Sentinel-1 Multitemporal SAR Products

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***Abstract*—In this paper, we present a new framework for high-level processing of time series images, with particular reference to Sentinel-1 data. The proposed methodology has the goal of enhancing the interpretation of SAR imagery through the production of physical-based RGB composites, which are particularly suited for being easily interpreted by the human photo-interpreter, lowering the expertise level required for managing SAR data.**

I. INTRODUCTION

Sentinel-1 started to acquire data on April 2014. The potential of the mission has been explored theoretically [1] and with the aid of simulated data [2], but its success strongly depends on the development of repeatable and reliable processing able to produce attractive products for the end-users community.

In this paper, we present a new framework for high-level processing of series of Sentinel-1 data. The framework has the goal of enhancing the interpretation of SAR imagery through the production of physical-based RGB composite and reducing the problems related with: i) the geometrical distortion induced by the side-looking acquisition mode, ii) the scattering mechanism and iii) the gray-scale displaying in non-polarimetric modality.

The choice of a color representation is recommendable because humans are used to interpret color images. Therefore this choice is expected to facilitate the comprehension of data [3] since it represents the best fitting with users visual mechanism, also bringing to the full exploitation of his/her exploration capability by interaction with data [4]. From this viewpoint, multitemporal datasets represent a reasonable mean for increasing the dimensionality of a single-channel SAR data through the fusion of information collected in different times [5]. The paper faces the two main points related with human vision: the information processing and the representation.

The proposed high-level processing consists of three steps: a pre-processing phase aimed at geometrical/temporal/radiometric calibration; a decomposition of the image information on a proper base accounting for mean intensity, mean variation and temporal outlier mapping; a fusion of the three channels.

As for the image representation, the information retrieved from data is dependent on the type of the chosen representation. In other words, the same data can be represented in different ways, and the choice made greatly affects successive processing phases since it makes explicit some information at the expense of other that could be hard to recover. A suitable representation is a powerful mean for mining data from the observed scene. In this work, we introduce a general-purpose multitemporal SAR data synthesis that produces Sentinel-1 products particularly suited for being easily interpreted by the human photo-interpreter.

The work is organized as follows. In Section II the data fusion technique is discussed. In Section III the physical interpretation of the retrieved products is provided. In Section IV we propose a land cover mapping application using neural networks. Conclusions are drawn at the end of the work.

II. DATA FUSION

The general workflow that brings to the proposed products is depicted in the block diagram of Fig. 1. The pre-processing block strongly gleans to the MAP3 framework introduced in [5] and mainly deals with data calibration and despeckling. The multitemporal analysis block concerns with the choice of

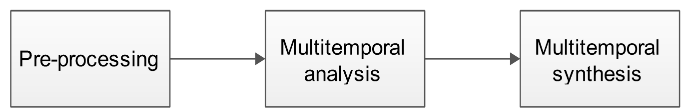


Fig. 1: Processing workflow

the physical quantities to be considered into the fusion.

Reference [6] proposed some goals this operation should achieve for preserving information and allowing interpretability. In particular, we want to highlight the three properties of summarization, consistent rendering and natural palette. In fact, an effective synthesis should provide an overview of the original dataset transferring to the user a series of information he/she can not reach otherwise (summarization). This is possible if the data rendering is consistent. The natural palette is of course the best way for interpreting data but in the case of SAR images is still far away to be produced. Hence, an advance towards this representation, is desirable. The products we are going to define try to give an effective answer to these requests solving appropriately the challenges relevant to the selection of the more suitable bands and to their fusion. The idea is to combine the mean values of the time series (green band) with some variability indicators. The usage of the variance (red band) is the simplest and more reasonable choice in order to evaluate the deviation with respect to the mean behavior. Another interesting information about the scene dynamics is represented by the maximum excursion of backscattered energy during the entire time series, which is an indicator of the presence of outliers. Therefore, we use as third element of our synthesis (blue band) the saturation map, as defined in [7]. The synthesis has a fourth participant, that is the interferometric coherence. This quantity is useful for separating high-reflective natural targets from man-made surfaces. The coherence image is used in combination with the saturation map. In particular, the saturation index is exhibited on the blue band if the coherence is below a user-defined threshold; otherwise, the target coherence is used.

Fig. 2: A small portion of one of the available Sentinel-1 images with 15 meters spatial resolution processed up to 15 ENL.

As for the last block, the fusion of the three above introduced channels is implemented by entropy maximization clipping recursively the image pdf for different percentages of the cumulative histogram. This procedure allows for obtaining more stretched histograms and highly contrasted images.

III. Physical interpretation

In this Section we will show some results of the proposed workflow using a time series of six single-look complex (SLC) Sentinel-1 images acquired between 3 October 2014 and 2 December 2014 in interferometric wide swath (IW) mode over the Saxony region, Germany.

In Fig. 2 we show a particular of the acquisition made on 3 October 2014. The SLC IW product has been processed by application of the Pre-processing chain (see Fig. 1) up to 15 equivalent number of looks (ENL) thanks to multitemporal De Grandi despeckling [8]. The image spatial resolution is about 15 meters in both azimuth and slant range directions. Preliminary data processing such as TOPS deburst, calibration and subswaths merging has been carried out using the tools made available for free by the European Space Agency.

In Fig. 4 we show the output of the proposed workflow. This representation allows for highlighting some macro-phenomena, which are characterized by a precise color response. As an example, lakes mainly appear in almost pure blue since the low contribution of the mean and variance bands and the high values of the saturation index due to spikes in electromagnetic response along the time axis (see Fig. 3c) caused by occasional wind-induced surface roughness. The absence of these spikes turns the response of the composition toward the black, such as in the case of the Elba river in its passage within the Dresden city (see Fig. 3a). Urban areas appears in cyan thanks to the combined contribution of the interferometric coherence and mean bands (see Fig. 3a and Fig. 3c). Grasslands and city parks are characterized by a strong dominance of the mean band and thus appear in green. Woods, instead, exhibit the response of their canopy envelope (see Fig. 3d). Thus, variance is small, and a mixture of low amplitude of the green (mean) and blue (saturation) colors gives the resulting color of the composition. Cultivated fields (see Fig. 3b) are expected to have high values of the mean and variance bands due to the volumetric contribution of the plants growth. For the same reason, the saturation index is also expected to be high. Therefore, these features exhibit high values in all the bands of the composition, but their balance is dictated by the physical dynamics of the scene. In fact, each kind of cultivation has its own characteristics and this can move the balance of the colors in the multitemporal product. Thus, a higher contribution of the mean (green band) or of the saturation index (blue band) results in the first case in a color that goes into yellow and in the second in a pink tonality. The difference between these two behaviors is due to kind of cultivations and its characteristic cycle and terrain roughness, foliage density, plants height and fruits dimensions.

IV. Using Neural Nets for Land Cover Mapping

In this Section, we propose the usage of Self-Organizing Maps [9] (SOMs) for land cover maps production [10], [11].

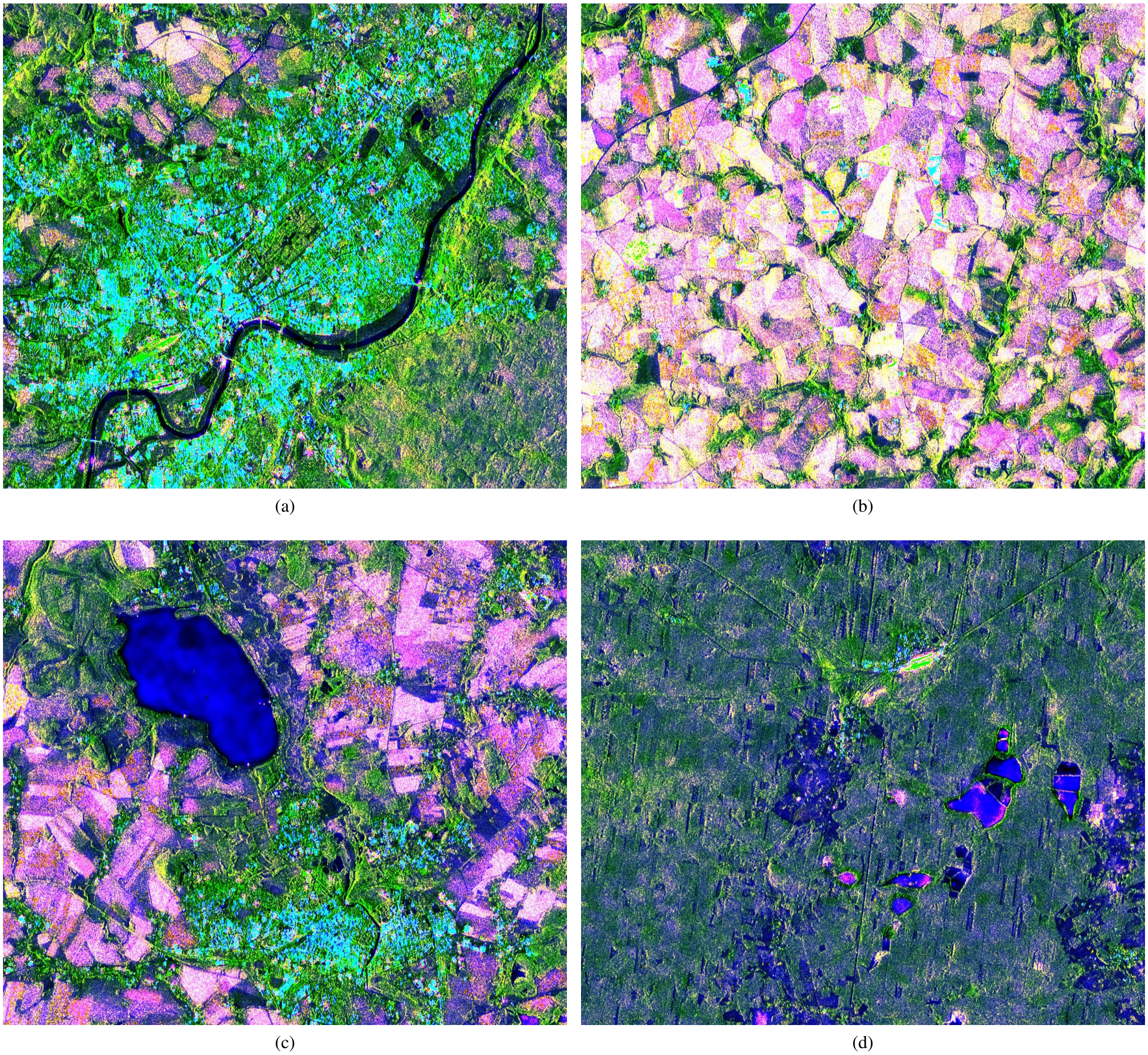
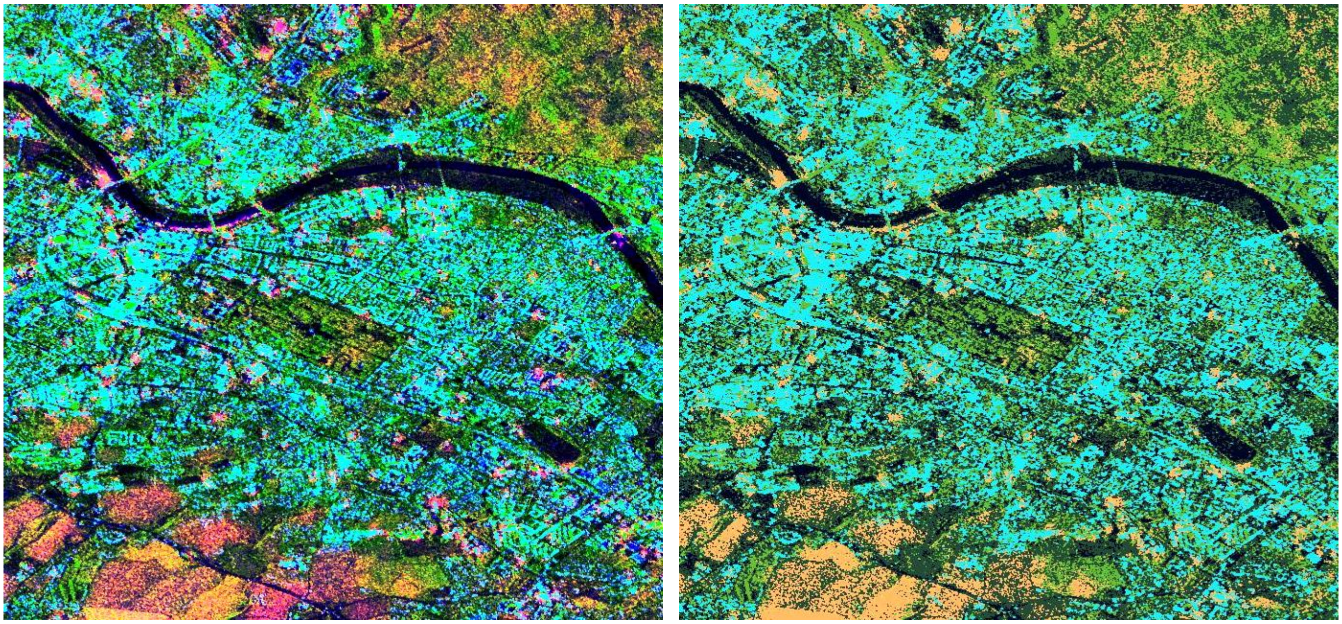


Fig. 3: RGB compositions of the study area: (a) city of Dresden, (b) cultivated fields, (c) Berzdorfer Lake at the boundary between Germany and Czech Republic and (d) wooded area in Czech territory.

SOMs are a machine learning technique used for the classification of the most diverse data types, thus finding application in different sectors [12], [13]. This widespread use of the SOMs is due to the extreme flexibility of the tool, which can be adapted to work with different data types and structures. The robustness to large amounts of data makes them a suitable instrument for unsupervised or semi-supervised classification in a big data scenario, which will be a key issue in remote sensing now on.

In our case, SOMs offer the possibility of an immediate semantic transferring from the RGB product to the classified map. In fact SOM nodes are updated to be representative of the training dataset elements, which are chosen within the RGB triplets constituting the input product. Thus, the resulting node colors will have the same semantic of the RGB composite.

We performed a land cover classification on a subset of the Sentinel-1 RGB composite relevant to the Dresden city area, obtaining a 5-class land cover product. The original RGB product and the SOM land cover classification are shown in Fig. 4a and Fig. 4b, respectively. The reader should note as the two maps appear very similar. However, the product depicted in Fig. 4a is defined in a color space of 256^3 colors, while its land cover map has only 5 classes. In particular, the following color-feature association can be performed: cyan-urban areas, orange-cultivated fields, black-weak scatterers (water, shadows, bare soils), green-grasslands, dark green-woods. These classes can be used for building masks exploitable in further processing based on the inversion of electromagnetic scattering



(a) (b)

Fig. 4: Dresden area: (a) RGB composition and (b) its 5-classes land cover map.

models [14].

V. Conclusions

In this paper, we introduced a new class of multitemporal SAR products. The proposed products have been designed for to helping the human operator, thanks to a rendering almost consistent with his/her view and close to the natural color palette, thus lowering the level of expertise required to correctly interpret data. The proposed products are thus particularly oriented towards the end-users community since they allows for a more easy and comfortable human-machine interaction.

We also tested the minability of the product and their suitability for data analysis techniques. The application of Self-Organizing Maps to the land cover mapping problem was selected for the robustness to big data, flexibility and the capacity to maintain the chromatic semantics of the RGB products.

The obtained results confirmed the reliability of our framework from the standpoints of data visualization/interpretation and applicability of automatic data analysis techniques.

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