Using Machine Learning Techniques to Analyze Acoustic Doppler Current Profiler Data

Kristen Falcinelli[1] and Osama Abuomar[1]

[1]Affiliation not available

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Abstract

Acoustic Doppler Current Profilers (ADCPs) are oceanographic tools that are capable of collecting large amounts of current profile data. Using unsupervised machine learning techniques such as principal component analysis, fuzzy c-means clustering, and self-organizing maps, patterns and trends in an ADCP dataset were discovered. Cluster validity algorithms such as visual assessment of cluster tendency and clustering index were used to determine the optimal number of clusters in the ADCP dataset. These techniques proved to be useful in analysis of ADCP data and may be of further use in the oceanographic field.

Using Machine Learning Techniques to Analyze Acoustic Doppler Current Profiler Data

Kristen Falcinelli[1], Sam Abuomar[2]

[1]University of New England, Biddeford, ME 04005, [2]Coastal Carolina University, Conway, SC 29528

[1]kfalcinelli@une.edu, [2]oabuomar@coastal.edu

Introduction

Goal: Use machine learning techniques to discover patterns and trends in oceanographic data.

Machine Learning Techniques- algorithms used to discover patterns in large data sets

- Principal component analysis (PCA), fuzzy c-means clustering, visual assessment of cluster tendency (VAT), Kohonen maps, and clustering index

Acoustic Doppler Current Profiler (ADCP)- uses the Doppler effect to measure 3-D current velocity profiles

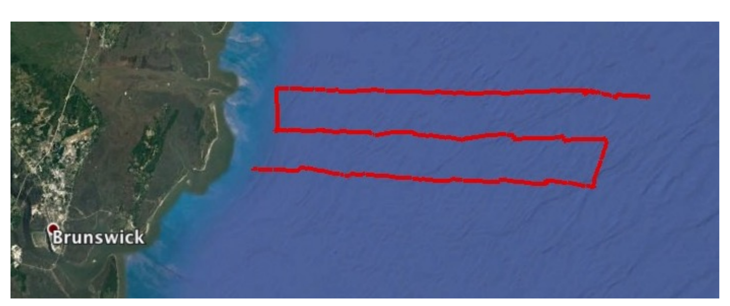

Figure 1. Track of the RV Savannah where ADCP data was collected. Satellite image courtesy of Google Maps 2017.

Type	Variables
Time	Day, time, time in date number format, number
Ship Motion	Pitch, roll, heading
Weather	Temperature
Bottom Track	East, North, vertical, and error velocities, range, X and Y displacement
Current Velocity	East, North, vertical, error
Navigational Velocity	East, North
Location	Latitude, longitude

Table 1. Variables (dimensions) collected from the ADCP that are used in analysis

Acknowledgements

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Materials and Methods

1. **Data organization and Interpolation**
   - 23 variables were organized into a matrix with 23 dimensions
   - Some velocity samples has missing data, so data was linearly interpolated
2. **Principal Component Analysis**
   - Reduced dimensions from 23 to 2
   - Allows data to be clustered
3. **Fuzzy c-means clustering**
   - Data points can have membership in multiple clusters
   - 3, 4, and 5 cluster outputs were produced
4. **Visual Assessment of Cluster Tendency**
   - Compares pairwise distances between all data points
   - Determines if data can be clustered
5. **Kohonen/ Self-Organizing Maps**
   - Neural network maps used to determine which dimensions are the most important in the ADCP dataset
6. **Cluster Separation Index**
   - Compares distance between points within clusters to distances between clusters

Results

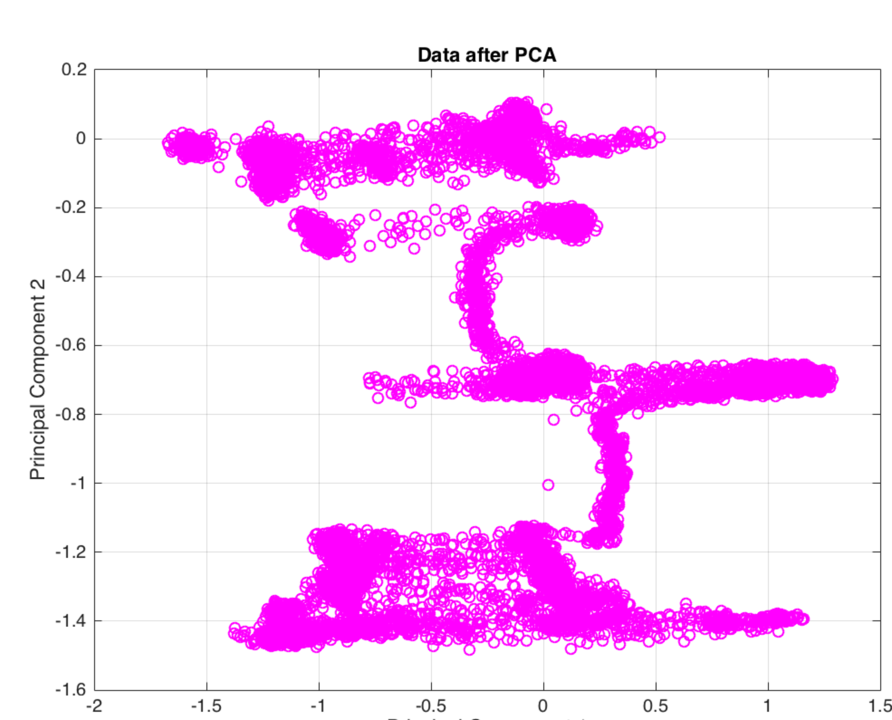

Figure 2. Visual representation of data after PCA.

Results

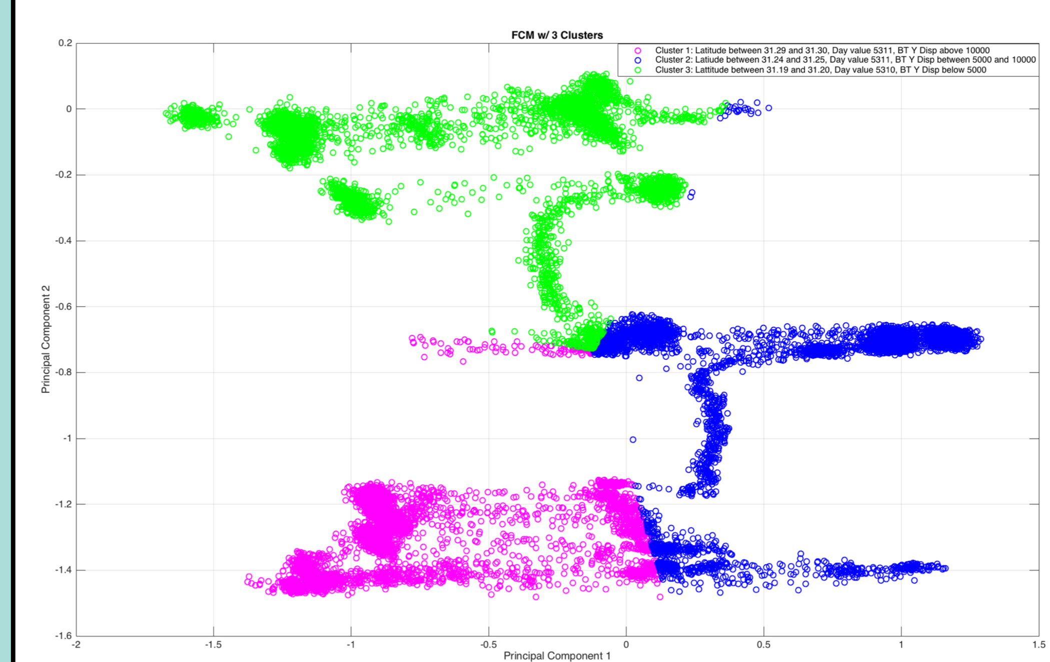

Figure 3. Reduced data represented by 3 clusters, as found through the fuzzy C-means clustering algorithm. All clusters are strongly influenced by day and latitude.

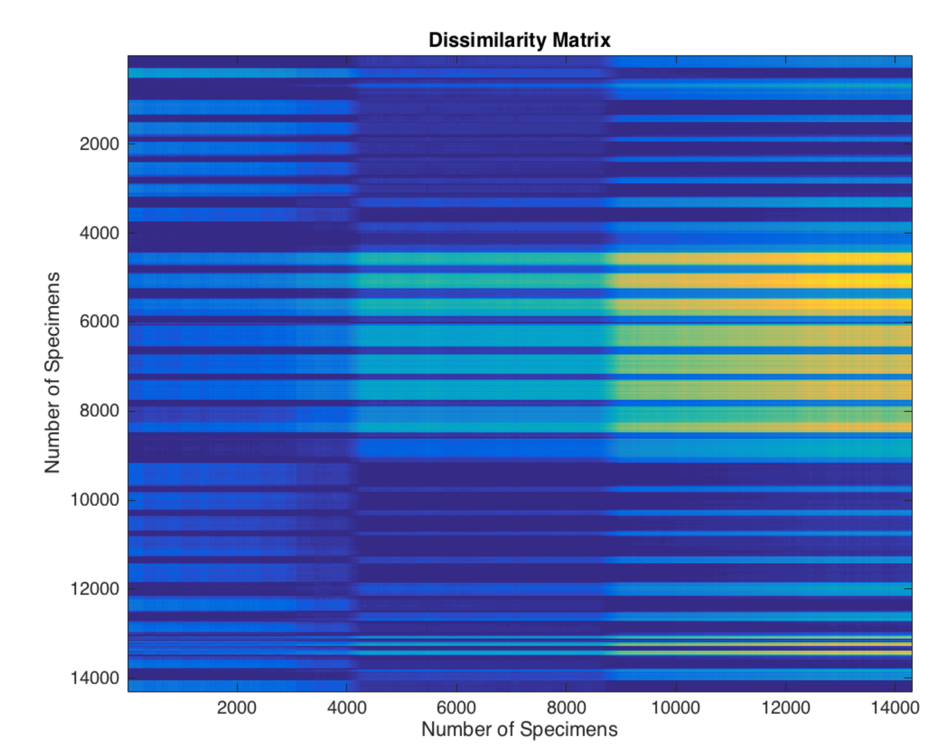

Figure 4. Visualization of the dissimilarity matrix, compared with the reordered VAT matrix to determine if clustering is possible.

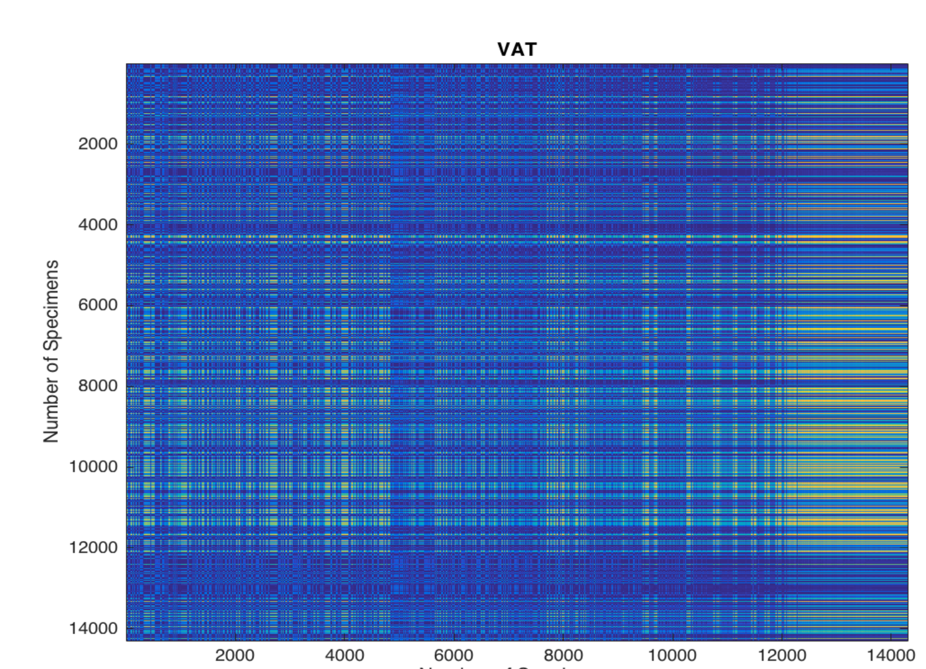

Figure 5. Visualization of the reordered dissimilarity matrix as computed by the VAT algorithm.

Results

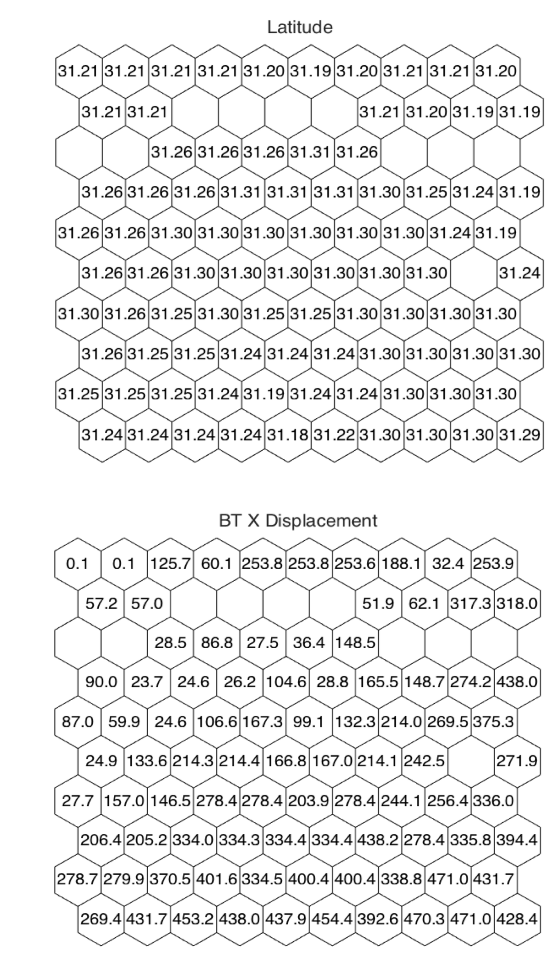

Figure 6. Kohonen maps for variables with clustering tendency- Latitude and bottom track X displacement are shown here, but bottom track Y displacement and bottom track range also show clustering tendency.

Number of Clusters	CS Index
3	0.0011
4	0.0035
5	0.0090

Table 2. Cluster separation (CS) index calculated for 3, 4, and 5 clusters. The smallest value indicates well separated clusters with data points relatively close together.

Conclusions

- Reducing the data set from 23 dimensions to 2 allows for the data set to be analyzed and visualized
- It is possible for this data set to be clustered, and 3 clusters is the optimal number of clusters
- Clustering tendencies can be observed when mapping day, latitude, bottom track X and Y displacements, and bottom track range via Kohonen maps indicating that these measures drive the overall design of the ADCP dataset
- Machine learning may be further applied to oceanographic datasets to discover more hidden patterns and trends