Automated large-scale tornado treefall detection and directional analysis using machine learning

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SUMMARY:
The Northern Tornadoes Project (NTP) was founded with the goal of capturing data on all tornadoes in Canada to improve severe weather climatology and prediction. Among other methods, NTP uses large-scale aerial photography captured by crewed aircraft or drones to collect data in inaccessible areas. The automation of treefall detection and direction is significant to the analysis NTP performs on rural tornadic events and for the use of tornado vortex models. Manually detecting and assessing the directions of fallen trees in large-scale aerial photography of tornado damage is labour intensive. This paper proposes machine learning and image processing techniques to extract the fallen trees, assess their fall directions, and produce a Fujita-style treefall direction vector field. Going forward, the model will be validated by comparing the vortex model's performance on both manual and automatic treefall direction vector fields. If successful, NTP will aim to incorporate this automated process during their analysis of Canadian tornadoes and assessment of rural tornado Enhanced Fujita scale ratings.

Keywords: treefall, tornadoes, machine learning

1. INTRODUCTION

When tornadic events occur, the analysis of a tornado's severity and damage intensity is rated using the Enhanced Fujita (EF) Scale based on its maximum wind speed (Fujita and Smith, 1993; McDonald and Mehta, 2006). This EF scale rating is acquired through observation of damage done to structures, such as houses, known as Damage Indicators. The Canadian version of the EF scale also includes supplementary damage indicators including ones for trees. These varying types of damage indicators have known correlations between wind speed and resulting damage, referred to as Degrees of Damage. In Canada, it is common for tornadic events to occur in rural areas, consisting of few buildings or structures. In these cases, the maximum wind speed is analyzed using Degrees of Damage based on the percentage of mature trees snapped or uprooted described in (Sills et al., 2020), as the "Box method".

The Northern Tornadoes Project (NTP) was founded with the goal of capturing data on all tornadoes in Canada in order to improve severe weather climatology and prediction (Sills et al., 2020). Among other methods, NTP uses large-scale aerial photography captured by crewed aircraft or drones to collect data in inaccessible areas. Once captured, each event consists of hundreds of large-scale aerial photos ($1km^2$, 2.5-5cm pixel resolution), which are then manually analyzed through a Fujita-style analysis (Fujita and Smith, 1993), noting average treefall directions, as well as, through the Box method. However, this process is labour intensive, as it requires detecting and assessing the directions of thousands of trees. Moreover, there previously existed no fully automated method to perform this task on wide range of tornadic events.

More recently, vortex models in conjunction with a Fujita-style treefall direction vector field (Fujita and Smith, 1993) have been used to generate an accurate measure of the tornado's maximum wind speed (Rhee and Lombardo, 2018). This model could be utilized as an additional factor for determining EF scale ratings, provided the required treefall direction vector field has been produced. This precipitates the need for an automated method for producing the required treefall direction vector field, which is the objective of this study.

2. AUTOMATED MACHINE LEARNING MODEL

2.1. U-Net Tree Segmentation Model

Figure 1. 38.4x38.4m section of aerial image (left) and corresponding manually segmented mask (right)

The first step in the proposed method requires producing a machine learning image segmentation model to extract the tree pixels from the large-scale aerial images. A U-Net architecture (Ronneberger et al., 2015) with a ResNet encoder (He et al., 2016) was chosen, with an input/output image size of 256x256 pixels. U-Net was chosen due to its demonstrated image segmentation performance by (Ronneberger et al., 2015). In order to train this model, ten images with an average size of 200x200m from four different rural tornado events were manually segmented to produce segmentation masks, as shown in Fig. 1. Two of the ten images were set aside for validation, with eight being used for training. Next, each manually segmented image and its corresponding mask were split into 256x256 pixel images using grids with various offsets, followed by performing data augmentation techniques including rotating, flipping, and adjusting of hue. The final training dataset contained just under 100,000 256x256 pixel images and corresponding tree masks. Various models with different hyperparameters were trained using the training data set until validation loss converged.

2.2. Tree Instance Segmentation

After segmentation of the tree pixels, the next step is to perform instance segmentation so that individual trees can be distinguished, and their direction later assessed. First, the mask is pre-processed using the (Guo and Hall, 1992), thinning algorithm followed by applying a 3x3 dilation and mean blur kernel. This pre-processing stage is done to ensure the trees in the segmentation mask are of uniform thickness, and to facilitate ideal conditions for extraction of individual trees. Once pre-processed, the Fast Line Segment Detection algorithm (Gioi et al., 2010) is used to fit lines to the edges of the segmented tree pixels. Lastly, to obtain a single line over each tree rather than on each of the tree's edges, an algorithm was constructed to join pairs of lines based on the similarity of their orientations and proximity of endpoints. Fig. 2 shows an example result of the automatically produced segmentation mask and fitted tree lines.

Figure 2. 50x50m aerial image (left), automatically extracted mask (centre), segmented tree lines (right)

2.3. Resnet Tree Direction Model

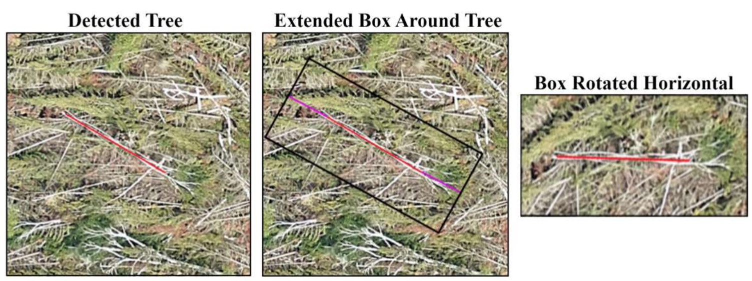

Figure 3. Diagram demonstrating extraction of horizontally rotated tree images

Following instance segmentation, a box is extended around each tree. Next, the fitted line's angle is calculated, and the box rotated horizontally to produce a 256x128 pixel image, as shown in Fig. 3. A dataset of 16,000 of these images was produced using the output of the tree segmentation model, with each tree's image being manually labelled as having fallen to the left, right or inconclusive (which notes either a false positive or the inability to assess the fall direction manually). Next, the dataset was randomly split in an 80/20 ratio for training/validation. Augmentation was performed, in a similar manner to the U-Net model, increasing the training datasets to 102,000 images. Various ResNet50-based image classifiers with different hyperparameters were trained on this dataset until validation loss converged. A ResNet-based model was chosen due to their image classification performance (He et al., 2016).

2.4. Production of Fujita-Style Treefall Direction Vector Field

Once the trees are segmented, each tree is fed through the tree direction model discussed in 2.3, and this result, along with the tree's original angle, is used to predict each tree's fall direction. After every tree's direction is predicted, the large-scale aerial images are split into a grid. The K-medoids clustering algorithm (Kaufman and Rousseeuw, 1990) is then used to cluster the tree directions in each grid square into one or two overall directions similar to a manual Fujita-style analysis. Grid square sizes can be manually defined by the user to best match the density of trees and event size. Fig. 4 shows an empirical test performed of manual vs automatically generated Fujita-style treefall direction vector fields for a section of the Brooks Lake, Ontario, tornado.

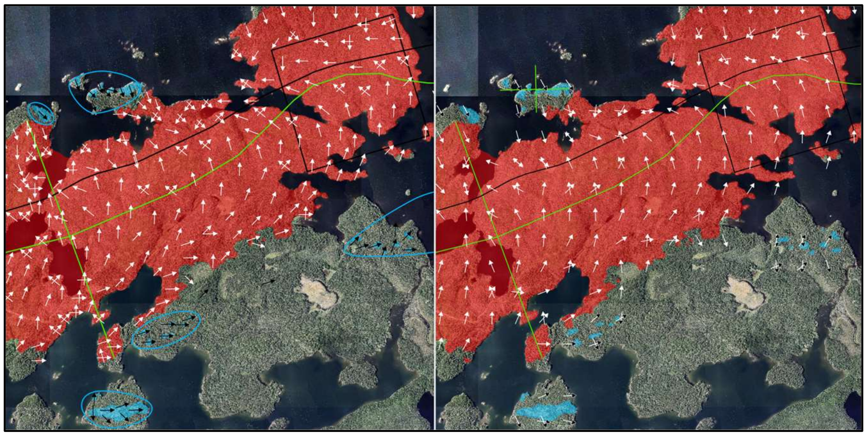

Figure 4. Manual (left) vs. automated (right), Fujita-style treefall direction fields, 4.25x4.25km, 250m grid size

3. CONCLUSION

Producing a Fujita-style treefall direction vector field for large tornadic events is labour intensive as it requires manually detecting and assessing the directions of thousands of trees. Using machine learning and image processing, an automated model was implemented. Further improvements are still being made, but initial testing as seen in Fig. 2/4, has demonstrated favorable results. Going forward, the model will be validated by comparing the vortex model's (Rhee and Lombardo, 2018) performance on both manual and automatic treefall direction vector fields. If successful, NTP will aim to incorporate this automated process during their analysis of Canadian tornadoes and assessment of rural tornado Enhanced Fujita scale ratings.

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