Quality Inspection and Intelligent Fusion Method for Automated Production of Large-Scale Remote Sensing Image Tiles

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Abstract

Web map services (such as Google Maps and Amap) have become an indispensable spatial information infrastructure in various fields of society. Their underlying image tile pyramid technology encompasses the entire process of slicing, publishing, and updating massive remote sensing images. In the tile production process, quality inspection and edge blending are crucial steps to ensure the visual authenticity and usability of the final map product. However, current tile production relies on manual sampling for quality inspection, and the blending process suffers from issues such as geometric misalignment and color inconsistency, which hinder production efficiency and product quality. This paper proposes a quality inspection and intelligent blending method for large-scale tile automation production, constructing a four-layer post-processing framework including a metadata quality inspection layer, an image quality inspection layer, an intelligent color coordination layer, and an automatic mosaicking layer. By establishing a rule engine to implement batch verification of metadata, combining pixel statistics and edge detection to achieve precise positioning of black/white edges and color anomaly recognition, using histogram matching and batch color correction to ensure color consistency across multiple batches of tiles, and implementing seamless blending between new tiles and online tiles based on an alpha channel null value filling mechanism, experiments conducted on the TianMap tile dataset show that this method significantly enhances the automation level and processing efficiency of tile production, reduces human errors, and enhances the visual consistency and reliability of web map products. This study provides a technical reference for the intelligent production of remote sensing image tiles and has practical application value in supporting high-quality updates for web map services.

1. Introduction

With the rapid development of social economy, geographic information data has garnered increasing attention. Governments and commercial enterprises are providing users with increasingly rich geographic information services through map websites. In addition to providing vector data (such as roads, buildings, green spaces) and image data (such as satellite images, aerial images) as standard layers, multiple platforms also offer terrain data and land cover classification data. For instance, the national geographic information service platform "Tianmap" (Wang et al., 2022) is one such platform.

Web map services, such as Google Maps and Amap, have become indispensable spatial information infrastructure in various fields of society. Their underlying image tile pyramid technology encompasses the entire process of slicing, publishing, and updating massive amounts of remote sensing images. Map tile technology was first pioneered by Google with the launch of Google Maps in 2005, which divides the map into several small blocks (tiles), each stored and transmitted as an image file, enabling fast map browsing and interactive experience through dynamic loading (Loechel & Schmid, 2013). Map tile technology has become the cornerstone of modern web map development and is widely applied in other map services and geographic information systems.

In the tile production process, quality inspection and edge blending are crucial steps to ensure the visual authenticity and usability of the final map products (Wang et al., 2024). However, the current tile production process faces significant challenges. Firstly, quality inspection relies on manual sampling, which is not only inefficient for tile production on the scale of millions to tens of millions, but also prone to missed inspections due to human fatigue. Secondly, during the blending process, geometric misalignment and color discontinuity issues inevitably exist between different batches of tiles, as well as between newly produced tiles and existing tiles in online services. Traditional methods struggle to achieve large-scale, automated, and seamless stitching and blending. Therefore, developing an integrated and automated tile quality inspection and blending method holds significant theoretical value and practical importance for promoting the intelligence of remote sensing image tile production and ensuring the quality and efficient updating of web map services.

In terms of automated quality inspection, existing research can be divided into rule-based methods and vision-based methods. Metadata quality inspection primarily focuses on the accuracy of core information such as spatial references. Practical experience has shown that missing or incorrect spatial references can lead to data misplacement and display anomalies. Although mainstream GIS platforms (such as ArcGIS) provide projection definition and verification tools, they still rely on manual inspection of individual data layers, lacking an automated rule engine that can be embedded into production processes for batch parsing and verification of massive tile metadata. In terms of image quality inspection, the detection of invalid pixels (such as black/white edges) is a research focus. For example, Gao et al. (2012) proposed a region growing algorithm with image corners as seed points to detect boundary invalid pixels. However, most methods only focus on the detection itself (Niu et al., 2018), and how to integrate with production processes and provide precise vectorized boundaries

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for subsequent repairs remains to be further studied. In terms of color consistency verification, related research has mostly focused on enhancing the color uniformity of single-scene remote sensing images, while research on real-time color difference diagnosis based on statistical indicators for the relationship between adjacent domains of discrete tiles is relatively scarce.In the field of tile fusion and updating, the main challenges lie in geometric edge alignment and color fusion. Recent research has focused on building high-performance real-time raster tile service systems. For instance, HTile innovatively proposes a tile generation process that supports data fusion (Chen & Kuo, 2024), enabling dynamic integration and visualization of multi-source data on the server side. This highlights the supportive role of efficient data fusion technology for online services.

In summary, current research on metadata quality inspection, apparent defect detection, color consistency processing, and edge fusion remains relatively fragmented (Xia,& Chen, 2015). Integrating these aspects into an end-to-end automated framework, encompassing metadata rule verification, visual anomaly detection and vectorization positioning, intelligent color consistency across multiple batches of tiles, and seamless edge fusion, has become the core focus of current research (Lu et al., 2014).

This paper aims to establish a quality inspection and intelligent fusion method for the automated production of large-scale remote sensing image tiles, achieving full-chain automation of the tile production post-processing workflow. The main contributions are as follows:
1.Propose a four-layer post-processing framework encompassing metadata quality inspection, image quality inspection, intelligent color coordination, and automatic stitching, forming a closed-loop, automated processing workflow (Gorelick et al., 2017);
2.Design and implement a metadata batch verification method based on a rule engine to achieve source isolation of non-compliant tiles;
3.Propose an invalid area detection method that integrates pixel statistics and edge detection to achieve precise positioning and vectorization output of black/white edges;
4.Develop a color consistency verification method based on four-neighborhood statistical features, and combine histogram matching with batch color correction to achieve uniform color across multiple batches of tiles;
5.A fusion mechanism based on alpha channel for identifying null value regions and filling with valid pixels in adjacent areas is proposed to achieve seamless stitching between new tiles and online tiles.

2. Data

To verify the effectiveness of the quality inspection and fusion method proposed in this paper, data from five batches, namely those from Liaoning, Gansu, Shanxi, Shaanxi, and Hainan, which were submitted recently, were selected. Each batch of data includes tile data generated based on different remote sensing image data, as well as its accompanying metadata files.
The remote sensing image data sources primarily involve satellites 1, 2, and 7 from the "Gaofen series", as well as satellites 2 and 3 from the "Beijing series", and also include some satellites from the "Jilin series". The spatial resolution of the image data is "0.5 meters" and "0.8 meters". Through resampling, tiles of levels 12-18 can generally be generated. Each batch of data covers a different number of cities and counties. For example, the Liaoning batch covers areas such as Dalian, Huludao, Panjin, Benxi, Jinzhou, Shenyang, Fuxin, Dandong, Liaoyang, Yingkou, Chaoyang, Anshan, Fushun, and Tieling; the Gansu batch covers the Gannan Prefecture area; the Shanxi batch covers areas such as Yangquan, Xinzhou, Shuozhou, Taiyuan, Datong, Jinzhong, Luliang, and Changzhi; the Shaanxi batch covers areas such as Tongchuan, Yulin, Xi'an, Baoji, Shangluo, Hanzhong, Xianyang, Weinan, Ankang, and Yan'an; and the Hainan batch covers areas such as Danzhou, Baoting County, Sanya, Ledong, Lingshui County, Wuzhishan, Qionghai, Tunchang, Wanning, Wenchang, Dongfang, Changjiang County, Baisha County, Qiongzhong County, and Lingao.

Metadata is stored in Shapefile format. The metadata files include .prj coordinate files, .dbf attribute table files, .xml metadata description files, etc., which are used to record information such as the spatial reference, geographical range, production time, regional coding, and source of image data for the tiles.

3. Methodology

This study adheres to the core principles of "automation-oriented, intelligence-driven, and reliability-guaranteed" and constructs a four-layer post-processing framework for tile production, consisting of "Metadata Quality Inspection Layer, Image Quality Inspection Layer, Intelligent Color Harmonization Layer, and Automatic Mosaicking Layer". Specifically, the Metadata Quality Inspection Layer focuses on the compliance verification of core tile attributes. The Image Quality Inspection Layer emphasizes the automatic identification of surface defects and color anomalies. The Intelligent Color Harmonization Layer is dedicated to optimizing color consistency across tiles. The Automatic Mosaicking Layer addresses seamless edge matching in multi-scenario tile applications. These layers are closely coupled and form a closed-loop linkage, significantly improving the automation level and product reliability of tile production, which meets the efficient processing requirements of large-scale tile manufacturing.

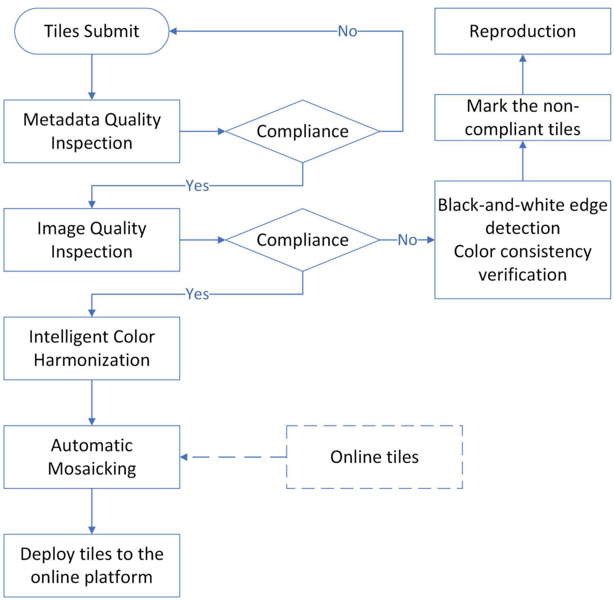

Figure 1 Operational flow about the automated quality inspection and intelligent fusion method.

3.1 Metadata Quality Inspection Layer

As the fundamental guarantee of the entire post-processing workflow, this layer is centered on the automated validation of key tile metadata attributes. It conducts comprehensive inspections on critical indicators such as the consistency of spatial references, the accuracy of temporal information, and the completeness of attribute fields to exclude invalid or erroneous metadata (Wulder et al., 2019). A standardized validation protocol is established to ensure data source compliance, providing attribute-error-free base tiles for subsequent image processing, color harmonization, and mosaicking stages, thereby avoiding full-process processing defects caused by metadata anomalies.

The requirements for image metadata are as follows: The metadata is stored in Shapefile format, utilizing the 2000 National Geodetic Coordinate System for the coordinate system. It describes the information of mosaic imagery results, distinguishing between different time phases. Specific attribute information such as administrative divisions, time phases, satellite names, resolutions, and providing units should be filled in according to Table 1.

Table 1 Image Metadata.

Serial number	Name	Mandatory or not	Type	Instructions	Range
1	Region	Yes	Text(50)	Province, City	Region Name
2	GB	Yes	Text(50)	City Administrative District	Code writing
3	Transducer	Yes	Text(20)	Sensor type	BJ2, BJ3, GF1, GF2, GF6, GF7, GJ1, GE1, K3A, KM2, KM3, KM4, PL0, SJ9A, SV1, SV2, WV2, WV3, WV4, ZY3, AP0, JL1, CB04, TH01, etc
4	Level	Yes	Text(30)	Level	List all levels in detail, separated by half-width commas between levels, such as: 15,16,17,18
5	Resolution	Yes	Text(20)	Resolution	Unit: m
6	Time	Yes	Text(50)	Time phase	Example: 202103 (yyyymm)
7	ORGA	Yes	Text(50)	Provide unit	Submitting unit
8	Remark	No	Text(50)	Remark	

The scope of inspection covers the following key indicators:
Spatial reference consistency: Verify whether the tile coordinate system conforms to preset standards;
Geographical consistency: Verify whether the actual geographical range of the tile is consistent with the theoretically calculated value;
Accuracy of time information: Check the format and logical consistency of tile production time and update time to avoid duplicate or incorrect time information;
Attribute field integrity: Verify the existence and correct format of essential fields such as region code and version number;
File format validity: Confirm whether the metadata file is parseable and undamaged.
For unqualified tiles, the system automatically marks and isolates them, preventing them from entering subsequent processing flows, thereby eliminating the risk of data pollution and process interruptions at the source.

3.2 Image Quality Inspection Layer

Relying on computer vision technology, this layer realizes automated control of image quality and serves as a key quality control link in the post-processing workflow. An optimized defect detection model is trained to accurately identify invalid regions (e.g., black borders, white borders) within tiles and simultaneously capture color anomalies such as color cast and uneven brightness (Zhu & Woodcock, 2014). Detected image defects are automatically labeled, and targeted preprocessing procedures are triggered to eliminate visual obstacles for subsequent intelligent color harmonization and automatic mosaicking, ensuring the basic image quality of tiles.

Black/white edge detection: using a fusion method of pixel statistics and edge detection. Firstly, calculate the pixel histogram of the tile image. If the proportion of pure black (0,0,0) or pure white (255, 255, 255) pixels exceeds the preset threshold (5%), it is preliminarily marked as abnormal. Subsequently, invalid area boundaries are extracted using edge detection algorithms and vectorized to generate boundary files, achieving precise localization of the problem area and providing support for targeted repairs in the future (Chai et al.,2022). This hybrid method combines the computational efficiency of statistical methods with the localization accuracy of edge detection methods.

Color consistency verification: Using the four neighborhood adjacency relationships between tiles, calculate the color statistical features (such as mean and standard deviation) of the inspected tile and adjacent tiles in the overlapping area. Automatically identify tiles with significant color deviation or visual discontinuity by comparing feature differences. The selection of four neighborhoods instead of eight neighborhoods or global statistics is mainly based on the following considerations: (1) computational efficiency. Four neighborhoods can significantly reduce the computational load of adjacent relationship judgment, meeting the efficiency requirements of large-scale tile processing; (2) The production rules for tiles are usually generated sequentially in the row and column directions, and the four neighborhoods can already cover the main splicing boundaries; (3) Edge continuity and color inconsistency are mainly manifested as abrupt changes at the boundaries of adjacent tiles, and the four neighborhood can effectively capture such problems. Compared to global color statistics methods, four neighborhood validation can more accurately locate local color anomalies. Only when there is a significant difference in statistical values, will it be used as a validation area for color inconsistency, and then the final color inconsistency area needs to be determined through human-machine collaboration.

3.3 Intelligent Color Harmonization Layer

Integrating a rule engine with advanced image processing algorithms, this layer aims to achieve color consistency calibration for batch tiles. It establishes an adaptive color calibration framework by analyzing the color distribution characteristics of tiles from different batches and regions, dynamically adjusting parameters such as brightness, contrast, and color gamut. This layer eliminates intra-batch and inter-batch color differences, outputting standardized tiles with uniform visual effects, which lays a stable visual foundation for the seamless mosaicking of multi-batch tiles and improves the overall perceptual consistency of products.

For tiles that have passed quality inspection, use lower level tiles or standard tiles in the same area as color reference templates. Using histogram matching technology to align the color distribution of the target tile to the reference template, achieving color uniformity. Specifically, histogram matching achieves color distribution conversion by mapping the cumulative distribution function of the target image to the cumulative distribution function of the reference image.

In addition, overall color balance processing is performed on different batches of tiles, including brightness balance, contrast adjustment, and color gamut alignment, to ensure consistency in color tone, brightness, and contrast. This layer eliminates color differences between batches and outputs standardized tiles with unified visual effects, laying a stable visual foundation for seamless splicing of multiple batches of tiles and improving the overall perceptual consistency of the product.

3.4 Automatic Mosaicking Layer

To meet the mosaicking needs of multi-batch tile connection and old-new tile update, an efficient automatic mosaicking mechanism is constructed. Edge feature precise matching and gradient transition algorithms are adopted to realize natural boundary connection between multi-batch tiles and between to-be-updated tiles and existing online tiles. This layer effectively avoids mosaicking issues such as stitching gaps and color discontinuities, adapts to the actual requirements of different update scenarios, guarantees the spatial continuity and user experience of tile products, and achieves the application goal of "seamless update".

Firstly, based on the tile production rules, identify incomplete PNG format tiles, analyze their alpha channels, and define the range of null values. Effective pixels are defined as pixels in tile images that do not belong to black, white, or null regions and have effective color information.

Subsequently, the effective pixels in adjacent tiles are used to supplement and fill the empty value area. For the fusion with online tiles, the same mechanism is adopted: using online tiles as supplementary data sources to fill the empty value areas of the tiles to be updated. During the fusion process, a gradient transition algorithm is used to ensure a natural transition between the filled area and surrounding pixels.

This layer adopts precise edge feature matching and gradient transition algorithm to achieve natural boundary connections between multiple batches of tiles and between tiles to be updated and online tiles, effectively avoiding problems such as splicing gaps and color discontinuity, adapting to the actual needs of different update scenarios, ensuring the spatial continuity and user experience of tile products, and achieving the application goal of "seamless updates".

4. Implemetation

This study presents a fully automated tile processing framework comprising four core modules: automatic metadata quality inspection, automatic image quality inspection, tile color uniformity adjustment, and edge fusion. The detailed implementation is elaborated as follows:

4.1 Automatic Metadata Quality Inspection

A rule engine is constructed based on predefined specifications to enable batch parsing and verification of tile metadata files. The inspection scope covers compliance of the spatial reference system, consistency between the actual geographic extent of tiles and theoretical values, absence of duplicate temporal information, completeness of attribute fields (e.g., area codes), and validity of file formats. Unqualified tiles are automatically marked and isolated to block their entry into subsequent processing workflows, thereby eliminating data contamination and process disruptions at the source.

We have integrated these tasks into the data submission system. Users submit data in batches. Before submitting tile data, users first upload image metadata files. The system automatically checks the metadata files. If the check fails, the tile data cannot be submitted. Because tile data is much larger than metadata files, this avoids duplicate submission of tile data caused by non-standard metadata, thereby saving submission time.

Because it is all rule-based verification, the quality inspection accuracy of metadata is basically 100%. If the newly added transducer is not included in the rule enumeration type, it is necessary to contact the system responsible personnel first to supplement the newly added transducer, otherwise the quality inspection will fail.

4.2 Automatic Image Quality Inspection

Black-and-white edge detection: A hybrid method integrating pixel statistics and edge detection is adopted. First, the pixel histogram of the tile image is computed; tiles are initially flagged as abnormal if the proportion of pure black (0,0,0) or pure white (255,255,255) pixels exceeds a preset threshold. Subsequently, boundaries of invalid regions are vectorized to generate vector boundary files, realizing precise localization of problematic areas to support targeted repairs.

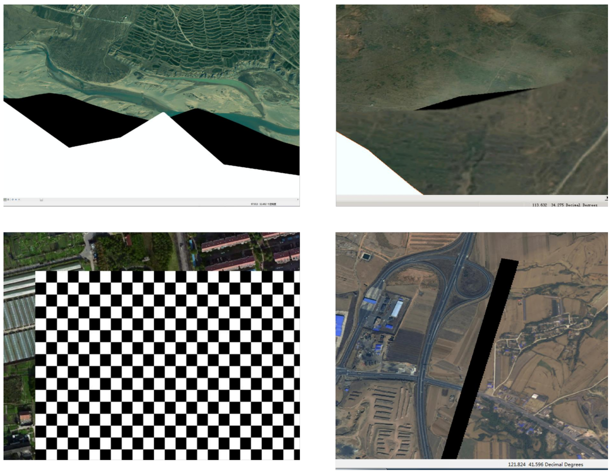

Figure 2 Example of Black-and-white edge.

The detection of mosaic images (located in the lower left corner of Figure 2) is more complex than the detection of ordinary pure black-and-white edges. Due to interference from factors such as snow, it is impossible to directly determine the proportion of black and white pixels. The method used in this paper is an adaptive checkerboard mosaic detection algorithm that achieves fully automatic detection without prior grid parameters through a combination of spatial multi-scale feature analysis and frequency domain periodicity verification. First, the image is converted to a grayscale image and binarized using Otsu's method (Figure 3). Then, a multi-scale sliding window is used to traverse the image, and the checkerboard response score is calculated based on local variance, contrast, and black-and-white proportion, to construct a response intensity map. Next, high-response areas are extracted through binarization, morphological filtering, and connected component analysis to obtain mosaic candidate masks. Subsequently, precise boundary localization is completed based on contours and minimum enclosing rectangles. Finally, projection difference and Fourier transform are used to analyze periodic features in the locked area to obtain the mosaic grid size. The entire process adapts to grid size, position, and area, without requiring manual parameter setting, and is highly robust. Therefore, it can effectively distinguish between highlighted areas and large white areas such as snow in real scenes, avoiding misjudgment.

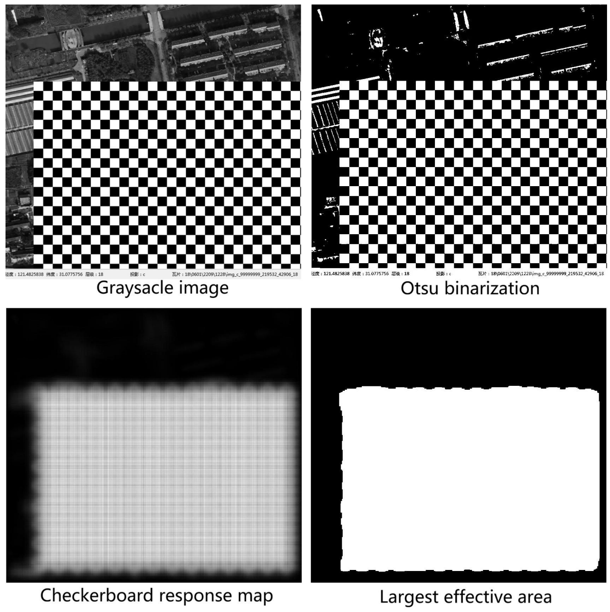

Figure 3 Some core steps and results of mosaic recognition.

Color consistency verification: Leveraging the 4-neighborhood adjacency of tiles, color statistical features (e.g., mean, standard deviation) between the inspected tile and its adjacent counterparts are calculated. Tiles with significant color deviations or visual incoherences are automatically identified by comparing these feature discrepancies.

This method achieves automated classification of remote sensing image color consistency based on the CIE Lab uniform color space and multi-dimensional color statistical features. Firstly, statistical features of the image in CIE Lab, HSV, and RGB color spaces are extracted, including CIEDE2000 color difference, HSV hue histogram distribution, three-dimensional RGB histogram Bhattacharyya distance, and five-region block color features. Then, a multi-index comprehensive similarity matrix is constructed to quantify the color differences between images, and the images are divided into different batches through hierarchical clustering algorithm. The mean value of the comprehensive distance matrix is used as the determination threshold to automatically identify images with significant color inconsistencies caused by uniform color templates, seasonal changes, or differences in lighting conditions. In addition, for the complexity of the project, human-computer interaction is required to adjust the threshold.

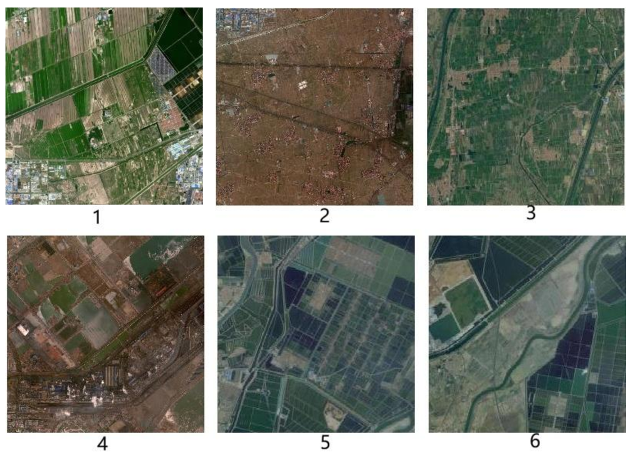

Figure 4 Images of different seasons.

For example, in the image shown in Figure 4, the threshold needs to be determined based on the actual engineering requirements. As can be seen from the combined column in Table 2, the method proposed in this paper can clearly distinguish images with different color differences.

Table 2 Comparison results of similarity among different images.

Image pair	ciede2000	hsv	bhattacharyya	five_region	combined	judgment
5.png-6.png	13.32	0.646	0.038	60.8	0.356	Yes
2.png-4.png	12.49	0.934	0.099	43.8	0.366	Yes
3.png-5.png	14.19	1.334	0.21	36.6	0.447	Yes
3.png-6.png	14.74	1.231	0.205	72.8	0.483	Yes
1.png-3.png	19.42	1.29	0.505	130.9	0.68	Yes
3.png-4.png	20.98	1.517	0.7	71.4	0.699	Yes
4.png-5.png	20.48	1.593	1.032	81.1	0.768	No
1.png-4.png	24.26	1.356	0.566	126.6	0.772	No
1.png-6.png	22.92	1.471	0.732	127.4	0.792	No
4.png-6.png	21.8	1.593	0.958	104.5	0.802	No
2.png-3.png	22.76	1.804	1.076	84.9	0.839	No
1.png-2.png	24.69	1.605	0.694	139	0.841	No
1.png-5.png	23.5	1.601	0.947	139	0.865	No
2.png-6.png	22.87	1.814	1.261	102.9	0.893	No
2.png-5.png	21.71	1.889	1.436	93.5	0.903	No

4.3 Tile Color Uniformity Adjustment

For tiles that pass quality inspection, lower-level tiles are employed as color reference templates. Histogram matching technology is utilized to align the color distribution of the target tiles with that of the reference templates, achieving color uniformity (Figure 5). Furthermore, overall color balance processing is performed on tiles from different batches to ensure consistency in hue, brightness, and contrast, laying a solid foundation for subsequent edge fusion.

Figure 5 Comparison chart before and after color balance. The above image is before calibration, and the following image is after calibration.

4.4 Edge Fusion

First, non-full tiles in PNG format are identified in accordance with tile production rules, and their alpha channels are analyzed to delineate the extent of null-value regions. Subsequently, effective pixels from adjacent tiles are used for complementary filling of these null-value regions (Figure 6). For fusion with online tiles, the same mechanism is applied: online tiles serve as supplementary data sources to fill null-value regions in the tiles to be updated, ultimately generating new tiles with visual consistency and seamless fusion.

Figure 6 The above two are adjacent tiles to be fused, with obvious null values. The following is the effect after tile fusion

5. Discussion

5.1 Advantages of Methods

The four layer framework proposed in this article achieves full chain automation of tile production post-processing, effectively solving key problems such as low manual inspection efficiency, inconsistent colors, and unnatural fusion in traditional methods. The metadata quality inspection layer eliminates data confusion from the source, the image quality inspection layer achieves precise defect localization and automatic labeling, the intelligent color coordination layer ensures visual consistency of multiple batches of tiles, and the automatic splicing layer achieves seamless integration with online tiles. The quantitative experimental results indicate that this method outperforms traditional methods in terms of efficiency and product quality.

Compared with traditional manual sampling methods, this method achieves 100% full coverage inspection and eliminates the risk of missed detections. In terms of color correction, the combination of histogram matching and batch processing color balance can better ensure the overall consistency between multiple batches of tiles compared to independent correction of single scene images. In terms of edge fusion, the null filling mechanism based on alpha channel can more accurately handle complex boundary situations compared to traditional feathering fusion methods.

5.2 Limitations

Although this method has achieved good results, there are still certain limitations:

Threshold setting: The black/white edge detection threshold is currently based on empirical settings and may need to be adjusted under different image sources or lighting conditions. In the future, an adaptive threshold mechanism can be introduced to enhance detection robustness.

Four neighborhood validation: For irregular grids or missing tiles, four neighborhood validation may not be sufficient. In areas where tile data is discontinuous, it may be considered to introduce more complex neighborhood relationships or global statistical information.

Adaptability to complex scenes: For special features such as cloud and snow cover, shadows, and water bodies, the color correction effect may be limited. These features often have special color distribution characteristics, which may be misjudged as color anomalies or affect the selection of calibration reference templates.

Data dependency: Histogram matching is sensitive to the selection of reference templates, and if the reference template itself has color deviation, it may affect the correction effect. In the future, methods based on multi template fusion or statistical distribution model can be explored to reduce dependence on a single template.

5.3 Future Work

Future research can be conducted in the following directions:
Introducing an adaptive threshold mechanism to enhance the robustness of black/white edge detection;
Explore color consistency correction methods based on deep learning to reduce dependence on reference templates;
Expand the framework to support tile production using multi-source remote sensing data such as SAR and thermal infrared;
Linking the quality inspection results with the repair process to achieve automatic repair of defective tiles;
Research on special processing strategies suitable for large-scale cloud snow coverage areas to enhance the adaptability of the framework to complex scenarios.

6. Conclusion

This study addresses the key challenges of low efficiency in manual quality inspection and poor consistency in edge fusion during large-scale tile production for web map services, successfully developing a fully automated and intelligent post-processing framework integrating metadata quality inspection, image quality inspection, color uniformity adjustment, and seamless edge fusion. By constructing a rule engine for batch verification of tile metadata, the framework achieves automatic identification and isolation of unqualified tiles, eliminating data confusion at the source and overcoming the limitations of manual sampling inspection in large-volume production. For image quality control, the hybrid method of pixel statistics and edge detection enables accurate localization of invalid regions (e.g., black/white edges), while the 4-neighborhood-based color consistency check effectively identifies tiles with abnormal color deviations. In terms of color uniformity and edge fusion, histogram matching and batch color balance processing ensure consistent hue, brightness, and contrast across tiles from different batches, and the alpha channel-based null-value filling mechanism realizes seamless fusion between new tiles and existing online tiles. Practical application shows that the proposed framework significantly improves the automation level and processing efficiency of tile production, reduces human errors, and enhances the visual fidelity and reliability of web map products. This research provides a technical reference for the intelligent upgrading of remote sensing image tile splicing production, and offers strong support for the high-quality and efficient update of spatial information infrastructure such as web map services. Future work can focus on optimizing the adaptability of the framework to multi-source remote sensing data and integrating deep learning algorithms to further improve the accuracy of abnormal tile detection and fusion quality.

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