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Experimental Study of Urban Growth Pattern Classification Using Moving Window Algorithm

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Abstract: Urban growth pattern can be generally categorized as either infill, expansion or outlying growth. Moving window algorithm determines urban growth pattern based on moving window analysis and a set of classification rules. However, literatures are concerned that the existing algorithm may produce incorrect classification result as it is strongly influenced by the size of moving window frame and classification rule. This study aims to investigate the effect of different moving window frames on the classification results and proposed an improvement to moving window algorithm with new classification rules. Results show that the existing algorithm is only able to classify outlying growth whereas the improved algorithm is not only able to classify outlying growth, it can also classify infill growth.

Key words: Urban growth pattern, moving window, classification rule, proposed, outlying

INTRODUCTION

Urban growth is defined as the expansion of major towns mainly caused by the rapid increase in population, rural migration and birth rates (Guneralp and Seto, 2008; Bhatta, 2010; Belal and Moghanm, 2011; Bagan and Yamagata, 2012). Though it is essential to accommodate the needs of urban population, an improperly planned urban development may lead to an uneven urban growth pattern, a condition commonly called as urban sprawl (Nechyba and Walsh, 2004). In order to overcome this problem, research should focus on creating an urban growth classification model for a better understanding of urban sprawl (Wilson *et al*., 2003). By studying the growth pattern of an urban area, one can observe whether the urban area is developed in a sprawling or non-sprawling manner.

The urban area expanded in various patterns which can be generally categorized as infill, expansion and outlying growth. Infill growth is the new urban development that occurs within existing urban areas. On the other hand, expansion growth takes place at the edge of existing urban areas while outlying growth occurs at a separate area from existing urban areas (Wilson *et al*., 2003). Urban growth pattern can be modelled by using satellite remote sensing data and suitable urban growth pattern classification techniques. Satellite remote sensing is a powerful tool in the analysis of urban growth due to its ability to produce high-quality data and updated information on the earth surface (Bagan and Yamagata, 2012). This information assists in differentiating the developed and undeveloped areas in satellite images. Furthermore, the availability of multi-temporal datasets makes it possible to detect the changes that occur over time and identifying the patterns of urban growth (Shahraki *et al*., 2011).

Recent studies are focusing on techniques to classify the urban area into a specific growth pattern and visualize the classification in an urban growth map. Moving window is one of the techniques that has been used for urban growth pattern classification. This technique processes an urban growth image in a pixel by pixel level. It uses moving window analysis and a set of classification rules to determine the urban growth pattern. In moving window analysis, a moving window traverses through each new urban pixel in the urban growth image and the percentage of old urban pixels surrounding the pixel of interest inside the moving window frame is calculated by using following Eq. 1:

$$P = 100\times\frac{O_u}{O_u+N_u} \quad (1)$$

Where:

O_u = The number of old urban pixels surrounding pixel of interest

N_u = The number of other pixels surrounding the pixel of interest

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Table 1: Literatures on moving window technique

Literature	Size of moving window frame	Classification rule
Hoffhine *et al*. (2003)	5×5	Infill growth: 100 = P = 40Expansion growth: 40>P>0 Outlying growth: P = 0
Guneralp and Seto (2008)	3×3	Infill growth: 100 = P = 40Expansion growth: 40>P>0 Outlying growth: P = 0
Pham *et al*. (2011)	5×5	Infill growth: 100 = P = 30Expansion growth: 30>P>0 Outlying growth: P = 0

The classification rule is based on the percentage of old urban pixels inside the moving window. However, the classification rule is not fixed and may vary to different literatures. Two literatures by Wilson *et al*. (2003), Kumar *et al*. (2009) defined that infill growth occurs when a new urban pixel is surrounded by at least 40% of old urban pixels, expansion growth occurs when new urban pixel is surrounded by <40% old urban pixels and outlying growth occurs when a new urban pixel is surrounded by 0% of old urban pixels. On the other hand, a literature by Pham *et al*. (2011) defined that infill growth occurs when new urban pixel is surrounded by at least 30% of old urban pixels, expansion growth occurs when new urban pixel is surrounded by <30% old urban pixels and outlying growth occurs when new urban pixel is surrounded by 0% of old urban pixels.

The size of moving window used in this technique also vary. To date, the sizes of moving window frame that have ever been used in urban growth studies are 3 by 3 (Kumar *et al*., 2009; Abiden *et al*., 2010) and 5 by 5 (Wilson *et al*., 2003; Pham *et al*., 2011; Ghani *et al*., 2011). Table 1 summarizes the literatures that implemented moving window techniques for urban growth pattern classification in terms of the sizes of moving window and classification rule. According to Ghani *et al*. (2011), different sizes of moving window frame may produce different classification results. Moreover, the improvement of moving window algorithm especially its classification rule needs to be taken into consideration in order to get better classification results (Pham *et al*., 2011). Thus, this study investigates urban growth pattern classification by using the existing moving window algorithm and proposes an improved moving window algorithm that produces better classification results.

MATERIALS AND METHODS

Data collection: The study area is the region of Klang valley with covering land area of latitude 2°54' South to latitude 3°10' South and longitude 100°30' East to longitude 101°47' east which is equal to 900 km^2 (30×30 km). It comprises of Kuala Lumpur area, its suburbs as well as adjoining cities and towns in Selangor. This area is chosen because it is one of the most rapid urban growth areas in Malaysia. The satellite image datasets are obtained from the Department of Survey and Mapping Malaysia (JUPEM). Six Landsat Thematic Mapper (TM) images at spatial resolution of 30 m are used where each pixel in the image represents the area of 900 m^2 on the ground (1:100000). All images are acquired on 1988, 1994, 1996, 2000, 2001 and 2003 with the temporal differences of 1, 2, 4 and 6 years between each data set.

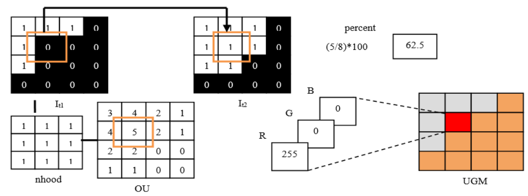

Fig. 1: Data structure of existing moving window algorithm

Data pre-processing: The satellite images are pre-processed into developed and undeveloped areas in ENVI. The process is carried out by using supervised classification which requires the user to select training sets as the basis for classification. The training sets are selected by defining two classes of Region of Interest (ROI); developed land and undeveloped land. Using ROIs that has been created, maximum likelihood comparison technique calculates and determines the class of each pixel. The resulting image is saved in a binary format representing only developed and undeveloped cells. Each image is in the form of bitmap image with the size of 827 pixels width and 467 pixels height, containing 386209 (827×467) data of both developed and undeveloped areas. Each pixel represents a ground area of 900 m^2 (1:100000). The developed area is denoted as white color with pixel value 1 while black color represents the undeveloped area with pixel value 0. Then, image correction procedure is performed to the binary images obtained from ENVI by checking for any classification error in the images. The classification errors denote the areas that change from developed to undeveloped. The corrected binary images are used for urban growth patterns classification.

Urban growth pattern classification using existing moving window algorithm: The classification of urban growth pattern is then implemented by using image processing toolbox in MATLAB Software. This research employs the existing classification rules (Wilson *et al*., 2003) and tests three sizes of moving window frame which are 3 by 3, 5 by 5 and 7 by 7 in order to examine the effect of varying moving window frames on the results of urban growth pattern classification. 7 by 7 is a new moving window frame that has not been used in the literature. Figure 1 shows the data structure of existing moving

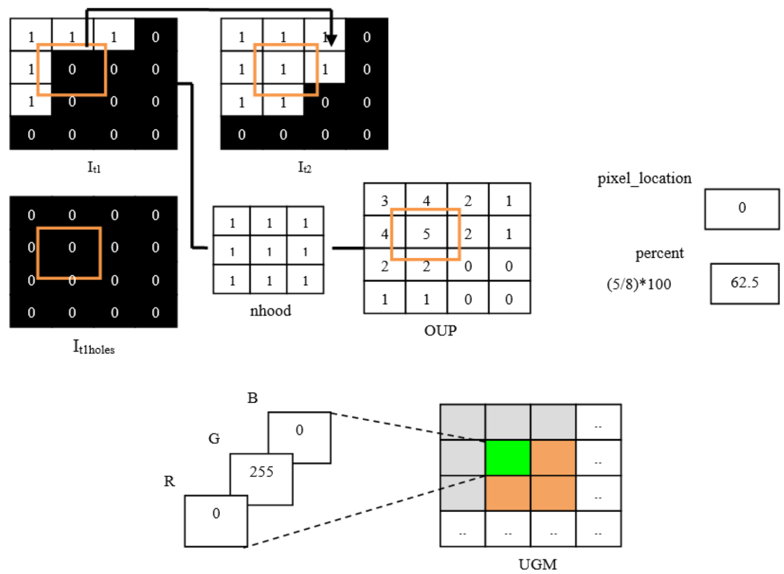

Fig. 2: Data structure of improved moving window algorithm

window algorithm. The algorithm requires reading two preceding and succeeding year binary images, I_{t1} and I_{t2}. Then, using a moving window of desired size, the number of developed pixels surrounding each pixel in I_{t1} are calculated and stored in a new matrix array, OUP. Next, both binary images are compared pixel by pixel to look for new urban pixels. The percentage of old urban pixels, percent, surrounding each new urban pixel is calculated by using the value in OUP. Based on the calculation, the urban growth form of the new urban pixel is determined and assigned to an urban growth image, UGM. New urban pixel with percent ≤ 40 indicates infill growth and is assigned to UGM with red colour (255, 0, 0). New urban pixel with percent >0 and <40 indicates expansion growth and is assigned to UGM with green colour (0, 255, 0). New urban pixel with percent equals to 0 indicates outlying growth and is assigned to UGM with blue colour (0, 0, 255).

Urban growth pattern classification using improved moving window algorithm: Improvements are made to the classification rule by taking into account the location of the new urban pixel and the percentage of old urban pixels surrounding new urban pixels inside the moving window frame. Any new urban pixel that is located inside old urban area is assigned to infill growth. Any new urban pixel that is located outside old urban area with percentage of old urban pixels <0 is assigned to expansion growth. Any new urban pixel that is located outside old urban area with percentage of old urban pixels equals to 0 is assigned to outlying growth. Figure 2 shows the data structure of the improved moving window algorithm. The algorithm requires reading two preceding and succeeding year binary images, I_{t1} and I_{t2}. Then, the undeveloped areas or holes inside the region in I_{t1} are located and assigned to $I_{t1holes}$. Then, using a moving window of desired size, the number of developed pixels surrounding each pixel in I_{t1} are calculated and stored in a new matrix array, OUP. Next, both binary images are compared pixel by pixel to look for new urban pixels.

For every new urban pixel, the region location is traced by comparing the pixel with the pixel of the same location in $I_{t1holes}$. If it is equals to 1, the pixel_location parameter is assigned equals to 1 and if otherwise, the pixel_location parameter is assigned equals to 0. Then, the percentage of old urban pixels, percent, surrounding each new urban pixel is calculated using the value in OUP. Based on these two parameters, the urban growth form of the new urban pixel is determined and assigned to an urban growth image, UGM. New urban pixel with pixel_location equals to 1 indicates infill growth and is assigned to UGM with red colour (255, 0, 0). New urban pixel with pixel_location equals to 0 and percent greater than 0 indicates expansion growth and is assigned to UGM with green colour (0, 255, 0). New urban pixel with pixel_location equals to 0 and percent equals to 0 indicates outlying growth and is assigned to UGM with blue colour (0, 0, 255).

RESULTS AND DISCUSSION

Figure 3 and 4 show the sample result of urban growth pattern classification using both existing and improved moving window algorithms for year 1988 until

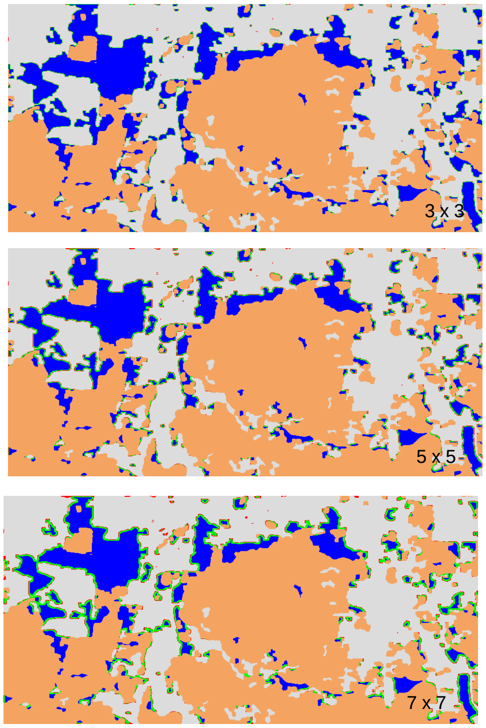

Fig. 3: Urban growth map of year 1988 until 1994 using existing moving window algorithm

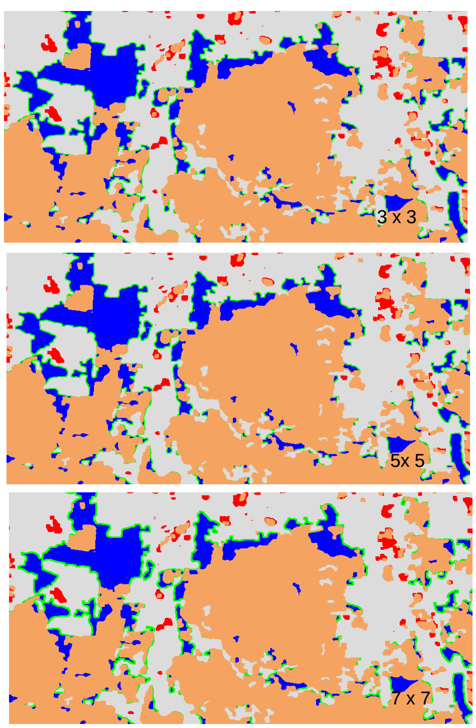

Fig. 4: Urban growth map of year 1988 until 1994 using improved moving window algorithm

Table 2: Predicted class (3×3)

True class	Class = Infill	Class = Expansion	Class = Outlying
Class = Infill	499	1836	4487
Class = Expansion	1079	5734	47544
Class = Outlying	0	25	935

Table 3: Predicted class (5×5)

True class	Class = Infill	Class = Expansion	Class = Outlying
Class = Infill	1631	2465	2726
Class = Expansion	3595	9261	41501
Class = Outlying	25	27	908

Table 4: Predicted class (7×7)

True class	Class = Infill	Class = Expansion	Class = Outlying
Class = Infill	1921	3405	1496
Class = Expansion	3881	14407	36069
Class = Outlying	25	56	879

Table 5: Predicted class (5×5)

True class	Class = Infill	Class = Expansion	Class = Outlying
Class = Infill	6822	0	0
Class = Expansion	0	6702	47655
Class = Outlying	0	0	960

Table 6: Predicted class (3×3)

True class	Class = Infill	Class = Expansion	Class = Outlying
Class = Infill	6822	0	0
Class = Expansion	0	12684	41673
Class = Outlying	0	0	960

Table 7: Predicted class (7×7)

True class	Class = Infill	Class = Expansion	Class = Outlying
Class = Infill	6822	0	0
Class = Expansion	0	18100	36257
Class = Outlying	0	0	960

1994. The color red, green and blue represent infill, expansion and outlying growth respectively. Using confusion matrices, the classification results are analysed with ground truth datasets obtained by Ghani *et al*. (2015). Table 2-7 shows the sample confusion matrices of both existing and improved algorithms for year 1988 until 1994. Analysis from the classification results show that the existing algorithm classify most of the new urban pixels as outlying growth and they have some problems in classifying infill and expansion growth. The distance between new and old urban pixels is influenced by an urban growth classification. New urban pixels that are the nearest to old urban pixels are classified as infill growth, followed closely by expansion growth and outlying growth pixels. When the size of moving window increases, the number of new urban pixels classified as infill and expansion growth also increase while the number of new urban pixels classified as outlying growth decrease. Analysis from the classification results show that the improved algorithm only solves the problem of classifying infill growth. Expansion growth is still incorrectly classified. The increasing size of moving window only increases the number of expansion growth pixels but does not change the urban growth pattern of the new urban areas.

CONCLUSION

This study focuses on improving the classification rule of moving window algorithm for urban growth pattern classification. Regardless of the percentage of urban pixels surrounding the urban pixel, infill growth occurs when location of new urban pixel is inside of the old urban area. Expansion growth occurs when location of new urban pixel is outside of the old urban area and percentage of urban pixels surrounding the urban pixel is <0. Outlying growth occurs when location of new urban pixel is outside of the old urban area and percentage of urban pixels surrounding the urban pixel is equal to zero. Since the improved algorithm is able to classify infill and outlying growth, future research can investigate on further improving the algorithm so that its weakness of misclassifying expansion growth can also be corrected.

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