REMOTE SENSING MONITORING LARGE-SCALE REPETITIVE CONSTRUCTION PROJECTS

Tuong-Thuy Vu[1], Darshana Wickramasinghe[2], Moataz Ahmed[3], and Tomas Maul[4]

1. University of Nottingham, Malaysia campus, School of Geography, Semenyih, Malaysia; tuongthuy.vu@nottignham.edu.my
2. University of Nottingham, Malaysia campus, School of Geography, Semenyih, Malaysia; khgx4dcs@nottingham.edu.my
3. University of Nottingham, Malaysia campus, School of Geography, Semenyih, Malaysia; khgx4mad@nottingham.edu.my
4. University of Nottingham, Malaysia campus, School of Geography, Semenyih, Malaysia; tomas.maul@nottingham.edu.my

ABSTRACT

Advances in remote sensing technologies now produce the vast amount of satellite images with better spatial, spectral and temporal resolutions. That enables the frequent monitoring of human activities on the ground such as construction projects. We proposed the use of satellite remote sensing in monitoring of large-scale repetitive construction project, which is mainly via ground visit and report checking in normal practice. Firstly, highest-resolution satellite images like Pleiades and TerraSAR-X were collected for a feasibility study. The findings revealed that optical images could capture clearly at least 4 different main construction stages but the radar counterpart could not. Radar images, however, is still useful to alert the change in the study area when no optical image is available due to cloud cover. Subsequently, we introduced a spatio-temporal detection framework based on content-based image retrieval from optical images. The preliminary experiment with Histogram of Gradient descriptors and Support-Vector-Machine classifiers produced promising results from optical images of Light Rail Transit construction project in Malaysia. Further development needs to extend the library of training samples to ensure a better accuracy and carry out the experiments on data of various situations. The automated detection framework will be the core processing of a web-based monitoring system enabling the accessibility of people involving in such large-scale construction projects.

INTRODUCTION

Urbanization is a rapid process and the world population data depict that more than half of the world population distributed over urban area. In 1950, the urban population was 746 million and it reached to 3.9 billion in 2014 after a half-century, and the future urban population will grow to 6.4 billion in 2050 (1). Urban development is a nonstop process, and it introduces numerous health, environment and socioeconomic issues (2,3). Assessing and mitigating the direct and indirect effects of urban activities on the socioeconomic and environmental phenomena are essential parts of sustainability. In general, the current urban monitoring process is not at a satisfactory level and it shall introduce the rising short- and long- term urban problems (4).

Remote sensing has been playing its important role, providing timely and relatively cost-effective synoptic view information for urban planning, monitoring and management (5). Remote sensing images with different spatial and spectral resolutions are unique in delineating urban areas from other land cover types or detecting objects like buildings and roads (6,7,8). The latter becomes more feasible with very-high-resolution (VHR) satellite images like IKONOS, QuickBird, GeoEye, Worldview, Pleiades, TerraSAR-X and Cosmo-Sky. In the past two decades, numerous research papers were published on building and road detection from VHR images (9). Such VHR images enable the contextual analysis far beyond simply spectral properties of pixels and object-based image analysis has become a new paradigm (10). Moreover, semantic information can be embedded in the context described by size, shape, texture, morphology, topology, temporal, etc. to help the scene understanding (11,12,13). On the other hand, smaller objects like the road vehicle, vessel, urban trees, power lines, oil pipes, refugee camps now can be detected from VHR images (14,15,16). Together with better temporal resolution, VHR images can be of use effectively in emergency responses, traffic monitoring, and pedestrian crowd monitoring, etc. (17,18,19).

It is promising that VHR images are suitable to monitor the large-scale construction project activities. Malaysia, as any developing counties, is going through rapid urbanization. In big Malaysia cities, many large-scale construction projects such as railways, city rail links, highways and new commercial complex and residential areas. The large-scale repetitive construction projects like rail link spreading over the large area with repetitive activities at every piers. In normal practice, the project managers rely on reports submitted by the sub-contractors and crosscheck them with field visits (20). The potential delays in the preparation of progress report and its delivery to decision makers cause inefficiency in communication process on construction progress (21). Remote sensing capturing timely synoptic view image can be of help to mitigate the delay in monitoring.

In this study, we started by assessing the feasibility of current VHR remote sensing images in construction monitoring taking a Light Rail Transit (LRT) construction project in Malaysia as a case study. Progress reports were used together with field visit as the ground truth. The findings are presented in the following section METHODS based on which we proposed an automated detection framework for monitoring the project activities. Different from buildings or roads, the appearances of objects involving with construction activities in remote sensing images are normally diverse and hard to be recognised by a general template or object-based rule-set. Therefore, in developing the automated detection framework, we adopted the content-based image retrieval technique. More details are given in section METHODS. The outcomes of our experiment with LRT construction project are discussed in section RESULTS prior to conclusions in the last section.

METHODS

Table 1 lists the remote sensing images collected for the experiment. The best resolution available images were Pleiades and TerraSAR-X.

Table 1: Collected satellite images.

Pleiades	5 June 2013	0.5 m panchromatic and 2 m multispectral
TerraSAR-X	17 June 2013	1 m HH
TerraSAR-X	5 October 2013	1 m HH
Pleiades	18 December 2013	0.5 m panchromatic and 2 m multispectral
Pleiades	31 January 2014	0.5 m panchromatic and 2 m multispectral

In comparison with progress report and other field visit data via visual interpretation, the optical image can reveal 4 main construction stages: 1) Bored pile platform and activities 2) Pile cap construction 3) Pier works and pier head construction 4) Segmented Box Girders (SBG) launching and post-tensioning activities (Figure 1).

SAR image, though the current spatial resolution cannot help to reveal the exact details, can highlight some on-going construction activities due to the corner reflectors. When the optical image is not available due to cloud cover, SAR image can be of help. Figure 2 illustrates the temporal monitoring using series of SAR and optical images for a pier. High backscatter in mid-June due to on-going machinery works of the 1st stage of construction, it got less backscatter in October as the construction moved to 2nd stage, and the pier construction completed in December. Based on that, it is possible to develop a spatio-temporal monitoring framework using either optical and SAR images depending on their availability.

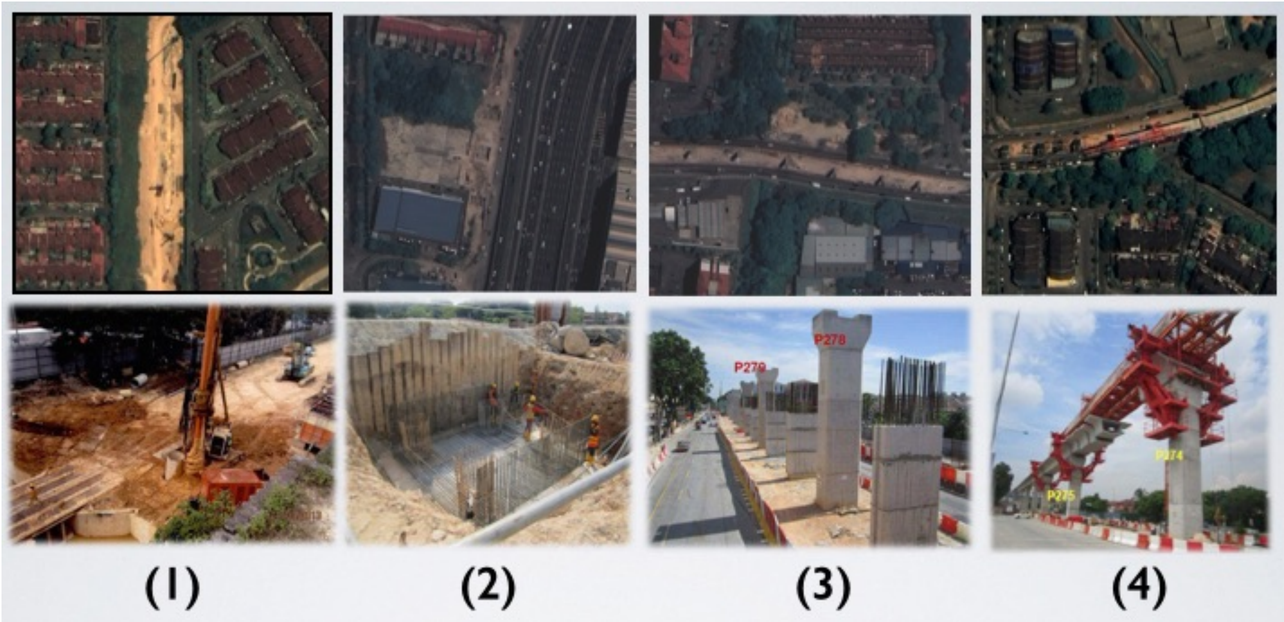

Figure 1: Optical image observes 4 main stages of construction: 1) Bored pile platform and activities 2) Pile cap construction 3) Pier works and pier head construction and 4) Segmented Box Girders (SBG) launching and post-tensioning activities

Figure 2: Temporal monitoring with optical and SAR image

In this paper, we focused in developing processing algorithms for optical images only. The visual interpretation of multi-temporal data sets showed that the appearance of objects highly depends on sun angles, look angles, and other disturbance factors on the ground. Initially, we tested with different settings of template matching and object-based image analysis but hardly found a general rule. Therefore, we adopted content-based image retrieval (CBIR) technique (22). In brief, at each location on an image, the local information in the neighbour will be extracted by a defined descriptor like Histogram of Gradient (HOG) (23). Support-Vector-Machine (SVM) classifier then works on this set of highly dense HOG features. Overall flowchart is shown in Figure 3, it also illustrates the idea of a spatio-temporal detection framework, though we focus only the part of optical image analysis here.

Firstly, three data sets including satellite images, construction site drawing, and construction progress report are spatially matched and joined. The construction site drawing provides the location of object of interest based on which the search for analysis is just around the location. Construction progress report plays as ground truth data for validation, and it also helps to initiate the training of future event image.

Secondly, training data are extracted from satellite images, both true and false samples to be considered. HOG training outcomes are the clues for the classifier. This is called the *learning phase*. Finally, it is the *recognition phase* to label each pier location with its corresponding construction stage. The final outcomes are then fed into our spatio-temporal database for future event detection. In this study, we applied the binary classification for each stage separately. It is noted that if no construction took place according to the spatio-temporal database, the processing will just simply check the land-cover change around the piers to check whether stage 1 started. *Learning* and *recognition*, in deed, work on the last 3 stages of construction.

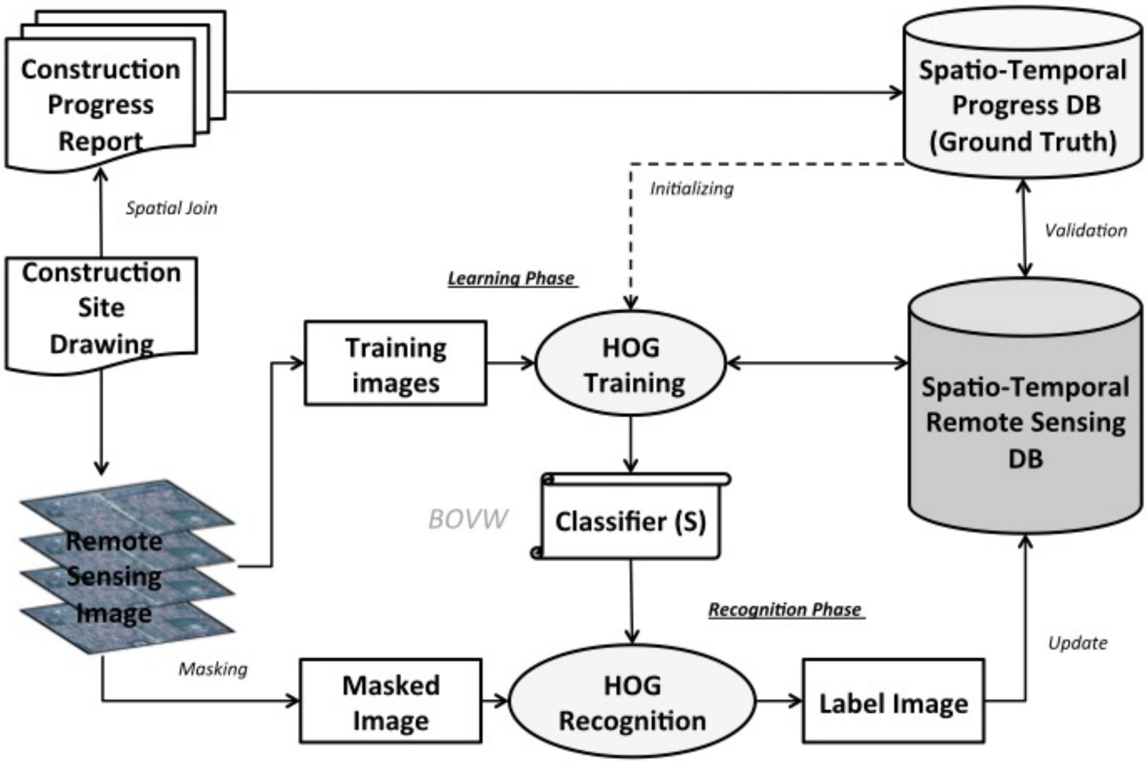

Figure 3: Overall flowchart of processing

RESULTS

We applied the proposed approach to about 500 piers of Kelana Jaya LRT line in Kuala Lumpur, Malaysia. At this stage of development, we just captured the static information; the temporal element will be considered in future studies. According to ground truth data, different segments of this Kelana Jaya were at different construction stages at the time the satellite image captured, enabling the possibility to test the 2nd, 3rd and 4th construction stages. Figures 4, 5, 6 present the examples of our detection and labelling the stage of piers at each construction stage. As aforementioned, according to the previous status of the pier in spatio-temporal database, the learning and recognition worked from that stage onwards in order. The best match will be recorded. The label points were not the final results, the majority around the location of a pier decided the pier's status crosschecking with temporal information in the spatio-temporal database.

Using the progress report and other field visit information as the reference data, we performed the quantitative accuracy assessment as shown in Table 2. The initial experiment yielded very good accuracy, and it is promising to extend further the test to other segments of LRT construction project to confirm the suitability of proposed CBIR approach. Obviously, it was harder to detect stage 3 due to the shadow, the orientation of the piers and especially, when LRT line goes through a narrow corridor between buildings, errors can increase due to similar behaviours of surroundings.

Figure 4: Labelling the piers at stage 2

Figure 5: Labelling the piers at stage 3

Figure 6: Labelling the piers at stage 4

Table 2: Accuracy assessment.

	Ground Truth					Producer
Image Recognition	Class	Stage_2	Stage_3	Stage_4	Other	Total	Accuracy (%)
	Stage_2	**94**	4	0	10	108	87.04
	Stage_3	6	**42**	0	6	54	77.78
	Stage_4	0	0	**70**	4	74	94.59
	Other	12	9	5	**184**	210	87.62
	Total	112	55	75	204	**446**	**87.44**
User Accuracy (%)		83.93	76.36	93.33	90.19		

Remote sensing monitoring will not be able to completely replace the current project monitoring and management practice. The synoptic-view images just provide the overall entire picture and cannot reveal all steps in the construction. It aims to minimise the time-consuming and tedious works of crosschecking tons of papers of report and to plan more effectively field visit. The overall accuracy 87% looks very promising for expanding this automated image-processing framework in the real practice. To better assist the different levels of project managers as well as other relevant involving parties, the detection framework will be mounted on a web-based system.

CONCLUSIONS

This paper firstly reported our investigation of the capability of existing very-high-resolution satellite images for monitoring large-scale repetitive construction project activities. Optical images proved to be possible to reveal at least 4 main construction stages and radar was recommended to use to alert any changes when optical image is not available. We developed an automated approach based on Histogram-of-Gradient descriptor to detect and label the construction stage of each pier taking a LRT construction project in Malaysia as a case study. Good accuracy could be achieved and the content-based image retrieval techniques proved to be promising in this particular application. The findings encourage the further experiments of developed approach in future studies for scrutinising the algorithms. This study also proposed a spatio-temporal detection framework with content-based image retrieval technique as the core processing. The framework aims to assist the large-scale construction project monitoring and management and that is the ultimate goal in future studies.

ACKNOWLEDGEMENTS

This study is a part of a research project funded by MOSTI (project no. 01-02-12-SF0177). TerraSAR-X images were provided by German Space Agency (DLR). We also thank Prasarana Malaysia Berhad (formerly known as Syarikat Prasarana Negara Berhad) for support and assistance during data collection of the study.

REFERENCES

1 United Nation, 2014. World Urbanization Prospect (United Nation), 32pp.

2 Worldbank, 2000. Beyond Economic Growth, chapter X (Worldbank), 162pp.

3 McCarthy MP, Best MJ & Betts RA, 2010. Climate change in cities due to global warming and urban effects. Geophysical Research Letters, 37: 5p

4 Dekker S & J Singer, 2011. Integrated Community Sustainability Plans: Monitoring & Evaluating Success (Canadian International Development Agency), 68pp.

5 Taubenböck H & T Esch, 2011. Remote Sensing – an effective data source for ubran monitoring. EarthZine, http://earthzine.org/2011/07/20/remote-sensing-an-effective-data-source-for-urban-monitoring (last date accessed: 10 June 2015)

6 Gamba P & FD Acqua, 2005. Urban remote sensing using multiple data sets: past, present and future. Information Fusion, 6(4): 319-326

7 Taubenböck H, T Esch, A Fellbier, M Wiesner, A Roth, and S Dech, 2012. Monitoring urbanization in mega cities from space. Remote sensing of Environment, 117: 162-176

8 Weng Q, 2012. Remote sensing of impervious surfaces in the urban areas: requirements, methods, and trends. Remote sensing of Environment, 117: 34-49

9 Blaschke T, 2010. Object-based image analysis for remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing, 65: 2-16

10 Blaschke T, GJ Hay, M Kelly, S Lang, P Hofmann, E Addink, RQ Feitosa, F van der Meer, H van der Werff, F van Coillie & D Tiede, 2014. Geographic Object-based image analysis – towards a new paradigm. ISPRS Journal of Photogrammetry and Remote Sensing, 87: 180-191

11 Andre S, D Arvor, & C Pierkot, 2012. Towards an Ontological Approach for Classifying Remote Sensing Images. In: Eigth International Conference on Signal Image Technology and Internet Based Systems (IEEE, Naples), 825-832

12 Andre S, C Pierkot & D Arvor, 2013. Towards a semantic interpretation of satellite images by using spatial relations defined in geographic standards. In: GEOprocessing 2013 (IARIA, Nice), 99-104

13 Yue P, L Di, Y Wei, & W Han, 2013. Intelligent services for discovery of complex geospatial features from remote sensing imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 83: 151-164

14 Galeon FA, 2008. Estimation of population in informal settlement communities using high-resolution satellite image. In: Proceedings of XXI ISPRS congress (ISPRS, Beijing), XXXVII (Part B4), 1377-1381.

15 Tiede D, S Lang, D Holbling, & F Fureder, 2010. Transferability of OBIA rulesets for IPD campus analysis in Darfur. In: Proceedings of GEOBIA (ISPRS, Gent), 6p.

16 Ardila JP, W Bijker, VA Tolpekin, & A Stein, 2012. Context-sensitive extraction of tree crown objects in urban areas using VHR satellite images. International Journal of Applied Earth Observation and Geoinformation, 15: 57-69

17 Meyer F, S Hinz, R Muller, G Palubinskas, C Laux & H Runge, 2007. Towards traffic monitoring with TerraSAR-X. Canadian Journal of Remote Sensing, 33(1): 39-51

18 Butenuth M, F Burkert, F Schmidt, S Hinz, D Hartmann, A Kneidl, A Borrmann & B Sirmacek, 2011. Integrating pedestrian simulation, tracking and event detection for crowd analysis. In: Proceedings of IEEE International conference on computer vision workshops (IEEE, Barcelona), 150-157

19 Vu TT, 2011. Building extraction from high-resolution satellite image for tsunami early damage estimation. Applied Geomatics, 3: 75-81

20 Kenley R & O Seppanen, 2009. Location-based management for construction: planning, scheduling and control (spon research) (Routledge), 584pp.

21 Dikbas A & R Scherer, 2012. eWork and eBusiness in Architecture, Engineering and Construction (CRC Press), 976pp

22 Wang M & T Song, 2013. Remote sensing image retrieval by scene semantic matching. IEEE Transactions on Geoscience and Remote Sensing, 51(5): 2874-2886.

23 Khan MNA, G Fan, DR Heisterkamp, L Yu, 2014. Automatic target recognition in infrared imagery using dense HOG feature and relevance grouping of vocabulary. In: CVPR2014 (IEEE, Ohio), 293-298.