Rapid wave model-based nearshore bathymetry inversion with UAS measurements

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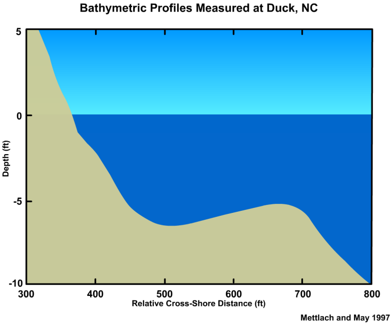
AGU Ocean Sciences Meeting 2020

2/20/2020

Nearshore Bathymetry Estimation

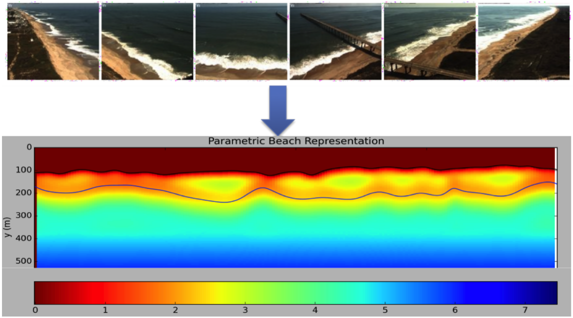
FRF site in DUCK, NC, USA



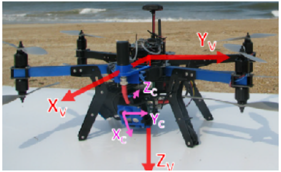
- Immediate understanding of bathymetry is crucial for coastal applications.
- Several survey methods such as direct sampling and airborne Lidar are not always applicable.
- Instead, easily measurable related quantities (e.g., imagery-based wave celerity) have been collected.
- Then, physics-based model (e.g. STWAVE) can be used to relate indirect observations to bathymetry through inverse modeling/data assimliation.

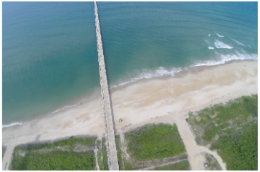
Nearshore Bathymetry Estimation - Imagery Data Acqusition

Imagery data has been collected mostly from fixed tower-based platforms:

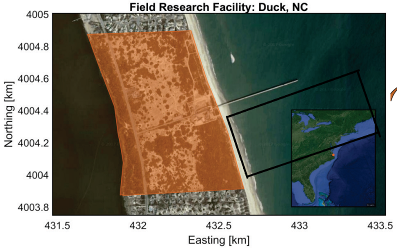


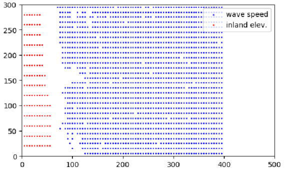
Recently, Unmanned Aircraft Systems (UAS) has been introduced (e.g., Holman et al., 2011):



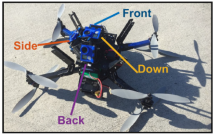


UAS Survey on July 22, 2016 in Duck, NC[1]





CBathy: wave celerity
SfM: inland elevation



Low-cost, multi-camera, multirotor UAS

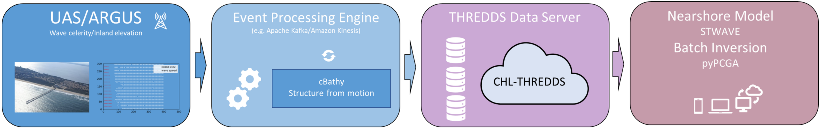
- UAS-derived imagery on a single flight along shoreline in the black box.
- CBathy and Structure-from-Motion (SfM) algorithms provide high-resolution wave celerity (blue dots) and beach topographic data (red dots).

[1] Brodie et al., 2019

Rapid Model-based Nearshore Bathymetry Inversion Framework

We propose a flexible and fast bathymetry estimation framework utilizing

1. low-cost commercial off-the-shelf UAS-based data acqusition
2. phase-averaging wave model: USACE's STWAVE
3. real-time batch-data inverse modeling approach, PCGA[1]



Principal Component Geostatistical Approach, PCGA, performs scalable Hierarchical Bayesian inversion by approximating the covariance matrix with its dominant principal components

[1] Lee and Kitanidis, 2014, Lee et al, 2016, Lee et al., 2018

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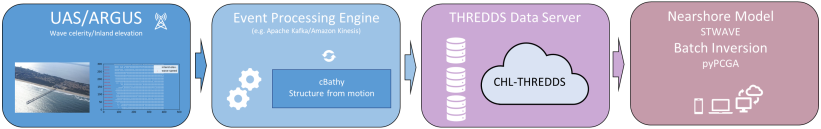


PCGA performs scalable Hierarchical Bayesian inversion:

- Modular (can be linked with any black-box nearshore models.)
- Jacobian-free
- Embarrasingly parallelizable
- Scalable: $\mathcal{O}(100)$ model runs in total for $> 10^7$ unknowns/obs. through fast linear algebra/dimension reduction without much loss of accuracy.
- Insenstive to initial guess
- Flexible prior assignment: prior mean structure can be derived from parameteric models such as linear or Dean's profiles.

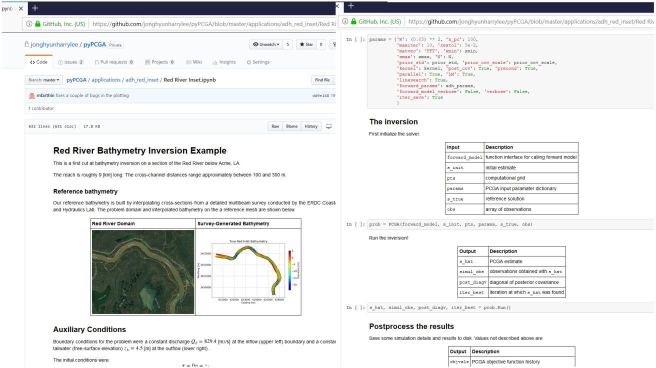
[1] Lee and Kitanidis, 2014, Lee et al, 2016, Lee et al., 2018

Public-domain Software for Reproducible Research

pyPCGA: Python interface for fast and scalable stochastic inversion[1]

google pyPCGA!

Users can perform close-to-real-time bathymetry inversion on Jupyter notebook environment in two lines of code (after preprocessing steps, of course)

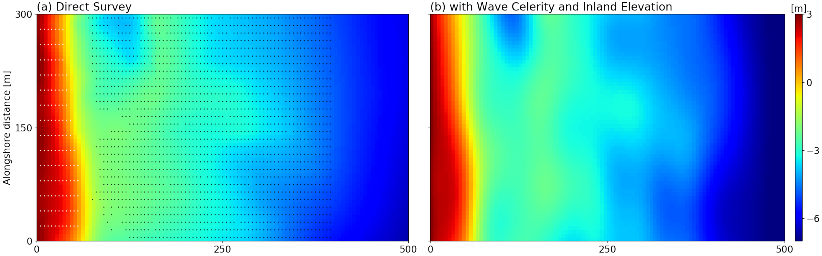


Check out Jupyter Notebook example!

Several notebook examples combined with USACE's STWAVE and AdH

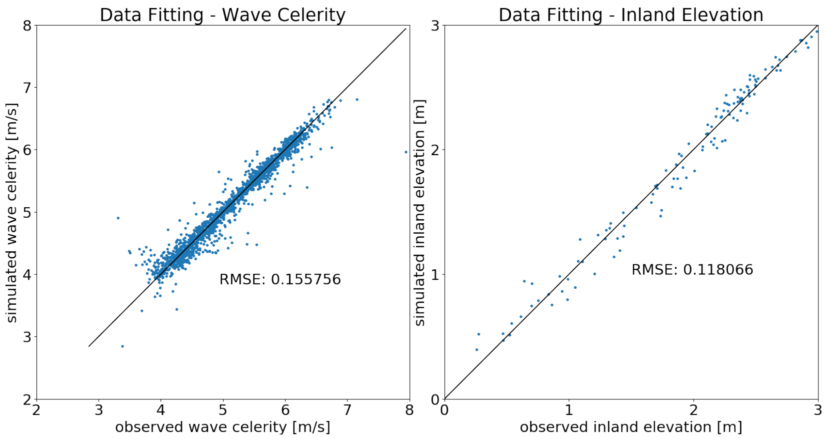
[1] https://github.com/jonghyunharrylee/pypcga

Results with Joint Inversion using Wave and Inland Data



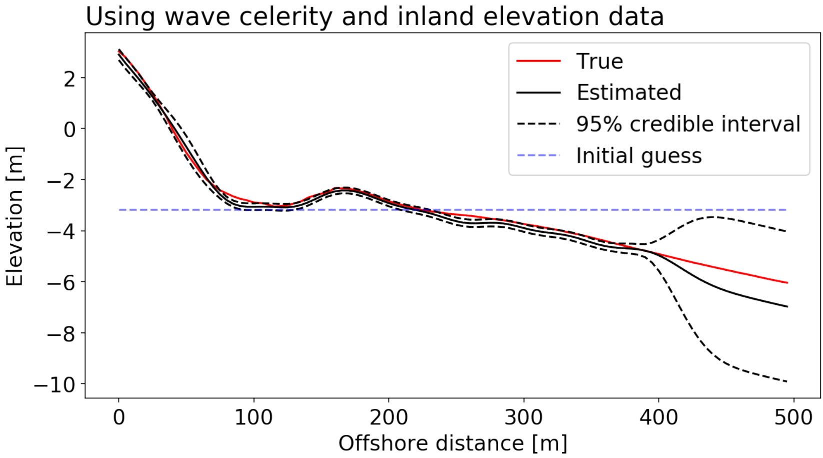
- Compare the estimation result with direct bathymetry profiles surveyed near the UAS flight date.
- RMSE = 0.28 m within observation area (300 x 400 m)
- Converged in 3 iterations with ∼150 STWAVE runs.
- 5 mins on a workstation equipped with 48 core Intel Xeon 8160 2.1 GHz.

Data Fitting



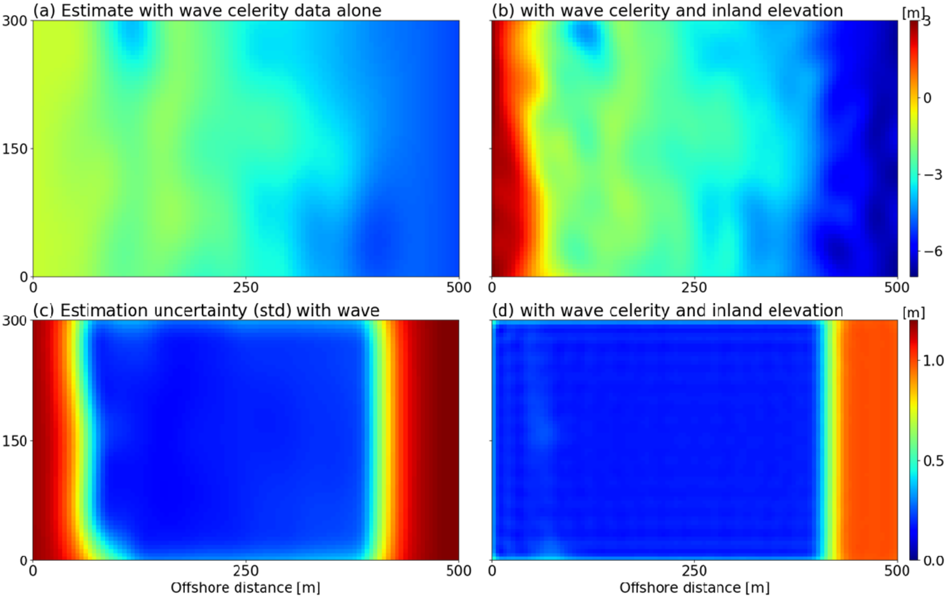
- Optimal measurement errors are determined through cross-validation /Bayesian hyperparameter estimation.
- Wave celerity (via STWAVE-based inversion) and inland elevation (via Kriging interpolation) data were fitted well.

Estimated Bathymetry Profile along a Transect

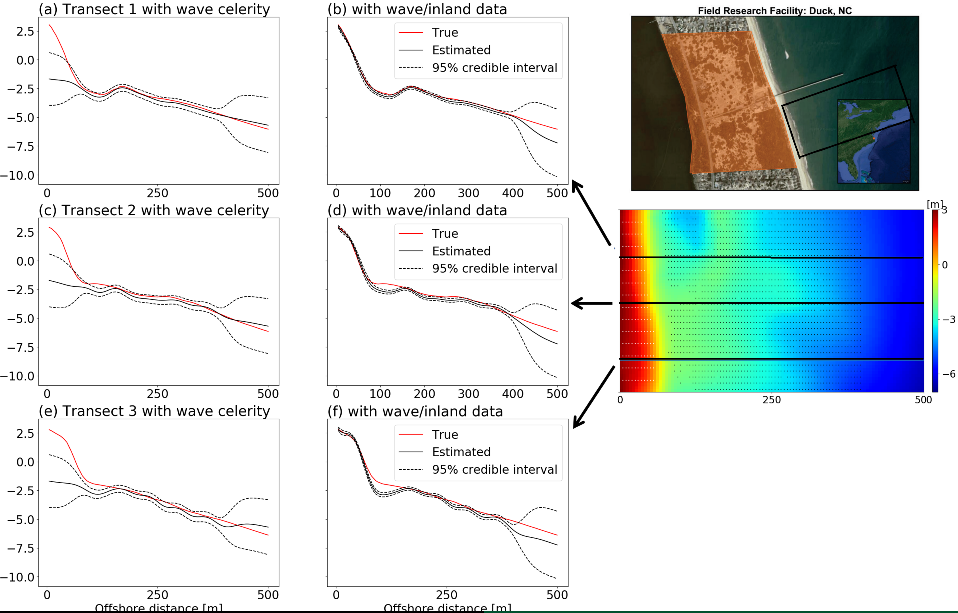


- Inversion results were not sensitive to initial guess assignments
- Direct surveyed profile is located within 95% credible interval.

Effect of Inland Elevation Data



Estimated Bathymetry Profiles with and without Inland Data



Concluding Remarks

- With low-cost, multi-camera, multirotor UAS system, we expect close-to-real-time bathymetry imaging will be feasible in the near future.
- Our inversion method took only around 5 minutes on a modern workstation, within the UAS-based data collection duration.
- Estimated bathymetry profiles are remarkably close to the direct survey data (RMSE $= 0.28$ m) within the estimation credible interval due to the additional use of inland elevation data.
- We provide inversion software package for scientists and engineers.
- Future works:
  - will test with data sets with more severe weather conditions.
  - will implement with advanced wave models such as WaveWatch III and FunWAVE.

pyPCGA github link
Clone Me!

Bathymetry Research Products

AGU Ocean Sciences Meeting 2020

1. OD43A-01 Thurs. 14:25 - 14:40 5A
   Adam Collins: A 2D Fully Convolutional Neural Network for nearshore and surf-zone bathymetry inversion from synthetic imagery of the surf-zone using the model Celeris
2. OD44A-3484 Thurs. 16:00 - 18:00 Poster Hall C-D
   Mojtaba Forghani: Deep learning techniques for nearshore and riverine bathymetry estimation using water-surface observations.

Recent papers about bathymetry

1. Ghorbanidehno et al., Deep learning technique for fast inference of large-scale riverine bathymetry, *under review*
2. Ghorbanidehno et al., Novel data assimilation for nearshore bathymetry, *Journal of Atmospheric and Oceanic Technology*, 2019
3. Lee et al., Riverine bathymetry imaging with indirect observations, *Water Resources Research*, 2018

References

- Brodie, Bruder, Slocum, and Spore, Simultaneous Mapping of Coastal Topography and Bathymetry From a Lightweight Multicamera UAS, *IEEE Transactions on Geoscience and Remote Sensing*, 2019
- Ghorbanidehno, Lee, Farthing, Hesser, Kitanidis, and Darve, Efficient data assimilation algorithm for bathymetry application, *Journal of Atmospheric and Oceanic Technology*, 2019
- Lee, Ghorbanidehno, Farthing, Hesser, Darve, and Kitanidis, Riverine Bathymetry Imaging with Indirect Observations, *Water Resources Research*, 2018
- Lee, Yoon, Kitanidis, Werth, and Valocchi, Scalable subsurface inverse modeling of huge data sets with an application to tracer concentration breakthrough data from magnetic resonance imaging, *Water Resources Research*, 52(7), 5213-5231, 2016
- Lee and Kitanidis, Large-scale hydraulic tomography and joint inversion of head and tracer data using the principal component geostatistical approach (PCGA), *Water Resources Research*, 50(7), 2014
- Holman, Holland, Lalejini, and Spansel, Surf zone characterization from unmanned aerial vehicle imagery, *Ocean Dynamics*, 2011

Inverse Problem in Hierarchcial Bayesian Framework

Consider the measurement equation

$$y_t = h(s_t) + v_t \qquad v_t \sim \mathcal{N}(0, R_t)$$

$y_t := n_{obs} \times 1$ noisy measurements
$h :=$ forward model
$s_t := n_{unknowns} \times 1$ bathymetry
$v_t :=$ measurement and model error

- Need to account for the uncertainty in model and data
- Treat parameters as random variables
- Hierarchical Bayesian[1] Geostatistical Approach[2]

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[1] Gelman, Calin, and Stern, 2013; Kitanidis, 2010
[2] Kitanidis, 1995

Geostatistical Approach

The posterior estimate $\hat{s}$ and covariance $\mathbf{\Gamma}_{\text{post}}$:

$$\arg\min_{s,\beta} \frac{1}{2}\|y - h(s)\|^2_{\mathbf{\Gamma}^{-1}_{\text{noise}}} + \frac{1}{2}\|s - X\beta\|^2_{\mathbf{\Gamma}^{-1}_{\text{prior}}}$$

Algorithm Bayesian geostatistical approach

1: **while** Not converged **do**

2: Solve the system of equations ,

$$\begin{pmatrix} J_k \mathbf{\Gamma}_{\text{prior}} J_k^T + \mathbf{\Gamma}_{\text{noise}} & J_k X \\ (J_k X)^T & 0 \end{pmatrix} \begin{pmatrix} \xi_{k+1} \\ \beta_{k+1} \end{pmatrix} = \begin{pmatrix} y - h(s_k) + J_k s_k \\ 0 \end{pmatrix}$$

where, the Jacobian $J = \frac{\partial h}{\partial s}\Big|_{s=s_k}$

3: The update $s_{k+1} = X\beta_{k+1} + \mathbf{\Gamma}_{\text{prior}} J_k^T \xi_{k+1}$

4: **end while**

5: $\mathbf{\Gamma}_{\text{post}} = \mathbf{\Gamma}_{\text{prior}} - \begin{pmatrix} \mathbf{\Gamma}_{\text{prior}} J^T & \mathbf{X} \end{pmatrix} \begin{pmatrix} J_k \mathbf{\Gamma}_{\text{prior}} J_k^T + \mathbf{\Gamma}_{\text{noise}} & J_k X \\ (J_k X)^T & 0 \end{pmatrix} \begin{pmatrix} J \mathbf{\Gamma}_{\text{prior}} \\ \mathbf{X} \end{pmatrix}$

Principal Component Geostatistical Approach (PCGA)[1]

Method	Adjoint-based method	PCGA
# of simulation runs	$n_{obs} + 1$	$\kappa + 1$
matrix multiplication	$\mathcal{O}(n_{obs} n_{unknowns})$	$\mathcal{O}(n_{unknowns} \kappa)$
storage	$\mathcal{O}(n_{obs} n_{unknowns})$	$\mathcal{O}(n_{obs} \kappa)$

- $\kappa + 1$ simulation runs in each iteration
- $\kappa \sim O(100)$ or less for many problems in earth science
- Can handle large measurements (e.g, 10^7 measurements)
- Easy to implement; treat multi-physics models as a "blackbox" like Ensemble-based methods
- Parallel executions

[1] Lee and Kitanidis, 2014

Computational Challenges

1. Computing and storing Covariance matrices are expensive!

$$\boxed{\mathbf{\Gamma}_{\text{prior}}\mathbf{J}^\top, \quad \mathbf{J}\mathbf{\Gamma}_{\text{prior}}\mathbf{J}^\top}$$

- $n_{unknowns} + 1$ number of forward model executions in each iteration
- $\mathcal{O}(n^2_{unknowns})$ storage

2. Computing and storing the Jacobian and its products are expensive (e.g., $n_{obs} \gg 10^6$).

- $n_{observation} + 1$ number of forward model executions in each iteration

Dimension Reduction in PCGA

Summary : we employed

1. $O(n)$ fast linear algebra (e.g., $\mathcal{H}$-matrices and FMM) for decomposition of the prior covariance matrix
2. Generalized Eigenvalue Decomposition to construct exact preconditioner of saddle-point matrix