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Accurate Extraction Method for Structural Features of Building Facades Through Texture Fusion

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ABSTRACT Facade structural features can represent the overall framework of buildings. However, structural features extracted by the current methods contain a quantity of trivial unstructured information. In this study, we proposed an accurate extraction method for structural features of building facades through texture fusion. By performing texture fusion on building facade images, the interference of textural elements on structural feature extraction could be eliminated. After texture fusion, the line segment detector (LSD) algorithm is used to extract the structural features from the building facade images, and random sample consensus (RANSAC) is used to improve the continuity of structural features. The accuracy and effectiveness of the proposed method was demonstrated by comparing results with the state-of-the-art methods, such as LSD, MLSD, CannyLines, and MCMLSD. Value setting of three important parameters is discussed in detail. The imagery facade features extracted through the proposed method provide valuable support for many fields, such as image feature registration and 3D reconstruction of building surfaces.

INDEX TERMS Structural features of building facades, relative total variation, gradient magnitude, texture fusion, feature extraction.

I. INTRODUCTION

Structural features of building facades are specific line segments, which represent the building surface segmentations, such as boundaries of windows, doors, pillars, and outer contours, are characterized by regular geometric shapes and high image contrast; these features can represent the overall framework of buildings. Thus, structural features are the most important research basis for building image stitching and 3D building reconstruction [1]–[4]. Given the easy acquisition of building image data and rich image feature extraction methods, the structural feature extraction of building facades based on image feature extraction has become an important research issue in many fields, such as photogrammetry and computer vision [5]–[10].

Generally, image feature extraction methods are divided into three main categories, namely, deep learning-based, structural constraint and texture suppression methods.

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The deep learning-based methods mainly use a learned convolutional neural network, such as U-Net, to predict some unknown factors (e.g., the pixel-wise junction confidence and directions) and then form line segments [11], [12]. The deep learning-based methods can extract line segments with high quality. However, these methods need rich training sample images exactly labeled line segments to train the network, which are very time and work consumption. On the contrary, when the training sample images are not enough, the neural network cannot work, restricting the application of these methods [10], [12]. Thus, how to extract accurate structural features merely depend on the local characteristics by few images, which is still the main research issue for image feature extraction methods.

In the structural constraint methods, unstructured features are removed on the basis of the regularity of structural features in images firstly. Then, real structural features can be preserved. In traditional structural constraint methods, such as Hough transform method [13], by using the linear parameter equations, the potential line segment structures are detected on the gradient boundary, where discrepancies of gradient magnitude are large. Given that only the gradient boundary information is considered, the traditional methods typically have very low precision and are error-prone (a lot of trivial unstructured features are extracted).

To obtain more accurate extraction results than traditional structural constraint methods, gradient direction and pixel chains have been proposed and used to describe the directions of feature points [14], [15]. By using gradient direction and pixel chains, the structural constraint methods, such as SURF algorithm and Canny algorithm, can match feature points with image pairs efficiently and eliminate discrete pixels or pixels with inconsistent gradient directions [16], [17]. On the basis of gradient direction, Desolneux *et al.* proposed a Helmholtz criterion that can effectively eliminate approximate unstructured features and improve the accuracy of feature detection results [18]. For example, edge drawing (ED) lines and line segment detector (LSD), which are believed to be the state-of-the-art line segment detection methods at present [19], are based on the Helmholtz criterion [20]–[22]. Furthermore, many improved line segment detector methods are proposed. For example, CannyLines which is based on a parameter-free Canny operator and MLSD which is a multiscale extension of LSD can extract more accurate line segments than ED lines and LSD [23], [24]. The recently proposed MCMLSD algorithm has a significant improvement in the integrity of the extracted line segments compared to LSD, EDLine, and CannyLine [25]. However, the structural constraint methods mainly detect structural features on the basis of the gradient variation and pixel value of images. However, these methods can detect features effectively using images with large-scale regular textures, and are not suitable for the feature extraction from images with irregular textures. Moreover, the detected results contain many trivial unstructured features that reduce the continuity and accuracy of detected results.

In the texture suppression methods, structural features are extracted through suppressing methods, such as Gaussian Filter [26], Bilateral Filter [27] and Rolling Guidance Filter [28], to reduce the influence of image textures. Through these suppressing methods, image textures are suppressed effectively to gain accurate structural features. Traditional suppressing methods, such as Gauss Filter, Average Filter [29] and Median Filter [30], treat textural elements and structural features equally. Thus, these methods can only improve extraction results from images with evident differences in textural and structural gradient magnitudes. Considering the difference gradient of texture and structure, Bilateral Filter, Guided Filter [31] and Weighted Median Filter [32] give different weight to textural elements and structure features. Nevertheless, the filters are not originally designed to smooth the texture, and can only achieve texture smoothing under specific conditions. For example, the Bilateral Filter can remove the texture with smaller amplitude in the image, but does not work well in textures of large gradient amplitude changes, because Bilateral Filter regards the texture features with larger gradient amplitudes as the structural features. In order to efficiently smooth the images, some filters, such as Bilateral Texture Filter [33], Rolling Guidance Filter and Static Dynamic Filter [34], are proposed. These filters can filter the scale space while smoothing the texture, and do not destroy the significant structural features of the image. But the filters easily blur the image edge structural features, and cannot solve the problem of edge structural loss of low contrast image. Overall, regardless of the suppression methods used, the structural features continue to be lost while textural elements are suppressed, thereby resulting in missing several important structural characteristics and reducing accuracy of structural feature extraction.

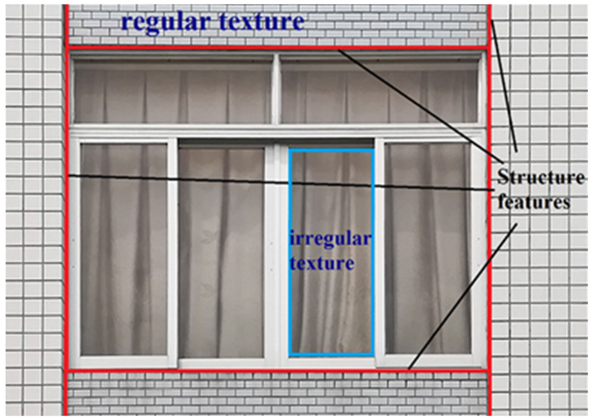

FIGURE 1. Structural features and textural elements of buildings.

The interference of textural gradient magnitude on structural gradient magnitude is a major problem in structural feature extraction of building facades. As shown in Fig. 1, many regular or irregular textural elements, such as tiles, paintings, and curtains, are present on facades. Current structural feature extraction methods of building facade images are mainly based on a gradient magnitude graph (Fig. 2), which is obtained by calculating the gray-level difference among local pixels in the image. Gradient directions of textural elements are inconsistent, and gradient magnitudes of textural elements are low, as exhibited in the circle section in Fig. 2. By contrast, gradient directions of structural features are consistent, and gradient magnitudes of structural features are high, as demonstrated in the rectangular frame in Fig. 2. When the gradient direction of textural elements is consistent, gradient boundaries of textural elements are evident in the building facade image, and the difference in textural and structural gradient magnitudes is unnoticeable. In this situation, the boundary of structural features cannot be located exactly. Thus, a quantity of trivial unstructured information is contained in feature extraction results. Once image textural elements are fused, then the interference of textural elements during the structural feature extraction can be eliminated, and the gradient magnitudes of structural features can be maximally highlighted. This condition is expected to improve the accuracy of the structural feature extraction of building facades remarkably.

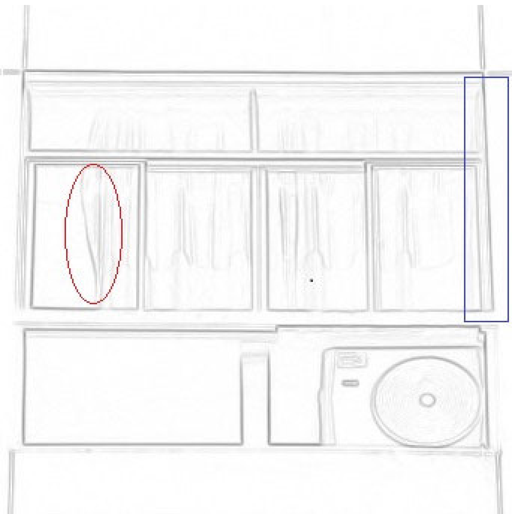

FIGURE 2. **Gradient magnitude graph of buildings.**

This study proposes a novel method for extracting structural features of building facades accurately through texture fusion. The innovation of this article is that the relative total variation is used to fuse texture information, which enhance the difference of structural feature gradient magnitudes, and facilitate the extraction of structural features. Moreover, to solve the problem of poor continuity of structural features extracted by LSD algorithm, random sample consensus (RANSAC) algorithm is introduced to enhance the integrity of structural feature extraction by connecting discontinuous contour lines.

The basic idea and details of the proposed method are introduced in Section II. A case study extracting the facade features from the six different building images is described in Section III. The effectiveness, value settings, and potential limitations of the method are discussed in Section IV. In Section V, the validity and accuracy of the method are concluded. The results show that the accuracy of the structural feature extraction for building facades is highly improved, and the imagery facade features extracted can provide data support for many fields, such as image feature registration and 3D reconstruction of building surfaces.

II. METHONDOLOGY

A. BASIC IDEA AND OVERALL DESIGN

Current image feature extraction methods heavily depend on image gradient magnitude. When changes in textural and structural gradient magnitudes are similar, the structural features of facades extracted from building images will contain a lot of trivial unstructured information. Thus, the extracted features in that situation cannot effectively represent the real structures of building facades. The trivial unstructured information is mainly caused by the interference of textural elements on the structural features. The elimination of the interference of textural elements is becoming a key issue in improving the quality of structural feature extraction results, and texture fusion is considered a favorable choice.

The total variation (TV) model, which is frequently used in the image noise processing field, has long been introduced to image texture fusion research [35], [36]. As the norm of image gradient, TV can effectively represent and separate textural elements and structural features [37]–[39]. On the basis of TV, Xu *et al.* developed the relative total variation (RTV) model [38]. RTV can balance the structural feature maintaining and texture fusion effectively. Thus, RTV can be used to eliminate the interference of textural elements on the structural feature extraction.

In this study, we present a new accurate extraction method of structural features for building facades through texture fusion. The basic idea of the proposed method is to perform texture fusion on building facade images. This operation aims to control the gradient magnitude of textural elements to be as small as possible, whereas maintaining the gradient magnitude of structural features as constant as possible. Thereafter, LSD is used to detect the structural features of building facades. These features are combined by reasonably setting parameter values. Consequently, the new method can be divided into the following two steps:

1) Texture fusion processing is conducted on the original building facade images by using the RTV.

2) The facade structural feature extraction is performed on images after texture fusion. The overall design is depicted in Fig. 3.

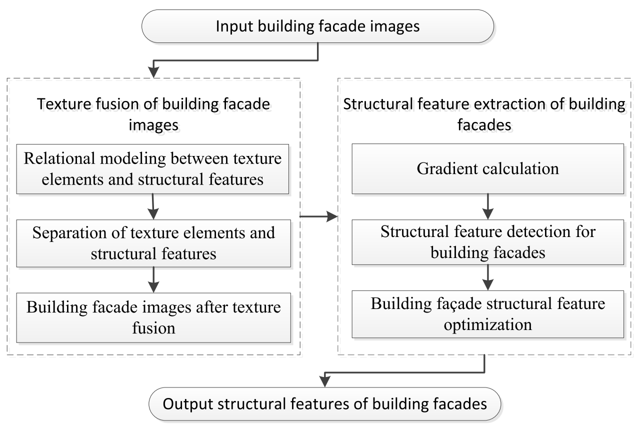

FIGURE 3. **Flowchart of the new extraction method of structural features for building facades.**

B. TEXTURE FUSION OF BUIDING FACADE IMAGES

The texture feature presents a series of certain regularity, and its basic primitives are similar and appear repeatedly. One example of texture features is the grooves on the surface of the object, such as curtains on building facades, which are generally irregular and show a visual perception of unevenness. Another example is the pattern on the object surface, such as tiles and graffiti on building surfaces, which is generally regular.

The image texture fusion aims to find several models, such as TV and RTV, to represent the relationship between texture and structure. On the basis of the models, local similar textural elements are removed. Aujol *et al.* proposed an L_2 paradigm of TV named as the TV–L2 model, which is effective on regular and irregular texture fusion [38]. The TV–L2 model is expressed as follows:

$$\arg\min_{S} \sum_{p} \left\{ \frac{1}{2\lambda} \left(S_p - I_p\right)^2 + \left| (\partial_x S)_p \right| + \left| \left(\partial_y S\right)_p \right| \right\} \quad (1)$$

In Formula (1), I_p represents the input image, p represents the indices of 2D image pixels, and S_p represents an output structural image with fused texture. $(\partial_x S)_p$ and $\left(\partial_y S\right)_p$ are the partial derivatives in the x and y directions for pixel p.

RTV contains general pixel-wise windowed TV measures, shown as Formulas (2). Furthermore, RTV can distinguish prominent structural features from the textural elements [34]. Thus, RTV is used for texture fusion.

$$\arg\min_{S} \sum_{p} \left(S_p - I_p\right)^2 + \lambda \left(\frac{D_x(p)}{L_x(p) + \varepsilon} + \frac{D_y(p)}{L_y(p) + \varepsilon} \right) \quad (2)$$

where,

$$D_x(p) = \sum_{q \in R(p)} g_{p,q} \left| (\partial_x S)_q \right|, \qquad D_y(p) = \sum_{q \in R(p)} g_{p,q} \left| \left(\partial_y S\right)_q \right| \quad (3)$$

$$L_x(p) = \left| \sum_{q \in R(p)} g_{p,q} (\partial_x S)_q \right|, \qquad L_y(p) = \left| \sum_{q \in R(p)} g_{p,q} \left(\partial_y S\right)_q \right| \quad (4)$$

where, q is a rectangular region centered on p, and $g_{p,q}$ is a spatially related weighting function, which is defined as Formula (5).

$$g_{p,q} \propto \exp\left(- \frac{\left(x_p - x_q\right)^2 + \left(y_p - y_q\right)^2}{2\sigma^2} \right) \quad (5)$$

Two parameters, namely, texture smoothness parameter λ and texture scale parameter σ, control the effect of texture fusion in the RTV model. λ controls the smoothness of texture fusion. A large λ value indicates an evident texture fusion effect. σ controls the window size for computing the windowed variations. The value setting of σ is related to the texture scale, which is the basic unit size of the texture. Different effects of texture fusion are obtained by setting different values for parameters λ and σ. The value setting of parameters λ and σ will be discussed in detail in Section IV (B).

The basic idea of texture fusion of building facade images is described as following:

1) An image for fusion is input and appropriate value for parameters λ and σ are set.

2) The spatially related weighting function ($g_{p,q}$), the windowed total variations ($D_x(p)$, $D_y(p)$) and the novel windowed inherent variations ($L_x(p)$, $L_y(p)$) in the x and y directions for each pixel are calculated. And then, the RTV model can be built.

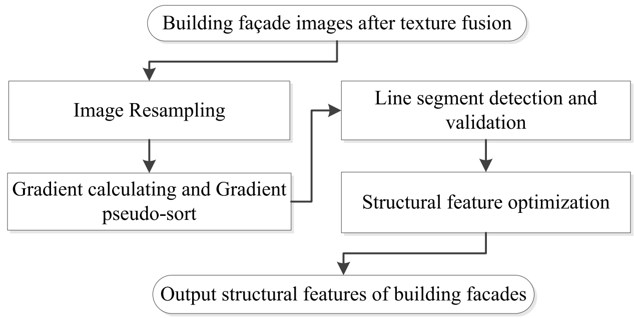

FIGURE 4. Flowchart of the structural feature extraction for building facades based on improved LSD algorithm.

3) By repeating step (2) to all the pixels, the texture fused image can be obtained. The effect of textural elements on structural feature extraction result can be eliminated.

C. STRUCTURAL FEATURE EXTRACTION OF BUILDING FACADES

By using conventional feature extraction methods, structural features for building facade images after texture fusion can be extracted. The gradient magnitudes of structural features for images after texture fusion are maximally highlighted, and the gradient boundaries of structural features are noticeable. LSD algorithm extracts structural line segment features based on the changes of gradient magnitude. LSD is characterized by rapid detection and low false detection rate and has been used extensively in the image feature extraction field. However, many incomplete and discontinuous line segments remain in the features extracted by LSD. Thus, optimizing initial structural features extracted by LSD is necessary to represent building facades accurately.

On the basis of the LSD algorithm, this study introduces RANSAC algorithm into the process of structural feature extraction and establishes an improved LSD algorithm. The RANSAC algorithm is extensively used to detect geometric elements, such as lines and planes [40]. Building facades contain many geometric features, such as edges of windows and gates [2]. Therefore, using RANSAC is feasible to optimize the initial facade features. The process of structural feature extraction for building facades based on the improved LSD algorithm is shown in Fig. 4.

The major steps of the new structural feature extraction method for building facades are described as follows:

1) Image resampling. The inputted building facade image is resampled on the basis of the scale factor S. To remove discontinuous and trivial information from the detected features, the LSD algorithm adjusts the size of image pixels and performs Gaussian interpolation on the resampled image. The effect of different scale factors on the extraction results will be discussed in Section IV (B).

2) Gradient calculation and pseudo-sorting. The gradients of each pixel are calculated in the x and y directions, and then the gradient magnitude called G(x, y) is calculated. G(x, y) is then subdivided into the range from 0 to 1024,

and the pseudo-sorting of the range of gradient magnitude is conducted.

3) Line segment extraction and validation. Starting from the maximum gradient magnitude, the region-growing method is used to search for boundary pixels of potential line segments, which are determined by the level-line angle of pixels [29]. The number of false alarms method is used to validate the line segments, and then the initial structural features of building facades can be extracted [25].

4) Structural feature optimization. The initial structural features of building facades are optimized by RANSAC algorithm. The key processes for this optimization algorithm are as follows. First, a line segment, marked as $\mathrm{L_i}$, is randomly selected from initial structural features. Second, the angle (marked as $\mathrm{A_i}$) between $\mathrm{L_i}$ and other line segment (marked as $\mathrm{L_j}$) is calculated. $\mathrm{L_j}$ is recorded into the maximum consensus set (MCS) of $\mathrm{L_i}$ if the angle $\mathrm{A_i}$ is smaller than the threshold, ξ. Third, the first and second steps are repeated until the initial structural features are all traversed. And then an optimized line segment can be obtained by merging the line segments in MCS. By using the optimization algorithm, certain discontinuous and trivial information can be eliminated, and accurate structural features of building facades can be achieved.

The gradient magnitude changes in textural elements for building facade images after texture fusion are unnoticeable. When the improved LSD algorithm is used to extract structural features, the pixels of textural elements are easily recognized and removed. The interference of textural elements on structural feature extraction is eliminated. Thus, we can considerably improve the accuracy of structural feature extraction for building facades.

D. EVALUATION METRICS

To evaluate the accuracy and performance of different extraction methods quantitatively, three evaluation metrics are proposed in this study.

1) ACCURACY EVALUATION METRIC p_f

p_f is a proportion for accuracy evaluation of different extraction methods. p_f is calculated as Formula (6).

$$p_f = \frac{n_f}{N_f} \tag{6}$$

where n_f is the number of structural facade features extracted by different extraction methods, and N_f is the number of manually extracted structural facade features which is believed as true value. The closer p_f is to 1, the more accurate the extraction method is.

2) CONTINUITY EVALUATION METRIC p_{l-f}

If there are a lot of trivial line segments extracted through a certain extraction method, indicates that the continuity of the method is poor. On this basis, p_{l-f}, as a proportion for continuity evaluation metric, is calculated as Formula (7).

$$p_{l-f} = \frac{n_l}{n_f} \tag{7}$$

where n_l is the number of line segments of structural facade features extracted by different extraction methods. The closer p_{l-f} is to 1, the more continuous line segments extracted through the extraction method are.

3) INHIBITION EVALUATION METRIC n_{tex}

There are a lot of non-feature line segments contained in the structural facade features. These non-feature line segments reduce the continuity and accuracy of the extraction methods. In this study, we use n_{tex} to represent the number of non-feature line segments. Thus, the smaller n_{tex} indicates that the extraction method has better continuity and accuracy.

III. CASE STUDY

The proposed method is verified and analyzed by the test images of various building facades from the YorkUrbanDB dataset, which is a compilation of 102 images of urban environments consisting mostly of scenes from the campus of York University and downtown Toronto, Canada [41], [42]. We select six standard images which contain complex building facades to carry out the structural feature extraction test. The results of structural features extracted by the six building facade images are presented as Fig. 5. The texture fused images (Fig.5b, e, h, k, n and q) show that the proposed method can suppress image textures effectively for various building facades. The images of structural features (Fig.5c, f, i, l, o and r) illustrate that the majority of continuous and complete structural features are extracted through the proposed method. In summary, the proposed method considerably reduces the influence of various facade textures and accurately extracts the structural features of building facades. The extracted structural features with favorable continuity can represent the building facades effectively.

IV. DISCUSSION

A. EFFECTIVENESS OF THE PROPOSED METHOD

To verify the effectiveness and accuracy of the proposed extraction method, two building facade images containing regular texture (tiles) and irregular texture (curtains) are selected from the YorkUrbanDB dataset, as illustrated in Fig. 6 (a), (g). Meanwhile, manually demarcated structural features as the standard of accuracy judgment, is showed in Fig. 6 (c), (k). On the basis of the two original building facade images, experiments are conducted through different extraction methods which are LSD, MLSD, CannyLines, MCMLSD, and the proposed extraction method. The structural features of building facades extracted through the five methods are depicted in Fig. 6 (d)-(h), (l)-(p), and the texture fused images through the proposed extraction method are proved in Fig. 6 (b) (g).

By comparing the structural features of building facades extracted through the five methods, we find that the structural features of building facades extracted through the first four methods contain numerous trivial non-feature line segments. Given that the difference between textural and structural gradient magnitudes is unnoticeable, LSD, MLSD, CannyLines,

FIGURE 5. Structural features of building facades extracted through the proposed method. (a), (d), (g), (j), (m), and (p) are the original facade images. (b), (e), (h), (k), (n), and (q) are the texture fused images through RTV. (c), (f), (i), (l), (o), and (r) are the structural features of building facades extracted through the proposed method.

and MCMLSD methods cannot distinguish them accurately. Given the interference of textural elements, the boundary of structural features cannot be located precisely. When the gradient direction of textural elements is consistent, this interference is serious. For example, more trivial non-feature line segments are found in the regular texture than the irregular texture.

However, the proposed method effectively suppresses regular and irregular textures and removes the interference of textural elements on the structural feature extraction. The texture fused images through the proposed extraction method confirm that the gradient magnitude changes in textural elements after texture fusion are unnoticeable, through the proposed method, and we can easily recognize and remove the pixels of textural elements during the structural feature extraction process. Thus, the building facade structural features extracted through the proposed method contain little trivial non-feature line segments. As shown in Fig. 7, the number of line segments extracted within the building facade through the proposed method is mostly less than that through LSD, MLSD, CannyLines, and MCMLSD methods. The interference of textural elements on structural feature extraction could be eliminated through the proposed method.

The three evaluation metrics are used to evaluate the accuracy and continuity of the five methods quantitatively. Tab. 1 shows the p_f values of the five methods. In addition

FIGURE 6. **Comparisons of the facade structural features extracted through different methods. (a) and (i) Original images. (b) and (j) The texture fused images through RTV. (c) and (k) manually demarcated structural line segments. (d) and (l) Facade structural features extracted through LSD method. (e) and (m) Facade structural features extracted through MLSD method. (f) and (n) Facade structural features extracted through CannyLines method. (g) and (o) Facade structural features extracted through MCMLSD method. (h) and (p) Facade structural features extracted through the proposed method.**

TABLE 1. **Accuracy evaluation of the extraction method by p_f.**

	LSD	MLSD	CannyLines	MCMLSD	The proposed method
Fig. 6(a)	0.97	0.88	0.97	0.97	1
Fig. 6(i)	0.94	0.37	0.96	0.97	0.96

to the MLSD method, the p_f values obtained by the other four methods are close to one, proving the accuracies of the extracted methods are high. Meanwhile, the extraction accuracy of the proposed method is highest. By comparing the proposed method with the LSD method, the accuracy of structural line segment extraction is improved through texture fusion. Tab. 2 shows the p_{l-f} values of the five methods. The p_{l-f} value of the proposed method is close to one, which prove that the proposed method can extract more continuous facade features than other methods. Tab. 3 shows values of the inhibition evaluation metric n_{tex} of the five methods. The n_{tex} value of the propose method is the smallest, which prove that the proposed method effectively eliminates the interference of textural elements on structural feature extraction.

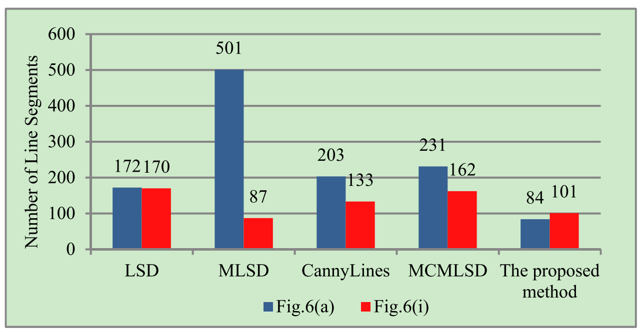

FIGURE 7. **The number of feature line segments extracted within the building facade through the five methods.**

B. VALUE SETTING OF PARAMETERS

The proposed method involves the following three important parameters: texture smoothness parameter λ, texture scale

TABLE 2. Continuity evaluation of the facade features by p_{l-f}.

	LSD	MLSD	CannyLines	MCMLSD	The proposed method
Fig. 6(a)	2.38	5.03	1.63	1.47	1.33
Fig. 6(i)	1.91	1.85	1.61	1.69	1.32

TABLE 3. Continuity evaluation of the facade features by n_{tex}.

	LSD	MLSD	CannyLines	MCMLSD	The proposed method
Fig. 6(a)	96	355	151	184	40
Fig. 6(i)	46	39	27	49	8

parameter σ in the texture fusion process, and the scale factor S in the structural feature extraction process. These parameters considerably affect the accuracy of the extracted structural features of building facades. Therefore, in this section, we focus on the effects of different values of the three parameters on the accuracy of the extracted structural features.

1) VALUE SETTING OF PARAMETER λ

A building facade image with regular textures is selected from the sample dataset, as displayed in Fig. 8 (a). By taking this building facade image as test data, we conduct several experiments by setting different values (0.01, 0.02, 0.05, and 0.1) to λ whereas keeping σ constant (σ is set as 3.0 for all experiments). By using the proposed method, the textural elements of the test data are initially fused under different values of λ, and then the structural features of building facades are extracted. The extraction results are presented in Fig. 8 (c)-(j). The number of line segments extracted through the proposed method under different values of parameter λ is shown as Fig. 9.

The results show that different value settings of parameter λ can affect the accuracy of the extracted structural features. When parameter σ remains fixed, with the increase in the value of λ, the textures with small gradient magnitudes will be gradually fused, and the effect of textural elements on facade structural feature extraction is minimal. Thus, the accuracy of facade structural feature extraction is gradually improved. Nevertheless, when the value λ is set as too large, the textural elements will be excessively fused, thereby resulting in the loss of facade structural features.

2) VALUE SETTING OF PARAMETER σ

We use the same building facade image as the test data. We conduct several other experiments by setting different values (0.5, 1.0, 5.0, and 10) to σ, whereas keeping λ constant (λ is set as 0.01 for all experiments). Similarly, the textural elements of test data are initially fused under different values of σ; then, the structural features are extracted separately. The extraction results are illustrated in Fig. 10 (c)-(j). The number of line segments extracted through the proposed method under different values of parameter σ is shown as Fig. 11.

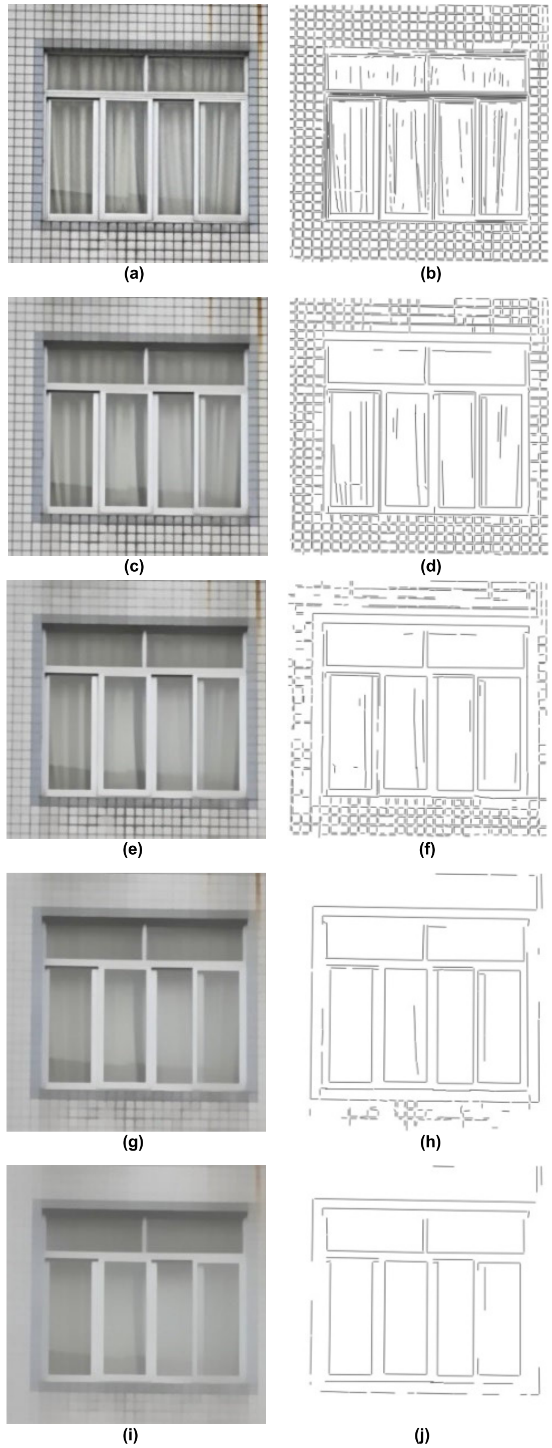

FIGURE 8. Extraction experiments for the proposed method under different values of parameter λ. (a) Original image. (b) Extraction results without smoothness. Images after texture smoothness and extraction results when (c) and (d) $\lambda = 0.01$, $\sigma = 3$; (e) and (f) $\lambda = 0.02$, $\sigma = 3$; (g) and (h) $\lambda = 0.05$, $\sigma = 3$; and (i) and (j) $\lambda = 0.1$, $\sigma = 3$.

The results reveal that when the λ value remains unchanged, the value of σ is large, the degree of texture fusion is high, and the interference of textural elements on the structural feature extraction is low. Then, the accuracy of structural feature extraction is also gradually improved.

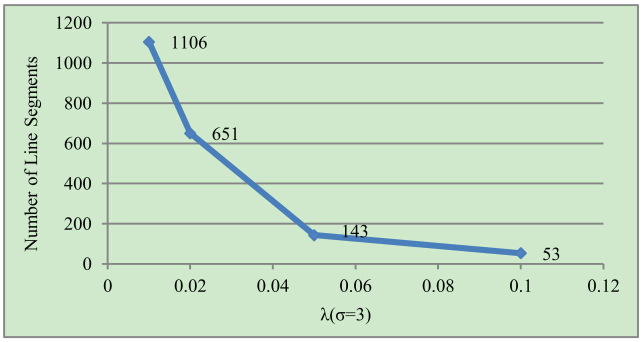

FIGURE 9. The number of line segments extracted through the proposed method under different values of parameter λ.

In terms of trend, when the value of σ exceeds a certain value, such as 5, the effect of texture fusion will not change significantly (Fig. 10 (h)). Thus, the accuracy of facade structural feature extraction for the proposed method stabilizes.

3) VALUE SETTING OF PARAMETER S

The value range of scale factor S is (0, 1]. When the value of S is less than 1, the facade images will be Gaussian resampled, and the resolution of images can be reduced. Considering the decrease in resolution, the nonadjacent feature pixels with similar gradient magnitudes can be connected, and several trivial non-feature line segments shorten and are easily removed. Thus, the accuracy of facade structural features can be improved. For example, Fig. 12 depicts the variation of building facade structural features when the parameter of S is set as different values. When the value of S gradually decreased from 1 to 0.2, the extracted facade structural features become gradually small, and the trivial non-feature line segments are gradually removed. Moreover, the continuity of the extracted structural features is gradually strengthened.

To extract the structural features of building facades with high accuracy, we must select the optimal values for parameters λ, σ or S on the basis of the characteristics of building facades. After numerous tests and literature reviews, we suggest that the value of parameter λ should be set as [0.01, 0.03] and the value of parameter σ should be set as [0.5, 10]. Furthermore, the default value of scale factor S should be set as 0.8. Then, we can not only maintain as many structural features as possible but also reject several trivial non-feature line segments.

C. POTENTIAL LIMITATIONS OF THE APPROACH

By fusing image textural elements, the proposed method can eliminate the interference of textural elements on structural feature extraction, and the accuracy of building facade structural feature extraction is considerably improved. However, the proposed method still has certain potential limitations. First, the proposed method is not sufficiently intelligent in value setting of parameters, and the optimal parameters cannot be automatically selected according to the characteristics of textural elements of building facade images. The extracted structural features of facades may be inaccurate if improper values are set for the parameters. Second, the proposed method only has relatively high extraction accuracy for line segment features of building facades. Because the proposed method is mainly used for extracting line segments, many prominent structural features will be lost when the structural

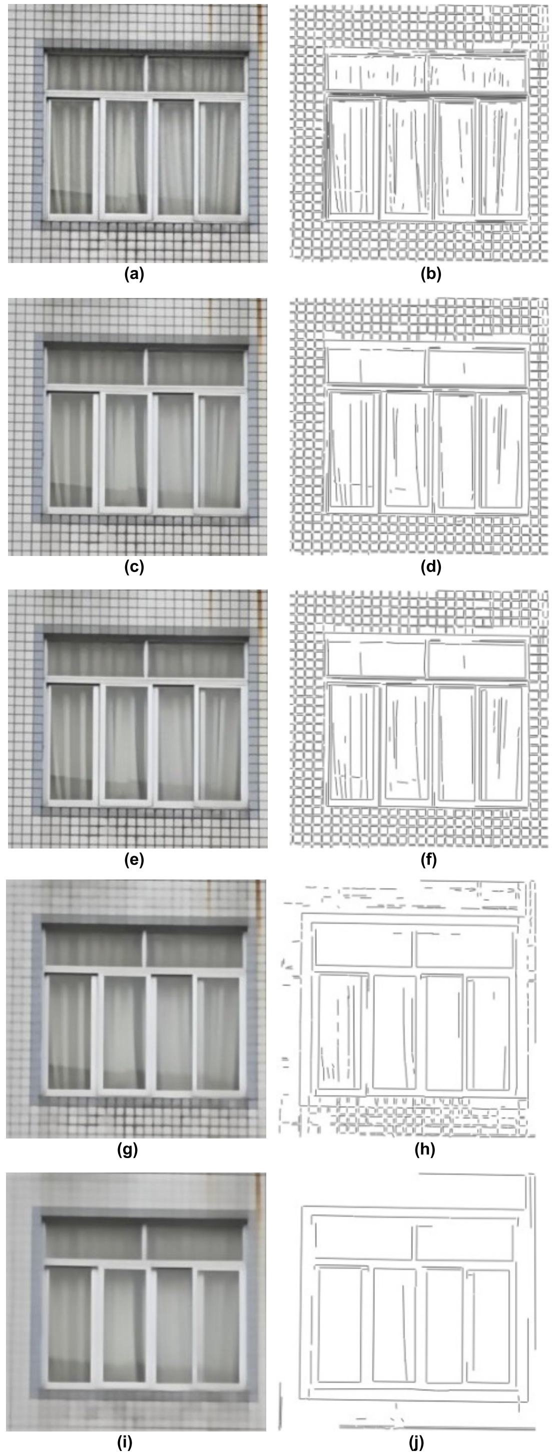

FIGURE 10. Extraction experiments for the proposed method under different values of parameter σ. (a) Original image. (b) Extraction results without smoothness. Images after texture smoothness and extraction results when (c) and (d) $\lambda = 0.01$, $\sigma = 0.5$; (e) and (f) $\lambda = 0.01$, $\sigma = 1$; (g) and (h) $\lambda = 0.01$, $\sigma = 5$; and (i) and (j) $\lambda = 0.01$, $\sigma = 10$.

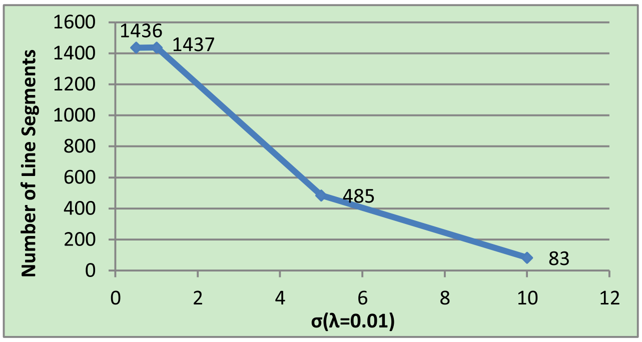

FIGURE 11. The number of line segments extracted through the proposed method under different values of parameter σ.

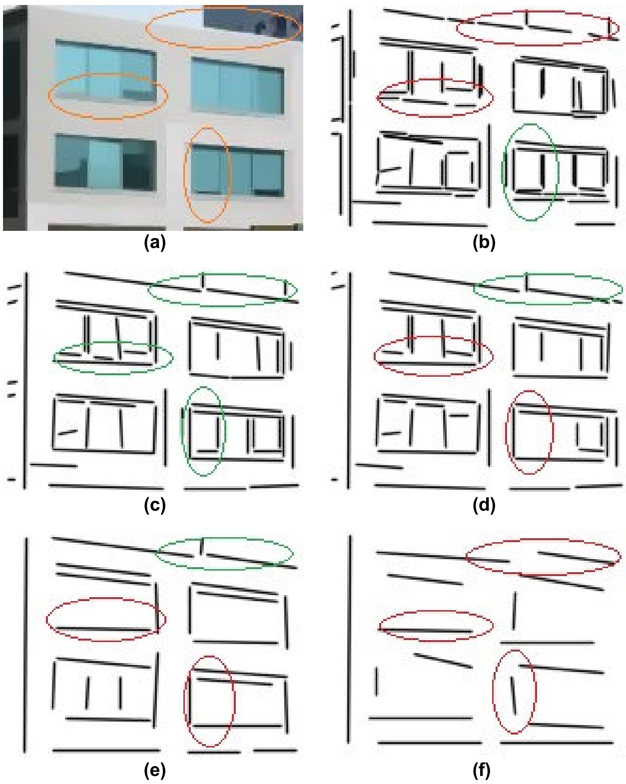

FIGURE 12. Extraction experiments for the proposed method under different values of parameter S. (a) Original image. Extraction results when (b) S=1, (c) S=0.8, (d) S=0.6, (e) S=0.4, and (f) S=0.2.

features (e.g., curvature structures) of building facades are complex or occluded. These potential limitations will be investigated further.

D. POTENTIAL USE OF THE APPROACH

The proposed extraction method has the potential to be used in various cases. For example, in the 3D reconstruction of building surfaces based on multi-view image sequences, the structural features of building facades extracted through the proposed method can improve the accuracy and efficiency of multi-view image sequence registration and promote the construction process of 3D building surface models. In addition, the proposed method can provide accurate 2D structural features of building facades for the 3D feature extraction based on 3D laser point cloud data. By establishing the mapping relationship between 2D image pixels and 3D laser point cloud, the 3D structural features of building facades can be extracted efficiently.

V. CONCLUSION

In this study, we propose an accurate extraction method for structural features of building facades through texture fusion. Texture fusion is performed on building facade images, and the interference of textural elements on structural feature extraction can be eliminated. Then, the LSD algorithm is used to extract the initial structural features of building facade images after texture fusion. Finally, the RANSAC algorithm is used to enhance the integrity and continuity of initial structural features. The effectiveness of the proposed method is demonstrated by comparing its results with those of classical methods.

The proposed method can remove the majority of non-feature line segments. Thus, the accuracy of the building facade structural feature extraction can be considerably improved. The imagery facade features extracted through the proposed method constitute valuable support for image feature registration and 3D reconstruction of building surfaces. Certain research, such as intelligent value setting of parameters and structural feature extraction for complex building facades, should be explored further in the future.

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