger data products - perhaps rendering tomorrow's computers no better than today's.

Fortuitously, the most computationallyintensive elements of the present method belong to the class of so-called "embarrassingly parallel" problems, so a relatively simple parallelisation across a handful of processing elements can be expected to produce high quality

To fit the other parameters, we begin with a compound model, F, containing only the Brown-like component. Initial values must be provided for all non-linear parameters except epoch (τ) which we estimate simply by sweeping through the data window and choosing the optimal value.

Before we consider the peaks, we add another model: thermal noise and optimise once more.

Finally, we introduce each peak into the mix for F and 'guess' its epoch in a similar manner (exhaustively by gate). The model is once more downhill optimised and another peak is added until all peaks have been fitted. The resulting parameter set is assumed to correspond to a global minimum of the metric function, G.



retracking streams in near real time.

REFERENCES

1. Halimi, A. et al. Parameter Estimation for Peaky Altimetric Waveforms. IEEE Transactions on Geoscience and Remote Sensing. 2012 Volume 50, number 9

2. Gomez-Enri, J. et al. Measuring Global Ocean Wave Skewness by Retracking RA-2 ENVISAT Waveforms. Journal of Atmospheric and Oceanic *Technology.* 2010 Volume 24, 1102-1116

