MPC-620

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Project Title

Visible and Thermal Imaging in a Deep-Learning Approach to Robust Automated Pothole Detection and Highway Maintenance Prioritization

University

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Research Needs

Potholes are a primary pavement distress that can compromise safety and cause expensive damage claims. Potholes are results of deterioration of pavements due to aging, weather and traffic overloads and are common problems across the U.S. According to a study by AAA in 2016, U.S. motorists suffer repair costs of $3 billion annually from damage caused by potholes. Potholes are even more common in the Mountain Plains region due to the snow and freeze/thaw effect. Identifying and repairing potholes is one critical aspect of highway maintenance. Accurate, robust and fast detection of potholes is critical to enabling timely and cost-effective pavement maintenance.

Assessing pavement condition typically involves three main tasks, i.e., raw data collection, distress detection, and distress assessment [1]. While the data collection is largely automated due to the advancement in sensing and imaging technologies, the distress detection and assessment still mainly involve manual identification [2], which is time-and-cost consuming and also limits the type of sensing and data that can be collected.

In terms of data collection, various sensing technologies have been developed for pavement condition data collection. However, sensing techniques such as 3D laser scanning (e.g., LiDAR), ground penetrating radar (GPR) are still very expensive with high instrument and setup cost. The postprocessing and interpretation of the corresponding results are also computationally expensive. 2D image-based sensing on the other hand presents as a low-cost option for rapid data collection of pothole information over large regions and has been found useful for detecting potholes [3,4]. However, quality of potholes detection using only visible images may be significantly compromised (e.g., false detections and un-detections) due to poor lighting, weather conditions (e.g., fog, rain), low contract to surrounding pavement. On the other hand, thermal images are more robust to lighting and weather conditions. Although thermal images may lack the texture details of visible images, they can offer additional unique features compared to visible images [5], e.g., temperature difference between pothole and surrounding pavement, which can be potentially used for pothole detection. In addition, recently image fusion techniques have been used to combine images by different types of sensors to generate informative fused images that combine the features extracted from different types of images for various applications [5,6]. However, so far, the great potential and effectiveness of integrating both visible and thermal images as well as using fused images to enable accurate and robust pothole detection have not been investigated.

In terms of pavement distress detection using the collected 2D images, different algorithms have been investigated (e.g., for crack detection, pothole detection using computer vision based algorithms) [7]. Recently, data-driven distress detection algorithms based on deep learning algorithms, which can automatically learn features from images and have been gaining popularity in the computer vision community, have attracted the attention of the pavement image analysis community [8]. However, overall the research on use of deep learning for robust, automated pothole detection is still limited.

To this end, efficient and robust algorithms that can automate the processing of collected visible and thermal image data and provide accurate and robust classification, detection, segmentation of potholes are needed to enable timely and cost-effective highway maintenance. The strong need for such automated tools motivates the proposed research, which aims to fill some of the above-mentioned research gaps.

Research Objectives

The goal of this project is to develop visible and thermal imaging and deep learning based approach for automated and robust detection of potholes to enable timely and cost-effective maintenance of highways. The following major objectives are designed to meet this goal.

1. Create a unique and valuable database of geotagged and labeled trios of visible, thermal and fused images for training pothole detection algorithms.
2. Develop deep learning algorithms for automated and robust pothole detection based on visible, thermal, and fused images.
3. Test the hypothesis that incorporation of thermal and fused images could lead to more accurate and robust pothole detection by comparing the detection performance for different cases.
4. Develop automated tools for pothole detection, pothole mapping and updating.

Research Methods

To address the above challenges, this project proposes the integration of both visible and thermal images captured by visible & thermal dual camera and the use of deep learning to enable robust, accurate and automated detection of potholes to help prioritize highway maintenance. An overview of the proposed research is shown in Figure 1. Instead of relying only on visible images, both visible and thermal images as well as the fused images with salient features from both visible and thermal images will be used to improve the robustness in pothole detection.

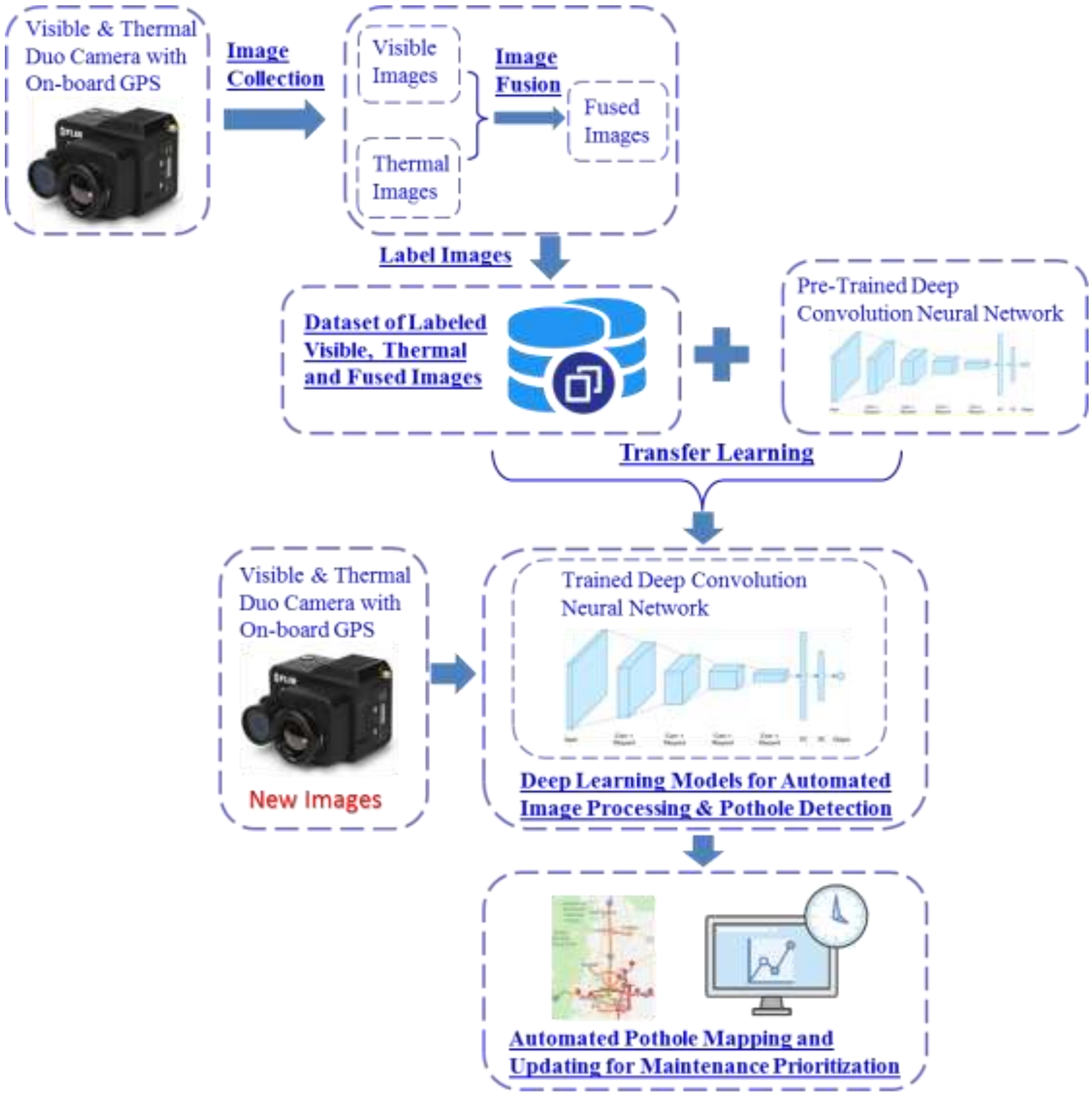

Figure 1. Overview of proposed research.

Firstly, a unique database of geotagged and labeled trios of visible, thermal and fused images will be created for training pothole detection algorithms. This will be achieved by using visible and thermal duo camera mounted on cars to take pictures and video of the same highway road surfaces. The images will include pavements with and without potholes. To include images under different lighting conditions and weather conditions in the image database, images will be collected for the same road segments during different time of the day and also under different weather conditions. Based on the collected visible and thermal images, image fusion techniques will be used to extract features from these images to establish corresponding fused images [6,9]. The collected images will be geotagged using the GPS information. To standardize the images, some preprocessing (e.g., cropping, resizing) will be applied to the images. Then, using tools such as LabelImg, these images will be manually labeled as with pothole or not, and for those with potholes, the potholes will be annotated. The annotation will be applied to all three types of images. Out of all the images, three sets will be created, including training set, validation set, and test set, with each set including corresponding visible, thermal, and fused images for both the positive case (i.e., with potholes) and negative case (i.e., without potholes) as well as corresponding annotations.

Secondly, based on the labeled images, deep learning algorithms (e.g., deep convolution neural network, which has been shown to be highly effective in extracting and identifying features from images [8,10,11]) will be trained to classify the images as with or without potholes and also for those with potholes further identify the pothole and its size through detection and segmentation. Data augmentation (including rotation, blurring, and contrast enhancement) will first be applied to increase the size of the training sets. To address the requirement of large annotated image dataset by deep convolution neural network, transfer learning will be used [10], where deep convolution neural network pre-trained on other existing large-scale image datasets will be fine-tuned through the collected images. This way the required number of labeled images can be reduced. Different deep learning algorithms will be investigated. The performance of the trained candidate deep neural networks will be compared in terms of accuracy and efficiency. The impacts of additionally incorporating thermal and fused images for pothole detection and segmentation on the pothole detection performance will be investigated. The results will provide guidance on how to best make use of images from different sensors.

Thirdly, develop automated tools for pothole detection, pothole mapping and updating. The established deep neural network models with best performance will be used for automated pothole detection when new images are collected and need to be processed. The location and picture of the potholes will be shown in maps using the GPS information for the images. Functionality in terms of statistics of the potholes and filtering of potholes by size, location will also be provided to facilitate prioritization of maintenance. The map and pothole information database will be automatically updated once new data are collected and processed through the automated deep learning algorithm.

Expected Outcomes

The expected outcomes include:

1. A unique and valuable database of geotagged and labeled trios of visible, thermal and fused images for training pothole detection algorithms.
2. A set of procedures for integrating images from multiple types of sensors to enhance accuracy and robustness of pavement distress assessment.
3. Automated tools for pothole detection, pothole mapping and updating for use by state DOTs and highway maintenance team.
4. A full report documenting image collection, image processing, training and performance of deep learning algorithms, and results will be provided, and one or more journal papers will be published.

Relevance to Strategic Goals

This project primarily addresses the USDOT Strategic Goal of “State of Good Repair”. This study will develop automated tools for accurate and robust pothole detection, pothole mapping and updating. The tools are expected to help enhance the capabilities of state DOTs and highway maintenance team in timely and cost-effective maintenance of highways.

Educational Benefits

A graduate research assistant will be hired to conduct the research described in this proposal. The student will be involved in collecting the visible and thermal images, labeling the images, and learning and applying deep learning techniques for pothole detection as well as developing automated tools. The student will gain valuable experience in applying deep learning techniques for image processing and road damage detection. The procedure and example from this project will be used in a graduate level course developed by the PI on surrogate models. Also, the example in this project will also be used for outreach activities jointly with the Drone Center at Colorado State University.

Technology Transfer

The developed automated tools will be presented to CDOT maintenance teams to promote the adoption of the developed tools. The research findings will also be disseminated through technical publications in conferences and journals as well as presentations in conferences and seminars.

Work Plan

The work plan of this project includes the following five major tasks:

<u>Task 1: Visible and Thermal Image Collection</u>

The FLIR DUO PRO R 640 thermal imaging camera from the CSU Drone Center, which has a high resolution, radiometric thermal imager, 4K color camera, and on-board GPS, will be used to collect geotagged visible and thermal images. The camera will be mounted on the car windshield and images/videos will be collected on segments of I-25 and I-70. Images will be collected at different times of the day and under different weather conditions. The expected completion date for this task is 6 months from the project start date.

<u>Task 2: Create Integrated and Labeled Image Dataset</u>

Based on the collected visible and thermal images, image fusion will be used to create the corresponding fused images. The trios of visible, thermal and fused images will first be preprocessed and then potholes will be manually annotated using the LabelImg tool. For each type of image, the dataset will be randomly split into training, validation, and test set, with each set including both images with and without potholes. The expected completion date for this task is 10 months from the project start date.

<u>Task 3: Train Deep Neural Network for Pothole Detection and Segmentation</u>

For pothole detection and segmentation, deep convolution neural networks (DCNN) for semantic segmentation will be trained. To address the requirement of large annotated image dataset by DCNN, transfer learning will be used. First, data augmentation (e.g., rotation, blurring, contrast) will be applied to increase the size of the training sets. Then transfer learning and the training sets will be used to fine-tune deep neural networks pre-trained on existing large dataset to establish the final deep neural networks. For the pre-trained deep neural networks, three candidate models, i.e., PSPNet, Mask R-CNN, DeepLabv3+, pre-trained on the PASCAL VOC dataset, will be used. Deep neural network models will be trained using PyTorch and established separately for visible, thermal and fused images. The expected completion date for this task is 15 months from the project start date.

Task 4: Validate and Compare Performance of Deep Learning Models

Using the validation and test sets, the performance of the trained candidate deep neural networks will be compared in terms of accuracy and efficiency; the impact of additionally using thermal and fused images for pothole detection and segmentation will be investigated. The expected completion date for this task is 18 months from the project start date.

Task 5: Develop Deep Learning Enabled Automated Tool for Pothole Detection and Mapping

The established deep neural network models will be used to drive the automated pothole detection tool, which can classify and detect potholes and provide updated mapping with locations, images, and size information of potholes as new images are collected to help state agencies to prioritize maintenance. The expected completion date for this task is 24 months from the project start date.

Project Cost

Total Project Costs:	$98,400
MPC Funds Requested:	$50,400
Matching Funds:	$48,000
Source of Matching Funds:	Colorado State University

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