RAPID SATELLITE-BASED MAPPING SOLUTION IN SUPPORT DISASTER ESTIMATION

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ABSTRACT: The availability of various remote sensing satellite data right after a catastrophe is not a question nowadays in emergency and disaster responses. The challenge, however, is how to quickly derive useful information from remote sensing images at this early stage. Tackling the challenge, this study develops a rapid high-resolution satellite mapping solution built upon a dual-scale contextual framework. On the coarse processing level, statistical region merging is deployed to group pixels into a number of coarse clusters. The rule-based analysis combining homogeneous texture, brightness, and greenness indices subsequently eliminates the irrelevant clusters as well as provides the only heterogeneous clusters for further detailed processing level. On the fine processing level, within each considering clusters, smaller objects are delineated via morphological, spectral and shape analysis. Breaking into 2 level processing helps to reduce the processed number of pixels and the redundancy of processing irrelevant information. In addition, it allows a data- and tasks- based parallel implementation. The initial development here focuses in responses to tsunami disaster. The performance is demonstrated with a QuickBird image captured a disaster-affected area of Phanga, Thailand due to the 2004 Indian Ocean tsunami. The developed solution will be implemented as a web processing service in operational uses.

1. INTRODUCTION

Providing quick and reliable captured information in hardest hit and difficult-to-assess areas, remote sensing products have been commonly used as the first and primary information source at the post-disaster response stage (Adams et al., 2004; Balz and Liao, 2010; Matsuoka and Yamazaki 1999; Saito et al., 2004; Stramondo et al., 2006; Vu et al. 2005). The activation of International Charter on Space and Major Disasters (www.disastercharter.org) together with the coordination of UN-SPIDER (www.un-spider.org) facilitates the acquiring and delivering timely remote sensing images to the bodies in charge of relief efforts and emergency responses. The fastest available information is damage extent that is manually extracted in such operational framework. The product accuracy with respect to the practices is far to meet (Kerle 2010). More quantitative and details of damages are expected from the damage analysts and disaster management practitioners. Researches in response to recent disaster events showed that detailed information derived from very high-resolution satellite images could accommodate their requirements (Chesnel et al. 2007; Gusella et al. 2005; Saito et al. 2004; Vu and Ban, 2010).

Richer information contained in such high-resolution images increases the complexity of image analysis. Numerous researches have been done either to develop or employ the object-based image analysis approach (Blaschke 2010), which proved to be the most suitable for high-resolution satellite images. Those, however, are impractically used under time pressure in the context of post-disaster and emergency responses due to the high computational cost and the requirement of experienced operators. Since no mature automated image analysis solution is available, the practitioners are seeking the collaborative mapping framework (Goodchild and Glennon 2010). GEO-CAN (Bevington et al. 2010), a practical work has been efficiently deployed in response to the 2010 Haiti earthquake, in which the huge time-consuming interpretation of damages from remote sensing images were divided into gird-based delegation to numerous contributors worldwide. As collaborative mapping platform is well developed, the mechanism to ensure the accuracy and consistency is the big challenge. Moreover, damage interpretation requires a certain level of expertise in remote sensing and structural engineering. The quick image processing outcomes would be a guideline for the contributors as well as a reference frame to ensure the quality of derived damage information.

To contribute to the current efforts, this research develops a rapid high-resolution satellite mapping solution built upon a dual-scale contextual framework to support damage estimation after a catastrophe. The initial development is formulated as a part of a tsunami-damage estimation system (Koshimura et al. 2010) integrating numerical modelling of tsunami inundation, remote sensing and GIS. High-resolution remote sensing images are acquired to update the surface roughness for tsunami modelling as well as mapping the structural damages. Thus, the target objects of image processing are building (or building blocks). Breaking into two levels of processing, the design and implementation are optimized for computation speed. Details of developed solutions are described in Section 2 and demonstrated with QuickBird images of Ban Nam Ken, Phanga, Thailand in Section 3.

2. METHODOLOGY

Image- and/or raster-based computation time heavily depends on image size. To cover a considerably large area, the size of a QuickBird, IKONOS, or WorldView-2 image becomes huge multiplied by its multi-spectral bands. On another hand, object-based image analysis exploits the scale property of objects in describing the context for segmentation and classification. The dual-scale processing proposed here takes into account the scale property not only categorise objects into different levels for segmentation and classification but also to decide the suitability level of complexity in processing in order to shorten the computation time.

The two levels of the main processing are described in the following sub-sections. It is noted that pre-processing such as geometric and radiometric correction, pan-sharpening may be necessary prior to the main processing. Those are easily done by any remote sensing packages and not repeated here.

2.1 Coarse level

On the coarse level, the simple but robust Statistical Region Merging (SRM) technique is adopted (Nock and Nielsen, 2004). SRM starts by sorting the pair of pixels in ascending order of *f*(*p,p'*), expressed as in Eq. 1.

$$f(p,p') = \max_{\forall a \in \{S\}} |p_a - p_{a'}|, \; a \text{ denotes a spectral channel of the multi-spectral space } S \quad (1)$$

Traversing the above order once and testing for any pair, if the region R and R' of the pair are different, R and R' will be merged if

$$|\bar{R}'_a - \bar{R}_a| \le \sqrt{b^2(R) + b^2(R')}, \forall a \in \{S\}, \quad (2)$$

where $\bar{R}$ denotes the average value of region R

$b(R) = g\sqrt{\frac{1}{2Q|R|}\left(\ln\frac{|\Re_l|}{\delta}\right)}$, with $|\Re_l| = (l+1)^{\min(l,g)}$, g denotes the number of grey value,

Q is tuning parameter, $\delta = \frac{1}{3|I|^2}$, $|I|$ and $|R|$ denote entire image and region R size, respectively.

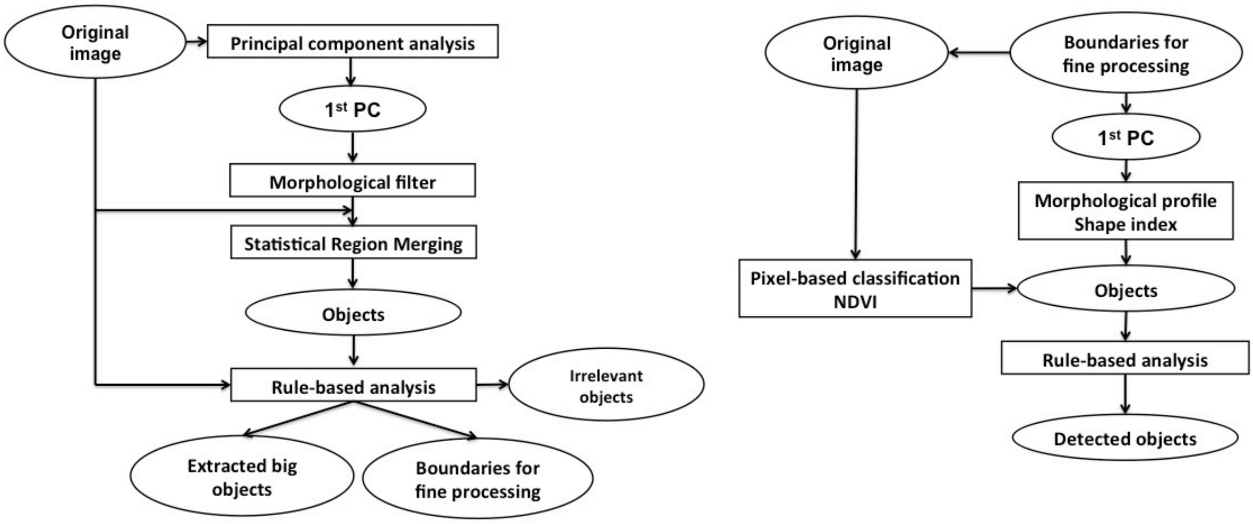
More details of SRM are proved and presented in Nock and Nielsen's papers (Nock and Nielsen 2004, Nock and Nielsen 2005). To delineate the big objects, the Q value is fixed at 64 whereas the g value is fixed to 256 so it is required to scale the simplified image grey value to 0-255. SRM is conventionally working on pixels that may take long time. To assist speeding up the conditional search based upon Eq. 2, the initial clusters are generated via morphological filtering (Vincent 1993). The filtering is to remove the small meaningless objects, less than 25 pixels, and is applied to the first component image derived by principal component analysis (PCA), which contains majority of information across multi-spectral bands. The main purpose of working on 1 band is also to speed up processing. After filtering, the pixels in a neighbour that have similar grey value will be merged into a cluster. Those clusters will play as the basic entity for SRM instead of pixels.

Subsequently, the rule-based analysis is carried out to decide which objects should be go further to fine level processing as well as remove irrelevant objects such as water and vegetation. First, homogeneous texture is measured, those with low homogeneous value is subject to go further. To discriminate water, vegetation from impervious surface, the brightness and greenness indices (Yarbrough et al. 2005) in combination with NDVI are employed. High level of greenness indicates the vegetation cover after confirmed with high NDVI value, whereas both low brightness and greenness values indicate the water body. The impervious surfaces have low greenness and high brightness values. The outcomes of coarse level processing, therefore, include the following types: homogeneous irrelevant objects such as water and vegetation, homogenous big impervious surfaces objects, and heterogeneous objects to go further to fine level processing. The very low homogeneous objects with low brightness and greenness values would be a cue to focus in mapping the damages. The whole process is illustrated in Figure 1a.

2.2 Fine level

In the detailed processing, a considerably large area has been masked out on coarse level with expectation that the time processing will be shortened. The flowchart of this fine level processing is shown in Figure 1b. Going into details, it is possible to reveal the geometrical beside the spectral properties of each object. The previously developed non-linear scale space transformation by the author (Vu and Ban 2010) is adopted here to derive the morphological profile and form the fine objects. Again, to speed up the processing, morphological profile is generated on only the first component of PCA. Briefly, morphological filtering with reconstruction with increasing template size is applied onto the first component analysis. The morphological profiles across the scale space provide the cue to group nearby pixels to a cluster via similarity measurement. It also helps to group the clusters with similarity profile to the same class. Since it works with only small objects, a limited number of sizes of increasing step of 1 can be used to generate the scale-space, named the scale range. Granulometry analysis is also employed to ignore the unnecessary sizes at which no significant changes on the granulometry spectrum within the scale range.

In addition, the compactness and elongated shape indices (Bogaert et al. 2000), ratio between object area and object perimeter/length, are exploited to discriminate building and road objects. The rest of spectral information is added back via a simple K-mean pixel-based classification. The spectral class of a fine object is decided based on the majority rule of pixel-based spectral classes within it.



(a) **(b)**

Figure 1. (a) Coarse level and (b) Fine level processing flowcharts.

New set of rule is established with regards to fine objects and their newly derived properties. As the potential damage area can be delineated from coarse level processing, this fine level processing mainly focuses in detection of intact building roofs. Frist, high NDVI and low NIR values are used here to eliminate small vegetation and water objects. The other 3 parameters, i.e. pixel-based spectral class, morphological profiles and shape index, are integrated in a decision-making scheme to decide the likelihood of an object to be a building. All of them are rescaled to 1-9. The shape index plays some form of quantitative measure, i.e. building is often a compact object, whereas the other two are more like qualitative measures. The higher the shape index value of an object is, the more likely it is a building roof. The result is then presented to the user for final decision in form of arithmetic formula (Eq. 3), which allows users learn easily the values contributed from each input parameter.

$$Class = 100 \text{ x } shape\text{-}index + 10 \text{ x } morphology + 1 \text{ x } spectral\text{-}pixel \quad (3)$$

The fully automatic processing can produce the detected objects using some predefined thresholds and rules. However, to ensure a good accuracy, the final step is designed for user's decision following the experiences that it is still difficult to detect the damage with current high-resolution satellite images (Ehrlich et al. 2009, Vu and Ban 2010). This is also the main reason why the rule-based analysis is chosen in development, which allows the users to input their knowledge to control the process. An automated classification, even adopting some complex machine learning algorithms, still cannot be reliable if the data has their own limitation.

2.3 Design for parallel implementation

As breaking into 2 levels, a big object formed on coarse level play as the tertiary to focus fine level processing within its boundary. The first goal of this design is not to analyse in details a homogeneous big object and hence, to speed up the processing. More importantly, the idea behind is to allow a parallel way of implementation in which the piece of information within each heterogeneous object will be delegated to a separate CPU. By this way, both data- and task- based implementation would be achieved. In addition, the most computational-time-consuming modules such as region merging and morphological profile will be implemented with MPI (Message Passing Interface) in line with implementing the tsunami damage estimation system (Koshimura et al. 2010). A test on image of different sizes of those two modules is depicted in Figure 2. Computation time drastically increases when the image size is 1024x1024 pixels. The implementation aspect is out of the scope of this paper and will be reported in next publication.

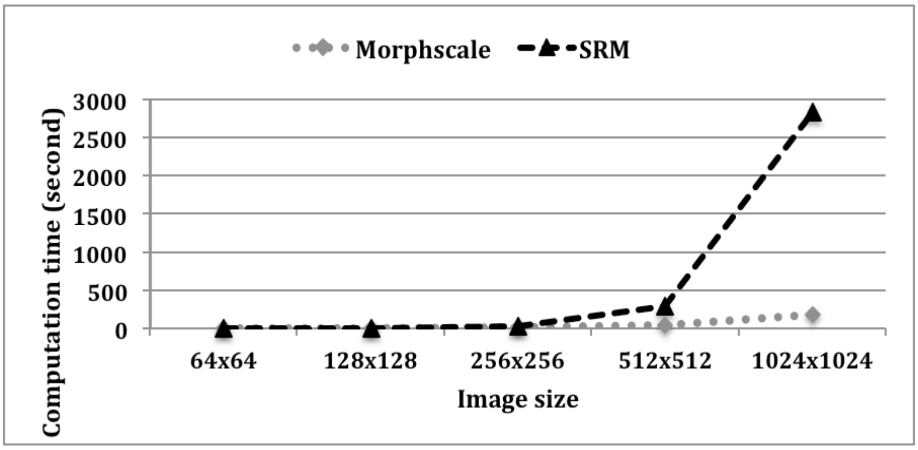


Figure 2. Illustration of computation time depends on image size (Morphscale for morphological profile, SRM for region merging)

3. TEST RESULTS AND DISCUSSION

Ban Nam Ken village, one of the most affected areas due to the 2004 Indian Ocean tsunami was selected as the study area with a QuickBird image captured on 2 January 2005, about a week after the tsunami attack. For demonstration of the developed solution, a portion of 1024x1024 was extracted, containing various surface types like vegetation, water, intact building roof, collapsed buildings and open soil, as shown in Figure 3a. The colour composite of brightness, greenness and homogeneous indices as the result of coarse level processing is illustrated in Figure 3b. It is obvious that the bluish areas, i.e. low brightness, low greenness and high homogenous values, are the homogenous surface water areas and ignored in further fine processing. The greenness areas, however, needed to be reconfirmed with NDVI value to know whether it would be vegetation. The red to orange areas, which lack of blue homogeneity and green vegetation, is more likely the concrete covered areas and damage areas, if working on a post-disaster image. This is particularly true for the area at the top-left of our study area.

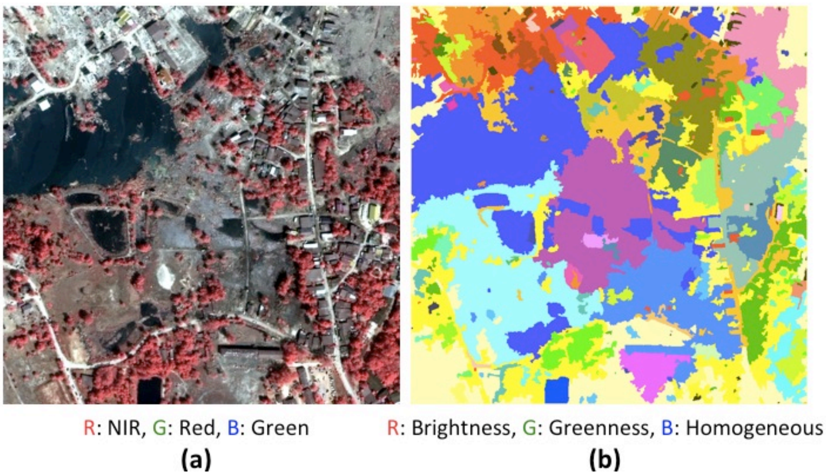


Figure 3. (a) False Colour Composite of original QuicBird image and (b) coarse level result.

Figures 4 and 5 present the results of fine level processing of two selected areas, in which the extracted features presented in their identification numbers (ID) and their ‘class’; the ‘class’ here is the combined results from pixel-based spectral, morphological, shape indices (Eq. 3). Figure 4 explores further the details of a damage area whereas Figure 5 presents the result from the non-damage area full of old rooftops.

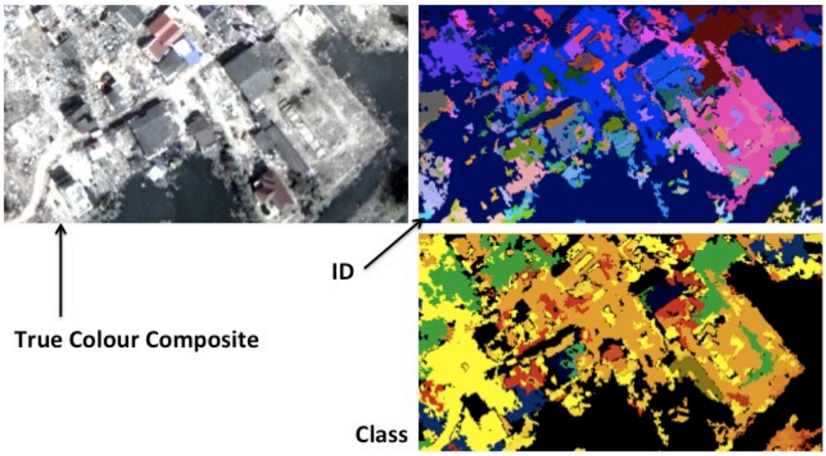


Figure 4. Fine level processing results of a damage area

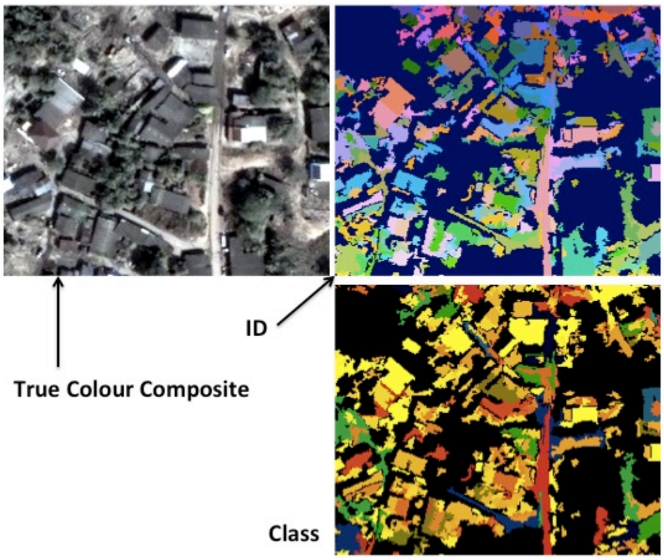


Figure 5. Fine level processing results of a non-damage area

Accuracy assessment of detected information from satellite image remains a problem though remote sensing images have been employed in disaster management for decades. It is mainly due to the gap between what remote sensing can produce and what the disaster management practitioners demands and get used to. There has been also a discussion on how damage information should be presented. Consequently, previous research (Gusella et al. 2005, Stramondo et al. 2006, Vu and Ban 2010) faced the difficulty in comparison with the 'ground truth' information. In this paper, the detected buildings are simply crosschecked with the visually detected ones. It showed that as Figures 3, 4 and 5, the extracted results were reasonably matched with the reference ones. Most compact objects, more likely to be building rooftop, were well detected. Visually, the old house rooftops in the study area are not distinguishable from the surrounding implying that it would be tough for an automated processing. The occlusion by the trees nearby also cleared a possible separation line between 2 objects introducing omission errors. More quantitative assessment will be reported in a mutual acceptable form with disaster management practitioners.

4. CONCLUSION

Dual-scale processing framework has been introduced to support the rapid damage estimation at the early stage after a disaster. The initial development is to serve as part of a system for tsunami disaster damage estimation while its ultimate goal is to serve as early damage estimation solution for multi-type disaster in support of emergency responses and to distribute for detailed damage assessment. The test with QuickBird image of Ban Nam Ken, Phanga, Thailand produced a reasonably good result. The result from coarse level delineated the highly suspected damage areas and produced the focused boundaries for fine level processing. The fine level processing designed as a semi-automatic approach then helps to explore the damage areas in further details and detect the intact buildings. The solution was designed aiming at a parallel implementation, and detailed report of the computation time will be reported in next publication. It is recommended to develop a suitable method for accuracy assessment dealing with objects and in the context of damage mapping.

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