Discrimination of residential and industrial buildings using LiDAR data and an effective spatial-neighbor algorithm in a typical urban industrial park

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Abstract
The Economic and Technological Development Zone (ETDZ) is a critical urban economic and functional area. Inefficient land exploitation and insufficient supervision have led to a great waste of land resources. The timely and precise extraction of residential and industrial building type, area and density information is urgently needed and essential for sustainable land use development. This study attempted to discriminate residential and industrial buildings by integrating LiDAR data, a lacunarity algorithm, object-based segmentation and a decision tree classifier. All buildings were identified using a normalized digital surface model (nDSM) and object-based segmentation. Lacunarity features and a decision tree classifier were then adopted to discriminate building types. An accuracy assessment indicated that the proposed method can effectively identify residential and industrial buildings. The overall classification accuracy was greater than 85.67% for both of the two test blocks. A comparison with results derived from the nDSM alone showed a significantly improved classification accuracy using the KHAT statistics from a Kappa analysis. The results not only confirmed the applicability and effectiveness of the combined method but also provided fundamental information for evaluating land use in the ETDZ.

Keywords: ETDZ, building, lacunarity, nDSM, classification.

Introduction
Large-scale industrialization and rapid development in Economic and Technological Development Zones (ETDZs) has consumed large amounts of land and arable resources and has led to environmental problems. Inefficient land exploitation and insufficient supervision have led to a tremendous waste of land resources within the zone. Although the government has conducted intensive land use evaluations every two years aiming to
improve the efficiency of land development, the lack of timely and reliable information, such as the scale of land development, building density and exploitation intensity, still falls short of the land use evaluation objective. In recent years, remote sensing, specifically high-resolution optical sensor imagery, has been widely used to evaluate the land use condition of the ETDZ and has generated promising results. However, detailed information about the type, area and distribution of building within ETDZ is in urgent need for effective land resource management and decision-making.

In fact, residential and industrial buildings are the predominantly distributed anthropic structure types in Chinese urban region, and present obvious differences in spatial size and pattern which can be identified through remote sensing techniques. For example, newly developed high-resolution laser scanning data have the obvious advantages of allowing for the precise identification of the build-up area and the discrimination of building types based on height information. First, the area of residential buildings is generally smaller than that of industrial buildings in Chinese ETDZs. In parcels of land of equal size, the number of buildings and the total area of gap are typically larger in residential areas. Second, residential buildings are often regularly distributed, whereas industrial buildings tend to be disorganized.

Previous studies have explored the extraction of building in urban mapping using high-resolution imagery or LiDAR data [Dorninger and Pfeifer, 2008; Chen et al., 2009; Guo et al., 2011; Rottensteiner et al., 2012; Aguilar et al., 2013; Bandyopadhyay et al., 2013; Forzieri et al., 2013; Guan et al., 2013a; Guan et al., 2013b; Niemeyer et al., 2013; Rottensteiner et al., 2013; Li et al., 2014; Niemeyer et al., 2014; Uzar, 2014]. Different information extraction techniques have been applied aiming at classifying urban objects or building reconstruction, such as hierarchical classification, random forest algorithm, data fusion/integration strategies, ANOVA tests, contextual classification etc. Among them, a benchmark study of building extraction based on LiDAR data was conducted and analyzed which enables a direct comparison of existing techniques for building recognition. However, it has to be noted that most of these researches only identified and classified all buildings in urban as a single object and few of them attempted to discriminate buildings into residential and industrial types. Furthermore, compared with general spectral and texture information presented in two-dimension, the specific spatial-pattern specified by building distribution such as “Spatial Gap and Lacunarity” has always been neglected for this task. Actually, the spatial neighbor pattern characterized by lacunarity was initially introduced to describe the distribution of gap sizes in a fractal sequence and can directly reveal the spatial distribution of a map occupied by a habitat of interest. If a geometric structure covers a wider range of gap sizes, it becomes more lacunar [Mandelbrot, 1983]. Structures that are heterogeneous at smaller scales may be homogeneous when observed at larger scales or vice versa, and then lacunarity can be thought of as a measure of gappiness or ‘hole-iness’ of a geometric structure [Plotnick et al., 1993]. Thus, the integration of LiDAR height data with Spatial Gap and Lacunarity would greatly improve discriminating residential and industrial buildings in Chinese ETDZ.

Considering the importance of accurate and subdivided building information, this study proposed a feasible and effective method for discriminating residential and industrial buildings by integrating LiDAR data and spatial-Lacunarity algorithm. This article is organized as follows: Data sets and study area are described in Section 2. Section 3 deals with our method, introducing object based building extraction; lacunarity feature calculation and selection; sample selection and analysis; building classification and accuracy assessment.
Results and discussion are outlined in Section 4, followed by final conclusions in Section 5.

Data and study area
A typical ETDZ that contains various industrial and residential buildings spatially distributed in a heterogeneous pattern located in Yangtze River Delta was selected as a case study. Limited by LiDAR data availability, two study blocks with areas of 4.9 km$^2$ and 6.7 km$^2$ within a park were adopted for building discrimination (Fig. 1).

![Figure 1 - Geographic location of the two study blocks in the economic and technological development zone.](image)

Airborne LiDAR data acquired by a Leica ALS70 sensor in 2013 were used in this study. The density of the LiDAR point cloud was approximately 0.5 points/m$^2$. The used LiDAR data contained only elevation (range) information, and the reflected intensity of the laser was not recorded. The corresponding normalized digital surface model (nDSM) was derived with 1m spatial resolution and 0.2 m vertical accuracy respectively. Aerial color images with a 0.5 m spatial resolution and field survey data, including GPS positions and photos, were adopted as reference data for an assessment of the building discrimination accuracy. The RGB imagery was ortho-rectified and processed into the same Universal Transverse Mercator (UTM) coordinate system as the LiDAR data.

Method
The proposed method consists of five steps including nDSM generation, binary image generation, calculation and selection of lacunarity features, classification comparison test, accuracy assessment and Kappa analysis (Fig. 2).
Figure 2 - Flow chart of the proposed method.

**Generation of the nDSM**

First, outlier points were identified using section view and manual editing. Second, the LiDAR points were filtered into on-terrain and off-terrain points based on the progressive triangulated irregular network densification algorithm as described by Axelsson [2000]. One version of the filtering algorithm was implemented in the commercial software TerraSolid. The modeling of urban areas with this software is considered to be stable and robust [Guan, et al., 2013a]. Third, the digital elevation model (DEM) and DSM were generated by exporting lattice model without and with off-terrain points. Fourth, the nDSM was acquired based on the difference between the DSM and DEM.

**Generation of building/non-building binary images using an object-based approach**

Calculation of lacunarity was performed to characterize the gap percentage and distribution of buildings. Reliable building extraction is, thus, a fundamental task and provides thematic building map. Object-oriented information extraction techniques have been demonstrated to have a large potential to improve the automatic extraction of information from very high-resolution imagery [Mathieu et al., 2007]. The object-centered classification prototype generally starts with the generation of segmented objects at multiple level of scales as fundamental units for image analysis, instead of considering a per-pixel basis at a single scale for classification [Myint et al., 2011]. The fundamental concept of an object based approach also differs from sub-pixel classification approach in that it does not consider spectra of different land covers that would quantify percent distribution of these land covers. Much of the work referred to as object based classification has been originated around the software eCognition. Two successive steps are involved in the object-based classification approach: image segmentation and object classification. The most crucial parameter of image segmentation is the scale parameter that controls object size. It is an abstract term that determines the maximum allowed heterogeneity for the resulting image objects. The object homogeneity to which the scale parameter refers is defined in the Composition of
Homogeneity criterion field; it is used as a synonym for minimized heterogeneity. Internally, three criteria are computed: color, smoothness and compactness. By modifying the shape criterion, the color criteria can be indirectly defined (color=1-shape) to change the relative weighting of reflectance and shape in defining segments. The smoothness criterion is used to optimize image objects with regard to smoothness of borders while the compactness criterion is used to optimize image objects with regard to compactness.

The shape parameter was set to 0.1 to give less weight to the shape and greater attention to the homogeneous pixels for the nDSM segmentation. The compactness parameter and smoothness were set to 0.5 to equally balance these two features of the objects. A scale parameter of 10 was considered to be appropriate for this study. The height threshold and manual editing of those generated objects can fit our requirement of accurately extracting buildings according to an image analysis (Fig. 3). Based on a trial-and-error analysis, a threshold value of 18m was used for building extraction. Hence, the values in the nDSM that were equal to or greater than 18m were assigned to buildings, and the other values were assigned to non-buildings. After this step, a visual examination and manual editing were conducted to guarantee that all buildings were accurately extracted. Finally, 848 (NE block) and 1594 (NW block) building polygons were derived and assigned values of 1 or 0 to create a binary map of buildings and non-buildings respectively.

Figure 3 - Illustration of building extraction.
Calculation and selection of lacunarity features

Lacunarity has been used to describe the distribution of the gap sizes in a fractal sequence and proved to be a scale-dependent measure of heterogeneity. A gliding-box algorithm for lacunarity estimation was proposed by Allain and Cloitre [1991]. The number of gliding-boxes with radius \( r \) and mass \( M \) is represented by \( n(M, r) \), the probability function \( Q(M, r) \) can be obtained by dividing \( n(M, r) \) by the total number of boxes. As a result, the lacunarity at scale \( r \) can be defined as [Eq. 1]:

\[
\Lambda(r) = \frac{\sum_{M} M^2 Q(M, r)}{\left( \sum_{M} MQ(M, r) \right)^2} \tag{1}
\]

This method was initially developed for lacunarity estimation of binary data and has already been implemented into a geographic information system (GIS) software extension for lacunarity analysis by Pinliang Dong [2009]. The principle of this method is the ratio of the variance and square of the arithmetic mean of the number of filled pixels within all \( r \)-sized unique square subsets of the larger subset \( P \) of the original binary image [Kit et al., 2012]. Lacunarity is a function of the size of the gliding box, the fraction of the map occupied by the habitat of interest and the geometry of the map [Plotnick, et al., 1993]. It is often reported that classification accuracy increases with a decreasing box size used in the lacunarity calculation [Myint and Lam, 2005; Kitada and Fukuyama, 2012]. Thus, a 3×3 box size was selected in this study. With respect to the window size, most publications tend to identify the optimal value using a lacunarity-box size plot. This value can be determined by plotting a linear fit through three consecutive points on the lacunarity curve. If the three points are linear, the coefficient of determination, \( r^2 \), of the linear fit approaches 1, and the image appears as a self-autocorrelation [Malhi and Román-Cuesta, 2008]. The size of moving window should not exceed the end point of a quasi-linear curve of the lacunarity-box size plot [Han et al., 2011].

Identification of residential and industrial buildings and accuracy assessment

To evaluate the role of lacunarity for building classification, a scheme incorporating two groups of variables was designed: (1) only use nDSM as an input and (2) only use lacunarity feature as an input. In addition, the extracted building layer was also participated in both of the two classification approaches to guarantee that classification was strictly limited on the basis of buildings. By using the same parameters as mentioned in building extraction, 6863 and 10015 building segments were generated after segmentation. Likewise, the same training and testing samples were collected for different groups of the same block. The decision tree classifier that has been implemented into eCognition Developer 8.7 was chosen to perform building classification.

A stratified random sampling scheme was applied and altogether 600 samples (no less than 150 for residential and industrial class) were collected to conduct accuracy assessment. Using a 0.5 m resolution aerial image and field survey data as references, attribute information of all 600 polygons were obtained by visual interpretation. Mismatched objects resulting from incompatible phases were determined with the help of Google Earth. Four confusion matrices
were generated based on 600 samples in NE and NW block each. A range of quantitative measures of classification accuracy can be derived by this matrix including producer’s accuracy (PA), user’s accuracy (UA), overall accuracy (OA), kappa coefficient etc. Producer’s accuracy refers to the measure of omission errors that corresponds to those pixels belonging to the class of interest that the classifier has failed to recognize. User’s accuracy represents the measure of commission errors that correspond to those pixels from other classes that the classifier has labeled as belonging to the class of interest. Overall accuracy is the percentage of correctly classified samples [Thapa and Murayama, 2009]. Kappa coefficient is a measure of overall statistical agreement of a confusion matrix, which takes non-diagonal elements into account. Therefore, it provides a more rigorous assessment of classification accuracy. Kappa analysis is a widely-used and powerful multi-variate technique for accuracy assessment. The estimate of kappa is the so-called KHAT statistic. It gives a measure that indicates whether the confusion matrix to be analyzed is significantly different from a random result. It is also used for comparing different matrices from different classifiers and determining if one result is significantly better than the other. Detailed information of this technique can be found in Congalton et al., [1983], Hudson and Ramm, [1987], Congalton, [1991], Smits et al., [1999]. A KHAT statistic, kappa variance and Z statistic were adopted in this study to analyze the randomness and compare the difference between four confusion matrices.

**Results and Discussion**

*Extraction of the building image*

It was shown from Figure 4 that the buildings were extracted successfully. According to the high-resolution aerial photos, six sample regions covering typical residential and industrial buildings from the NE and NW blocks were selected for a lacunarity calculation and to explore the difference of the two building types respectively. The relationship between box-size and lacunarity was further analyzed based on two considerations: to demonstrate the possibility of discriminating the two types of buildings theoretically and to identify the optimal window size for the subsequent feature calculation.

**Discrimination of residential and industrial buildings**

*Lacunarity calculation analysis based on samples*

The application of the lacunarity algorithm to building/non-building binary images illustrated the feasibility of measuring building spatial distributions at different scales. Figure 5 a and b illustrated how the lacunarity plots vary with increasing scale in two blocks. Normalization of the curves (c,d) by division by ln[Λ(1)] enabled direct comparison among curves. As the box size increases, the lacunarity values decreased dramatically. Because the increase in the box size lead to an increase in the box mass (i.e., the mean value of the box mass increases while the variance of the box mass decreases), the lacunarity value decreased.

Lacunarity is a function of the size of gliding box, the fraction (P) of the map occupied by the habitat of interest and the geometry of the map [Plotnick et al., 1993]. For one thing, sparse maps shall have higher lacunarites than dense maps for the same gliding box sizes. In the NE block (Fig. 4a and Fig. 5c), for example, three types of residential buildings characterized by disparate gap content but similar gap geometry were significantly distinct from each other in lacunarity. R3 featured a much larger percent of gap compared with R1 and R2, lacunarity of this region was also much higher than that of the other two.
Therefore, a lower number of occupied pixels corresponded to a larger lacunarity value if the variance of the box mass were similar. An extreme case would be a sample region (in our study 282×219) that was completely covered by a large building; in this case, the mean value of the box mass became quite large, whereas the variance of the box mass approached 0. Therefore, the lacunarity would be close to its smallest value: one. For another, higher lacunarity normally represent fewer but larger gaps for a given P. In NW block (Fig. 4b and Fig. 5d), for example, R2 and R1 were occupied by almost the same percent of building pixels, but lacunarity of R2 was significantly higher than R1 because of their geometry distinction. Same conclusion could be derived from I1 and I2 in NE block whose P were also similar. Moreover, lacunarity of the residential buildings tended to be smaller than that of the industrial buildings in the two blocks. But the conclusion might be just the opposite when it was calculated in a small scale. R2 and R3 in NW block seemed to be an exception to this rule, a careful examination of the map would find that they were quite different with other samples of residential building. Thus, confusion could have occurred between this class and industrial class. But the limited number of R2 buildings could not significantly influence our classification result. They were only a very small proportion of all the buildings in this block.

Residential buildings appear as smaller patchy areas with larger percent of gaps within all sample regions, however, variance of distribution of gaps in residential regions were also much smaller than that of industrial buildings. Consequently, industrial buildings present higher lacunarity due to their large heterogeneity of building distribution.

![Figure 4](image_url) - Industrial and residential building samples of the NE (a) and NW (b) block. Samples are 282×219. I and R represent industrial and residential, respectively. P denotes the fraction of map occupied by the habitat of interest.
Binarization based on nDSM and building extraction is a type of directional transform. The spatial pattern and self-autocorrelation characters can be extracted by applying a lacunarity algorithm to this binary image. Hence, two types of buildings can be discriminated theoretically.

Window selection analysis
In general, the buildings appeared self-similar on scales around 3.3 implied by the quasi-linear decrease in the lacunarity plot (ln29≈3.36). Therefore, optimal window size for NE and NW blocks were 29×29. Meanwhile, this makes eminently good sense. The length of two residential buildings in the two blocks were around 29 meters. From the third residential building on, they became similar with the previous one. Below this length scale, some elements of self-similarity could be found in the architecture of two residential buildings. On the other hand, a tendency towards spatial invariance could be introduced by the regularity of building position and roof size above this scale.

Figure 5 - The relationship between the box size and lacunarity values for all samples in the NE (a, c) and NW blocks (b, d). Note that a, b were original and c, d were normalized result.

Accuracy assessment analysis
By qualitative evaluation (visual examination on screen) of the output maps, we noticed that
the output map generated by the nDSM group contains many mistakenly identified objects of classes (Fig. 6 c, d), whereas the output map generated by the lacunarity group looks more accurate (Fig. 6 a, b). It was anticipated that the classification of building classes with the nDSM approach might not be very effective, since many urban buildings were height similar and nDSM approach did not consider spatial arrangements of building objects. This was also demonstrated later in the confusion matrices and kappa analysis result.

From Table 1, it can be observed that the nDSM group produced low overall accuracy (68.5%/60.67%) and kappa coefficient (0.3339/0.2814) in both of the two blocks. As expected before, there was significant signature confusion among the two types of buildings. In NE block, almost thirty percent of the total sample points identified as residential were found to be industrial on the ground (84 out of 380). It was also found that about one fourth of the sample points identified as industrial were found to be the residential category in this block (85 out of 220). The user’s accuracy of the residential category was exceptionally low (56.49%). In NW block, the situation became even worse. Although the producer’s accuracy of the residential was really high (92.92%), the corresponding omission error of 60.83% and
commission error of 49.55% and a low kappa of 0.2814 indicated that industrial buildings were very poorly distinguished; many industrial buildings were mistakenly classified as residential building objects.

Table 1 - Overall accuracy, producer's accuracy (PA), user's accuracy (UA), and kappa coefficient produced by different approaches.

| Classified Data | Reference | Industrial | Residential | Total | PA(%) | UA(%) |
|-----------------|-----------|------------|-------------|-------|-------|-------|
| Industrial      | 276       | 85         | 361         | 72.63 | 76.45 |
| Residential     | 104       | 135        | 239         | 61.36 | 56.49 |
| Total           | 380       | 220        | 600         |       |       |

Overall Accuracy = 68.50%  Overall Kappa = 0.3339

| Classified Data | Reference | Industrial | Residential | Total | PA(%) | UA(%) |
|-----------------|-----------|------------|-------------|-------|-------|-------|
| Industrial      | 297       | 3          | 300         | 78.16 | 99    |
| Residential     | 83        | 217        | 300         | 98.64 | 72.33 |
| Total           | 380       | 220        | 600         |       |       |

Overall Accuracy = 85.67%  Overall Kappa = 0.7133

In contrast to the nDSM group, the lacunarity group produced a significantly higher overall accuracy (85.67%/87.00%) and kappa coefficient (0.733/0.7400). The good performance of this approach can also be observed from Figure 5 where significant improvement of industrial
class can be found. Nonetheless, the two building types still had problems in this map. This could have been due to the fact that some industrial buildings around and on the edges of industrial buildings might have been partly included as residential building objects. Overall, the separation of industrial and residential buildings is successful using the proposed object-based building extraction and lacunarity strategy with some useful parameters contributing to the process. A common fault, nevertheless, that is present in our lacunarity method in the two blocks is the deficiency in identifying small industrial buildings. The small industrial buildings in the two blocks are mostly dwarfed by residential buildings that share similar lacunarity feature. The omission error of industrial buildings can also be caused partially by the low density of LiDAR point.

The statistics of a confusion matrix of every group were presented in Table 2. The Z value of each group was larger than 1.96, meaning that all classification results were better than random at a 95% confidence level. These Z values also indicated the importance of both the lacunarity and nDSM features. Paired kappa analyses suggested that lacunarity group were statistically significant different from the nDSM group at a 95% confidence level. That is, the percentage and geometry of unoccupied pixels characterized by lacunarity feature is more suitable for the discrimination of building classes as compared to the elevation. This result is in good agreement with our hypothesis.

Table 2 - Comparison of the Kappa analysis results for different confusion matrices.

| Block | Group | KHAT | Variance | Z_Single | Sig.   | Z_pairwise | Sig.   |
|-------|-------|------|----------|----------|--------|------------|--------|
| NE    | nDSM  | 0.339| 0.0019   | 7.6602   | S(95%) | 6.6045     | S(95%) |
| NE    | Lacunarity | 0.7133| 0.0014 | 19.0637 | S(95%) |           |        |
| NW    | nDSM  | 0.2814| 0.0014 | 7.5207 | S(95%) | 8.2367     | S(95%) |
| NW    | Lacunarity | 0.7400| 0.0017 | 18.0363 | S(95%) |           |        |

Note: Z_single = Single matrix Z statistic; Z_pairwise = Two matrices Z statistic; S = Significant; NS = Not significant.

Conclusions

The buildings in a residential district are generally built simultaneously by one developer, whereas industrial buildings are built sequentially at different periods according to the actual demand. Consequently, the percentage and geometry of unoccupied pixels should be universally discrepant between residential and industrial buildings. The analysis of lacunarity curves of 12 samples illustrated the potential of using lacunarity features to quantify those two characteristics.

Lacunarity features and nDSM data are both important variables for building classifications. Building patterns characterized by lacunarity features are universal phenomena. In addition, lacunarity can be deemed as a second-order product of nDSM as explained by its calculation. As a result, lacunarity should yield the best accuracy. This hypothesis was upheld using a trial classification of two groups in which lacunarity features yielded the highest accuracy. The classification results of the lacunarity group were significantly superior to those of
the nDSM group at the 95% confidence level, indicative of the critical role of lacunarity features in the discrimination of the two classes. This study also highlights important issues associated with the use of LiDAR data and lacunarity features. Although the presented method exhibited flexible results in discriminating residential and industrial buildings, the identification of initial building information could be improved by integrating high-resolution multispectral images. Future work should focus on a detailed multi-class classification of urban areas using multispectral and LiDAR point data to provide an accurate basis for the evaluation of land use status.

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