Mind the Gap: Computer Vision Applied to Concrete Maintenance

Glass of Water
Malachi Harper
Kaleb Lott
Alex Beeston

Dr. Mario Harper
Programme - CS 5890
Department - Computer Science
Institution - USU
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Introduction

Automation of concrete maintenance by identifying and filling cracks and fractures will mitigate costly human intervention and extend the life of critical infrastructure. Concrete naturally erodes and cracks over time due to the free-thaw cycle of weathering and underground growth of nearby root systems (see figure 1).

Figure 1: Cracked concrete to the natural weathering processes

The system will identify regions of cracked concrete, localize the cracks, then fill the cracks with sealant (see figure 2).

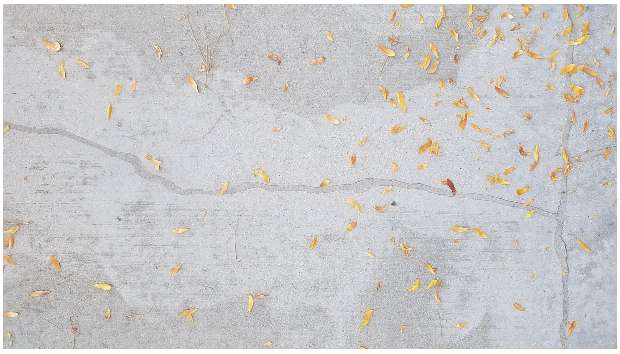

Figure 2: Cracked concrete that has been patched with sealant.

This research addresses the following questions:

- How can an image classifier distinguish between seams and cracks in concrete given that both have a similar size and color?
- What is the best way to distinguish between different types of surfaces, specifically, darker surfaces such as asphalt where it is more difficult to detect damage?

The robot will combine the effects of image classification and segmentation with motion planning by making decisions about how to move based on what it sees. This robot will help improve workers' safety in the construction industry by lowering human contact with heavy machinery that can potentially cause back injuries. This will result in construction companies filing fewer health insurance claims on their workers and increasing worker productivity. By automating the locating and repairing of concrete, a worker's job is reduced to robot operation and maintenance thereby increasing the longevity of infrastructure.

Literature review

This project primarily deals with computer vision and robotic arm manipulation.

Computer Vision

Convolutional Neural Networks are great candidates for image classification machine learning tasks because they do not require feature extraction and, when configured properly, have proved exceptionally accurate results. [1] In 2012, Alex Krizhevsky et. al. won the ImageNet classification challenge and brought an end to the "dead era" of neural networks by introducing a novel network that later became known as the AlexNet. This model consists of the following layers:

- 11x11 convolution (stride 4)
- max pooling
- 5x5 convolution
- max pooling
- 3x3 convolution
- 3x3 convolution
- 3x3 convolution
- max pooling
- fully connected layer (4096 neurons)
- fully connected layer (4096 neurons)
- softmax classification (1000 classes)

The model avoids overfitting by employing dropout among the layers and data augmentation among the training images. [2]. This model can be easily extended to fit a variety of computer vision tasks.

Manipulators

In robotics, a manipulator is a device used to manipulate materials without direct contact from a human. There are a variety of reasons a manipulator would be needed, for example, robotic surgery, handling radioactive material, and welding. [3] Every joint in the manipulator provides an additional degree of freedom which increases the complexity of the manipulator's maneuvers.

Research design and methods

The robot first decides if the concrete has a crack in it. It performs this task using convolutional neural networks. If the network determines that an image has a crack, then the robot advances to the image segmentation phase. In this phase, the robot assumes the concrete shown in the image has a crack and is then tasked with generating an ordered list of coordinates that, when drawn end to end, represent the crack. The segmenter then passes this list of coordinates to the manipulator, which applies cement to the crack at the specified locations.

Research Design

Research will be based on how well the robot will be able to classify a crack in an image and how well the manipulator can fill the cracks. Since the robot will be collecting data on cracks in concrete, the robot will be focused on collecting original data about its surroundings and making decisions on what does and does not constitute a crack in concrete.

Methods and Sources

Classifier

The classifier will build upon the AlexNet convolutional neural network by replacing the softmax classification layer, which classifies into 1000 classe, with a binary softmax classifier, which classifies an image of concrete as “cracked” or “intact.” The Python Pytorch package will be used to accomplish this. To train the classifier to recognize the difference between seams and cracks in concrete, which look similar, the classifier will be trained on images of concrete with and without seams.

Segmenter

The camera will look from a bird’s-eye view directly downwards towards the concrete. The camera should always be a fixed distance from the ground, roughly 3 feet, to ensure the arm moves properly. The image will be segmented into areas identified by the training examples as cracked regions and non-cracked regions (figure 3).

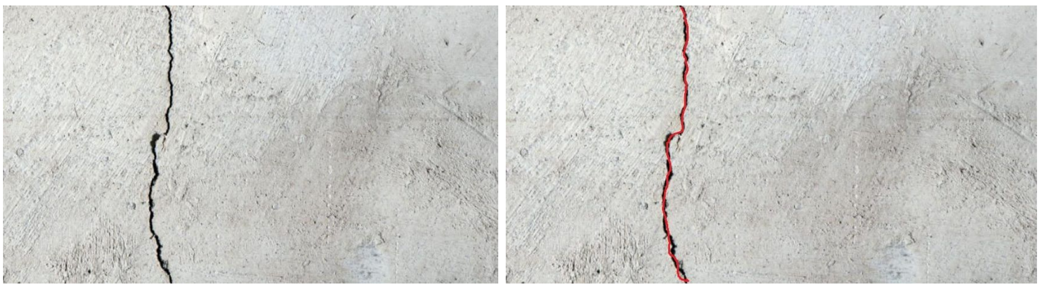

Figure 3: image before segmentation (left), image after segmentation (right)

Manipulator

The manipulator will be implemented as a cartesian coordinate robotic arm. For a cartesian robot the three axes of control (x,y,z) are linear and are at right angles to each other. [4] Each joint of the arm can only change the manipulator’s position in its relative dimension. This will be ideal for manipulating the arm to the correct distance from the concrete while also following the path generated by the image segmenter. The arm will be mounted to an ackermann vehicle and will patrol pads of concrete looking for cracks.

Data Sets

180 images and concrete (cracked and uncracked) have already been acquired. The images were taken with a Samsung S7 smartphone, so all images are of the same dimensions and resolution. An additional 200-300 images will be acquired with two other smartphone cameras. By using three cameras only, scaling the images to the same dimensions will require, at most, three manipulations. The images will be grouped by the phone on which they were taken until all images have been processed to the same dimensions and resolution. The images are taken orthogonal to the concrete at waist level to imitate the angle from which a robot would view concrete. Humans will label the images as cracked and uncracked. Data augmentation techniques, such as horizontal flips, vertical flips, and rotations, will then be used to at least quadruple the size of the data set.

Practical Considerations

Gathering, processing, and labeling the remaining images will require a fair amount of effort. This should be finished quickly so that adequate time remains to implement the classifier, segmenter, and manipulator. The research does not pose any physical, environmental, or ethical threats to any party.

Implications and contributions to knowledge

The findings of this project could help to improve the process of concrete maintenance and repair. By automating part of the workflow, resources can be relocated to other parts of construction, possibly getting the work done faster. This work is intended to learn how to combine existing methods and models into a single application. After completion, the project could be extended to eliminate certain assumptions about the robot's mobility, power consumption, collision detection capabilities, etc.

References

[1] Y. Lecun, L. Bottou, Y. Bengio and P. Haffner, "Gradient-based learning applied to document recognition," in Proceedings of the IEEE, vol. 86, no. 11, pp. 2278-2324, Nov. 1998, doi: 10.1109/5.726791.

[2] A. Krizhevsky, I. Sutskever, G. E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks,” Communications of the ACM., vol. 60 no. 6 pp. 84-91, 2012, doi: 10.1145/3065386

[3] Automation, LJ Welding. "Welding Manipulators | Subarc Welding & CMT Manipulators". www.ljwelding.com

[4] Zhang, Dan; Wei, Bin (2016). Mechatronics and Robotics Engineering for Advanced and Intelligent Manufacturing. Cham: Springer. p. 31. ISBN 978-3-319-33580-3.

Research schedule

Research phase	Objectives	Deadline
Information Gathering	Gather a data set of at least 300 images of cracked and non-cracked concrete	November 6
Information Gathering	Compile research information	November 6
Design	Implement an image classifier	November 13
Design	Implement an image segmenter	November 13
Implementation	Implement a simulation of a robot arm manipulator	November 13
Submission	Final submission	December 18