COLLAPSED BUILDINGS EXTRACTION USING MORPHOLOGICAL PROFILES AND TEXTURE STATISTICS -A CASE STUDY IN THE 5.12 WENCHUAN EARTHQUAKE

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ABSTRACT

Locations of collapsed buildings (CBs) caused by earthquake are the most needed information by the disaster reduction team, due to their strong correlation with losses of properties and human lives. Optical remote sensing images with high spatial resolution (OIHR) play an important role in extracting CBs. Currently there are mainly two approaches: manual interpretation and change detection [8, 9]. Manual interpretation requires too many costs both on labor and time, and can not easily satisfy urgent demands in the emergency response. Change detection is effective only when pre-disaster OIHR are available. However, getting pre-disaster OIHG is always difficult especially in the suburban areas in the developing countries. This problem became apparent in the 5.12 Wenchuan earthquake which struck southwest area of China with magnitude of 8.0 on May 12, 2008.

From visual interpretation of the post-disaster 0.5m ADS40 airborne images, CBs show three properties: (1) covering a certain amount of area with no uniform shape; (2) having a rough surface but no uniform texture; (3) all these properties can be visually detected from a single green band. Taken into considerations of these properties, we propose a CBs extraction method using only the post-disaster ADS40 images. The essence is to project the CBs information onto a high dimensional feature space where CBs are easier to be extracted through pattern recognition methods. Morphological profiles are adopted to extract changing patterns of each pixel within multi-scale objects [1, 2, 4, 7]. This pattern works like “spectral signature” in the spatial context and is effective in represent small and low contrast objects in the OIHR. Rotation invariant texture features are employed to differentiate objects with different texture statistics [5, 6]. Finally, SVM classifier is used to extract CBs with manually extracted training and validation samples [3]. The workflow of method is shown in Fig.3.

A subset of ADS40 image with a size of 400*400 was selected in our experiment as shown in Fig.2. The data covers the area of Pingwu County and was acquired on May 16 2008. It has a spatial resolution of 0.5m.Totally 3475 samples are selected for CBs. They are randomly divided into 250 for training and 3225 for validation respectively. With the same procedure, 250 training and 3129 validation simples are selected for other targets. All the parameters used to build features are shown in Table 1 and 2. The resultant images are shown in Figure 2. Classification results with various feature combinations are shown in Table 3.

From Fig 2, MPs and texture statistics together achieve a reasonable result, texture features alone are inefficient mainly due to border effects and the MPs features alone are inefficient mainly due to their inability to fully represent the CBs. From Table 3, features including MPs and texture statistics gain the highest overall accuracy.

As there are still apparent classification errors in the MPs and texture derived CBs image, further research may include more features through increasing the number of window sizes and/or statistics. Feature selection method may be adopted to select the core features. Also the proposed method needs to be tested on more images covering various landscapes.

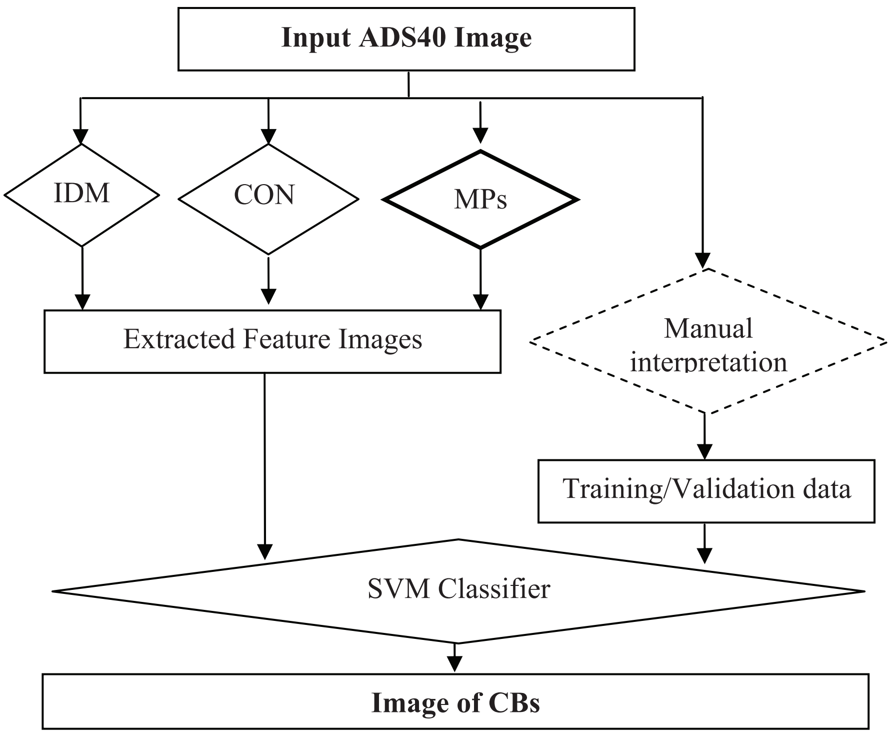

Fig.1 workflow of CBs extraction method

Table 1 Parameters for extracting texture features

Features from Texture	data	Window Size	Statistics	Gray Level	Displacement	Rotation Invariant Operator
FT1	green band	3*3	Contrast	64	[1,1],[1,0],[0,1],[-1,1]	MIN( )
FT2	green band	5*5	Contrast	64	[1,1],[1,0],[0,1],[-1,1]	MIN( )
FT3	green band	3*3	Inverse Difference Moment	64	[1,1],[1,0],[0,1],[-1,1]	MAX ( )
FT4	green band	5*5	Inverse Difference Moment	64	[1,1],[1,0],[0,1],[-1,1]	MAX( )

Table 2 Parameters for extracting MPs features

Features from MPs	Data	Window Size	Type	Features from MPs	Data	Window Size	Type
FM1	green band	3*3	opening	FM5	green band	3*3	closing
FM2	green band	7*7	opening	FM6	green band	7*7	closing
FM3	green band	9*9	opening	FM7	green band	9*9	closing
FM4	green band	15*15	opening	FM8	green band	15*15	closing

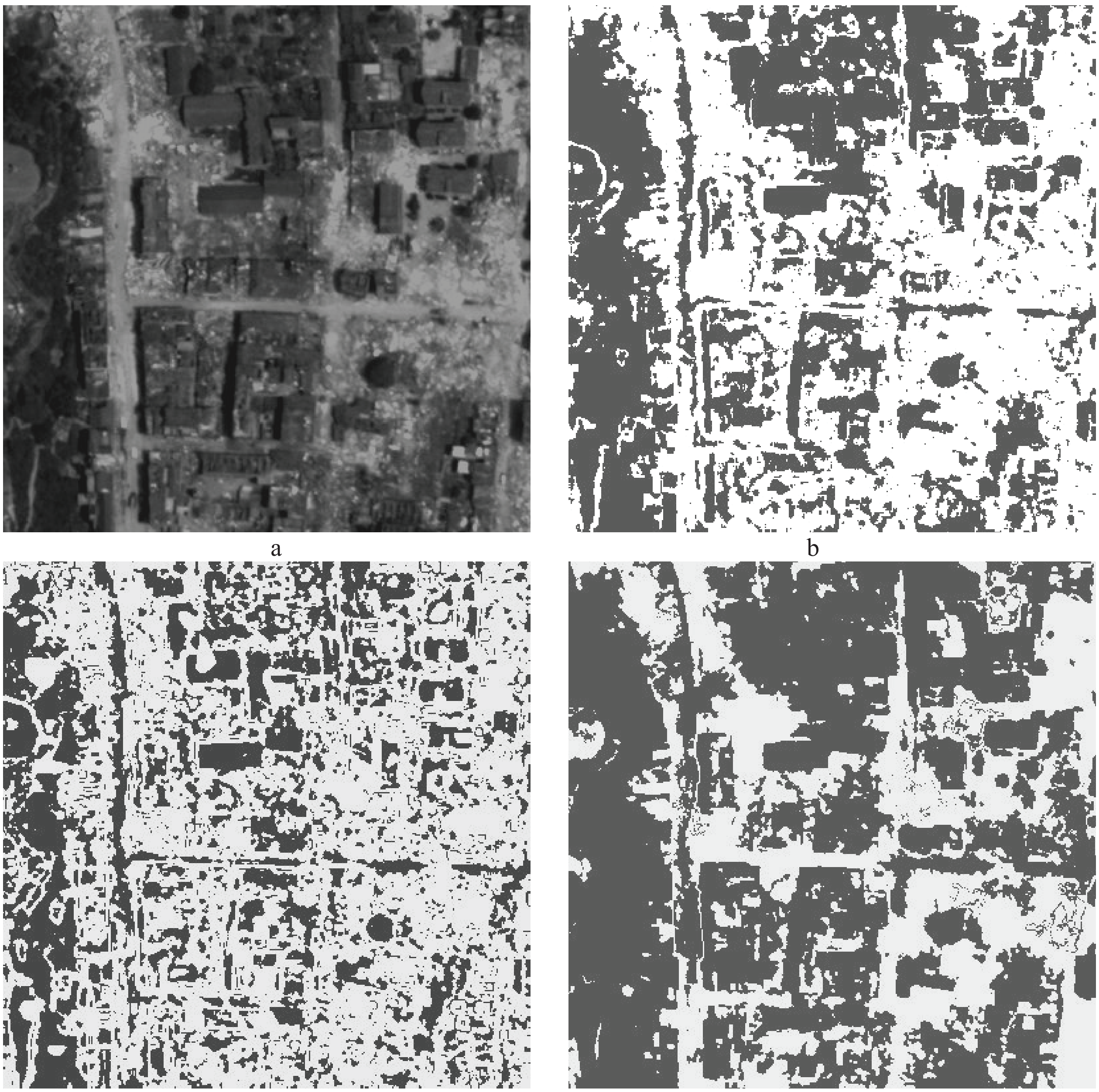

Fig.2 a shows the green band image, and b, c, d show the resultant images derived from features including MPs and textures, Textures alone, MPs alone respectively.

Table 3 Comparison of validation accuracies from different combination of features

No.	Features(number)	Overall Accuracy	Kappa Coefficient
1	Texture statistics + green band (4)	79.7%	59.4%
2	MPs + green band (8)	83.6%	67.4%
3	MPs + Texture statistics + green band (12)	90.5%	81.0%

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