

RATIONALE

Geolocation methods have been applied to electronic tagging data to estimate locations of groundfish species. Such information can improve stock assessments and fishery management plans that account for population structure, including movements across stock boundaries. Many popular geolocation methods have limitations including low horizontal resolution, flawed land boundary treatment, and long computational time. The particle filter is a state-space approach that has been applied to localization problems and addresses the aforementioned issues. We present a geolocation method based on the particle filter that is accelerated with the graphics processing unit (GPU).

PARTICLE FILTER

We developed a GPU-accelerated Python particle filter (PF) geolocation package for data storage tag (DST) data (<https://git.io/vD64j>).

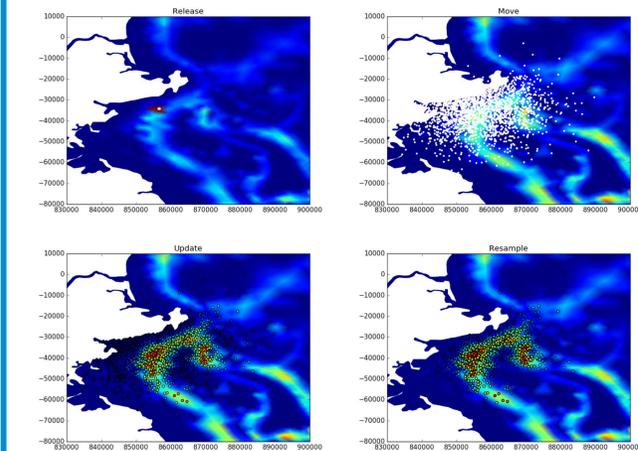


Figure 3: Demonstration of the four steps of a particle filter iteration

Summary workflow of PF geolocation algorithm:

1. Initialize the particles by releasing them in the release location.
2. Loop over each day the fish is at large:
 - (a) Prediction: move the particles horizontally using a random walk.
 - (b) Update: weight the particles by interpolating the observation likelihood function to the particles, and normalize the weights.
 - (c) Resample: particles with low weights are removed and replaced by those with higher weights.
3. Determine the most probable track by calculating the accumulated weight for each particle and select the one with the highest accumulated weight.

TAGGING



Figure 1: Data storage tags attached to an Atlantic cod (left) and a yellowtail flounder (right).



Figure 2: Example of the depth (blue) and temperature (red) data from a DST attached to an Atlantic cod.

Cod were tagged with Star-Oddi DSTs that record time series of temperature and pressure data. 45 fish were recaptured.

GPU BENCHMARK

In PF, each particle is handled independently in the main loop, making it viable to speed up the computation using parallelization. We compared the performances of PF geolocation between CPU and GPU, and across different GPUs. Results suggest that GPU implementation provides approximately 5× speedup.

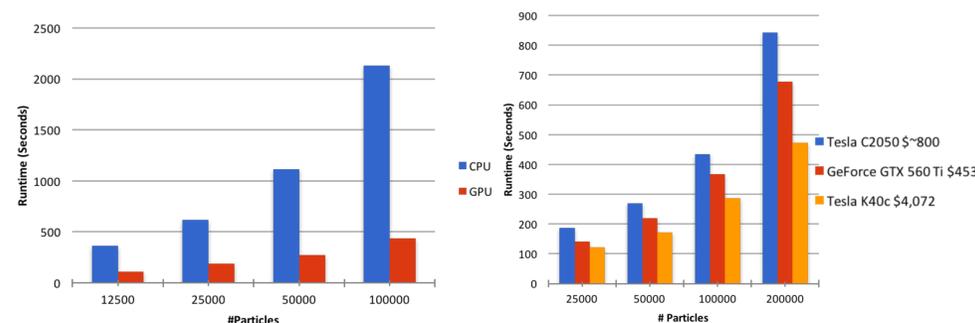


Figure 4: Comparison of PF geolocation performances between CPU and GPU (left) and across different GPUs (right).

VALIDATION RESULTS

To examine the performance of the PF geolocation method it was applied to two classes of DST datasets (including depth and temperature) with known locations. The first, bottom-mooring tags, challenge the model to maintain a fixed position over time.

The second class of dataset consists of double-electronic-tagged fish that provide known locations that enable direct quantification of model skill when they pass through acoustic receiver arrays.

Validation method	Mooring	Double-tagging
# tag deployments	14	10
Days of data	762	222
Error range (km)	0.03–27.51	1.15–78.40
RMS error (km)	13.78	34.85
Median (km)	6.95	35.61
S.D. (km)	8.67	17.09

Table 1: Summary of validation results for mooring and double-tagging

Geolocation of stationary tags indicated that the PF geolocation method is able to provide highly accurate location estimates for fixed-location objects. In comparison, location estimation error was nearly doubled for the double-tagging experiment of free-swimming cod. Validation results suggests that the PF geolocation method produces more accurate results than previous tidal- or light-based methods using archival tags.

GEOLOCATION TRACKS

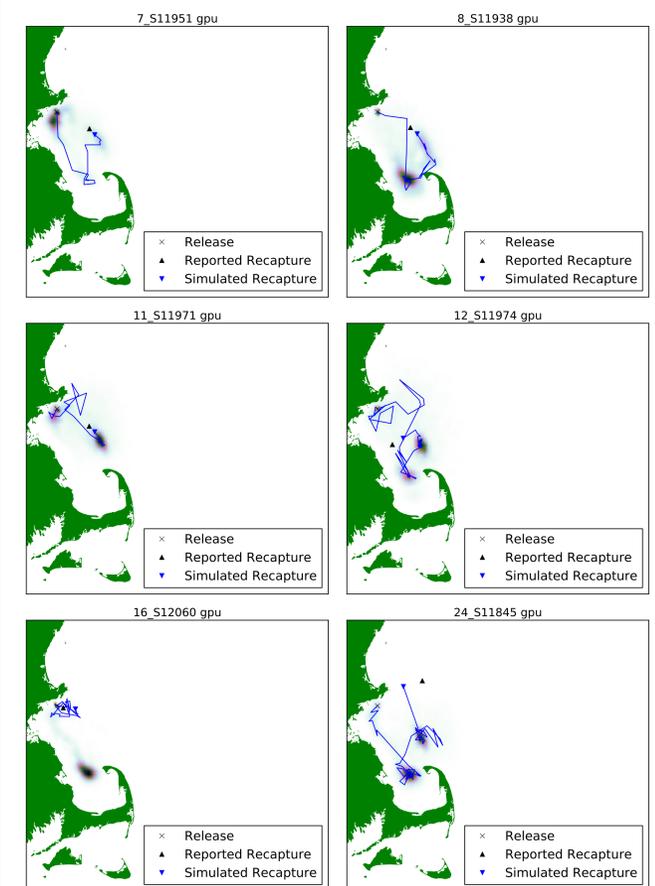


Figure 5: The most probable tracks and the associated total probability distribution for four double-electronic-tagged cod, estimated using the particle filter geolocation method.

The GPU-accelerated PF geolocation method was applied to the double-electronic-tagged cod. Geolocation results demonstrated that cod moved off-shore after spawning, and most cod remained in the western Gulf of Maine.

FUTURE RESEARCH

- Compare the geolocation and skill assessment results with those from the existing Hidden Markov-based HMM geolocation method.
- Implement behavior state estimation using state-space models.

Acknowledgements This research is supported by a NOAA Saltonstall-Kennedy Grant and UMass IMS. We thank the Center for Scientific Computing and Visualization Research at UMass Dartmouth for providing computational resources.