

Deep Active Learning for Civil Infrastructure Defect Detection

Chen Feng, Ph.D. Research Scientist

Computer Vision Group Mitsubishi Electric Research Laboratories (MERL) August 21, 2017

Chen Feng et al. International Workshop on Computing in Civil Engineering, 2017

Outline

- Importance of Defect Detection
- Previous Methods
- Problem Formulation
- Our solution
 - Deep Residual Network
 - Active Learning
- Results and Discussions



IN 2016 56,000 OF THE NATION'S BRIDGES WERE STRUCTURALLY DEFICIENT

188 MILLION TRIPS ARE TAKEN ON STRUCTURALLY DEFICIENT BRIDGES

Inspection & Maintenance: Bridge



(FHWA 2012, Bridge inspector's reference manual)

Inspection & Maintenance: Bridge



(FHWA 2012, Bridge inspector's reference manual)

Inspection & Maintenance: Tunnel



Inspection & Maintenance: Dam



http://www.ropeworks.com/service.htm



http://news3lv.com/news/local/gallery/hooverdam-concrete-spillways-need-different-safetymeasures-than-oroville-dam-erosion#photo-2



https://www.usbr.gov/lc/region/featu re/Rope_Access_Team_130628.html

Robots are coming!



Robots are coming!



NYPA 2013



http://www.xyht.com/aerialuas/m ulticopter-profiles/



http://www.ece.rutgers.edu/node/ 1135



http://echord.eu/essential_grid/arsi/



https://ara.cse.unr.edu/?page_id=183

How to Teach Robots to Inspect?

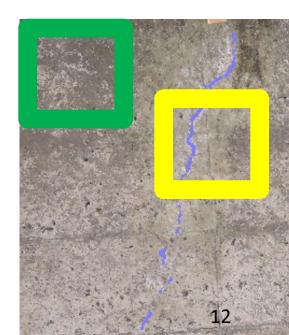
- Challenge: large amount of data
 - Rapid and accurate decision-making
- Existing works: Supervised Learning (Koch et al. 2015)
 - Shallow methods
 - SVM, Random Forrest, etc. (Prasanna et al. 2012, 2016)
 - Deep methods (Soukup and Huber-Mork 2014; Protopapadakis and Doulamis 2015; Zhang et al. 2016)
 - Convolutional Neural Networks (CNN)

Problems of Existing Methods

- Shallow methods
 - Feature engineering
 - Hand-crafted features
 - Tedious for many tasks
 - May require expert knowledge
- Deep methods
 - Requires large amount of labeled data
 - Need time/money/experts

Our Problem Formulation

- Input: image patch $x \frac{y}{y} = f_{\theta}(x)$
- Output: defect probability $\mathbf{y} = [y_0, y_1]$
- Our contributions
 - ResNet (He et al. 2015) for four types of defect detection
 - Active learning (Settles 2010) for training, with a novel sampling strategy



Deep Residual Learning

• ResNet as the classifier $y = f_{\theta}(x)$

$$-z_{1} = f_{\theta_{1}}(x) + x, ..., z_{n} = f_{\theta_{n}}(z_{n-1}) + z_{n-1}$$
$$-y = f_{\theta_{n+1}}(z_{n}) + z_{n}$$

- Efficient learning of a deeper network (30+ layers)
- Loss Function: weighted cross-entropy loss

$$-E = \frac{-1}{N} \sum_{n=1}^{N} w\left(l_n\right) log\left(y_{n,l_n}\right)$$

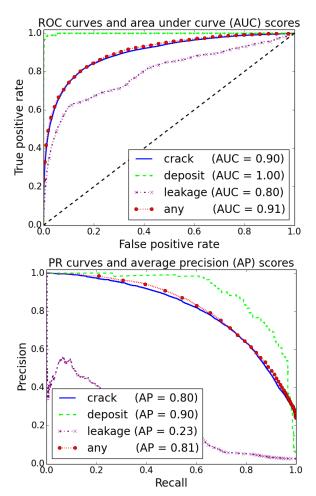
Handle unbalanced positive-negative ratio

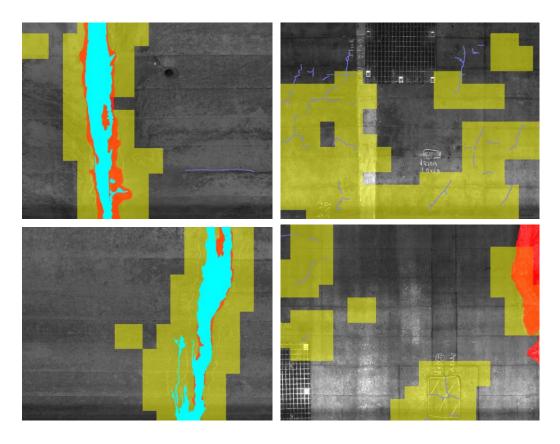
Experiments

- Experimental Dataset: 289440 patches
 - Train : validation : test = 3 : 1 : 1
 - Train four classifiers



Defect Detection Results

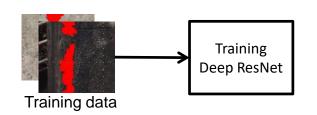




Data annotation for supervised learning
Tadiaua (averaging (averaging))

Tedious/expensive/qualified annotator

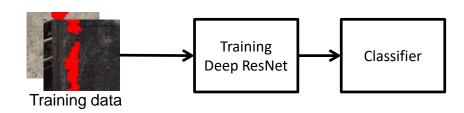
• AL: aims for the most efficient data annotation



Data annotation for supervised learning
Tadiaua (averaging (averaging))

Tedious/expensive/qualified annotator

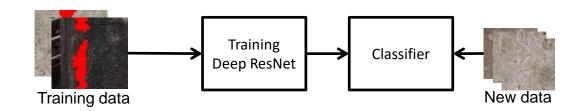
• AL: aims for the most efficient data annotation



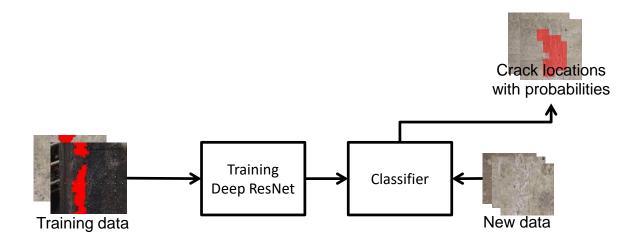
Data annotation for supervised learning
Tadiaua (averaging (averaging))

Tedious/expensive/qualified annotator

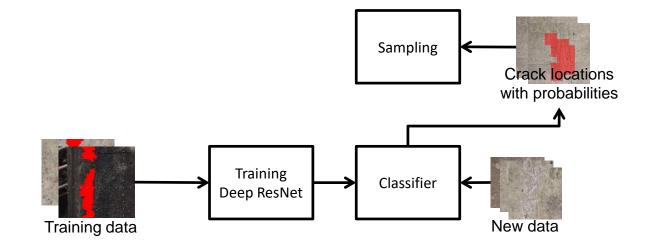
• AL: aims for the most efficient data annotation



- Data annotation for supervised learning
 Tedious/expensive/qualified annotator
- AL: aims for the most efficient data annotation



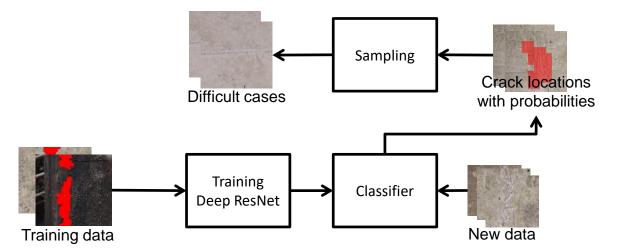
- Data annotation for supervised learning
 Tedious/expensive/qualified annotator
- AL: aims for the most efficient data annotation



Data annotation for supervised learning

Tedious/expensive/qualified annotator

• AL: aims for the most efficient data annotation

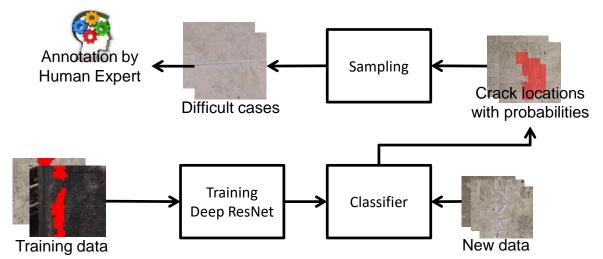


Data annotation for supervised learning

Tedious/expensive/qualified annotator

• AL: aims for the most efficient data annotation

- Fewer data to achieve same accuracy

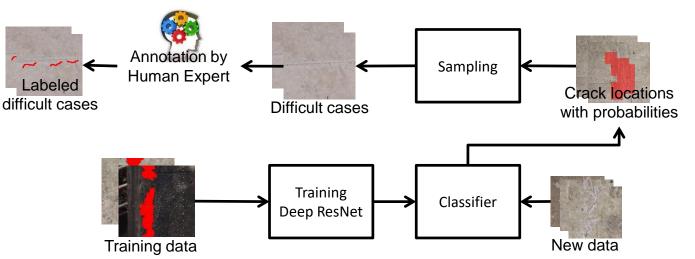


14

Data annotation for supervised learning

Tedious/expensive/qualified annotator

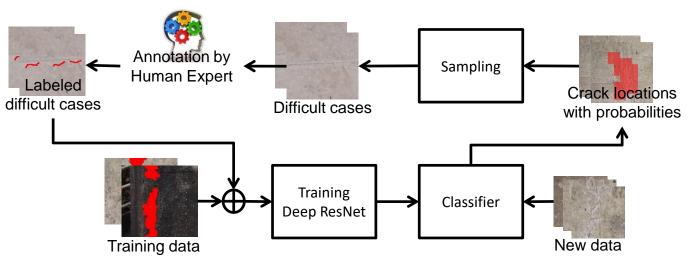
• AL: aims for the most efficient data annotation



Data annotation for supervised learning

Tedious/expensive/qualified annotator

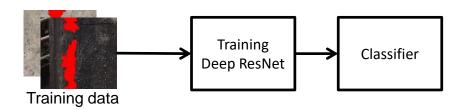
• AL: aims for the most efficient data annotation



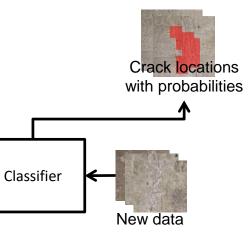
AL Analogy: Initial Training





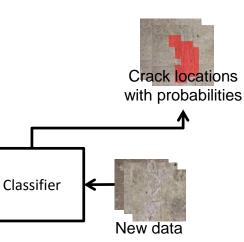




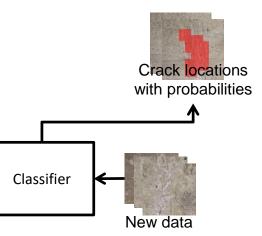








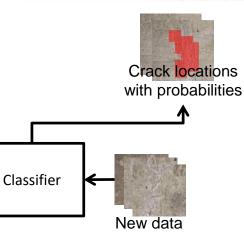




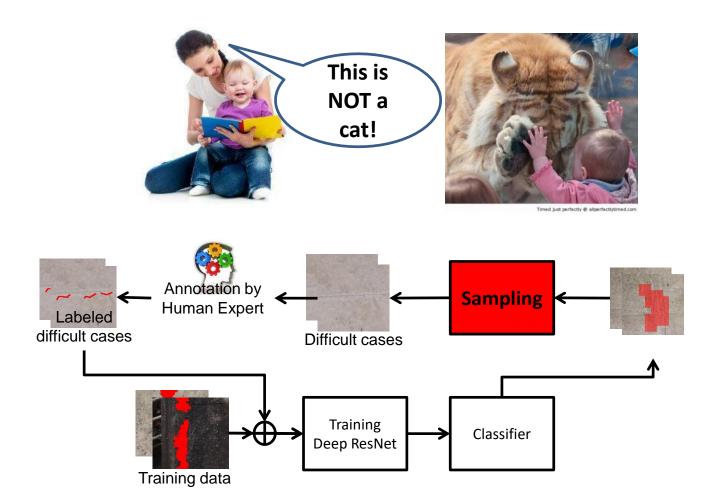




Timed just perfectly @ allperfectlytimed.com



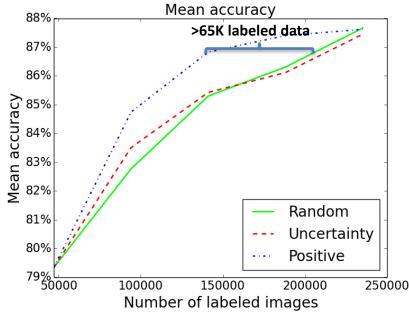
AL Analogy: Selected Feedbacks



17

Active Learning Results

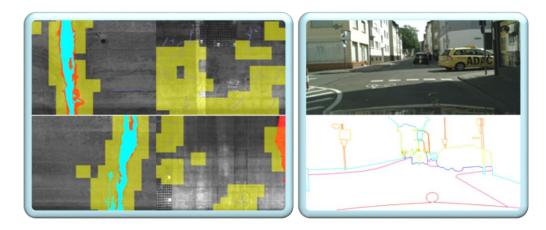
- Positive AL
 - "Robot says this is defect, can you verify it?"
- Uncertainty AL
 - "Robot is not sure..."
- Test AL on "any" detector
 - "train+validation"
 - Positive AL saves 30%



Recap: Deep Active Learning

- Defect detection is important for civil infrastructure
- Deep Learning avoids explicit feature engineering
 Need more data
- ResNet allows deeper networks for higher accuracy
- Active learning samples most informative data to improve classifier
 - Positive sampling strategy for defect detection

Thank you! Questions?





Chen Feng (in Chinese: 冯晨) Ph.D., Research Scientist Computer Vision Group MERL E-mail: <u>cfeng@merl.com</u> Web: https://simbaforrest.github.io