APPLICATION OF DEEP LEARNING IN COLORIZATION OF LIDAR – DERIVED INTENSITY IMAGES

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ABSTRACT: Most aerial LiDAR systems have accompanying aerial cameras in order to capture not only the terrain of the surveyed area, but also its true – color appearance. However, there are surveys wherein only LiDAR information is available. Usual causes of absence of aerial photographs are presence of atmospheric clouds during survey, poor lighting conditions are aerial camera problems. These leave areas having terrain information but lacking aerial photographs. Intensity images can be derived from LiDAR data but they are only grayscale images. A deep-learning model can be developed to create a complex function in a form of deep neural networks from the pixel values of LiDAR-derived intensity images and true-color images. This complex function can then be used to predict the true-color images of a certain area using intensity images from LiDAR. The predicted true-color images do not necessarily need to be accurate compared to the real world. They are only intended to look realistic so that they can be used as base maps.

1. INTRODUCTION

Aerial LiDAR surveys are commonly accompanied by aerial photography. However, there are instances where aerial photographs are not available due to absence of sufficient light source. Unlike LiDAR instruments, aerial cameras utilize passive remote sensing and need sunlight to capture good aerial photographs. Aerial surveys conducted at dawn or at night, presence of dense clouds or a broken aerial camera are the common causes of not having supplementary aerial photographs in a LiDAR survey. Some end users require aerial photographs along with LiDAR data for various applications such as feature extraction or visualization purposes. Without aerial photographs, such tasks won't be accomplished. Fortunately, grayscale intensity images derived from LiDAR point cloud data could be used as alternative to missing aerial photographs. Colorized versions of these intensity images are even more suitable replacement. However, colorizing grayscale images in general is not an easy task. Predicting pixel values across three (3) bands, red, green and blue, based on a single band input is complex.

2. RELATED LITERATURES

2.1 Intensity Images and Aerial Photographs

Intensity images can be derived from LiDAR point cloud data by obtaining the intensity values of each point. The intensity of each point is highly related to the surface reflectance of the portion of the terrestrial object it represents. According to (Kashani, et al, 2015), devices either known as photomultiplier tube, avalanche photodiode or other photodetector is used to convert the optical signal detected into an electrical signal. Various ranging methods are used to derive intensity values from the electric signals. Photodetectors present in commercial topographic LiDAR systems are used designed to have photocurrent linearly proportional to the operating range's input optical power (Shan and Toth, 2008). Intensity images are then produced based on intensity values of points by dividing the LiDAR point cloud with a planimetric grid and computing the intensity in each pixel usually through averaging.

2.2 Colorization

There could be several ways to produce a colored image based on a given grayscale image. This process could be done manually but could be tedious and slow if done for multiple and large images. Recent developments in computer vision allow automated techniques fulfilling this task. Examples are multimodal predictions approach (Charpiat, et al, 2008) are support vector regressions (Ho and Ramesh, 2014). However, a new trend in computer science which is deep learning, provides a more robust solution for tasks like colorization by training the computer to colorize grayscale images on its own.

2.3 Deep Learning

It is very common for a computer to be given step-by-step instructions in order to perform its tasks and provide desirable output. However, this limits the computer on just doing its task and not given opportunity to optimize it because the workflow and instructions are solely based on human decisions. This is called a knowledge-based approach. Recent developments in computer science give way to artificial intelligence.

3. METHODOLOGY

3.1 Preprocessing of inputs

Two (2) datasets are prepared for training the CNN. These are the intensity image dataset and aerial photograph dataset. The intensity image dataset is produced by uploading LiDAR point cloud data in the TerraScan software. The LiDAR point cloud data should be classified because even though classification has no direct effect on intensity values, they are still needed for filtering out points with 'low point' or 'low intensity' classification. If not filtered, these points could cause irregularities in the produced intensity image. Each intensity image produced by TerraScan covers an area of 1 km by 1 km with a resolution of 0.5 meters. Therefore, each image is composed of 2000 pixels by 2000 pixels.

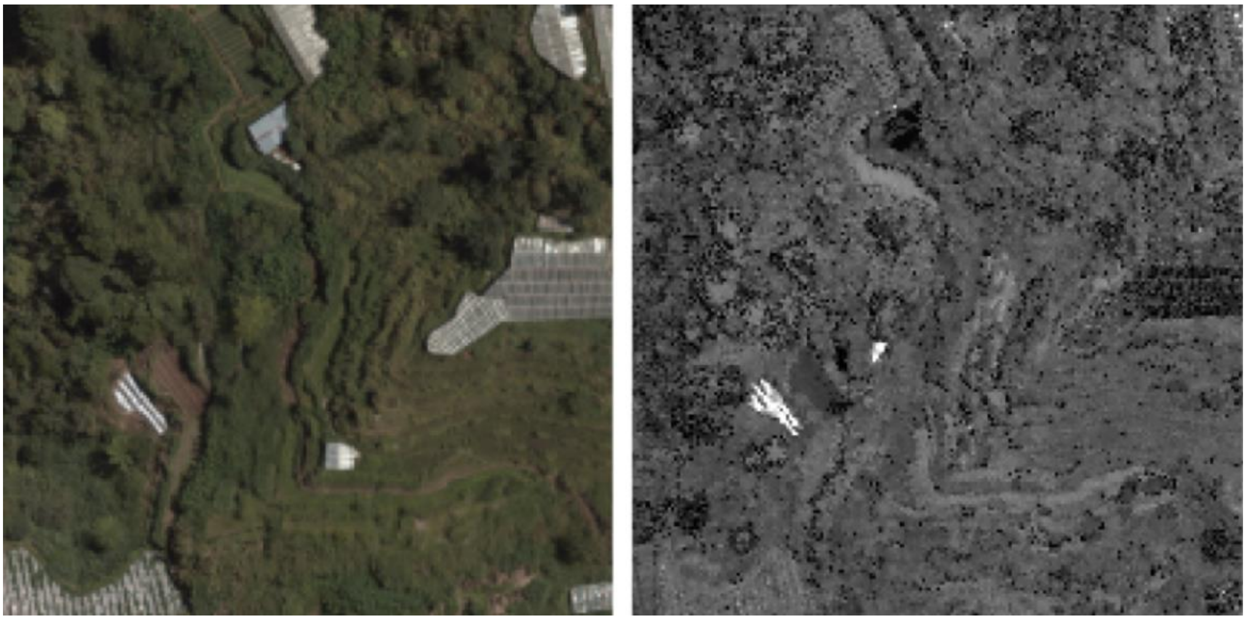

Figure 1 A 200 pixel by 200 pixel intensity image with its corresponding LiDAR - derived intensity image

The aerial photographs on the other hand are produced using the TerraPhoto software. These photographs have similar area coverage and resolution as the intensity image to simplify the training process. An image with 2000 pixels by 2000 pixels is a relatively large input compared to what is commonly used CNNs. Therefore, both the intensity image dataset and aerial photograph dataset were sliced into smaller tiles with 200 pixels by 200 pixels each. One hundred (100) smaller tiles are produced from every one large tile. Each intensity image tile has a corresponding aerial photograph tile with similar dimensions. However, there are instances where an intensity image tile and its corresponding aerial photograph tile do not have the exact same area coverage. Sometimes, the intensity image tile has complete coverage of the tile while the aerial photograph tile has portion with no data, or vice versa. This will cause errors in training the CNN because the CNN will assume that no data portions in either intensity image tile or aerial photograph tile are black in color. This will cause inconsistency in the training process. To prevent this, a Python script is created to detect if an intensity image tile and aerial photograph tile pair has a complete coverage. Only then they will be allowed to be used for training the CNN.

3.2 Neural Network

Aside from image classification, one of the common applications of CNNs are colorization of grayscale images. In these colorization CNNs, terrestrial photographs or images captured at ground level such as personal or landscape photographs are commonly used. Aerial photographs are not yet used to train colorization CNNs before. Using aerial photographs has both advantages and disadvantages for training colorization CNNs. It is expected that training CNNs using aerial photographs is easier since all images have similar orientation. Another advantage is aerial photographs are composed of fewer object classes like bare earth, vegetation, man-made structures and water. Terrestrial photographs on the other hand can capture too many kinds of objects which will complicate the training process. The problem with pairing aerial photographs to LiDAR-derived intensity images is that there are no direct correlation between the two (2) since most LiDAR instruments employ the infrared band while aerial photographs use visible light.

Existing algorithms that colorize grayscale images and applies deep learning in the process are available. The algorithm used in this script is based on the work of Cameron Fabbri and is available in GitHub (https://github.com/cameronfabbri/Colorful-Image-Colorization). The scripts use Tensorflow. The original training script uses only RGB images and then converts these images into grayscale to produce grayscale image and colored image pairs for training. For this research, the training script is modified to accommodate both the intensity image dataset and aerial photograph dataset. The CNN used has leaky ReLU (He, et al, 2015) as its activation function and Adam Optimizer as its optimization method.

4. RESULTS AND DISCUSSION

A colorized intensity image can be validated by comparing each of its pixel values to those of the corresponding aerial photograph. However, it is nearly impossible to colorize a grayscale image and will look exactly like its aerial photograph counterpart. A more logical way of validating the colorized intensity images is by applying a Turing test. In the context of grayscale image colorization, a colorized intensity image passes a Turing test if it can deceive the human observer that it is an aerial photograph, which it isn’t.

Various hyper-parameters are adjusted in order to produce a decent colorized intensity image. Unlike most CNN applications, fewer training images can be used as long the area covered by the intensity image to be colorized is spatially near and has a very similar environment to the area covered by the training images. Figure 2 shows the intensity image, aerial photograph and the colorized intensity image. The colorized intensity image is still saturated and lacks color variation. Perhaps, a more rigorous training process or a further pre-processing for both the inputs may be needed.

Figure 2 Intensity image, aerial photograph and the colorized intensity image.

5. CONCLUSION

Applying deep learning to produce colorized intensity images and replace missing aerial photographs is feasible. However, a more thorough research on deep learning is needed to conceive a specialized deep learning architecture designed to specifically colorize grayscale remotely-sensed images.

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