Using Regularized Least Squares to Break the Data Requirements of Tidal Harmonics Analysis

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Key Points:

• A new algorithm is proposed to determine the tidal ranges based on satellite altimetry data
• A numerical experiment shows that the new algorithm could achieve low error in determining tidal amplitudes
• The proposed algorithm is shown reliable in analyzing real satellite data

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Abstract
Recent observation reveals a stunning fact that the coastal tides are experiencing a rapid change in the last century at several places in the world. High-accuracy tide level data is needed to achieve a wide and refined understanding of the phenomenon. In-situ measurements – the traditional and main data source to support tidal harmonic analysis – are often sparse and limited to fixed locations, which are insufficient to provide information about the spatiotemporal variability of tidal processes beyond the tidal gauges. Satellite altimetry may fundamentally change the situation. This technology measures water level with much wider spatial coverage and higher resolution, but it has not been used in tidal analysis due to two major limitations in the harmonic analysis: a) a minimum length of sampled observed data is required to recognize a sufficient number of tidal constituents according to the Rayleigh criterion and b) data sampling/acquisition frequency must be at least two times the major tidal frequencies to avoid the aliasing issue dictated by the Nyquist theorem. To address these issues, a novel Regularized Least-Square approach is proposed to break the limitations. In this method, the prior information of the regional tidal amplitudes is used to support a least square algorithm to obtain the amplitudes and phases of the tidal constituents for data series with different lengths and time intervals. A numerical experiment showed that the proposed method can determine the tidal amplitudes with a low level of error and the sampling interval can be relaxed to the application level equal to altimetry satellite revisit intervals. The proposed algorithm was also tested using the data of the altimetry mission, Jason-3, and the performance was excellent. The potential use of this method could help identify the changing tides with climate change and anthropogenic activities in the coastal area.

Plain Language Summary
It is a long-lasting challenge to use satellite data to directly measure the amplitude of the tidal rises and falls because the interval between satellite visits to the same location on the earth’s surface is too long. We developed a new algorithm to enable the direct measurements and validated it through numerical experiments. The tests showed that the new algorithm is outperforming the peers and reach the application requirements. The new algorithm paves a way to understand the global changes of tidal motion, which could help governments and coastal communities understand the changing risk of coastal flooding and promote informed decisions to create and improve local infrastructure.

1 Introduction
Coastal tides have been experiencing ubiquitous changes in the past century due to anthropogenic activities (e.g., dredging and land reclamation) and environmental processes (e.g., erosion and sea-level rise). These changes may potentially increase the risks of property damage, loss of life, ecosystem degradation, and environmental injustice. A remarkable example of the consequence is the increase of high tide flooding (also called “blue sky” flooding or “sunny day” flooding), which is shallow (several centimeters) but widely spread (Sweet et al., 2018). NOAA (National Ocean and Atmospheric Agency) reported that 75% of the US East and Gulf Coast’s monitored locations witnessed an increasing trend of high tide flooding (Sweet et al., 2018). NOAA (National Ocean and Atmospheric Agency) reported that 75% of the US East and Gulf Coast’s monitored locations witnessed an increasing trend of high tide flooding (Sweet et al., 2018), which disrupts transportation, sewage, and other infrastructure systems, devalues real estate, reduces income and jobs, exposes health hazards, increases public health risks, salinizes groundwater, and deteriorates coastal ecosystems (Moftakhari et al., 2017). These relatively more frequent, smaller floods, at some locations, may be proved more costly than large, infrequent extreme events (Moftakhari et al., 2017; Li et al., 2021).

Coastal tidal changes have been understudied until the recent observation of rapidly evolving tidal ranges in some estuaries (Talke & Jay, 2020). For example, the tidal range at Albany, New York is having an increasing trend of 0.5 cm per year since 1920. Sim-
ilar observations have been made at Philadelphia, Wilmington, and Jacksonville. The secular (i.e., nonperiodic and long-term) tidal range changes are accompanied by the changing tidal phases, e.g., a decrease of about 30 degrees was found in Philadelphia (Ross et al., 2017). But tidal ranges remained the same level in other estuaries after removing the 18.61-year nodal cycle, e.g., at Sandy Hook in New Jersey and Boston in Massachusetts. Changing tides can alter fundamental coastal processes, e.g., the turbulent mixing changed between 1954 and 2005 in the Ems estuary in the Netherlands (de Jonge et al., 2014), and the overtide (M4) decreased with the changing tides in Argentina (Santamaria-Aguilar et al., 2017). The accumulating data are revealing the stunning fact that the coastal tides are experiencing rapid and significant changes in the past decades, and the rate is varying from place to place.

High-quality and widely-coverage data is demanded to fully recognize and systematically examine the change of coastal tidal dynamics, but data scarcity remains an ongoing issue for coastal monitoring programs (Barnard et al., 2015; Pianca et al., 2015; Turner et al., 2016). The tidal range analysis almost solely relies on tidal gauge data (Parker, 2007), which is constrained to fixed-point measurement and cannot fully reveal the multiple spatial scales and processes involved (Devlin et al., 2019). The emerging satellite data has a great potential to improve the observation frequency, coverage, and resolution.

The coastal satellite altimetry technology, which sends radar pulses and receive the echoes reflected from the surface below to measure sea surface heights, has now reached the accuracy of centimeters within 5 km from the coast (Cipollini et al., 2017; Valle-Rodríguez & Trasviña-Castro, 2017; Passaro et al., 2016; Birgiel et al., 2018). The technological improvement is driven by multiple aspects of the technological advance: 1) new platforms are proven more precise and accurate than the traditional altimetry in measuring coastal sea levels, e.g., the SARAL/AltiKa mission operating in Ka band, CryoSat-2 operating in Synthetic Aperture Radar (SAR) [also called Delay-Doppler Altimeter (DDA)] mode and in the interferometric mode (SARin), and Sentinel-3A/B operating in SAR mode; 2) new and dedicated data processing schemes have developed to enhance the quality and quantity of coastal altimeter data such as the Adaptive Leading Edge Subwaveform (ALES) retracker (Passaro et al., 2014, 2018) and 3) progress has been made in the dry and wet tropospheric correction (Benveniste et al., 2019). The breakthrough of coastal altimetry empowered a series of applications, e.g. the estimation of ocean currents (Jebri et al., 2016, 2017; Salazar-Ceciliano et al., 2018; Valle-Rodríguez & Trasviña-Castro, 2017), inland flow (Gleason & Durand, 2020; Biancamaria et al., 2017), tidal mixing fronts (Dong et al., 2018), tidal energy dissipation (Egbert & Ray, 2001), storm surge heights (Ji et al., 2019), and vertical land motion (Oelsmann et al., 2020). Because this technology is free of cloud or significant weather impacts (Wang, 2022), it is considered as an ideal tool to continuously monitor the earth surface. However, the analysis on tidal ranges is challenging and no applicable method has been developed to the authors’ knowledge.

However, rare efforts have been made to improve the understanding of the complicated coastal tides using the coastal altimetry data. The major bottleneck is the challenge to extract tidal ranges with the temporal resolution of altimetry satellites – the long revisit time cannot support the data requirement of harmonic analysis (HA), which is the main method to analyze tidal ranges and phases. Specifically, Sea Surface Height (SSH), $h_H$, is assumed to follow a series of harmonic series in HA, i.e.

\[ h_H = m + at + \sum_{k=1}^{n} [A_k f_k \cos(\omega_k t + \phi_k + u_k)], \]  

(1)

where $t$ is time, $a$ is the slope of the mean sea level change, $m$, $\omega$, $\phi$, $f$, and $u$ are the mean water level, the frequency, the astronomical phase angle, and the nodal corrections for the amplitude and phase of each tidal constituent, and $n$ is the number of tidal constituents (Le Provost, 2001). Popular tools such as UTide (Codiga, 2011) and Pytides
While this traditional harmonic analysis method is dictated by the strict data requirements of the Rayleigh criterion and the Nyquist–Shannon sampling theorem. The Rayleigh criterion requires a sufficiently long period of data to differentiate tidal constituents of close frequencies and it was shown that data of one year is necessary to recognize 39 key tidal constituents (Parker, 2007). The Nyquist–Shannon sampling theorem dictates that the sampling frequency must be greater than two times the frequency of the targeted phenomenon. In tidal analyses, this means that the sampling interval must be shorter than 6.2 hours to capture M2, the dominant constituent in most places of the world. Unfortunately, no altimetry satellites can provide such a high frequency measurement, e.g., Jason-3, the major altimetry satellite, revisits the same location of the earth surface every 9.9 days.

Recognizing the gap between the satellite measurement and data analysis, scientists developed data-science methods to resolve the issues: An interpolation method called Constrained Harmonic Analysis (CHA) was proposed to estimate tidal ranges, where data is fitted into two harmonic series of the neighboring tidal gauges (Matte et al., 2018). By assigning a series of weights between 0 to 1 (“0” means the same as the first gauge and “1” means the same as the second), tidal amplitudes and phases can be “interpolated” between the two reference gauges to fit the observation. A good agreement with tidal gauge data was shown (Matte et al., 2018). However, this method cannot reach the necessary frequency requirement to enable satellite altimeters to be used to assess tidal amplitudes, which will be shown later.

To address these issues, a novel regularized least-square approach is proposed to break the data limitations to estimate the tidal dynamics in the coastal area to enable satellite-based tidal amplitude estimation. In Section 2, we describe this new method and explain the rationale behind it. Section 3 showed the results of a numerical experiment to validate the method and a demonstration of its application in processing satellite altimetry data.

2 Method

We propose an algorithm called Regularized Least-Square Harmonic Analysis (ReLSHA) to address the strict data requirements posed by the Rayleigh criterion and Nyquist–Shannon sampling theorem. Regularized Least-Square has been used in compressed sensing that can reconstruct a signal compressible by a known transform (e.g., wavelet) or prior information subject to fewer measurements than the nominal frequency of sampling (Eldar & Kutyniok, 2012; Tsaig & Donoho, 2006). Numerous examples demonstrated that such compressed sensing methods can be used to break the limit of Nyquist–Shannon sampling limit (Eldar & Kutyniok, 2012; Tsaig & Donoho, 2006; McLean et al., 2005). The algorithm is designed to minimize an objective function by

$$\min_{A_k f_k, \phi_k + u_k} J = (1 - \lambda) \| h_H (A_k f_k, \phi_k + u_k) - h_0 \| + \lambda \| A_k^2 f_k^2 - A_0^2 \|,$$

where $h_0$ is the time series of the measured water level data, $\lambda$ is the regularization weight, and $A_0$ are the amplitudes of a reference station (a good choice of the reference site is the nearest tidal gauge), $k = 1, 2, \cdots n$, and $n$ is the targeted number of constituents. In this study, we assign $n = 37$ to be consistent with the number of the major constituents used in NOAA tidal gauges. The strategy of this algorithm is thus to determine the coefficients of the harmonic series to “best fit” the measured water level data with a penalization to the difference of the harmonic amplitudes between the model and the reference. Note that only the amplitude difference of the harmonic series is penalized while
the phase difference is ignored because the phases of a harmonic series could be very different from the reference, e.g. they could have different time origins or time zones.

Since the harmonic series involves nonlinear trigonometric functions and thus the minimization method could be challenging to solve, we developed a Regularized Least-Square based strategy to solve the problem. First, the mean and linear components of the measured water level are removed. Then, Equation 2 is linearized as following

\[ J = (1 - \lambda) \left| \sum_{k=1}^{n} [A_k f_k \cos(\omega_k t_i + \phi_k + u_k)] - h_{0,i} \right| + \lambda \left| A_k f_k^2 - A_{0,k}^2 \right| \]

\[ = (1 - \lambda) \left| \sum_{k=1}^{n} [A_k f_k \cos(\omega_k t_i) - A_k f_k \sin(\omega_k t_i)] - h_{0,i} \right| + \lambda \left| A_k f_k^2 - A_{0,k}^2 \right| \]

\[ = (1 - \lambda) (Hx - h)^T (Hx - h) + \lambda (K(x \odot x) - q)^T [K(x \odot x) - q], \]

where \( \odot \) is the Hadamard product sign, which performs the elementwise multiplication, the harmonic matrix \( H \) is

\[
H = \begin{bmatrix}
\cos(\omega_1 t_1) & \cos(\omega_2 t_1) & \cdots & \cos(\omega_n t_1) & \sin(\omega_1 t_1) & \sin(\omega_2 t_1) & \cdots & \sin(\omega_n t_1) \\
\cos(\omega_1 t_2) & \cos(\omega_2 t_2) & \cdots & \cos(\omega_n t_2) & \sin(\omega_1 t_2) & \sin(\omega_2 t_2) & \cdots & \sin(\omega_n t_2) \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots \\
\cos(\omega_1 t_m) & \cos(\omega_2 t_m) & \cdots & \cos(\omega_n t_m) & \sin(\omega_1 t_m) & \sin(\omega_2 t_m) & \cdots & \sin(\omega_n t_m)
\end{bmatrix},
\]

the vector \( x \) to solve is

\[
x = \begin{bmatrix}
A_1 f_1 \cos(\phi_1 + u_1) \\
A_2 f_2 \cos(\phi_2 + u_2) \\
\vdots \\
A_n f_n \cos(\phi_n + u_n) \\
A_1 f_1 \sin(\phi_1 + u_1) \\
A_2 f_2 \sin(\phi_2 + u_2) \\
\vdots \\
A_n f_n \sin(\phi_n + u_n)
\end{bmatrix},
\]

the measured water level vector, \( h \), is

\[
h = \begin{bmatrix}
h_{0,1} \\
h_{0,2} \\
\vdots \\
h_{0,m}
\end{bmatrix},
\]

the transformation matrix, \( K \), is used to extract tidal amplitudes,

\[
K = \begin{bmatrix}
1 & 1 & \cdots & 1 \\
1 & 1 & \cdots & 1 \\
\vdots & \ddots & \ddots & \vdots \\
1 & 1 & \cdots & 1
\end{bmatrix},
\]

and the reference vector, \( q \) is

\[
q = \begin{bmatrix}
A_{0,1}^2 \\
A_{0,2}^2 \\
\vdots \\
A_{0,n}^2
\end{bmatrix}.
\]
This linearized function is convenient to solve. Once $x$ is obtained, the tidal amplitudes $A_k$ can be generated using

$$A_k = \sqrt{(K(x \odot x))_k}. \quad (9)$$

To promote the quick convergence, the Jacobian of $J$ was derived, i.e.

$$\frac{dJ}{dx} = 2(1 - \lambda)H^T(Hx - h) + 2\lambda Diag(x)K^T[K(x \odot x) - q], \quad (10)$$

where $Diag(x)$ is a function to convert the vector $x$ into a diagonal matrix.

Since this proposed ReLSHA method requires a reference vector of tidal amplitudes, a rational choice would be the data from the nearest tidal gauge. GESLA provides an exhaustive dataset of tidal harmonic constants worldwide. We performed a geographic study and found for any point along the coastline of the Contiguous United States one can always find a reference tidal gauge within $\sim 73$ km (Fig. 1). Note that the longest distance was found in Southern Florida and a few places in Southern California are also close to this distance.

A numerical experiment was conducted to validate the method and reveal the tidal range changes in the Delaware Bay. We analyzed 37 major tidal constituents using the tidal level data of the year 2021 from the NOAA station Brandywine Shoal Light (BSL). The tidal amplitudes at Atlantic City (AC) were used as the reference, which was deliberately chosen to set the distance at the level of 73 km and the two sites are located in different hydrodynamic environments – BSL is inside Delaware Bay and AC faces to the open ocean (Fig. 2).

The tidal amplitudes and phases of two neighboring NOAA sites at Cape May, NJ and Lewes, DE were used as the reference sites for the input of CHA. The NOAA’s time series of the water level data collected every 6 mins was resampled with a range of in-
tervals from 12 mins to 11 days and cut randomly to prepare the data of various sampling intervals and total lengths to explore how much the Nyquist-Shannon theorem and the Rayleigh criterion can be relaxed. The tidal amplitudes of the 37 constituents at BSL provided by NOAA were used as the ground truth (denoted as $A_{k,true}$) to evaluate the performance of the methods – the Relative Root Mean Square Error (RRMSE) of the 37 tidal constituents, 

$$RRMSE = \sqrt{\frac{\sum_{k=1}^{37} (A_k - A_{k,true})^2}{\sum_{k=1}^{37} A_k}} \times 100,$$

is used to compare the performance among different algorithms.

After the validation, ReLSH was applied to analyze the sea surface height (SSH) using the data of Jason-3. The data of the 1-Hz alongtrack altimeter data of Jason-3 was collected from Sea Level Anomalies Along-track Level-2+ Product (L2P) provided by the platform of Cnes AVISO-SALP (https://www.aviso.altimetry.fr/). The measurements of Pass 288 close to the NOAA tidal gauge of Cape May were selected for analysis (Fig. 2). Note that some cycles have no data of Pass 288 due to data quality control or other reasons. In this validation task, BSL was used as the reference site and the tidal amplitudes based on NOAA tidal gauge at Cape May was considered as the ground truth.

3 Results

The proposed ReLSHA is shown to outperform the traditional HA and CHA in Figure 3. Figure 3a-c show that the tidal amplitude RRMSE for ReLSH is generally much lower than the other two algorithms. Specifically, the range of the examination can be divided into two regions depending on the number of unknowns and measurements: “overdetermined” and “underdetermined”. In the overdetermined region, the number of measurements is more than unknowns ($= 37 \times 2 = 74$), while in the underdetermined region the number of unknowns is more than measurements. Traditional HA is required to only applied in the “overdetermined” situation, otherwise the number of equations is less than the unknowns so that no unique solution can be obtained. We observed that low RRMSE is found for the overdetermined region where the sampling interval is short and the total data length is long. This result is expected, because the resampled data are close to meet the data requirements of sufficient total data lengths and short sampling intervals. In comparison, high RRMSE was found in the underdetermined region

Figure 2. The map of the NOAA tidal gauges and the location of the Jason-3 measurements near Cape May used in this study.
Figure 3. The comparison of the three harmonic analysis methods. (a-c) the RRMSE of HA, CHA, and ReLSHA methods (the white dashline marks the boundary between overdetermined and underdetermined regions); (d-f) the error for the three methods for comparison with (d) in the overdetermined region and (e) and (f) in the underdetermined region.

where the observation data points are relatively less than the unknowns. Also, high RRMSE was found for the intervals of $\sim12$ hours, $\sim24$ hours, etc. in the results of HA and CHA, which is due to the tidal “aliasing” issue when the sampling interval is close to the periods of major tidal constituents. This issue was relatively trivial for ReLSHA – the RRMSE only showed peaks for three sampling frequencies. The RRMSE quickly increased for longer sampling intervals and shorter data periods for HA and CHA, whereas the error of ReLSHA remains relatively low in the range of the experiment. The highest error of Figure 3c is up to 10% at the lower left corner, where the total data period is short and the sampling frequency is high.

To reveal the error distribution and estimate the applicability of the algorithms to satellite data, a side-by-side comparison with three sampling intervals of 6 mins (the highest frequency), 9.9 days (revisit interval of Jason-3), and 11 days (the revisit interval of SWOT) was created in Figure 3d-f using the one-year data. At the sampling interval of 6 min, the error of all the methods declines quickly when the total data period increases, and CHA shows the best performance. However, at the intervals of 9.9 days and 11 days, the error of the CHA method is much higher than the others. HA maintains an error level of 15%, while the proposed ReLSHA method could keep the error to $\sim3\%$. This comparison shows that in addition to achieving high accuracy, the ReLSHA method can even reach the capability to process the satellite altimetry data. In other words, ReLSHA with the input of prior tidal information of the region can break the constraints by the Nyquist-Shannon theorem and Rayleigh criterion to determine the tidal amplitudes and track the changes within an acceptable error tolerating the data quality of the satellite altimetry.

Encouraged by the high performance, we applied ReLSHA to the Jason-3 data for year 2016 to 2021 and compared the result with the ground truth, which are the obtained tidal amplitudes using the traditional HA for the water level data of the NOAA tidal gauge.
Figure 4. The ReLSHA based tidal amplitude measurements using Jason-3 altimetry data near the NOAA tidal gauge at Cape May: (a) The determined tidal amplitudes for the leading five constituents; (b) The difference between the ReLSHA result and the gauge-based harmonic analysis.

The critical component in ReLSHA is the selection of the reference tidal amplitudes. The present study focused on the tidal dynamics in Delaware Bay, where the tidal basin geometry is relatively simple, so the present result shows an exceptional performance even with a reference site far from the altimetry location. Further validation with more complicated hydrodynamics conditions is required to test the generality of the method. In processing the real data such as from the Jason missions, the performance might be compromised due to the extreme long sampling interval and missing cycles. We would suggest use caution to apply ReLSHA with the best search of the reference information. The reference site should also be selected for the best similar hydrodynamic characteristics – sometimes the nearest site might not have similar hydrodynamics in a complicated tidal basin. At last, it is worth noting that validated numerical models could provide good reference information to serve as virtual reference sites, so it will be attractive, and a future study, to test whether the ReLSHA result can be further improved using coastal hydrodynamics models.
4 Conclusion

A new algorithm is proposed to accomplish a long-lasting, challenging task: how to use satellite altimetry data to estimate tidal amplitudes. The proposed algorithm of ReLSHA based on the Regularized Least-Square scheme provides a potential solution, which is to fit the tidal harmonics to the observation data with penalization to the difference of tidal amplitudes from a reference – the prior information about the local tidal amplitudes. A numerical experiment using resampled NOAA tidal gauge data was conducted to validate the proposed algorithm, which shows much lower error than the traditional harmonic analysis and the best existing method, CHA. Since the testing sites are located strategically in different tidal basins with a long separation distance and different hydrodynamic conditions, the success of the numerical experiment showed that the tidal amplitudes along the Contiguous United States shoreline could potentially be determined with a reasonable accuracy using the proposed algorithm if the satellite altimetry data is available. The application of ReLSH to the Jason-3 data further validated the method using real satellite altimetry data. The proposed method has a great potential to increase the coverage and resolution of tidal range observation worldwide, especially for the place where monitoring infrastructure is lacking, and provides a useful tool to analyze the coastal tidal ranges under climate change and human impacts.

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