Automatic Colorization of Grayscale Aerial Imagery Using XGBoost Regression

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KEY WORDS: Grayscale Aerial Imagery, Colorization, Machine Learning, Statistics Variables, XGBoost Regression.

ABSTRACT: In this study, a machine learning technique is applied to automatically colorize grayscale aerial imagery. Grayscale aerial imagery and color aerial imagery of the same area in different time periods are used to extract unchanged areas by applying the PIF (Pseudo Invariant Feature) extraction technique. Color aerial imagery is composed of 3 channels of RGB and converts it into CIE Lab color space information. The training data set is constructed by the pixel values of the grayscale aerial imagery and the a and b values of the color aerial imagery for each pixel in the unchanged region. To improve color prediction, statistical variables of adjacent regions are utilized in addition to pixel values of grayscale aerial images. The pixel values of grayscale aerial images and five statistical variables (median, mean, maximum, minimum, and variance) are used and applied to the XGBoost (eXtreme Gradient Boosting) regression model. The results applied to grayscale images made from color aerial images and those applied to real grayscale images are compared and analyzed. The grayscale image produced showed excellent colorizing results, but the real grayscale image with noise was not good.

1. INTRODUCTION

Most of the past aerial images were taken in black and white, it is difficult to identify buildings and terrain, and time series grayscale aerial images are inconvenient to grasp land change information. Recently, there has been a lot of research on colorization of snapshots at home and abroad, but there is not much research on colorization of aerial images. There are two previous studies on colorization. Firstly, there is a study to restore the color of 5m resolution aerial images using Convolutional Neural Network (CNN) (Seo and Lee, 2017). This research has the disadvantage that it is impossible to express the color of the actual ground in high resolution grayscale aerial images. Second, there is a study on the colorization of 1m high-resolution aerial images (Seo et al., 2018) using GLCM feature information and random forest technique, which shows excellent color colorizing results in high-resolution aerial images, but also has the disadvantages of partially red noise.

2. COLORIZATION METHOD

2.1 Machine Learning

In this study, we propose a method of colorizing by applying machine learning. Colorization refers to the assignment of one-dimensional grayscale images to three-dimensional (RGB) pixel values. It is difficult to predict the three pixels values of the red, green, and blue bands only by the grayscale image pixel values. Therefore, most colorization preceding studies use RGB by converting it into CIE Lab color space. In the CIE Lab color space, L represents the brightness, a represents the color between Green and Red, and b represents the color between Blue and Yellow. Since grayscale images have a brightness L, they can be colored by predicting a and b colors. Since the color prediction cannot be made solely from the pixel values of grayscale aerial images, additional information is required for variables such as texture that correlate with pixel values (Seo et al., 2018). Therefore, the statistical value of the adjacent area for each pixel is utilized. The Statistical variables were selected as median, mean, maximum, minimum and variance. The algorithm to be applied to machine learning was selected as XGBoost regression model. The XGBoost regression model shows high performance on most datasets and is the model most used by competition winners in Kaggle, a predictive and analytical competition platform. XGBoost is an extreme gradient boosting algorithm that can automatically perform parallel calculations and is generally 10 times faster than Gradient Boosting (Chen, T. and Guestrin, C., 2016).

2.2 Colorization

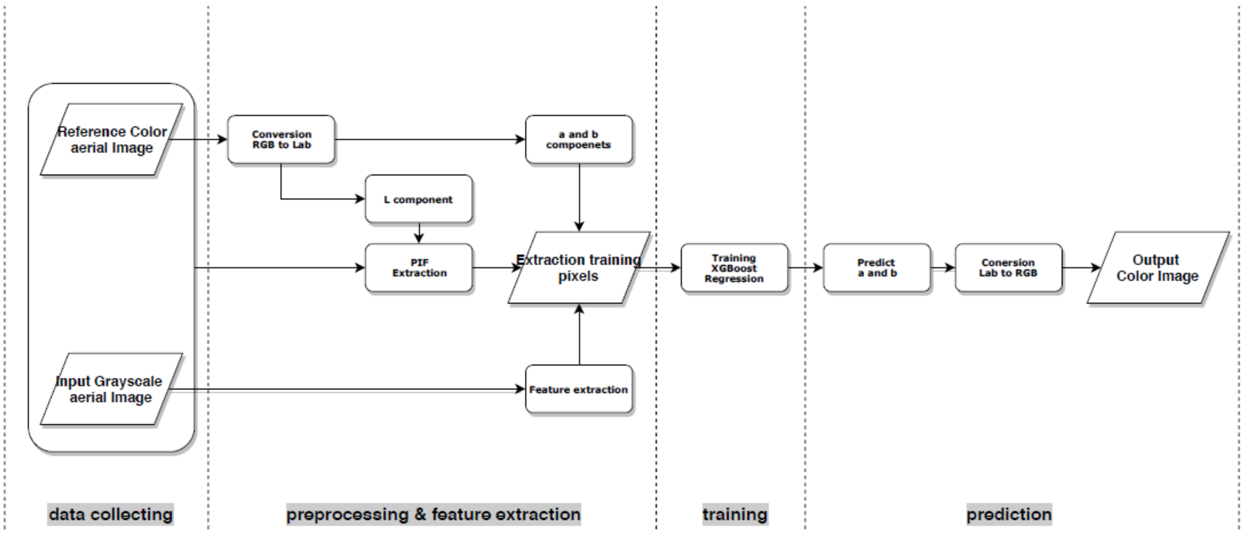


Figure 1. The Flowchar of Colorization

Figure 1 shows the colorization process for a grayscale aerial image. The color aerial image of the same region with different timing is converted from RGB to CIE Lab color space, and the grayscale image extracts feature values of selected variables. The change detection is performed by applying the PIF extraction method to the brightness value L of the color image and the grayscale image, and the unchanged region is extracted. Construct training data for unchanged regions and train the XGBoost regression model. Predict a and b by inputting a data set of all areas and then converted into RGB along with pixel values of a grayscale image. Finally, the performance evaluation indexes of the colored images are compared and analyzed.

2.3 Evaluation

The quantitative evaluation of the colorization results compared the PSNR values. PSNR (Peak Signal-to-Noise Ratio) is the maximum signal-to-noise ratio and represents the power of the noise to the maximum power that a signal can have. It is mainly used to evaluate image quality loss information in image or video loss compression, as shown in Eq. (1):

$$PSNR = 10 \cdot log\left(\frac{3mn\,(MAX)^2}{\sum RGB \sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[u(i,j)-u_0(i,j)]^2}\right) \qquad (1)$$

Where MAX is the maximum pixel value of the image (i.e., 255 on an 8-bit image) and ∑RGB represents the sum of the red, green and blue bands (Seo et al., 2018). The unit is db, and the smaller the loss, the higher the value.

3. EXPERIMENT AND RESULTS

3.1 Study region and data

The experimental area was selected around Seoul Children's Grand Park in Gwangjin-gu, Seoul. The experimental images were provided through the Seoul Aerial Images Service for academic research. As shown in Figure 2, the three images used 1m high-resolution aerial images of the same region and at different times and the pixel size of images was 1200 x 1200. Figure 2 (a) is a real grayscale aerial image taken on May 3, 2006. Past grayscale aerial images are taken by analog cameras and then scanned and stored, so they contain a lot of noise compared to recent aerial images. Figure 2 (b) shows grayscale image made from a color aerial image on June 10, 2013. The equation used to convert from RGB to gray is shown in Equation (2).

$$grayscale = 0.21 * R + 0.72 * G + 0.07 * B \qquad (2)$$

Where R is the pixel value of the Red band, G is the pixel value of the Greed band, and B is the pixel value of the Blue band. Figure 2 (c) is a reference image for colorization, consisting of RGB three bands, taken on June 2, 2016. Looking at the three images, you can see changes in the building over time.

(a) (b) (c)

Figure 2. Experiment images

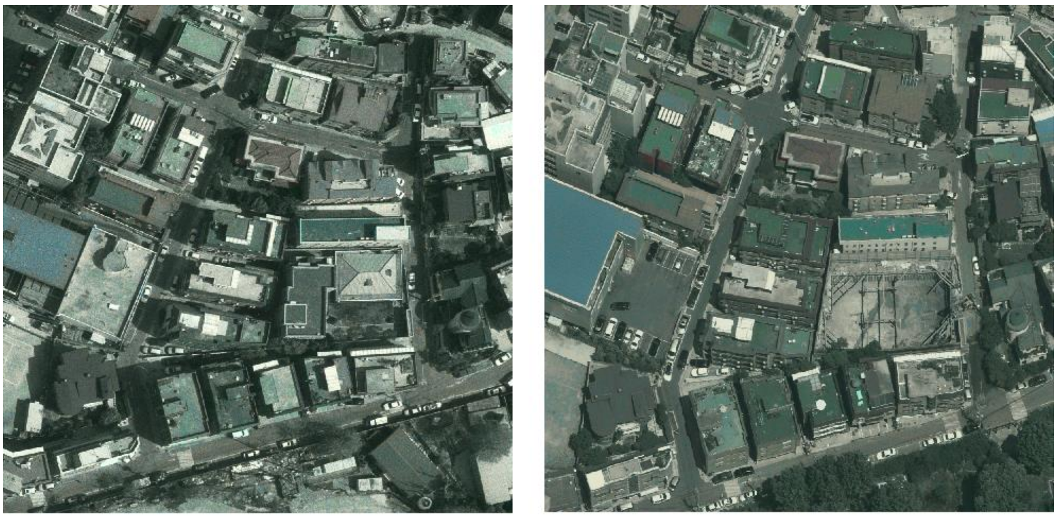
3.2 Experiment

The experimental environment for learning was shown in Table 1. According to the process of colorization in Figure 1, the training data of the unchanged regions were composed, trained on the XGBoost regression model, and color prediction was performed. The execution time was taken an average of 7 minutes per image.

Table 1. Experimental Environment.

Operating System	Windows 10
CPU	Intel core i7-7700 CPU @ 3.60GHz
RAM	16GB
Language	Python 3.7
Toolkit	XGBoost, Scikit-learn, Sicik-image

Figure 3(a) is the result of colorization of the real grayscale image of Figure 2(a) and Figure 3(b) is the result of colorization of the grayscale image made from color image of Figure 2(b). Visual analysis shows better results in grayscale images produced than real grayscale images. The colorization results of the grayscale image produced show better results than the research of the existing Seo's method. Red noise occurs less and can be seen naturally colored like the color of a real building. In real grayscale images, however, the noise from the original image was reflected and painted darkly, and the results were not as good as the grayscale image produced. For quantitative evaluation, the calculation of PSNR by viewing 2(c) colored aerial images as ground truth shows that 3(a) is 12.44 and 3(b) is 15.48. We can see that the result of colorizing the grayscale image produced both visually and quantitatively is better.



(a) (b)

Figure 3. Colorization Results

3.3 Results

In this study, we propose a machine learning method using XGBoost regression model for automatic colorization of grayscale aerial images. As input image, we applied to real grayscale aerial image and grayscale aerial image made from color aerial image. The grayscale images produced showed less noise in red color than the previous studies and showed natural coloring results with colors like those of actual buildings. However, the real grayscale images did not produce good color results, as the original images contained a lot of noise, which was darkly colored. Compared to the previous study using GLCM variables, the use of statistical variables reduced the execution time and the use of XGBoost regression model produced less red noise. This study has the advantage of automatically colorizing grayscale aerial images without requiring high-performance PC specifications. In the future studies, various preprocessing will be performed such as removing noise from the grayscale image and performing colorization, or converting the reference color image to grayscale, matching histogram to the real grayscale aerial image, and colorizing it.

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ACKNOWLEDGEMENT

“This research was supported by Basic Science Research Program through the National Research Foundation of Korea(NRF) funded by the Ministry of Education (No.2016R1D1A1B03933562)”