INSPECTING AND PRESERVING
INFRASTRUCTURE THROUGH
ROBOTIC EXPLORATION

A Training Framework of Robotic Operation and Imaging Analysis for Decision-Making in Bridge Inspection and Preservation

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Region of Interest Detection in Bridge Inspection

Outline

- Background
- Multi-scale convolutional neural network feature extracting and matching
- Multi-scale Siamese neural network and one-shot learning
  - One-shot learning
  - Siamese neural network
  - Region of interest detection
  - Multi-scale Siamese neural network
  - Results
- Method comparison
- Conclusion and future work

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Problems with bridge inspections currently performed

- Access is difficult, dangerous, and disruptive

Problems with bridge inspections currently performed

- Requires heavy lifting equipment

Problems with bridge inspections currently performed

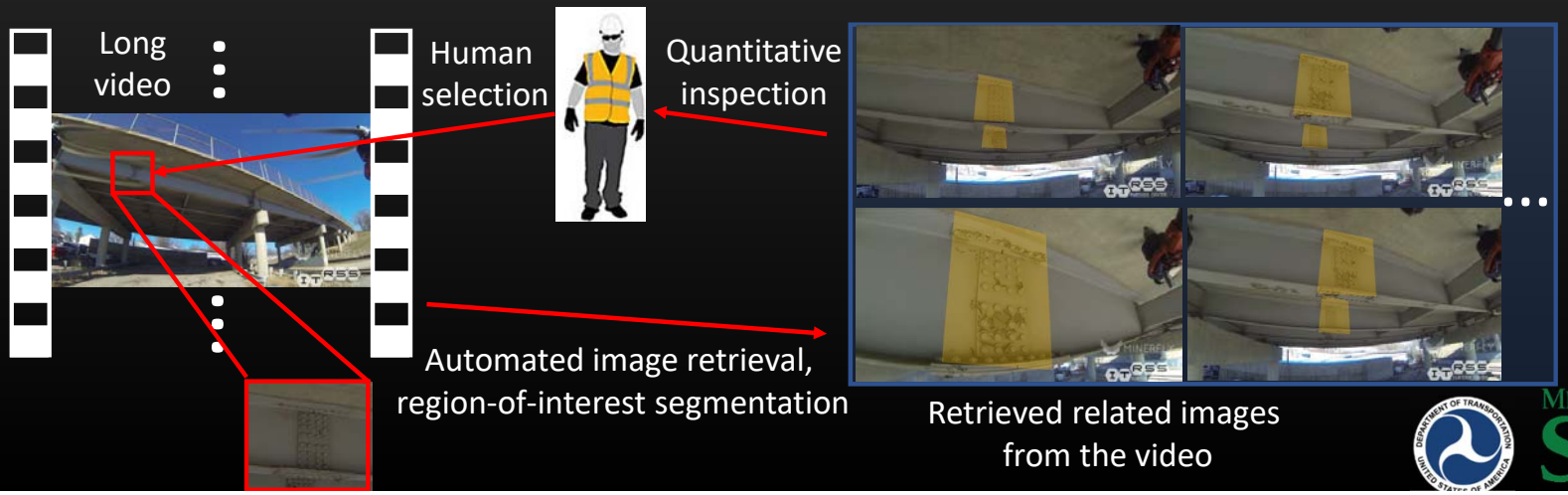
- Manual inspection is time-consuming & costly

Inspect bridges using robotics

- Faster, safer, better, and less expensive
- Big data of inspection videos are collected

Image analysis to provide decision-making support

- 30 frames/second × 3600 seconds/hour = 108,000 frames/hour
- Boring and inefficient to watch long videos collected for bridge inspection
- What can we help?



Challenges in processing the videos

- Different viewpoints of camera
- Different scales of an object in images
- Camera vibration
- Different models or types of an object to be inspected

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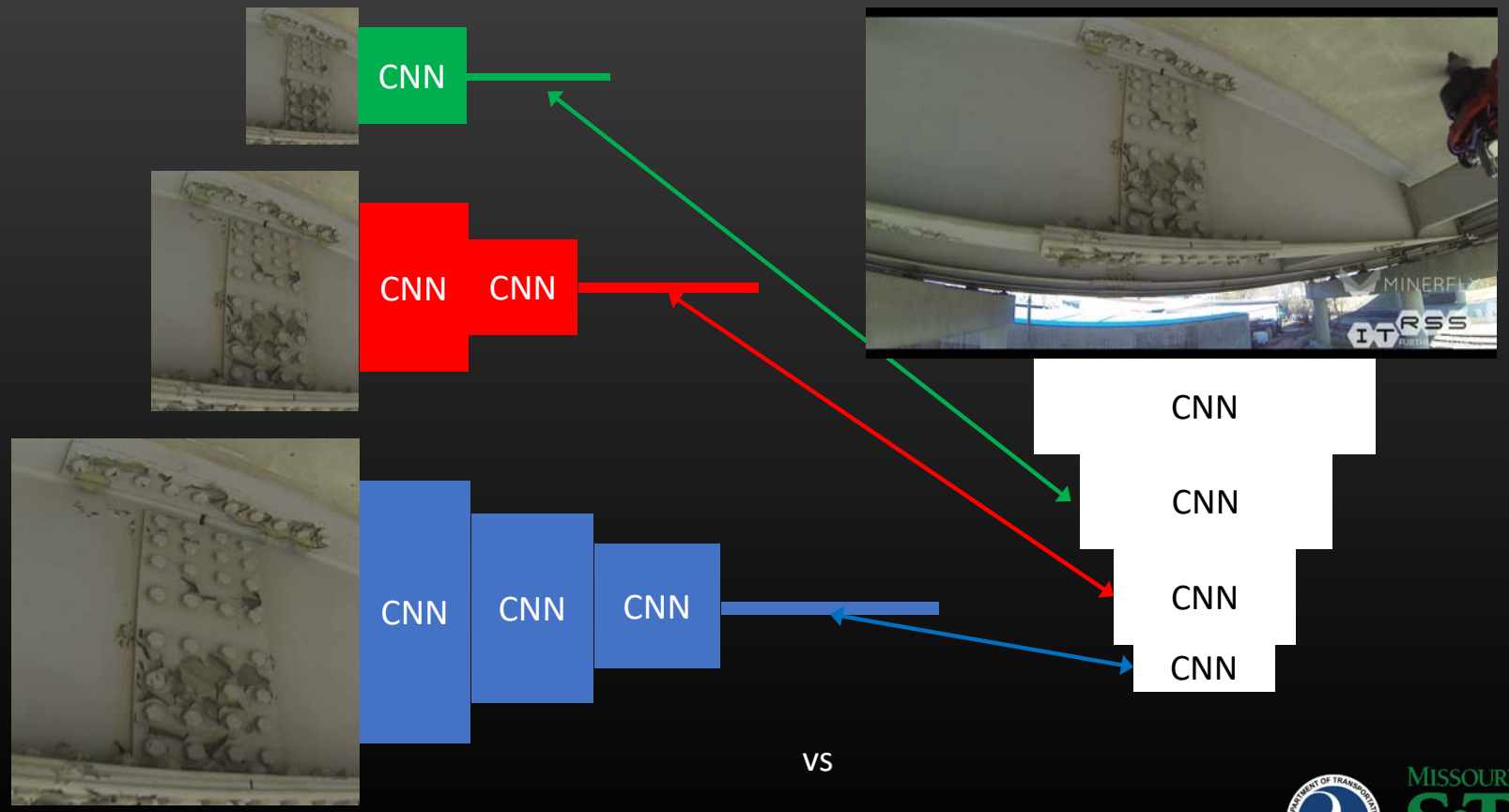
Multi-scale convolutional neural network (CNN) feature extraction and matching



Multi-scale convolutional neural network (CNN) feature extraction and matching

Issues with the current CNN model

- Deployed from other dataset whose domain is different than bridges
- Generates false-positive noise

Improve the image retrieval algorithm

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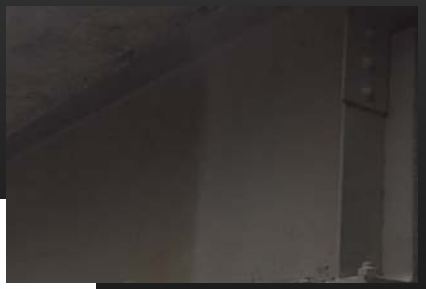
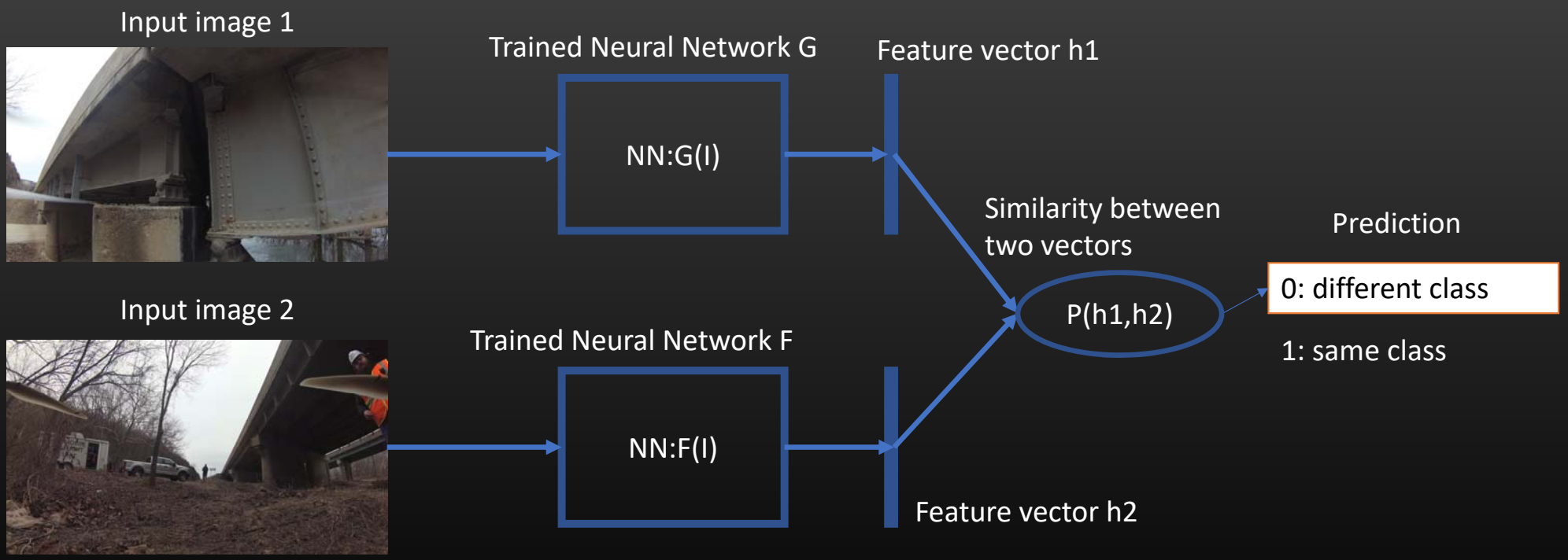
One-shot learning

- To correctly make predictions given only a single example of each new class

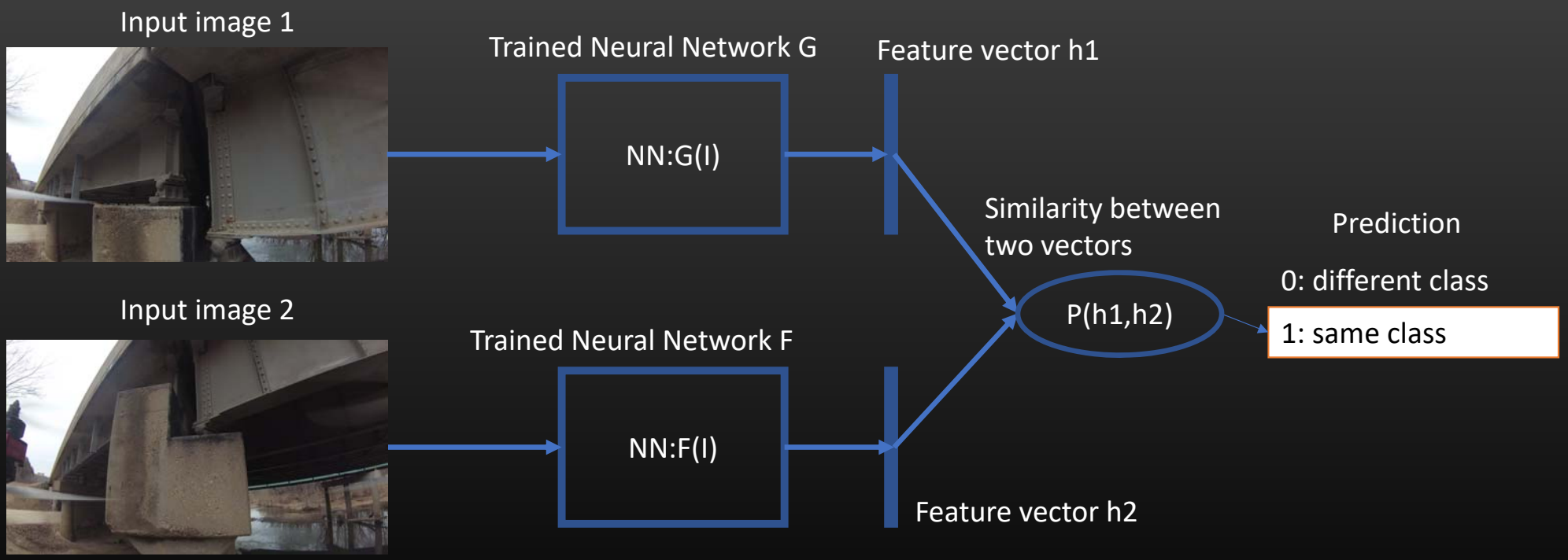
Region of Interest → VS ← Background



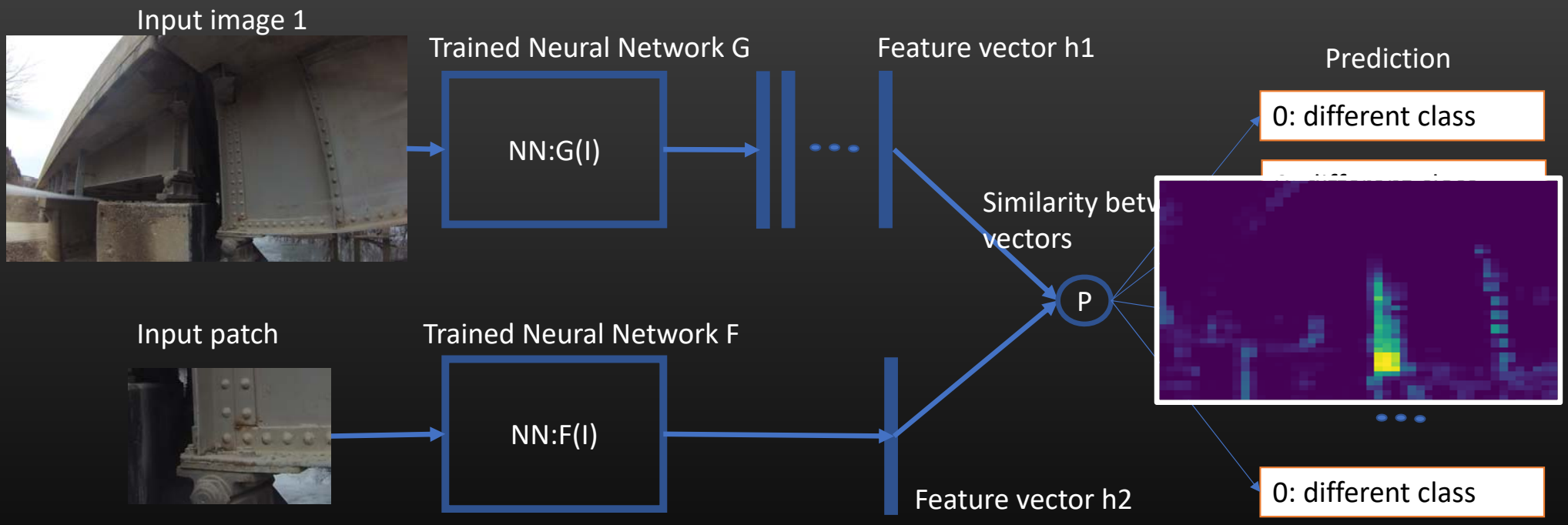
Siamese neural network



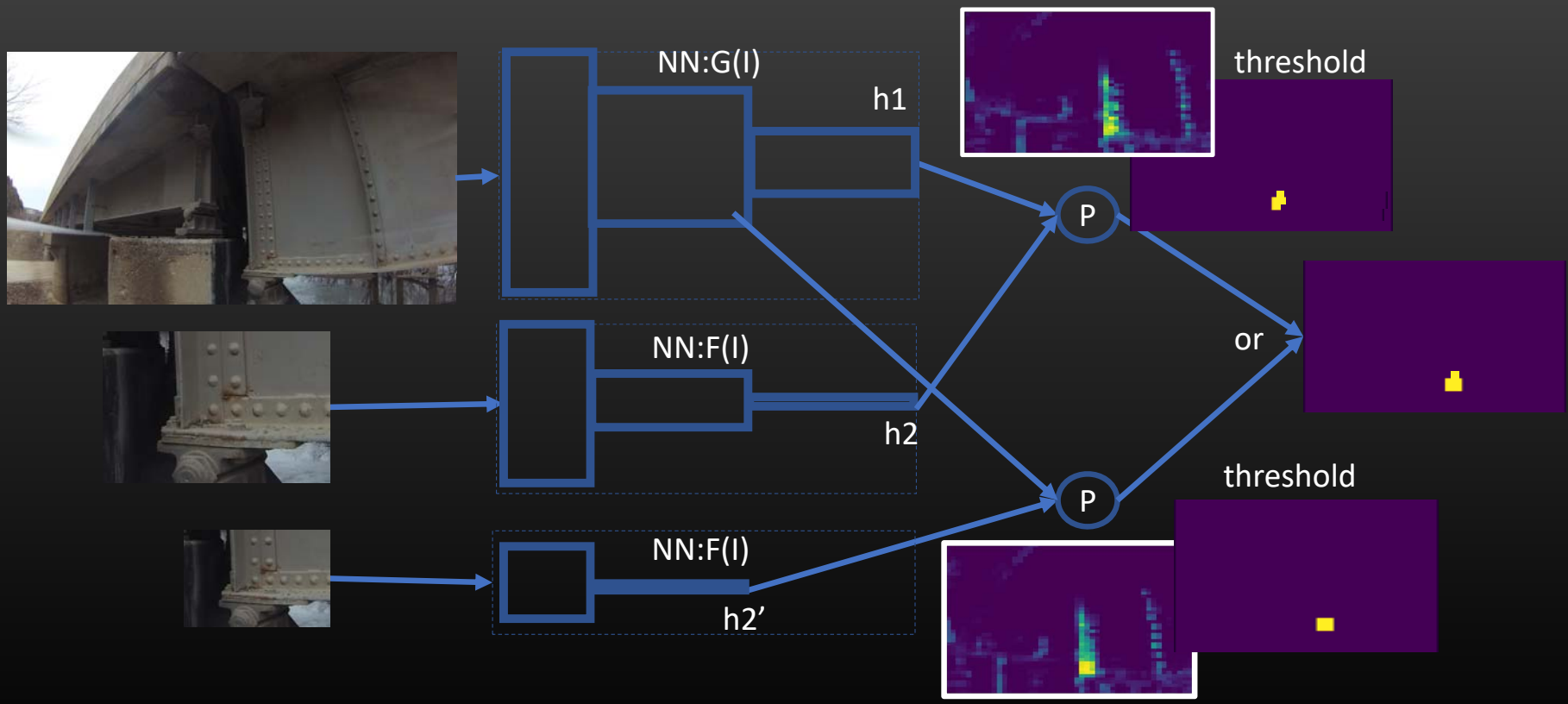
Siamese neural network

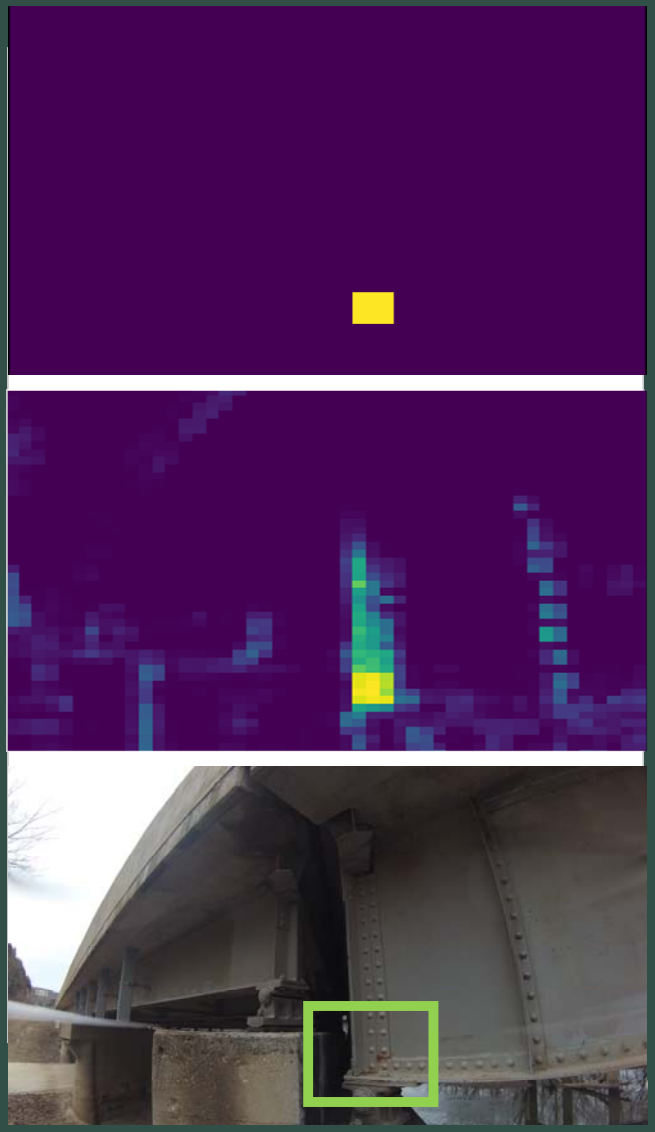


Region of interest detection (region vs image)



Multi-scale Siamese neural network





Multi-scale Siamese neural network

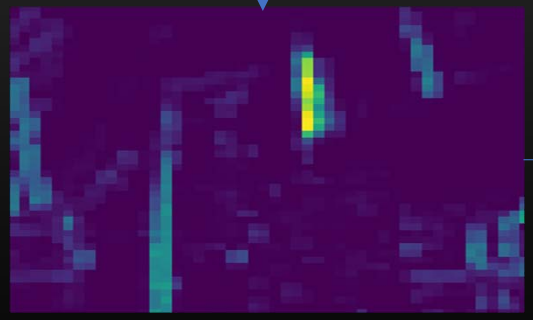
- Formula
  - $P(h1, h2) = Sigmoid(\frac{h1\ h2}{|h1||h2|})$
  - $Loss = -\mathrm{y}\log(P) + \alpha(1-y)\log(P^2)$
- Training:
  - Stochastic gradient descent (SGD)
  - Learning rate = 0.01
  - α=0.05
  - Fine-tune from Alexnet

Result

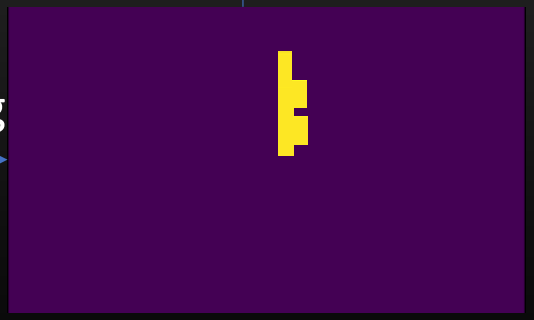
region of interest

input image

similarity map



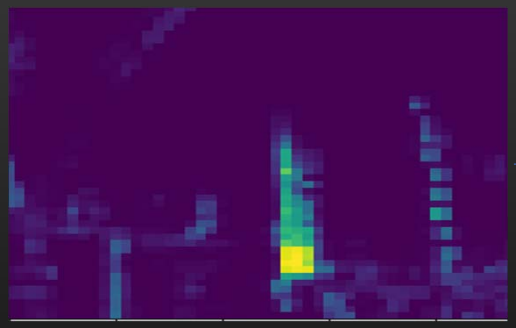
thresholding



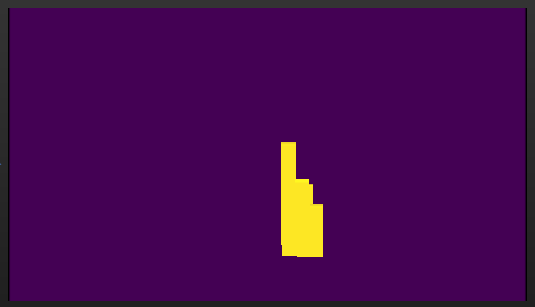
Mask overlap on original image

Result

similarity map



thresholding



Mask overlap on original image

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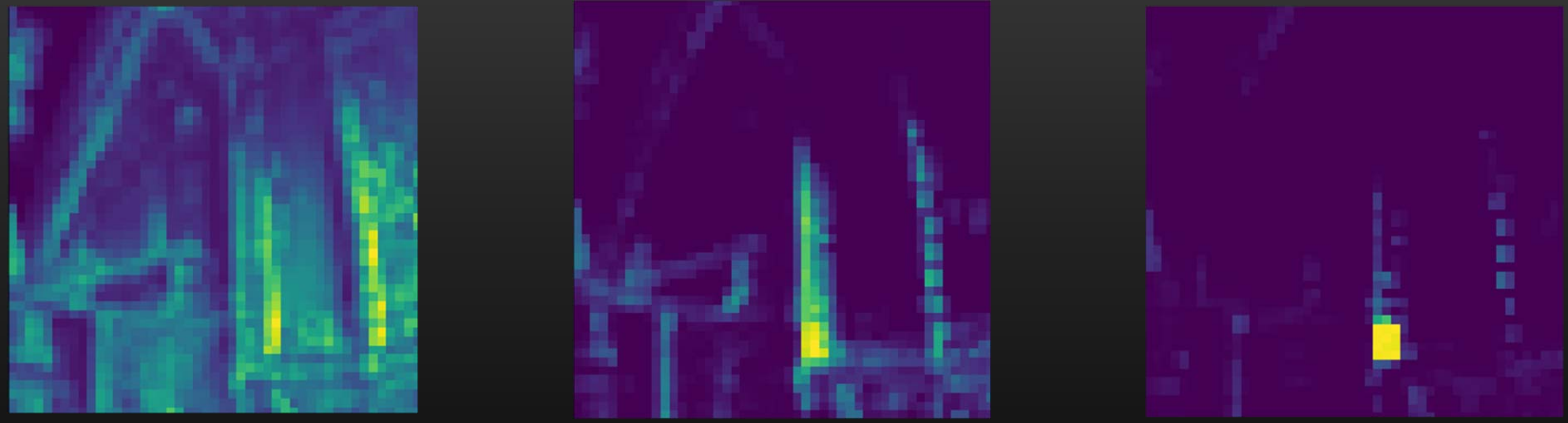
Method comparison

Iteration 0 → 15000 → 30000



- After learning, the result become more stable and accurate

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Conclusion

- A video analysis framework that keeps engineers in the loop of inspection
  - Multi-scale convolutional neural network for feature extraction and matching
  - Multi-scale Siamese neural network and one-shot learning

Future work

- Problem: One-shot learning has data limitation
  - Limited amount of data
  - Unrelated background inside the region leads to false-positive detection and thus may detect background as region of interest

- Proposed: post-process to smooth the result and denoise

Acknowledge

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Q&A