

# HOUSEDIFF: A MAP-BASED BUILDING CHANGE DETECTION FROM HIGH RESOLUTION SATELLITE IMAGERY USING GEOMETRIC OPTIMIZATION METHOD

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## ABSTRACT:

This paper presents a novel structural image analysis method based on geometric optimization techniques towards automatic building change detection. The aim of this method is to efficiently detect the changes of various buildings such as small houses and houses with complex roof in an urban area from high resolution satellite imagery by comparing with spatial database (maps). The previous research has indicated of the effectiveness of a map-based building change detection approach, and further investigation suggests the following three problems; (1) the large diversity of building types, roof shape, roof materials, illumination condition and shadow, (2) the difficulty of imagery and maps matching which normally leads to considerable position error, (3) the capacity of extracting various types of newly-built buildings. To solve these problems, we propose a new geometric optimization method which consists of the following two steps; (1) the building recognition based on a combinatorial optimization method for optimal building boundary extraction, (2) the newly-built building extraction based on an optimal building hypothesis search method. The experimental results showed that the detection rate was approximately 89% for existing and changed buildings, and approximately 83% for newly-built buildings. These results demonstrate the effectiveness of the proposed geometric optimization methods to integrate bottom-up and top-down analysis. By combining the locally detected image features with consideration of regional contexts from map, our method can achieve highly accurate building change detection in urban area. The method has been applied to a building change detection service named "HouseDiff" and succeeded in assisting users.

## 1. INTRODUCTION

Timely and precise update and maintenance of spatial database has been a challenge for the practical GIS applications such as land use management and disaster management. As shown in advanced examples of QuickBird, WorldView-1, and WorldView-2 from DigitalGlobe, the recent development of high resolution satellite in image accuracy and coverage, and short observation repetition makes it an ideal data source for the purpose of automatic building change detection.

This paper presents a novel structural image analysis method based on geometric optimization techniques towards automatic building change detection. The aim of this method is to efficiently detect the changes of various buildings such as small houses and houses with complex roof in an urban area from high resolution satellite imagery by comparing with spatial database (maps). Several different approaches have been proposed for building change detection as well as map feature extraction, such as feature-based (Kazama et al, 2010; Guo et al, 2010), rule-based (Ishimaru et al, 2005), model-based (Fisher et al, 1998; Huertas et al, 1998), and map-based (Ogawa et al, 1999). The previous research, map-based approach, has indicated of the effectiveness of top-down (model-driven) image analysis approach using map polygons as building models. The simulated high resolution satellite imagery was applied in the research, and our further investigation using the actual high resolution satellite imagery suggests the following three problems. First is the large diversity of building types which range from the simple

buildings with dark flat roof to the complex buildings with various types of roof shape, roof materials, illumination condition and shadow. Second is the difficulty of imagery and maps matching which normally leads to considerable position error especially in the case of using simplified map. Third is the capacity of extracting various types of newly-built buildings. To solve these problems and improve the recognition accuracy, we propose a new geometric optimization method which consists of the following two steps. The first step is the building recognition based on a combinatorial optimization method for optimal building boundary extraction so as to solve the first and second problems. The second step is the newly-built building extraction based on an optimal building hypothesis search method to solve the first and third problems. Figure 1 shows an overall framework of a map-based building change detection algorithm.

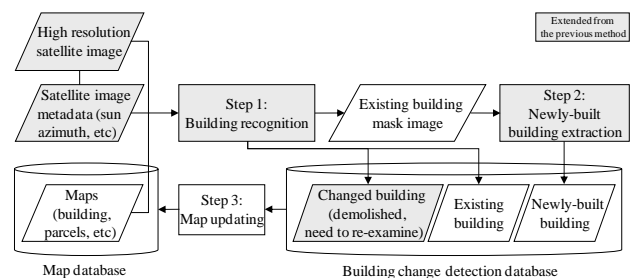


Figure 1. Framework of a map-based building change detection algorithm

By matching and comparing imagery with maps to automatically identify a building status on maps as "existing", "changed (demolished and need to re-examine)" or "newly-built", this method realizes a service which provide "building change detection information" to users. The service named "HouseDiff" allows users to investigate only the parts of imagery that are most likely changed, which will lead to the reduction of cost and labour.

The remainder of this paper will focus on the two steps extended from the previous method (Ogawa et al, 1999), which are, the building recognition (Step 1) in chapter 2, and the newly-built building extraction (Step 2) in chapter 3. Chapter 4 provides the experimental results that demonstrate the validity of the proposed method and discussion. Finally, chapter 5 gives a conclusion.

## 2. BUILDING RECOGNITION

The first step is the building recognition. It determines whether the buildings still exist by matching the new imagery and the old map. This step focuses on the boundaries of buildings to evaluate the difference between imagery and maps. The boundaries can be extracted effectively if map figures are utilized as a guide of those presence, position, and direction. We regard the building boundary extraction as a combinatorial optimization problem of light-dark and dark-light edge segments along the building map figure using graph theory known as the shortest path search method. The shortest path is calculated by Dijkstra method using weighted undirected graph of edge segments. The evaluation of the difference between imagery and map figures is done by an energy cost of the shortest path search calculation considering the edge quality information (i.e. distance from map figure line, edge power, edge continuity, and edge presence). The optimization method allows to resolve the large and complex combinatorial problem and to extract the optimal boundaries with the acceptable position error and various types of target buildings (i.e. brighter than background, darker than background, and its

combination). Furthermore, it becomes possible to extract a building with weak boundaries due to similar materials of roof and background, and partly occluded by trees.

Figure 2 and 3 show the algorithm outlines. Figure 4 shows an example of results that confirmed the validity of this algorithm.

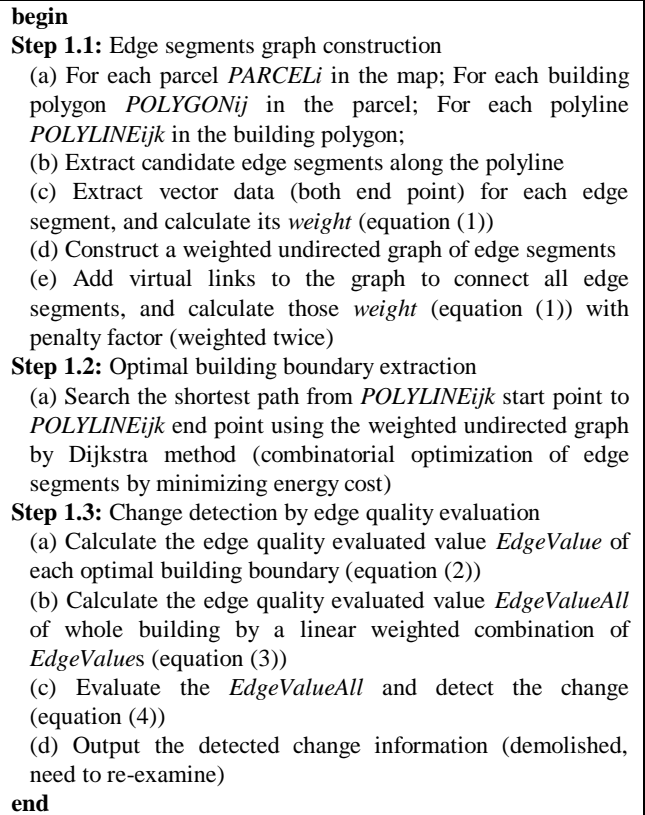


Figure 2. Optimal building boundary extraction algorithm

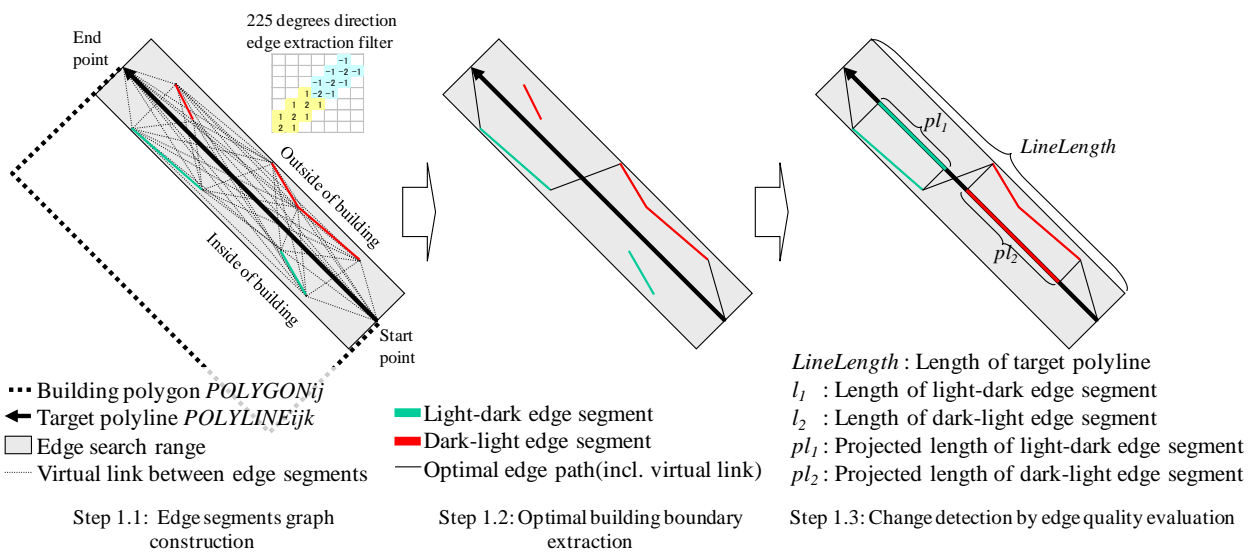


Figure 3. Optimal building boundary extraction

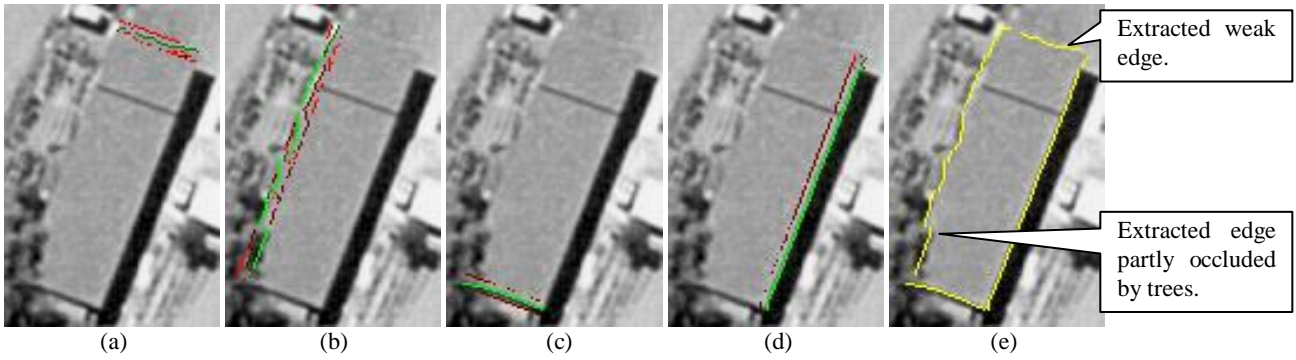


Figure 4. Example of optimal building boundary extraction result. (a)(b)(c)(d)Extracted edges. (e)Extracted building boundary. (green=light-dark direction edge, red=dark-light direction edge, color brightness=edge strength)

The edge evaluated values provide scores between 0 and 1, and are defined as follows (see also Figure 2 and 3):

$$weight = \frac{EdgePower + EdgeDistance}{2} \times I_i \quad (1)$$

where  $EdgePower = 1 - (\text{mean edge power of segment} / \text{max edge power constant})$   
 $EdgeDistance = \text{line distance evaluated value} / \text{max edge distance constant}$

$$EdgeValue = \frac{EdgeStrength + EdgeContinuity + EdgePresence + EdgeLinearity}{4} \quad (2)$$

$$w_i = LineLength_i / \sum_i LineLength_i$$

$$EdgeValueAll = \sum_i (w_i \times EdgeValue_i) \quad (3)$$

$$eval(EdgeValueAll) = \begin{cases} \text{Existing} & : \text{if } 0.5 < EdgeValueAll \leq 1, \\ \text{NeedToRe-examine} & : \text{if } 0.4 < EdgeValueAll \leq 0.5, \\ \text{Demolished} & : \text{if } 0 \leq EdgeValueAll \leq 0.4 \end{cases} \quad (4)$$

where  $EdgeStrength = \text{edge segment weight} / \sum pl_i * 0.5$   
 $EdgeContinuity = \sum l_i / \text{Total length of edge path}$   
 $LineLen = \text{length of target polyline}$   
 $EdgePresence = \sum pl_i / LineLength$   
 $EdgeLinearity = LineLength / \text{Total length of edge path}$   
 $n = \text{number of polyline}$

### 3. NEWLY-BUILT BUILDING EXTRACTION

The second step is the newly-built building extraction. It uses a new optimal building hypothesis search method based on a general building model considering roof shapes and relation between sun azimuth and the shadow of building. We investigate the building hypothesis by using the most fundamental shape of buildings: rectangular. The optimal building hypothesis search method is realized as a process to generate a number of building hypotheses, repeat hypotheses testing and modification, and aggregate hypotheses. The process comprises generating combinations of building candidate regions corresponding to roof surfaces, rectangular fitting, and rule-based region merging, respectively. The optimal building hypothesis search method allows efficient

extraction of complex buildings consisting of multiple roof surfaces such with bright or dark colored roof surface, or its combination.

Figure 5 shows the candidate region types. Figure 6 through 8 and Table 1 show the algorithm outlines. Figure 8(b) shows an example of results that confirmed the validity of this algorithm.



Figure 5. Candidate region types for newly-built building extraction (solid line=candidates, dashed line=non-candidates)

**begin**

**Step 2.1:** Building candidate region generation

- Detect edges using the 8-directional edge filter
- Mask the edge regions/pixels on the image
- Mask the other regions/pixels not corresponding to the buildings (i.e. existing building, its shadow, tree, road, etc.)
- Generate building candidate regions by region segmentation except the masked pixels

**Step 2.2:** Building hypotheses generation (region combinations by the sun and shadow context analysis)

- Select two directional edges which are the most orthogonal to the sun vector as building candidates
- Generate an adjacent candidate regions list for each building candidate edge (describing region type in Figure 5)
- Generate instances of rectangular building model (generating combinations of the candidate edge and the candidate regions, and calculating initial fulfillment rate by rectangular fitting)

**Step 2.3:** Optimal building hypothesis search

- Sort the rectangular building model instances in descending order of the fulfillment rate. For each instance;
- Aggregate hypotheses (rule-based region merging considering the spatial relationship among instances, Table 1)
- Hypotheses testing and modification (rectangular fitting, Figure 8)
- Repeat **Step 2.3** until convergence

**Step 2.4:** Post-processing

- Remove result(s) with low fulfillment rate ( $< 0.4$ )
- Output the extracted newly-built building information

**end**

Figure 6. Newly-built building extraction algorithm

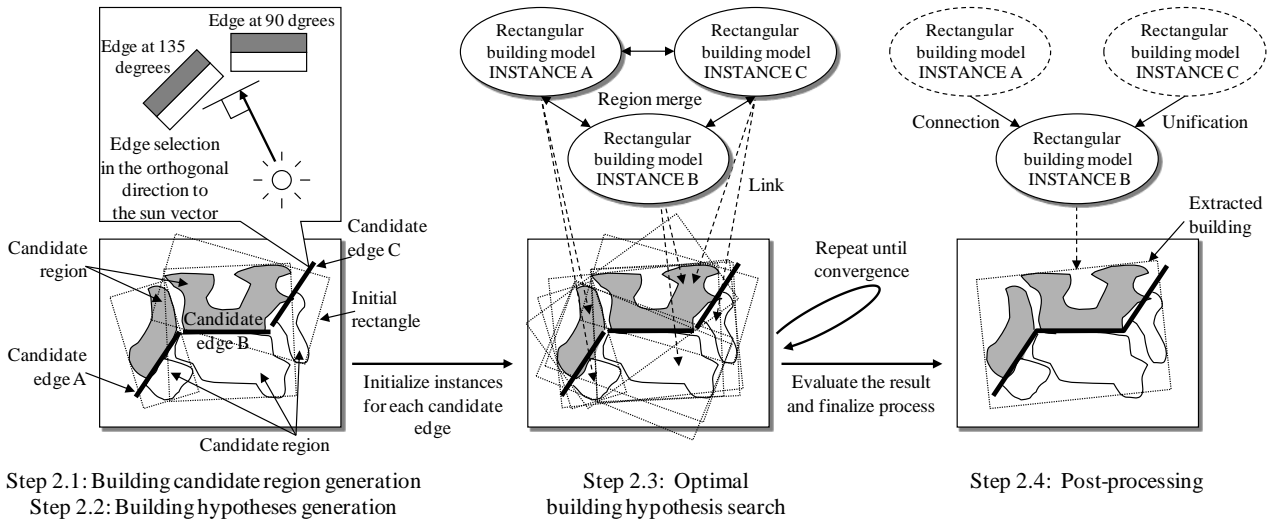


Figure 7. Newly-built building extraction

Rule type	Inclusion	Connection	Unification
Geometry relationship	contain / inside / covers / equal	touch / adjacent	overlap / intersect
Merge rules	<ul style="list-style-type: none"> <li>Merged to the one which includes (the other)</li> <li>Merged to the any when the range is equal</li> </ul>	<ul style="list-style-type: none"> <li>Merged to the BRIGHT dominant one only when the rectangular fulfillment rate improves</li> </ul>	<ul style="list-style-type: none"> <li>Merged to the one with a higher rectangular fulfillment rate</li> <li>Merged to the one with a longer edge when rectangular fulfillment rate is the same</li> </ul>
Examples			

Table 1. Rule-based region merging (bold line=building candidate edge)

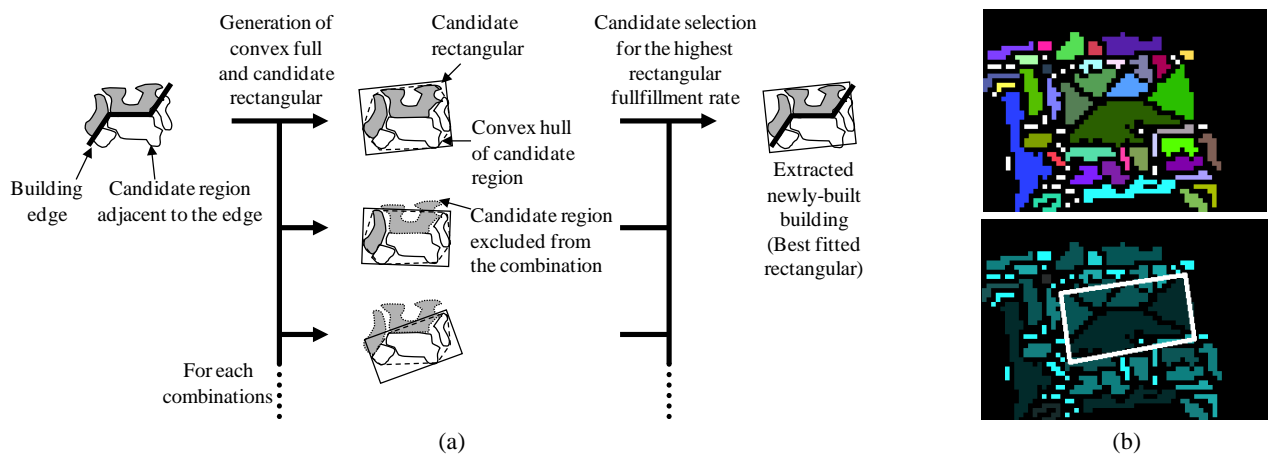


Figure 8. Rectangular fitting. (a)Algorithm.

(b)Example of rectangular fitting result (5 or 41 regions selected, rectangular fulfillment rate 0.45).

## 4. EXPERIMENTAL RESULTS AND DISCUSSION

### 4.1 Experimental Results

The experiments have been performed using actual high resolution satellite imagery and experimental maps. The experimental area is located in Hamamatsu city, a residential area in Shizuoka Pref., Japan. The satellite imagery is panchromatic QuickBird imagery (geometrically corrected 0.7m resolution). The map is digitized manually. Approximately 5% (23 of 490) of building polygons in the map are removed randomly to evaluate the newly-built building extraction accuracy. The result is shown in Figure 9 and indicates that the changes of small buildings (i.e. 10m wide) could be detected while using high resolution satellite imagery which spatial resolution is relatively low compared with that of aerial photography, especially in dense urban contexts.

### 4.2 Discussions

**4.2.1 Overall accuracy:** Table 2 shows building detection accuracy. The meaning of "changed" buildings includes "demolished" and "need to re-examine" buildings.

For existing and changed buildings, the detection rate was approximately 89%. About half of the 54 misdetections were caused by digitizing errors of the experimental map figures (they looked almost changed). This result suggests that even a possibility of a small change can be detected by this method. Misdetections were caused by buildings with highly dark colored roof or very complex roof structure (i.e. half-hipped roof, monitor roof). Meanwhile, there were a few misdetections of buildings with simple flat roof. The results indicate the efficiency of the optimal boundary extraction with the acceptable position error and various types of buildings. Furthermore, the ability of extracting buildings with weak edges by similar materials of roof and background, and partly occluded by trees are confirmed. For newly-built buildings, the detection rate was approximately 83%. Misdetections were caused by buildings located too closely to other buildings so that the region segmentation process failed, and colored too dark to see even with human eyes. False detections were caused by only cars and vegetation. The results indicate that the complex buildings consisting of multiple roof surfaces with bright or dark colored, or its combination, were extracted efficiently.

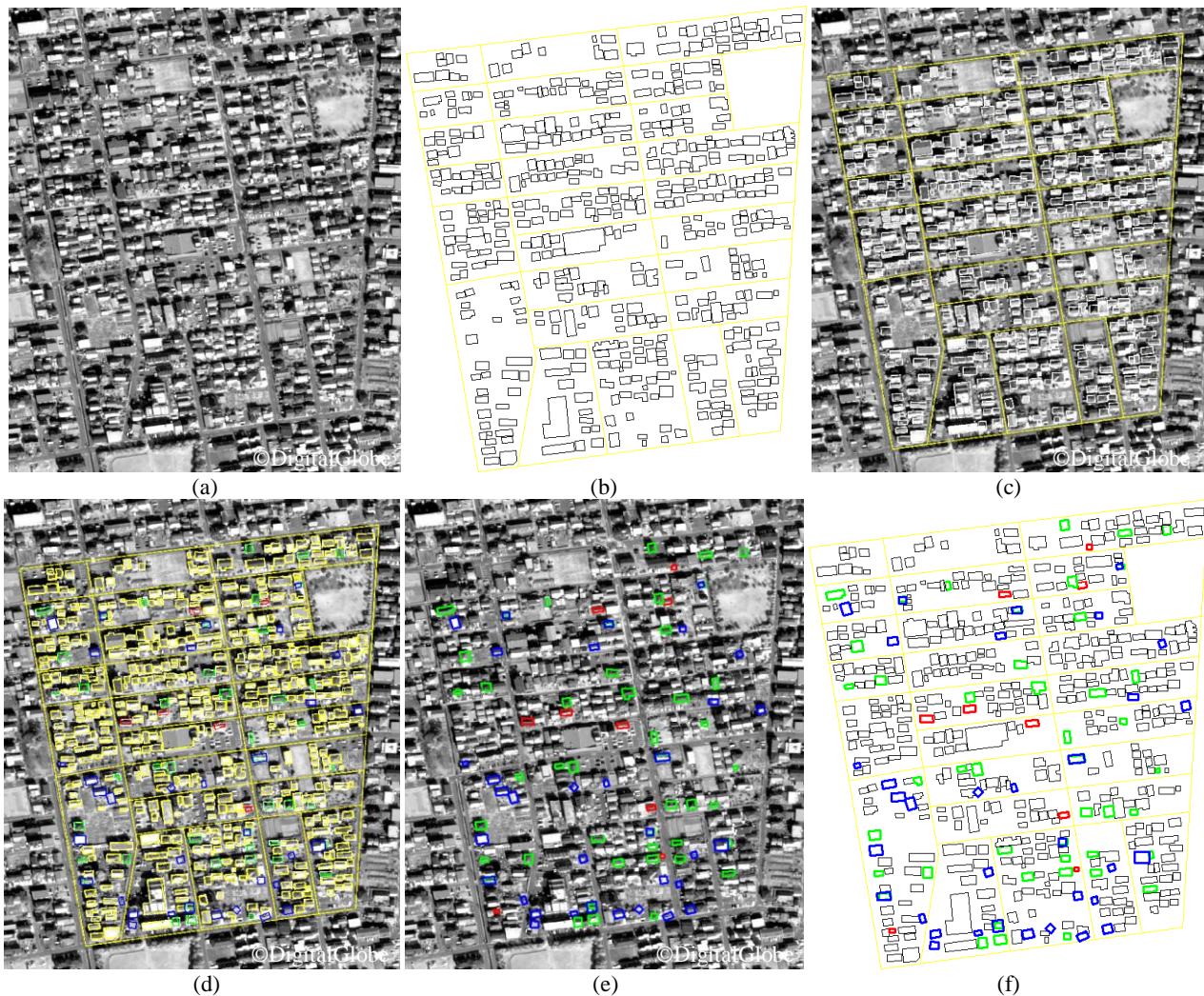


Figure 9. Experimental result of building change detection. (a) QuickBird satellite imagery (Hamamatsu city, Japan). (b) Experimental map (buildings, parcels). (c) Overlaid imagery and map. (d) Detected results. (e) Changed and newly-built buildings. (f) Updated map. (yellow=existing, red=demolished, blue=newly-built, green=need to re-examine)

	Detection rate	Mis-detection rate	False detection rate
Existing	89% (=436/490)	11% (=54/490)	-
Changed	-	-	11% (=54/490)
Newly-built	83% (=19/23)	17% (=4/23)	35% (=8/23)

Table 2. Overall accuracy of the result using proposed method

**4.2.2 Comparison with previous method:** Both Table 3 and Figure 10 show a comparison of the result by the proposed and previous methods. The results indicate that proposed method improves the accuracies in both existing/changed building recognition and newly-built building extraction. For the existing and changed building recognition, in the previous method, when the region segmentation process failed, the buildings tended to be misdetected as the region of the buildings was expanded. However, in the proposed method, buildings were correctly detected as existing buildings, even the weak edges can be extracted as a boundary if they locate in the right position as well as right direction. For the newly-built building detection, in the previous method, a lot of parking or open space whose boundary was similar to nearby buildings was extracted as candidate regions. However, in the proposed method, while the types of target buildings were extended to those with combination of bright and dark colored roofs or those with different shapes from nearby buildings, the detection results were reasonably stable and reliable.

Those results are much better than those of the previous method while using actual high resolution satellite imagery and detection of various types of target buildings. Therefore, the validity of the proposed method was confirmed. The proposed method has been applied to an actual building change detection service named "HouseDiff" (Carroll, 2001) as a part of recognition engine, and succeeded in assisting users such as local governments to maintain highly accurate, up-to-date building data.

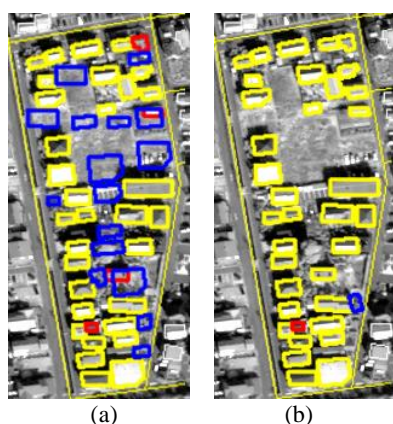


Figure 10. Comparison of results. (a)The previous method. (b)The proposed method. (yellow=existing, red=changed, blue=newly-built)

	Previous method	Proposed method	Improvement rate
Existing (correct detection)	32	35	+9.4%
Changed (false detection)	4	1	-75.0%
Newly-built(false detection)	16	1	-93.8%

Table 3. Result assessment of previous and proposed methods

## 5. CONCLUSIONS

This paper has presented a map-based building change detection algorithm using geometric optimization method, which consists of the building recognition based on a combinatorial optimization method and the newly-built building extraction based on an optimal building hypothesis search method. The experimental results indicate the effectiveness of the methods to integrate bottom-up and top-down analysis to achieve highly accurate building change detection in urban area, and confirmed the validity of the method while using actual QuickBird high resolution satellite imagery and detection of various types of target buildings. The method was applied to an actual building change detection service named "HouseDiff" and succeeded in assisting users. Further research should include improvement of the robustness of the algorithms by applying pattern recognition and machine learning methods to expand the HouseDiff service widely.

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