A NEW CLASSIFICATION METHOD FOR SEMI-ARID REGIONS BASED ON SAR AND LIDAR DATA FUSION

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ABSTRACT

This paper aims at developing a new enhanced algorithm for mapping semi-arid areas based on fusion techniques of Synthetic Aperture Radar (SAR) and Light Detection And Ranging (LiDAR) datasets. Firstly, both datasets are preprocessed to remove geometric and radiometric errors; then features of interest are extracted from SAR and LiDAR products to build masks and identify meaningful classes. Finally, classification results are refined with morphological filters. The new algorithm has been tested on data acquired by TerraSAR-X and an airborne LiDAR sensor over the Natural Reserve of Maspalomas in Canary Islands. Results show an overall classification accuracy of 85% with an absolute increment of more than 14% compared to a classification in which only LiDAR data are used.

Index Terms— SAR, LiDAR, land classification, SAR texture, Gray Level Co-occurrence Matrix.

1. INTRODUCTION

Arid and semi-arid regions represent a quart of the total land surface of the Earth with a third of global population living in these areas. Arid ecosystems endure insensitive land-use pressure and are highly sensitive to climate perturbations and degradation yielding to an increment of areas at risk of desertification [1]. Such changes are usually very rapid and understanding the dynamics and causes is crucial to establish more efficient land management resources at both local and regional levels.

The role of Earth Observation in monitoring and land coverage mapping of semi-arid areas is widely recognized and well introduced in literature [2]. These regions are often affected by the lack of reliable *in-situ* data and, in many cases, it is necessary to improve this data availability by developing cost-effective monitoring techniques based on remote sensing. Recent developments in satellite and airborne technologies for remote sensing have led to diversification of downstream activities and the development of novel techniques fusing multiple input data [2-3].

Research activities combining SAR and LiDAR have increased in recent years, especially in applications of classification of natural and forestry environments. Both SAR and LiDAR have their assets and drawbacks, and their combination aims at compensating the drawbacks of a single sensor by adding input/information from the other. For example, a LiDAR point cloud is able to provide detailed structure information about vertical objects, and multiple returns information is an efficient criterion to distinguish tree canopy from buildings. Moreover, accuracy and spatial resolution of LiDAR data are usually higher than the radar ones. From the other side, the main drawback of LiDAR surveys is the higher cost and limited spatial coverage of airborne data acquisition. Conversely, global and continuous coverage together with a synoptic view independent from daylight and cloud coverage represent the main strengths of radar acquisitions, while its main limitations remain the accuracy, the geometric distortions and the coarser spatial resolution. For example, the SAR-LiDAR data fusion conducted in [4] produces high-resolution above-ground biomass maps for large areas in tropical forests. This technique combines information from dual-polarization SAR data and the LiDAR Digital Elevation Model (DEM) to initially isolate the vegetated areas and then evaluate the biomass units with distinct biophysical parameters. In [5], the authors have conducted a set of experiments by employing the LiDAR data to improve the quality of SAR focusing and the interpretation of the SAR data in urban areas. This paper, instead, investigates the benefits of fusing SAR and LiDAR data for classification purposes and a new fusion scheme at feature level is here presented.

The paper is organized as follows: in section 2, the fusion scheme rationale is introduced and the relative block diagram discussed; in section 3 the Maspalomas case study is presented along with the input datasets; in section 4 results of the fusion are shown and compared with the outcomes obtained by using LiDAR data only; in section 5 conclusions and future perspectives are briefly drawn.

Fig. 1: Fusion algorithm flowchart.

2. FUSION TECHNIQUE

The new fusion algorithm merges SAR and LiDAR datasets at feature level. First of all, input products need to be preprocessed because images obtained from different satellites or digital airborne system present different spatial resolutions, geometric distortions (i.e. layover and shadowing in SAR) and radiometric characteristics. Pre-processing aims at making the datasets spatially comparable and geometrically consistent. Regarding the SAR dataset, the input Single Look Complex product is radiometrically calibrated (conversion from Digital Number to Sigma Naught domain), orthorectified (by applying a Terrain Correction step) and, optionally, filtered to reduce the intrinsic speckle noise affecting all SAR products. LiDAR product, instead, are able to store information from multiple returns (usually up to five) and initial point cloud is pre-processed to extract the following information bands: DEM, Digital Surface Model (DSM), Intensity (a measure of reflectance in near infrared band relative to each point of the cloud), RGB Orthophoto (a combination of LiDAR data with an orthorectified aerial imagery in RGB bands) and Multiple Return (the difference between the first and last Intensity return for each point of the cloud). Then, the pre-processed products are coregistered in order to geometrically align the input datasets: the product with the highest spatial resolution is selected as master, ground control points are then isolated on both images and, finally, the slave images are transformed to obtain a set of images with equal resolution, dimension and orientation.

The fusion step represents the novel contribution. In the proposed approach, the classes of interest are detected in order of priority by creating a series of masks. Each mask is created by extracting features from both SAR and LiDAR data. Then, the final classification map is created by building a decision tree in which the masks previously created are sequentially applied to the co-registered datasets to produce the output classes. Fig. 1 shows the flowchart of the fusion strategy: SAR and LiDAR data represent the input of the decision tree; at each step one mask is applied to the input data to produce one output class.

Fig. 2: Masks formation built up from feature extraction of the input data.

At each step the classified pixels are masked out from the input data and the final map is simply obtained by grouping together the classes retrieved at each step of the decision tree. Fig.2 shows how a mask is retrieved from the analysis of SAR and LiDAR data. Firstly, relevant features for the class at issue are extracted from SAR and LiDAR bands; then these features are fused together and thresholds are chosen in order to binarize the input data. Finally, a supervised labelling process assigns a semantic meaning to one of the two segments obtained after the thresholding to produce the output class.

3. CASE STUDY

The new fusion algorithm is tested over the Maspalomas Special Natural Reserve located in the Canary Islands in Spain within the ARTeMISat project [6]. The Maspalomas natural reserve embraces 403.9 hectares of sand dunes, a lagoon of great ecological value, a palm grove of enormous landscape, geomorphological, botanical and faunistic significance, and a bird nesting centre. The semi-arid dune field extends over a surface of 4 square kilometers and is one of the most ecologically relevant areas of the reserve. This area was declared as Natural Protected Area of National Interest in 1987, and it was classified as Special Natural Reserve in 1994. It is an ecologically sensitive area, whose environment is strongly influenced by human presence, and this poses a serious threat to its survival [6]. The Maspalomas Natural Reserve is shown through an RGB Google Earth image in Fig.3(a).

Regarding the SAR acquisition, a Spotlight (1.4m x1.4m spatial resolution) image with HH polarization was acquired by the German TerraSAR-X sensor in 2008 over the area of interest. The SAR amplitude image is shown in Fig.3(b) after all the preprocessing steps have been applied.

The LIDAR flight campaign over Canary Islands was carried out during 2009 and data are provided by the Plan Nacional de Ortofotografía Aérea, PNOA. The average density is of 0.5 points per square meter and the mean vertical accuracy of registered points is around 0.20 meters. LiDAR Intensity, RGB orthophoto, DEM and DSM preprocessed bands are shown in Fig.3(c)-(d)-(e)-(f), respectively.

In order to support the environmental conservation, the ARTeMISat project aims at developing a classification map of this area including the following main land cover features:

sea, pond and swimming pools, asphalt (roads, parking areas, footpaths and other paving), sand (beaches, dunes), terrain (soil not covered by any type of vegetation or buildings), grass, shrubs (low vegetation), trees (high vegetation) and buildings (any man-made structure above ground). In the next section, the solution to isolate the identified classes is explained and results are presented, discussed and compared against a solution in which only the LiDAR product was used.

4. RESULTS

The classes of interest are identified according to the following priority and rationale:

1. Sea mask is obtained by considering all pixels with null elevation in the LiDAR DEM band.
2. Ponds and swimming pools mask is computed from the Normalized Difference Swimming Pool Index (NDSPI) [7] and by applying a threshold based on the analysis of NDSPI histogram. Water bodies present a high NDSPI therefore ponds and pools can be isolated by selecting all the pixels above the chosen threshold.
3. Sand pixels appear homogeneous in SAR image and are selected from the analysis of SAR texture. In particular, the dissimilarity from the Grey Level Co-occurrence Matrix (GLCM) [8] is computed and sand pixels are isolated by choosing dissimilarity value below a chosen threshold.
4. A second mask is computed on the dissimilarity to discriminate two macro-classes: a) asphalt, terrain and grass (low values) b) buildings, shrubs and high vegetation (high values). Then, the asphalt class is isolated by considering the low dissimilarity values in conjunction with low values in the LiDAR Intensity band.
5. Grass pixels are chosen by considering low values of dissimilarity in conjunction with the high Normalized Difference Vegetation Index (NDVI) computed from the LiDAR Intensity and RGB Orthophoto bands.
6. Terrain class is identified by isolating low dissimilarity and low NDVI values.
7. The remaining classes are identified by considering the brightest pixels of the dissimilarity classes (macro-class b) of step 4). In particular, vegetation (shrubs and high vegetation) was isolated by considering pixels with a positive value in the LiDAR Multiple Return band. Finally, high vegetation pixels were chosen by inserting a threshold of 2m in the LiDAR DSM band and selecting the pixels with DSM value above the threshold.
8. The shrub class is selected by choosing the macro-class b) with the same Multi Return mask and the inverse DSM mask of the high vegetation class.
9. The building class is computed by considering the macro-class b) with inverse Multi Return mask of the high vegetation class.
10. Finally, the remaining pixels are considered unclassified.

Before overlapping all the masks, morphological filters are applied to smooth the results. In particular, classes are expanded to fill small holes (dilate operation) and reduced to remove small islands of pixels (erode operation).

Classification outcomes, along with the colour legend, are shown in Fig. 4. From a visual inspection and a comparison with the ground truth provided by the ARTEMISat project, the proposed algorithm is able to correctly identify all the classes of interest.

In order to quantitatively assess the goodness of the proposed fusion approach, the confusion matrix and the accuracy statistics were computed. The ground truth available at the moment of the analysis did not cover all the classes considered for this study, so the confusion matrix computed refers only to four macro-classes: vegetation (including grass, shrubs, high vegetation), water (including sea and swimming pools), bare soil (including sand and terrain), and built soil (including asphalt and buildings). The category of bare soil provides the best results, with an accuracy of 90.63%. Differently, many forest areas were assigned as bare soil with a very high omission error (21.88%). Moreover, the overall classification accuracy reaches 85.20% and the kappa coefficient 0.8021. In order to assess the improvement in classification accuracy brought by this fusion technique, a pixel-based supervised classification was performed using LiDAR data alone and by choosing a Maximum-Likelihood classifier. In this case, the overall classification accuracy reaches 71.00% and the kappa coefficient was 0.6146. The LiDAR classifier performs well on the water class, with an accuracy of 93.75% with a few commission errors mainly from built soil. Vegetation, instead, is classified with an accuracy of only 71.88%, and suffers from high commission error (36.11%). Finally, built soil shows the lowest accuracy (25.00%). The assessment of the two techniques demonstrates that the proposed data fusion algorithm significantly improves the quality of classification compared to LiDAR data alone and this is witnessed by an increment of the overall accuracy of 14.80% and a reduction of misclassification equals to 48.97%.

Fig. 3: Google Earth Image of the Maspalomas Natural Reserve (a); TerraSAR-X amplitude image (b); LiDAR Intensity band (c); LiDAR orthophoto (d); LiDAR DEM (e) and LiDAR DSM (f).

Fig. 4: Classification outcomes deriving by the fusion of SAR and LiDAR datasets.

5. CONCLUSIONS

Multi-sensor (SAR and LiDAR) data fusion was discussed in this paper and a new fusion algorithm for classification purposes in semi-arid areas is presented. Preliminary results show an outstanding improvement in the overall classification accuracy (more than 14%) when compared with a classifier based only on LiDAR data. It is worth to note that the overall accuracy is affected by a bias related to the temporal gap of one year between the SAR and LiDAR acquisitions, and of around six years between the datasets and the available ground truth. Temporal differences can play a large factor in many of the misclassifications observed in the final map, due to vegetation growth and urban construction. In the future, the authors will assess this technique applied to datasets acquired at the same time as the ground truth.

6. REFERENCES

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