Post-War Building Damage Detection

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Abstract: Natural disaster and wars wreak havoc not only on individuals and critical infrastructure, but also leave behind ruined residential buildings and housings. The size, type and location of damaged houses are essential data sources for the post-disaster reconstruction process. Building damage detection due to war activities has not been thoroughly discussed in the literature. In this work, an automated building damage detection technique that relies on both pre- and post-war aerial images is proposed. Building damage estimation is done using shadow information and Gray Level Co-occurrence Matrix features. Accuracy assessment applied over a Syrian war-affected zone near Damascus, reveals the excellent performance of the proposed technique.

Keywords: Damage Detection; Post-War Analysis; Building Extraction; Remote Sensing.

1. Introduction

Wars are among the most catastrophic disasters to affect mankind. One of the critical post-war activities is damaged building assessment. The area, amount, rate, and type of the damage are essential information for rescue, humanitarian and reconstruction operations in the affected area [1].

Following a war or a natural catastrophic disaster (such as earthquake), special teams are formed with responsibility to scan (survey) affected area, in order to evaluate the degree of damage in properties and buildings. This traditional approach of building damage assessment is time consuming and requires huge labor hours in order to cover the affected zone, especially in case of nation-wide war, and thus, is not a practical and effective practice to rely on.

Remote sensing techniques can play an important role in obtaining building damage information, mainly due to their wide availability at relatively low cost, wide field of view, and fast response capacities. The contribution behind this paper lies in introducing an automated framework for building damage detection, for war-affected areas based on high resolution satellite images.

The proposed approach depends on both pre- and post-war images. Affine transformation is firstly used as a pre-processing step to correct geometric distortions or deformations that occur with non-ideal camera angles. Next, building detection is applied on the pre-war image. Detected buildings positions will be projected on the post-image, resulting in a set of damaged buildings candidates. Finally, thorough damage analysis is done using three main features: *(i)* Shadow, *(ii)* Variance, and *(iii)* Correlation.

The remaining of this manuscript is organized as follows. Section II presents a literature review of published research on building damage detection. Section III introduces the framework of our proposed methodology. Performance analysis and experimental results are shown in Section IV. Finally, Conclusion is given in Section V.

2. Literature Review

Many techniques have been introduced in the literature for destruction recognition mainly due to natural disasters like earthquakes. However, war damage detection and estimation has not been thoroughly studied.

Building damage detection based on color information is presented in [9]. Gray level histogram features are used to separate the housing construction units from complex background. After that, a building damage detection algorithm based on regional statistical information is implemented.Experimental results applied on Haiti post-earthquake images captured from Google Earth show that proposed approach is effective and feasible.

Indonesia Earthquake damage detection is presented in [4]. The idea is based on image classification technique applied to post-earthquake QuickBird images to detect areas covered with bricks (damaged buildings). The classification technique is based on the spectral reflectance of surface materials, where the distribution of the building damage is evaluated using a proposed $DamageIndex$.

Authors in [7] used shadow information to evaluate buildings damage state. They define the degree of damage in buildings to be the area of the rooftop segment over the area of the corresponding shadow segment. For damaged buildings, shadow region will be smaller which leads rooftop to shadow ratio to have higher values.

Object oriented change detection of buildings using images captured for Thailand December 2004 Tsunami is implemented in [6]. A robust rectangular building detection process is introduced to discover buildings with different sizes. Damage detection is carried on by comparing size, height, width, orientation, and **RGB** spectral properties of buildings in pre- and post-disaster images.

Pixel-based classification based on the maximum likelihood method was carried over the aerial images captured for affected areas both before and after the 2007 Indonesian earthquake [8]. In addition to that, object-based classification is conducted to overcome some highlighted limitations of the pixel based classification. Debris of collapsed buildings is extracted correctly with reasonable effectiveness results.

Istanbul earthquake damage assessment was conducted in [3], where the building damage analysis was performed using **HAZTURK** software. Results from the damage analysis for districts and sub-districts is presented and compared with other studies, showing an acceptable building damage estimation results.

3. Proposed Methodology

In this section, we will discuss in details our proposed building damage detection algorithm that depends on both pre- and post-war images.

3.1. Damaged Building Candidates

Pre- and post-war images may be captured in different conditions, camera type, angle and capturing conditions. Then, our first pre-processing step is to apply affine transformation in order to uniformly reference both images.

Then, any building detection algorithm can be applied on the pre-war image to extract the set of existing buildings in the region of interest. For the scope of this work, we used building detection algorithm proposed in [10] without loss of generality. We construct an array of the centroids of the detected buildings in the pre-war image, which we refer to as Pre-war Buidings' Centroids Set **PBCS**.

Damaged buildings candidates are obtained through the projection of **PBCS** on the post-war image. Shadow detection algorithm is also implemented on the post-war image where potential shadows areas that surrounds damaged buildings candidates are extracted. The discussion of the details of the used shadow and building detection algorithms are beyond the scope of this manuscript.

3.2. Features Calculation

Its well known that buildings shadows reflect the geometric representation of the building unit. Thus, if the building get affected by an explosion or air strike, its corresponding shadow will be deformed. In our approach, pre- and post-war shadow area are computed and compared. If their difference exceeds a certain threshold, then the building structure is labeled as potentially damaged.

Gray Level Co-occurrence Matrix (**GLCM**) represents second order statistical texture features of an image. **GLCM** is a matrix where the number of rows and columns is equal to the number of gray levels, G, in the image. The matrix element $P(i, j \mid \Delta x, \Delta y)$ is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighborhood, one with intensity i and the other with intensity j.

GLCM is a popular statistical method of extracting textural feature from images. In this paper, two features are utilized in order to locate damaged buildings within the post-war image: *(i)* Variance and *(ii)* Correlation.

Variance is used to measure the image homogeneity as shown in Equation 1:

$$Variance = \sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i - \mu)^2 . P_{ij} \tag{1}$$

where i, j are the spatial coordinates of the function $P(i, j)$, G is the number of gray level used and μ is the mean intensity value.

Correlation, defined in Equation 2, measures the linear dependency of gray levels on those of neighboring pixels. This is often used to measure deformation, displacement, strain and optical flow.In our proposed algorithm, we use the correlation parameter in order to measure spatial deformations in building structure in pre- and post-war images.

$$Correlation = \frac{\sum_{i=0}^{G-1} \sum_{j=0}^{G-1} (i, j) P_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{2}$$

As a decision making process, three hypothesis are checked: *(i)* First, Shadow Area Difference, SAD, between pre- and post-war images should exceed a predefined threshold. *(ii)* Second, Variance Difference, VD, should also exceed a predefined threshold and the same applies for *(iii)* Correlation Difference, CD.

If no building shadow exists in the post-war image, then the building will be classified directly as a damaged building. Threshold selection is done experimentally for the scope of this work. In future work, machine learning techniques will be used in order to design an optimal classifier.

Figure 3 shows the block diagram of the proposed building damage detection algorithm.

4. Experimental Results

The literature does not provide for the best of our knowledge a relevant dataset for war affected areas to benchmark against. And thus, we focused in this work on images taken in 2015 during the Syrian civil war for Zabadani region near Damascus. Figures 1a and 1b depict the pre- and post-war original images captured on May 18, 2015, and August 5, 2105, respectively using GeoEye-1.

Table 1 shows the values for SAD, VD and CD, respectively, for 5 buildings labeled in Figure 2a (post-war Zabadani Study Area). Damaged buildings are labeled using red color, while normal ones are labeled using green. Results for remaining buildings are omitted due to space limitation.

For Building Number 4, no shadow is detected in the post-war image and thus the relative building is considered as totally damaged. Generally speaking, normal buildings have high spatial relation between its gray levels in addition to higher homogeneity, and vice versa. Therefore, normal buildings Variance and Correlation values are higher than those of damaged buildings. Building Number 5 is misclassified as a normal building due the absence of noticeable major structure deformation in the post war image, thus having low **VD** and low **CD** values.

(a)   **(b)**

Figure 1. Figures 1a and 1b show the pre- and post-war original images, respectively, for Zabadani Study Area.

Table 1. Damage Assessment parameters for Zabadani Study Area.

Building Number	Shadow Area		SAD	Variance		VD	Correlation		CD	Algorithm Classification	Ground Truth
	Pre	Post		Pre	Post		Pre	Post			
1	870	560	310	81.3	75.51	5.79	31.76	28.04	3.72	Normal	Normal
2	2650	2295	**355**	119.04	76.21	**42.83**	40.47	25.93	**14.54**	**Damaged**	**Damaged**
3	1604	2135	**531**	115.96	72.12	**43.84**	47.59	29.26	**18.33**	**Damaged**	**Damaged**
4	356	No Shadow	**NA**	120.51	80	**40.51**	43.28	26.61	**16.67**	**Damaged**	**Damaged**
5	250	100	150	88.75	76.64	12	39.64	30.86	8.78	Normal	**Damaged**

Figure 2b shows the resultant image of applying proposed building damage detection algorithm on Zabadani study area, where truly detected normal buildings are labeled with a green tic-mark, truly detected damaged buildings are labeled with a red tic-mark, and finally, undetected damaged buildings are marked by a black cross. Table 2 shows the accuracy assessment results for the proposed building damage detection algorithm using three metrics defined as follows:

$$Branching\ Factor\ (BF) = \frac{FP}{TP} \tag{3}$$

$$Miss\ Factor\ (MF) = \frac{FN}{TP} \tag{4}$$

$$Quality\ Percentage\ (QP) = 100 \times \frac{TP}{TP + FP + FN} \tag{5}$$

where TP stands for True Positive, FP False Positive and FN False Negative.

As shown in Table 2, out of a total of 16 damaged buildings within Zabadani Study Area, 13 were truly classified. The overall quality percentage of building damage detection is **81.25**%, revealing the robustness and good performance of the proposed method, due to the integration of shadow information and texture characteristics.

Table 2. Accuracy assessment of Zabadani Study Area that includes 37 buildings objects .

Algorithm	True Positive	False Positive	False Negative	Branching Factor	Miss Factor	Quality Percentage
Normal Building Detection	22	1	0	0.04	0	95.65%
Damaged Building Detection	13	0	3	0	0.23	81.25%

(a)   **(b)**

Figure 2. Figure 2a shows 5 labeled buildings investigated in details in Table 1 and Figure 2b shows building damage assessment results of the proposed algorithm.

5. Conclusion

In this paper, we propose an automated building damage detection algorithm from high-resolution satellite data. Shadow information is utilized in addition to variance and correlation ***GLCM*** features. Experimental results of applying the proposed algorithm on pre- and post-war images captured for Zabadani area in Syria, reveals the good performance and robustness of the proposed algorithm with **81.25**% quality percentage. In future work, we will carry on pixel based buildings damage analysis, in addition to using machine learning techniques to devise an optimal classifier. Moreover, future work includes the extension of the proposed approach to classify damaged buildings into several states based on destruction severity.

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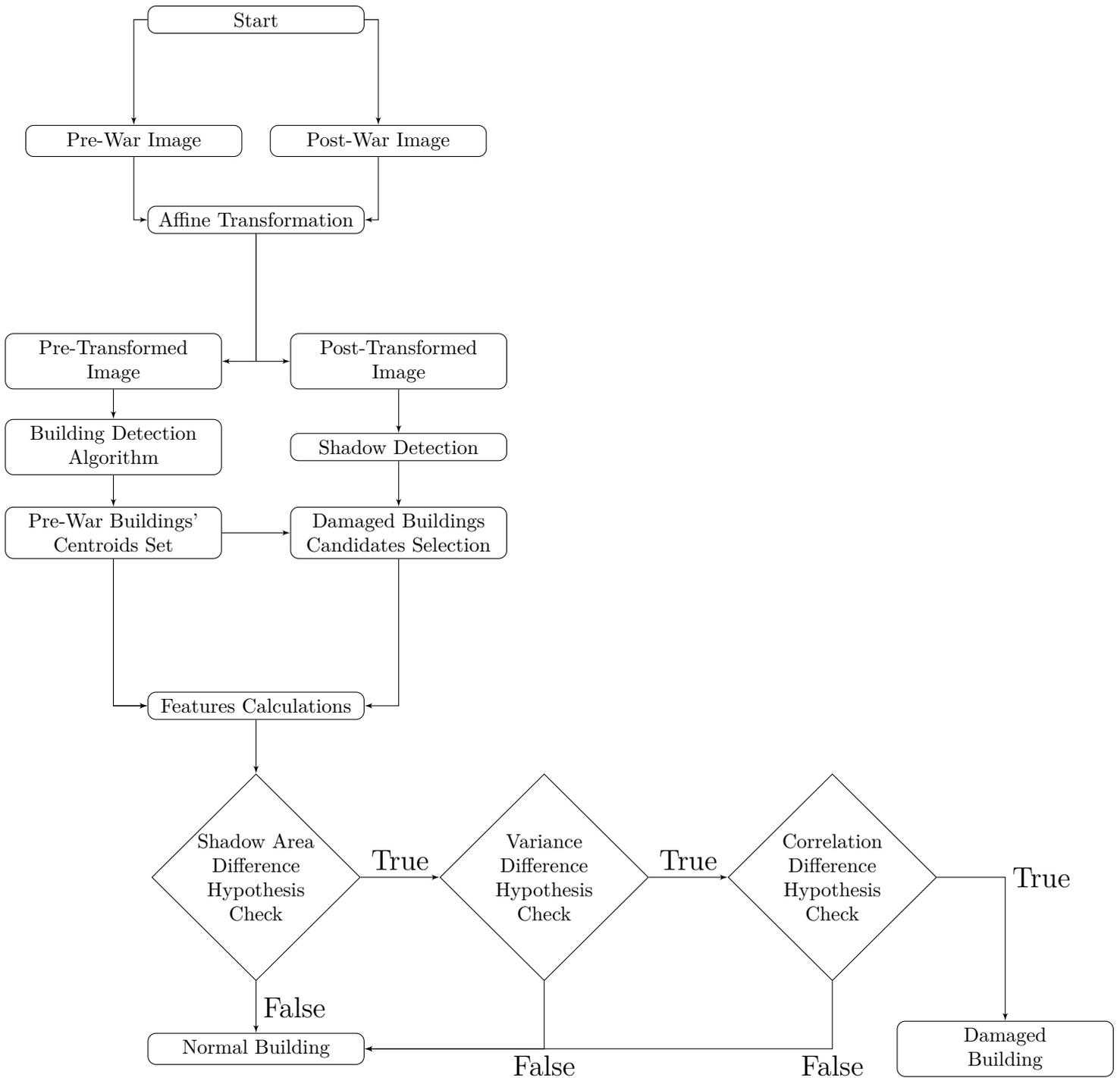
Figure 3. Proposed Building Damage Detection Block Diagram.