Rapid Identification of Post-Earthquake Collapsed Buildings via Multi-Scale Morphological Profiles With Multi-Structuring Elements

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ABSTRACT Rapid identification of post-earthquake collapsed buildings can be conducive to capturing an immediate disaster assessment, which can help design effective emergency response strategies. At present, earthquake disaster assessment in practice mainly relies on time-consuming artificial field investigations, which cannot adapt to the demands of a timely rescue. However, morphological methods have proved to be of great potential in describing the disaster characteristics of building as for size, shape, directionality and contrast. Conventionally, boundaries of intact building appear flat and smooth, thus it can be reasonably depicted by linear structural element, while collapsed buildings generally emerge dispersedly distributed without regular geometry which can be suitably described by disk structural element. Based on these intuitive findings, we propose an approach for extracting intact and collapsed buildings via multi-scale morphological profiles with multi-structuring elements from post-earthquake satellite imagery. This approach consists of three core components: 1) Linear and disk structuring elements are established through top-hat reconstruction for extracting the initial intact and collapsed building, respectively. 2) Purified intact and collapsed buildings can be obtained by a straightforward threshold segmentation and further post processing, such as area, normalized green plant index (NGPI) and the length-width ratio for image noise suppression. 3) Boolean set operations are adopted to distinguish the intact and collapsed buildings. Experiments demonstrate that the proposed method has achieved satisfactory results and exerted great superiority in computational efficiency.

INDEX TERMS Morphological profile, earthquake damage, building detection, differential morphological profiles.

I. INTRODUCTION

Earthquake is one of the most emergency situations, which not only causes heavy casualties and economic losses, but also causes various secondary disasters [1]. Damages to buildings have been considerable when earthquake events occur. Besides, if collapse occurs in a chemical factory, a mass of noxious chemical will be discharged to the environment, thereby causing serious environmental pollution. In addition, the collapse of buildings can also cause a large number of solid wastes [2], [3]. Consequently, rapid and accurate identification of earthquake-damaged buildings has significant meaning for reducing the ecological environment destruction.

Obviously, it is very difficult to obtain an immediate assessment of such large-scale natural disasters only relying on artificial field investigation, since secondary disasters such as landslides, mudslides and quake lakes may serious obstruct ground transportation and disrupt communication [4], [5]. Remote sensing technology has proved to be a convenient, rapid and cost-effective way to help extraction and monitor earthquake damage information. Currently, a variety of algorithms have been used for earthquake-damaged buildings extracting at home and abroad and obtained a series
of achievements [6]–[12]. For multi-temporal technology is sensitive to the registration accuracy [6], [8], [10], [13], [14], and pre-earthquake images in the same area are often difficult to obtain, studies on earthquake-damaged building extraction are mostly focused on the single-temporal detection technology [15], [16], which can be divided into pixel-based detections [13] and object-oriented detections [16], in accordance with the different information processing units. However, the pixel-based classification method cannot fully explore the characteristic information from high-resolution seismic image, and liable to cause misclassification of ground objects, thereby making it difficult to meet the high accuracy requirements in practice. In order to make full use of rich spatial information, geometric structure and texture information on high-resolution seismic image for ground object extraction, the object-oriented detection methods have come into being [16]–[18]. Object-oriented detection methods usually adopt the strategy of first segmentation and then classification. Images are usually divided into several meaningful homogeneous regions first, and then each region becomes the basic processing unit rather than each pixel. The object-oriented detection methods can take full advantage of the spectrum, shape, texture information of the object, even including semantic and topological relations, thus can preserve the boundary information of ground objects. However, the traditional object-oriented classification methods usually have a large number of parameters required to be prescribed, some researches revealed that the major limitation of object-oriented methods was the inaccurate spatial relation between objects and segments [19], thus the segmentation results can not accurately describe the position, shape and context of objects. Moreover, the extraction results can be easily affected by the subjectivity of operator, thereby reducing the classification accuracy. Representative object feature is essential to the information extraction of seismic image. There has been a lot of research on feature-based building extraction [6], [7], [9], [13], [20]–[23], most of which are mainly focusing on the features designed through human observation and analysis, such as spectral features [24], normalized difference vegetation index (NDVI) [25]–[27], modified normalized difference water index (MNDWI) [28], texture feature [29]–[31], etc. Besides, mathematical morphology is promising approach for exploring building features. Feathers of the intact building and collapsed building can be extracted respectively via mathematical morphology with different shaped structuring elements. Over recent years, several morphological methods have been proposed for building detection and a series of results have been obtained [10], [32]–[37]. Zhang proposed a straightforward building detection method based on the observation that vegetation can be filtered on significantly smaller filtering scales [38]. Vu considered LiDAR data within a multi-scale morphological space to conduct building detection via some clustering method [39]. Meanwhile, Chen improved progressive morphological filtering by additionally applying a region growing algorithm based on RANSAC [40]. Huang proposed a novel morphological building index (MBI) for automatic building extraction [41]. However, the previous studies only focused on the extraction of intact building, without considering the extraction of collapsed building, thus cannot be applied to the seismic damage information extraction field.

This study presents a rapid extraction method for earthquake damage building based on differential morphological profiles (DMP) via multiple structuring elements. The linear structural element and disk structural element were selected to extract the intact building and collapsed building respectively, since intact building usually present a smooth and linear structure in image, while the collapsed building are usually scattered and without regular geometry. For the purpose of evaluating the proposed method, three sets of ADS40 digital aerial images captured from Wenchuan and Yushu were adopted as the experimental districts. Effectiveness of the proposed method has been demonstrated by the experimental results for its rapid and accurate identification of earthquake-damaged building.

The study mainly devotes to introduce the concept of multiple structuring elements and, in particular, the functional description of disk structural element to characterize collapsed building boundaries are emphasized, as well as linear structural element to depict the intact building boundaries. Furthermore, these two structuring elements are then combined organically to play a more important role for achieving rapid identification of earthquake-damaged building. The remainder of this paper is organized as follows: The methodology was introduced Section II. Section III elaborates the study area and datasets used in this study. In Section IV, the experimental are undertaken to evaluate the proposed method and a detailed analysis is made towards the experimental results. Section V and Section VI give the discussion and conclusions respectively.

II. METHODOLOGY

This study presents a rapid extraction method for earthquake damage building based on DMP via multiple structuring elements. Figure 1 illustrates the logical flowchart of the proposed method, which involves linear structural element and disk structural element.

The proposed method mainly consists of the following five steps:

Step 1) Top-hat reconstruction via multiple structuring elements: The image is reconstructed by using linear and disk structural element to achieve the extraction of damaged building boundaries in a single constant direction.

Step 2) Top-hat reconstruction in multi-direction: In order to extract more feature information of the damaged building boundaries, the top-hat reconstruction (THR) with two structuring elements is employed to reconstruct the image from multiple directions. Besides, the averaged top-hat reconstruction result is calculated to enhance the building boundary features.
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Step 3) Construction of the building’s morphological features: This step devotes the construction of DMP via differentiating a THR sequence from different scales to extract building boundaries. Then, the average DMP is calculated and used as the second feature to indicate the morphological features of damaged building.

Step 4) Earthquake-damaged buildings acquisition: In order to obtain more precise earthquake-damaged buildings, a series of post processing operations are carried out in this step to eliminate the non-building area and reduce background noise impact.

Step 5) Classification of earthquake-damaged buildings: The intersection and subtraction operations are conducted respectively upon morphology features extracted with the linear and disk structural element so as to distinguish intact building and collapsed building.

Figure 2 shows the schematic diagram of the proposed method, of which the detailed descriptions are given in the following sub-sections.

A. TOP-HAT RECONSTRUCTION VIA MULTIPLE STRUCTURING ELEMENTS

In this step, the top-hat reconstruction of image via linear structural element and disk structural element are employed to extract the boundary information of intact building and collapsed building in a fixed direction.

Structuring elements are small sets or sub-images used to probe the characteristics of interest in images. Since the structural element plays an essential role in mathematical morphology, careful considerations should be taken into the selection of appropriate structural element for extracting the features of interest. In general, structural element can be any shape; some common structuring elements include linear, rectangular, disk, diamond, and ellipse. Furthermore, disk structural element is suitable for the extraction of isotropic features, such as sand, while linear structural element can better describe the features with certain regular edges, such as building. Small structuring elements can efficiently filter out small objects while keep larger objects remain preserved at the same time. Although a larger structuring element provides a solution to this problem, on the other hand it flattens terrain details such as mountains’ peaks, ridges, and cliffs [42]. Therefore, the shape and scale of structural element should be selected according to the characteristics of the image to be processed. In seismic image, intact building usually present a smooth and linear structure, while the collapsed buildings are usually scattered and without regular geometry. Therefore, they can be extracted by linear structural element and disk structural element respectively.

Buildings usually have the features with high reflectance, Therefore, the maximum of RGB bands for each pixel is...
where $M_k(X)$ indicates the spectral value of each pixel $X$ at band $K$, and $b(X)$ represents its brightness.

The morphological opening operation involves two basic operators, erosion $\varepsilon$ and dilation $\delta$. The erosion and dilation of input image $b$ using structural element $s$ are denoted by $\varepsilon^s(b)$ and $\delta^s(b)$, respectively. The opening operation of input image $b$ using structural element $s$ is calculated as follows:

$$\gamma^s(b) = \delta^s(\varepsilon^s(b)).$$

The top-hat transformation $\text{TH}^s(b)$ is defined as the difference between the input image $b$ and its morphological opening $\gamma^s(b)$. This technique can separate features that are smaller than or equal to structural element, with the corresponding formulas as follows:

$$\text{TH}^s(b) = b - \gamma^s(b).$$

It should be noted that not all structures from the input image will be recovered when opening and top-hat filters are applied [43] for the difference between the traditional opening operation result and the input image is often large. To cope with this issue, reconstruction filters is introduced for making use of an interaction between structural features of interested objects and shapes of the structural element, due to its superior capacity of shape preservation than classical morphological filters [43], [44].

Morphological reconstruction employs two input images, marker and mask images. Both images must have the same size and the mask image must have gray values greater or equal to the marker image. The marker image is dilated by a structuring element and the resulting image is forced to remain below the mask image. This means, the mask image acts as a limit for the dilated marker image. Accordingly, top-hat reconstruction is defined as the difference between the input image and the morphological reconstruction. The top-hat reconstruction of input image $b$ using linear and disk structuring elements is shown in Equation (4) and (5), respectively:

$$\text{THR}^l_s(b) = b - r^l_s(b),$$

$$\text{THR}^d_s(b) = b - r^d_s(b),$$

where $r^l_s(b)$ and $r^d_s(b)$ are morphological reconstruction result of image $b$ using linear structural element and disk structural element respectively, $\text{THR}^l_s(b)$ and $\text{THR}^d_s(b)$ are top-hat reconstruction of image $b$ using linear structural element and disk structural element, respectively.
B. TOP-HAT RECONSTRUCTION IN MULTI-DIRECTION
In this step, the top-hat reconstruction via multiple structuring elements is carried out in multiple directions to capture more information of building boundaries. In the seismic images, boundaries of damaged building are often disorderly distributed. The top-hat reconstruction via a single directional structural element can only extract the boundary of caving zone in a single fixed direction. In order to extract information about damaged building more comprehensively, the multi-directional top-hat reconstruction via linear structural element and disk structural element are carried out respectively. The formulas of top-hat reconstruction in multi-directions are given by Equation (6) and (7) as follows:

$$\text{THR}_{l}^{s} (b) = \text{mean}_{\text{dir}}\left( \text{THR}_{l}^{s \text{dir}} (b) \right),$$

(6)

$$\text{THR}_{d}^{s} (b) = \text{mean}_{\text{dir}}\left( \text{THR}_{d}^{s \text{dir}} (b) \right),$$

(7)

where $\text{THR}_{l}^{s \text{dir}} (b)$ and $\text{THR}_{d}^{s \text{dir}} (b)$ represents the top-hat reconstruction in multi-direction via linear structural element and disk structural element, respectively; $\text{THR}_{l}^{s} (b)$ and $\text{THR}_{d}^{s} (b)$ represents the average value of the top-hat transformation in multi-directions via linear structural element and disk structural element, respectively.

C. CONSTRUCTION OF BUILDINGS’ MORPHOLOGY FEATURE (BMF) BASED ON MULTIPLE STRUCTURING ELEMENTS
Earthquake damaged buildings in seismic images usually have different scales. In order to extract different buildings with various sizes, a series of linear structuring elements with different lengths and disk structuring elements with different radius were selected to reconstruct the image in multi-directions. After that, the differential operation was successively applied to the obtained results so as to generate DMP. The formula is shown in Equation (8) and (9) as:

$$\text{DMP}_{l} (s) = \left| \text{THR}_{l}^{s + \Delta s} (b) - \text{THR}_{l}^{s} (b) \right|, \ \ s_{\text{min}} \leq s \leq s_{\text{max}}$$

(8)

$$\text{DMP}_{d} (s) = \left| \text{THR}_{d}^{s + \Delta s} (b) - \text{THR}_{d}^{s} (b) \right|, \ \ s_{\text{min}} \leq s \leq s_{\text{max}}$$

(9)

where $\text{THR}_{l}^{s + \Delta s} (b)$ represents the average value of top-hat reconstruction in multi-direction by using linear structural element with scale of $s + \Delta s$, $\text{DMP}_{l} (s)$ represents the DMP of linear structural element. $\text{THR}_{d}^{s + \Delta s} (b)$ represents the average value of top-hat reconstruction in multi-direction by using disk structural element with scale of $s + \Delta s$, $\text{DMP}_{d} (s)$ represents the DMP of disk structural element, $\Delta s$ is the change step of structural element size.

For depicting the complete morphology features of earthquake-damaged buildings, the average DMP is calculated attempting to cover as many structural features in different scales as possible. Morphological features of intact building are defined as the average value of DMP obtained by using linear structural element, while the morphological features of collapsed buildings are defined as the average value of DMP obtained by using disk structural element. The formulas of these two type buildings’ morphology feature (BMF) are shown by Equation (10) and (11) as follows:

$$\text{BMF}_{l} = \text{mean}_{s} \left( \text{DMP}_{l} (s) \right),$$

(10)

$$\text{BMF}_{d} = \text{mean}_{s} \left( \text{DMP}_{d} (s) \right),$$

(11)

where $\text{mean}_{s} \left( \text{DMP}_{l} (s) \right)$ represents the average value of a series of DMP obtained through linear structural element, $\text{BMF}_{l}$ represent the morphology features of intact building, $\text{mean}_{s} \left( \text{DMP}_{d} (s) \right)$ represents the average value of a series of DMP obtained through disk structural element, $\text{BMF}_{d}$ represent the morphology features of collapsed building.

D. EARTHQUAKE-DAMAGED BUILDINGS ACQUISITION
After the above processes, the morphological features of building have been obtained, together with a small amount of noise being involved. Moreover, there are still some non-building areas, such as roads, nudation, and vegetation, etc. These factors make the identification of earthquake-damaged building difficult.

In order to improve the extraction accuracy of earthquake-damaged building, a series of thresholds should be prescribed to eliminate the non-building areas and background noise. Experimental results indicate that buildings have larger BMF, so a certain threshold value is set for the acquisition of earthquake-damaged building. Considering the commission errors caused by the vegetation, nudation and river, the normalized green plant index (NGPI), shape feature and area feature are successively employed to elaborate the extraction results. The pixels that satisfy (12) are determined as earthquake-damaged buildings.

$$D_{\text{building}} = \left\{ x \mid \text{BMF} (x) \geq M_1; \text{NGPI} (x) \leq M_2; \text{ratio} (x) \leq M_3; \text{area} (x) \geq M_4 \right\}$$

(12)

where $\text{BMF} (x)$ represents the value of $\text{BMF}_{l}$ or $\text{BMF}_{d}$, $\text{ratio} (x)$ represents the aspect ratio of the area, and $\text{area} (x)$ represents the area; $M_1$, $M_2$, $M_3$, $M_4$ are threshold.

After those processes mentioned above, there are still some small noise holes exist in the earthquake-damaged building areas, in order to improve the extraction accuracy, the noise holes that lower than threshold $M_5$ is eliminated by using Matlab built-in function “bwareaopen”.

E. CLASSIFICATION OF EARTHQUAKE-DAMAGED BUILDINGS
After the above steps, earthquake-damaged buildings have been extracted via linear structural element and disk structural element respectively. In this step, the intersection operation and subtraction operation are performed to obtain intact building and collapsed building respectively.

The disk structural element is isotropic, so it is more suitable for the extraction of collapsed building. The linear structural element is anisotropy, so it is more suitable for...
the extraction of intact building. However, in the practical operation process, due to the interior of intact building is isotropic, the disk structural element can extract the collapsed building and intact building simultaneously. Therefore, intact buildings can be obtained by making intersection operation between BMF$_l$ and BMF$_d$, and the collapsed buildings can be obtained by making subtraction operation between BMF$_l$ and BMF$_d$. The formulas are shown in Equation (13) and (14) as:

\[
\text{collapsed\_building} = BMF_l \cap BMF_d \quad (13)
\]

\[
\text{intact\_building} = BMF_d - BMF_l \quad (14)
\]

where BMF$_l$ represent the morphology features of intact building, BMF$_d$ represent the morphology features of collapsed building. collapsed\_building represents the extraction result of collapsed building, and intact\_building represents the extraction result of intact building.

### III. THE TEST CASE AND AVAILABLE DATA

#### A. WENCHUAN EARTHQUAKE

Wenchuan is located in the southwestern region of China, and had been stricken by a violent Ms 7.9 earthquake (centered at approximately 30.98° N and 103.36°E) on May 12, 2008. According to the official report issued by the State Council Information Office of the People’s Republic of China (SCIO-PRC), this earthquake has caused not only great casualties and property losses, but also great damage to the earth’s surface, causing landslides, debris flows, barrier lakes, and serious damage to land and river ecosystems.

#### B. YUSHU 2010 EARTHQUAKE

On April 14, 2010 at 8:52 (Beijing time), an earthquake hit Yushu city, Qinghai province. The mainshock was rated 7.1 on the moment magnitude (Mw) scale; the epicentre was located near Giegy town, at a depth of about 14 km, and was followed in the next seven hours by 18 aftershocks. Yushu and the surrounding villages suffered the highest damage. The earthquake caused damage to thousands of buildings in the medieval city centre of Yushu. Over 90% buildings fully collapsed, thus leading to a very challenging situation for satellite damage assessment.

#### C. GROUND TRUTH DATA

After the catastrophic event, several groups of researchers, in one week of fieldwork, collected information related to the type of building and its vulnerability class, and the suffered damage. The damage buildings are divided into intact buildings and collapsed building. The inventory data were collected by a visual inspection, looking from outside the buildings, because people were not permitted to enter the edifices for safety reasons.

#### D. EARTH OBSERVATION DATA

We carried out the present work using three ADS40 digital aerial images taken from the RGB sensors mounted on an aerial platform. The two Wenchuan images are dated May 15, 2008, the third day after the earthquake, while the Yushu image was collected on April 14, 2010. The spatial resolution of the Wenchuan earthquake image is 0.5 m, while the Yushu earthquake image has a 0.4 m resolution. Figure 3 and Figure 4 illustrates the overview of two ADS40 digital aerial images of Wenchuan earthquake. Figure 5 illustrates the overview of ADS40 digital aerial images of Yushu earthquake.

For the purpose of validating the capability of the proposed method, three small-size images (T1-T3) and five large-size images (T4-T8) were selected from Wenchuan images. six sub-regions from Yushu image (T1-T6) covering damaged building were selected. In Table 1 and Table 2 the main characteristics of the sub-regions are reported.

### IV. EXPERIMENTAL RESULTS

In this section, performance analyses of the proposed method are carried out upon the three ADS40 digital aerial images, and evaluated with the overall accuracy (OA), false alarm rate (FAR), kappa coefficient ($\kappa$) and confusion matrix based on the number of pixels. Moreover, the classical SVM [47] and
eCognition [48] with the same experimental areas are used to compare with the performance of the proposed method.

eCognition is a popular software which had been widely used in high-resolution remote sensing images processing [45], [46]. Using eCognition software to extract seismic damage information extraction mainly consists of three steps: image segmentation, feature extraction and supervised classification. Image segmentation refers to the process of dividing images into small regions according to the features, such as color, shape, gray value and so on, pixels in each region have similar features, and there is no consistency between adjacent regions. In the segmentation phase, eCognition’s multisresolution segmentation algorithm is chosen to delineate the image into objects for classification. Multiresolution segmentation is a bottom up region-merging approach [48], and the assignment of parameters are crucial as they have several different influences on classification accuracy. Related parameter descriptions are shown in Table 3.

Ideally, objects are wished to be perfectly delineated by the object boundaries and comprise a single object. However, in seismic images, buildings and other objects generally differ in size to a significant degree, thus several levels of segmentation may be needed using different parameters at each level. That is to say, the building areas needs to be extracted first, and the intact and collapsed buildings are extracted in the building area. In the feature extraction phase, samples of all recognizable object classes within the whole image are randomly selected to train a supervised classification algorithm. eCognition provides a feature space optimization (FSO) tool to perform feature selection, which provides the best class separability by providing a set of training samples and feature names. In this experiment, 5 features (brightness, length-wide ratio, shape index, and grayscale symbiosis matrix) that maximized separation distance in the FSO tool are chosen, which are all pre-configured and available in eCognition. Finally, in the supervised classification phase, features and samples identified in the previous step are put into the classifier, and the nearest distance method is used. If the classification results are not acceptable, the training inputs or the classifier parameters need to be further refined in the former phase. If the results are accessible, the result will be applied to lower levels in the segmentation hierarchy and start the process over again [45]. The flowchart of eCognition is shown in Figure 6.

### A. EXPERIMENTS ON WENCHUAN EARTHQUAKE IMAGES

In order to illustrate the influence of image size on experimental results, the experiment was divided into two groups. Group 1 was conducted on the small-size image (T1-T3), and the group 2 was conducted on the large-size image (T4-T8). For both experiments, a series of threshold combinations were selected to obtain the optimal threshold combinations, and the optimal threshold selection for group 1 are as follows: four directions 0°, 45°, 90°, 135° are selected for top-hat reconstruction in multi-direction, the NGPI threshold $M_2$ is set as $M_2 = 2 \times \text{median}(BMF(b))$, where median (BMF) represent the band medium value of BMF, is an adaptive threshold that does not require manual intervention. $M_3$ represents the threshold of length-wide ratio, which is used to estimate the road areas. In different images,
road has certain differences, and the structural features of buildings are also different, so M3 various in different images. M4 represents the threshold of area, which is used to estimate the bare land. Similarly, the bare land area varies from image to image. Therefore, for different images, the selection of M4 is also different. The selection of M3 and M4 are shown in Table 4. M5 is used to eliminate the noise, and it is set to 50 for all images. Also, in eCognition experiments, several experiments are carried out by transforming different parameters until the final results showed the best segmentation effect. The optimal parameters used in eCognition are shown in Table 5.

Figure 7 demonstrate the extraction results of group 1 (T1-T3). Generally speaking, collapsed building is relatively difficult to be extracted since its dilapidated edges are normally not regularly distributed.

### Table 4. Parameter selection of group 1.

| SE    | Parameters | T1       | T2       | T3       |
|-------|------------|----------|----------|----------|
| Linear SE | Size      | $2 \leq s \leq 20$ | $1 \leq s \leq 20$ | $2 \leq s \leq 20$ |
|        | $\Delta s = 2$ | $\Delta s = 1$ | $\Delta s = 2$ |
| M3     | 2          | 5        | 2        |
| M4     | 250        | 100      | 250      |

| Disk SE | Size      | $5 \leq s \leq 25$ | $1 \leq s \leq 20$ | $4 \leq s \leq 20$ |
|         | $\Delta s = 5$ | $\Delta s = 1$ | $\Delta s = 4$ |
| M3     | 5          | 5        | 5        |
| M4     | 80         | 80       | 80       |

Note: M3 represents the threshold of length-wide ratio; M4 represents the threshold of area; s is the size of structural element, $\Delta s$ is the change step of structuring elements size.

### Table 5. Parameter selection of group 1 using eCognition.

| Parameters | T1 | T2 | T3 |
|------------|----|----|----|
| Scale      | 100| 100| 80 |
| Shape      | 0.5| 0.4| 0.5|
| Compass    | 0.2| 0.3| 0.3|

In image T1, the damaged buildings are disordered, and collapsed buildings tend to have darker color features. From the macro perspective, those three methods can extract most intact building. However, there is a lot of noise exist in the extraction results of SVM, as show in circle 1, and the eCognition method cannot extract the building as a whole, as show in circle 2. Compared with the SVM and eCognition methods, the proposed method making full use of the structural characteristics of buildings to extract damaged buildings, which can avoid the above problems. From the micro perspective, SVM method extracts the damaged buildings mainly according to the color feature, resulting in partial shaded areas being mistakenly classified as collapsed building areas, while the brighter parts in collapsed building areas are classified as intact building areas, as is shown in circle 3.

In image T2, the intact building areas are brighter while the collapsed building areas are darker. All the three methods have achieved good extraction results. However, it can be seen from the circle 4, some brighter parts in collapsed building areas are still misclassified as intact building areas when using SVM method, and this phenomenon also exists in image T3, as is shown in circle 8. Compared with eCognition method, the collapsed building area extracted by the proposed method is more complete. As is shown in circle 5. Moreover, the building boundaries extracted by the proposed method is more similar to the original building boundaries, as is shown in circle 6.

In image T3, the size of buildings is various, and the collapsed building presents a rough feature. When compared with the SVM method extraction result, the proposed method has little noise, such as in circle 7. When compared with the eCognition extraction result, the proposed method can extract all the buildings, while the eCognition will miss the building with small size, as show in circle 9. In addition, for the extraction of collapsed building with rough surface, the proposed method has better extraction capability than eCognition, as show in circle 10.

Table 6 summarizes the extraction results based on the proposed method, SVM method and eCognition software. The proposed method was found to have the highest extraction accuracy among the three methods. The highest extraction accuracies of the intact building and collapsed building were to 94.15% and 94.74%, respectively. The overall accuracy reached 94.01%, and $\kappa$ was 0.9294. The FAR of intact building and collapsed building is 4.87% and 4.17% on average.

When compared with the extraction result using SVM method, the proposed method had improved the results by...
8.02% on average and had reached up to a 18.60% improvement for the extraction of intact building. Also, for the extraction of collapsed building, the proposed method was improved by 2.17% on average, and up to 3.41%. The OA and $\kappa$ were improved by 3.3% and 0.28 on average, and up to 4.9% and 0.44 respectively.

When compared with the extraction results of eCognition. For the extraction of intact building, the proposed method had improved the results by 9.85% on average and had reached up to a 13.48% improvement. Also, for the extraction of collapsed building, the proposed method was improved by 19.77% on average, and up to 30.51%. The OA and $\kappa$ were improved by 16.20% and 0.03 on average, and up to 19.3% and 0.07 respectively.

In earthquake rescue, the identification of collapsed buildings is more important than that of intact buildings. Although the FAR of intact buildings obtained by the proposed method is slightly higher than that of SVM method (0.43% on average) and eCognition software (0.45% on average), the FAR of collapsed buildings is significantly lower than that of SVM method (3.1% on average) and eCognition software (3.51% on average). The overall results indicated that the proposed method had successfully enhanced the accuracy of the extractions.

Table 7 shows the confusion matrix of group 1 by using the three methods. IB, CB, and BG represent the intact building, collapsed building, and background, respectively. Regarding the detection error of intact building, there have been only a few pixels that should belong to intact building are undetected when using the proposed method and the SVM method, while there are many undetected pixels when using eCognition software. That is to say, the proposed method and SVM method can better distinguish the damaged building from the background than eCognition. In addition, the number of intact building which had been misclassified into collapsed building using the proposed method was found to be less than that of the SVM method. So the proposed method can distinguish intact buildings and collapsed buildings more accurately than the SVM method.

Regarding the detection error of collapsed buildings, when using the proposed method and the SVM method, undetected pixels are far less than those of the eCognition. In addition, the number of collapsed building which had been misclassified into intact building using the proposed method was found to be less than that of the SVM method in the majority of the images. Also, the false alarm recognition of SVM method is significantly outnumber the proposed method and eCognition. Although the false alarm recognition of the
TABLE 6. Accuracies of the building extraction results of dataset 1.

| Metrics                                | Methods     | T1         | T2         | T3         |
|-----------------------------------------|-------------|------------|------------|------------|
| Intact buildings(%)                    | Proposed    | 93.17      | 94.09      | 94.15      |
|                                         | SVM         | 86.43      | 75.49      | 95.43      |
|                                         | eCognition  | 86.73      | 80.61      | 84.51      |
| Collapsed buildings (%)                 | Proposed    | 94.74      | 93.58      | 83.59      |
|                                         | SVM         | 91.44      | 93.78      | 80.18      |
|                                         | eCognition  | 64.23      | 75.62      | 69.33      |
| OA(%)                                   | Proposed    | 94.01      | 93.68      | 88.15      |
|                                         | SVM         | 89.11      | 90.06      | 86.77      |
|                                         | eCognition  | 74.71      | 76.63      | 75.89      |
| FAR of Intact buildings(%)              | Proposed    | 3.66       | 5.22       | 5.73       |
|                                         | SVM         | 6.88       | 4.47       | 1.95       |
|                                         | eCognition  | 5.28       | 1.41       | 6.56       |
| FAR of collapsed buildings(%)           | Proposed    | 5.91       | 1.58       | 5.02       |
|                                         | SVM         | 11.41      | 6.25       | 4.15       |
|                                         | eCognition  | 11.44      | 0.82       | 10.78      |
| \(\kappa\)                             | Proposed    | 0.9018     | 0.9294     | 0.8923     |
|                                         | SVM         | 0.4667     | 0.8395     | 0.5745     |
|                                         | eCognition  | 0.8349     | 0.9721     | 0.8239     |
| Running time (min)                      | Proposed    | 0.2        | 0.2        | 0.25       |
|                                         | SVM         | 2          | 2          | 3          |
|                                         | eCognition  | 15         | 12         | 18         |

TABLE 7. Confusion matrix of Group 1.

| Images | Proposed method | SVM method | eCognition |
|--------|-----------------|------------|------------|
|        | IB   | CB   | BG   | IB   | CB   | BG   | IB   | CB   | BG   |
| T1     | IB   | 1868 | 137  | 0    | 1733 | 271  | 1    | 1739 | 191  | 75   |
|        | CB   | 71   | 2180 | 50   | 128  | 2104 | 69   | 97   | 1478 | 726  |
|        | BG   | 457  | 2373 | 8584 | 538  | 4037 | 6839 | 523  | 1449 | 9442 |
| T2     | IB   | 1305 | 82   | 0    | 1047 | 340  | 0    | 1118 | 34   | 235  |
|        | CB   | 72   | 5086 | 277  | 49   | 5097 | 289  | 16   | 4110 | 1309 |
|        | BG   | 19   | 766  | 11443 | 0   | 878  | 11350 | 2   | 289  | 11937 |
| T3     | IB   | 3154 | 195  | 1    | 3197 | 153  | 0    | 2831 | 369  | 150  |
|        | CB   | 192  | 3682 | 531  | 775  | 3532 | 98   | 199  | 3054 | 1152 |
|        | BG   | 356  | 3924 | 22161 | 652 | 5457 | 20332 | 232 | 3079 | 23130 |

The proposed method outnumbers the eCognition method, its omission classification and misclassification are much more than the proposed method. Therefore, among the three methods, the proposed method achieved the best identification result.

The optimal threshold selection for group 2 are as follows: four directions 0°, 45°, 90°, 135° are selected for top-hat reconstruction in multi-direction, the NGPI threshold M₂ is set as M₂ = 2 × median (BMF (b)), where median (BMF) represent the band medium value of BMF, the noise estimate threshold M₅ is set to 60, and the rest related parameters selection are shown in Table 8. The optimal parameters used in eCognition are shown in Table 9.

Figure 8 to 12 demonstrate the extraction results of group 2 (T4-T8). As is shown in Figure 8, image T4 is located in mountainous area. Restricted by topographic factors, buildings in mountainous area are of different sizes and distributed in a chaotic way. After the earthquake, the damage to
buildings is more serious in mountainous area, and the rescue is more difficult. Therefore, accurate identification of damaged buildings in mountainous areas is particularly important. The SVM method is pixel based classify method, leading to a lot of noise contains in result, as is shown in circle 1. In addition, the SVM method cannot effectively utilize the structural features of buildings, thus the buildings cannot be identified as a whole, resulting in many “hole” exist in the

### TABLE 8. Parameter selection of Group 2.

| SE      | Parameters | T4           | T5           | T6           | T7           | T8           |
|---------|------------|--------------|--------------|--------------|--------------|--------------|
| Linear SE | Size       | 2 ≤ s ≤ 22   | 2 ≤ s ≤ 22   | 1 ≤ s ≤ 10   | 2 ≤ s ≤ 10   | 2 ≤ s ≤ 22   | Δs = 5       | Δs = 5       | Δs = 1       | Δs = 1       | Δs = 5       |
| M3      | 5          | 5            | 2            | 5            | 5            |              |             |             |             |             |             |
| M4      | 250        | 250          | 200          | 50           | 250          |              |             |             |             |             |             |
| Disk SE | Size       | 2 ≤ s ≤ 22   | 5 ≤ s ≤ 25   | 1 ≤ s ≤ 22   | 1 ≤ s ≤ 10   | 2 ≤ s ≤ 22   | Δs = 5       | Δs = 5       | Δs = 1       | Δs = 1       | Δs = 5       |
| M3      | 5          | 5            | 2            | 5            | 5            |              |             |             |             |             |             |
| M4      | 250        | 250          | 200          | 50           | 250          |              |             |             |             |             |             |

Note: M₃ represents the threshold of length-wide ratio; M₄ represents the threshold of area; s is the size of structural element, Δs is the change step of structuring elements size.

### FIGURE 8. Experiment results of T4.

(a) Original image  
(b) Result of the proposed method  
(c) Result of the SVM  
(d) Result of eCognition  
(e) Groundtruth

- **Intact buildings**
- **Collapsed buildings**
TABLE 9. Parameter selection of Group 2 using eCognition.

| Parameters | T4 | T5 | T6 | T7 | T8 |
|------------|----|----|----|----|----|
| Scale      | 80 | 70 | 60 | 50 | 60 |
| Shape      | 0.5| 0.5| 0.5| 0.5| 0.4|
| Compass    | 0.3| 0.3| 0.2| 0.3| 0.4|

result, as is shown in circle 2. Moreover, as the color of some intact building is similar to that of collapsed building, there are some misclassify phenomenon exist between the intact building and collapsed building, as is shown in circle 3. eCognition software is an object based classification method, which adopts the strategy of first segmentation and then classification. In the segmentation step, part of collapsed building is grouped with the background for it is similar to the background, resulting in the missing classification of the collapsed building, as is shown in circle 4. Compared with those two methods, the proposed method can avoid the above problems.

In image T5, there are road areas which are similar to the collapsed building exist. It can be seen from Figure 9 that the proposed method can distinguish them, while the SVM and eCognition misclassified the road areas into collapsed building, as shown in circle 1 and circle 2. In addition, there is commission error exist in eCognition extraction result, as shown in circle 3. Also, the noise and “hole” problems mentioned above still exist in the SVM result, as is shown in circle 4 and circle 5.

Image T6 is located near the terraced fields, where the surrounding farmland is very similar to the collapsed building in grayscale. However, it can be seen from Figure 10 that the SVM method and eCognition identified them as collapsed building while the proposed method not, as shown in circle 1 and circle 2. In addition, the proposed method can extract intact building with uneven roof surface, while eCognition identified them as collapsed building, as show in circle 3.
There are many smaller buildings in the image T7, it can be seen from Figure 11 that the proposed method can extract them, while eCognition cannot, as shown in circle 1 and circle 2. Meanwhile, SVM method and eCognition will identify the ground which around the intact building as collapsed building for they are similar in grayscale, while the proposed method will not, as shown in circle 3 and circle 4.
Image T8 is located near the river, as shown in Figure 12. The proposed method can eliminate the road part, while the SVM method and eCognition cannot, as shown in circle 1 and circle 3; and there is a lot of noise exist in the SVM result, as shown in circle 2. In addition, as shown in circle 4, there are small objects such as containers on the ground, eCognition identified this area as collapsed building, while the proposed method did not. Moreover, the proposed method can better extract the boundaries of building, as shown in circle 5. Also, the eCognition extraction result exists misclassification, as shown in circle 6.

Table 10 summarizes the extraction results based on the three methods. The proposed method was found to have the highest extraction accuracy among the three methods. The highest extraction accuracies of the intact building and collapsed building were 98.84% and 87.77%, respectively. The overall accuracy reached 92.84%, and \( \kappa \) was 0.9532.

When compared with the extraction result using SVM method, the proposed method had improved the results by 4.06% on average and had reached up to a 15.92% improvement for the extraction of intact building. Also, for the extraction of collapsed building, the proposed method was improved by 14.79% on average, and up to 35.07%. The OA and \( \kappa \) were improved by 8.68% and 0.34 on average, and up to 18.35% and 0.61 respectively.

When compared with the extraction results of eCognition, for the extraction of intact building, the proposed method had improved the results by 18.58% on average and had reached up to a 27.25% improvement. Also, for the extraction of collapsed building, the proposed method was improved by 8.06% on average, and up to 14.47%. The OA and \( \kappa \) were improved by 15.36% and 0.27 on average, and up to 26.01% and 0.45 respectively.

Under precondition of assuring precision, the FAR of identification is also important. The FAR of intact buildings obtained by the proposed method is 12.58% and 4.11% lower than that of SVM method and eCognition software on average, the FAR of collapsed buildings obtained by the proposed method is 5.57% and 19.06% lower than that of SVM method and eCognition software on average.

From the two experiments above, it can be founded that with the increase of image size, the OA of proposed method was stable at about 90%. Thus the proposed method was effective with strong robust and adaptive capability, and it can be applied to the earthquake rescue work.

Table 11 shows the confusion matrix of group 2 by using the three methods. IB, CB, and BG represent the intact building, collapsed building, and background, respectively. In regard to the misclassifications of the intact building, the extraction error of both the three methods is mainly the misclassification to collapsed building, nevertheless, the number of intact building which had been divided into collapsed building when using the proposed method was found to be much less than that of SVM method in most images, and significant less than that of eCognition in all images. In regard to the misclassifications of the collapsed building,
the extraction error of the proposed methods and eCognition method is mainly due to the undetected collapsed building. While the extraction error of the SVM method is mainly due to the misclassification between intact building and collapsed building. Moreover, the false alarm recognition of SVM method and eCognition is significantly outnumber the proposed method in most images, especially for the collapsed building. Therefore, among the three methods, the proposed method achieved the best identification result.

### B. EXPERIMENTS ON YUSHU EARTHQUAKE IMAGE

The second experiment was carried out on the Yushu earthquake image. In the Yushu earthquake, the damage to buildings was more serious, so the Yushu earthquake image is more complex and difficult to identify. In this experiment, four directions $0^\circ$, $45^\circ$, $90^\circ$, $135^\circ$ are selected for top-hat reconstruction in multi-direction, the NGPI threshold $M_2$ is set as $M_2 = 2 \times \text{median}(\text{BMF}(b))$, where median (BMF) represent the band medium value of BMF, the noise estimate threshold $M_5$ is set to 80, and the rest related parameters set are shown in Table 12 Figure 13 demonstrate the extraction results of Yushu earthquake image (T1-T6). The details in Yushu earthquake image are prominent. In image T1, the color feature of damaged buildings and background is close. From the macro perspective, almost intact building had been extracted by using SVM method. However, there is a lot of noise exist in the extraction results of SVM, while the proposed method extracted all intact buildings with little noise. From the micro perspective, the SVM method cannot extract building as a whole, as show in circle 1, while the proposed method can make full use of the buildings’ morphological characteristics, which can avoid this problem. In addition, SVM method can’t make use of the morphological characteristics to distinguish collapsed buildings from bare land. Therefore, the proposed method utilized morphological, thus can distinguish collapsed buildings from bare land.

### TABLE 10. Accuracies of the building extraction results by using the proposed method.

| Metrics                  | Methods          | Images |
|--------------------------|------------------|--------|
|                          | Proposed         | T4     | T5   | T6    | T7    | T8    |
| Intact buildings(%)      |                  |        |      |       |       |       |
|                         | Proposed         | 98.84  | 88.02| 87.61 | 93.35 | 97.85 |
|                         | SVM              | 82.92  | 87.41| 90.14 | 85.64 | 99.25 |
|                         | eCognition       | 75.25  | 81.94| 67.10 | 66.10 | 82.38 |
| Collapsed buildings(%)   |                  |        |      |       |       |       |
|                         | Proposed         | 81.61  | 80.48| 79.87 | 86.88 | 87.77 |
|                         | SVM              | 76.09  | 47.81| 90.41 | 75.64 | 52.70 |
|                         | eCognition       | 67.14  | 72.74| 74.44 | 75.30 | 86.67 |
| OA(%)                   |                  |        |      |       |       |       |
|                         | Proposed         | 85.96  | 85.37| 87.18 | 92.84 | 92.40 |
|                         | SVM              | 77.81  | 73.48| 90.15 | 84.86 | 74.05 |
|                         | eCognition       | 69.19  | 78.70| 67.50 | 66.83 | 84.71 |
| FAR of Intact buildings(%)|                |        |      |       |       |       |
|                         | Proposed         | 22.41  | 1.56 | 0     | 0.58  | 2.66  |
|                         | SVM              | 40.10  | 15.09| 0.23  | 1.54  | 33.13 |
|                         | eCognition       | 33.03  | 13.47| 0     | 1.08  | 0.16  |
| FAR of collapsed buildings(%)|             |        |      |       |       |       |
|                         | Proposed         | 0.44   | 16.06| 64.98 | 39.72 | 2.02  |
|                         | SVM              | 6.51   | 10.79| 64.71 | 67.89 | 1.18  |
|                         | eCognition       | 10.98  | 30.96| 87.61 | 78.56 | 10.39 |
| $\kappa$                |                  |        |      |       |       |       |
|                         | Proposed         | 0.8131 | 0.8474| 0.4834| 0.7048| 0.9532|
|                         | SVM              | 0.5057 | 0.2393| 0.3696| 0.6113| 0.3621|
|                         | eCognition       | 0.5759 | 0.5653| 0.1569| 0.2574| 0.8772|
| Running time (min)       |                  |        |      |       |       |       |
|                         | Proposed         | 0.13   | 0.15 | 0.25  | 0.25  | 0.13  |
|                         | SVM              | 2      | 3    | 3     | 2     | 3     |
|                         | eCognition       | 10     | 15   | 12    | 14    | 16    |
In image T3, the color of collapsed buildings was close to that of bare land, and part of the intact buildings were dark, also, there were cars on the road. All those above having increased the identification difficult. According to the results, the SVM method classified almost bare land into collapsed buildings according to the color features, as show in circle 5, and some intact buildings with darker colors were misclassified into collapsed buildings, resulting in low accuracy, as show in circle 6. While the proposed method was able to distinguish collapsed buildings from bare land areas. In addition, since the color of cars was similar to that of intact building, the SVM method misclassified them as intact building, as show in circle 7. While the proposed method can avoid this problem by adjusting the scale of the structuring elements.

In image T4, the color of road area was uneven, and the color of collapsed buildings was similar to that of bare land. For the extraction of intact buildings, some “dark point” in intact building were misclassified as collapsed building when using SVM method. Thus brooked the integrity of buildings. As show in circle 8. In addition, when using SVM method, road areas with bright color are misidentified as intact buildings and road areas with darker color are misidentified as collapsed buildings, which not only reduced the identification accuracy, but also increased the image noise, as show in circle 9. While the proposed method can avoid this problem.

In image T5, the complete building greatly different. The collapsed buildings were similar to the surrounding bare land, and there was a large amount of debris on the ground, which makes the image more complex. Compared with the result

| Images | Proposed method | SVM method | eCognition |
|--------|----------------|------------|------------|
| T4 | IB 2887 CB 31 BG 3 | IB 4224 CB 458 BG 41 | IB 2198 CB 716 BG 7 |
| T5 | IB 6559 CB 623 BG 270 | IB 6514 CB 234 BG 704 | IB 6106 CB 1319 BG 27 |
| T6 | IB 4716 CB 464 BG 203 | IB 4852 CB 519 BG 12 | IB 3612 CB 1647 BG 124 |
| T7 | IB 6411 CB 336 BG 121 | IB 5882 CB 939 BG 47 | IB 4540 CB 1620 BG 708 |
| T8 | IB 3694 CB 81 BG 0 | IB 3747 CB 28 BG 0 | IB 3110 CB 448 BG 217 |
| | CB 101 CB 3912 BG 444 | CB 1856 CB 2349 BG 252 | CB 5 3863 589 |
| | CB 409 CB 3101 BG 42573 | CB 2708 CB 11148 BG 32227 | CB 240 7789 38054 |

Note: M_3 represents the threshold of length-wide ratio; M_4 represents the threshold of area; s is the size of structural element, Δs is the change step of structuring elements size.
| Images | Original image | Proposed method | Result of SVM | Groundtruth |
|--------|----------------|-----------------|---------------|-------------|
| T1     | ![Original image](image1.png) | ![Proposed method](image2.png) | ![Result of SVM](image3.png) | ![Groundtruth](image4.png) |
| T2     | ![Original image](image5.png) | ![Proposed method](image6.png) | ![Result of SVM](image7.png) | ![Groundtruth](image8.png) |
| T3     | ![Original image](image9.png) | ![Proposed method](image10.png) | ![Result of SVM](image11.png) | ![Groundtruth](image12.png) |
| T4     | ![Original image](image13.png) | ![Proposed method](image14.png) | ![Result of SVM](image15.png) | ![Groundtruth](image16.png) |
| T5     | ![Original image](image17.png) | ![Proposed method](image18.png) | ![Result of SVM](image19.png) | ![Groundtruth](image20.png) |
| T6     | ![Original image](image21.png) | ![Proposed method](image22.png) | ![Result of SVM](image23.png) | ![Groundtruth](image24.png) |

**FIGURE 13.** Experiment results of Yushu earthquake images.
using the SVM method, the proposed method can better preserve the integrity of buildings, while buildings extracted by the SVM method contain a large number of "holes", as show in circle 10. In addition, the proposed method can distinguish the road from the intact building through the restriction of the length-width ratio, while the SVM method cannot, resulting in a lot of misclassification, as show in circle 11.

T6 was a full-size image that contains a large number of damaged houses. As can be seen from the image, the roof color of damaged building was untidy, and the road was narrow, which makes the image more complex. However, the proposed method also achieved relevant good result. Compared with the result using the SVM method, the proposed method can distinguish the road and square from the intact building through the restriction of the length-width ratio and area, while the SVM method cannot due to the color of road and square is similar to the building roof, as show in circle 12 and 13. In addition, compared with the result obtained by the proposed method, the result obtained by SVM method contain a lot of noise.

Table 13 summarizes the extraction results based on the proposed method and the SVM method. The proposed method was found to had better extraction accuracy than the SVM method. The highest extraction accuracies of the intact building and collapsed building were to 92.63% and 90.30%, respectively. The overall accuracy reached 91.04%, and \( \kappa \) was 0.7597. In addition, the extraction accuracies of all the results based on the proposed method were observed to be above 80%, and most to be above 85%. For the extraction of intact building. The proposed method had improved the results by 20.62% on average and had reached up to a 27.32% improvement compared with the extraction results using the SVM method. For the extraction of collapsed building, the proposed method was improved by 25.40% on average. The OA and \( \kappa \) were improved by 21.63% and 0.46 on average, and up to 36.89% and 0.56 respectively. The FAR of intact buildings obtained by the proposed method is 20.62% lower than that of SVM method on average, and the FAR of collapsed buildings obtained by the proposed method is 13.15% lower than that of SVM method on average.

Table 14 shows the confusion matrix of Yushu earthquake image by using the three methods. IB, CB, and BG represent the intact building, collapsed building, and background, respectively. In regard to the misclassifications of the intact building, for both the proposed method and the SVM method, the omission classification and misclassification result in the extraction error. Nevertheless, the number of undetected pixels and misclassified pixels when using the proposed method was found to be only around one tenth of the SVM method. In regard to the misclassifications of the collapsed building, the extraction error of both the two methods is mainly due to the undetected collapsed building, nevertheless, the number of undetected collapsed building when using the proposed method was found to be much less than that of SVM method in all the images. In addition, the SVM method has significantly more false alarm recognition than the proposed method in majority images, especially for the collapsed building. Therefore, among the three methods, the proposed method achieved the best identification result. From the experiments above, it can be founded that the proposed method has a higher accuracy in earthquake-damaged buildings extraction, the experiment was run on the MATLAB platform with an average running time of around 10 seconds, compared with the SVM method of around 3 minute and eCognition of around 10 minute. In addition, the SVM method is a supervised classification method, before each classification,
samples need to be selected manually, which directly affects the classification accuracy. The earthquake damage image is very complex, in high-resolution earthquake damage image, the details are more prominent, which reduces the difference between ground objects and increases the difficulty of sample selection, resulting in poor classification effect. Compared to the SVM method, the proposed method is an unsupervised classification method. It utilized morphology to extract damaged buildings, which not only saved the time, but also reduced the error caused by sample selection. Moreover, although several tools have been developed to automate some of the parameter selection [49], human interpretation of the results and subsequent adjustments to the parameters is still a common practice that yields acceptable results when using eCognition [45], while the proposed method only had a few parameters which required adjustments. Therefore, the method described in this study displayed obvious advantages, both in extraction accuracy and operational convenience.

V. DISCUSSION

However, experiments in this study are carried out under ideal conditions. In practical, some complex situations should be taken into account. First of all, images took directly from satellites usually covers a broad area, while the method proposed in this study emphasizes on extracting the distribution information of earthquake-damaged building after the earthquake. In order to improve the timeliness of the extraction of earthquake-damaged building, a real seismic image can be divided into several small-scale sub-areas, which will be parallel computed by the proposed algorithm with high-speed. Furthermore, the thematic maps of damaged buildings can be generated through synthesizing those marked sub-areas. Secondly, the time of eliminating noise and abnormal information should also be considered in practical, the results shown in this study may be obtained with a longer time if the time of image processing is included. Thirdly, sometimes the high resolution space-based image cannot be acquired in time after the earthquake; under this situation, the proposed method can be applied by adjusting the parameters to choose structuring elements with a larger scale, in this case, the obtained damaged building information is relatively rough, usually are the aggregate of earthquake-damaged buildings. However, it can still provide certain support for the post-earthquake relief work, and can be further refined to obtain individual earthquake-damaged building.

VI. CONCLUSION

Earthquake events are one of the most extraordinarily serious natural calamities. Such events are devastating, and have far-reaching influences. As the main disaster bearing body in earthquake, buildings are often seriously damaged. If collapse occurs in a chemical factory, a great deal of noxious chemical will be discharged to the environment, causing serious environmental pollution; in addition, the collapse of the building can also cause a large number of solid wastes. Therefore, the rapid and accurate identification of post-earthquake collapsed buildings has significant meaning for ecological environmental protection following disaster events. In this study, a rapid identification of post-earthquake collapsed
building method via multi-scale morphological profiles with multi-structuring elements is proposed, in order to extract earthquake-damaged buildings in single-phase seismic image for the first time. And the experimental result confirmed the effectiveness of the proposed method. The main conclusions reached in this study can be summarized as follows:

1. Intact building usually present a smooth and linear structure in image thus can be extracted by linear structural element; the collapsed buildings are usually scattered and without regular geometry, thus can be extracted via disk structural element; and the earthquake-damaged building can be identified effectively by combining two structuring elements organically and to give full play to their role.

2. The entire experiment was run on the MATLAB platform, which is particularly suitable for image processing. Also, the proposed method only had a few parameters which required adjustments. Therefore, the new proposed method possessed the feature of quick implementation and was able to extract earthquake-damaged building within a few seconds, which will potentially save a great deal of precious time in future post-earthquake rescue measures.

However, there were still some aspects which required further refinement and improvement in this proposed method. In the follow-up research, the following aspects will be considered. First, the proposed method has a high accuracy when extracting building with a regularity roof, however, when considering of the building which has an uneven roof, the accuracy is lower. Therefore, in the following work, a series of image preprocessing will be considered to make the roof more even. Second, in reality, damaged building often need to be graded in detail, such as serious disaster building, secondary disaster building, mild disaster building, and the no-disaster building, while this proposed method only divides the buildings into intact building and collapsed building. Therefore, in the next step of work, the structural element will be further study to obtain a more detailed division of earthquake-damaged building.

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