Exploring Sandbar Evolution using a Convolutional Neural Network

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Introduction

Sandbar Evolution

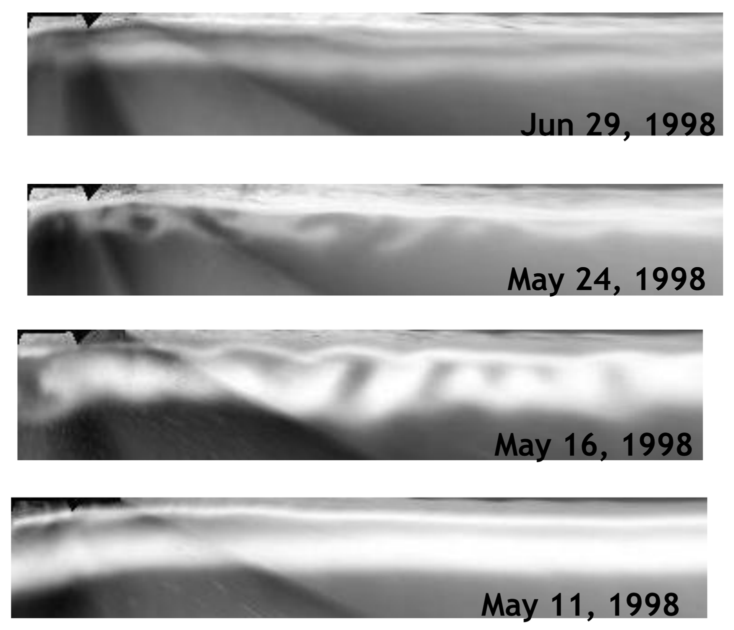


Fig 1. Sandbar evolution pattern.

Sandbars exist into different shapes for a period of time. Evolution into different shapes is dictated by the preceding beach state and the background forcing (wave) conditions.

In this study, we use a convolved neural network (CNN) to automate the categorization of Duck, NC, Argus imagery of sandbars from 1984-2016 into shapes.

Hypothesis: Background wave conditions will determine the evolution of sandbar transitions.

Methods

Sandbar Shape Categories

Lippman and Holman (1990) developed a categorization scheme for the different shapes, which we use in this study.

In an automated method, the CNN must be able to categorize images which are not clear and outside of the categorization screen.

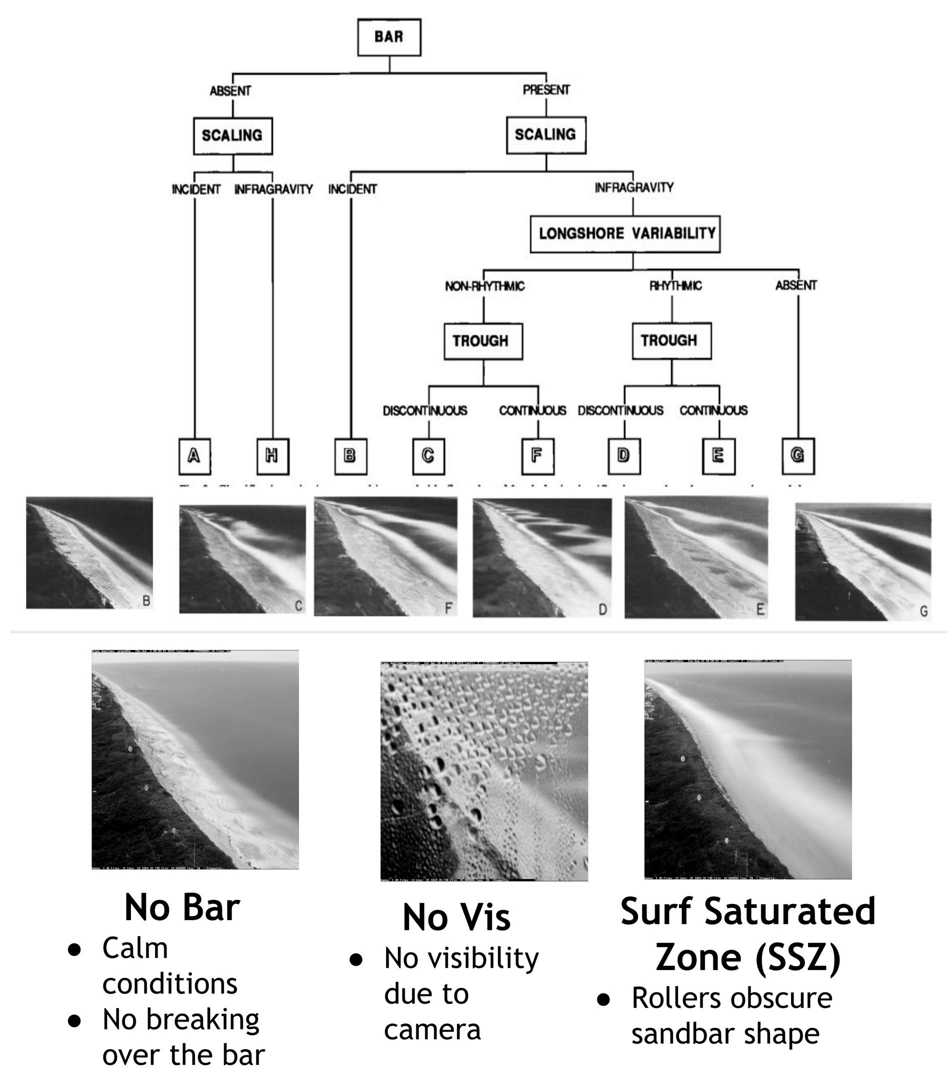
Three additional bar categories are included.

Argus imagery is from years 1987-2016 taken from the north side of the pier at Duck, NC. The numbers of images for each category are:

B: 56	D: 56	F: 57	SSZ: 37
C: 90	E: 36	G: 59	NoBar: 108
			NoVis: 55

70% of the images were used for training, and 30% were used for validation.

A 50-layer pre-trained ResNet was trained using pytorch.



No Bar
- Calm conditions
- No breaking over the bar

No Vis
- No visibility due to camera

Surf Saturated Zone (SSZ)
- Rollers obscure sandbar shape

Fig 2. Sandbar categories. The top panel is reproduced with permission from Lippman and Holman, 1990. The bottom three categories are additional categories for this study.

Preliminary Results

Accuracy

A confusion table shows how the CNN misclassifies certain shapes for others.

Classified As	B	C	D	E	F	G	SSZ	NoBar	NoVis	Accuracy
B	8	0	0	0	1	0	1	3	0	62%
C	4	20	4	1	0	0	3	9	0	48%
D	1	4	9	1	0	2	0	0	0	53%
E	1	0	1	2	1	1	0	0	1	29%
F	0	1	1	4	6	1	0	1	0	43%
G	2	2	1	3	7	12	4	4	0	35%
SSZ	0	0	0	0	0	0	4	1	0	80%
NoBar	1	1	0	1	0	0	0	15	0	89%
NoVis	0	0	1	0	0	2	0	0	16	85%

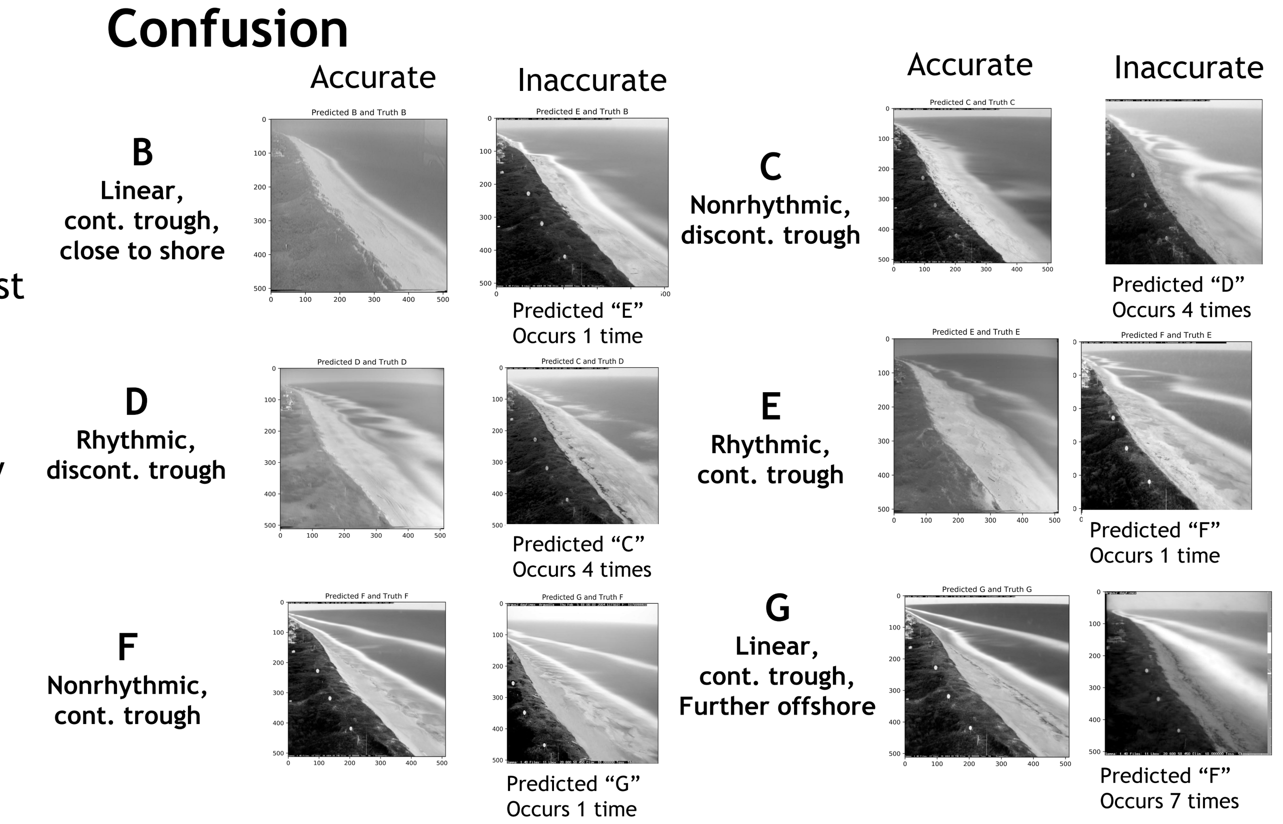
- All images are classified more accurately than random guess. (11%)
- No Bar has the highest accuracy.
- E has the lowest accuracy and the least number of images.

Confusion

The sandbar categories represent a continuum of shapes, and sandbars can exist anywhere within that continuum.

Some bar states can be easily confused for the other.

Some confused states are clearly one or the other.



Classified As	B	C/D	E/F	G	SSZ No Bar No Vis	Accuracy
B	8	0	1	0	4	62%
C/D	5	37	2	2	12	63%
E/F	1	3	13	2	2	62%
G	2	3	10	12	8	34%
SSZ/No Bar /No Vis	1	2	1	2	36	85%

The classes are grouped into broader categories with similarities, and the accuracy increases.

Discontinuous bars are most often confused with SSZ/NoBar/NoVis categories

Continuous bars (E/F and G) are confused for each other.

State Transition Time Series

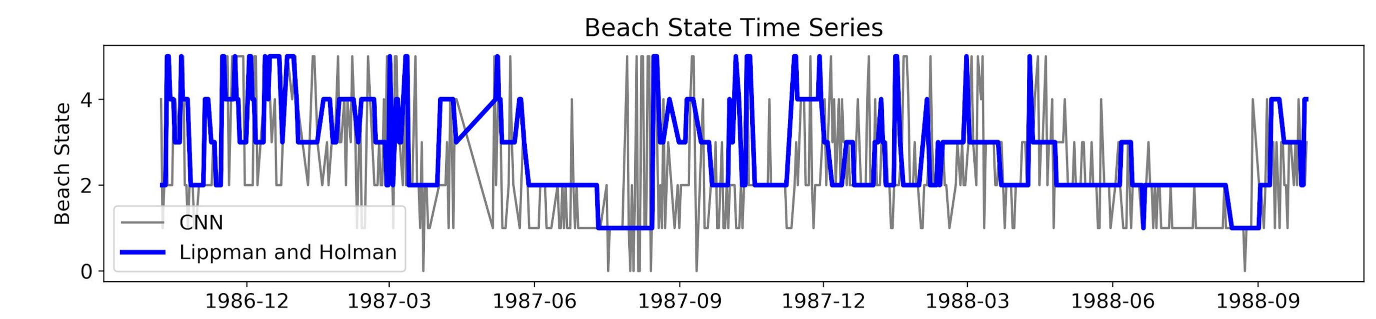


Fig 3. Beach state time series comparison between the CNN and Lippman and Holman for the years 1986-1988.

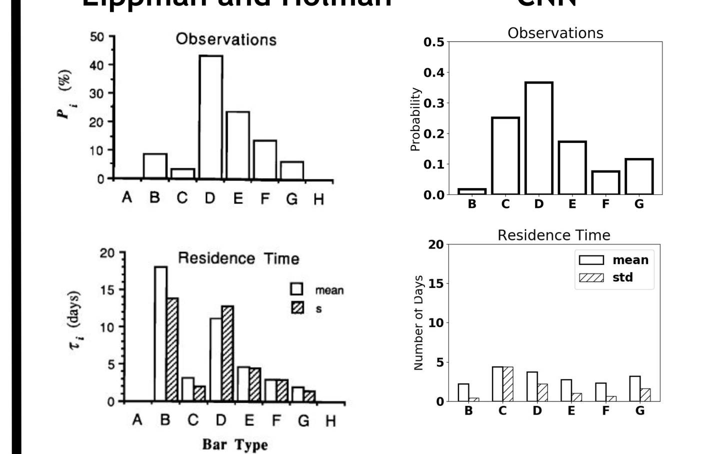


Fig 4. Comparison of probability of observations and residence time for each bar state. Left figures reproduced from Lippman and Holman, 1990.

- The CNN produces a noisier time series of beach states
- Beach state D is most likely to occur for both analyses, and bar states E/F/G occur less frequently.
- Residence times for CNN are shorter than for Lippman and Holman.
- For the CNN series, Bar state B is confused with C and G resulting in larger values for these states and smaller values for B.

Wave Conditions: States

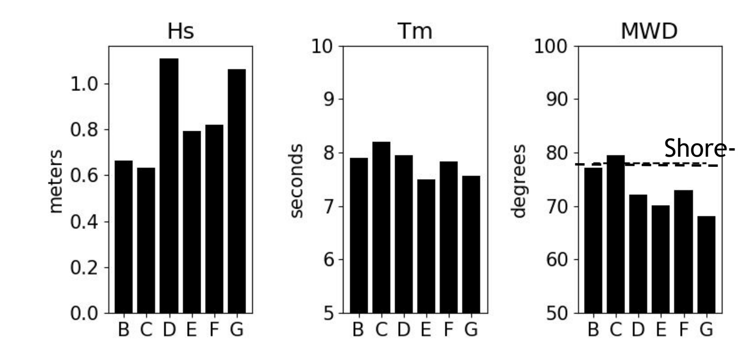


Fig 5. Mean wave conditions for each bar state for the entire dataset.

- The highest wave height occurs for states D and G, and lowest for state C.
- Lowest mean periods occur for states E and G
- The most shore-normal wave direction is for state C, and most oblique wave direction is for state G

Wave Conditions: State Transitions

Mean values of wave parameters show that:

- Onshore (offshore) bar migration transitions are associated with a decrease (increase) wave height.
- Onshore (offshore) bar migration transitions are associated with an increase (decrease) in mean period
- Onshore (offshore) are associated with a transition from oblique (shore-normal) to shore-normal (oblique) waves

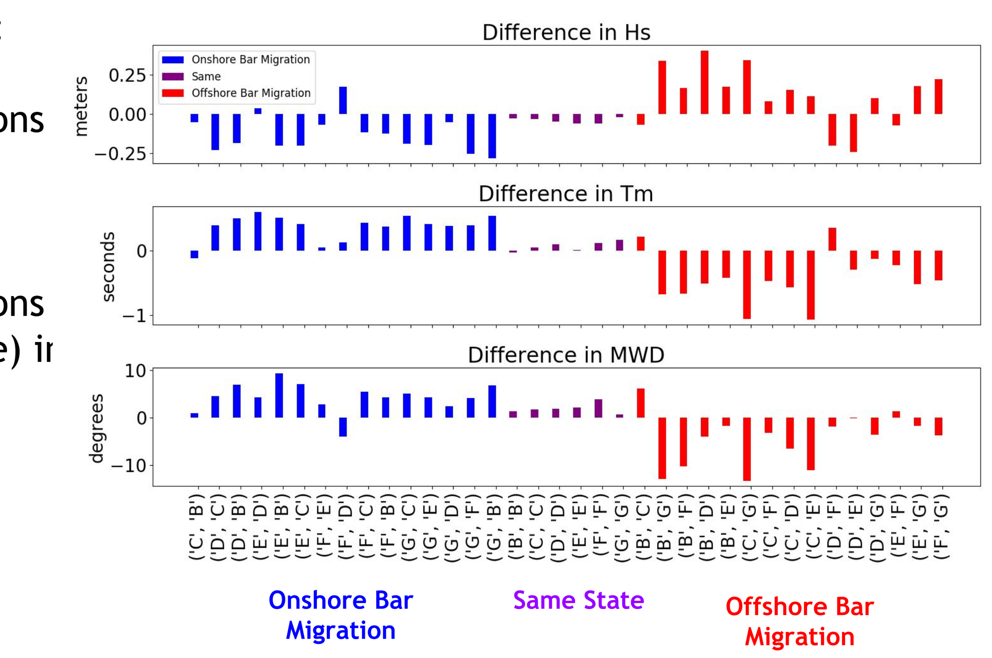
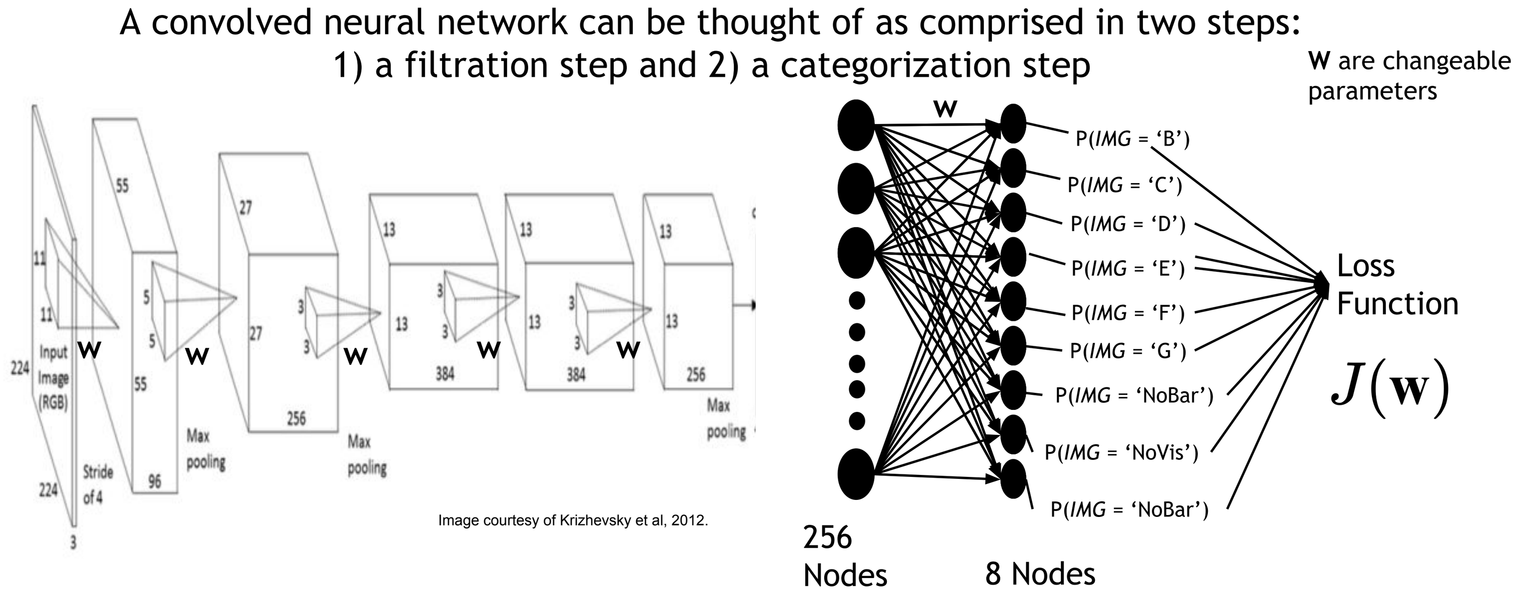


Fig 6. Mean wave conditions during beach state transitions.

Convolutional Neural Network Theory

What is a Convolutional Neural Network?

A convolved neural network can be thought of as comprised in two steps:
1) a filtration step and 2) a categorization step



During the filtration step, the original image with dimensions (3x224x224) is transformed to a volume of size (256x13x13) through a series of filters which are convolved over the image sequentially.

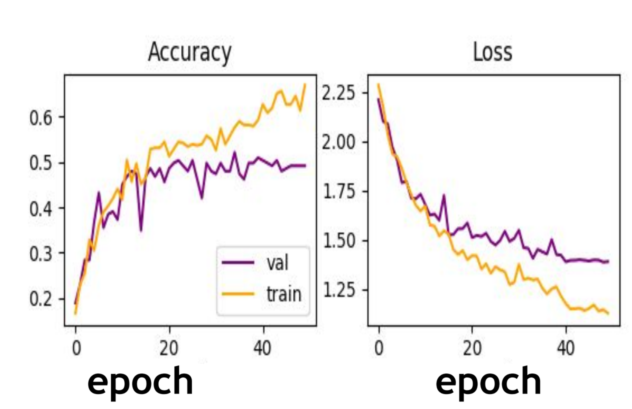
The filters are designed to capture relevant image information, such as edges or shapes. These are parameters that can be optimized during training.

During the categorization step, the probability that the image belongs to each category is calculated using a fully connected neural network.

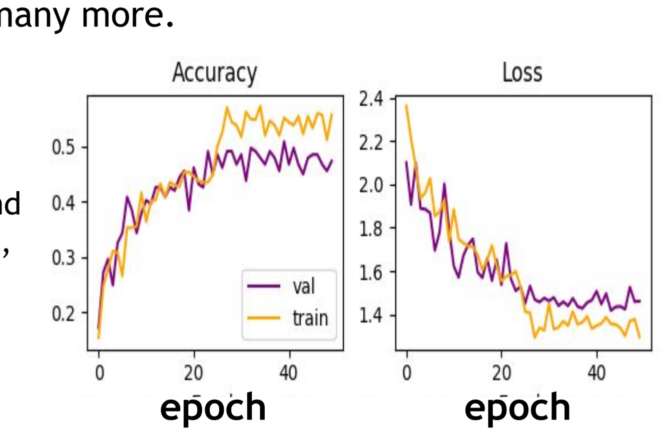
The accuracies of these probabilities are determined using a loss function, J. This loss function is a function of parameters, w.

The Process of Deep Learning: Tuning Hyperparameters

Hyperparameters are the knobs turned used to tune the accuracy of the algorithm. Examples of hyperparameters include batch size (how many images are considered when updated the weights) and learning rate (the step size used during stochastic gradient descent). There are many more.



In this training, the batch size is large and the step size is small, leading a smoother convergence



In this training, the batch size is small and the step size is large, leading a greater oscillations in the convergence.

In order for the network to "learn," the loss function is optimized to increase the probability that the guess is correct.

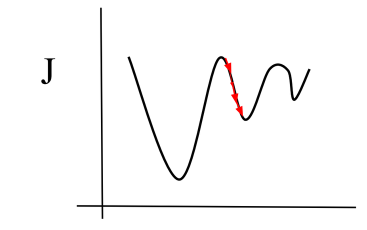
The loss function is minimized by taking the derivative of it with respect to the parameters of the fully connected layer and the convolutional filters and setting this equal to zero.

$$\frac{\partial J}{\partial \mathbf{w}} = 0$$

To find the weights that would find the minimum of the loss function, stochastic gradient descent over each batch, i, is used.

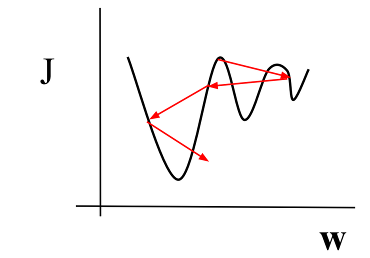
$$\mathbf{w}_{i+1} = \mathbf{w}_i + \alpha \frac{\partial J}{\partial \mathbf{w}}$$

Small step size (α)



If α is small, learning is slow and could take many steps to converge, maybe to a local minimum

Large step size (α)



If α is large, the weights will oscillate rapidly and convergence might not occur.

Conclusions and Future Work

CNN Method:

- The CNN currently performs better than random guess for all bar categories, which is increased further if the classes are grouped by similar shape.
- Future work will include increasing accuracy by including more training data examples, and quantification of uncertainty of bar state prediction.

Beach State and Wave Forcing Time Series:

- The CNN produces a time series with more frequent oscillations between states as compared with Lippman and Holman (1990).
- Discontinuous bar states occur with more oblique waves, slightly shorter wave periods, and slightly larger wave heights as compared with continuous bar states.
- Future work will include an analysis of the sequencing between bar states.

References and Acknowledgements

Lippmann, T. C., & Holman, R. A. (1990). The spatial and temporal variability of sand bar morphology. *Journal of Geophysical Research: Oceans*, *95*(C7), 11575-11590.

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