Evaluating Strike-Slip Fault (SSF) Evolution with 2D CNN: Identifying the Geohazard Zones?

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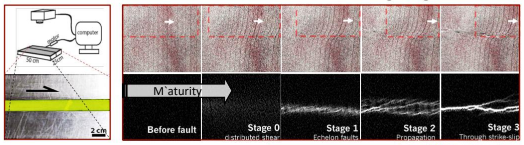
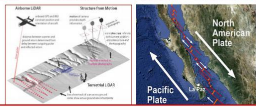
1a. What's strike-slip fault? Lateral displacement induces deformation

- Claybox analogs SSF development at surface due to displacement at depth [1].
- Stages of SSF (0→3) intensify with amount of displacements of basal metal plate.
- Attractive dataset: records deformation evolution from *the beginning to the end.*



- SSF example: San Andreas and other faults along USA's west coast
- Access to only faults' *current stage;* yet they are spatially heterogenous
- Applicable to real-world data: submarine topography, terrestrial LiDAR



1b. How to infer 'maturity' of these faults? Model's Input & Output

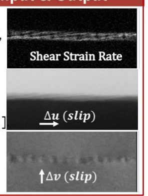
Goal: End-to-End Workflow that allow prediction of fault stage from a single 'current-day' surface data. Given a ***trained model***, which has seen all fault stages from Claybox experiments.

Input: A single 2D-image (3-channals), representing fault's geometry and slips

- Extracted 2D maps, shear strain rate, Δu, and Δv, are the products of time-series images (~250 images/experiment) [1]

Output: A prediction of fault 'maturity' stage

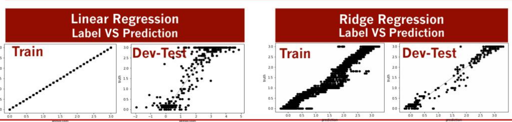
- **Regression** problem to predict a single-digit float that best describe stage of SSF.



2. Baseline Model of SSF Stage Prediction

- There is no existing ML, DL study on fault stage prediction or on this dataset.
- Simple linear regression and best performing ridge linear regression with tuned regularization are established for baseline performance.
- Linear Regression is extremely overfit to training dataset (overdetermined system 128x32x3 features for ~6,000 training samples).
- Slightly improved generalization with regularization. But model does not perform well on dev-test sets

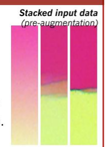
	Regularization	Train MSE	Dev-Test MSE	Dev-Test Bracket Accuracy
Linear Regression	None	0.00	0.40	53%
Ridge Regression	α = 0.8	0.03	0.04	61%



3. Generating and Preprocessing Data

Labeling Strategy

- [1] defines 4 discrete fault stages (0,1,2,3).
- Alternatively, I use continuous labelling technique, only label near transition + midway, then interpolate the rest



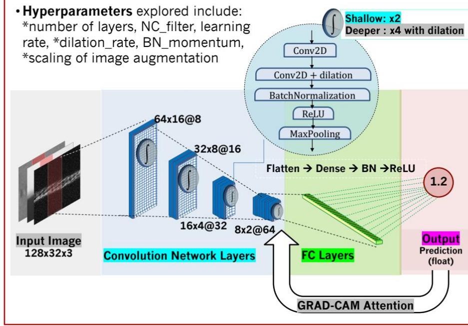
Experiment choices: 3 experiments are ensembled with criteria on their distributed shear zone (1.5cm) B.C., motor speed =0.5cm/min, and both deep and shallow fault depth.

Data Pipeline:

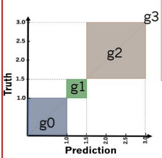
- Raw physical values (.mat) of shear strain, Δu, Δv are (1) normalized for DataGenerator (and also (2) scaled for data labeling).
- Clipped raw image to 128x32 subimages (~25% overlap), ~7,500 subimages (c,u,v), ~2,500 stacked images/experiment.
- Split **{Train: Dev: Test}** = **{0.85: 0.10: 0.05}**
- **Image Augmentation:** I experimented and found augmentation combination that best generalizes SSF geometry related to input size and characters: zoom_range=0.1, horizontal and vertical_shift=0.2, horizontal and vertical flips, all are randomly applied using keras.ImageGenerator

4. 2D-Neural Network Architectures and Hyperparameters

- Both shallow and deeper CNNs (added dilation) are explored.
- **Hyperparameters** explored include: *number of layers, NC_filter, learning rate, *dilation_rate, BN_momentum, *scaling of image augmentation



5. Bracket_Loss_Function and Bracket_Accuracy Explained



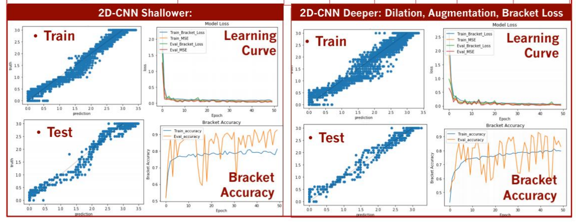
$$\mathcal{L} = mse + (g0)^2 + (g1)^2 + (g2)^2 + g3$$

$$
\begin{array}{ll}
y<1 & : g0 = \max(0, \hat{y}-1) \\
1 \le y < 1.5 & : g1 = \max(\max(1-\hat{y}, 0), \max(0, \hat{y}-1.5)) \\
1.5 \le y < 3.0 & : g2 = \max(\max(1.5-\hat{y}, 0), \max(0, \hat{y}-3.0)) \\
y = 3 & : g3 = \max(0, 3-\hat{y})
\end{array}
$$

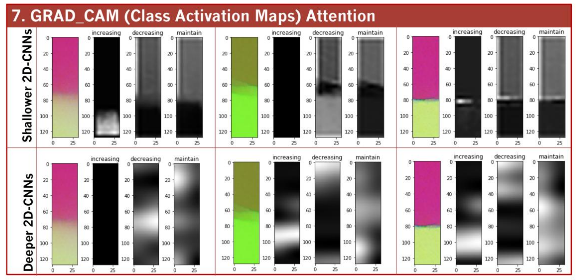
- MSE is a reasonable metrics for regression problem
- '**Bracket Loss**' has MSE with extra penalization to predictions that fall outside their characteristic groups (g0, g1,g2, g3)
- Co-efficient terms or choices of adding alone or adding with square are tuned during training.

6. Summary

Tested Models	Params	MSE		Bracket Loss		Bracket Accuracy	
		Train	Test	Train	Test	Train	Test
2D CNN : shallower Bracket Loss	AdamOptimizer, Lr = 5e-3 Epoch=50, Batch-size = 32 momentum = 0.8	0.038	0.024	0.029	0.048	81.19%	85.82%
2D CNN : deeper Dilation + Augmentation + Bracket Loss		0.031	0.022	0.036	0.026	87.55%	89.80%
2D CNN : deeper Dilation + Augmentation + MSE		0.027	0.020	0.051	0.028	74.60%	67.55%



7. GRAD_CAM (Class Activation Maps) Attention



8. Discussion

- The CNNs models are able to predict fault maturation stages with > 86% and 89% accuracy in shallower and deeper models, a significant improvement from baseline.
- The deeper CNNS outperforms shallow CNNs, due to image augmentation designed to scaled and shift faults away from center & dilation_rate applied to help handle it.
- GRAD_CAM Attention [2, 3] helped identify models during development that did not look at the faults to make predictions.
- GRAD_CAM Attention will be important for future architecture choices. Though, deeper CNNs perform better, the shallower CNNs' attention maps are more interpretable.

Future Work

- Better understand how CNNs make prediction. Go deeper into attention map, hopefully to identify empirical relationships for fault deformations
- Expand to detection and localization () problems based on magnitude of displacement, which will remove the subjective labeling stage from geologists.
- Apply model to real-world example with appropriate dataset.

References

[1] A. E. Hatem, M. L. Cooke, and K. Toeneboehn, "Strain localization and evolving kinematic efficiency of initiating strike-slip faults within wet kaolin experiments," J. Struct. Geol., 2017.
[2] R. Kotikalapudi & contributors, https://github.com/raghakot/keras-vis, 2017
[3] R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-CAM: Visual Explanations from Deep Networks via Gradient-Based Localization," in Proceedings of the IEEE International Conference on Computer Vision, 2017.