ASSESSMENT OF THE RWANDA RURAL ROAD NETWORK DEVELOPMENT USING PAN-SHARPENED LANDSAT 8 DATA

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ABSTRACT

In many low-income economies such as Rwanda development of the rural road network is ongoing. Rapid and frequent surveys of the road network development are needed to keep maps up-to-date and to monitor the potential impacts of road development on agricultural practices and production and other economic development. Crowd-sourced data can be one option, but there are no guarantees that the network will be mapped accurately with timely updates. Fine resolution commercial satellite imagery is another option, but expense and relatively small field of view can limit its timely application on a larger scale. To overcome these limitations we demonstrate a method to combine free medium resolution images such as obtained with Landsat 8 or Sentinel 2 together with ©OpenStreetMap data to rapidly identify new road construction and update the rural road network in Rwanda using an SVM classifier. We demonstrate the method and assess its accuracy using reference data (vector GPS data) collected by the Rwanda Feeder Roads Development Project at three sites in the Southern Province of Rwanda.

INTRODUCTION

Rwanda is a small Central African country (2° S, 30° E), which is developing at a high rate with strong emphasis on reaching the Sustainable Development Goals that grew out of the Millennium Development Goals (UNDP 2016). The Government of Rwanda is implementing its second Economic Development and Poverty Reduction Strategies (EDPRS II) as a roadmap to achieving the goals. The rapid development of Rwanda requires new infrastructure development such as energy sources and rural roads rehabilitation, upgrading, and maintenance as one priority within the strategy (MINECOFIN 2013). The Rwanda Feeder Road Development Project and the Rwanda Transport Development Agency (RDTA) expect to upgrade all season road connectivity to agricultural market centres in selected areas. The reason is that the network can highly contribute to the rural region development. In order to be aware of any change, the digitization of high-resolution satellite imagery and site visit are currently used in Rwanda; with this method however, there are no sureties that the system can be mapped precisely with opportune upgrades. Moreover, it takes a long time to be successful and too costly. Alternatively, it is better to carry out fast and successive overviews of the road system advancement to stay up with the latest. In line, different strategies were recently developed to carry out quick and frequent surveys of road network development. The most of these available methods extract the road network segment from high resolution remotely sensed data by line detection technique and the fewest ones starts with an image segmentation followed by fuzzy classification and then road centre line detection. Wiedemann et al. (1998) suggest an automated
extraction and evaluation of road network from high-resolution imagery method. The extraction technique uses a differential geometry approach in row with building a weighted, planar graph from the line and then the real road network is obtained based on topological criteria. Zhang and Couloigner (2006) proposed an automated method to segregate the road network from high resolution multispectral imagery, which starts with an image segmentation, and road class is automatically highlighted with a fuzzy classifier relies on a collection of given membership functions for road surface and the related normalized digital values in multi-spectral band. Florence et al. (1998) argued that a linear feature (road) can be extracted from high-resolution imagery with knowledge of parameters by fusing results from two distinct line detectors; but result in insufficient output in mountain area and reasonable result in flat area. Including the roads statistics information, road network extraction from high-resolution image can be enhanced (Gianni, et al. 2006). In addition, some methods try to combine different methods to develop a powerful automatic network extraction method. For example, Karin et al. (2010) modelled the road network from high-resolution imagery by combining the two line extractors; and the condition to select these algorithms is that one can be good to rural Scenes and other to urban areas. Thus, the road network is gained by the feature fusion. Moreover, fine resolution imagery is another alternative, but the cloud cover and accessibility of expert investigation can make this a costly choice. Yandong and John (2000) argued a method that maps road network from low-resolution imagery with hierarchical gathering technique. This method mostly rely on line operator to extractor lines from the original image with spatial resolution of 11.25 m, and eliminates false road segments based on the information about network.

This paper focuses on assessment of the Rwanda Feeder Road Development Project using pan-sharpened Landsat 8 data demonstrating that data acquired using this satellite are sufficient for consultancy in Rwanda. We propose a strategy to consolidate spatio-temporal free medium resolution imagery (data collected with Landsat 8) together with ©OpenStreetMap data (one of free crowd-sourced data that provides road structural information) to rapidly distinguish a new change and upgrade of provincial rural roads in Rwanda using a Support Vector Machine (SVM) classifier. Using both structural and radiometric information, the method presented in this paper includes smoothness (texture), greenness of surrounding vegetation, and tries to fill gaps due to occlusion and aliasing effects by post processing technique given that road is long, continuous line.

**METHODOLOGY**

**Data Acquisition**

The Landsat 8 satellite pictures the whole Earth at regular intervals of 16 days in an 8-day offset from Landsat 7 and the gathered data can be accessible to download at no charge from GloVis, EarthExplorer, or by means of the LandsatLook Viewer inside 24 hours of gathering (usgs.gov, 2015). The temporal data collected with Landsat 8 commercial satellite gives a vital insight about Rwanda land cover and use in mapping the Rwanda District Rural Road network development. Compared to Landsat 7, Landsat 8 has an improved signal-noise ratio and radiometric performance quantized over 12-bit dynamic range or 4096 potential grey levels in image compared with 256 grey levels in previous 8-bit grey levels. For better Rwanda Rural Road mapping, we can estimate the Earth’s surface reflectance information. We used optionally surface reflectance ordered through http://espa.cr.usgs.gov/ordering; we did not perform any further processing other than pan-sharpening. Along with the images collected on 13/07/2013, 01/08/2014, and 19/07/2015, we included ©OpenStreetMap to effectively enhance the road network extraction. ©OpenStreetMap is
a representation of whole world made by crowd-sourcing and allowed use is generally open (©OpenStreetMap project, 2016). Since this paper targets rural road segment extraction, nothing other than a road class is needed as an output. The testing sites (Cyanika, Maraba, and Rusatira sectors) lie in Huye District, Southern Province in Rwanda. The study area shown in Figure 1 is roughly bounded by 2°27’29.6" S  29°40’19.9" E (upper left) and 2°28’10.0" S  29°41’22.7" E (lower right).

![Figure 1](image_url)

**Figure 1**  Three dates of Landsat 8 images of the study site before, during, and after rural road construction. Left, 13/07/2013; Middle, 01/08/2014; Right, 19/07/2015.

**Work Flow**

This research is proposing a novel strategy (Figure 2) to rapidly and subsequently assess the Rwanda Rural Road network development. It relies on extraction of road network from temporal data acquired with Landsat 8 (Figure 1). The method starts with data fusion and generation of relevant bands for impervious features extraction. For example, band six and seven contain more Rural Road objects details than the remaining bands. Most unpaved features (Rural Road in this case) can have meaningful variability in intensity due to their high spatial frequency. So, a combination of several generated bands and object texture information can critically help to exploit the spectral information for the network extraction. This method rejects some bands based on road object information they hold. The thermal bands were excluded in the analysis because they have almost zero road object information due to their lower spatial resolution (100m resampled to 30m), and band 1, 5 due to less information content about road object. SVM classifier was used to create a binary image and then ©OpenStreetMap data applied to extract the network segment by eliminating non-target pixels. The method closed with post processing to fill the line breaks/gaps based on road is a long, continuous line.

**Image Fusion/Pan-Sharpening:** Data pre-processing can be an important task the data analysts may start with when they are exploiting the remotely sensed data. This task mostly aims to effectively enhance the data quality in either visual or machine point of view. In other words, whenever data pre-processing task is clearly carried out the features within data, in an image for example, will be much better delineated and any data analysis technique will produce more accurate results. This section is introducing one of an image pre-processing technique so called an image fusion. Sascha and Ehlers (2007) defined image fusion as a mechanism of consolidating the appropriate information from high spatial resolution panchromatic (pan) image and high spectral
resolution multi-spectral image to create a high spatial and spectral resolution multi-spectral image. Several image pan-sharpening methods were recently developed, but not all try to give an optimal output. Sascha and Manfred (2009) evaluated a number of pan-sharpening methods. Based on number of bands restriction, spectral information preservation, spatial improvement, computation complexity, and sensitivity to the area to be sharpened, CN spectral sharpening was the method chosen here. Since the data quality enhancement in both spectral and spatial information is the main goal of this section, we use CN spectral sharpening method to combine spatial data from pan image and spectral information from multi-spectral image collected with Landsat 8 satellite. This sharpening method starts with clustering the input image bands into spectral segment identified by the spectral range of the pan-band image and then band segments are treated together. Equation 1 summarizes all image fusion with this technique:

\[
h_i = \frac{i \times \text{pan} \times s}{\sum_j s_i \times s}
\]  

(1)

Where \( h_i \) stands for the CN sharpened band \( i \); \( i \) for the input band \( i \); \( \text{pan} \) for panchromatic band; \( s \) for the number of bands in the segment; and \( s_i \) for input band \( s \) in the segment. The improvement in spatial data quality at this stage is sufficient to warrant further analysis to extract road pixels. We therefore need a mathematical tool that will assist in successfully extraction of roads segment. In this case we can use a binary classifier since we are interested in extracting a single class. Here we choose to use a Support Vector Machine as an accurate and appropriate approach given the requirements for our goal. This algorithm is briefly described in the following section.

**Support Vector Machine (SVM) Classifier:** Today many mathematical algorithms are available for land cover and land use analysis. Some of these algorithms strongly require the user intervention to carry out the task, Support vector machine, maximum likelihood, and so on for example, and others do not considerably rely on the user interventions, IsoData and K-means. The performance of all these algorithms can be measured by their overall accuracy, and Kappa coefficient, which are generated while comparing the classification result with the ground truth information. (Abbas et al., 2015) and (Congcong et al., 2014) assess these techniques with the two key parameters (overall accuracy and kappa coefficient) and they have shown that support vector machine algorithm can
SVM performs well in higher dimensional spaces and lack of training data is often not severe problem based on minimizing an approximate of test error as opposed to the training error, robust with noise data, and does not suffer as much from the curse of dimensionality and prevents over fitting. The details of our approach are described more fully in Durgesh and Lekha (2010) but the most important points are summarized here. Briefly, a linear SVM supposes that a collection of N points are linearly separable and the SVM algorithm clusters the points into two classes with a separating hyper-plane putting the largest possible amounts of points of the same group on the same side of the hyper-plane. In our case this is a binary separation and the goal is road pixels on one side and all other classes on the other side of the hyper-plane. The optimal hyper-plane has to maximize a distance from the hyper-plane to a nearest point of either class, which is a so called “hard margin”. Since class data distribution for Landsat 8 data may not be linearly separable, a linear SVM was modified to handle misclassification by introducing a variable to measure the misclassification and a Kernel function to perform a transformation from a non-separable space to high dimensional separable space. The kernel function chosen here is the radial basis function. This SVM binary classification technique was applied to the multi-temporal data collected with Landsat 8 satellite to extract the road pixels.

RESULTS AND DISCUSSION

We carried out assessment of road construction and improvement under the Rwanda Feeder Road Development Project with pan-sharpened multi-temporal data. The chosen time series of images provides snapshots of the progress of road construction. Beginning with Figure 3, the method identifies few road pixels at the study site. The detected pixels, shown in red, represent the rural road class. In this case, our method detects few rural roads in the selected area before 13/07/2013 and most transportation would be by foot or bicycle. A year later (01/08/2014), Figure 4 shows the classification result identifies a significant increase in the density of detected pixels corresponding to rural roads object and meaningful road lines start to appear on the image. We can conclude a certain number of roads were under construction process before 01/08/2014.

Figure 5 shows the state of rural road development at the study site on 19/07/2015. The rural road object shown in red was clearly segregated from surrounding. New roads were constructed since 2014. For example, the road at the top left corner did not exist before, but a road detection is made. Overall, the road network construction and improvement is near completion by 19/07/2015.

While our detection process uses image data, for many applications vector road data is sufficient and even preferable for ingesting into a GIS, for example. To represent the roads with a more continuous line to be overlaid on a base map, we can close some of the gaps in the road apparent in Figure 5. These gaps in our classification may arise from a variety of circumstances such as aliasing and occlusion by trees. Morphological processing provided some filling of short gaps in the road. Outliers are eliminated outside a buffer zone provided by ©OpenStreetMap. We then converted the result into a vector object (see Figure 6, red lines).

We finally compared the result in 2015 with exact data from RTDA. We still presented our findings in red and data from RTDA in blue (Figure 6). By comparison, the method output and the RTDA approximately match each other. Therefore, the proposed method successfully extracts the road network from pan-sharpened images collected with Landsat 8.
Figure 3  Raster image result of the binary SVM road detection algorithm when applied to the 12/07/2013 image. Detected road pixels are red, all other classes are grey. This date is prior to commencement of the rural road improvement activity.

Figure 4  Raster image result of the binary SVM road detection algorithm when applied to the 01/08/2014 image. Detected road pixels are red, all other classes are grey. This date is after commencement of the rural road improvement activity.

The Rwanda Feeder Road Development Project was initiated to overcome difficulty in transportation of agricultural goods to market, and hence its focus on rural road construction and rehabilitation. For example, transportation was difficult in Simbi, Mbazi, and sections of Cyanika, Maraba, and Rusatira Sectors due to the Roads absence in the area before 13/07/2013 and became better later because of development of Road network. In line with this goal, the proposed method mapped accurately the road network with data collected with Landsat 8. By conclusion, the pan-
sharpened Landsat 8 data are sufficient to map Rwanda rural road network and it can be recommended for consultancy in Rwanda.

Figure 5  Raster image result of the binary SVM road detection algorithm when applied to the 19/07/2015 image. Detected road pixels are red, all other classes are grey. This date is after completion of the primary rural road improvement activity.

Figure 6  Comparison of the vector road network (red lines) extracted from the 19/07/2015 image (Figure 5) to GPS-based road vector data (blue lines) supplied by RDTA.

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REFERENCES


