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Earthquake damage mapping techniques using SAR and Optical remote sensing satellite data.

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1. Introduction

The objective of this chapter is to show how it is possible to determine damages caused by seismic events in urban areas using optical and radar data, and automatic or semi-automatic remote sensing techniques. These techniques have revealed themselves a suitable monitoring tool for disaster management since they provide a quick detection of land changes in wide areas, especially in remote areas or where the infrastructures are not well developed to ensure the necessary communication exchanges. Indeed, in the aftermath of these severe disastrous events one of the most urgent needs is to estimate with sufficient reliability and rapidity the amount of population and infrastructures affected for different degrees of damage (Voigt et al., 2007).

The use of these sensors has been addressed to scenario classification procedures, which allow also to recognize objects and changes occurred in the area. Automatic classification procedure concerning changes in urban areas could be used for mapping damage caused by earthquakes as well, being seismic events not so frequents.

Actually, timely and accurate change detection of Earth's surface features is extremely important for understanding relationships and interactions between human and natural phenomena, especially in supporting better decision making. In general, change detection involves the application of multi-temporal datasets to quantitatively analyse the temporal effects of the phenomenon. Because of the advantages such as repetitive data acquisition, synoptic view, and digital format suitable for computer processing, remote sensing data are primary sources which have been using extensively for change detection since the last decades (Lu et al., 2004).

The contribution of space technologies has been demonstrated to be effective for regional/continental damage assessment using low- or medium-resolution remotely sensed data (ranging from 30m to 1 km), and both automatic and manual interpretation approaches have been successfully used for extraction of information at a nominal scale ranging from 1 : 100 000 to 1 : 1 000 000 (Belward et al., 2007).

The space technologies have also been demonstrated their effectiveness for damage assessment at local scale, ranging from 1 : 10 000 to 1 : 25 000 nominal scales. The information extracted at this level was crucial for calibration and estimation of the reliability of low- and medium-resolution assessment, for planning logistics for relief action on the

field immediately after the event, and for planning the resources needed for recovery and reconstruction.

Today, local or detailed damage assessment can also be addressed using Very High Resolution (VHR) satellite data with a spatial resolution ranging from 0.6 to 1m. At the beginning, , the operational methodology for extracting the information at this scale of details was based on manual photo-interpretation of the satellite images, which were processed on the screen by the photo-interpreter as for any other aerial imagery. However, the traditional photo-interpretation methodology has some drawbacks firstly linked to the time (and cost) needed for manual processing of the data and, secondly, to the difficulty in maintaining coherent interpretation criteria in case a large number of photo-interpreters, working in parallel in wide areas in a short time, is available. The long required processing time is in conflict with the need for rapid damage estimation, and the solution to involve parallel photo-interpreter teams often leads to an increase of time-consuming organizational problems and additional coherency lack in the information produced (Pesaresi et al., 2007). Accordingly, some automatic procedures for exploiting these data have been developed in order to give information at this scale of detail. The most innovative automatic approaches will be described in this chapter.

For an operational use of this kind of techniques the major limitation is the availability of the images within a short time to manage the crisis. This is a key point for Civil Protections who needs a fast and draft overview of the epicentral area, quick information relative to the extension and distribution of damages, and the evaluation of infrastructure (roads, bridges) conditions. A single satellite can provide access time to a specific site in the order of some days, as a result the necessity to use any kind of satellites data available and an integration of those data is mandatory to increase the chance to collect information on near real time.

The following paragraphs are addressed to the analysis of the different aspects leading to obtain maps representative of damage caused by earthquakes.

2. SAR and Optical satellite sensors and missions

Earth observation satellites have a major mission to observe the entire Earth, so they circle the most suitable Sun-synchronous sub-recurrent orbit. A Sun-synchronous orbit refers to the orbit where the positioning between the satellite and the Sun is always identical . Namely, the incidence angle of sunlight to the land surface is always the same. This orbit characteristic allows to accurately observing radiation and reflection from the land surface. While the sub-recurrent orbit means that after a certain number of days, the satellite repeats its original orbit. Thus, Earth observation satellites utilize the combination of these two orbits, which allow observing the same area at regular intervals under the condition of the same sunlight angle to the land surface.

Furthermore, sensors can be divided into two types: Optical and Microwave sensors.

Optical sensors observe visible lights and infrared rays (near infrared, intermediate infrared, thermal infrared). There are two kinds of observation methods using optical sensors: visible/near infrared remote sensing and thermal infrared remote sensing. The first one consists in acquiring visible light and near infrared rays of sunlight reflected by objects on the ground. By examining the strength of reflection, we can understand conditions of land surface, e.g., distribution of plants, forests and farm fields, rivers, lakes, urban areas. During period of darkness this method cannot be observe. Instead, the latter method acquires

thermal infrared rays radiated from land surface heated by sunlight. It can also observe the high temperature areas, such as volcanic activities and fires. By examining the strength of radiation, we can understand surface temperatures of land and sea, the status of volcanic activities and forest fires.

Microwave sensors transmit and/or receive microwaves, longer wavelength than visible light and infrared rays, and the observation is time and weather independent. There are two types of observation methods using microwave sensor: active and passive. In the first one the sensor aboard earth observation satellite emits microwaves and observes microwaves reflected by land surface, as the case of Synthetic Aperture Radar (SAR). The second one observes microwaves naturally radiated from land surface. It is suitable to observe sea surface temperature, snow accumulation and thickness of ice.

While optical sensors are affected by cloud cover limitations, SAR is widely used in environmental studies due to its fairly synoptic view in almost completely weather and time independent conditions. Moreover, like the optical sensors which have reached resolution less than one meter (e.g. QuickBird, Ikonos, WorldView – 1, GoeEye-1) since 2001, SAR has overtaken its own limitations in terms of ground resolution with the launch of the new generation satellite missions TerraSAR-X and COSMO-SkyMed .

Destructive earthquakes challenge satellite remote sensing damage mapping techniques to demonstrate their usefulness in supporting intervention and relief actions. The use of remote sensing data in a disaster context has been widely investigated from a theoretical point of view, but only recently the developed methods seem to be useful for the operational use (Chini et al., 2008d).

Nowadays the implementation of satellite constellations is reducing the access time with the same sensor to 12 hours, as in the case of the Italian COSMO-SkyMed system. One the most important aspects of this new satellite mission is that the COSMO-SkyMed system is a constellation of four satellites (three of which are already in orbit, the first of which was launched in June 2007), developed to provide fast, meter level-resolution, all-weather imagery for disaster management (Stramondo et al., 2008). COSMO-SkyMed is a project in cooperation between the Italian Space Agency (ASI) and the Italian Defence Ministry (MD) and it is the first satellite constellation devoted to the Earth's observation for both civil and military purposes. The system hosts a flexible, multimode X-band synthetic aperture radar (SAR), with right and left looking imaging capabilities, an incidence angle range of 20°–60°, and a minimum revisit time of 12 hours. The fixed antenna has electronic scanning capabilities in both the azimuth and the elevation planes. It has been designed to implement three different operation modes in order to acquire the images at different resolutions: i) Spotlight mode, for metric (1m) resolutions over small images; Stripmap mode for metric resolutions (5 m) over tenth of km images; iii) ScanSAR mode, for medium to coarse (100 m) resolutions over large swaths (Boni et al, 2008).

3. Damage mapping by SAR data

Multi-temporal observations from SAR can be used to detect urban changes either looking at the image intensity changes, as in the case of optical images, but also taking advantage from the information on the phase of the returned signal. This is specific of the radar technique and in particular of the interferometric SAR (InSAR). The intensity correlation and the InSAR complex coherence are two important features for recognizing changes on

the surface caused by an earthquake. These two features hold different information concerning changes in the scene (Stramondo et al., 2006). The complex coherence is prevalently influenced by the phase difference between radar returns, a distinctive parameter measured by a coherent sensor. It is particularly related to the spatial arrangement of the scatterers within the pixel and thus to their possible displacements. Conversely, the intensity correlation is more related to change in the magnitude of the radar return (Bignami et al., 2004).

Changes in SAR intensity and phase backscattering have been largely studied by many scientists for earthquake damage mapping purposes. An index to estimate damage level from SAR data by combining image intensity changes and the related correlation coefficient has been achieved and applied to some case studies: the Hyogoken-Nanbu earthquake (Aoki et al., 1998; Matsuoka & Yamazaki, 2004) and the Izmit and Gujarat seismic events (Matsuoka & Yamazaki, 2002; Stramondo el al., 2006). Yonezawa & Takeuchi (2001) have compared changes in the SAR intensity and phase backscatter with damage observed in Kobe. Ito et al. (2000) have assessed different SAR change indicators, derived from L- and C-band sensors, and evaluated the frequency-dependent effects of spatial and temporal decorrelations. Chini et al. (2008a) have detected wide uplift and subsiding areas, as well as large modifications of the coastline associated to the Indonesian earthquake of 2004, using only pre- and post-earthquake SAR backscattering.

It is commonly acknowledged that due to speckle effects (Li & Goldstein, 1990), single-pixel classification of SAR images leads to unsatisfactory results, and this seems to hold true also when damage assessment is concerned. Satisfying results may be achieved if the damage is assessed at a block level, mitigating the speckle noise (Bazi ert al., 2005) by means of averaging in somehow the unreliable results of pixel-wise comparing pre-and post-event images (Gamba et al., 2007). The partition of the image into blocks can be made by visual inspection or using a GIS layer provided by local authorities during crisis phase; otherwise procedures for segment images starting from SAR or optical images are reported in literature. Indeed, city blocks are generally marked by their respective bounding urban roads, which allow to segmenting the urban area.

Nowadays the new very high resolutions SAR sensors, few meters resolution, allow to classifying urban areas, producing reliable land use maps exploiting contextual information from backscattering data. Chini et al., 2009b have investigated the use of contextual information with TerraSAR-X backscattering images for classifying urban land-use. The anisotropic multi-scale morphological filters, coupled with the pruning neural network as a features selection tool, was able to provide urban land-use maps with accuracies of about 0.90 in terms of K-coefficient. This kind of techniques will allow producing damage map at building scale using very high resolution SAR data as it is already done using Very High Resolution (VHR) optical images.

4. Damage mapping by Very High resolution Optical data

The presence of shadows, variations in solar illumination, and geometric distortions may prevent the use of automatic damage detection procedures in optical images. Because of these problems, visual image inspection is still the most widely used method to produce a realistic and reliable inventory of damage (Saito et al., 2004; Yamakaki et al., 2004). Sakamoto et al. (2004) compared with an automatic technique combined with visual

interpretation results using QuickBird data. Matsuoka et al. (2004) proposed to detect damage by analyzing edges in high-resolution images. More in general, automatic change-detection algorithms using either QuickBird (Pacifici et al., 2007; Chini et al., 2008) or SAR images (Inglada & Mercier, 2007) are also present in the literature, even if using SAR data have been only exploited the medium resolution.

One of the most important issue when we set a change detection classifier for mapping damages is the rapidity for producing damage maps, especially if we are supporting rescue teams during crisis phase. This characteristic is related to the number of inputs, which are the bands used for classifying, the number of samples for training the supervised classifier and the time spent for selecting training samples representative of the classes we want to identify.

Usually, the unsupervised classifiers are used for overcoming the time consuming step for selecting training pixels, since the post processing task for labelling the classes of interest is faster. The use of an unsupervised classifier, with QuickBird panchromatic images, has provided a damage map at a pixel scale of 0.6 m which allow to detect the complete or partial collapse of individual buildings in the Bam city (Iran) caused by the earthquake occurred on 2003 (Chini et al., 2009a). Moreover, the mathematical morphology (Benediktsson et al., 2003; Benediktsson et al., 2005; Soille, 2003) has proved to be a powerful tool for automatically analyze the panchromatic images. Furthermore, the unsupervised classifier, the mathematical morphology and very high resolution images have permitted to give damage level at building scale which is a more realistic damage degree and more useful for civil protection activity. The damage level at building scale is closer to damage index provided by ground survey team (Chini et al. 2008c).

When the number of training pixels is fixed or limited by whatever factor (including the cost of gathering them by in situ campaigns), experience has shown an initial increase in the classification accuracy by adding features, followed by a subsequent decay in classification skill as more features are considered (Hughes, 1968).

The increase in dimensionality (i.e., number of inputs) of the data worsens the parameter estimates, overcoming the expected increase in class separability associated with the inclusion of additional features. Therefore, one needs to use a robust method to estimate parameters or to reduce the number of inputs. For instance, principal component analysis is used to diminish the number of features (Landgrebe, 2003). Regularization methods have also been proposed in the literature, as discussed in (Berge & Solberg, 2004), attempting to stabilize the estimated class covariance matrix by replacing it with a weighted sum of the class sample covariance matrix or the common (pooled) covariance matrix. Additional methods include regularizing discriminant analysis (Friedman, 1989), leave-one-out covariance estimation (Hoffbeck & Landgrebe, 1996), and pruning methods when we deal with neural networks (Pacifici et al., 2009).

A robust method for estimating parameters has been proposed by Chini et al., (2008b), which is different respect to method presented previously. The number of inputs is not reduced, but they are composed differently in the new architecture to overcome the difficulty of having poor training samples for some classes. This method speeds up the overall analysis time (computation plus error correction) and increases the change detection accuracies. It consists on using a parallel approach to exploit the multi-spectral and multi-temporal characteristics of two scenes, thus combining two approaches which are typically used for supervised change detection, the post classification comparison (Del Frate et al.,

2004; Serra et al., 2004; Sunar Erbek et al., 2004) and the direct multi data classification (Sunar Erbek et al., 2004; Castelli et al., 1998).

The post classification comparison detects changes by comparing the classification maps obtained by independently classifying the two sequential remote sensing images of the same scene. This method does not require normalization to compensate for atmospheric conditions and sensor differences between the acquisition dates. At the same time, this method does not exploit the correlation between multi-temporal data sets, and its accuracy depends on the product of the accuracy of single classification maps (Yuan & Elvidge, 1998). The change detection in direct multi data classification is directly performed by considering each transition as a class in a unique vector obtained by stacking the features related to the individual images; this method is more sensitive to solar and atmospheric conditions.

An efficient method for reducing the number of inputs and selecting the most important features for classifying a certain typology of urban landscape has been implemented by Pacifici et al., (2009), using QuickBird and Worldview-1 panchromatic images. This work has investigated on the potential of these very high resolution panchromatic imageries (the most resolute optic satellite sensors) to classify the land-use of urban environments. Usually spectral-based classification methods may fail with the increased geometrical resolution of the data available. Indeed, improved spatial resolution data increases within-class variances, which results in high interclass spectral confusion. In many cases, several pixels are representative of objects, which are not part of land-use classes defined. This problem is intrinsically related to the sensor resolution and it cannot be solved by increasing the number of spectral channels. To overcome the spectral information deficit of panchromatic imagery, it is necessary to extract additional information to recognize objects within the scene. The multi-scale textural (Haralick, 1979; Haralick et al., 1973) approach exploited the contextual information of panchromatic images. Moreover, neural network pruning (Kavzoglu & Mather 1999; Del Frate et al., 2005) and saliency (Yacoub & Bennani, 1997; Tarr, 1991) measurements have allowed to give an indication of the most important textural features for sub-metric spatial resolution imagery and different urban scenarios.

This has to be a preparatory work, it should be done before the emergency phase, because it gives very useful information concerning the minimum number of inputs necessary for obtain reliable classification maps. Another important aspect of this study is that it uses a very small dataset, only one panchromatic image, all others inputs are contextual information, second order spatial statistic, extracted from the original panchromatic image. The latter aspect is crucial during crisis, where it is necessary processing data as soon as they are acquired from satellites.

5. Conclusions

In this chapter the sensitivity to the urban damage level of different parameters extracted from different types of remotely sensed images has been analyze. It has been highlighted that the parameters to be extracted are strictly related to the type of exploited data (i.e., their resolution and spectral channels). Additionally, this chapter aimed to demonstrate how very high resolution (VHR) images can detect damage at the pixel scale (≤ 1 m) with automatic techniques. Associated problems have been pointed out and ways to overcome them have been proposed.

The chapter has provided a quite realistic view of what remote sensing can offer for this application and which methods and sensors worth to be further developed in the future. From our experience in this field it is possible to affirm that damage products can be obtained at different ground scales and with different satellite data. Those products can be valuable for managing different phases of the crises, and especially mitigation of the effect in the course of the event and precise inventory of the damage in the post-event phase.

It has been pointed out that an operational use of remote sensing for earthquake damage assessment strongly depends on the number of available images, their type (SAR, optical, or both), and quality and timeliness of the data sets (i.e., time delay of the post-seismic images with respect to the destructive event). In particular, the availability of images within a short time to manage the crisis is a key point for Civil Protections who needs a fast and draft overview of the epicentral area, quick information relative to the extension and distribution of damages, and the evaluation of infrastructure (roads, bridges) conditions. Since, a single satellite can provide access time to a specific site in the order of some days, the use of any type of satellites data available, an integration of those data and the exploitation of data provided by constellation missions is mandatory to increase the chance to collect information on time.

The conclusive indication on the effectiveness of remote sensing for earthquake damage detection requires the accumulation of many analyses by different scientists and the work done here will hopefully contribute to this end. For all of these reasons, research of change detection techniques is still an active and very challenging topic and new techniques are needed to effectively use the increasingly diverse and complex remotely sensed data available.
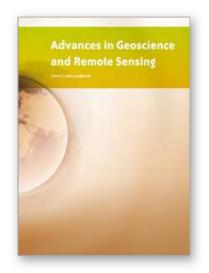
6. References

Aoki, H.; Matsuoka, M. & Yamazaki, F. (1998). Characteristics of satellite SAR images in the damaged areas due to the Hyogoken-Nanbu earthquake, Proceedings of 19th Asian Conference on Remote Sensing 1998, Vol. C7, pp. 1–6.

Bazi, Y.; Bruzzone, L. & Melgani, F. (2005). An unsupervised approach based on the generalized Gaussian model to automatic change detection in multitemporal SAR images, IEEE Transaction of Geoscience and Remote Sensing, Vol.43, No.4, pp. 874-887.

Belward, A. S.; Stibig H. J.; Eva, H.; Rembold, F.; Bucha, T.; Hartley, A.; Beuchle, R.; Khudhairy, D.; Michielon, M. & Mollicone, D. (2007). Mapping severe damage to land cover following the 2004 Indian Ocean tsunami using moderate spatial resolution satellite imagery, International Journal of Remote Sensing, Vol. 28, No. 13–14, pp. 2977–2994.

Benediktsson, J. A.; Pesaresi, M. & Arnason, K. (2003). Classification and feature extraction for remote sensing images from urban areas based on morphological transformations, IEEE Transactions on Geoscience and Remote Sensing, Vol. 41, No. 9, pp. 1940–1949.

Benediktsson, J. A.; Palmason, J. A. & Sveinsson, J. R. (2005). Classification of hyperspectral data from urban areas based on extended morphological profiles, IEEE Transactions on Geoscience and Remote Sensing, Vol. 43, No. 5, pp. 480–491.

Berge, A. & Solberg, A. S. (). A comparison of methods for improving classification of hyperspectral data, Proceedings of IEEE IGARSS 2004, Anchorage (Alaska, USA), Vol. 2, pp. 945–948, September 20-24, 2004.

Bignami, C.; Chini, M.; Pierdicca, N. & Stramondo, S. (2004). Comparing and combining the capability of the detecting earthquake damages in urban areas using SAR and optical data, Proceedings of IEEE IGARSS 2004, Vol. 1, pp.55-58, Anchorage (Alaska, USA), September 20-24, 2004.

Boni, G.; Castelli, F.; Ferraris, L.; Pierdicca, N.; Serpico, S. & Siccardi, F. (2007). High resolution COSMO/SkyMed SAR data analysis for civil protection from flooding events, Proceeding of IEEE IGARSS 2007, pp. 6 – 9, Denver (CO - USA), July 23-28, 2007.

Castelli, V.; Elvidge, C. D.; Li, C. S. & Turek, J. J. (1998). Classificationbased change detection: Theory and application to the NALC data set, In: Remote Sensing Change Detection: Environmental monitoring methods and applications, pp. 53-73, R. S. Lunetta and C. D. Elvidge, Eds. Chelsea, MI: Ann Arbor Press, 1998.

Chini, M.; Bignami, C.; Stramondo S. & Pierdicca, N. (2008a). Uplift and subsidence due to the 26 December 2004 Indonesian earthquake detected by SAR data, International Journal of Remote Sensing, Vol. 29, No. 13, pp. 3891–3910.

Chini, M.; Pacifici, F.; Emery, W. J.; Pierdicca, N. & Del Frate, F. (2008b). Comparing statistical and neural network methods applied to very high resolution satellite images showing changes in man-made structures at Rocky Flats, IEEE Transactions on Geoscience and Remote Sensing, Vol. 46, No. 6, pp. 1812–1821.

Chini, M.; Bignami, C.; Stramondo, S.; Emery, W. J. & Pierdicca, N. (2008c). Quickbird Panchromatic Images for Mapping Damage at Building Scale Caused by the 2003 Bam Earthquake, Proceedings of IEEE IGARSS 2008, Vol. 2, pp. 1029-1031, Boston (USA), July 7 – 11, 2008.

Chini, M.; Bignami, C.; Brunori, C.; Atzori, S.; Tolomei, C.; Trasatti, E.; Kyriakopoulos, C.; Salvi, S.; Stramondo, S. & Zoffoli, S. (2008d). The SIGRIS project: a remote sensing system for seismic risk management, Proceedings of IEEE IGARSS 2008, Vol. 3, pp. 624-627, Boston (Massachusetts, USA), July 7 – 11, 2008.

Chini, M.; Pierdicca, N. & Emery, W. J. (2009a). Exploiting SAR and VHR optical images to quantify damage caused by the 2003 Bam earthquake. IEEE Transaction on Geosciences and Remote Sensing, Vol. 47, No. 1, pp. 145 - 152.

Chini, M.; Pacifici, F. & Emery, W. J. (2009b). Morphological operators applied to X - band SAR for urban land use classification, Proceedings of IEEE IGARSS 2009, Cape Town (South Africa), July 13 – 18, 2009.

Del Frate, F.; Schiavon, G. & Solimini, C. (2004). Application of neural networks algorithms to QuickBird imagery for classification and change detection of urban areas, Proceedings of IEEE IGARSS 2004, Anchorage (Alaska, USA), pp. 1091–1094, September 20-24, 2004.

Del Frate, F.; Iapaolo, M.; Casadio, S.; Godin-Beekmann, S. & Petitdidier, M. (2005). Neural networks for the dimensionality reduction of GOME measurement vector in the estimation of ozone profiles, Journal of Quantitative Spectroscopy & Radiative Transfer, Vol. 92, No. 3, pp. 275−291.

Friedman, J. (1989). Regularized discriminant analysis, Journal of the American Statistical Association, Vol. 84, No. 405, pp. 165–175.

Gamba, P.; Dell'Acqua, F. & Trianni, G. (2007). Rapid Damage Detection in the Bam Area Using Multitemporal SAR and Exploiting Ancillary Data, IEEE Transaction of Geoscience and Remote Sensing, Vol.45, No.6, pp.1582-1589.

Haralick, R. M.; Shanmuga, K. & Dinstein, I. H. (1973). Textural features for image classification, IEEE Transactions on Systems, Man, and Cybernetics, Vol. SMC-3, No. 6, pp. 610−621.

Haralick, R. M. (1979). Statistical and structural approaches to texture. Proceedings of the IEEE, Vol. 67, No.5, pp. 786−804.

Hoffbeck, J. & Landgrebe, D. (1996). Covariance matrix estimation and classification with limited training data, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 18, no. 7, pp. 763–767.

Hughes, G. F. (1968). On the mean accuracy of statistical pattern recognizers, IEEE Transactions on Information Theory, Vol. IT-14, No. 1, pp. 55–63.

Inglada, J. & Mercier, G. (2007). A new statistical similarity measure for change detection in multitemporal SAR images and its extension to multiscale change analysis, IEEE Transactions on Geoscience and Remote Sensing, Vol. 45, No. 5, pp. 1432–1445.

Ito, Y.; Hosokawa, M.; Lee, H. & Liu, J. G. (2000). Extraction of damaged regions using SAR data and neural networks, Proceedings of 19th ISPRS Congress 2000, vol. 33, pp. 156–163, Amsterdam, (NETHERLANDS), July 16–22, 2000.

Kavzoglu, T. & Mather, P. M. (1999). Pruning artificial neural networks: An example using land cover classification of multi-sensor images. International Journal of Remote Sensing, Vol. 20, N. 14, 2787−2803.

Landgrebe, D. A. (2003). Signal Theory Methods in Multispectral Remote Sensing, Hoboken, NJ: Wiley, 2003.

Li, F. K. & Goldstein, R. M. (1990). Studies of multibaseline spaceborne interferometric synthetic aperture radar," IEEE Transaction of Geoscience and Remote Sensing, Vol. 28, No. 1, pp. 88–97.

Lu D.; Mausel, P.; Brondizio, E. & Moran, E. (2004). Change detection techniques. International Journal of Remote Sensing, Vol. 25, No. 12, pp. 2365–240720.

Matsuoka, M. & Yamazaki, F. (2002). Application of the damage detection method using SAR intensity images to recent earthquakes, Proceedings of IEEE IGARSS 2002, Vol. 4, pp. 2042–2044, Toronto (CANADA), June 24-28, 2002.

Matsuoka, M. & Yamazaki, F. (2004). Use of satellite SAR intensity imagery for detecting building areas damaged due to earthquakes, Earthquake Spectra, Vol. 20, No. 3, pp. 975–994.

Matsuoka, M.; Vu, T. T. & Yamazaki, F. (2004). Automated damage detection and visualization of the 2003 Bam, Iran, earthquake using high resolution satellite images, Proceedings of 25th Asian Conference on Remote Sensing 2004, pp. 841–845, Chiang Mai (THAILAND), November 22-26, 2004.

Pesaresi, M.; Gerhardinger, A. & Haag, F. (2007). Rapid damage assessment of built-up structures using VHR satellite data in tsunami-affected areas, International Journal of Remote Sensing, Vol. 28, No. 13–14, pp. 3013–3036.

Pacifici, F.; Del Frate, F.; Solimini, C. & Emery, W. J. (2007). An innovative neural-net method to detect temporal changes in high-resolution optical satellite imagery, IEEE Transactions on Geoscience and Remote Sensing, Vol. 45, No. 9, pp. 2940–2952.

Pacifici, F.; Chini, M. & Emery, W. J. (2009). A neural network approach using multi-scale textural metrics from very high resolution panchromatic imagery for urban land-use classification, Remote Sensing of Environment, Vol. 113, No. 6, pp. 1276 – 1292.

Saito, K.; Spence, R. J. S.; Going, C. & Markus, M. (2004). Using high resolution satellite images for post-earthquake building damage assessment: A study following the 26 January 2001 Gujarat earthquake, Earthquake Spectra, vol. 20, No. 1, pp. 145–169.

Sakamoto, M.; Takasago, Y.; Uto, K.; Kakumoto, S. & Kosugi, Y. (2004). Automatic detection of damaged area of Iran earthquake by high-resolution satellite imagery," Proceedings of IEEE IGARSS 2004, vol. 2, pp. 1418–1421, Anchorage (Alaska, USA), September 20-24, 2004.

Serra, P.; Pons, X. & Saurì, D. (2004). Post-classification change detection with data from different sensors: Some accuracy considerations, International Journal of Remote Sensing, Vol. 24, No. 16, pp. 3311–3340.

Soille, P. (2003). Morphological Image Analysis—Principles and Applications, 2nd ed. Berlin, Germany: Springer-Verlag, 2003.

Stramondo, S.; Bignami, C.; Chini, M.; Pierdicca, N. & Tertulliani, A. (2006). The radar and optical remote sensing for damage detection: results from different case studies, International Journal of Remote Sensing, Vol. 27, No. 20, pp. 4433 – 4447.

Stramondo, S.; Chini, M.; Salvi, S.; Bignami, C.; Zoffoli, S. & Boschi, E. (2008). Ground Deformation Imagery of the 12 May 2008 Sichuan Earthquake, EOS Transaction American Geophysical Union, Vol. 89, No. 37, pp. 341-342.

Sunar Erbek, F.; Ozkan, C. & Taberner, M. (2004). Comparison of maximum likelihood classification method with supervised artificial neural network algorithms for land use activities, International Journal of Remote Sensing, Vol. 25, No. 9, pp. 1733–1748.

Tarr, G. (1991). Multi-layered feedforward neural networks for image segmentation, Ph. D. dissertation, School of Engineering, Air Force Institute of Technology. Wright-Patterson AFB OH.

Voigt, S.; Kemper, T.; Riedlinger, T.; Kiefl, R.; Scholte, K. & Mehl, H. (2007). Satellite image analysis for disaster and crisis-management support, IEEE Transaction on Geoscience and Remote Sensing, Vol. 45, No. 6, pp. 1520–1528.

Yacoub, M. & Bennani, Y. (1997). HVS: A heuristic for variable selection in multilayer artificial neural network classifier. In: Intelligent engineering systems through artificial neural networks, pp. 527-532, Dagli, C.; Akay, M.; Ersoy, O.; Fernandez, B. & Smith, A. (Eds.), Missouri, USA: St Louis.

Yamakaki, F.; Matsuoka, M.; Kouchi, K.; Kohiyama, M. & Muraoka, N. (2004). Earthquake damage detection using high-resolution satellite images, Proceedings of IEEE IGARSS 2004, Vol. 4, pp. 2280–2283, Anchorage (Alaska, USA), September 20-24, 2004.

Yonezawa, C. & Takeuchi, S. (2001). Decorrelation of SAR data by urban damage caused by the 1995 Hoyogoken-Nanbu earthquake, International Journal of Remote Sensing, Vol. 22, No. 8, pp. 1585–1600.

Yuan, d. & Elvidge, C. (1998). NALC land cover change detection pilot study: Washington D.C. area experiments, Remote Sensing of Environment, Vol. 66, No. 2, pp. 168–178.

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Remote sensing is the acquisition of information of an object or phenomenon, by the use of either recording or real-time sensing device(s), that is not in physical or intimate contact with the object (such as by way of aircraft, spacecraft, satellite, buoy, or ship). In practice, remote sensing is the stand-off collection through the use of a variety of devices for gathering information on a given object or area. Human existence is dependent on our ability to understand, utilize, manage and maintain the environment we live in - Geoscience is the science that seeks to achieve these goals. This book is a collection of contributions from world-class scientists, engineers and educators engaged in the fields of geoscience and remote sensing.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

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