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Geometric Regualrization of Irregular Building Polygons: A Comparative Study

Gunho Sohn[1] · Yoonseok Jwa[2] · Vincent Tao[3] · Woosug Cho[4]

Abstract

3D buildings are the most prominent feature comprising urban scene. A few of mega-cities in the globe are virtually reconstructed in photo-realistic 3D models, which becomes accessible by the public through the state-of-the-art online mapping services. A lot of research efforts have been made to develop automatic reconstruction technique of large-scale 3D building models from remotely sensed data. However, existing methods still produce irregular building polygons due to errors induced partly by uncalibrated sensor system, scene complexity and partly inappropriate sensor resolution to observed object scales. Thus, a geometric regularization technique is urgently required to rectify such irregular building polygons that are quickly captured from low sensory data. This paper aims to develop a new method for regularizing noise building outlines extracted from airborne LiDAR data, and to evaluate its performance in comparison with existing methods. These include Douglas-Peucker's polyline simplication, total least-squared adjustment, model hypothesis-verification, and rule-based rectification. Based on Minimum Description Length (MDL) principal, a new objective function, Geometric Minimum Description Length (GMDL), to regularize geometric noises is introduced to enhance the repetition of identical line directionality, regular angle transition and to minimize the number of vertices used. After generating hypothetical regularized models, a global optimum of the geometric regularity is achieved by verifying the entire solution space. A comparative evaluation of the proposed geometric regulator is conducted using both simulated and real building vectors with various levels of noise. The results show that the GMDL outperforms the selected existing algorithms at the most of noise levels.

Keywords : LIDAR, Building, Geometric regularization, 3D Reconstruction

1. Introduction

3D building geometric modeling in urban areas is in great demand for a variety of applications such as urban planning, mobile communication, 3D city modeling and virtual reality (Sohn and Dowman, 2007). Since human-centric building modeling is time consuming and very costly, a fast and general method for simplifying irregular building boundary lines based on segmentation results is highly required in dynamically changing urban areas. In the last few decades, considerable research efforts have been directed toward mainly reconstructing building models using aerial imagery and airborne laser scanning data obtained from passive and active sensors such as camera and laser scanner (Weidner et al., 1995; Ameri, 2000; Sohn and Dowman, 2007; Sohn et al., 2007; Sampath et al., 2007). However, the current state-of-the-art techniques in 3D building reconstruction have not been matured yet, and still produce large errors in reconstructed building outlines. Thus, many enthusiastic researchers have introduced different techniques in the geometric regularization. However, these research efforts have gained only limited success in constrained environments requiring many pre-specified thresholds to control the geometric regularity which are not often the case in practice. Therefore, developing the new technique to implicitly drive

1) GeoICT Lab, Earth & Space Science and Engineering, York University, Canada (E-mail: gsohn@yorku.ca)
2) GeoICT Lab, Earth & Space Science and Engineering, York University, Canada (E-mail: yjwa@yorku.ca)
3) GeoICT Lab, Earth & Space Science and Engineering, York University, Canada (E-mail: tao@yorku.ca)
4) A Full Member, Department of Civil Engineering, Inha University (E-mail: wcho@inha.ac.kr)

regularization rules from given data domain is urgently required. This study is organized into six sections. Section 2 discusses the existing regularization methods selected for current comparative performance test. In Section 3, we introduce a new geometric regulator developed based on Minimum Description Length (MDL). Section 4 presents a comparative analysis of the proposed technique's performance with the selected geometric regulators. Quality assessment for each method is provided using the geometric regularity error matrix in Section 5. Finally the paper will end with some concluding remarks and recommendations for future research.

2. Existing Building Polygon Regulators

There are several techniques of geometric regularization on irregular building polygons. Amongst them, we selected five representative regulators from the literature for comparing their performance over noisy building outlines. These include: (1) Douglas-Peucker's algorithm (Douglas and Peucker, 1973), (2) Local Minimum Description Length (Weidner and Förstner, 1995), (3) Feature Based Model Verification (Ameri, 2000) and (4) Rule-based Rectification (Sampath and Shan, 2007). In this section, we briefly describe the selected techniques, which performance will be later compared to a new regularization method proposed in this study.

2.1. Iterative Polyline Simplication

The classical Douglas-Peucker (DP) line-simplication algorithm has been widely recognized as the most visually effective line simplication algorithm (Ramer, 1972). This simple algorithm start to construct a polyline with edge segments which link *a prior* initial vertex selected from edge points. The process recursively discards the subsequent vertices whose distance from the initial polyline less than $\zeta > 0$ error tolerance, but accepts the vertex as part of the new simplified polyline if it is farther away from the line larger than ζ, which becomes the new initial vertex for further simplication. The starting points, which can be initial vertices, are vertices with maximum and minimum coordinate according to horizontal direction. After detecting all initial vertices, the process continues until the initial plotlines from all initial vertices are less than ζ.

2.2. Model Hypothesis-Verification

Weidner and Förstner (1995) adopted a local Minimum Description Length (LMDL) to rectify noisy building outlines extracted from high-resolution DSM using MATCH-T based on. The MDL principal is well-known optimization theory to obtain a good balance between model likelihood and model complexity based on Occam's razor. Starting from the initial building boundary obtained from the DP algorithm, the method selects four consecutive points as a local unit of the polyline regularization. With this local point set, ten different hypothetical regularization models are generated (Fig. 1). The hypotheses are generated in order to impose the orthogonal regularity on between consecutive lines, either by moving two middle points or to enhance the simplicity by removing one of the middles points.

For each hypothesis, the description length, *DL*, is measured on the goodness-of-fit between the hypothe-

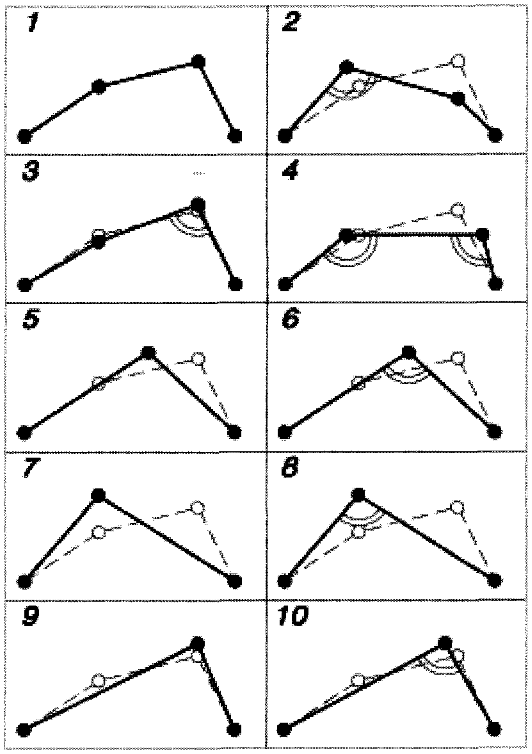


Fig. 1. Ten alternative hypotheses for local configuration with optimum case 10 (Weidner et. al., 1995).

sized model and its corresponding observations and on the model complexity. Given a regularization hypothesis, *H*, and the observation, *D*, *DL* is now defined as

$$DL = L(D \mid H) + L(H) \tag{1}$$

where $L(D|H)$ is the likelihood of *H* describing *D* and $L(H)$ is the complexity measure of *H*. Weidner and Förstner (1995) suggested $L(D|H)$ and $L(H)$ in Eq. (1) as

$$DL = -\frac{\Omega}{2} ln\, 2 + \frac{(N_p - N_c)}{2} \log_2 N \tag{2}$$

In Eq. (2), Ω is the weighted sum of the squared residuals between *D* and *H*. *H*'s complexity in the last term of Eq. (2) depends on the number of unknown parameter, N_p (i.e., the number of vertices associated to generate *H*), constraints, N_c (i.e., the number of parameters to constrain the orthogonality), and a set of *N* observations. The optimal hypothesis, H^*, is determined by simultaneously minimizing Ω and the number of vertices used to generate *H*. Due to the local nature of LMDL, the method may produce different results according to starting point when regularization process is performed. To resolve this problem, the orthogonal and parallel regularities must be constrained by hypothesizing and verifying regularizing models in a global manner.

2.3. Total Least-Squared Adjustment

Ameri (2000) introduced the Feature Based Model Verification (FBMV) for regularizing 3D polyhedral building shape extracted from high-resolution multiple airborne images. The method is developed based on the total least-squared adjustment. In here, the approach is implemented by using only laser scanning data. The first step of FBMV is to extract initial value for vertices and line parameters by DP algorithm. Then, these edge points serve to compute building planar parameters. Finally, the total least-squared adjustment is performed based on linearity, connectivity, coplanarity, and orthogonality as shown in Eq. 3. Linearity is used to minimize the perpendicular distance between LiDAR data and representative lines each segment based on line equation. The intersection coordinate of two adjacent lines can be computed based on connectivity constraint. Coplanarity is used under the assumption that the building points classified as the same group exist in the same plane polygon. Since constraints in Eq.3 are formed as nonlinear equation, the equations must be used after changing to a linearized form.

$$\begin{aligned}
&L(\theta_j, \rho_j) = x_i \cos\theta_j + y_i \sin\theta_j - \rho_j \quad \underline{e} \sim N\left(\underline{0},\ \sigma_0^2 P_L^{-1}\right) \\
&C(\theta_j, \rho_j, x_j^I, y_j^I) = x_j^I \cos\theta_j + y_j^I \sin\theta_j - \rho_j \quad \underline{e} \sim N\left(\underline{0},\ \sigma_0^2 P_C^{-1}\right) \\
&P(x_j^I, y_j^I, z_j^I) = a x_j^I + b y_j^I + c - z_j^I \quad \underline{e} \sim N\left(\underline{0},\ \sigma_0^2 P_P^{-1}\right) \\
&O(x_j^I, y_j^I, z_j^I) = a_1 a_2 + b_1 b_2 + c_1 c_2 \quad \underline{e} \sim N\left(\underline{0},\ \sigma_0^2 P_O^{-1}\right)
\end{aligned} \tag{3}$$

Where

- x_i, y_i, z_i : 3D coordinates from LiDAR data
- θ_j, ρ_j : Angle between the edge and x-axis. distance between the origin and the line
- x^I_j, y^I_j, z^I_j : 3D coordinates of intersections between edges
- a, b, c : Plane parameters
- a_1, b_1, c_1 : Direction vectors for two edges at intersection point
- a_2, b_2, c_2 :
- L, C, P, O : Linearity, Connectivity, Coplanarity, Orthogonality

In case of orthogonality, if α (angle between vectors) exists within $t > 0$ the acceptable tolerance, the orthogonal property is applied to the vertex as shown in Eq. (4).

$$90^0 - t \le \alpha \le 90^0 + t \tag{4}$$

When this approach is developed by only using LiDAR data, the final result depends on initial values obtained from DP. That is, the quality of regularization for irregular building lines may be subject to the performance of DP. However, based on FBMV principal, this approach can derive the good description of building boundary lines using total least-squared adjustment. In addition, conditional constraints such as orthogonality, parallelity and symmetricity can easily be applied to the model for the high quality reconstruction.

2.4. Rule-based Rectification

Sampath & Shan (2007) developed a rule-based regularization for refining a coarse building boundaries extracted by classical supervised classification using IKONOS imagery. The method consists of two-step regularization processes. A coarse building boundary is obtained by DP, thereby eliminating noisy boundary points. The second step is to further rectifying outlying points with perpendicular constraints which is pre-specified. After dividing slopes into two groups in horizontal and vertical direction, a simple least square adjustment is performed to regularize boundary lines with irregular shape. Since the slope direction is only divided into two directions, in case of the building polygon with more than two directions, the proposed regularizing process is not working well. However, this approach can rapidly provide the good solution for regularization in the building with simple shape. The line equation and orthogonal constraint equation can be used as shown in the following equation.

$$L(A_i, B_i) = A_i x_j + B_i y_j + 1 \quad \underline{e} \sim N\left(\underline{0},\ \sigma_0^2 P_L^{-1}\right)$$
$$O(A_i, B_i, M_s) = \frac{A_i}{B_i} + M_s \quad \underline{e} \sim N\left(\underline{0},\ \sigma_0^2 P_O^{-1}\right) \tag{5}$$

Where

x_i, y_i : Horizontalcoordinates from LiDAR data

M_s : Slope for vertical or horizontal line ($= -\frac{1}{M_h}$ or $-\frac{1}{M_v}$)

L,O : Linearity, Orthogonality contraint ($M_h M_v = -1$)

3. A New Building Shape Regularization

In this section, we propose a novel method for incrementally regularizing noisy building outlines by considering newly driven geometric regularity parameters in MDL framework. The optimal shape regularity is achieved by testing hypothetically regularized models with regularity favored objective function.

3.1. LMDL Limitations

As shown in Weidner and Förstner (1995), the most benefit taken from the MDL regulator is that the method is generic not to require hard-constraints (i.e., pre-specified thresholds) to explicitly constrain the domain knowledge on the shape regularity. For instance, both FBMV and RR pre-specify an if-then rule set to facilitate the regulator following the orthogonality and parallelity, which is only working well with certain limited condition. However, the MDL provides more flexibility to implement such regularization rules with soft-constraints (i.e., cost function or objective function). In LMDL, the cost function is to minimize the description lengths which bitwise encode the cost to select a hypothetical model when it is true in terms of the residual likelihood and the model complexity. The optimization of LMDL is achieved by verifying entire model candidates that are generated with different model complexity. An optimized model will be achieved to produce reasonable residuals with the simplest model. Although LMDL was successfully applied to the building shape regularization problem, we have observed two major limitations that could be improved; (1) locality and (2) limited encoding scheme for the model complexity. LMDL is conduced over a local set of four consecutive points, by which: firstly, the regularization result by LMDL depends on starting local point set and secondly, the orthogonality and parallelity to generate hypothetical models are relatively determined in relation to the positions of the two (starting and ending) anchor points of the local point set. Moreover, the model complexity is only penalized by the number of the vertices forming the model. However, with the same number of vertices, polygons with different model complexity can be made.

3.2. Geometric MDL

We propose a new method to regularize noisy building outlines, called Geometric MDL (GMDL), which encodes the model complexity with different regularity measurements from LMDL. In GMDL, we define the shape regularity to show: (1) the directional repeatability, (2) the regular angle transition, and (3) the number of model parameters. That is, the optimal model is selected if the polyline has as many as possible identical line directions, N_D; smoother or more orthogonal inner angle transition between adjacent lines, $Q_{\Delta\theta}$; and smaller numbers of vertices, N_D. This can be described in MDL framework as

$$DL(H) = -\frac{\Omega}{2} ln 2 + \frac{1}{2} \log_2 N(W_D N_D + W_P N_P + W_{\Delta\theta} Q_{\Delta\theta}) \tag{6}$$

In Eq. (6), the first term describes the closeness between model and observation as in Eq. (2), and the last term indicates the model complexity. Note that the weight factors (W_D, W_P, $W_{\Delta\theta}$) are firstly settled as default value such as one. Ω is the sum of the squared residuals between model and observation. An optimization strategy to determine H^* that minimizes Eq. (6) is comprised of following tasks as shown in Fig 2.

In the step of initial vectorization, after ordering building boundary points by using a modified convex-hull method, an initial building outlines are reconstructed with linked edge segments obtained by DP algorithm. In order to quantize the direction of polygon slopes, Compass Line Filter (CLF) developed by Sohn et al. (2007) is applied to initial line segment, which is quantized into one of eight line directions. CLF is designed as a set of quantized line direction {θi: i=1,⋯,8}, where the direction of the first compass line is horizontal and the others are spaced with equally 22.5 degree as shown in Fig. 3.

All line directions $\{\theta\}$ are measured by $x\sin\theta - y\cos\theta = d$ and assigned into one of eight CLF numbers, where θ indicates the angle between a line segment and *x-axis*, and d is the line distance from the origin. Finally, the representative line directions with respect to each CLF number are calculated by weight-averaging cumulative directions belonging to the same CLF number. Once all the lines are grouped with respect to CLF, the model complexity is calculated. The total numbers of line directionality (N_D), which are ranged between one and eight, forming building outlines are determined. The angular transitional regularity ($Q_{\Delta\theta}$) are determined to have the minimum score of 0 (i.e., favored regularity) if the inner angle difference between two consecutive lines close to 90° or 180°, while the maximum score of 2 (i.e., un-favored regularity) as in general the building outlines with the acute angle at one vertex is rare, the penalty value must be assigned with higher value compared to the other index numbers (Table 1).

For each vertex, GMDL generate a number of regularizing model hypothesis in two different ways. Instead of selecting the four local point set used in LMDL, GMDL selects three vertices to generate hypothetical solutions (Fig. 3): (1) the anchor point, v_1, that are fixed during the hypothesis generation; (2) the floating point, v_2, that could be movable; (3) the guiding point, v_3, that provides a guidance how v_2 moves.

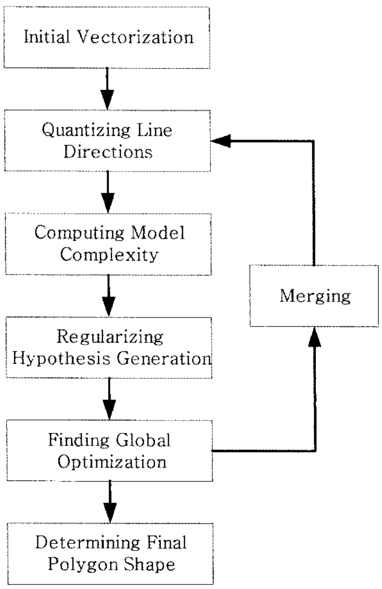


Fig. 2. The schematic diagram of the proposed approach for regularization

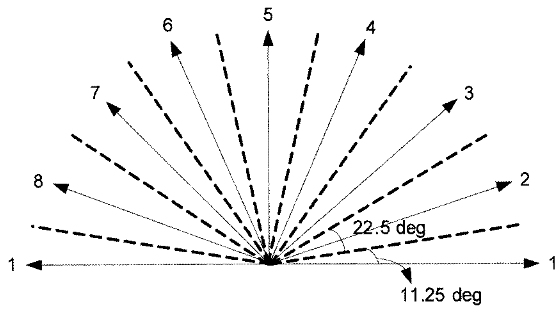


Fig. 3. Illustration of CLF: A set of quantized line directions with 22.5°

Table 1. Quantized $Q_{\Delta\theta}$.

i	$\Delta\theta i$	$Q_{\Delta\theta i}$
1	0.0 ~ 11.25	2
2	11.25 ~ 33.75	1
3	33.75 ~ 56.25	1
4	56.25 ~ 78.75	1
5	78.75 ~ 101.25	0
6	101.25 ~ 123.75	1
7	123.75 ~ 146.25	1
8	146.25 ~ 168.75	1
9	168.75 ~ 180.00	0

As illustrated in Fig. 4(a), a number of hypothetical models are generated by moving v_1. A floating line centered at v_1 can move along the anchor line passing through v_2 and v_3 by replacing the floating line's direction with CLF's ones. By intersecting the floating and anchor lines, a new vertex is computed for hypothesizing a regularized model. Fig. 4(b) shows alternative hypothesizing method by eliminating v_2. Once v_2 is eliminated, the floating lines are generated by the same way illustrated in Fig. 4(a) and then, the floating and guiding point are changed to v_3 and v_4. Finally, a new vertex will be computed by intersecting the newly computed floating and anchor lines. The following Fig. 5 and Table 2 show an example of GMDL regularization.

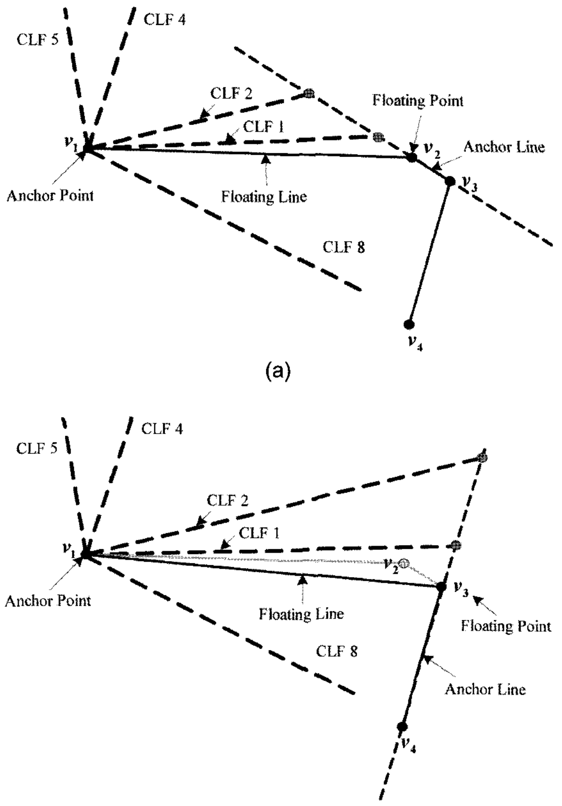


Fig. 4. The possible alternative hypotheses at anchor point: (a) by moving v_2 and (b) by eliminating v_2.

Fig. 5(a) shows initial outlines formed by using boundary points extracted based on modified convex-hull algorithm after building detection. Fig. 5(b) is the initial simplified polygon simplified by DP and initial DL value for the null hypothesis is calculated. In the next step (c), after computing {DL} for the entire vertices, the optimal hypothesis to produce the minimum DL, which is smaller than the null hypothesis, is selected (see the dotted box in Fig. 4(c)). In Table 2, the null hypothesis's DL (Fig. 4(b)) is larger than the one in Fig. 4(c) because the configuration eliminating one of vertices from building outlines mainly contributes to the optimal configuration. If neighboring line's directionality has the same CLF value, a simple merging procedure is performed as shown in Fig. 5(d). The last step (Fig. 5(e)) presents the final optimal outlines after recursively conducting the processes illustrated in Fig. 5(c) and (d) until the minimum DL obtained at the current iteration is larger than the one at the previous iteration.

4. Experimental Result

The performance of the proposed shape regularization

Table 2. The values of DL elements in each step.

Step	N_P	N_D	$Q_{\Delta\theta}$	$L(M)$	Ω /2ln2	DL
(b)	12	4	3.33	34.65	22.61	57.26
(c)	11	4	2.66	30.55	23.62	54.17
(d)	9	4	3.11	25.53	24.26	49.79
(e)	4	2	0.0	6.00	15.82	21.82

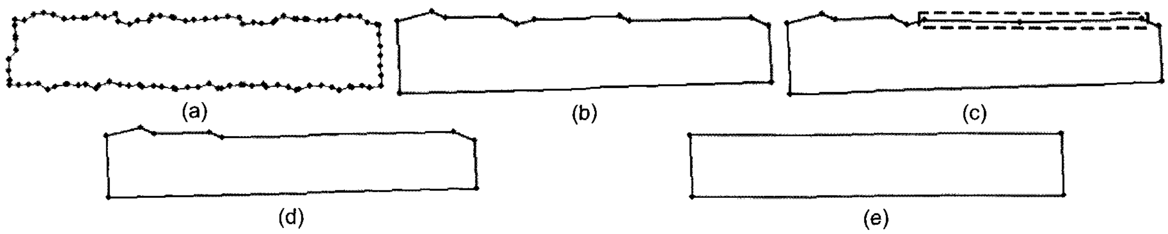


Fig. 5. Principal steps of the regularization of irregular building boundary lines: (a) initial shape, (b) vectorization based on Douglas-Peucker approach, (c) reconstruction of lines within dotted line, (d)merge, (e) final optimal configuration

techniques was estimated based on simulated 3D building points. 3D reference building vectors were manually captured, with which LiDAR points were generated by intersecting LiDAR rays with digitized 3D building vectors. The reference points were simulated to have a mean density of 11 points/m^2 (~0.3 m point spacing).

The reference building shown in Fig. 6 was simulated with noise free condition, in which all points were generated with equal point spacing. To evaluate different shape regularization methods under various noise levels in LiDAR data, we intentionally added the random noises with five different levels (±5 cm, ±10 cm, ±15 cm, ±20 cm and ±25 cm) to the building boundary points extracted from the reference building vectors. Note that these random errors are only considered in x-y horizontal directions because this study focuses on 2D shape reconstruction. The boundary points were extracted in a 2D buffer zone made around initial building outlines obtained by DP algorithm. The buffering size was heuristically determined based on the data domain knowledge of average point spacing for each test set. The first column of Figure 7 presents initial boundary lines extracted from the building test datasets simulated with five different noise scales. Based on these datasets, we applied the building polygon regularization methods (DP, LMDL, FBMV, RR, GMDL) that were discussed in previous sections. From the second to the sixth column in Figure 7 show the final results of regularization obtained by applying the five regulators to the first column in Figure 7.

In addition to the simulated building data, we also evaluated the performance of the five regulators over buildings acquired from the Optech's ALTM-3070 system, which collected laser points at the point density of 2 (points/m^2) over Ilsan Area in South Korea on July 28, 2005 (Figure 8(b) and Figure 9(b)). From this test site, we manually digitized two buildings (Figure 8(c) and Figure 9(c)), referred BL1 and BL2, from a high-resolution airborne imagery captured from the Intergraph Z/I Imaging's DMC (Digital Mapping Camera) with the ground sampling distance of 0.10m (Figure 8(a) and Figure 9(a)). Figure 8(e)-(i) and Figure 9(e)-(i) show the final results of the building polygon regularization methods over BR1 and BR2 respectively obtained from initial building outlines of Figure 9(d) and Figure 10(d).

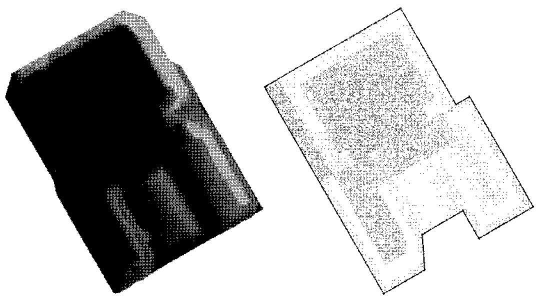


Fig. 6. Simulated reference building points and boundary line in 3D (left) and 2D (right).

5. Quality Assessment

In order to achieve an optimal model selection in building boundary modeling, performance and cost factors of each model must be taken into account. Therefore, before selecting the optimal model to a building shape, the performance of each regularization model must be tested with respect to various factors. The quality of each reconstructed model is evaluated based on error matrix shown in Eq. (7), where R, E, P and V refer to Reference, Extracted, Polygon and Vertex. The score, which is used to judge the suitability of each model, is calculated by summing each element of error matrix. The value closer to zero indicates to have higher shape regularization.

$$\text{Vertex Complexity (VC)} = \sqrt{\left(\frac{N_{RV}-N_{EV}}{N_{RV}}\right)^2}$$

; N : number of vertices

$$\text{Angle Complexity (AC)} = \frac{\sqrt{\sum(\delta\theta_{RP})^2} - \sqrt{\sum(\delta\theta_{EP})^2}}{\sqrt{\sum(\delta\theta_{RP})^2}}$$

; $\delta\theta$: difference between inner angles

$$\text{Corner Difference (CD)} = \sqrt{\sum(V_{RV}-V_{EV})^2}$$

; V : position of vertex

$$\text{Orientation Difference (OD)} = \sqrt{\sum(S_{RP}-S_{EP})^2}$$

; S : slop of main direction

$$\text{CM Difference (CMD)} = \sqrt{\sum(CM_{RP}-CM_{EP})^2}$$

; CM : center of mass

$$\text{Area Difference (AD)} = \sqrt{\left(\frac{A_{RP}-A_{EP}}{A_{RP}}\right)^2}$$

; A : Area

(7)

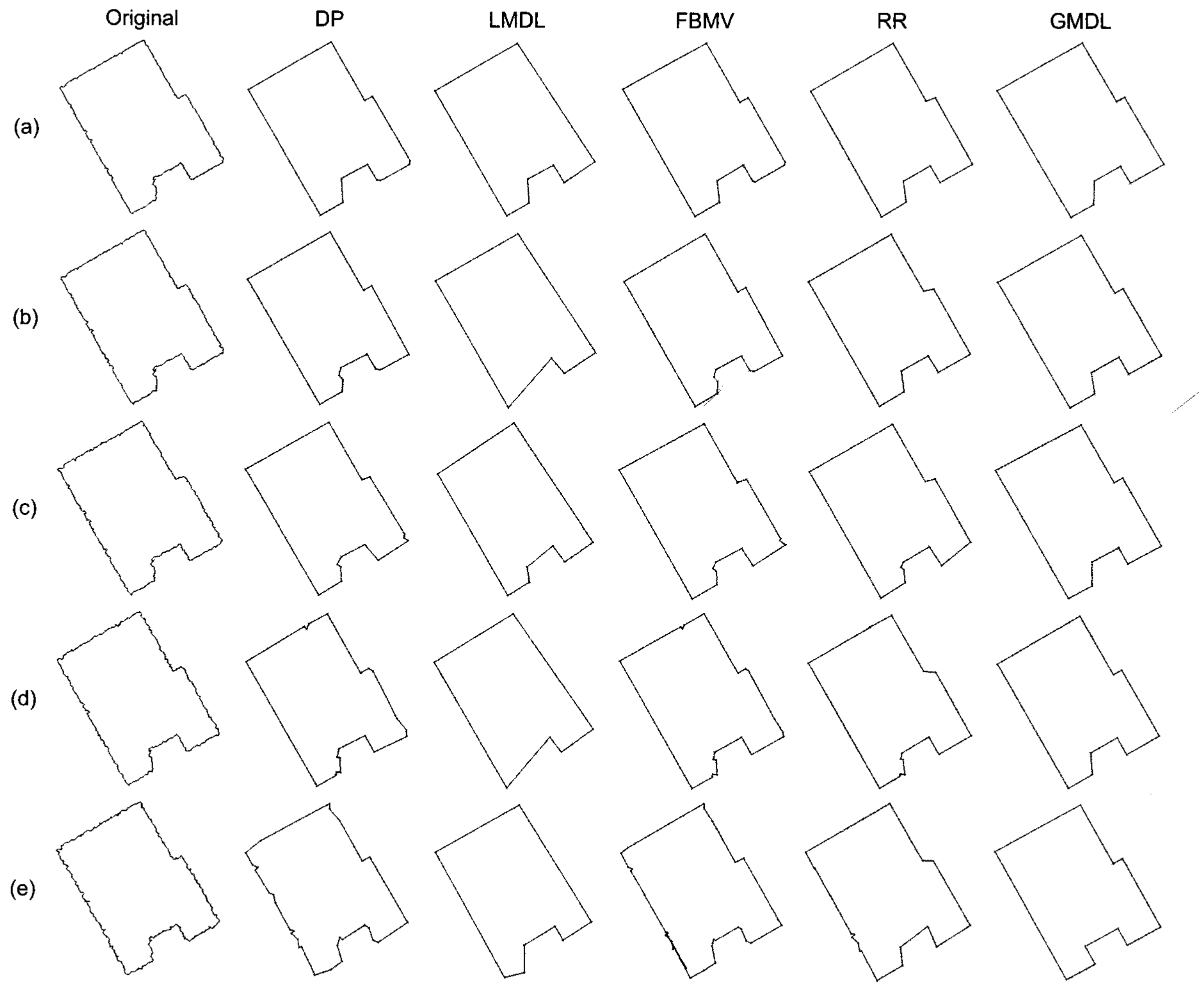


Fig. 7. The results of the five geometric regulators (DP, LMDL, FBMV, RR, GMDL) obtained from original building outlines with randomly corrupted horizontal errors of (a) ±5 cm, (b) ±10 cm, (c) ±15 cm, (d) ±20 cm, and (e) ±25 cm.

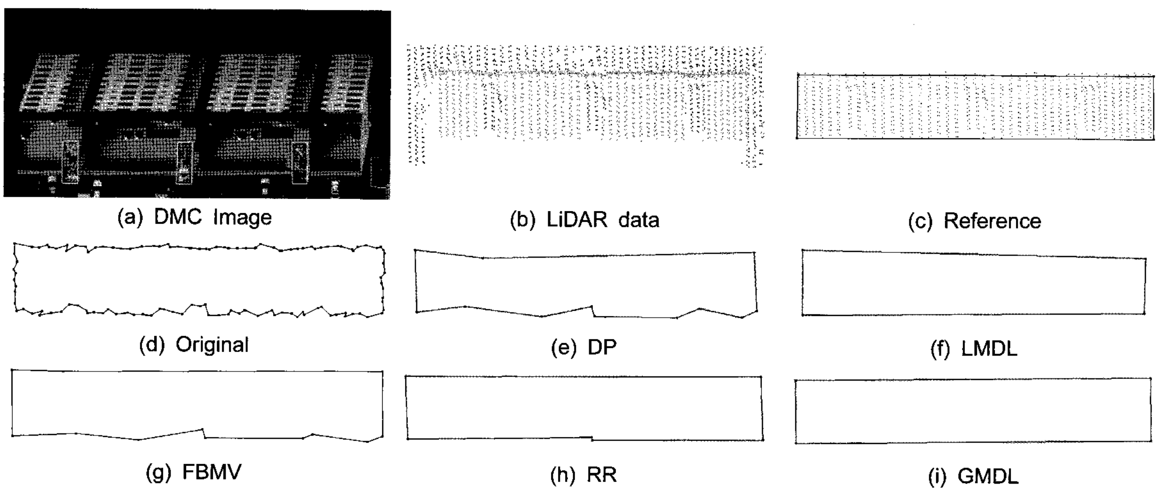
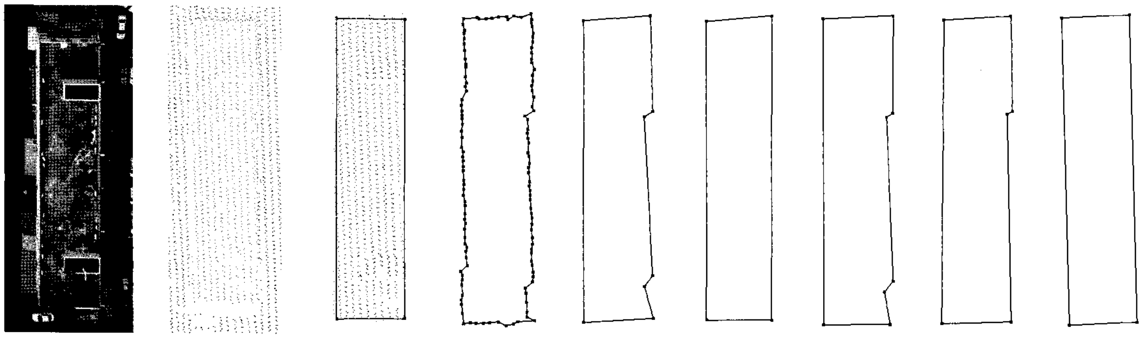


Fig. 8. The results of building polygon regularization over BR1.



(a) DMC Image (b) LiDAR data (c) Reference (d) Original (e) DP (f) LMDL (g) FBMV (h) RR (i) GMDL

Fig. 9. The results of building polygon regularization over BR2.

Table 3. Performance evaluation of tested geometric regulators according to different noise levels.

Category		Error (cm)					Building (#)	
		±5	±10	±15	±20	±25	BL1	BL2
Vertex Complexity (VC)	LMDL	0.20	0.40	0.20	0.40	0.20	0	0
	FBMV	0.20	0.30	0.40	1.00	2.00	2	1
	RR	0.00	0.00	0.20	0.60	1.00	0.5	0.5
	GMDL	0.00	0.00	0.00	0.00	0.00	0	0
Angle Complexity (AC)	LMDL	0.08	0.06	0.46	0.10	0.09	2.96	4.57
	FBMV	1.98	3.00	4.41	8.19	21.0	306.06	79.4
	RR	0.16	0.28	2.48	4.22	6.99	25.64	25.8
	GMDL	0.23	0.17	0.19	0.04	0.88	0.23	3.29
Corner Difference (CD)	LMDL	2.41	2.61	4.76	3.43	6.80	4.98	2.38
	FBMV	2.82	2.55	2.24	2.12	2.32	3.01	2.45
	RR	1.86	2.24	2.87	3.02	3.41	2.45	1.77
	GMDL	1.94	1.80	2.37	1.79	3.44	2.54	2.87
Orientation Difference (OD)	LMDL	0.32	0.16	0.36	0.15	0.29	3.15	0.01
	FBMV	0.3	0.42	0.57	0.53	0.21	2.54	1.04
	RR	0.01	0.01	0.32	0.21	0.82	3.66	0.52
	GMDL	0.01	0.02	0.00	0.00	0.08	3.13	0.02
CM Difference (CMD)	LMDL	0.25	0.13	0.55	0.15	0.28	1.79	0.44
	FBMV	0.23	0.22	0.20	0.10	0.03	0.48	0.82
	RR	0.04	0.04	0.06	0.05	0.03	0.47	0.41
	GMDL	0.05	0.06	0.07	0.07	0.03	0.53	0.41
Area Difference (AD)	LMDL	0.03	0.03	0.00	0.02	0.03	0.085	0.01
	FBMV	0.00	0.01	0.00	0.01	0.01	0.058	0.02
	RR	0.02	0.02	0.01	0.01	0.01	0.047	0.03
	GMDL	0.02	0.02	0.01	0.02	0.01	0.048	0.02
Score	LMDL	3.31	3.42	6.35	4.27	7.71	12.96	7.40
	FBMV	5.56	6.52	7.85	11.9	25.6	314.15	84.67
	RR	2.11	2.62	5.97	8.14	12.2	32.77	29/05
	GMDL	2.27	2.09	2.68	1.95	4.48	6.48	6.62

Table 3 shows error measurements across tested regularization methods according to different noise levels from ±5 cm to horizontal ±25 cm horizontal random errors. As shown in Figure 7-9 and Table 3, DP efficiently eliminated the most of noisy polygon vertices. However, the method failed to produce geometrically regularized shape, thereby still showing irregular outlines. These unregularized results are mainly caused by the fact that DP's regularity optimization is achieved only by minimizing maximal distance from hypothesized model, but there is no mechanism to augment polygonal regularity (e.g., the repetition of identical angles, length, orthogonality, symmetricity, parallelity and etc). The overall performance of LMDL shows better than DP and FBMV, but similar quality to RR. The most critical problem of LMDL is that the method shows a tendency to over-simplify building boundaries as shown in Figure 7(b) and (d) or degrade the orthogonal and parallel regularity present in Figure 8(f) and Figure 9(f), which lead to more or less larger CD scores. These two constraints are imposed subjectively to a local configuration of anchor vertices to generate regularizing hypotheses. FBMV's score significantly increases as the random noise level becomes higher. This is because FBMV does not consider achieving the model simplicity by eliminating noisy vertices. Thus, the produced errors become very high in VC and AC. In this context, we can conclude that FBMV is not suitable for regularizing building outlines corrupted with high noise level. In case of RR, the score shows better performance at the low noise level, but was rapidly lowered as the noise level becomes higher as pre-fixed simple rules cannot efficiently handle very noisy boundaries. However, it can be clearly shown in Figure 7-9 and Table 3 that the performance of GMDL is outstanding compared to the other regulators. Irrespectively of increased error rate, final building outlines show very good agreement to human's perceptions. Table 3 shows that the total performance of GMDL was estimated approximately more than three times higher than by the others at the highest noise level. It can be concluded that newly driven regularity factors (i.e., directional repeatability and the regular angle transition) efficiently contributed to augment the orthogonal and parallel regularity although the same optimization framework is adopted as in LMDL. In addition, we observed that the GMDL's successful performance is also achieved by considering a global regularity minimization strategy. Moreover, the results indicate that GMDL can be successfully performed over real buildings with different outline noise level. GMDL's robustness to various signal-to-noise ratio has promising aspect as it is applied in spatio-temporal domain where GMDL incrementally rectifies building polygon errors using temporal remote sensing data with different noise levels.

6. Conclusion and Future Work

This study investigated existing building polygon regularization methods and proposed a new geometric regulator, called GMDL, which dynamically re-arranged quantized line vectors based on MDL theory. The main aspect of proposed GMDL method is to provide a robust solution to incrementally regularize noisy building boundary by minimizing both residual errors and model complexity. A new objective function was introduced to augment geometric regularity in terms of the repetition of identical line directionality, regular angle transition and the number of vertices used. We conducted a comparative evaluation of GMDL's performance with the four existing algorithms including DP, LMDL, FMBV and RR using both simulated and real building data with different signal-to-noise ratio. The results showed that GMDL outperforms all the regulators over various levels of noise, and GMDL's performance was measured approximately more than three times higher than by the others at the highest noise level. Achieving the robustness against high noise level by GMDL is important for applying it to the real-setting environment. As future researches, we will extend GMDL from 2D vectors to 3D polyhedral cases, by which large-scale 3D building models can be incrementally refined in temporal domain.

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References

Ackermann, F., (1999), Airborne laser scanning-present status and future expectations, ISPRS Journal of Photogrammetry and Remote Sensing, 54(2), pp. 64-67.

Ameri, B., (2000), Feature-Based Model Verification (FBMV): a new concept for hypothesis validation in building Reconstruction, In: IAPRS, Vol. XIX, Part 3, in press, Amsterdam, the Netherlands.

Brunn, A., Weidner, U. and Förstner, W., (1995). Model-based 2D-Shape Recovery, In Sagerer, G., Posch, S., and Kummert, F., editors, Mustererkennung, 1995, pp. 260-268.

Douglas, D.H. and Peucker, T.K., (1973). Algorithms for the reduction of the number of points required to represent a digitized line or its caricature. Canadian Cartographer, 10(2): 112-122.

Ramer, U., (1972). An iterative procedure for the polygonal approximation of plane curves. Computer graphics and Image Processing, 1:224-256.

Rissanen, J., (1984). Universal coding, information, prediction, and estimation. IEEE Transaction of Information Theory, 30(4), pp. 629-636.

Sampath, A., Shan, J., (2007). Building Boundary Tracing and Regularization from Airborne Lidar Point Clouds, Photogrammetric Engineering & Remote Sensing, 73(7), pp. 805-812.

Sohn, G. and Dowman, I., (2007). Data fusion of high-resolution satellite imagery and LiDAR data for automatic building extraction. ISPRS Journal of Photogrammetry and Remote Sensing, 62(1):43-63.

Sohn, G., Huang, X. and Tao. V., (2007). Using a binary space partitioning tree for reconstructing polyhedral building models from airborne LiDAR data. Photogrammetric Engineering & Remote Sensing. In print.

Weidner, U., Förstner, W., (1995). Towards Automatic Building Extraction from High Resolution Digital Elevation Models, ISPRS Journal, 50(4), pp. 38-49.

Weidner, U., (1996). An Approach to Building Extraction from Digital Surface Models, in: Proceedings of the 18^{th} ISPRS Congress, Comm. III, WG 2, Vienna, Austria, pp. 924-929

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