A GIS-based approach for earthquake loss estimation based on the immediate extraction of damaged buildings

Hamid Reza Ranjbar a, Hamid Dehghani a, Ali Reza Azmoude Ardalan b and Mohammad Reza Saradjian b

aMalek Ashtar University of Technology, Tehran, Iran; bDepartment of Geomatics, Faculty of Engineering, Center of Excellence in Geomatics Engineering and Disaster Prevention, University of Tehran, Iran

ABSTRACT

With the remote sensing technology is possible to predict estimations of the expected number of killed or injured people. In this study, a loss estimation method is proposed by combining data from remote sensing technology and geographic information system (GIS). For the image processing, we assume the damage area with a rougher texture when compared with undamaged areas. Extracted textures were later considered as the decision-making basis for the building damage level determination. We prepared the GIS database with information on the land use, structural material and building occupancy. Considering the influence of time in the building occupancy, two periods were considered (activity and inactivity) for each land use. The model estimates casualties based on the population residing in each building and according to the time of the earthquake, structure material of each building and destruction percentage. The approach was tested on Ahar and Varzaghan cities of Iran using 0.5 m resolution pan-sharpened Geo-Eye 1 imagery. The root-mean-square error (RMSE) for the number of injured and killed people was determined, considering field teams’ data and predicted data. RMSE for injured population was estimated in 0.040 and RMSE for fatal casualties was estimated in 0.025.

KEYWORDS

High spatial resolution satellite image; texture; fuzzy inference system; GENIE algorithm; casualty estimation model

1. Introduction

Earthquakes are among the most devastating natural events affecting humanity (Sengar et al. 2013). Between 2001 and 2011, natural events accounted for 780,000 deaths, 60% of these deaths were caused by earthquakes (Bartels & VanRooyen 2012). Over time, the threat of earthquakes will increase in parallel with the growing demand for global urbanization and millions of people will be vulnerable to earthquakes (Voigt et al. 2007; Lantada et al. 2009; Hosseinali et al. 2014; Cvetković et al. 2015). Iran experiences a number of the most destructive and deadliest earthquakes every year due to a very active seismic location (Moradi et al. 2015). On average, a strong earthquake, with high financial losses occurs every 7 years in Iran.

Buildings are among the structures highly affected by the greatest degree of destruction (Tong et al. 2012; Ranjbar et al. 2015). They are the most important urban areas in which most of the population resides. Therefore, the damage inflicted on these physical structures is the main reason for the number of casualties in earthquake events (Tong et al. 2013). The rescue and inspection operation requires identification of the affected areas, estimation of loss of life, allocation of personnel...
and adequate medical supplies, search for survivors under the ruins, prevention of the spread of communicable diseases in the region in turmoil, psychological assistance to survivors and the reconstruction of areas hit by the earthquake (Zhang et al. 2012; Rastiveis et al. 2013; Erdik et al. 2014). Among these, building damage detection and casualty estimation are essential to the whole relief and rescue operation (Zhang et al. 2011; Feng et al. 2013). Therefore, the development of methods for rapid gathering of this information is emphasized. Today, there are damage maps on which the building conditions whether destroyed or not, as well as the building damage level, can be precisely prepared using high spatial resolution satellite image (Ranjbar et al. 2014b); however, there is no accurate and reliable method for rapid estimation of casualties caused by the earthquake (Maqsood & Schwarz 2011; Feng et al. 2013).

Previous methods for determining the loss of life caused by the earthquake can be divided into two categories (So & Spence 2013). In the first category, empirical functions for estimating earthquake losses are presented using the relationship between earthquake parameters and the number of casualties reported from historical data (Feng et al. 2013; So & Spence 2013). Despite taking into account seismic parameters in the first category of research (Jaiswal & Wald 2010), the accuracy of casualty estimation models was not very satisfactory, because seismic characteristics do not directly reflect the number of deaths. Thus, in the second category, the focus of research was changed on the relationship between the amounts of damage of buildings and the number of casualties (So 2009; Feng et al. 2013). The amount of damage of buildings is evaluated using the damage index ($D_i$) (Dong & Shan 2013; Rastiveis et al. 2013). This index is measured in a $D_1$ to $D_5$ scale, where $D_1$ corresponds to ‘no damage’ and $D_5$ corresponds to ‘state of ruin’, according to the European Macro Seismic Scale (EMS98) (Grünthal 1998). Estimating the deaths caused by low or moderate damage of $D_1$ and $D_2$ is a difficult process (Coburn & Spence 1992); therefore, the focus of research is on the damage levels of $D_4$ and $D_5$. In addition to the damage inflicted on buildings, the type of materials used in buildings is another factor affecting the number of casualties (Maqsood & Schwarz 2011). For example, if reinforced concrete buildings are destroyed, far more casualties result as compared with the destruction of masonry buildings (Coburn & Spence 1992). To explore the relationship between the damage inflicted on buildings and the number of casualties, Okada and Takai (2000) conducted studies on damaged buildings and a complete classification was presented for the relationship between the type of building materials, the damage level and the loss of life. Based on this classification, Lu et al. (2003) offered the distribution of casualties for each category of damage and the main reason for casualties was considered as the lack of the survival space in the damaged structures. AhadNejad et al. (2010) performed an earthquake vulnerability modelling for buildings using hierarchical analysis in a geographic information system (GIS) environment. Different scenarios for a variety of intensities, casualty numbers and financial losses were estimated for the Zanjan city of Iran. Hashemi and Alesheikh (2011) assessed earthquake-associated damage on buildings in Tehran, Iran, using GIS-based studies. The assessment of casualties and street blockage due to collapsed buildings was used to design the earthquake scenario associated with the Mosha fault. According to Hashemi and Alesheikh (2011), 64% of the existing buildings were damaged, 33% of the population died and 27% of the population was injured. Wang et al. (2011) predicted life casualties by a neural network model considering different key factors, such as earthquake magnitude, depth of hypocentre, intensity of epicentre, level of preparedness and population density. The results fit for most cases of earthquake in the study area. Esfandeyari et al. (2015) determined the seismic coefficient of the major fault around Ardabil city in Iran and estimated the number of human casualties caused by the earthquake at different time intervals. However, most of these studies did not consider occupant dynamics in the building, which may result in an inaccurate estimation of casualties (Wei et al. 2015), since the occupants are not uniformly distributed at the time of building collapse.

In recent years, researchers have been able to collect essential information, immediately after the earthquake with the development of informatics techniques (Dong & Shan 2013). Some studies used local seismic intensity information to calculate the amount of damage to buildings and to estimate the number of casualties (Porter et al. 2008; Wyss & Trendafiloski 2011). Aghamohammadi
et al. (2013) used a neural network as a function of damage to buildings for modelling and estimating the magnitude and distribution of losses. A normal root-mean-square error (RMSE) observed for data and calculated data, indicates the high accuracy of this model in estimating casualties. Feng et al. (2013) proposed a model for estimating casualties immediately after an earthquake event using high spatial resolution satellite images. The model was developed based on the assumption that damage to buildings was the main cause of the increase in the number of casualties in the earthquake event. In this research, the damage to buildings was extracted based on changes in the digital elevation model (DEM) information provided before and after the earthquake. Finally, this information was integrated with GIS base data to estimate casualties. The accuracy and speed of this model was dependent on the algorithm developed to determine the $D_i$. Feng et al. (2014) proposed another model based on the mechanism of casualties in comparison with a machine vision or a fitting method. Although this method is more accurate when compared with other methods, it showed a lower speed in estimating the death toll.

Previous methods may be acceptable predictors of earthquake effects for a block of buildings. They are, however, not accurate predictors for a specific building. Building-specific estimation is definitely more accurate and reliable than the above-mentioned methods if it is used for an area because it is based on the properties of a particular building. The only human casualty estimation in Iran is the Japan International Cooperation Agency’s Investigation on Seismic Microzoning of Tehran, which estimated the casualty on block level (JICA 2000). Moreover, few studies provide the estimation on standard occupant distributions in a building after earthquakes. In this paper, we propose a method that can provide estimations on casualty by considering occupant dynamics in a building, immediately after earthquake occurrence. The method was implemented in the Ahar and Varzaghan district in Azarbaijan Province of Iran as a case study. The paper is organized as follows. The proposed approach for earthquake-induced casualty estimation is described in Section 2. The performance and limitations of the method is evaluated in Section 3. Some conclusion remarks are summarized in Section 4.

2. Methodological framework

Taking into account the limitations of previous methods and integration of rapid damage detection techniques, a GIS-based framework is presented to estimate casualty numbers. The proposed algorithm consists of three sections of pre-processing and data preparation, damage detection, and casualty estimation. In the proposed algorithm, spectral and textural features were used to determine the condition of buildings after building extraction. The obtained textural features offer important indicators to differentiate the homogeneous and heterogeneous images of the area. The assumption that the damaged areas have uneven textures when compared with undamaged areas is used in determining earthquake-associated damage using texture analysis. In the proposed method, after the extraction of optimum features using visual techniques from the images, necessary measures were taken to determine the amount of damage. $D_i$ calculated in the previous step, along with the building material was extracted, in order to calculate the death rate and population residing in each building, as an input for the casualty estimation model. It must be noted that the proposed model attempts to estimate the potential population that was present in different building types at the time of the earthquake occurrence. The human casualties estimated by this method, will be closer to the real numbers achieved by field teams, because the number of casualties is estimated immediately after the earthquake. Figure 1 shows the overall process of the proposed system.

2.1. Pre-processing

Preparation and information pre-processing phases include measures for preparation of required information layers such as high spatial resolution satellite images before and after the event. In the pre-processing phase, the algorithms are applied on the images to improve their quality (histogram
matching). Considering the resolution of Geo-Eye-1 satellite images is 0.5 m in the panchromatic mode and 2 m in the colour mode. To increase the colour image resolution, we integrated both sources of data to generate a high-resolution coloured image. Following the image improvement process, geo-referencing is performed using the existing digital vector maps. A GIS database was later prepared containing field information such as building land use, the material of buildings, activity time, the inactivity time for each land use, the time of the event, and the population residing in each building.

2.2. Damage detection

2.2.1. Building extraction
Extraction of the building with high precision is considered as the main prerequisite for many applications (Guo et al. 2015), such as urban planning (Durieux et al. 2008), map updating (Chaabouni-Chouayakh et al. 2013), landscape analysis and also in the process proposed for estimating casualties in this research. At first glance, buildings are seemingly considered as simple structures that are easily recognizable (Sumer & Turker 2013). However, the automatic detection of buildings from satellite images with somewhat complex shapes and sizes is very difficult. Studies on building extraction from imagery have been widely considered by scientists in the fields of photogrammetry, remote sensing, and machine vision since the 1970s (Fazan & DalPoz 2013; Guo et al. 2015). Several approaches have been developed in order to extract the two-dimensional data of buildings based on the use of multispectral high spatial resolution satellite images. Most of the previous studies were exclusively developed based on the use of spectral information extracted from the image bands (Dong & Shan 2013; Sumer & Turker 2013). In addition to the provision of fixed dimensions and
satisfactory performance of conventional classifiers in this space, spatial relationships, such as texture, shape and proximity, also provide us valuable information on the effects of the extraction process. Such additional information can be used with spectral information. There is already great potential to perform studies on the integration of this kind of information.

GENIE, by Perkins et al. (2000), is an algorithm formed by a set of candidate tools using basic image processing operators such as arithmetic, logical and textural operators. It is possible to evaluate the capability to extract building features for each chromosome in the population by assigning a fitness value. In another study carried out by Perkins et al. (2005), a system titled GENIE Pro was developed. GENIE Pro, similar to GENIE, is a tool for the automatic extraction of features from aerial and satellite images using training data. The GENIE Pro system merged spectral and spatial characteristics in a complex manner, such as texture, local morphologies and information obtained from shapes.

The performance of genetic algorithms (GAs) is quite sensitive to control parameters, for example, there is the possibility of losing a chromosome with a good performance as a result of a high likelihood of cross-over operator. On the other hand, the low probability of cross-over may lead to the lack of production of better cases; therefore, faster convergence is not guaranteed (Nicoara 2009; Sumer & Turker 2013; Malik & Wadhwa 2014). Such negative effects lead to early or untimely convergence. The use of fuzzy logic controllers in determining genetic parameters is a possible solution for overcoming these limitations and improving the performance of the GA. To solve this problem and select optimal operators for extracting building features, Sumer and Turker (2013) presented a fuzzy-genetic approach, which showed very satisfactory efficiency in separating the two classes of building and non-building structures. GENIE algorithm showed better performance when compared with existing classifiers, such as the minimum distance, maximum likelihood, Mahalanobis distance, spectral angle mapping and binary encoding. In this study, we use the fuzzy-genetic approach proposed by Sumer and Turker (2013) to separate buildings from other structures in the image, which is the main prerequisite for the casualty estimation process.

In this method, training and testing areas are initially marked in the image. Afterwards, image bands are reduced to a single-band binary image using Fisher linear image analysis (Duda et al. 2001) (in the temporary areas of buildings). According to temporary output and reference data, the fitness value of the selected samples is calculated by comparing the pixel which belongs to the selected areas. This calculation is done as part of the GA operators, such as selection, cross-over and mutation. The selection operator keeps the successful solution (chain-making operator), while the cross-over and mutation operators diversify the remaining solutions for the next-generation. In the next step, GA operators are improved by employing the adaptive fuzzy logic controller in order to improve algorithm performance. The improved parameters are used in the next generation. The above evolutionary process is repeated until a certain number of generations are achieved. In the final stage, post-process operators are selected to remove the wrong areas and distortions are applied to the image. To learn more about this method, it is recommended to refer to Sumer and Turker (2013). Finally, the location of buildings was extracted using the mentioned method in the pre-event imagery. The extracted corners of buildings were later mapped, in order to find the boundaries of the buildings in the post-event imagery. In order to remove the effect of other classes in the building class, the value of zero was allocated to pixels outside the building boundaries.

2.2.2. Damage detection catalogue
After extracting the location of buildings, selecting an appropriate standard for calibration of the damage to the buildings as a result of the earthquake is an important factor in the research process. Damage is usually measured in degrees. In spatial resolution of 10 m and less, the damage caused by earthquakes to buildings is just detectable at the block level. In spatial resolution of 1 m or better, more accurate detection of building level damage is possible (Dong & Shan 2013). Therefore, the damage classification for different types of buildings has been raised and studied for decades. For
example, a European standard EMS98 (Grünthal 1998), presents five levels (Table 1) (slight, medium, heavy, very heavy damage and destruction) for the classification of damage to reinforced concrete and masonry buildings, which is used as a standard, in order to detect the damage in satellite images in this study.

2.2.3. Texture analysis

In photogrammetry and computer vision, information and features from the images can be categorized into structural, textural and spectral categories. The textural features obtained in the image classification present important indicators of homogeneous regions (Mirmehdi et al. 2008; Russ 2015). When the building structure is even, the phenomenon acts like a mirror and is brighter in the image. On the contrary, when the building structure is uneven, with a rough surface on it, some of the reflected light from the rough building is dispersed and slightly reaches the sensor, or the photographic film, contributing for the darker appearance of the phenomenon (Dehghani 2012). In this study, the status of the building was determined using the difference in textural features in the pre- and post-earthquake images. The type of textural information affects the accuracy in such a way that more appropriate texture makes better resolution and, therefore, leads to better accuracy. In this study, 22 textural features in five categories were implemented, including the first- and second-order statistics, geostatistics, Gabor and fractals given in Table 2. Based on the determined visual

Table 1. Classification of damage to masonry and reinforced concrete buildings (Grünthal 1998).

| Damage classification | Reinforced concrete buildings | Masonry buildings |
|-----------------------|-------------------------------|------------------|
| Grade 1: slight damage (no structural damage, slight non-structural damage) $D_1$ |
| Grade 2: moderate damage (slight structural damage, moderate non-structural damage) $D_2$ |
| Grade 3: basic to heavy damage (moderate damage to structures, heavy non-structural damage) $D_3$ |
| Grade 4: very heavy damage (heavy structural damage, very heavy non-structural damage) $D_4$ |
| Grade 5: destruction (very heavy structural damage) $D_5$ |
status, eight features were used from the list along with the spectral characteristics in the process of determining damage (these features are displayed in bold format in Table 2). The details of the implementation of the eight features are mentioned below.

First-order statistical features: first-order statistical features, such as the mean and variance, are used to calculate the similarity amount of a grey level, which is selected randomly, to the neighbouring pixels in an area of the image and does not process pixel spatial relationships. The first-order statistical features can be extracted using image brightness histograms (Srinivasan & Shobha 2008; Aggarwal & Agrawal 2012). In this study, the average grey levels of adjacent pixels were used as statistical features in the process of determining the damage. This feature is calculated using Equation 1:

\[
\mu = \frac{1}{M^2} \sum_{i=1}^{M} \sum_{j=1}^{M} I(i,j)
\]  

(1)

where \(\mu\) is the mean grey level of adjacent pixels and \(I(i,j)\) and \(M\) are the grey level and total number of pixels within the neighbourhood window, respectively.

Second-order statistical features: the second-order statistical features which consider the spatial relations among neighbouring pixels were first proposed by Haralick et al. (1973). The features are based on a two-dimensional co-occurrence matrix. This is a square matrix with dimensions \(N_g \times N_g\), where \(N_g\) is the number of grey levels in the image. Each element of this matrix represents the number of pixel pairs, which have grey levels of \(i\) and \(j\) and are away from each other equal to \(d\) pixels along \(\theta\). \(d\) is not the Euclidean distance, but is obtained based on pixel counting. Typically, this matrix can be defined for the four cardinal directions. In the process of counting couples, considering the inclusion of four out of eight directions, the arrangement of the grey level pair is not important since this is a symmetric matrix. But this matrix can be defined for arranging different pairs of pixels that otherwise would not be symmetrical (Srinivasan & Shobha 2008; Dehghani 2012). Several statistical features can be extracted from the co-occurrence matrix such as mean, entropy, energy, contrast, variance, the maximum probability, inverse difference moment, dissimilarity, homogeneity, sum mean, correlation and cluster tendency. Among these features, descriptors such as homogeneity, sum mean, correlation and cluster tendency have the ability to create appropriate separation among pixels of damaged and non-damaged classes. The four features, which are calculated using

| Texture features                  | First-order statistical | Second-order statistical | Geostatistics | Gabor | Fractal |
|----------------------------------|-------------------------|--------------------------|---------------|-------|---------|
| Mean                             |                         | Mean                     | Simple variogram (SV) | Mean | Expected value |
| Variance (MA)                    |                         | Entropy                  | Madogram      |       |          |
| Standard deviation               |                         | Second angular moment (energy) | Standard deviation |       |          |
| (RO)                             |                         |                           | Radogram      |       |          |
| Contrast                         |                         |                           | Cross variogram (CV) |       |          |
| Homogeneity                      |                         |                           |               |       |          |
| Sum mean (mean)                  |                         |                           |               |       |          |
| Variance                         |                         |                           |               |       |          |
| Correlation                      |                         |                           |               |       |          |
| Maximum probability              |                         |                           |               |       |          |
| Inverse difference moment (IDM) |                         |                           |               |       |          |
| Cluster tendency                 |                         |                           |               |       |          |
| Dissimilarity                    |                         |                           |               |       |          |
Equations 2–5, respectively, were selected to reveal the damage level:

\[
\text{Homogeneity} = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \frac{p(i,j)}{1+(i-j)^2}
\]  

(2)

\[
\text{Sum mean} = \frac{1}{2} \sum_i^{N_g} \sum_j^{N_g} (ip[i,j] + jp[i,j])
\]  

(3)

\[
\text{Correlation} = \sum_{i=0}^{N_g-1} \sum_{j=0}^{N_g-1} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j}
\]  

(4)

\[
\text{Cluster tendency} = \sum_i^{N_g} \sum_j^{N_g} (i+j-2\mu)^k p[i,j]
\]  

(5)

where \(N_g\) is the number of grey levels, \(p[i,j]\) is the count of the number of pixel pairs having the intensities \(i\) and \(j\), \(\mu_i\) and \(\mu_j\) are the means and \(\sigma_i\) and \(\sigma_j\) are the standard deviations, respectively.

Geostatistics features: statistically, the image texture can be defined by two components of local changes and spatial dependence. Local changes often show the degree of separation from the mean value by the variance parameter in a window. The spatial dependence assumes that the grey level in an image is not distributed randomly and spatially close pixels have more grey-level dependence (Van der Meer 2012). Geostatistics tries to quantify with respect to these two parameters, i.e. the variance and spatial dependence.

Semi-variograms are basic tools for geostatistics and have a wide range of applications in remote sensing sciences, such as damage assessment and detection of changes (Balaguer et al. 2010; Rastiveis et al. 2013). The features of geostatistics include simple variogram, madogram, radiogram, cross variogram and pseudo-cross variogram. Simple variogram have better performance on the differentiation between normal and damage pixels (Rastiveis et al. 2013). In this study, we use simple variogram to detect damage in buildings. This feature is calculated using Equation 6:

\[
\gamma_k(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [DN_k(x_i) - DN_k(x_i + h)]^2
\]  

(6)

where \(\gamma_k(h)\) is the variogram amount with different ranges of variogram \(h\), \(DN\) is the values of the grey level pixels of \(x_i\) and \(x_i+h\), and \(n(h)\) is the number of pairs of points at a distance \(h\) in an area inside the image.

Gabor features: each Gabor filter is a linear filter output which is defined by multiplying a harmonic function in a Gaussian function (Khan et al. 2016). Gabor features are extracted for an image using the Gabor function. For an image \(I(x,y)\), a Gabor discrete wavelet transform is calculated using Equation 7:

\[
G_{m,n}(x,y) = \sum_s \sum_t I(x-s,y-t) \psi^*_m s(n,m)(s,t)
\]  

(7)

where \(s\) and \(t\) are variables determining the size of the filter mask, \(\psi^*_m\) is the complex conjugate operations on \(\psi_{mn}\), \(m = 0, 1, \ldots\) and \(n = 0, 1, \ldots, N - 1\) specifies the order and scale of the wavelet, respectively (Rastiveis et al. 2013). In this study, the mean and standard deviation of the magnitude of transform coefficients are used in the process of damage identification.
2.2.4. Damage assessment by using fuzzy inference system

After extracting optimum features from pre- and post-event images, their status was determined regarding the amount of damage. Most of the tools used in modelling, reasoning and calculation have a definitive nature, and are clear and accurate in terms of structure (Mavi et al. 2013). There is no doubt that the identification of buildings destroyed by the earthquake is associated with a lot of ambiguity and uncertainty (Ranjbar et al. 2014a). In this study, fuzzy logic was used to reduce the uncertainty of data and vague human knowledge (Hamedianfar & Shafri 2013; Shahabi et al. 2013). In this fuzzy system, after extraction of optimum features for the building in question, the difference calculated by the features from the images before and after the event was considered as input variables of the system. The output is a linguistic classification labelling the building damage level. From 0 to 70% is considered undamaged, over 70% is considered heavily damaged and 100% is reserved for destroyed buildings. The inference phases in the fuzzy-inference system are as follows.

Fuzzification of input parameters: the input parameters are features selected in the previous stage. The outputs of this stage are linguistic parameters or variables along with the degree of membership of these variables to each of the fuzzy sets.

The use of fuzzy operators: in this stage, a consensus has been established among linguistic variables obtained from the previous step by using fuzzy AND, OR operators.

Fuzzy inference: the inference system used in this study is a Mamdani inference model.

Collection of results in rules: in the fuzzy inference system, for each existing law, the corresponding output of each rule is returned by applying the inference method. A set of fuzzy union and intersection operators is used for adaptation of the outputs and achieving a single value.

Defuzzification: after the above processes, the building status is determined by a single number, from 0 to 100% regarding the damage level. This number allows the categorization of the building into different levels of damage.

2.3. Casualty estimation

Estimating casualties is always a difficult process due to the variable number of deaths in the historical records of previous earthquakes and lack of information available from this earthquake (Coburn & Spence 1992). The statistics show that many factors could cause the loss of life, which include direct and indirect factors such as fires, tsunamis, landslides and other secondary phenomena after the earthquake (Spence & So 2009). During the twentieth century, about 75% of the earthquake-associated casualties were caused by the destruction of buildings and people trapped in collapsed buildings (Coburn & Spence 1992), and if secondary phenomena are excluded, this per cent would be almost 90% of earthquake-related deaths (Coburn & Spence 2003). This indicates the broad relationship between the destruction caused by earthquakes and number of deaths (Furukawa et al. 2009; Spence & So 2011).

Each building class has its own lethality rate which is defined as the ratio of the number of people killed to the number of occupants trapped in the collapsed building of that class (Hashemi 2011). Lethality rate was used in order to apply the building material in the calculation of casualty toll (Hashemi & Alesheikh 2011). Thus casualty estimation derives from the number of collapsed building of each class and lethality ratio for that class. Lethality ratio depends on different parameters such as mechanism of collapse, the seismic intensity, building type, level of occupancy, number of floors, the time of earthquake occurrence, occupant behaviour, search and rescue operations effectiveness (Coburn & Spence 1992). Also, population living in buildings is completely changeable at different times of the day, so the appropriate population at the time of the event should be the basis for calculating the earthquake. Lack of attention to this important dimension will lead to unrealistic results. In this study, based on historical demographic data of the study area, the rate of occupants residing in each land use at two activity and inactivity periods was prepared. The occupancy rate for the residential land use within the activity and inactivity time was presented in Figure 2.
To estimate the overall casualty levels, information of the building damage, building typology and their occupancy levels, extent of earthquake impact and population of a specific building are required. The results of casualty estimation would be precise when data gathering is done in parcel based approach, while in block based approach the results would be far from reality. Based on the method presented by Coburn and Spence (1992), the proportion of occupants killed at collapse and the proportion of those trapped who are eventually rescued with light injury, moderate injury or threatening cases are calculated respectively using Equations 8 and 9:

$$K_{S1} = C \cdot [M_1 \cdot M_2 \cdot M_3 \cdot (M_4 + M_5(1 - M_4))]$$

$$K_{S2} = C \cdot [M_1 \cdot M_2 \cdot M_3 \cdot (\alpha \cdot (1 - M_4) \cdot (1 - M_5))]$$

In these equations, a set of $M$-parameters is used (Figure 3) to estimate the proportions of occupants rescued and trapped at each stage. Each building class has its own set of $M$-parameters completely different from any other building class. $K_{S1}$ and $K_{S2}$ are, respectively, the number of occupants killed and those consequently rescued at collapse, $C$ is the number of collapsed buildings, $M_1$ is the number of occupants residing in each building, $M_2$ is the rate of occupants residing in the building at the time of the earthquake, which is variable based on the type of land use and also earthquake occurrence time (Figure 2), $M_3$ is the proportion of occupants trapped by collapse which is strongly influenced by building type (Table 3), $M_4$ is the proportion of occupants killed at collapse which also depends on building type (Table 3), $\alpha$ is the coefficient for $1 - M_4$ parameter which used to estimate the number of people with uninjured, moderate or threatening cases, and $M_5$ is the mortality rate after building collapse which crucially depends on the effectiveness of relief operations after earthquake event. The rescue operations arrival time and effectiveness influence the number of fatalities due to trapped people in collapsed buildings (Table 3).

3. Implementation and evaluation of results in the study area

3.1. Study area description

The convergence of Arabia and Eurasia plates results in the emergence of many faults in Iran (Karimzadeh et al. 2015). One of the most seismically active faults in Iran is Tabriz fault (Ommi & Zafarani 2016). Near cities of Ahar and Varzeghan in the East-Azerbaijan province in northwest of Iran, a
twin earthquakes of 6.4 and 6.3 on the moment magnitude scale (MW) occurred at 12:23 coordinated universal time (UTC) of 11 August 2012 (Razzaghi & Ghafoory-Ashtiany 2012; Ghods et al. 2015) 60 km away from the apparently active North Tabriz Fault (Karimzadeh et al. 2013). Following this earthquake, more than 20 villages have completely destroyed (Yaghmaei-Sabegh & Ruiz-García 2016) and cities of Varzaghan, Ahar and Heriss suffered different levels of the damage. The earthquake killed 327 people, claimed more than 3000 injuries and left more than 30,000 homeless (Heidari 2016). Buildings in the stricken area experienced different levels of damage. Most of the adobe buildings in villages were collapsed and several masonry and framed buildings were damaged (Trendafiloski et al. 2011). The extent of Varzaghan city as shown in Figure 4 because of having different levels of damage to buildings was selected as the study area in this research.

3.2. Results

To evaluate the proposed method in this study, Matlab software was used for the implementation. In the first stage, after preparation of two pre- and post-event Geo-Eye-1 images with four spectral bands and pixel size of 1310 × 1702 which one was acquired on the 31 July 2011 at 7:54:00 AM and the other was acquired on 15 August 2012 at 7:36:00 am (4 days after the earthquake), a pre-processing stage was done on the raw data. At this stage, histogram matching algorithms were applied on the images. In order to increase the spatial resolution in the colour mode, colour and panchromatic images were integrated, and finally the two images were geo-referenced using the required control points with RMSE of 0.3861. The spatial database needed in this project was prepared along with

| Type of building     | $M_2$ (%) | $M_3$ (%) | Light injury | Injuries requiring hospitalization | Severe injury | Dead | $M_5$ (%) |
|---------------------|-----------|-----------|--------------|-----------------------------------|---------------|------|-----------|
| Un reinforced masonry| 58        | 5         | 20           | 30                                | 30            | 20   | 60        |
| Reinforced concrete  | 58        | 10        | 40           | 10                                | 40            | 10   | 90        |

Table 3. The mean value used for $M$ parameters in the casualty estimation model.
data fields, such as land use type, structure type, activity time, inactivity time, population of the activity period, population of the inactivity period and the time of event occurrence in the study area.

For the extraction of the building location, with its complex procedure associated, we use the fuzzy GA presented by Sumer and Turker (2013). The main characteristics of the selected areas in this study are the density and various forms of buildings. To assess the classification accuracies, a reference dataset was prepared for the test scene by means of manually delineating and labelling the buildings from the image. The approach used to identify buildings includes the process of determining parameters such as the number of generations, population size, size of the chromosomes, mutation probability and cross-over probability, which were, respectively, considered as 30, 20, 5, 0.8 and 0.2. GA performance metrics, such as average, maximum fitness value and control parameters (probability of cross-over and mutation) considered as criteria upon which the performance of the adaptive fuzzy logic controller relies. The controller later determined the corrective parameters for use in the next generation of the GA cycle. After determining new possibilities for cross-over and mutation operations, the next generation is built using the new population. The number of generations will be repeated depending on the expected level or the end of the specified number. Each test was repeated 10 times and the highest average of fitness values was calculated for the selected area. In the 20th generation of the algorithm, the fitness value was calculated to be 904. The calculated fitness value cannot be used to assess the quantitative results; therefore, to assess the results, criteria such as producer accuracy (PA), user accuracy (UA), and kappa coefficient (κ) were used. In order to apply post-processing in this study, a structural element with a radius of 3 was used for both opening and closing operations. The intended threshold to remove the artifacts was 100, because this amount represents half of the smallest area (200 m²) among the existing areas in the reference data.

In order to enhance the extraction accuracy, the existing vector data, which were not up to date, were also used for the detection of buildings in the extraction which the proposed algorithm was unable to achieve. A total of 791 buildings were identified in the study area. The output binary image as well as the highest fitness values and PA, UA and κ criteria are shown in Figure 5(a). The extracted locations of the buildings in the pre-event imagery was then mapped to the post-event imagery and was used as the basis for exploration of the disappeared boundaries of the buildings in the after-event image. Finally, the zero value was assigned to the pixels of the outside of the building boundaries as shown in Figure 5(b), and the difference between grey levels of pixels within each
building in the images before and after the earthquake were considered as criteria for assessment of the damage level.

In this study, different textural features were extracted using $3 \times 3$ neighbourhood pixels in four spectral bands. A total of 22 textural features were extracted in each band. The optimum features including mean, homogeneity, sum mean, correlation, cluster tendency, simple variogram, Gabor (mean) and Gabor (standard deviation) were selected using the visual interpretation and were used as the input parameters of the fuzzy inference system to estimate the degree of damage. Afterwards, some linguistic labels were allocated to each variable (input/output). Trapezoidal and triangular membership functions were defined for each linguistic parameter. The value and form of the membership functions were defined by an expert based on his experience in damage degree estimation. The membership functions used as input (difference between the extracted features) and output of the fuzzy system in this study (the damage level) are shown in Figure 6(a). To apply the user’s knowledge in the applied logic, a Mamdani system with rules was created. These rules were considered as the basis for decision-making in relation to the damage in this study, which in Figure 6(b), the if-then rules are expressed by applying fuzzy logic operators. The proposed algorithm was implemented in the study area, as shown in Figure 7. In the resulted damage map of the test area, 740 buildings were classified in the undamaged class (0%), while 51 buildings were classified in the destroyed (100%) and the heavily damaged classes (70%).

In order to assess the accuracy of the proposed algorithm in identifying the damage levels, 291 buildings were randomly selected as reference data of the area. The status of the reference data was then determined visually by an expert operator. The status of these buildings was also determined using the proposed algorithm. Table 4 shows the confusion matrix calculated for the proposed algorithm. The accuracy of any class classification is calculated based on parameters, such as producer accuracy and user accuracy in this table. Finally, the overall accuracy of 82% and kappa coefficient of 0.68% were obtained.

After calculating the damage percentage for each building, the information needed for the casualty estimation model for each land use was extracted from the GIS database, such as the structure material, the time of the accident and dynamic population proportional to the operation time of that land use. The approach was implemented using a program written in the ArcGIS 10.2.2 programming environment. Results of casualties’ estimation showed that about 103 people out of 3185 would be killed and about 3082 would suffer injuries. Figures 8(a) and (b) shows the number of rescued and killed people calculated using the casualty estimation model, respectively. To evaluate the accuracy of the proposed model, the number of casualties collected by the field teams (the result of the report presented by the International Institute of Earthquake Engineering and Seismology...
(Razzaghi & Ghafory-Ashtiany 2012)) for 143 buildings was used as a criterion for evaluating the results. RMSE was calculated between the values estimated by the model and the values collected by the field teams. The RMSE calculated for the number of injured and killed people was 0.040 and 0.025, respectively. Comparison between our results and observed field data shows suitable accuracy of model for the number of fatalities and injuries for each building.

### 3.3. Discussion

According to the attained results from this study, one of the limitations of the method is its weak performance in detecting buildings that have completely collapsed. The proposed algorithm detects these buildings in the undamaged class. With knowledge of the building height before and after the earthquake, this problem can be solved. It is suggested to use the data from other sources, such as

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**Figure 6.** Different parts of the fuzzy inference system: (a) membership functions of the input and the output linguistic variables and (b) fuzzy rules for estimating damage degree of a building.
light detection and ranging data along with satellite images, integrate them together or even generate (DEM) using stereo images to solve these problems and examine data efficiency in future research.

A GIS database is the prerequisite of the proposed casualty estimation method. This database includes the following information, that is, prepared before the earthquake: type of land use, type of building structure and population living in each building separately based on the periods of activity or inactivity. \( D_t \) is calculated immediately after the event in the stage of processing satellite images and also the time of the accident is dynamically updated in the database. The proposed casualty estimation model was extracted from the GIS database based on the damage level, structure type and the population living in the building at the time of accident in order to predict and estimate the casualty toll. One of the limitations of this algorithm is the impossibility of estimating the casualty toll for buildings, the relevant information which is not available in the database. Moreover, the human casualty rate obtained from this method will be close to reality to an acceptable level, but it

Figure 7. Damage map of the study area. Based on the degree of damage, three levels of undamaged (in green), heavily damaged (in yellow) and destructed (in red).

Table 4. Confusion matrix obtained by comparing the algorithm results with the reference data.

| Algorithm results | Destructed | Heavily damaged | Un damaged | Rows total | Omission error | Producer accuracy | Total accuracy | Kappa coefficient |
|-------------------|------------|-----------------|------------|------------|----------------|------------------|---------------|------------------|
| Reference data    | Destructed | 911             | 123        | 77         | 1111           | 0.18             | 0.82          |                  |
|                   | Heavily damaged | 115           | 778        | 115        | 1008           | 0.23             | 0.77          |                  |
|                   | Undamaged   | 201            | 401        | 3103       | 3705           | 0.17             | 0.83          |                  |
| Columns total     | 1227        | 1302           | 3295       | 5824       | 0.82           | 0.68             |               |                  |
| Commission error  | 0.26        | 0.40           | 0.06       |            |                |                  |               |                  |
| User accuracy     | 0.74        | 0.60           | 0.94       |            |                |                  |               |                  |

Note: In this algorithm, the overall accuracy of 82%, kappa coefficient of 68%, average producer accuracy of 81% and an average user accuracy of 76% were obtained.
cannot cover all losses. In this study, only the destruction caused by the earthquake has been investigated as the most important parameter causing the high number of casualties after the event. It is recommended to take into account the effect of secondary factors following an earthquake, including fire, tsunami, rock fall, landslide, and many other factors caused by the earthquake in future research using probabilistic modelling parameters.

Figure 8. Maps obtained from the proposed casualty estimation model in the study area: (a) map of the calculated number of people injured and (b) map of the calculated number of people dead.
4. Conclusion

The most critical stage of the relief and rescue operation after the accident is to determine the number of dead and injured people. This issue will help managers in allocating resources and deploying rescue workers. If the death toll is not being estimated immediately after the accident, results are used only for assessing the damage after the earthquake and are not of efficient use in managing the relief supplies in the golden moments after the accident. Remote sensing technology, with features such as wide coverage, low cost, short return period and high spatial resolution, allows detection of the building damage level immediately after the event. In this study, the proposed method is based on the use of high spatial resolution satellite images and integrating it with data obtained from the GIS database, in order to estimate the number of deaths and injuries after the accident. The output of the model will be made available to the relief managers and planners immediately after being estimated in order to manage and allocate adequate supplies and relief workers.

The method proposed in this study consists of two main parts. In the first part, an algorithm was used based on the use of the textural features on pre- and post-event satellite imagery, in order to detect early the amount of damage to the building. The proposed algorithm was developed based on the assumption that the damaged areas have rougher texture when compared with the undamaged areas and appear equally darker on satellite images. Texture features and building damage level are used as input and output to the proposed system, respectively. By evaluating the proposed method using the available dataset of the city of Ahar and Varzaghan, 82% overall accuracy and a kappa coefficient of 68% were obtained. These results prove the capability of the method for damage map creation using high resolution satellite images.

The second part of the proposed method consists of the casualty estimation model. This model does not only consider the building damage level as the most effective parameter on the number of casualties after the event, but also takes into account other effective characteristics including any building structure type in the model. According to statistics, these two factors have the greatest impact on the high number of casualties after the earthquake. The time parameter was of high importance in increasing the accuracy of the model used in the study. By dividing the population of each land use of the population in the activity and inactivity periods, dynamic population estimates were extracted from the GIS database proportional to the time of the event and were later used as the basis for the estimation model. Moreover, the casualty estimation was done for each building individually which could have more accurate results in comparison with other block based research works. The difference between the actual and anticipated number of casualties of the model is not significant, which shows the ability of the model to estimate the casualties immediately after the earthquake.

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No potential conflict of interest was reported by the authors.

ORCID

Hamid Reza Ranjbar http://orcid.org/0000-0002-7462-0566
Hamid Dehghani http://orcid.org/0000-0002-7449-0132
Ali Reza Azmoude Ardalan http://orcid.org/0000-0001-5549-3189
Mohammad Reza Saradjian http://orcid.org/0000-0002-1734-5860
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