Road Change Detection for Map Updating Using Geometric Boundary Deviation Between Digital Maps and Aerial Segmentation Results

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Abstract

Road change detection is essential for maintaining up-to-date digital maps; however, conventional update processes rely heavily on the manual interpretation of aerial imagery, leading to high labor costs and inconsistent outcomes. To address these limitations, this study proposes an automated road change detection method that integrates aerial orthophoto-based segmentation with geometric boundary deviation analysis. Road areas are first extracted from high-resolution aerial orthophotos using SegFormer, a Transformer-based semantic segmentation model. The segmentation results are then converted into vector polygons for geometric analysis. Structural changes, such as newly constructed or removed roads, are detected through a difference-based comparison with historical digital maps. Simultaneously, shape changes are quantitatively analyzed by measuring geometric deviations between road boundaries. Specifically, vertex-wise distances between corresponding boundaries are computed, and the overall deformation is evaluated using Root Mean Square Error (RMSE), incorporating Z-score-based outlier removal to ensure robustness against noise.
Experimental results demonstrate that the proposed method effectively detects both structural changes and subtle geometric variations, including road expansions and boundary shifts. Furthermore, the method enables clear object-level classification of change types, providing a practical and efficient framework for digital map updating workflows.

1. Introduction

Cities are constantly evolving in response to continuous development and infrastructure expansion, and these changes directly influence the structure and form of the various elements that constitute urban space. As one of the primary components of urban infrastructure, roads serve as a core framework that shapes traffic flow and maintains spatial connectivity, functioning as the fundamental spatial structure that supports intra-city mobility and logistics. Furthermore, because road networks are utilized as critical baseline data for various urban services and spatial information-based decision-making, road alterations transcend simple physical changes and impact the overall spatial information system. Due to these characteristics, structural changes—such as the construction, expansion, and decommissioning of roads—directly affect not only urban transportation systems but also the utility and reliability of various spatial information-based services. Consequently, accurately identifying road change information and reflecting it in the latest spatial datasets has been recognized as a vital task within the national spatial information management framework.

In South Korea, the National Geographic Information Institute (NGII) takes a leading role in establishing and managing digital maps at a 1:5,000 scale, maintaining their currency through periodic update processes (National Geographic Information Institute, 2025). Generally, the map update workflow involves identifying changed road sections by comparing existing digital maps with newly acquired aerial orthophotos and subsequently reflecting these changes in the map database. However, this updating process relies heavily on manual methods based on the visual interpretation of human operators, which presents significant limitations in efficiently processing large-scale spatial data. Particularly for tasks performed repeatedly on nationwide aerial orthophoto and digital maps, substantial time and costs are required, and the consistency of the results may diminish depending on the operator's proficiency. Furthermore, in cases where road boundaries undergo partial changes or possess complex geometries, it is difficult to accurately determine the occurrence of a change, leading to the potential for omissions or false positives.

To overcome these limitations, research aimed at automatically detecting road change sections using aerial orthophoto and existing map data has recently been actively pursued. Change detection technology is being utilized in various fields, such as urban development monitoring, map updating, and environmental change analysis. In particular, research continues to focus on automating the update process of spatial information data by integrating aerial orthophoto with existing map information. Existing studies related to road change detection can be categorized into several types based on their methodological approach. First, in centerline-based approaches, changes in the road network are analyzed by comparing road centerlines between two temporal points. For instance, Wang et al. (2024) proposed a method to detect road changes by comparing bi-temporal road centerlines. While this approach has the advantage of effectively reflecting the connectivity and topological changes of the road network, it has inherent limitations. Since a centerline is a simplified representation of the actual road shape, it is insufficient for precisely reflecting detailed geometric changes, such as variations in road width or boundary shifts.

Meanwhile, image-based change detection methods, which directly compare images from two different time points, are also widely utilized. Ding et al. (2024) proposed a deep learning-based method that detects changed areas by learning spatiotemporal features. While this approach offers the advantage of directly extracting changed regions at the pixel level, it is inherently limited by its high sensitivity to various external disturbances, such as illumination changes, shadows, and tree occlusion. Specifically, even within the same road area,

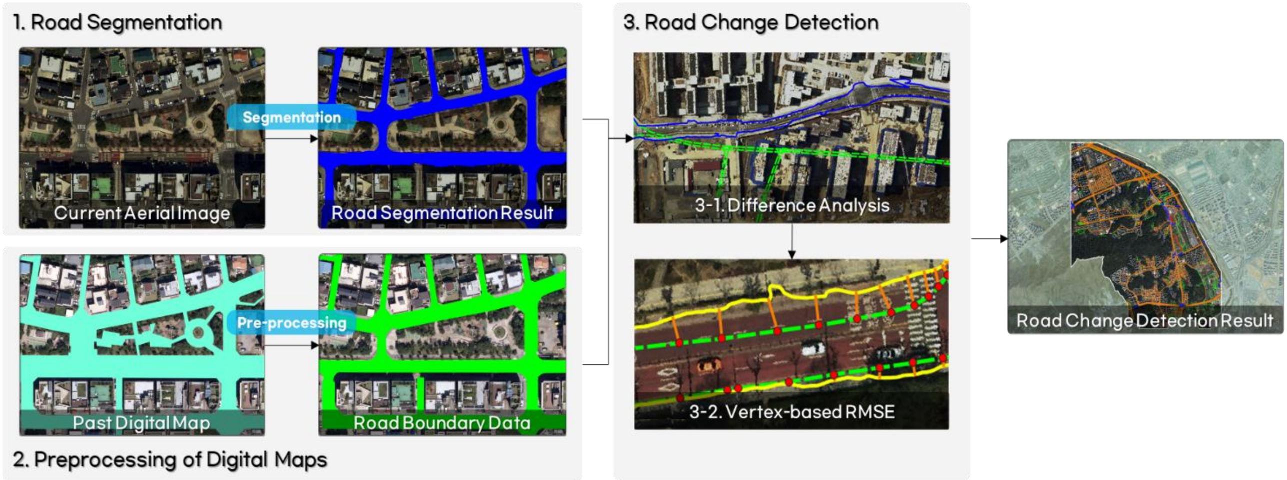

Figure 1. Workflow of Road Change Detection based on Geometric Boundary Deviation

discrepancies between images can arise due to variations in capturing conditions, making it difficult to ensure stable change detection performance. Furthermore, because these methods rely primarily on pixel-level differences, they are restricted in their ability to precisely reflect geometric information, such as road boundaries.

In light of these limitations, road change detection requires geometric analysis that can reflect the actual shape of the road, moving beyond simple pixel differences or centerline comparisons.

A key feature of this study is the proposal of an integrated framework capable of detecting both the existence of roads and shape changes at the boundary level. This allows for the effective reflection of not only road construction and decommissioning but also subtle changes such as road expansion and boundary shifts. Furthermore, it offers practical advantages in that change detection is possible using only previous digital maps and current aerial orthophoto, allowing it to be integrated into existing map update workflows without the need for additional multi-temporal data. These characteristics can contribute to the automation and increased efficiency of the update process for large-scale spatial information data.

2. Methodology

2.1 Overview

This study proposes a method for automatically detecting road changes by comparing road extraction results from aerial orthophotos with road polygons from existing digital maps of a previous time point. To this end, a change detection framework was developed that integrates deep learning-based road inference with boundary-based geometric analysis. As illustrated in Figure 1, the proposed method consists of four stages: road area inference from aerial orthophoto, digital map preprocessing, road change detection, and change type classification. First, a semantic segmentation model is employed to infer road areas from the latest aerial orthophotos to generate road masks, which are then used to construct road polygons through a vectorization process. Next, to refine the existing digital map data into a comparable format, sidewalk areas are removed to secure a roadway-centered area, and overlapping structures such as interchanges are organized and reconstructed into single road polygons. Subsequently, the road data from the two time points are compared to determine the occurrence of changes. For this purpose, the nearest-neighbor distance to the segmentation-based boundary is calculated based on vertices generated along the boundary of the existing digital map, thereby quantifying the deviation between boundaries. In the final stage, the analysis results are synthesized to classify road changes into specific types: New, Removed, Updated, or Unchanged.

2.2 Road Segmentation based on Aerial Orthophotos

To infer road areas from current aerial orthophotos, imagery with a spatial resolution of approximately 12 cm was utilized as input data. For the efficient processing of large-scale aerial orthophoto datasets, training and inference were conducted by dividing the input images into patches of 512 × 512 pixels. SegFormer (Xie et al., 2021), a Transformer-based semantic segmentation model, was employed for road area inference. SegFormer integrates hierarchical Transformer encoders with a lightweight decoder structure, enabling the effective fusion of feature information across various resolutions, which results in stable road segmentation performance even in complex urban environments. Road segmentation was defined as a binary classification problem distinguishing between road and non-road classes, and the model was trained using a supervised learning approach with ground-truth data. The trained model outputs pixel-level probability maps for the entire image, which were then converted into binary masks based on a threshold to infer road areas. Subsequently, the binary masks were transformed into polygon formats for vector-based analysis. During this process, objects were separated based on connected road regions, and small objects below a certain area threshold were removed as noise. Furthermore, a morphological closing operation was applied to compensate for boundary disconnections and voids occurring during the segmentation process, thereby improving the continuity of the road areas. This post-processing stage plays a critical role in ensuring the stability of the subsequent boundary-based geometric analysis.

2.3 Preprocessing of Digital Maps

To ensure a precise comparison between the aerial orthophoto-based road segmentation results and the road data from previous digital maps, a preprocessing step was performed to achieve geometric consistency between the two datasets, as illustrated in Figure 2. Significant differences exist in the definition and representation of roads between digital maps and aerial orthophoto-based segmentation results.

While digital maps include not only roadways but also sidewalk areas, aerial orthophoto-based segmentation results tend to extract regions centered primarily on the roadway where vehicle traffic occurs. This discrepancy leads to misalignments between the boundaries of the two datasets, which can cause a problem where a segment is incorrectly identified as an Updated case despite there being no actual change. To compensate for this, this study maintained only the roadway-centered road polygons by removing sidewalk areas from the digital maps.

Additionally, in sections with complex structures such as interchanges and intersections, multiple road polygons are often represented in an overlapping manner. Such structures cause issues where multiple correspondences occur for a single location during the boundary-based distance calculation process, leading to instability in the distance results. To prevent this, overlapping or intersecting road areas were merged and reconstructed into single road polygons. Through this preprocessing, the representational discrepancies between the two datasets were minimized, enhancing the accuracy of the subsequent boundary-based geometric analysis.

Figure 2. Digital Map Data Refinement Process

2.4 Road Change Detection and Classification

Road changes were classified into four types: New, Removed, Updated, and Unchanged by comparing road data from two different time points. To achieve this, an integrated framework was constructed to determine changes in road existence based on differences and to identify shape changes through boundary-based geometric analysis. First, as shown in Figure 3, changes in the existence of roads were detected by directly comparing the previous digital maps with the current aerial orthophoto-based road segmentation results. Road areas present only in the segmentation results were identified as New, while those existing only in the previous digital maps were classified as Removed. This difference-based method features a simple structure and high computational efficiency, providing stable detection performance when changes in road existence are distinct. However, shape changes—such as variations in road width, boundary shifts, and alignment changes—are difficult to distinguish through difference operations alone while the existence of the road is maintained. To address this, this study applied a method to analyze the geometric differences between road boundaries, as illustrated in Figure 4.

First, vertices were generated at regular intervals along the boundaries of the existing digital map road polygons, serving as representative points for the entire road boundary. For each vertex, the Euclidean distance was calculated by searching for the nearest point on the road boundary derived from the aerial orthophoto-based segmentation. The calculated distance represents the positional discrepancy of the road boundaries between the two time points, allowing for a quantitative representation of boundary-based shape changes. Unlike centerline-based comparisons, this approach directly reflects actual changes in road boundaries, enabling the effective detection of fine-grained shape variations such as road expansion or contraction. However, segmentation results based on aerial orthophotos may contain noise caused by shadows or tree occlusion, which can result in abnormally large distance values. To compensate for this, Z-score-based outlier removal was applied to eliminate extreme distance values. Subsequently, the RMSE was calculated based on the filtered distance values to evaluate the degree of deformation across the entire boundary. As an indicator of the average deformation level of the boundary, RMSE can stably reflect overall shape changes while mitigating the influence of localized noise. A higher RMSE value indicates a greater boundary discrepancy between the two time points, which served as the criterion for determining whether a shape change—classified as Updated—had occurred.

Finally, the road changes were classified by integrating the difference-based detection results with the boundary-based geometric analysis. Cases existing only in the aerial orthophoto-based segmentation results were classified as New, while those present only in the digital maps were classified as Removed. For road areas common to both datasets, the boundary-based analysis results were applied: segments where the RMSE exceeded a predefined threshold were classified as Updated, and those below the threshold were classified as Unchanged. This integrated framework allows for the reflection of both structural changes, such as the creation and disappearance of roads, and subtle shape variations, such as road expansion or boundary shifts. Furthermore, since change types can be clearly distinguished at the object level, road sections requiring actual revisions can be efficiently identified during the digital map update process.

Figure 3. Detection of road existence changes
(New and Removed)

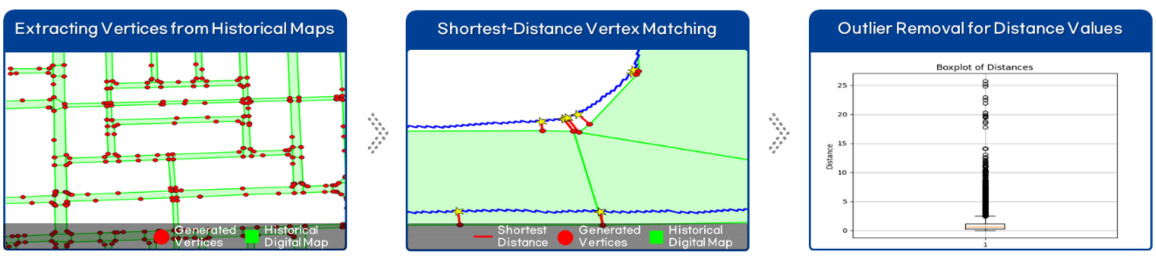

Figure 4. Determination of Road Boundary Changes based on Geometric Deviation Analysis

3. Experiments

3.1 Study Area and Dataset

In this study, experiments were conducted in Gangnam-gu, Seoul, South Korea. This area is characterized by a high-density urban structure and a complex road network, making it suitable for evaluating the performance of road change detection. The total area of the experimental site is approximately 12.01 km². The input data consisted of the latest aerial orthophotos and digital maps from a previous time point. For the digital maps, refined data from the 1:5,000 scale national basic map were used, provided in the form of road polygons. To detect changes between two time points, datasets from different periods were utilized, where the aerial orthophoto reflects the current road conditions and the digital maps represent the past road information.

3.2 Data Preprocessing and GT Construction

To quantitatively evaluate the performance of road change detection, Ground Truth (GT) for the change types was established based on road data from two different time points. The two datasets were aligned to the same spatial reference to allow for direct comparison and were converted into a raster format for pixel-level analysis. Subsequently, the change types were defined for each location by comparing the presence or absence of roads between the two periods. Instances where a road exists only in the current time point were defined as New, and those existing only in the previous time point were defined as Removed. Locations where roads exist in both time points were classified as Unchanged, while cases where the road location remains consistent but the boundary discrepancy exceeds a certain threshold were defined as Updated. The GT generated through this process served as the reference data for evaluating the road change detection results. Although a similar geometric criterion is used for defining Updated cases, the GT is generated from ideal road datasets at two time points, without the influence of segmentation errors. In contrast, the proposed method relies on road boundaries derived from aerial orthophoto-based segmentation, which inherently include noise, occlusion effects, and boundary uncertainty. Therefore, the evaluation does not represent a trivial agreement with the GT but rather reflects the robustness of the proposed method under realistic conditions.

3.3 Evaluation Metrics

To quantitatively evaluate the performance of road segmentation and change detection, Precision, Recall, F1-score, and Intersection over Union (IoU) metrics were used. The evaluation of road segmentation performance was conducted based on the results of the binary classification distinguishing between road and non-road classes. Precision represents the ratio of areas correctly predicted as roads by the model relative to all areas correctly identified as roads, and is defined as shown in Eq. 1:

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

Recall represents the ratio of actual road areas that the model correctly detected, as defined in Eq. 2:

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

The F1-score is the harmonic mean of Precision and Recall, serving as a metric to evaluate the balance between the two, and is calculated as shown in Eq. 3:

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{3}$$

IoU represents the degree of overlap between the predicted and actual road areas, as defined in Eq. 4:

$$IoU = \frac{TP}{TP + FP + FN} \tag{4}$$

Here, TP, FP, and FN denote True Positive, False Positive, and False Negative, respectively. The evaluation of road change detection performance was conducted for each change type. Precision, Recall, and F1-score were calculated for each category: New, Removed, Updated, and Unchanged. Since the change classes account for a small proportion of the total dataset, the F1-score, which considers both Precision and Recall, was utilized as the primary evaluation metric.
To provide a more intuitive evaluation of the change detection results, this study conducted assessments using two distinct approaches: object-level and area-based evaluations. The area-based evaluation calculated each metric by aggregating the area of TP, FP, and FN based on the object matching results.

The object-level evaluation was performed by treating each road polygon defined in the GT as a single individual object. For each GT object, among the predicted polygons intersecting with it, the one with the highest overlap ratio relative to the area of the GT object was selected as the matching candidate. Here, the overlap ratio was defined as the area of intersection between the two polygons divided by the area of the GT object. A match was considered valid only if the overlap ratio with the selected predicted object was equal to or greater than a predefined threshold (0.60).

A GT object was defined as a TP if a valid match existed and the predicted change type was consistent with the GT. Conversely, if no match existed, the overlap ratio was below the threshold, or the predicted class differed from the GT, the corresponding GT object was regarded as a FN. Furthermore, predicted objects that were not matched with any GT object were defined as FP.

This object-level evaluation was carried out by selecting a single predicted object with the highest overlap ratio for each GT object. This matching strategy is based on a GT-wise best matching scheme rather than enforcing a strict one-to-one correspondence between GT and predicted objects. Even in cases where a single object was split into multiple parts or multiple objects were merged into one, the evaluation was based on a single optimal matching result without applying any additional multi-matching schemes. This approach aims to intuitively assess the existence and specific types of change objects at the object level, enabling a consistent and interpretable evaluation in complex scenarios.

4. Results and Discussion

4.1 Road Segmentation Results

In terms of the aerial orthophoto-based road segmentation results, SegFormer demonstrated the best overall performance in comparative experiments with various state-of-the-art segmentation models, as shown in Table 1. According to the quantitative evaluation, SegFormer recorded an F1-score of 0.882 and an IoU of 0.788, showing higher accuracy compared to existing models such as DeepLabV3+, HRNet, LOANet, U-Net, and ViT. In particular, it showed a distinct performance gap compared to other models in terms of IoU, which implies that it can segment road areas more precisely even in complex urban environments.

Model	Recall	Precision	F1	IoU
SegFormer	0.827	0.961	0.889	0.8
DeepLabv3+	0.816	0.92	0.865	0.762
HRNet	0.778	0.932	0.848	0.736
LOANet	0.764	0.874	0.815	0.688
ViT U-Net	0.671	0.642	0.657	0.488
U-Net	0.766	0.849	0.805	0.674

Table 1. Pixel-Level Road Segmentation Performance

Furthermore, as shown in Figure 5, the model tended to extract elongated linear objects like roads continuously without disconnection. This is attributed to the structural characteristics of SegFormer, which effectively integrates feature information from various resolutions. Such performance superiority serves as a crucial foundation for ensuring the reliability of boundary-based comparisons in the subsequent change detection process. However, in some areas, incomplete boundary extraction was observed where road edges were partially obscured by disturbances such as trees or shadows. These errors can lead to partial omissions of road areas or shape distortions, potentially acting as a source of false positives or false negatives during the change detection process.

Figure 5. Visual Comparison of Road Segmentation Results

4.2 Road Change Detection Results

The quantitative evaluation of road change detection results was conducted in two ways: object-level (Table 2) and area-based (Table 3). The analysis was performed for four categories: New, Removed, Updated, and Unchanged. In the object-level evaluation, each road polygon defined in the GT was treated as a single object, and detection performance was evaluated based on the change type assigned to each object.

First, according to the object-level evaluation results, relatively high detection performance was confirmed for the New and Removed classes, with a Recall of 0.8 and 0.991, respectively. This indicates that clear structural changes, such as the creation or disappearance of roads, were effectively detected at the object level. In contrast, Precision for the New and Removed classes was lower, at 0.174 and 0.353, respectively. This is partly attributed to class imbalance, where the proportion of change classes is extremely low. Additionally, false positives are mainly caused by discrepancies between segmentation results and digital maps, including boundary errors due to occlusions and differences in road representation. For the Updated class, the Recall was 0.465; this relatively lower performance is due to the nature of the evaluation method, where an entire object may be treated as a missed detection if the specific changed area is not precisely identified, even if parts of it are detected. This highlights the higher difficulty of detecting shape changes compared to new construction or decommissioning, as the former is defined based on subtle differences in boundary positions. Finally, the Unchanged class showed high performance with a Precision of 0.995 and an F1-score of 0.907, reflecting that most road objects are being maintained stably.

Class	New	Removed	Updated	Unchanged
TP	4	122	20	1243
FN	1	1	23	248
Recall	0.8	0.991	0.465	0.834
Precision	0.174	0.353	0.318	0.995
F1	0.286	0.52	0.377	0.907

Table 2. Object-Level Road Change Detection Performance

In the area-based evaluation results, overall performance was higher than that of the object-level evaluation, with significantly high detection rates confirmed by a Recall of 0.95 for New and 0.995 for Removed classes. The Updated class also showed improved performance compared to the object-level results, with a Recall of 0.713; this is attributed to the difference in evaluation methods, where even partial detection of an area is reflected in the performance metrics. However, Precision remained relatively low at 0.532 for New and 0.266 for Removed classes. This is partly attributed to the imbalanced data distribution, where the extremely small proportion of changed areas amplifies the effect of false positives. Additionally, boundary discrepancies between segmentation results and digital maps—caused by occlusions and differences in road representation—generate pixel-level false positives that accumulate and reduce precision. The Unchanged class maintained very high performance, with a Precision of 0.99 and an F1-score of 0.925.

Class	New	Removed	Updated	Unchanged
TP (m^2)	12722	26306	37480	977560
FN(m^2)	671	135	15125	148954
Recall	0.95	0.995	0.713	0.869
Precision	0.532	0.266	0.315	0.99
F1	0.695	0.419	0.436	0.925

Table 3. Area-Based Road Change Detection Performance

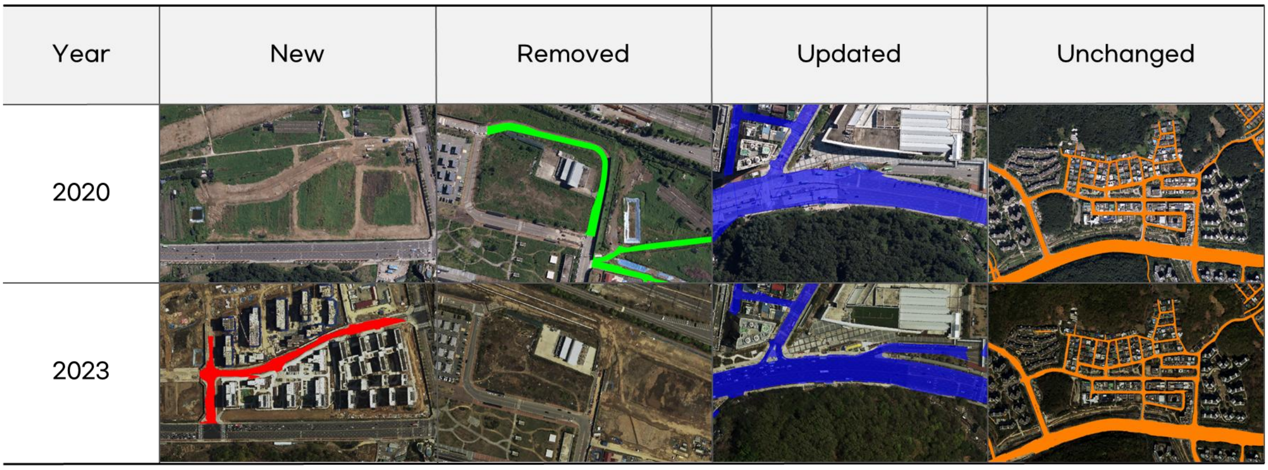

Figure 6. Examples of Four Road Change Types (2020–2023)

4.3 Qualitative Analysis

Through a qualitative analysis of the road change detection results, it was confirmed that the proposed method can effectively distinguish between various types of changes.

As illustrated in Figure 6, the existence or absence of roads between the two time points was clearly reflected in the New and Removed areas, showing that actual change segments were accurately detected. In particular, in the Updated areas, actual geometric changes such as road expansions were visually confirmed, demonstrating that boundary-based geometric analysis can effectively reflect subtle shape variations of the roads. These results suggest that an approach directly utilizing road boundary information enables more precise analysis than simple pixel-based comparisons or centerline-based methods.

Meanwhile, in some cases, false positives were observed due to environmental factors such as tree occlusion or shadows, which led to the incomplete extraction of road boundaries. This stems from the limitations of aerial orthophoto-based segmentation results and demonstrates that change detection performance is inherently affected by the quality of the input data.

4.4 Discussion

The results of this study demonstrate that the proposed method effectively detects not only clear structural changes, such as the construction or removal of roads, but also shape variations like road expansions. In particular, by quantitatively reflecting the positional shifts of road boundaries through boundary-based geometric analysis, this approach addresses the limitations of conventional pixel-based or centerline-based methods.

However, relatively low precision and recall were observed in the Updated class, as the boundary-based analysis is inherently sensitive to the accuracy of the aerial orthophoto-based segmentation results. In practice, discrepancies between segmentation results and digital maps—caused by occlusions (e.g., trees and shadows) and differences in road representation—can lead to boundary inconsistencies that are interpreted as change regions. While these effects contribute to false positives, they also indicate that the proposed method is capable of capturing fine-grained geometric variations that are difficult to detect using conventional approaches.

Furthermore, the difference between object-level and area-based evaluation highlights the characteristics of the proposed method. Object-level evaluation is more sensitive to strict matching conditions, where even small boundary inconsistencies may result in an entire object being classified as incorrect, whereas area-based evaluation reflects partial detections and is more tolerant to localized discrepancies. This suggests that the proposed method provides complementary strengths depending on the evaluation perspective.

Future research should focus on applying road segmentation techniques that are more robust to environmental factors, such as shadows and tree occlusion, and enhancing the precision of shape change detection by incorporating additional geometric information, such as road width and the number of lanes.

5. Conclusion

In this study, we proposed an automated road change detection method that integrates aerial orthophoto-based segmentation with geometric boundary deviation analysis. The proposed framework enables the comprehensive detection of both structural changes (New and Removed) and subtle geometric variations (Updated) by combining difference-based analysis with boundary-based geometric comparison.

Experimental results demonstrated that the proposed method achieves high detection performance for structural changes, while also effectively capturing fine-grained shape variations such as road expansion and boundary shifts. In particular, the boundary-based analysis provides a meaningful advantage over conventional pixel-based or centerline-based approaches, as it directly reflects geometric changes in road structures.

Furthermore, by providing both object-level and area-based evaluations, this study highlights the complementary characteristics of different evaluation perspectives. While object-level evaluation emphasizes strict change identification at the road-object scale, area-based evaluation reflects partial detections and offers a more tolerant assessment of localized discrepancies. This dual evaluation provides a more comprehensive understanding of the method’s performance in practical map updating scenarios.

Although relatively low precision was observed in change classes, this is largely attributed to the sensitivity of the proposed method to boundary discrepancies arising from segmentation uncertainty,

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occlusions, and differences in road representation between datasets. This sensitivity, however, also enables the detection of subtle geometric variations that are difficult to capture with existing approaches.

Overall, the proposed method provides a practical and efficient framework for digital map updating, enabling the identification of road segments that require revision at both structural and geometric levels. Future work will focus on improving the robustness of road segmentation under challenging environmental conditions and enhancing shape change detection by incorporating additional geometric attributes such as road width and lane configuration.

Acknowledgements

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