IDENTIFICATION OF MODE CHOICE USING MOBILE CALL DETAIL RECORDS

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ABSTRACT: Rapid urbanization and modernization are increasing around the world including Myanmar. Mobile phone call detail records (CDRs) provide new opportunities to measure the origin-destination trips, travel distance, travel duration and origin-destination matrix, which are essential for urban planning and transport management. The purpose of this research is to identify transportation modes using one-week mobile CDRs provided by Myanma Posts and Telecommunications (MPT). In this research, daily origin-destination trips have been generated to detect various transportation modes such as public transit, private car, taxi and walk based on their travel speeds. Travel speeds of each mode were predefined based on Global Positioning System (GPS) probe data from ground truth data collection. When the speed is within the predefined range, the traveler is using a specific transportation mode. These mode shares using CDRs data were validated by person trip survey of Yangon Urban Transport Plan of the Greater Yangon (YUTRA). These data are very helpful in the prediction of passenger demand for transport services. We hope that this study will help to improve Yangon City traffic planning and public facility management.

1. INTRODUCTION

Travel surveys are one of the most important instruments to establish a complete understanding of the travel patterns within the study area. Evaluating the impact of travel patterns on the environment depends on knowing how large populations move about in their daily lives and which modes of transportation are being used. Cities in developing countries struggle to forecast the passenger demand for transport services in the absence of travel survey and census data. Mobile call detail records generate the new opportunities to measure the demand, problems and planning for the future in transport sectors. Therefore, CDRs data were used in the identification of mode choice because of its huge volume, wide coverage, real-time production, automated collection, and low cost. Due to the expensive roadside surveys and infrequent data collection of census data, CDRs data have become a powerful tool to analyze travel behavior patterns and are useful for transportation planning. A call detail records (CDRs) is a data record produced by a telephone exchange or other telecommunications equipment that documents the details of a telephone call or other telecommunications transaction (e.g., text message) that passes through that facility or device (Wikipedia). Cell phone usage of each region can be used to generate trip numbers of traffic analysis zone within the certain time frame and time windows. The objective of this study is to identify mode choice using mobile call detail records.

The structure of this paper is organized as follows: related relevant study backgrounds are presented in Section 2. Section 3 states why the study area is selected as a case study. Section 4 briefly describes data to be used in this study and how to extract origin-destination pair and various transportation modes. Mode shares of the study area are discussed in Section 5. Finally, conclusions and future works are presented in Section 6.

2. RELEVANT STUDY BACKGROUND

The number of researchers studied the various topics of mode choice using mobile call detail records. The mobility patterns of mobile phones are intrinsically linked to human travel behavior. It can be used to reveal some of the space-time behavior patterns relating to human mobility (Gonz’alez et al. 2008, Song et al. 2010), social structure (Onnela et al. 2007) and land use (Reades et al. 2007). Rose, 2006 applied data on the use of mobile phones as traffic probes, noting several issues and opportunities in the extraction of transport-related information. Caceres et al. 2008 reviewed traffic data estimations using a variety of metrics extracted from mobile phone networks. The development of origin-destination matrices for traffic flow estimates, travel speed, travel time calculations, and traffic volumes were also presented. J. Doyle et al. 2011 constructed and analyzed the journey specific trajectories using the concept of virtual cell path for each qualified pre-processed list of activities from each unique user. After classification, kernel density paths for each route were generated both for illustration and validation purposes. They provided the means to infer transportation modes or major routes taken by mobile telephone users between regions of interest via their anonymized billing records. By focusing on the likelihood, a user travelling along a spatial transportation route, given their recorded travel path through the mobile phone network, users with similar travel times but different travel modes can readily be segregated. H. Ishizuka et al. 2015 proposed an automated method to generate an alignment of cell
towers for a specific transportation route using unsupervised machine learning techniques. They focused on distinguishing different types of motorized transport such as train, bus, and subway. Their proposed system can estimate a specific name of transport line which a user rode on by sequence matching between cell tower sequences of a user and pre-learned cell tower sequences for each route. Wang et al. 2010 examined transportation mode inference from mobile billing records based on travel time. In this study, modes of transportation are identified using mobile call detail records based on predefined travel speed from ground truth survey.

3. STUDY AREA: YANGON

There are 45 townships in Yangon Region which are classified as central business distinct (CBD), inner city, outer city, old suburbs, new suburbs, and periphery Area. Among all of these townships, thirty-three townships (CBD, inner city, outer city, old suburbs, and new suburbs) have selected as the study area. Yangon has an area of 598.750 km$^2$ with a population of 5.211 millions in 33 Townships of the urban area and has played a key role as the transport intersection of the mainland in Myanmar, connecting the regional and international. Yangon is not only the former capital city but also the heart of the commercial center of Myanmar. Many people are also migrating from rural areas to the city for their better lives and income by the attraction of the city. The current urbanization and motorization become worse and worse day by day on the existing transport infrastructure in Yangon city. In order to provide good transportation planning, it is necessary to understand the modal shares of Yangon City. Therefore, the urban area of Yangon was selected as a case study. The location of the study area based on districts is shown in Figure 1.

![Map of Yangon City](image)

**Figure 1. Location of the Study Area**

4. METHODOLOGY

4.1 Data

Two types of datasets: Call Detail Records (CDRs) data and GPS data were used in this analysis. CDRs data were used for estimation of origin-destination trips and GPS data were used for predefining of travel speeds for each mode.

4.1.1 CDRs Data

The CDR data containing all mobile phone voice calls and other means such as short message service (SMS) and internet were collected from base transceiver stations (BTS) towers which are located in the study area from 1$^{st}$ December 2015 to 7$^{th}$ December 2015. It was provided by Myanmar Posts and Telecommunications (MPT) which is one of the biggest mobile operators in Myanmar. There are 657 BTS towers of MPT services with about 57 dead BTS towers in 33 townships of Yangon. The dataset of the studied period contains around 2 million anonymous mobile phone users per day. Both voice calls and data were used for the analysis of origin-destination of the study area.
Individual phone numbers were anonymized by the operator before leaving their storage facilities and were identified with a security ID (hash code) to safeguard personal privacy. CDRs contain Timestamp (date and time), Caller’s ID, Call duration in second and Caller’s connected cell tower ID.

4.1.2 GPS Data

This paper also used the GPS data of taxi, car, and bus to predefine the speed of the vehicle. The GPS data of Hello Cab taxis and traditional taxis were used to predefine speed of taxis. In this study, we used one-month GPS trajectory data acquired in June 2017 provided by Hello Cab taxi company in Yangon. The data of “on demand taxi” included twenty-four days from 6th June to 29th June, 2017. From these GPS data, 6680 taxis were recorded and 21582 trips of occupied trips and 24223 trips of vacant trips were used as the dataset for analysis. The travel speed varied according to the different time period in a day. The data consists of latitude, longitude, taxi ID, direction, speed of the vehicle, track time, status and location. Most of “traditional taxis” in case of study area are have not installed GPS devices yet. But smart phones with GPS system on taxis were used to monitor the operation of each taxi for disaster management from Science and Technology Research Partnership for Sustainable Development (SATREPS) Project. The GPS data of traditional taxi were collected for the duration of 31 days from 19th March 2017 to 11th July 2017 during 7:00 AM to 6:00 PM. The dataset of taxi trips has complete information of 3027 trips made during study time, including temporal and spatial information acquired by GPS such as id, user, GPS date and time, longitude, latitude, accuracy, speed, and bearing are automatically collected approximately every 5 seconds (Mo, 2018).

Moreover, the speed of passenger cars along major roads of the study area was recorded with GPS (Linn, 2018). In this study, we also used one-month GPS trajectory data acquired in December 2017 provided by bus company limited of Yangon Bus Service (YBS). Bus GPS trajectory data include position of bus location recorded in every 30 seconds plus bearing and speed information.

4.1.3 Other Data

Walking speeds were collected along the sidewalk in some areas of the study area. In addition, secondary data such as road network map was also used to analyze travel distance.

4.2 Methods

In this paper, various transportation modes were identified using mobile call detail records. Overview of research flow for this analysis is shown in Figure 2.

4.2.1 Determining Trip

For each mobile user, it is assumed that a trip is made between two consecutive calls occurring within a study period with different BTS. The number of trips (flows) can be defined as the movement of people who travel from the starting point in the origin region and ending in the destination region. Traffic Analysis Zones (TAZs) were considered as origin and destination.

4.2.2 Preprocessing of CDRs Data

Firstly, preprocessing of CDRs data was done to extract O-D pairs. In preprocessing steps, CDRs data were clean to correct wrong coordinates and township name. And, all missing data were removed and numbers were formatted to string. Geographic locations (Longitude, Latitude) were added to each cell IDs after formatting. CDRs data alone could not know the location of a person because it is only CELLLID with the mobile subscriber. Therefore, the geolocation of CELLLID needs to join with latitude and longitude to trace the location. It is possible to trace the location of people when they make trips through mobile phone data because this data set includes latitude and longitude of each BTS tower. Both formatted voice and data usage were merged by individual subscribers. From these CDRs data, PID, DTIME, and CELLLID data were only used in this analysis. Therefore, required fields were filtered from big data by SQL queries using BigGIS RTX Research Toolbox (Lwin et al. 2018). These data were extracted by TAZs because TAZs are considered as origin and destination datasets to extract O-D pairs, travel distance and travel time. Traffic analysis zones of the study area were extracted and ordered by PID and DTIME for O-D pairs creations.

4.2.3 Processing of CDRs Data

O-D pairs were extracted for three hours interval such as 06-09, 09-12, 12-15, 15-18, 18-21 for only Tuesday for typical weekdays and Sunday for the weekend. Only two days data from one-week data were analyzed because of travel distance analysis is much more time-consuming. Morning peak period (06-09) and evening peak period (15-
18) intervals for weekdays and weekend datasets were analyzed for this study. And, travel distance, duration and travel speed were calculated for each O-D pair with the road network.

Figure 2. Overview of Research Flow
Source: (Lwin et al. 2018)

4.2.4 Predefining of Travel Speed and Identifying of Mode Choice

In this analysis, mode choices were identified based on predefined travel speed. Driving car, public transit, and walking are considered as available transportation modes. Therefore, the travel speed of driving a car, public transit and walking are predefined from car, bus and taxi GPS probe data, and walking speed survey of ground truth data. Figure 3 and 4 show sample travel speed distribution of Hello Cab taxi.

According to these GPS data and walking speed data collection, travel speed of 4 kph (1.14 m/s) is walking, that greater than 4 kph and that less than equal 20 kph is a bus driving in weekday and 25 kph in the weekend. And, travel speed greater than 20 kph in weekday and 25 kph in the weekend is driving the car as predefined in the transportation modes. The number of trips and number of travelers for each speed group were extracted using SQL queries from BigGIS RTX Research Toolbox (Lwin et al. 2018). The outliers of travel speed were removed before determination of mode shares of the study area. After that, various transportation modes were identified based on predefined travel speed. Finally, modal shares were calculated and these results were validated by YUTRA-JICA person trip survey data.
5. RESULTS AND DISCUSSIONS

5.1 Identification of Mode Choice Based on CDRs Data

After preprocessing and processing of CDRs data, O-D pairs were extracted and travel distance was calculated using the study area’s road network. The travel speed of each trip was determined to identify various transportation modes. Each speed group and the number of travelers/number of trips were extracted using SQL queries. The following Figures 5 and 6 show travel speed distribution during the interval of 06:00-09:00 and 15:00-18:00 on weekdays and weekend respectively.

Figure 3. Sample Travel Speed Distribution of Hello Cab Taxi during Morning Peak Period (09:00) in Weekday

Figure 4. Hourly Travel Speed of Hello Cab Taxi
Source: SATREPS Project

Figure 5. Travel Speed Distribution during Morning and Evening (Weekday)
Outlier of travel speeds were removed before identifying transportation modes. All records with the travel speed of less than 4 kph were removed since it is the rare case for a traveler to walk less than 3 kph. And, all records with the travel speed are greater than 85 kph were also removed since it is the outlier of travel speed. Speed distribution after reduction in weekday and weekend are shown in Figure 7 and 8.

From Figure 7, it can be identified as 4.78 % of travelers are making in their trip by walking, 46.48 % are using public transit and 19.46 % are driving car in weekday. On weekend, it is found that 4.67 %, 47.06 % and 15.58 % of travelers are using in their trips by walking, public transit and driving car respectively.
5.2 Validation by JICA Person Trip Survey (YUTRA, 2014)

After identifying mode choice using CDRs data, these results were validated by YUTRA-JICA person trip survey (Takashi Shoyama, 2014). Comparison of mode shares are shown in the following Table 1.

<table>
<thead>
<tr>
<th>Day</th>
<th>Mode Shares Based on CDRs Data (2015)</th>
<th>Mode Shares (YUTRA Survey, 2014)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Walking (%)</td>
<td>Public Transit (%)</td>
</tr>
<tr>
<td>Weekday</td>
<td>4.78</td>
<td>46.48</td>
</tr>
<tr>
<td>Weekend</td>
<td>4.67</td>
<td>47.06</td>
</tr>
</tbody>
</table>

From this report, 50.50% and 15.80% of the trips are made using public transit and car/van/taxi in the study area. Identifying of mode shares using CDRs data are 47.06% and 19.46% for public transit and car/van/taxi. Comparison between two data sources are very close and small difference could be explained by limitations of CDRs data.

5.3 Limitations of CDRs Data

Some limitations of CDRs data were used in this study. While CDRs data were used in this research, it in tracing location, O-D (Origin-Destination) trips are based on call activities. Therefore, although people are moving from one place to another place, this trip cannot account for a trip if he/she does not use the mobile phone in this analysis. Routes were estimated based on the shortest-path analysis. Travel distances were measured based on this analysis, and also speeds were calculated using these distances. Positions may also change slightly due to load balancing. This study can be analyzed with CDRs data from only MPT is available although there are three telecommunications in Myanmar such as Ooredoo, Telenor and MPT services due to difficulties in data acquisition of privacy issues.

6. CONCLUSIONS

This paper identified mode choice based on travel speed using mobile call detail records and validated with JICA person trip survey. When the speed is within the predefined range, the traveler is using a specific transportation mode. The small difference can be seen between mode shares using CDRs data and those of YUTRA-JICA person trip survey. This method can be easily applied for the large population of the large-scale area such as
country/state/division/township levels. Therefore, it is a cost-effective solution to complement traditional survey without time consuming. These data are very helpful in the prediction of passenger demand for transport services. We hope that this study will help to improve new transport services of Yangon City traffic planning and public facility management.

As for further studies, trip purposes, traffic assignment and relationships among the primary elements of a traffic stream such as flow, density, and speed will also be analyzed to measure on a roadway system.

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REFERENCES


Estimation of Population Distribution Using Satellite Imagery and GIS Data

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KEY WORDS: Population Mapping, Machine Learning, Building Extraction, Mobile Application.

ABSTRACT: Spatial distribution of population map at a finer scale is useful for planning and policy development. A number of population estimation techniques have been developed to disaggregate census data and predict density of population at finer scale. Therefore, this research is one of those attempts to improving high resolution on human population distributions, by presenting a new modeling approach to map the population using census, building footprints, satellite imagery, and ancillary data. The data were processed through four main steps: (1) data collection and pre-processing including: population and building footprints extraction from census data and cadastral map and/or satellite data, respectively; socioeconomic and building information survey using DRM Survey mobile application which developed by Geoinformatics Center, Asian Institute of Technology (GIC-AIT, Thailand); and ancillary data collection, including: topographic, infrastructure, river network, road network, satellite data, and night-time light imagery; (2) covariates preparation for fitting and predicting randomForest models; (3) model adjustment and estimation population at building level; and (4) geospatial population distribution mapping at 30m spatial resolution.

Validation of results was made by comparing the estimation with the observation data at building level, which showed a good correlation with $R^2 = 0.83$. We found that RF model performs better than several other commonly used models. An assessment of covariates is important for accurately estimating population. The values of variable importance may fluctuate as the number of covariates is reduced. However, relative ranking is quite stable among top covariates, for example: distance to function area (hospital, school, post office, ...), road networks, or night-time light are most important predictors for reducing amount of variability left in log population of training data. An advantage with the approach is that we can aggregated population can be re-distributed to a fine scale, providing quantitative information of planning and policy development.

1. INTRODUCTION

Population maps play an important role in the economic geographical evaluation of national economic planning, construction of buildings, accomplishing public service activities, etc. Moreover, population map itself shows the location and pattern of the settlement of the population, and socioeconomic characteristics. Indeed, representation of population in spatial units different from the census data may be essential for a better performance of various spatial applications (Ural et al., 2011). Some of these applications include criminal investigation, public health, natural hazards risk, environmental risk and accessibility analysis, facilities and retail planning, land use planning, resource allocation, emergency planning, and spatial interaction modeling (Chen, 2002; Langford, 2006; Mennis, 2009).

There are many approaches to conduct population mapping and the method firstly developed is dasymetric by the Tian-Shansky in 1920. Different algorithms to dasymetric mapping have been...
used in various applications. Land use land cover, soil type, geological unit or similar ancillary information may be used in dasymetric mapping (Eicher and Brewer, 2001; Mennis, 2003; Mennis and Hultgren, 2006; Langford, 2006; Maantay et al., 2007; Lwin and Murayama, 2009; Gaughan et al., 2013; Stevens et al., 2015; and Alegana et al., 2015). Recent advantages in geographic information systems, as well as increased availability of opensource digital datasets, have revitalized the concept of population mapping. Nevertheless, a difficulty has been finding ancillary data that highly corresponds with population distribution. Topographic maps, infrastructure dataset, satellite images, OpenStreetMap (OSM), and land use maps were used as ancillary data for population mapping method. These sources allow an analysis of the suitability of the natural environment for settlement. Night-time lights imagery has been shown to demonstrate a reasonable correlation with population distribution (Stevens et al., 2015; Sutton, 2003).

In other hand, land cover maps which interpreted from satellite imagery with high spatial resolution is a good indicated to map the spatial distribution of population. But a question here is how to distribute the population among the land cover classes. Stevens et al., (2015), Alegana et al., (2015), Deville et al., (2014), Gaughan et al., (2013), and Tatem et al., (2007) have proposed the methodologies to produce WorldPop datasets. This is an open access archive of high resolution gridded population distribution datasets (100m) using the most recent and finest level census, official population estimate data, and ancillary geospatial datasets. One limitation of this population map is that the spatial resolution (100 m) is coarse in case of city or provincial level for further analysis task. Therefore, population mapping at building level to grid cells with high spatial resolution is needed for socioeconomic management.

Sorichetta et al., (2013) demonstrated that the classifiers most likely to be the best was Random Forest (RF) according to hundreds of classification methods to map the real world. Hence, RF is selected to downscale population data in Ha Giang city. Furthermore, it is possible to accurately estimate the prediction error of the RF model. This can be done by averaging all mean squared errors calculated using the ‘out-of-bag’ (OOB) data that represent one third of the observations withheld from the bagging iteration process for each tree in the forest (Breiman, 2001). The OOB error can be also used to evaluate the importance of each covariate by considering how much the OOB error increases when only the OOB data for that given covariate are permuted (Liaw et al., 2002; Breiman, 2002). Besides, RF are a popular ensemble method that can be used to build predictive models for both classification and regression problems. In the RF-based dasymetric population mapping approach developed by Stevens et al., 2015, a RF algorithm is used to generate gridded population density estimates that are subsequently used to dasymetrically disaggregate population counts from administrative units into grid cells. However, we have modified Stevens et al., (2015) approach to estimate and map population at building level. A suite of covariates which present highly correlation with population density (i.e., land use, road network, public facilities: hospitals/clinics, school/university, shopping mall, ...) were calculated at the building level, then used the fitting a RF model for predicting number of population at the buildings itself with those raster-based covariates (i.e., night time light data, DEM, satellite image).

2. METHODOLOGY

2.1 Study area

Ha Giang city located on the banks of the Lo river in the northeast region of Vietnam. The city has an area of 135.33 km² and a population of 71,689 people in 2010. Population density in the city was 530 people/km². In addition, population is composed of 22 different ethnicities. Aside from the Kinh, the most numerous ethnic groups are the Tay, the Dao, and the Hmong.
2.2 Method

To predict and map population at building level, this research was adopted by 4 steps, including data collection and preprocessing, covariates preparation, to fit a RF model and predict number of population, and population mapping.

Population data was obtained from the 2009 census data. The mapping unit for population density was ward (urban area)/commune (rural area), the lowest level of administrative division in Vietnam. In the city, population density (people/ha) showed vary significantly from center wards to surrounding wards (Figure 3.). Urban wards are relatively small and of homogeneous population density, while surrounding wards are typically much larger, and have a much more heterogeneous population distribution.
The second important dataset is building footprints. The building footprints was extracted from cadastral map in 2009. There are 6,312 buildings which distributed in 8 wards in the city (Phuong Thien, Nguyen Trai, Quang Trung, Ngoc Duong, Ngoc Ha, Phuong Do, Minh Khai, and Tran Phu wards). As presented in the Figure 4., the most of building footprints has distributed in the central wards of the city, for example: Minh Khai (1124 buildings), Nguyen Trai (1167 buildings), Quang Trung (1124 buildings), and Tran Phu (847 buildings). Phuong Thien, Phuong Do, and Ngoc Duong wards has low density of population. Number of building footprints and the building itself in those wards is scattered due to terrain and geography.

Socioeconomic indicators and building information collected from field survey using mobile app (533 samples was collected from the field). And other datasets which are often highly presented correlated with spatial distribution of population such as: land use land cover (LULC), night time light (high intensity of light means high of population density), geospatial data such as: road networks, rivers/stream systems, infrastructure (water supply, electricity system, ...), topography are collected. Data is listed as Table 1.
Table 1. Summary datasets used for input to the RF model

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Covariate</th>
<th>Description</th>
<th>Year</th>
<th>Resolution/Scale</th>
<th>Remark</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Census</td>
<td>Commune level</td>
<td></td>
<td>2009</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Socioeconomic</td>
<td>Socioeconomic indicators</td>
<td></td>
<td>2018</td>
<td></td>
<td>Point</td>
<td>Survey</td>
</tr>
<tr>
<td>Building footprints</td>
<td>Shape of buildings</td>
<td></td>
<td>2009</td>
<td>1:5000</td>
<td>Polygon</td>
<td>Royal Haskoning DHV VN</td>
</tr>
<tr>
<td>Land use/Land cover (LULC)</td>
<td>Land use types/units</td>
<td></td>
<td>2009</td>
<td>1:5000</td>
<td>Polygon</td>
<td>Royal Haskoning DHV VN</td>
</tr>
<tr>
<td>Raster data</td>
<td>Satellite imagery</td>
<td></td>
<td>2017</td>
<td>0.8 m</td>
<td>TripleSat data</td>
<td>Royal Haskoning DHV VN</td>
</tr>
<tr>
<td>Suomi VIIRS-Derived</td>
<td>Density of light at night</td>
<td></td>
<td>2012</td>
<td>1000 m</td>
<td></td>
<td>NOAA</td>
</tr>
<tr>
<td>DEM</td>
<td>30 m</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>USGS</td>
</tr>
<tr>
<td>Vector data</td>
<td>Road network</td>
<td>Nearest distance</td>
<td>2009</td>
<td>Line, point, polygon</td>
<td>OSM/LULC</td>
<td></td>
</tr>
<tr>
<td>Waterway system</td>
<td>Streams, River bank, Canal, Pond lake reservoir</td>
<td>Nearest distance</td>
<td>2009</td>
<td>Line, point, polygon</td>
<td>OSM/LULC</td>
<td></td>
</tr>
<tr>
<td>Culvert system</td>
<td>Culvert</td>
<td>Nearest distance</td>
<td>2009</td>
<td>Line</td>
<td>Royal Haskoning DHV VN</td>
<td></td>
</tr>
<tr>
<td>Electric system</td>
<td>Pole, Line, Station</td>
<td>Nearest distance</td>
<td>2009</td>
<td>Line, point, polygon</td>
<td>Royal Haskoning DHV VN</td>
<td></td>
</tr>
<tr>
<td>Water supply</td>
<td>Water source, Water tower</td>
<td>Nearest distance</td>
<td>2009</td>
<td>Point</td>
<td>Royal Haskoning DHV VN</td>
<td></td>
</tr>
<tr>
<td>Population center</td>
<td>Populated area</td>
<td>Nearest distance</td>
<td></td>
<td>Point</td>
<td>OSM/Royal Haskoning DHV VN</td>
<td></td>
</tr>
<tr>
<td>Irrigation sluice</td>
<td>Sluice</td>
<td>Nearest distance</td>
<td>2009</td>
<td>Line</td>
<td>Royal Haskoning DHV VN</td>
<td></td>
</tr>
<tr>
<td>Transceiver station</td>
<td>Station</td>
<td>Nearest distance</td>
<td>2009</td>
<td>Point</td>
<td>Royal Haskoning DHV VN</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>Embankment, Landmark, Port, Function area</td>
<td>Nearest distance</td>
<td>2009</td>
<td>Line, point, polygon</td>
<td>Royal Haskoning DHV VN</td>
<td></td>
</tr>
</tbody>
</table>
Ancillary data (topographic, infrastructure, transportation and river systems) was used to create covariates for fitting and predicting RF models.

- Infrastructure: including special structure (ancient tower, city gate, monument, fountain, memorial, and flag tower), electricity systems (electric line, pole, and station), function areas (administrative agency, bank, cemetery, church, clinic/hospital, school/university, cultural house, fire prevention center, gas station, government office, hotel, market, pagoda, museum, police office, post office, shrine, temple, tomb, theater, and military camp), observation stations (meteorological and hydrological station), population centers, transceiver station, and water tower.
- River system: including pumping station, water sources
- Transportation system: including port, railroad junction and line, road (road junction, road alleyway, road center line, road edge, road culvert, and road talus), traffic light, and bridge.
- Topography: including elevation contour and landscape.

### 2.2.2 Covariates preparation

Covariates for input to the RF method were derived as follows.

- Building footprints converted from vector polygons to points (centroid). The main objective is to extract value of raster datasets as well as nearest distance from vector datasets to building footprint points and socioeconomic survey points (will called prediction data and input data, respectively). Then, the location of household and its socioeconomic indicators (socioeconomic survey) is checked for further processing steps.
- Raster datasets: night-time lights (NTL) data was resampled to 30m resolution as same as DEM. Then, all raster datasets extracted value to points (input data and prediction data).
- Vector datasets such as infrastructure, road network, water system, and topographic are used to calculate nearest distance from points of input data and prediction data to the variables itself.

The calculation was done to generate a dataset representing the population response variables. We have created 102 covariates in total from the collected datasets for input data for fitting a RF model, and prediction data for predicting a RF model.

### 2.2.3 RF regression model

The input data was used to create RF model to predict log of population. RF model is an ensemble, nonparametric modeling approach that grows a “forest” of individual classification or regression trees and improves upon bagging by using the best of a random selection of predictors at each node in each tree (Breiman et al., 2001). In many cases the predictive performance for RF is on par with boosted regression trees but have advantage of having fewer tuning parameters (Sikonja, 2004). In methodology this is especially important part of the fitting process.

Model estimation, fitting and prediction were all completed using R and the randomForest package. First, we fit a series of models using the tuneRF function with all available covariates. The tuneRF function uses a step function to tune the mtry parameter. This parameter determines the number of covariates to randomly select and choose from the best covariate for each node during the tree growing process. Prediction accuracies can be sensitive to the mtry parameter and tuneRF uses the minimization of OOB prediction error as an objective function to select an appropriate value for mtry (Stevens et al., 2015). In this case, the RF model showed the best result when mtry = 10, and ntree = 300.
Figure 5. Top 20 covariates important to fit the RF model. Those covariates are highly correlated with population distribution such distance to: road network, population center, electricity, function areas (church, clinic/hospital, school/university, pagoda, post office, shrine, and temple), water system, and night time light density.

The next step is a covariate selection process for the resulting of RF model. We performed this step to reduce the number of covariates in final RF model. For any covariate that has a variable less importance, we remove it from the list of covariates and rerun tuneRF with the reduced set of data. This is iterated until only positive importance scores remain for every covariate included in the modeling process. After fitting the RF model, it is applied for predicting a RF model using prediction data. Finally, we get the number of population at building level.

3. MAPPING RESULT AND DISCUSSION

The number of people in each building estimated using predicting a RF model. Figure 6. shows the linear relationship between observed data (field survey, y axis) and predicted data (RF model result, x axis). We can see that the result presents a good relationship with $R^2 = 0.83$. Then, the RF model is used to predict population for the test data. And the population in each ward calculated based on building location itself (Table 2).
Table 2. Comparison between census and estimation population

<table>
<thead>
<tr>
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</thead>
<tbody>
<tr>
<td>Minh Khai</td>
<td>10500</td>
<td>7020</td>
<td>-3480</td>
</tr>
<tr>
<td>Ngoc Duong</td>
<td>2943</td>
<td>3170</td>
<td>227</td>
</tr>
<tr>
<td>Ngoc Ha</td>
<td>3957</td>
<td>4030</td>
<td>73</td>
</tr>
<tr>
<td>Nguyen Trai</td>
<td>8861</td>
<td>10741</td>
<td>1880</td>
</tr>
<tr>
<td>Phuong Do</td>
<td>4347</td>
<td>3717</td>
<td>-630</td>
</tr>
<tr>
<td>Phuong Thien</td>
<td>3510</td>
<td>9382</td>
<td>5872</td>
</tr>
<tr>
<td>Quang Trung</td>
<td>4047</td>
<td>5159</td>
<td>1112</td>
</tr>
<tr>
<td>Tran Phu</td>
<td>7121</td>
<td>2565</td>
<td>-4556</td>
</tr>
</tbody>
</table>

Population counts were showed the highest error in Phuong Thien ward (+5872 people), follow by these wards: Nguyen Trai (+1880 people), Quang Trung (+1112 people). The highest overestimation was denoted in Phuong Thien ward (167.29%) and the lowest (1.84%) in An Cuu ward. The population mapping result presented in the Figure 7. creates based on resampling building-based population data with 30 m resolution. The population in grid cells are presented number of people in 0.9 ha. The blue color means less populated and the yellow color shows high populated. The most population is concentrated surrounding central ward such as: Minh Khai, Nguyen Trai, Tran Phu,…

Figure 7. Spatial distribution of population in the Ha Giang city. Mapping result was resampled using building-based population data from the predicting the RF model. The blue color presents that area less population density and the yellow color shows high concentrated of population.

The crucial impact on the quality of population redistribution (especially in a fine scale) have ancillary data sources. However, many findings concerning data quality are commonly available in the literature. In addition, data that are derived by native government are generally more reliable
than those from open source data (i.e., OSM, POI, etc.). The data are generally freely available and some available for a payment. This research used official data, which are accurate and credible but for some areas are not up-to-date (i.e., building footprints in Phuong Thien, Nguyen Trai, Quang Trung wards). A limitation of this research is time consuming and high cost of obtaining information about the buildings, in particular building structural type, volume and height (building survey). One other limitation is that we did not focus on number of level(s) and building use (public, commercial, industrial, and residential) when estimated the number of population. The overall accuracy of estimation result reduced due to those limitation. In further studies, we will try to overcome disadvantages here. This certainly contributes significantly to increase the accuracy of estimation the population totals in buildings.

4. CONCLUSION

This research successfully applied a new population mapping method to estimate density of population at building level. Validation was made by comparing the estimation result with the population data at ward level, which yield fairly agreement. The RF model performs substantially better than several other commonly used. An assessment of which of the ancillary data covariates are important for accurately estimating population at the building level is produced by the RF algorithm. During the variable selection phase of the algorithm, the values of variable importance may fluctuate as the number of covariates is reduced. However, the relative ranking is quite stable among the top covariates. For example, distance to function area (hospital/clinic, school/university, post office, or religion lands such as pagoda, church, or shrine), road networks, or NTL are the most important predictors for reducing the amount of variability left in the log population of the training data. This indicates that ancillary datasets are extremely valuable. The appropriateness and quality of the ancillary data used influence the accuracy and level of detail of population distribution techniques and algorithms. One of the advantages with the approach put forward in this paper, is that the data set (building footprints) used has the capacity to provide information about the characteristics of the population distribution in a finer scale. Thus, the elaborated population surface could be used in risk exposure and risk evacuation or mitigation plans.

References from Journals:


References from Books:

References from Other Literature:
Reconstruction of 3D Urban Environment for the Immersive Planning of Elevated Railway Systems

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Keywords: Building Model, Infrastructure Planning, Landscape, Photogrammetry, Visualization

Abstract: One of the most important issues in the renewal for civil infrastructure is to examine the harmonization between the construction body and the existing environment. By comparing all optional scenarios through virtual visualization, the decision can be optimized. The owner and the general public will be more likely to accept the renewal plan, accordingly. To practice this immersive planning idea, this paper reports an on-going renewal project of elevated railway systems in ChiaYi, Taiwan. The major work of this study comprises three major parts: (1) 3D building modelling, (2) landscape generation, and (3) integration of the planned construction body, existing buildings, and landscape. The integrated system provides planners a chance not only to optimize the plan, but also to communicate with the owner as well as to accommodate public opinions to create a win-win situation.

1. Introduction
The renewal of civil infrastructure is to advance the living quality for the general public. However, it may draw concerns from the changes of the existing environment. To reach a consensus among the owner, the resident, and the planner on the environment issue, effective communication is a crucial work for the renewal project. To expedite the communication effectiveness, an augmented reality tool to simulate the future plan is desirable. With the rapid development of 3D visualization technology and the 3D planning for construction body, implementation of immersive plan in a virtual environment provides understandable information for system optimization as well as a good platform for communication. This paper is to report a case, which relates to an on-going project for a railway renewal project in Taiwan.

The renewal project of elevated railway systems in ChiaYi, Taiwan started in 2017, involving land acquisition, building demolition, and new constructions. To examine the harmonization between the city environment and the engineering body, 3D environment as reconstructed with photogrammetry and construction plan of elevated railway system (including railroad stations) were integrated into a visualization platform. The compatibility between the planned railway systems and the current transportation systems can, thus, be scrutinized. It is also expected that the developed system will provide planners an effective way to optimize the engineering system as well as to improve the communication effectiveness dealing with the public.
2. Methodology

The reported case comprises three major components. The first part reconstructs 3D building models for ChiaYi City. The second part generates landscape by combining oblique aerial photogrammetry and unmanned aerial vehicle (UAV) images. The third part acquires the geometric plan model of the elevation railway systems. Three components are, then, integrated into a 3D visualization platform.

2.1 3D Building Modelling

Three dimensional building models of ChiaYi City were reconstructed using digital aerial photogrammetry. Digital photos were acquired with metric camera UltraCam-XP. Ground control points(GCP) and independent check points(ICP) were surveyed by GNSS. Aerial triangulation was performed using massive number of tie points and sufficient ground control points to meet the accuracy specification of 1/1,000 scale map. Table1 and Table2 list calibrated interior orientation parameters (IOPs) of the camera and aerial triangulation results, respectively. Fig.1 illustrates the flight plan, including camera stations, GCPs, and ICPs, in the working area.

<table>
<thead>
<tr>
<th>Camera</th>
<th>UltraCam-XP</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frame Size</td>
<td>17,310 pixels × 11,310 pixels</td>
</tr>
<tr>
<td>Pixel Size</td>
<td>6.00 um*6.00 um</td>
</tr>
<tr>
<td>Focal Length</td>
<td>100.5 mm</td>
</tr>
<tr>
<td>FOV</td>
<td>55 degree</td>
</tr>
<tr>
<td>Flight Altitude</td>
<td>1400 m</td>
</tr>
<tr>
<td>GSD</td>
<td>8 cm</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Location</th>
<th>ChiaYi City</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area</td>
<td>60 km²</td>
</tr>
<tr>
<td>Photo Number</td>
<td>814</td>
</tr>
<tr>
<td>Ground Control Points</td>
<td>47</td>
</tr>
<tr>
<td>Independent Check Points</td>
<td>10</td>
</tr>
<tr>
<td>Absolute Accuracy</td>
<td>0.029 m / 0.041 m</td>
</tr>
<tr>
<td>(Average Error)</td>
<td>(Horizontal / Vertical)</td>
</tr>
<tr>
<td>Absolute Accuracy</td>
<td>0.036 m / 0.053 m</td>
</tr>
<tr>
<td>(RMS Error)</td>
<td>(Horizontal / Vertical)</td>
</tr>
</tbody>
</table>

For 3D modelling, building outline segments of ChiaYi City were renewed by stereoscopic observations in the first place. Then, the second step collected building height for LOD1 building modelling. In addition, 60 landmark buildings along the railway area as requested by ChiaYi City Government were modelled with textured LOD2, which were reconstructed by the measured roof 3D line segments. Fig. 2 illustrates the work flow of the 3D building modelling.
LOD1 Building Modelling

LOD1 is known as block model comprising prismatic building with flat roof structures (OGC, 2012). To collect building height, roof form was simplified into two types, slope roof and flat roof. For the slope roof, each building height was measured from the lowest point of roof by stereoscopic measurements. For the flat roof, the building height was measured from the wall top to the ground. Fig. 4 illustrates LOD1 building models.
**LOD2 Exquisite Building Modelling**

3D line segment were measured by stereoscopic observations, including building outlines and detailed structure segments, then Split-Merge-Shape (SMS) method was employed to reconstruct LOD2 building models, as shown in Fig. 5 (Rau and Chen, 2003). To facilitate the model reality, building textures were draped by close-range photos for walls and true orthoimages (Tsai et., 2006) for rooftops. Fig. 6 illustrates LOD2 exquisite building models.

![Figure 5. 3D Line Segment Measurements and SMS Modelling (Rau and Chen, 2003)](image)

![a. ChiaYi City Museum  b. ChiaYi City Council](image)

**Figure 6. LOD2 Exquisite Building Models**

**2.2 Landscape Generation**

One of the feasible and effective solutions to represent landscape is the incorporation of 3D mesh models, which includes high-density 3D point clouds in triangulation form. From photogrammetric perspective, those point clouds may be generated by image matching. Point clouds with high density provide a rich description of the object (Alby and Grussenmeyer, 2012). To improve the side texture details of building surface, oblique photography is needed to capture images from different angles. Fig. 7 illustrates the work flow of landscape generation using oblique photos.

![Figure 7. Work Flow of Landscape Generation](image)
**Oblique Aerial Photogrammetry**

Oblique airborne cameras acquire birds-eye view images that can be employed to generate point clouds for building facades, vegetation, and other features. Thus, the images can be used to reconstruct landscape for 3D city modelling (Fritsch and Rothermel, 2013). In this study case, oblique photos were taken by AOS-7 system in conjunction with one nadir camera and six oblique cameras, as shown in Table 3. Referring to Fig.8a, initial photo triangulation using nadir photos was performed to derive preliminary orientation parameters. Referring to Fig.8b, the second photo triangulation included oblique photos using image matching to generate more tie points to reach higher accuracy. At last, aerial triangulation for all images was adjusted. Because of the large number of photos with multiple image connection, the reliability and accuracy were assured due to the high redundancy configuration, as shown in Fig.8c. Automatic matched tie points and estimated errors are also illustrated in the figure.

Table 3. AOS-7 Camera Parameters

<table>
<thead>
<tr>
<th>Camera</th>
<th>Nadir Camera</th>
<th>Oblique Camera</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phase One IQ180 x 1</td>
<td>Nikon D800E x 6</td>
<td></td>
</tr>
<tr>
<td>Photo Number</td>
<td>1462</td>
<td>8759</td>
</tr>
<tr>
<td>Frame Size</td>
<td>10,328 pixels × 7,760 pixels</td>
<td>7360 pixels x 4912 pixels</td>
</tr>
<tr>
<td>Pixel Size</td>
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<td>4.87 um * 4.87 um</td>
</tr>
<tr>
<td>Focal Length</td>
<td>55 mm</td>
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</tr>
<tr>
<td>Flight Altitude</td>
<td>1100 m</td>
<td>1100 m</td>
</tr>
<tr>
<td>Nadir GSD</td>
<td>10 cm</td>
<td>--</td>
</tr>
</tbody>
</table>

Based on the orientation parameters derived from aerial triangulation, high density 3D point clouds were generated followed by the 3D mesh modelling. To assure the data compatibility, data format is exchangeable for different 3D platforms in the demonstration of ChiaYi City, as shown in Fig.9.
Unmanned Aerial Vehicle (UAV)
For some significant landmarks, such as a Chinese style temple with complex appearance, UAV is an efficient and economic tool to collect high resolution photos for the generation of detailed 3D mesh models. Fig. 10 illustrates two cases as reconstructed by UAV photos.

2.3 Geometrical Planning of Elevated Railway Systems
To achieve the future reality of elevated railway systems, planning data including railway main points, route profile, bridge profile section, pier type, and new train station plan were acquired, as shown in Fig 12. Considering the operational efficiency in a current 3D platform, data simplification is needed. Appearance structure that is visible in the 3D environment was selected to establish 3D models using SketchUp (Fig. 13). Each element was an independent object in the model and stored in the component library. Thus, discussions in the planning process can be visualized to reach an optimal plan.
2.4 3D Platform

To meet the requirements, two different 3D platforms were selected to represent the multiple 3D models. By taking the advantage of good interactivity and smooth operation, Skyline TerraExplorer for Desktop is a good choice for demonstration of engineering concepts in public communication (Fig.14). ESRI ArcGIS Portal, on the other hand, has complete nested analysis functionalities and strong support for database access, and thus is suitable for municipal management system with massive spatial data storage (Fig.15).
3. Implementation Results

3.1 Virtual Visualization
Integration of construction body, buildings, and landscape makes the future real in a virtual environment. The appearance of the completed project can be presented realistically. By taking the advantages of visualizable environment, the plan can be discussed in an immersive way.

3.2 Conflict Review
Railway elevated projects are usually accompanied with extended issues, such as urban planning changes, land acquisition, and existing building demolition. Those key difficulties should be overcome to reach a success for public engineering promotion. With 3D model in an appropriate platform, conflict situation can be discovered and the number of buildings to be demolished can be estimated, as shown in Fig.16. Full-fledge of information and visualization platforms help us to efficiently communicate with the owner and the public as well as to optimize the construction plan.
3.3 Public Opinions Accommodation

In the planning stage, 3D visualization environment is used in the citizen participation workshop, as shown in Fig.17. The approach helps the public to participate in the engineering concept discussions and gives opinions from different perspectives. Thus, the public have opportunities to foresee and imagine their expectations (Yang, 2011). The construction plan tends to be accepted, accordingly.

4. Conclusions

This paper presents a real case that uses 3D virtual visualization to include reconstructed 3D urban environment by photogrammetry and elevated railway planning data, for the promotion of public construction project. The integrated system provides planners a solid base to examine the harmonization between the engineering body and the city environment as well as to accommodate public opinions. This study demonstrates the power of 3D spatial information for the enhancement of civil infrastructure.
5. References


