URBAN CHANGES WITH SATELLITE IMAGERY AND LIDAR DATA

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ABSTRACT:

It is important to know how urban areas change for monitoring the evolution of demographics, lifestyles, and economic trends. The objective of this paper is to present a method for determining the occurrence of building change between two dates. The information on buildings for the first date comes from digital cartography and for the second date comes from spatial imagery and LIDAR data. A Support Vector Machine algorithm with automatic training was applied to detect the buildings on the second date and then the results were compared with the buildings of the first date, represented by vectorial data from the digital cartography. It is argued how urban vegetation change could also be derived from the building change study. Two areas of four square kms each, from central Spain, were considered to test the proposed approach. The first area corresponds to the university Campus of Alcala, where few changes have happened in the last years; and the second area corresponds to a new residential area in the suburb of the city of Alcala, with many constructions in the last years. Results showed a 1% and 7% increase of buildings respectively. The proposed method was evaluated for efficacy and suitability using ground truth obtained manually for the second area. Some discussion and conclusions are stated about the approach to be used and the best data entry in order to obtain an optimal performance.

1. INTRODUCTION

The Earth surface is being significantly altered mostly due to anthropogenic activities. Land use and land cover change (LULC) has become a central factor in current strategies for managing natural resources, monitoring environmental changes and estimating urban growth. Detecting land-cover land-used changes using spatial data bases and remote sensing imagery is one of the most important applications of remote sensing. But monitoring and mapping requires reliable data and regular intervals. Currently, the interpretation of high-resolution satellite images is carried out "manually" by visual interpretation. This is so because traditional classification algorithms that were used for low resolution data are too limited in dealing with the complexity of high-resolution data available today.

In this paper we examined changes in urban and suburban areas; specifically, we focused on buildings, which are good indicators of urban dynamics. In the LULC for Spain, the national mapping agency (The National Geographic Institute) has developed the program *Sistema de Información del Suelo de España* SIOSE (Valcarcel et al., 2008). This is a new LULC for Spain designed according to the INSPIRE principle, and ISO TC/211 standards. It divides the territory into parcels or polygons; each parcel was assigned one or several simple covers. Each cover was given a percentage of occurrences of this cover within the parcel. Among the different land cover types, in this paper we studied only the one for buildings, using as a measure of change the percentage of change on the buildings' occurrence within the parcel. The first SIOSE was completed in 2009, in subsequent years there will be a need for updating it. Updating is usually done using photointerpretation and terrain visits. This is similar to what happened in the rest of Europe when updating their LULC cartography. There is a general need for automatic or at least semi-automatic methods to help in the updating process.

Changes between two dates can be studied with different types of data. It can be compared by vectorial data with vectorial data, vectorial with raster, or raster with raster. In this paper vectorial data is compared with raster. Within each type of data, vectorial and raster, it can be used with aerial imagery, satellite imagery, optical or radar, LIDAR, or miscellanea from secondary sources such as cartography. It can be used at different resolutions and scales. Therefore the different numbers of combinations is large. It is important to know the optimal combination of the type of data for tackling a specific problem.

In this way Grey et al. (2004), have studied urban change in the UK using satellite radar interferometry. Many other types of data have been used for change detection. Only considering multi-spectral imagery and LIDAR data there are many possibilities of data combinations for studying change detection. Knudsen and Olsen (2003) studied change detection for updating map databases. Olsen (2004) stated that spectral information of buildings is ill-defined and proposed using LIDAR in assisting the change detection for updating the TOP10DK database map. A paper by Sohn and Dowman (2007) proposes a new building extraction method from IKONOS imagery and LIDAR. The approach detected dominant features comprising the urban scene isolating construction from surrounding features. As a case study the technique was applied to a sub-scene of the Greenwich area in London and the results

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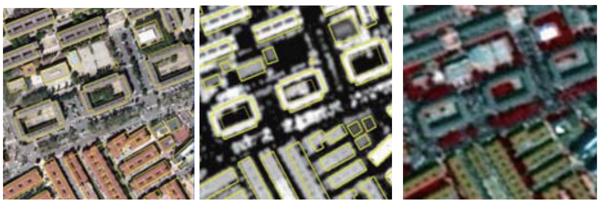
showed that the approach successfully delineated most buildings in the scene.

The measurement of impervious surfaces has become a necessity for a number of applications. Hung and Germaine (2008), using multispectral and LIDAR, obtained 91% accuracy, while when adding LIDAR it increased to 94%. In general, when LIDAR is added the detection of buildings and other classes are improved (see Alonso and Malpica, 2008).

We present a method for automatic building change detection, based on the Support Vector Machine (SVM) algorithm. The input to the algorithm is the four pansharpened bands (2.5 meters of resolution), the normalize Digital Surface Model (nDSM) and the vector layer from the Spanish national cartographic data base. The output from the algorithm is the layer of probability for buildings that is converted to a binary image with a threshold. Once the percentage of building occurrence in the area is calculated, a comparison with the percentage of building occurrence in the cartography for a previous date is obtained.

Results confirm the findings presented in other symposiums and journal works that height is fundamental when detecting buildings. For that reason, the introduction of LIDAR has been a key to the success of the proposed method, since it has obtained a detection rate superior to 90% in most cases.

2. MATERIALS AND STUDY AREA



(a) (b) (c)

Figure 1. (a) Aerial Image with Vectorials, (b) nDSM with Vectorials, and (c) False Color Pansharpened SPOT5 Image (© SPOT Image Copyright 2004)

In this paper we studied the change in buildings between two dates 6 years apart of an area of central Spain, the city of Alcala de Henares and surroundings in Madrid. The first data belonging to the year 1999 consists of only vectorial cartography. While the second set of data from 2006 comprise SPOT5, aerial imagery and LIDAR data.

The digital cartography used in this work is taken from a Spanish digital database called *Base Cartográfica Nacional* (BCN), the part we are studying was compiled in 1999. It has a scale of 1:25000. Figure 1 (a) and (b) show an example of the vector cartography overlaying the aerial image and the LIDAR, respectively.

There are many high resolution satellites today, from them we took SPOT5, which is the fifth satellite of the SPOT series program designed by the *France Centre National D'éstudes Spatiales*. The image we used was taken at 11:23 GMT on August 6, 2006, the sun had an elevation of 62.37º and an azimuth of 150.06°. This image was obtained with spatial resolutions: 2.5 m in panchromatic mode and 10 m for three multispectral bands in the blue, red and short infrared, and 20 m resolution for a middle infrared band. Applying Principal Component Analysis all bands were pansharped to a resolution of 2.5 meters.

LIDAR systems record data elevation by measuring the time delay between a pulse emission (from an aeroplane to the terrain) and their detection by the reflected signal. The resulting data gives rise to a very dense network of points. It provides data not only for the first return but also the second and third, providing heights of buildings and vegetation. A significant advantage to this technology is that data can be captured independent of atmospheric conditions. For instance, data collection can be performed from an airplane in flight at night or in low visibility conditions. The point density of the LIDAR data used in our experiment was 0.5 point per square metre, which represents about three points for each SPOT5 pixel.

A Digital Terrain Model (DTM) is a numerical data structure that represents the spatial distribution of the ground surface altitude. The DTM provides the so-called bare earth model, devoid of landscape features. In contrast, a Digital Surface Model (DSM) can be useful for modelling landscapes, shaping cities, and allowing the development of visualization applications. The LIDAR data used in this work were derived as a subtraction of the DSM from the DTM; in that way the normalized digital surface model (nDSM) (Figure 1 (b)) was obtained. See Martinez de Aguirre and Malpica (2010) for more details on how this was done.

Aerial imagery was used only for representation purposes. It was taken from the Spanish Mapping Agency PNOA (Arozarena et al., 2005). This image has a resolution of 0.5 meters. The reason to use SPOT5 instead of aerial images is that SPOT has two infrared bands while aerial had none (during the time of the study in 2006), and infrared bands are useful for detecting vegetation, and separating it from the buildings. Currently, most aerial surveying in Spain is done with RGB and infrared.

3. METHOD

The problem is that in the normalized DSM (see Figure 1 b) buildings cannot be distinguished from vegetation automatically. Developing algorithms for the automation of this task is a key point for full automatic building change detection.

The support vector machine (SVM) is a popular classification technique that was first proposed by Boser et al. (1992) who applied SVM to solve optical character recognition problems. From a theoretical point of view, SVM is based on the statistical learning theory proposed by Vapnik (1995). SVM is basically a binary classifier that maximizes the margin between the training patterns and the decision boundary. SVM has been shown to be superior to other classification methods, such as to Mahalanobis distance (Rodríguez- Berrocal and Malpica, 2010; García-Gómez et al., 2010) or artificial neural networks (Rodriguez and Malpica, 2010).

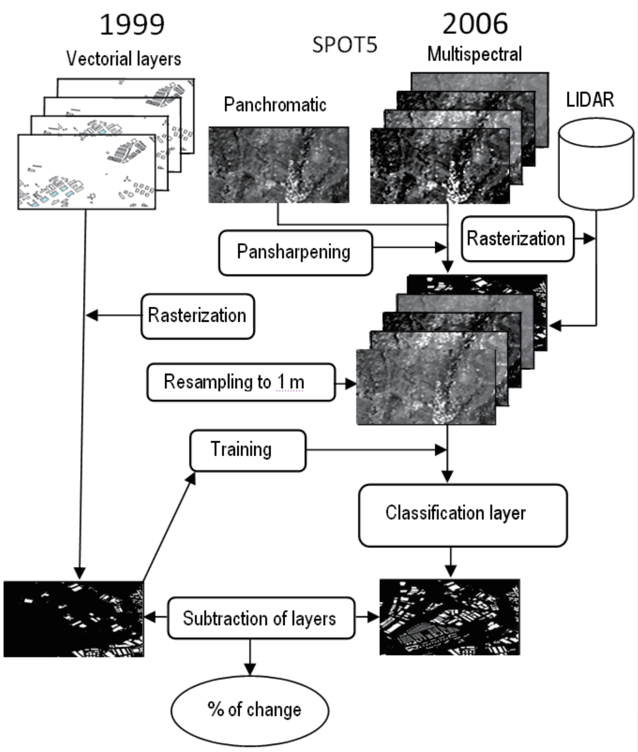


Figure 2. Flow chart

Our research group in Alcala implemented an algorithm using SVM to separate high vegetation and buildings. Using it a classification for the buildings was obtained. A schematic representation of the sequence of operation of the method can be seen in the flow diagram of Figure 2. The training for the algorithm was taken automatically from the cartographic data base BCN. The accuracy of the results is presented by the Receiver Operating Characteristic (ROC) (Swets, 1979). A detailed explanation of the algorithm will be published elsewhere (Malpica and Alonso, 2010).

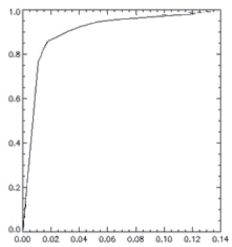


Figure 3. ROC for the SVM Algorithm

The accuracy of a classifier can be measured by the area under the ROC curve, in our case (Figure 3) was at 0.95. The shape of the ROC curve tells us that it depends where the threshold is considered to have more or less false positives or negatives.

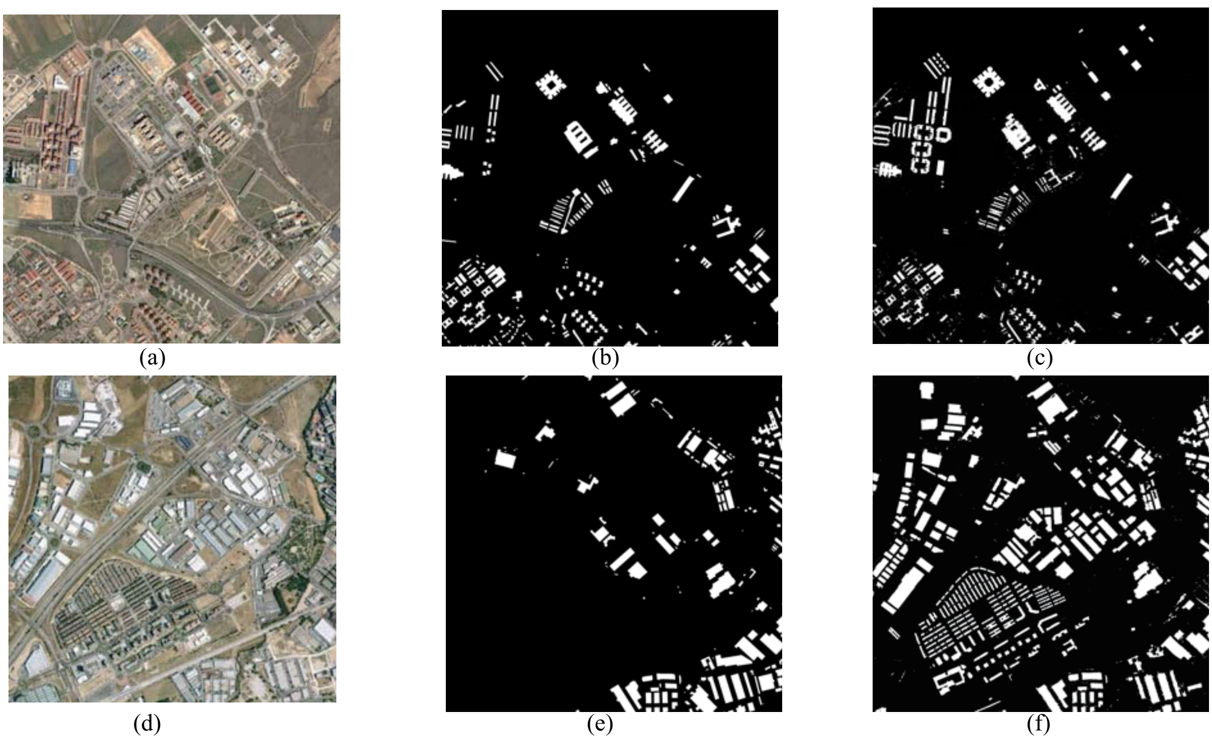


Figure 4. (a) Aerial Image of the University Campus of Alcala; (b) 1999 Building Mask, (c) 2006 Building Mask from SVM Classification (d) Aerial Image of the La Garena; (e) 1999 Building Mask, (f) 2006 Building Mask from SVM Classification

4. RESULTS AND DISCUSSION

The proposed approach has been tested for two chosen areas in Madrid, Central Spain. One belongs (Figure 4 (a)) to the university campus of Alcala and the other to a residential neighborhood of Alcala called La Garena (Figure 4 (d)). Each has 2000 by 2000 pixels, where each pixel has been re-sampled to one meter; therefore, each area represents 2 km by 2 km.

Figure 4 (b) was obtained from the digital cartographic database of 1999 producing a mask from the vectorial cartography. Figure 4 (c) was obtained from applying the SVM algorithm to the SPOT5 imagery and LIDAR data for 2006.

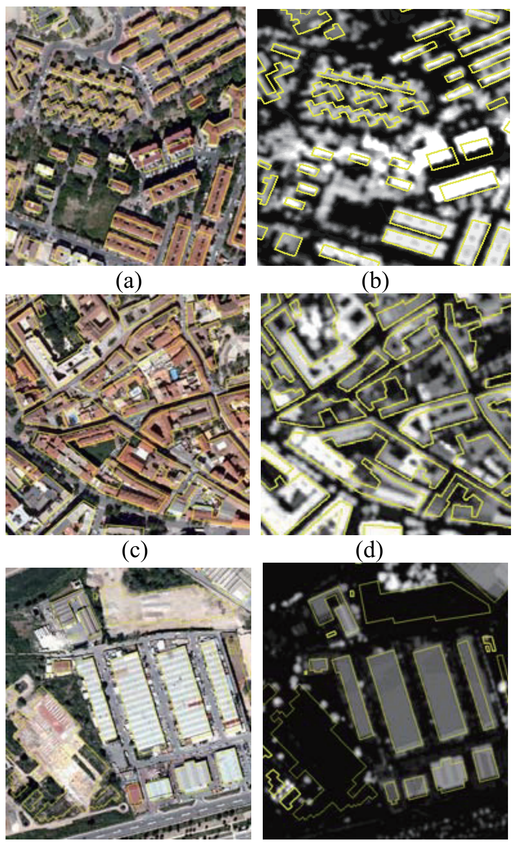
As stated above, the full scene has 4.000.000 pixels, from which 220487 pixels belong to buildings (5.51%) for the digital cartography of 1999 (Figure 4 (b)), and 260175 building pixels (6.50%) for building detection algorithm (Figure 4 (c)). There was only an increase of 1% in buildings for this area in the seven years period 1999 to 2006). Visually, can be observed on the upper right corner that four new buildings that were constructed, this belonged to a technological centre constructed within the campus in this period. The lower left corner corresponds to an old residential area so not much change has happened. In contrast, the upper left corner corresponds to a new residential area and it is where most of the changes have happened. Apart from this, little has changed in the campus in the period 1999-2006.

The area in Figure 4 (d) corresponds to a new residential area, called La Garena, in the suburb of Alcalá de Henares. In the year 1999 (Figure 4 (e)) there were 286549 pixels (to discuss pixels is the same as discussing square meters) or what is the same 7.16% of the land was dedicated to buildings. However in the year 2006 (Figure 4 (f)) there were 635.598 pixels, or 15.89%. There was an increase of more than 7%.

The images in Figure 4 (c) and Figure 4 (f) were obtained by the automatic algorithm SVM. This means that the errors committed by the algorithm are translated to the change detection process. To determine to what degree this could affect the results of the SVM algorithm, a mask of buildings for the last area, La Garena, was made editing the LIDAR layer of the nDSM by removing the vegetation manually with the help of the PNOA aerial imagery for 2006. Terrain visits, facilitated because the areas are well known to the authors since one (Figure 4 (a)) is the university campus where they work; and the other, La Garena, is only a few kilometres away. With minimum tuning of a threshold for the LIDAR data the manual detection was 670.422 pixels or 16.76%. In order to compare the number of pixels detected as buildings in the digital cartography with the SVM several considerations should be made.

There were several special cases coming from different situations, which were difficult to eradicate. Some came from the way the human operator performed the job, such as generalizing the cartographic entities, and the other came from the parameters to be tuned in the SVM algorithm and the LIDAR data itself. See for instance Figure 5 for some of these cases. Clearly the mistakes in the digital cartography, normal when performed by human operators, could be translated to the final results. Figure 5 (a) can be seen as an aerial image with vectorial cartography overlying it. Two buildings on the right middle side of the image had been displaced when the vectorial cartography was done. Now this can be seen with the LIDAR in Figure 5 (b). In the final count of pixels this could compensate itself automatically, since what is lost when the building is outside the vectorial delineation, is gained when it is inside. A different problem occurred with generalization; some of it can be observed in other buildings of this same image in Figure 5 (a) and Figure 5 (b). But where generalization can be seen more clearly is in Figure 5 (c) and (d). The generalization of the central buildings will affect the calculation of the increase of building construction occurrence during the studied period. In this case, the SVM using LIDAR data will detect fewer pixels than those obtained by rasterizing the vectorial cartography for the same features.

Another situation was with the buildings that had been demolished. For instance, in Figure 5 (e) and (f) can be seen two large industrial buildings that were demolished in the period 1999-2006. These pixels will be subtracted from the final result as it should be. Therefore, this does not pose a problem, only that one should be take into account that the final quantity is not only the increase in construction but the total number also includes the decrease by the demolitions of certain buildings.



(a) (b) (c) (d) (e) (f)

Figure 5. Some Special Points from Cartographic Considerations

From our study we deduce that the optimum would have been to have two LIDAR layers, one for each date, with a good method for removing the vegetation this would be the best method to know how much area has changed due to building construction. If possible, to have two LIDAR layers, this is the best option as put forward by several authors, Choi et al. (2009) compared two individual LIDAR data sets, subtracting the two DSMs obtaining not only the changed areas but also the types of the changes with a sufficient degree of accuracy. Five years before, Thuy et al. (2004) proposed to have a building inventory in LIDAR because of the quick and reliable updating in the case of an earthquake, to detect damaged buildings. As a case study they studied the change in buildings with two LIDAR surveying flights in 1999 and 2004 over Tokyo, Japan. They used a high dense LIDAR, even proposed to integrate pulse intensity in the processing for future studies. The question is how much density is needed for LULC mapping. In our work we have used half a point per square meter. This density is not difficult to obtain for big areas and we think it gives the necessary precision that is needed for LULC.

It is important to note that when buildings have been extracted from the nDSM, what remains is the urban high vegetation. To have this information about high vegetation would be essential for some application such as urban planning and urban ecology. If LIDAR data is available for both dates the proposed approach would allow determining the changes in high vegetation between both dates. Thanks to the multispectral imagery it would permit also to determine the changes in low vegetation, such as grass and lawns.

5. CONCLUSIONS AND FUTURE WORK

The proposed algorithm gives an approximation of the percentage of occurrence for building change between two dates; when the buildings on the first date come from a vectorial database and the second from spatial and LIDAR data. The classification is performed automatically with SVM. A previous manual editing can reduce the error in classification and consequently improve the detection rate change. Today there is a compromise between how much manual editing to do and what accuracy is to be expected.

If LIDAR data is not available for both dates a good option would be to use digital cartography for the first date. The advantages and disadvantages of this approach have been shown. The main conclusion of this paper is to recognize the importance of having LIDAR data, if possible, for both dates. Subtracting one from the other would give the change in buildings, but also in high vegetation. Therefore, it is also important to have an algorithm to automatically discriminate between vegetation and buildings for the nDSM. Without the algorithm it would be necessary to remove vegetation manually from both LIDAR layers.

REFERENCES

Alonso, M.C. and Malpica, J.A, 2008. Classification of Multispectral High-Resolution Satellite Imagery Using LIDAR Elevation Data. In Bebis G. et al. (Eds.): *Advances in Visual Computing ISVC08*, Part II, Lecture Notes in Computer Science 5359, pp. 85–94. Springer-Verlag.

Arozarena, A., Villa, G., 2005. Plan Nacional de Ortofotografía Aérea de España (PNOA). *Topografía y cartografía: Revista del Ilustre Colegio Oficial de Ingenieros Técnicos en Topografía,* ISSN 0212-9280, 22(127), 2005, pp. 30-41.

Boser, B.E., Guyon, I. and Vapnik, V.N., 1992. A Training Algorithm for Optimal Margin Classifiers. In: D. Haussler, editor, *Proceedings of the Fifth Annual Workshop on Computational Learning Theory* pp. 144-152, Pittsburgh. ACM Press.

Choi, K., Lee, I. and Kim, S., 2009. A feature based approach to automatic change detection from LIDAR data in urban areas. Laserscanning09. Vol XXXVIII part 3/W8, on CDROM.

García-Gómez, A., Fernández-Álvarez, D., Malpica, J.A., 2010. Comparative analysis of Support Vector Machines and Mahalanobis algorithms for road extraction from high resolution satellite imagery. To appear in *Advances in Geoinformation Technologies 2010*. Ostrava University, Czech Republic.

Grey, W.M.F., Luckmana, A.J. and Holland, D., 2004. Mapping urban change in the UK using satellite radar interferometry, Remote Sensing of Environment, 87, pp. 16-22.

Hung, M.C. and Germaine, K., 2008. Delineating Impervious Surfaces Utilizing High Spatial Resolution Multispectral Imagery and LIDAR Data. In: *ASPRS 2008 Annual Conference,* Portland, Oregon.

Knudsen, T., and Olsen, B.P., 2003. Automated Change Detection for Updates of Digital Map Databases. *Photogrammetric Engineering and Remote Sensing*, vol. 69 (11), pp. 1289-1297.

Malpica, J.A. and Alonso, M.C., 2010. Change detection with SVM algorithm. Internal Report. Mathematics Department. Alcala University. Madrid. Spain.

Martinez de Agirre, A. and Malpica, J.A., 2010. Constructing a Digital Terrain Model from LIDAR data. To appear in *Advances in Geoinformation Technologies 2010*. Ostrava University, Czech Republic.

Olsen, B.P., 2004. Automatic change detection for validation of digital map databases. In: International Archives of Photogrammetry and Remote Sensing, Vol. XXX IV, Part B2, pp.569-574, July 2004, Istanbul, Turkey.

Rodríguez- Berrocal, F. and Malpica, J.A., 2010. Comparison of Support Vector Machines and Mahalanobis distance algorithms for the detection of vegetation changes in high resolution satellite imageries. To appear in *Advances in Geoinformation Technologies 2010*. Ostrava University, Czech Republic.

Rodríguez, G. and Malpica, J.A., 2010. Satellite remote sensing classification with Artificial Neural Networks and Support Vector Machines. *Proceedings of Symposium GIS Ostrava 2010* (in CDROM 8 p). ISBN 978-80-248-2171-9.

Sohn, G. and Dowman, I., 2007. Data fusion of high-resolution satellite imagery and LIDAR data for automatic building extraction. *ISPRS Journal of Photogrammetry & Remote Sensing* 62, pp. 43–63. Options Méditerrannéennes – Série B, nº 46 (in CDROM).

Swets, J.A., 1979. ROC analysis applied to the evaluation of medical imaging techniques. *Investigative Radiology,* Vol. 14, pp. 109–121.

Thuy Vu, T., 2004. LIDAR-based Change Detection of Buildings in Dense Urban Areas, *Geoscience and Remote Sensing Symposium,* 2004 IGARSS, 5, pp.3413-3416.

Valcarcel, N., Villa, G., Arozarena, A., Garcia-Asensio, L., Caballlero, M.E., A. Porcuna, Domenech, E. and Peces, J.J., 2008. Siose, a Successful Test Bench towards Harmonization and Integration of Land Cover /Use Information as Environmental Reference Data. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences.* Vol. XXXVII. Part B8: 1159-1163. Beijing 2008.

Vapmik, V., 1995. *The Nature of Statistical Learning Theory.* Springer Verlag. New York.

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