Multitemporal Synthetic Aperture Radar for Urban Planning and Critical Infrastructure Monitoring

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***Abstract*—Earth observation technologies can provide a significant contribution to the monitoring urban areas and critical infrastructures. In this paper, we show how to exploit the recently introduced multitemporal SAR RGB images of the Level-1α and Level-1β family in these applications. Simple, *ad hoc* algorithms are discussed to adapt these generalist products to the specific case study. In particular, self-organizing map clustering and object-based image analysis are used for urban area mapping. As for infrastructure monitoring, an application concerning railway monitoring is discussed.**

I. Introduction

In the last decades, a deep transformation occurred on Earth, determining a strong impulse to urbanization. Today, the number of people living in urban areas has exceeded that of those living in rural regions, and the trend is expected to increase in the next years. In particular, cities in Asia and Africa are growing quickly, spreading across large portions of landscape that, until recently, was rural or used for agricultural production.

The increasing urbanization poses new challenges in urban planning and monitoring. Satellite technologies are a powerful tool for large scale observation and to mitigate (and possibly avoid) the negative effects that such a rapid growth of cities could have on the environment. The remote sensing community is well aware of the role it can play in the understanding of these phenomena. This is testified by the extended literature published in the last years on this topic (see, as an example [1]–[4]). International agencies also demonstrated great interest on this issue, launching several initiatives related to the urban environment, just think to the creation of the Urban Atlas [5]. Recently, the European Space Agency started the Urban project in the framework of the Thematic Exploitation Platform (TEP). The Urban TEP is providing data, methods and infrastructure to help the creation of sustainable urban environments through a centralized platform for data analysis. In fact, the effective management of the urban development requires knowledge about how dynamic urban systems interact with the surrounding landscape. What are the damages induced by the urbanization in terms consumption of land and resources? What is their effect on air and water quality? What is the exposure of cities to natural hazards? These are just some of the questions to be addressed in order to plan a sustainable urbanization in the following decades. Earth observation can greatly contribute to the answer to these questions, delivering comprehensive images of our world with high temporal frequency, documenting at the same time its changes over time.

Recently, the introduction of multitemporal SAR RGB composites of the Level-1α and Level-1β family (see [6] and [7] for details) made available a new tool to support decision-makers through an easy-to-read and general-purpose representation of the world as filtered by synthetic aperture radar (SAR) sensors. In this paper, we propose new ideas for the exploitation of such products in urban area and critical infrastructure monitoring applications. In particular, in Section II, we discuss a new algorithm for urban area mapping based on object-based image analysis (OBIA). In Section III, an example of infrastructure monitoring concerning railways is presented. Conclusions are drawn at the end of the work.

II. Urban area mapping using object-based image analysis

The block diagram of the proposed algorithm for urban area mapping is shown in Fig. 1. The input product is an RGB image of the Level-1α or Level-1β family. Level-1α images are change-detection-oriented products constituted by a couple of amplitude images (one representing the reference situation for changes evaluation) and their interferometric coherence. Level-1β images, instead, are classification-oriented products whose channels are represented by temporal indicators such as the mean backscattering, the variance, the mean interferometric coherence, and the time series saturation index.

As shown in Fig. 1, the input product is treated with self-organizing map (SOM) clustering [8] for dimensionality reduction. As discussed in [7], the use of SOM clustering allows for obtaining a discrete product, with few classes, in which the semantic of the input RGB product is mainly preserved. This way, a coarse urban area map can be easily produced by selecting (automatically or with supervision) the classes most relevant with the urban environment. This coarse map initializes the OBIA, whose purpose is to connect sparse objects identified as urban, avoiding an unreliable fragmentation of the retrieved urban area. In fact, the urban environment is very heterogeneous, mixing several land cover which should

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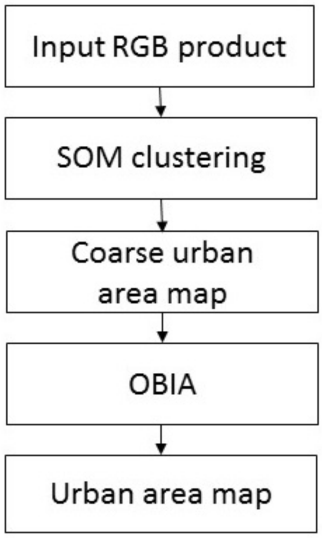
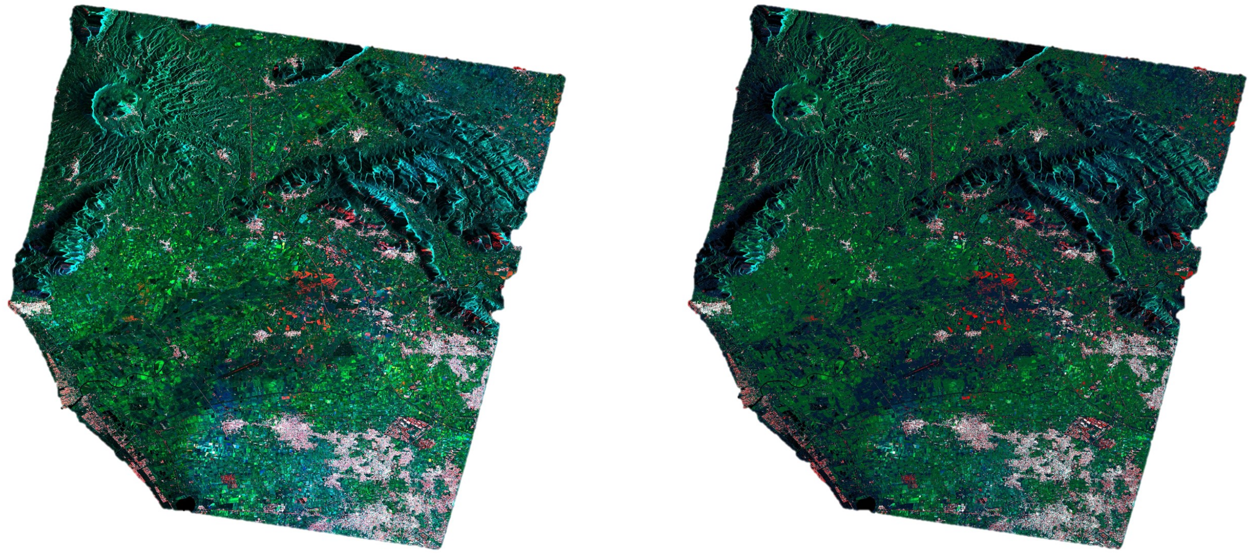


Fig. 1: Block diagram of the proposed workflow for urban area mapping.

be opportunely managed at algorithmic level in order to output a map reflecting effectively the development of a city [9]. As an example, a city park is an integral part of an urban agglomerate, even if it does not exhibit any built-up feature. As a consequence, this element should be included in the retrieved urban area map, although it is desirable that the correspondent area is marked in such way to be identified univocally on it.
In Fig. 2a we show the input Level-1α product for the outlined algorithm. Data have been acquired by the sensor COSMO-SkyMed in the year 2011 over an area located between the cities of Napoli and Caserta (Italy). As stated in [6], in Level-1α images the built-up feature is rendered in white (or in cyan, if spatial/temporal decorrelation occurs [4], [10]).
In Fig. 2b, the product obtained through SOM clustering of the input Level-1α image is shown. As aforementioned, it represents the basis for the OBIA. The reader should note that the classified (discrete, 49-class) product looks very similar to the continuous RGB product, and this allows for the preservation of the scene semantic.
In Fig. 3, the output of the proposed algorithm is shown. The retrieved urban area map has been re-projected into the Urban Atlas grid. Four levels of urban density ("High density", "Medium density", "Low density" and "Very low density") have been identified depending on the concentration of the built-up feature within the Urban Atlas polygons. In particular, the category "Very low density" identifies areas not characterized by significant built-up coverage, but completely surrounded by urban structures. As an example, city parks fall in this category.
The performance of the algorithm has been assessed by comparison with a Urban Atlas-derived ground truth. A good agreement between the two maps has been registered. In fact, we found an overall accuracy higher than 80% for the Napoli area and higher than 90% for the Caserta area.
Obviously, the urban density categories retrieved using SAR have a completely different meaning with respect to those indicated in the Urban Atlas. In fact, in the first case, the urban area is characterized by its built-up part. In the second, impervious surfaces are considered, of which the built-up is a sub-category.

III. Railway monitoring

Monitoring of critical infrastructures, like airports, railways and public buildings, is another key aspect of urban remote sensing, involving structures in which people live/work or used to move people from one point to another.
Among transportation infrastructure, railways are today object of great attention by the space community, with a number of study and applications proposed at academic/research and industrial level, especially in the field of positioning, navigation, and communication. This is also due to international initiatives, such as the ESA Space4Rail programme, which are highly contributing to the development of the sector.
Remote sensing applications in railway monitoring are increasing, as well. However, it is crucial to understand in what satellite observations can help decision makers and in what it is better to prefer other sources of data. To this end, the interaction between the academy and the stakeholder is crucial. As an example, the exploitation of PS-InSAR techniques for the monitoring of rails alignment probably is not the best solution, since this activity is usually done using laser sensors mounted directly on a coach with daily repetition.
On the other side, Earth observation technologies can be very useful, as an example, for the monitoring of the area adjacent to the railroad, which can be implemented in a change-detection framework using Level-1α product.
This idea, presented by some of the authors in the frame of the 2016 ESA Copernicus Masters challenge, was awarded as finalist in "The BMVI Earth observation challenge for digital transport applications" sponsored by the German Federal Ministry of Transport and Digital Infrastructure. In the following, we briefly report its main concepts.
As aforementioned, Level-1α products are bi-temporal images constituted by two amplitude channels and their interferometric coherence. Amplitude images are usually loaded on the blue (reference image) and green (test image) channel, respectively. The reference image is the reference situation for changes evaluation. In Fig. 4, we show four patches of a larger Level-1α product representing an area near the city of Caserta (Italy). The reference image has been acquired on 24 February 2011. Test images have been acquired on 29 April 2011, 18 July 2011, 19 August 2011, and 22 October 2011 (see Fig. 4a, Fig. 4b, Fig. 4c, and Fig. 4d, respectively).
In the middle of the pictures, a small portion of the Alifana railway is depicted (see annotation on Fig. 4a). It is a regional railway connecting a number of small cities between Piedimonte Matese and Santa Maria Capua Vetere. The proposed framework is useful to register activities in the nearby of the railway. In this case, the attention is focused in the area circled on the pictures. We assume that the start of the monitoring corresponds with the scene state depicted in Fig. 4a. It arises that, on 22 October 2011 (see Fig. 4c), a significant variation of the backscattering of the test image is registered. Therefore, the monitoring system should launch a warning to trigger an action of the railway manager which should consist in an *in situ* campaign performed with the aid of expert operators or drones. This way, the nature and the entity of the changes detected through radar imagery, which could be difficult to



(a)

(b)

Fig. 2: (a) Input Level-1α product, and (b) 49-class product obtained through SOM clustering.

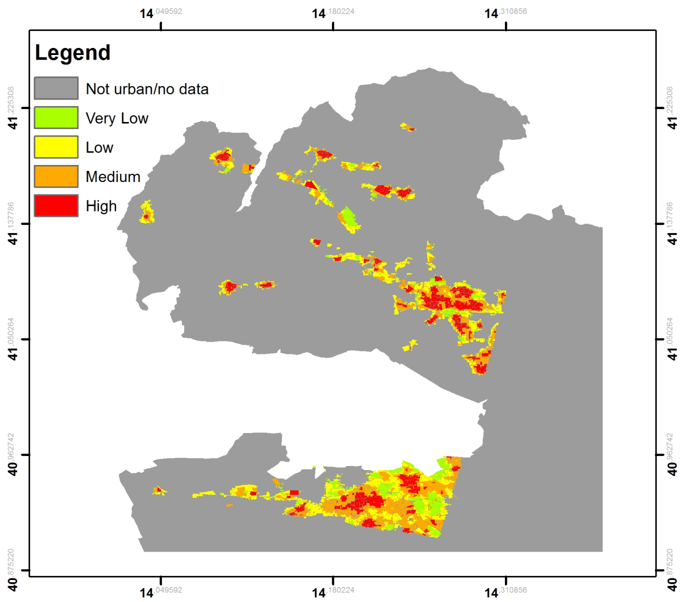


Fig. 3: Final urban area map re-projected into the relevant Urban Atlas grid.

assess exploiting only satellite technologies, can be evaluated and, if necessary, adequate interventions can be planned. This should allow the railway operator to move from a find-and-fix maintenance model (expensive and scarcely efficient) to a predict-and-prevent or just-in-time approach, depending on the kind of threat. In fact the phenomena of interest in this application are very variegated, from vegetation growth to unauthorised construction of buildings or landfills.
Such an integrated system can allow for significant savings in the maintenance costs, representing an effective example of exploitation of satellite data for the improvement of the monitoring/management of a critical infrastructure like a railway.

IV. Conclusions

In this paper, we introduced a new algorithm for urban area mapping exploiting multitemporal RGB SAR products of the Level-1α and Level-1β family. The proposed technique exploits self-organizing map clustering and object-based image analysis to output a map avoiding the fragmentation of the urban environment (typical of pixel-based techniques), through an effective management, at algorithmic level, of its intrinsic heterogeneity. In the second part of the paper, we propose an application concerning railway monitoring. We showed how to exploit Level-1α products to monitor the area in its adjacency in a change-detection framework. The proposed approach could bring significant savings in maintenance costs for railway managers. In fact, the automatic detection of potential risks for the railway structure allows for the reduction of *in situ* campaigns, limiting them to areas for which the system launched a warning.

Acknowledgments

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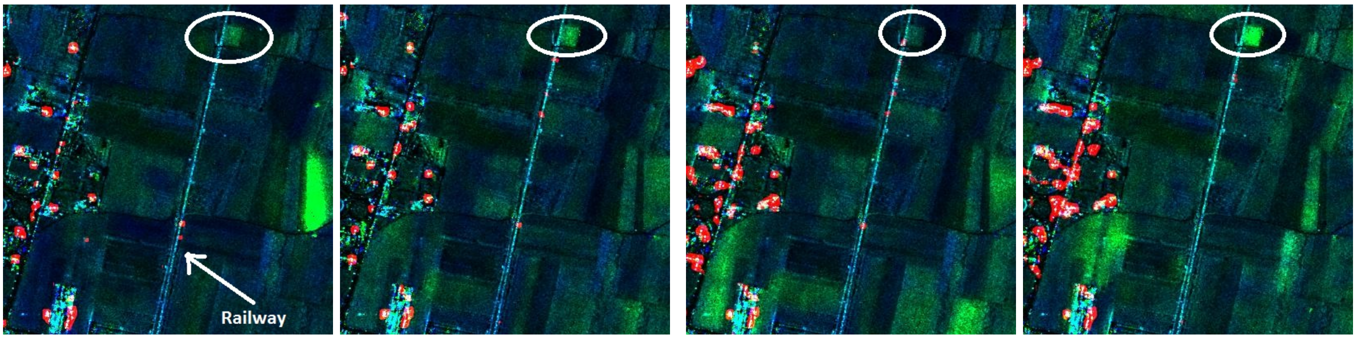

(a) (b) (c) (d)

Fig. 4: Railway adjacency monitoring using Level-1α products sharing the same reference image (acquired on 24 February 2011), i.e. the reference situation for the detection of changes. Test images (a) 29 April 2011, (b) 18 July 2011, (c) 19 August 2011, and (d) 22 October 2011. A significant backscattering variation is registered on 22 October 2011, which should be verified through an *in situ* inspection.

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