Improving Seismic Interpretation: Convolutional Neural Networks with Wavelets

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INTRODUCTION

- **Seismic images show rock boundaries** and are generated by recording reflections of sound waves propagated through the ground.
- Identifying certain features in seismic images can be used to **predict anything from oil locations to upcoming earthquakes**.
- **Goal of the TGS Salt Identification Challenge**[1]: Use deep learning to identify salt pockets in thousands of seismic images.
- The goal of this work is to test if adding wavelet decompositions of seismic images to inputs for a given U-Net will **increase salt prediction accuracy**.

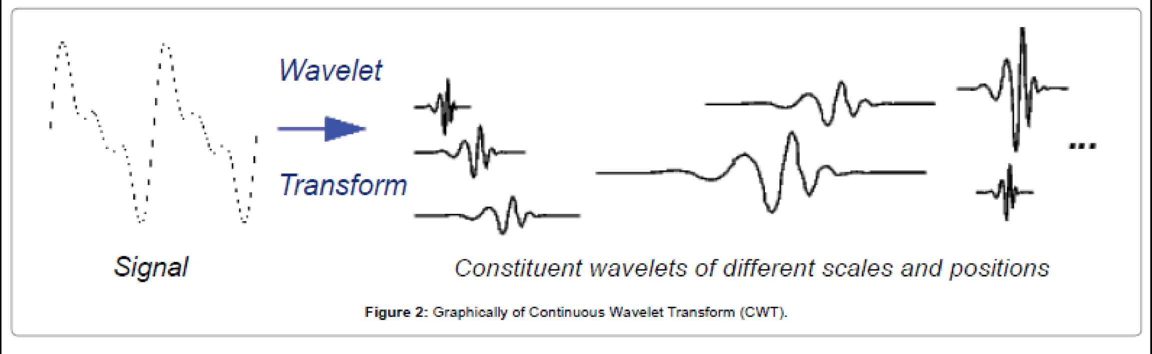
BACKGROUND

Convolutional Neural Network (CNN)[2]

- One of the most successful types of neural networks for **image data analysis.**
- Consists of **convolution** and **pooling** layers:
  - Convolution: Moves small **filters** over input images; the **values of the filters are adjusted** by the network as it trains.
  - Pooling: **Resizes input images** by performing an operation (e.g. maximum, average) on small groups of pixels.

Wavelet Transforms[3]

- Wavelet functions are useful for identifying **abrupt changes** in data.
- There are two types of 2D wavelet transforms--**discrete** and **continuous**:
  - Discrete Wavelet Transform (DWT): Passes **series of filter coefficients** over an image to produce four decomposition images.
  - Continuous Wavelet Transform (CWT): Passes a **wavelet function kernel** over the image at different scales to produce result images.



1D CWT Example – from https://www.omicsonline.org/articles-images/applied-computational-mathematics-wavelet-transform-5-305-g002.png

METHODS

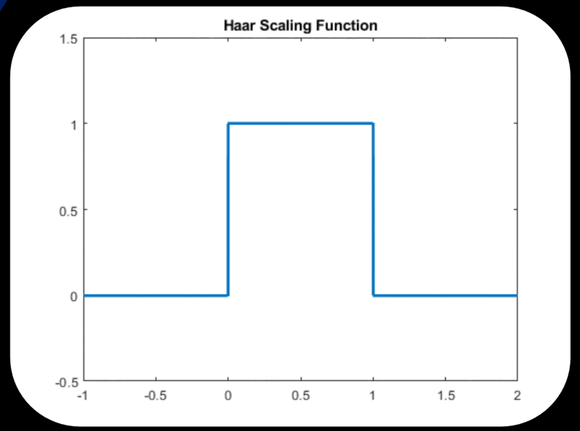
U-Net

- Specific CNN architecture that **captures image details of various sizes**.
- **Consists of blocks** where inputs are passed through convolution layers and resized in a pooling layer.
- Using specific **Python U-Net base code** found online[4].

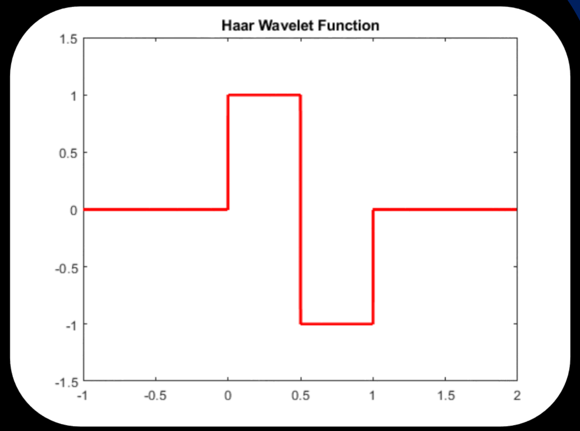
Wavelet Preprocessing

- **This work used a few different approaches** in Python, each taking in various preprocessed image sets:
  1. **Four first-level Haar DWT decompositions**, each resized from 64x64 to 128x128 pixels and concatenated with original seismic images.
  2. The first- through fourth-level Haar DWT decompositions **concatenated with outputs from pooling layers**.
  3. **Ricker (Mexican Hat) CWT on scales 1, 2, 4, 8, 16, and 32** concatenated with original seismic images (CWT images generated in MATLAB).

Haar (Discrete)

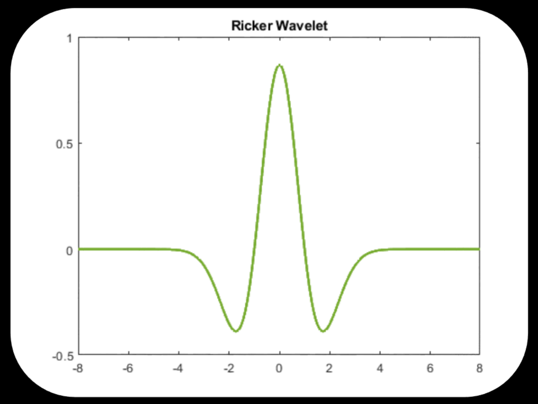


High Pass Filter Coefficients: $\left(\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}\right)$



Low Pass Filter Coefficients: $\left(-\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}\right)$

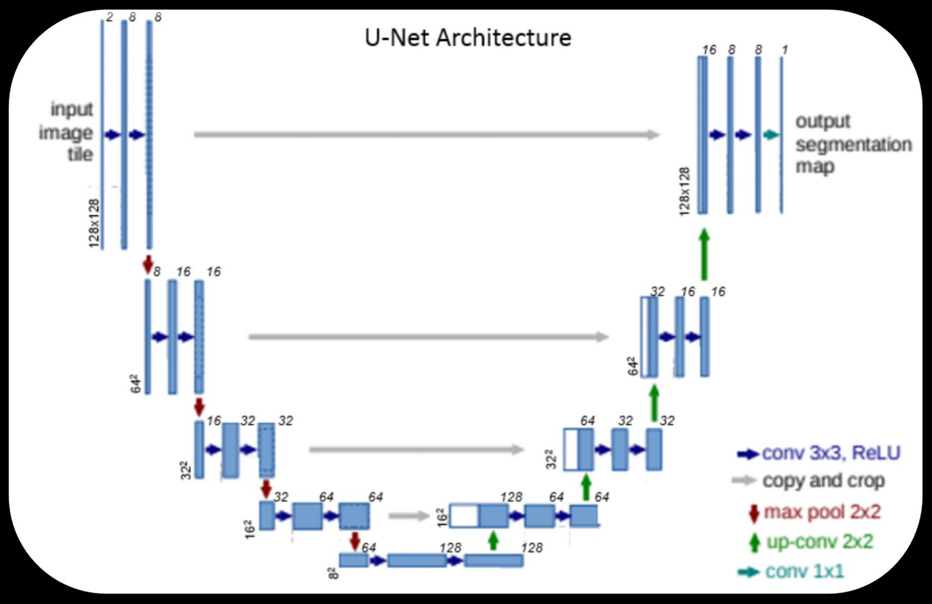
Mexican Hat (Continuous)



$$\varphi(x) = c * e^{-\frac{x^2}{2}} * (1 - x^2),$$

where $c = \frac{2}{\sqrt{3} * \pi^{0.25}}$

U-Net

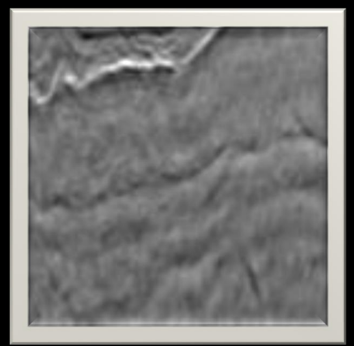


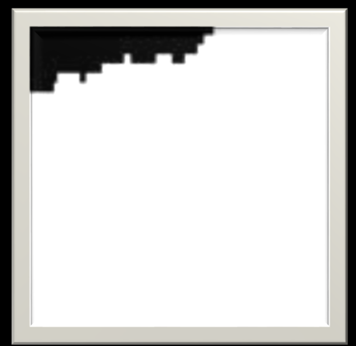
Edited image from https://arxiv.org/pdf/1505.04597.pdf

RESULTS

	U-Net without Wavelet	U-Net with Wavelet		
	Original	Approach 1	Approach 2	Approach 3
Correct Pixels	93.9%	93.9%	93.5%	93.1%
False Positive	4.3%	4.1%	4.6%	5.0%
False Negative	2.8%	3.0%	2.8%	3.4%
Cross-Entropy Loss	0.1672	0.1705	0.1756	0.1897

- Results gathered taking average over **600 validation images**, with pixel percentages of target similarity.
- All results generated in Python on Google Colab.


Seismic Image


Target


Original


Approach 1


Approach 2


Approach 3

DISCUSSION

- **Approaches 2 and 3 did worse** than the original U-Net without wavelet preprocessing.
- The Original and Approach 1 are **not different enough** to be able to make any conclusions.
- Because the U-Net has many layers, **it may already train itself to capture details** that the wavelets give.

CONCLUDING REMARKS

Conclusion
- The more we can improve segmentation with wavelets, the more we can **understand the subsurface in the present** and **prepare for the future.**

Future Directions
- Try **different** CNN architectures, wavelets, and/or seismic datasets.
- Try similar approaches with **1D time series data** (e.g. financial data).

REFERENCES

[1]: https://www.kaggle.com/c/tgs-salt-identification-challenge/overview
[2]: Ketkar, Nikhil. *Deep Learning with Python: A Hands-on Introduction*: 2017
[3]: Alexandridis, Antonios K. and Achilleas D. Zapranis. *Wavelet Neural Networks: With Applications in Financial Engineering, Chaos, and Classification*, 2014
[4]: https://github.com/llSourcell/Kaggle_Challenge_LIVE/

- Various MATLAB tutorials: mathworks.com

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