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Optimal Location Estimation and Anomaly Quantification for a Mobile Information Carrier: Prior Feeds for Deep Learning

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Abstract

Smart geo-intelligence systems consisting of mobile information carriers, driven by an information field, often face geo-intelligence problems possessing two aspects which need to be addressed to institute actions. First is estimation of the location state of a mobile information carrier where the dynamical law for state change is unknown but where the information field responsible for state change is known. The second is the characterization of the anomalous statistical structure in captured signals at predicted locations. A two-tier statistical approach is adopted here for the purpose of demonstrating optimal location estimation and anomaly quantification addressing the dual problem of *where* a mobile information carrier is and *what* anomalous structure exists in an acquired signal.

In the first tier the least absolute shrinkage and selection operator (LASSO) along with Gaussian process (GP) nonlinear regression is used to optimally estimate the location of a mobile information carrier, a buoy, drifting due to a multivariate driving information field. This field emanates from a surface current and wavefield. The use of an ensemble of estimators emanating from the multivariate data is envisioned as the optimal estimator of location where estimator coupling is the ultimate means for reducing error producing noise. The multivariate data used in modelling the relationship between latitude and longitude, and the information field and then making future predictions of location is buoy data emanating from a SOFAR spotter buoy moving in the mid-Atlantic Ocean around the mean latitude and longitude of 38º and 320º (-40º) respectively. Two location variables (latitude and longitude) and seven information variables were measured by the SOFAR spotter buoy. The information field variables consist of the mean wave directional spread, mean wave direction, mean wave period, wave peak directional spread, wave peak direction, wave peak period, and significant wave height. The two location variables and the seven measured information field variables were used in the LASSO-GP nonlinear regression location estimator consisting of a LASSO-based feature extraction stage, a GP training stage, and a GP prediction stage aimed at optimal forecasting of location based only on data and utilizing no dynamical constraints.

LASSO-GP estimation is a nonparametric Bayesian approach where the measured location and multivariate information fields are modelled as stochastic processes where latitude and longitude are the predictands and the information field is the predictor. LASSO results for latitude and longitude allow for extraction of three dominant oceanic information field variables, which are different for each location variable, as the most important for location estimation. Nonlinear fits of latitude and longitude data with mean wave directional spread demonstrate rough fits over a training data set (priors) of 300 points. Extrapolation over 50 future data points for location using these wave information field variables yield erratic location estimates for both latitude and longitude with longitude being better predicted. This large variance in estimates is explained by no allowance for smoothness of wavefield information. Latitude and longitude forecasts over 50 future points using smoothed GP estimated wavefield information values for the six predictor variables provide reasonable average estimates of latitude-longitude location. These optimal location estimates which utilize no dynamical constraints are taken as prior information estimates to be passed to neural network processors to attain more precise forecasts of mobile information carrier position.

Estimated location allows for the next stage of the smart geo-intelligence processor where it is envisioned that the mobile information carrier 'listens' and acquires acoustic information from an acoustic sensor on the buoy. This acoustic information lies outside the driving information field. The aim is to characterize acquired signals in terms of the average number of high energy events as a function of their local scale or period. The purpose for estimation of this statistic is also to provide a signature label furnishing feature patterns to be used in understanding future acquired signals.

A processor based on empirical mode decomposition (EMD) analysis and Morlet wavelet transform (MWT) analysis is used to estimate a high energy event (HEE) statistic associated with acoustic signals. Chordal-based music signals generated from custom made cigar box guitars (cbgs) are used as known acoustic signals to test the algorithm. Two C-major chords were played on two different cbgs possessing guitar backs made of different materials (African sepele and African mahogany) but otherwise possessing the same dimensions. The EMD method was used to generate a series of intrinsic mode functions (IMFs) from the acquired time series signals both of which possesses multi-scale HEEs. Two sets of IMFs for each acoustic signal represent sets of signal atoms possessing average spectral bandwidths that only mildly overlap each other in frequency space, making the atoms pseudo-orthogonal. The generated IMFs were decomposed using MWT analysis to reveal HEEs distributed in MWT time-scale space. These HEEs were exhumed using a nine-point square box filter and a maximum threshold.

Histograms of the HEEs reveals local maxima at the frequency scales associated with the notes comprising the C-major chord including the dominant period of middle C which is 0.0035 s as well as sub and super harmonic periods of the notes forming the chord including 0.005s (G-2), 0.0013s (G-5), and 0.000625s (G-6). The algorithm captures differences in cbg HEE statistical structure which can be linked to known differences in resonant structure of the wood material responsible for signal amplification. In particular, the mahogany back cbg possesses the ability to sustain lower frequency modes accounting for higher peaks in the HEE at low frequencies. These results provide evidence that the EMD-MWT algorithm can capture nonlinear local HEEs consistent with differences in the acoustic generation process for the nonlinear signals.

***Keywords*:** latitude, longitude, LASSO, Gaussian process, SOFAR buoy, mean wave directional spread, mean wave period, wave peak period, significant wave height, location estimation, empirical mode decomposition, intrinsic mode functions, Morlet wavelet transform, high energy event statistic

1. Introduction

Smart geo-intelligence naval systems are an important and innovative type of technology crucial to accomplishing the missions of geo-intelligence leadership. The development of this technology is often algorithmically based on addressing two areas in signal processing. These are the predictive estimation of location of a mobile information carrier or buoy being driven by a surface wave and current field, and techniques for the detection and quantification of temporally local events in acquired acoustical signals from the buoy where priors are unknown. A two-tier statistical approach is explored for the purpose of optimal location estimation and anomaly quantification addressing the dual problem of *where* a mobile information carrier is and *what* anomalous structure exists in an acquired acoustic signal. The two problem aspects are explicated below.

Many geo-intelligence problems are based on the estimation of the location state of a mobile information carrier where the dynamical law for state change is unknown but where the information field responsible for state change is. In such cases traditional signal processing techniques are not always useful for state prediction necessitating approaches dependent on predictive estimation of location from the driving information field alone. In situations where a limit on data plethora exists, techniques based purely on neural networks can be inappropriate whereas Bayesian statistical techniques offer a way to maintain a datacentric focus while affording optimal estimation of state. In Bayesian processing, state estimation is provided along with a quantification of uncertainty emanating from treating data as a known and the contingent state parameter as random. The least absolute shrinkage and selection operator (LASSO) along with Gaussian process (GP) nonlinear regression is used to optimally estimate the location of a mobile information carrier (buoy) drifting due to a multivariate driving information field emanating from a surface current and wavefield. The use of an ensemble of estimators is envisioned as the optimal estimator of location where estimator coupling is the ultimate means for reducing error producing noise.

With optimal estimation of location comes the second part of the geo-intelligence processor. Acoustic signals of all types carry structured information that can give insight into temporal variability which in turn provides for state understanding. In particular, nonlinear acoustical anomalies provide a rich source of state labeling via the analysis of how signals depart from linearity. This occurs in the form of quantification of non-periodicity and temporal locality of acoustical signal events. Emitted and captured acoustic signals therefore require innovative methods for statistical anomaly characterization which afford an advanced form of signal labeling. Empirical mode decomposition (EMD) and Morlet wavelet analysis are used to estimate nonlinear signal atoms, which span the structure of an analyzed signal, as well as to detect anomalous high energy events in Morlet wavelet transform time-scale space for each signal atom. Such techniques allow for multiple-scale nonlinear analysis of captured signals whose statistical labeling via likelihood function estimation allows for solving the inverse problem of estimating statistical state from data observations.

2. Ocean Wavefield Data Structure and LASSO Analysis

The multivariate data used in modeling the relationship between latitude and longitude, and the information field and then making future predictions of location is buoy data emanating from a SOFAR spotter buoy. This buoy was situated in the mid-Atlantic Ocean moving around the mean latitude and longitude 38º and 320º (-40 º to left of Greenwich meridian) respectively. Two location variables (latitude and longitude) and seven information variables were measured by the SOFAR spotter buoy. The information field variables consist of the mean wave directional spread, mean wave direction, mean wave period, wave peak directional spread, wave peak direction, wave peak period, and significant wave height. The 2 location variables and the 7 measured surface wave-current information field variables driving the spatial change of the buoy were used in a LASSO-GP nonlinear regression location estimator consisting of a LASSO based feature extraction stage, a GP training stage, and a GP prediction stage aimed at optimal estimation or forecasting of location based only on data and utilizing no dynamical constraint. LASSO is an inverse problem solver which utilizes the L1 norm regularization constraint to find the relative ranking and relationship of the information field to the location variables [1,2]. GP is a nonparametric Bayesian approach where the measured location and multivariate information fields are modelled as stochastic processes which are causally related emanating from infinite dimensional multivariate normal distributions [3].

GP priors are specified using a radial basis covariance kernel function [4] specifying how measured data points from both variable types are statistically related by similarity and smoothness. Once the kernel function hyperparameters are parameterized using past location and surface wave and current information field training data, predictions about location can be made from the most potent or heavily LASSO weighted information field variables.

3. Acoustical Data Structure and EMD-Morlet Wavelet Analysis

Acoustical waves emanating from musical instruments are used as a proxy for ocean acoustical waves emanating from a buoy SONAR system in this analysis. This acoustical field represents an information field lying outside the wave-current field responsible for driving the buoy through space and time. A Sony digital sound recorder was to use to record the acoustical chordal signals of a C major chord emanating from 2 cigar box guitars (cbgs) shown in Fig 1a-b.

a) b)

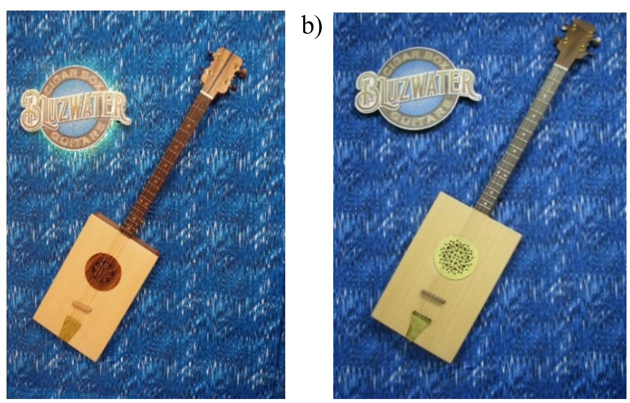


Figure 1: Custom made cigar box guitars (cbgs) by Bluz Water Cigar Box Guitars, LLC representing acoustical signature emitters. Both cbgs have spruce tops with a) having an African sepele back and b) having an African mahogany back. Both guitars are tuned to open C.

EMD analysis was performed in part where eight intrinsic mode functions (IMFs) were generated for each C major chordal signal [5]. A sample signal from the left cbg and its Fourier spectrum is shown in Fig 2 a-b.

a) b)

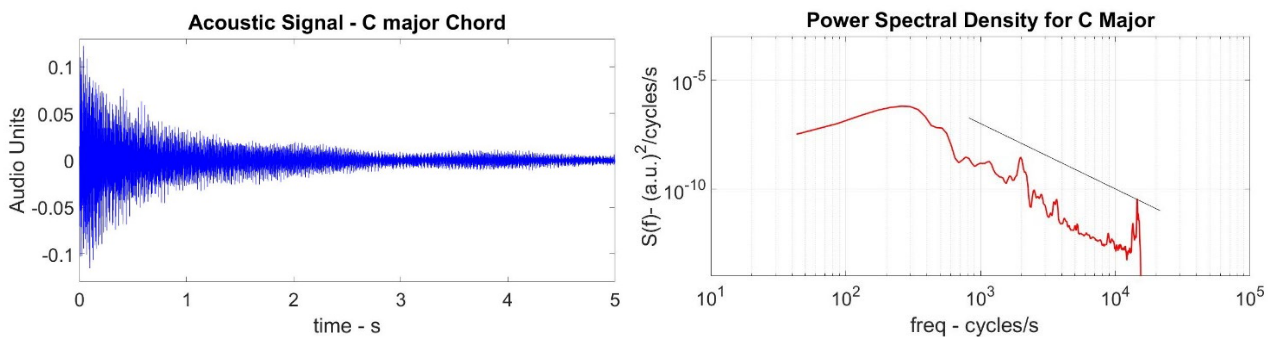


Figure 2: a) C Major chordal acoustic signal captured for 5 s from left cbg. b) Fourier power spectrum of signal showing local maxima at 255 Hz (~C-4) with super harmonics of 770 Hz (G-5), 1100 Hz (C-6), 2100 Hz (C-7), 2650 Hz (E-7), 4200 Hz (C-8), and 8600 Hz (C-9). Black line is a slope of -4.

IMFs shown in Fig. 3a-b represent nonlinear, empirically derived signal atoms spanning each cbg signal. Each IMF captures signal fluctuation structure over a finite average spectral bandwidth with initial IMFs capturing high frequency signal structure and later estimated IMFs capturing low frequency or longer time scale structure [5].

a) b)

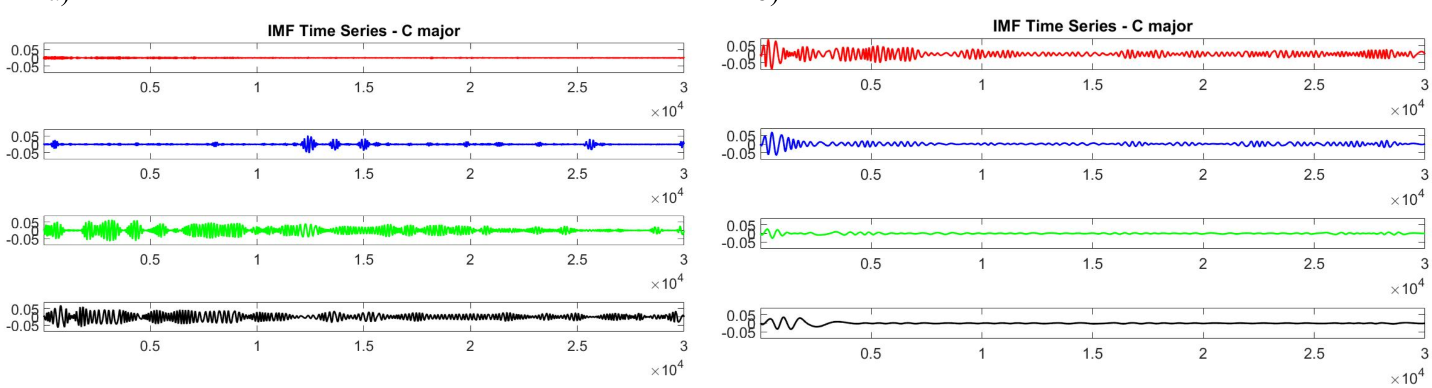


Figure 3: a) - b) 8 IMFs calculated from a 30,000-point segment of the complete acoustical signal. High frequency information is extracted first followed by increasing amounts of low frequency information. Note the local nonlinear modulations which contain high energy events.

Each IMF underwent the Morlet wavelet transform (MWT) which further decomposes IMF fluctuation structure using local, Gaussian envelope modulated sinusoids situated over each point in time. Fig. 4 a-f depicts examples of the MWT for 6 generated IMFs for the C major chordal signal emanating from the left cbg. The MWT is normalized such that energy appearing in a signal at different scales is constant or preserved. The MWT unfolds the local periodic structure of an IMF in scale-time space where each scale has a Fourier frequency or period label. Fig. 4 a-f displays the MWT for IMFs 2-7. With increasing period label, each IMF carries larger period fluctuations which is reflected in the high energy events whose scales appear
at increasing periods. High energy events are exhumed in MWT time-scale space via a 9-point square box filter which finds local maxima over the mask exceeding a threshold of 20 as it is moved over the domain [6]. The tallying of high energy event asterisks as a function of period or scale for each Morlet wavelet transformed IMF is performed yielding the high energy event (HEE) statistic or likelihood function. This statistic is like the steep wave statistic used in characterizing steep and breaking wave events in an ocean wavefield [6].

a) b)

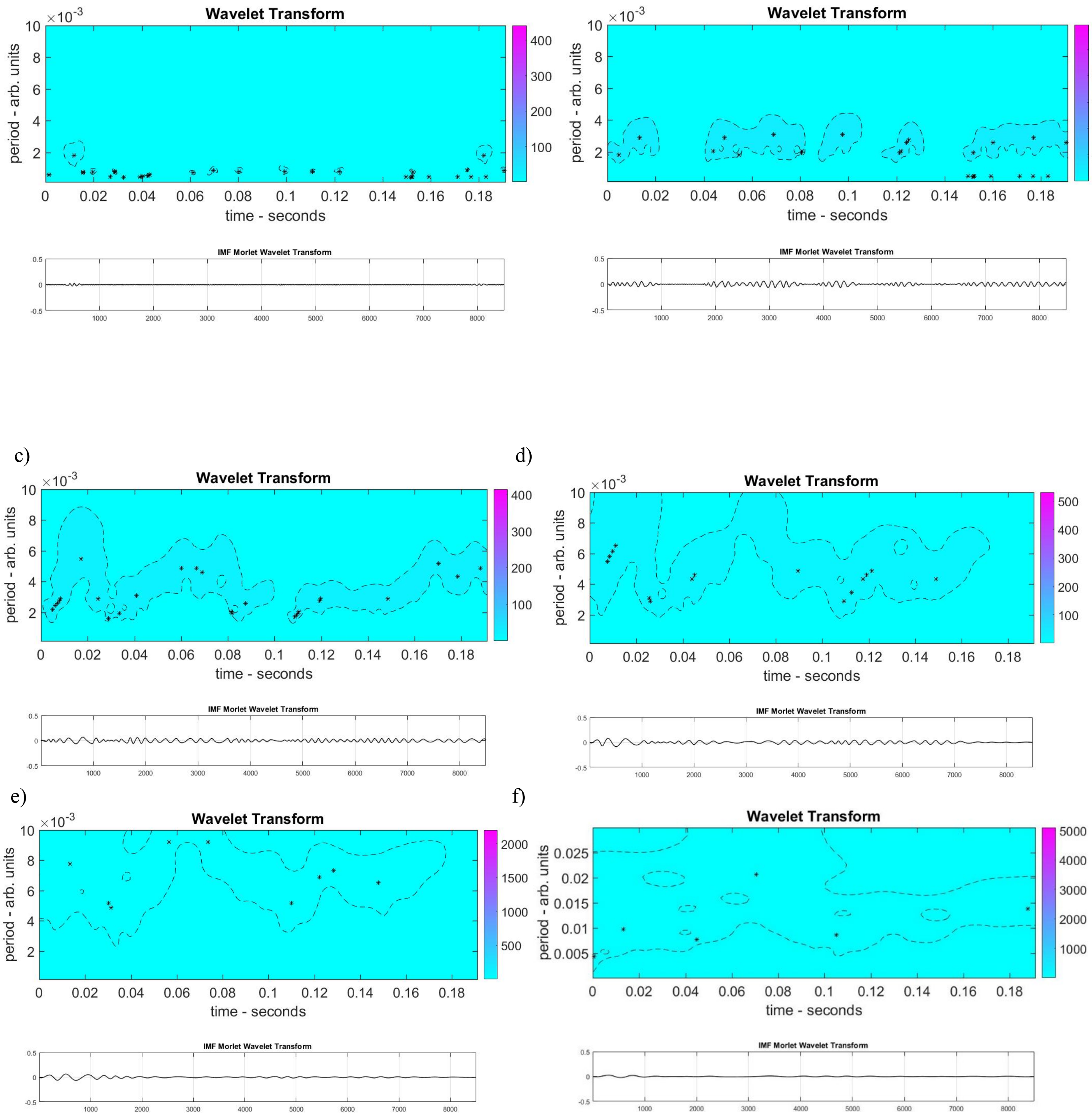


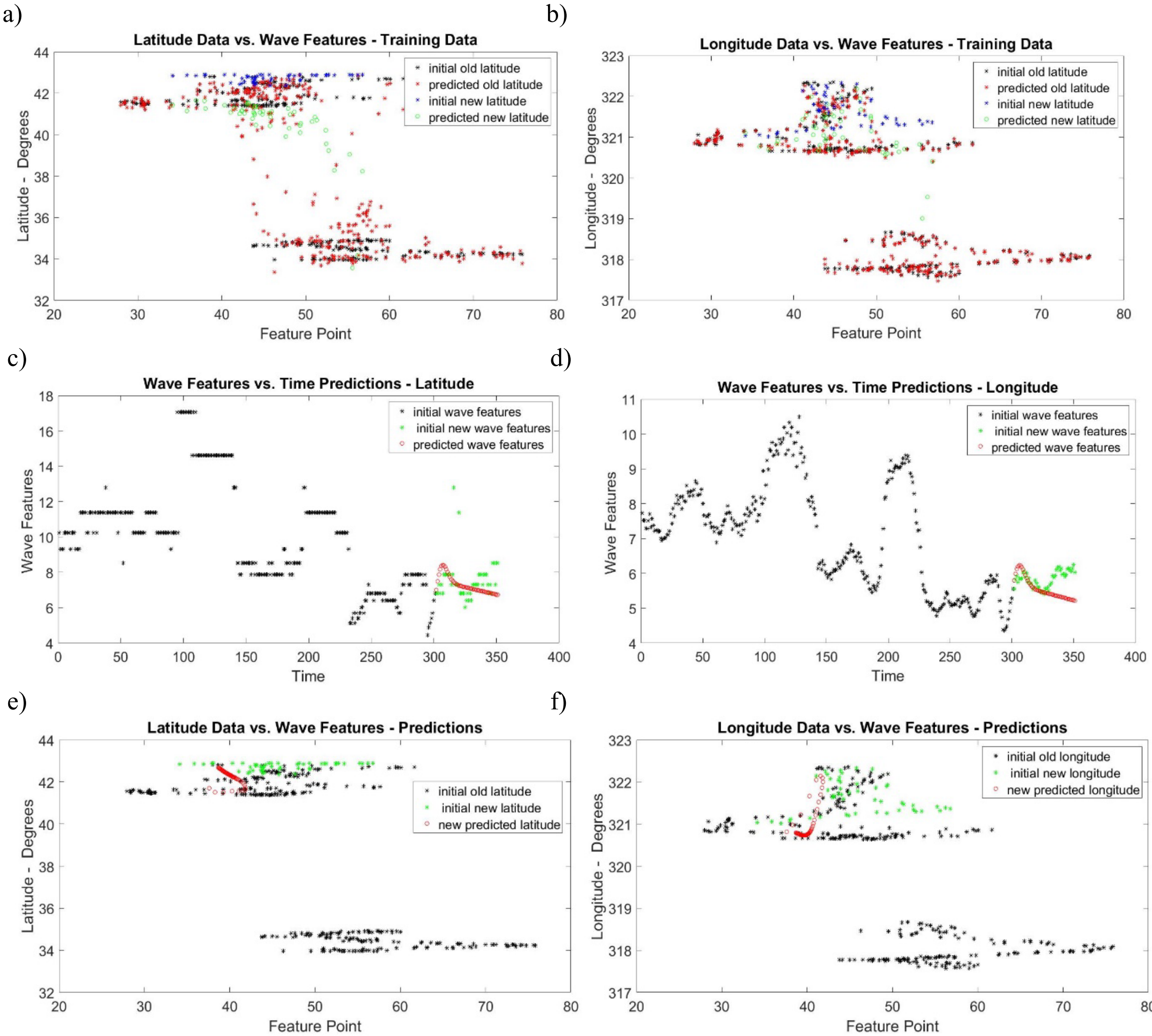
Figure 4: MWT on top and IMF on bottom for a) IMF 2 b) IMF 3 c) IMF 4 d) IMF 5 e) IMF 6 and f) IMF 7. Time axis is on the horizontal and period or scale axis appears vertically. High energy events above the threshold of 20, signified by region enclosed by the dotted line, appear as asterisks in time-scale (period) domain.

4. LASSO-Gaussian Process Nonlinear Regression Analysis Results

LASSO results for latitude and longitude allow for extraction of 3 dominant oceanic information field variables as the most important for estimation of location. Note that the variables are different for latitude and longitude. The LASSO results for latitude show that the three dominant information variables are mean wave directional spread, wave peak period, and significant wave height. LASSO results for longitude show that mean wave directional spread, mean wave period, and wave peak period are dominant. Nonlinear fits of latitude and longitude data with mean directional spread in Fig. 5a-b demonstrate rough fits over a training data set (priors) of 300 points. Extrapolation over 50 future data points for location using these wave information field variables yield erratic location estimates for both latitude and longitude with longitude being better predicted. This large variance in estimates is explained by no allowance for smoothness of wavefield information in the GP estimation. Wave peak period (for latitude) and mean wave period (for longitude) modelled using the GP to obtain forecasts of 50 new smooth estimates of these information fields, shown in Fig. 5c-d, demonstrate that over a limited time interval, smoothed wavefield information field variables are possible. These smooth variables are attainable via use of the radial basis covariance kernel function for data similarity.

Latitude and longitude forecasts over 50 future points using smoothed GP estimated wavefield information values, forecasted over the same time interval, are shown in Fig. 5e-h and Fig. 6a-b. All six estimates provide reasonable average estimates of latitude-longitude location where no dynamical constraints are used to provide optimal location estimates. In other words, smooth estimates of latitude and longitude are attainable by using LASSO attained information variables. The location estimates exhibit high but reasonable variance given lack of dynamical constraints and represent better location estimates over estimates where smoothing is not used. Moreover, LASSO-GP derived location estimates can be taken as prior information estimates which can be passed to neural networks processors to attain more precise forecasts of mobile information carrier position.

a) b) c) d) e) f)



g) h)

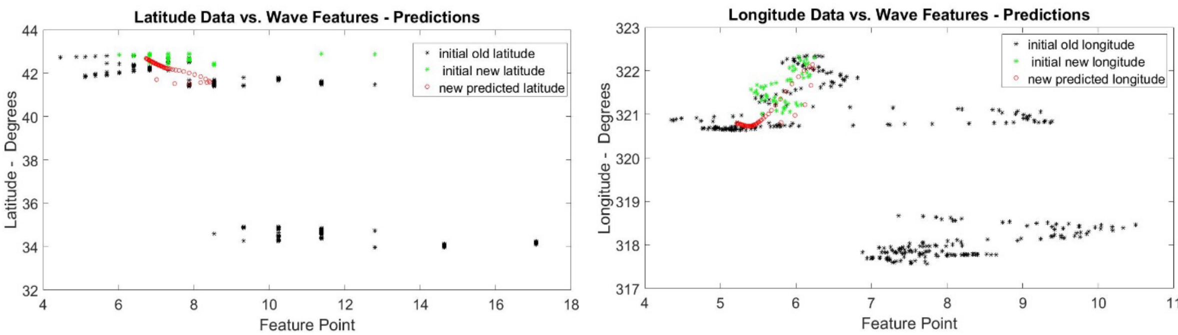


Figure 5: Nonlinear fit of a) latitude and b) longitude data with mean wave directional spread values. Training data, estimates of training data, new data, and estimates of new data are shown. c) Wave peak period field for latitude and d) mean wave period for longitude modeled using the GP to obtain 50 new smooth estimates over time based on 300 previous training data points. e) Latitude and f) longitude forecasts over 50 future points using smoothed GP estimated mean wave directional spread values for both location variables forecasted over the same time interval. g) Latitude forecasts and h) Longitude forecasts over 50 future points using smoothed GP estimated wave peak period values and mean wave period values respectively forecasted over the same time interval. Training data and true future values also shown.

a) b)

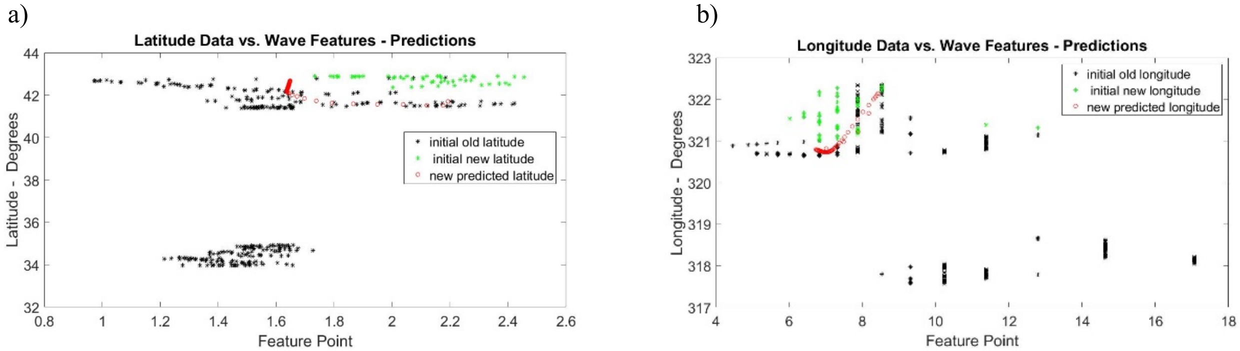


Figure 6: a) Latitude forecasts over 50 future points using smoothed GP estimated significant wave height values forecasted over the same time interval. b) Longitude forecasts over 50 future points using smoothed GP estimated wave peak period values forecasted over the same time interval.

5. Empirical Mode Decomposition-Morlet Wavelet Analysis Results

The HEE statistic for IMF 2 and IMF 6 for the cbg shown in Fig. 1a is shown in Fig. 7a-b. It depicts how HEE information for each IMF average bandwidth spans frequency regions which are different making the IMF atoms pseudo-orthogonal.

a) b)

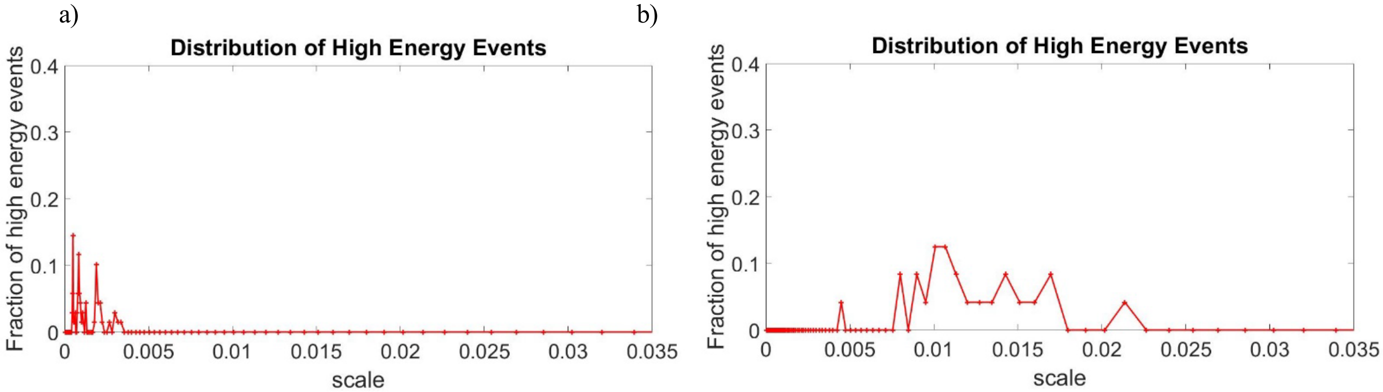
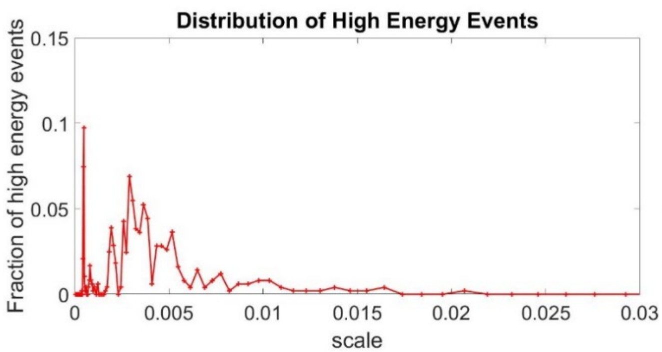


Figure 7: High energy event statistic quantifying the fraction of high energy events as a function of scale or period for a) IMF 2 and b) IMF 6 for the cbg in Fig. 1a. Note appearance of high energy events at larger periods for IMF 6 relative to IMF 2 corresponding to the EMD spline algorithm's filtration of information at different average bandwidths.

The HEE statistic for both cbgs using all eight IMFs has a different structure with multiple peaks at the component chordal frequencies and a noticeable dip occurring before the period of 0.003 s or 300 Hz for the left cbg shown in Fig. 1a. This is shown in Fig. 8a suggesting a two-level frequency group structure. HEE statistic for the right cbg shown in Fig. 1b. (Fig. 8b) has a slightly different form than the left cbg, having slightly larger amounts of lower period information. This is most likely due to the difference in resonator back material where is it known that African mahogany has the capability of sustaining more energy in the low frequency bass modes.

a)



b)

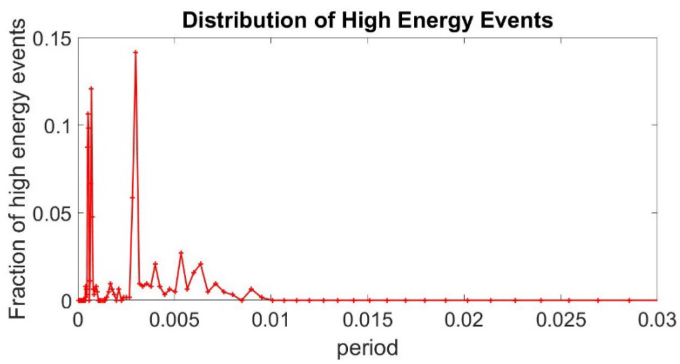


Figure 8: a) Total HEE statistic for C major chordal signal emanating from left cbg (Fig. 1a). b) Total HEE statistic for C major chordal signal emanating from right cbg (Fig. 1b). Peaks in the HEE statistic appear at increasing and decreasing component chordal frequencies around dominant period of 0.003 s (300 Hz). Note strong HEE information occurs at high sub and super dominant periods including 0.005 s (200 Hz ~G-2), 0.0013 s (800 Hz ~ G-5), and 0.000625 s (1600 Hz ~ G-6).

Generation of IMF atoms from test signals along with application of the MWT represents a clear method for extracting high energy events which characterize nonlinear anomalous structure. The statistical labelling of such structure is crucial for identifying signals which can carry information crucial for decision making. From an inverse problem perspective, the two-tier algorithm can distinguish and characterize signals emanating from signal emitters which seemingly are alike by examining higher order nonlinear structure. The ability to robustly distinguish signal state from observations has great implications for real-time processing of geo-intelligence information if included in robust geo-intelligence processing pipelines designed with an ensemble of different signal anomaly detectors and estimators.

6. Conclusions

In conclusion, smooth estimates of buoy latitude and longitude are attainable, via use of LASSO-GP analysis, which exhibit high but reasonable variance given lack of dynamical constraints. The location estimates serve as initial location points for neural network processors to improve upon given more data. Initial results pertaining to anomaly signal analysis also suggests that the HEE statistic can successfully quantify known differences in acoustic signals generated from different emission resonant sources. Quantification of differences in acoustical statistical structure suggests that the HEE statistic could also be useful for signal state discernment if used in conjunction with data intensive based neural network algorithms aimed at generative acoustical state estimation.

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