I. INTRODUCTION

DATA fusion emerged as a new topic in the late 1980s, but it was only by the first half of the following decade that the availability of remotely sensed data in digital form by different sources allowed the consideration of remote-sensing data fusion. At that point, the Data Fusion Technical Committee (DFTC) of the IEEE Geoscience and Remote Sensing Society recognized the need for a Special Issue on the IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING about “data fusion,” which was published in May 1999. That pioneering issue brought to the attention of many researchers the need for an increased effort toward the joint exploitation of multiple data or information sources.

In the following years, and until now, some of the fields highlighted in that issue have come to full maturity. This is the case for multitemporal data fusion, which is currently investigated by a very active community gathered by Bruzzone and Smits [1] in the MULTITEMP Workshops.

Many other research fields have however emerged, as results of the continuous improvement in data quality and quantity, and the fast changing electronic and optical technologies, that allow recording, transmitting, and storing of a huge amount of information. For instance, spatial and spectral resolutions of remotely sensed data are steadily increasing, going toward very high-resolution sensors, both in the spatial and in the spectral sense. This requires combined spectral and spatial analyses, and fusion of features extracted and selected at different scales from the same data set, as in [2].

Moreover, the third dimension is no longer an option for remotely sensed data, and multiple bidimensional view analysis of the same area and multiple 3-D data comparison and combination are some new faces of the same data-fusion problem [3], [4].

At a higher level, feature fusion has also been increased by the larger CPU power and memory capacity of modern processors, which is still to be pushed by the use of multiple CPUs and grid/distributed computing [5].

Fusion of geographical information and remotely sensed data is requiring fusion architectures that are fully aware of the multiple levels of “fusion” discussed in [6], and feature extraction and combination at a geometrical level is felt as a possible common practice in the near future to improve classification [7], change detection [8], and also preanalysis processing steps [9]. It is not certainly by chance that ENVI has recently announced the release of a feature extraction toolbox.

Similarly, the contemporary use of 2-D features and 3-D data was suggested in [10] using geographic information system data, but this is just the simplest part of the work. As a matter of fact, 2-D features and 3-D data may concur to improve the information extracted from each other, as considered for instance in [11]. Three-dimensional building shapes help in distinguishing patches of the same material covering objects at different heights or in correcting errors in patches with different reflectances but at the same level [12].

For a recent general survey paper with classification on information fusion, please refer to [13].

II. DATA FUSION AND REMOTELY SENSED DATA PROCESSING

In an effort to highlight these and other newly emerging research lines, this Special Issue on the topic of “data fusion” provides to interested readers a sort of quick look on approaches currently evolving. The effort of the Guest Editors, and the purpose of this Special Issue, is to put the papers that form the core of the issue in a more general framework, thus helping those who are interested to the topic to easily pick up their choice. To this aim, the remaining part of this Special Issue is organized according to the schematic processing flow in Fig. 1, starting from data and leading to information through a number of mandatory and optional steps.

A. Registration

As shown in Fig. 1, nowadays, the most realistic assumption for a problem facing the use of remotely sensed data is that more data sources are available. They might come from more platforms, more sensors onboard the same platform, ancillary data sources, and so on. This situation usually requires the user to manage a multisensor and, possibly, a multitemporal data set. The first problem to be faced is coregistration. While this processing step has been analyzed for a long time in technical literature, it remains a crucial step in numerous applications and still gathers a lot of attention [14]. As a matter of fact, every kind of data requires some specific development: SAR data [15], [16] or multispectral (MS) data [17] and hyperspectral data [18]. For an increased accuracy, subpixel registration might be the ultimate step in the field [19], [20].

In this Special Issue, the paper proposed by Cariou and Chehdi [21] tries to solve one of the problems that are still open: the lack of adequate ancillary data. In particular, the use of “mutual information” between the data and a reference

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orthophoto is shown as a suitable mean to obtain accurate georeferencing of pushbroom scanners’ data.

B. Resolution Enhancement

The spatial resolution is one key characteristic of remote-sensing data. Be it high or low, uniform or not, it directly impacts the results of the processing and the potential applications. Consequently, a lot of energy is devoted to tackle this limitation. By merging different sources of information, data fusion can actually enhance the available resolutions.

1) Pansharpening: The synthesis of MS images at a higher spatial resolution can be achieved by exploiting an alternate high-resolution image acquired in another modality. These synthetic images should be similar to the MS images that would have been observed with a sensor at the higher resolution [22], [23]. When the higher resolution image is panchromatic (Pan), i.e., a single wide spectral-band image acquired across the visible and possibly near-infrared wavelengths, this fusion process is usually called pansharpening of MS images.

Spaceborne sensors, such as SPOT, Ikonos, or QuickBird, provide images with different characteristics: on the one hand, images with high spectral resolution but low spatial resolution, and on the other hand, images with low spectral resolution but high spatial resolution. Several works have demonstrated the usefulness of fused products offering high spectral and spatial resolutions at the same time in various environmental applications [24], [25]. Pansharpened products are becoming very popular (for example, Google Earth), and data providers are offering higher and higher amounts of them at lower and lower costs. The Data Fusion Contest organized by the DFTC at the IEEE Geoscience and Remote Sensing Symposium 2006 [26] was meant as the ultimate word on the subject, after the book by Wald [27] and the authoritative papers by Alparone et al. [28], [29].

As recalled in [26], a variety of pansharpening techniques take advantage of the complementary characteristics of spatial and spectral resolutions of the data [30], [31]. Among them, component substitution (CS) methods [32] are attractive because they are fast and easy to implement. When exactly three MS bands are concerned, the most widely used CS fusion method is based on the intensity–hue–saturation (IHS) transformation [33]. The spectral bands are resampled and coregistered to the Pan image before the IHS transformation is applied. The smooth intensity component I is substituted with the high-resolution Pan and transformed back to the spectral domain via the inverse IHS transformation.

Multiresolution analysis (MRA) is the alternative; it provides effective tools like wavelets and Laplacian pyramids to help carry out data-fusion tasks. MRA-based fusion requires the definition of a model establishing how the missing high-pass information is to be extracted from the Pan image and then injected into the MS bands [23], [34]–[36].

In this Special Issue, the necessity to take physical considerations into account when designing a pansharpening algorithm is clearly established by Thomas et al. [37]. A pansharpening method using a multiscale mapped least squares support vector machine (SVM) is proposed by Zheng et al. [38], whereas the popular MRA based on wavelet analysis is brought one step forward by Shah et al. [39] by using contourlet decomposition, for a better representation of edges. Finally, Aanaes et al. [40] introduced a model-based fusion and describe a novel approach to improve the spatial resolution even when no simple ratio between the coarse and the finer resolution data is available.

2) Subpixel Processing: Beyond the continuous improvement of the sensors in terms of spatial resolution, there is a need for even more accurate processing and analysis; subpixel processing is on stake. As already mentioned, this addresses the task of registration. Two more papers of this Special Issue can fit in this category.

1) In the case of hyperspectral images, Gu et al. [41] propose using some spectral unmixing and superresolution mapping to enhance the spatial resolution while preserving the spectral diversity.

2) Beyond spectral unmixing, subpixel classification is addressed by Robin et al. [42]. This ill-posed problem is solved by injecting some further information (time series) and some prior structural knowledge.

3) Downscaling: It is worth noting that spatial enhancement sometimes is based on fusion of ancillary information, even if the ancillary information has sparse and somehow spatially irregular sampling on the ground. This is the case for many models for hydrology or environmental analysis, whose inputs are both remotely sensed data, usually at coarse spatial resolution, and locally very detailed in situ measurements. It is increasingly important to develop methodologies aimed at combining these two very different sources of information and to provide jointly spatially enhanced and calibrated data by means of a downscaling approach. This is what is proposed by Kaheil et al. [43] for soil moisture measurements.

C. Data Level Fusion

The first way to exploit the georeferenced and spatially enhanced data sets achieved by means of the previous processing step is to directly proceed to information extraction. Joint per-pixel analysis is usually labeled as “data level fusion.” Typical outputs are land-cover/land-use classification in the
case of multisensor Earth observation data and change detection maps for multitemporal data sets. A good example of these techniques is presented in [44]. In this Special Issue, an image fusion technique based on partial differential equation is proposed. By means of diffusion and inverse diffusion, the information from multiple stocks of seismic measurements is enhanced with respect to the extraction of fault structures.

A similar approach for the fusion of multiple runs from the same (kind of) sensor is proposed in [45], where multiple inverse synthetic aperture radar measurements are combined to a more effective target detection. It is a very interesting approach that exploits the spatial frequency space where SAR images are formed as the framework in which data fusion is implemented. Proposed rules allow the combination of sensors with different spatial and frequency resolutions by means of the proposed matrix Fourier transform algorithm.

A relatively less new, but still active, research line is instead the one referring to the exploitation of multisensor data. This Special Issue brings in an excellent example. In [46], the combination of different properties of the atmosphere, as they are measured by multiple sensors, is used to achieve better characterization of the aerosol properties than that available from any single sensor. The fusion rules are based on a priori knowledge on the meteorological phenomena and their effect at different wavelengths and on different measured quantities.

On the same subject, and on one of the innovative research lines in data fusion highlighted in the introduction, Dalponte et al. [47] show the combination of 2- and 3-D data sets. In particular, in this Special Issue, hyperspectral and lidar data are jointly considered for forest analysis. The approach is very similar to a stack of the 2- and 3-D data, but a feature extraction is run before in order to select the best information for the task.

Finally, this Special Issue carries an example of data fusion for change detection. The paper by Mercier et al. [48] is extracting change areas by comparison of statistical behavior of pre- and postdata sets that might be very different as for acquisition conditions. The paper works in the opposite direction than most of the similar works. It tries to define the similarity in unchanged areas and, in the statistical sense, to learn when a change has happened as a nonstationary statistics is recognized.

D. Feature Extraction

Data fusion at the feature level consists in extracting different, and most of the time complementary, features from the data; these features become the inputs of one single processing (e.g., a classifier). These features can be of different natures (statistical, geometrical, and so on); they can be extracted from the initial data or after some transform.

In this Special Issue, Roy et al. [49] present an application of how such features can be extracted and merged for the analysis of microbarographs. In this case, a transformed representation of the data is used, namely, the Huang–Hilbert transform, decomposing nonstationary signals in order to highlight moving trends and break it into locally orthogonal components.

In remote-sensing imagery, an important trend consists in using simultaneously the spectral information (multi- or hyperspectral data) and the spatial information [50]–[53]. This is particularly helpful for the classification of man-made structures where the shape of the objects actually helps recognize the corresponding structures, such as in urban areas.

E. Decision Fusion

For most of the usual tasks in remote sensing (detection, classification, segmentation, etc.), an abundant literature can be found, with numerous algorithms being proposed. Most of the time, every algorithm has its own merits, and it is rare to find one that systematically outperforms all the others. As a consequence, a key issue in data fusion consists in simultaneously using different algorithms, trying to take advantage of their respective merits, thus increasing the overall performances. This process is generally referred to as “decision fusion” [54]–[56]. Multiple classifier systems (MCSs) can also fit in this framework (see [57] for a recent overview of MCS in remote sensing).

The fusion can look for complementarity between the algorithms when they are based on different properties (for instance, morphological and statistical detectors [58]). On the contrary, it can look for redundancy to decrease the false-alarm rate [59], assuming that the noise is not redundant. When the different sources of information agree, the final output remains the same as with an individual algorithm, but the confidence in this result increases. When they disagree, there is a chance to actually increase the individual performances by picking the right output up. The key point hence lies in defining the reliability of every output in order to select the most reliable one [60]. This can be an adaptive criterion or a criterion based on some prior knowledge.

In this Special Issue, the task of target recognition in the frame of hyperspectral imagery is addressed by Prasad and Bruce [61]. The initial hyperspectral space is partitioned into contiguous subspaces based on the optimization of a performance metric. Local classification decisions are then met in every subspace using an MCS. Decision fusion with an adaptive weight assignment (based on the strengths of individual local classifiers) makes the final decision.

Waske and van der Linden [62] propose a joint classification of multiple segmentation levels from multisensor imagery using SAR and optical data which are first separately segmented, creating independent aggregation levels at different scales. Each individual level from the two sensors is preclassified by an SVM. The original outputs of each SVM, i.e., images showing the distances of the pixels to the hyperplane fitted by the SVM, are used in a decision fusion to determine the final classes.

On a different level of decision fusion, in [63], the stress is on classifier outputs’ fusion by means of robust algorithms. The author introduces two different algorithms for fault-tolerant classifier combination. The goal is to find an approach that is sufficiently robust to work well in case of corrupted classification maps in input. The overall methodology is tested in a multisensor environment, exploiting optical, passive, and active radar data acquired onboard the ENVISAT satellite.
F. Fuzzy-Model-Based Fusion

Fusion operators based on fuzzy models and/or fuzzy combination rules play a major role. As a matter of fact, these operators can handle imprecise or uncertain information, which is very important when different sources of information are conflictual. They also allow one to postpone the final decision to every last step of the processing, thus preserving as much information as possible, as long as possible. Another advantage is the possibility offered to handle semantic data and to model some very rough expert’s knowledge. Finally, by using fuzzy distributions, the models are very flexible and not too sensitive to parameter settings.

These models have already proved their efficiency in various remote-sensing applications [59], [64], [65]. For a milestone paper by Bloch, please refer to [66].

In this Special Issue, following a previous work, Milisavljevic and Bloch [67] present different fusion strategies based on possibilistic models or belief functions for antipersonnel mine detection [68]. Fuzzy fusion rules offer a wide range of behaviors (indulgent, severe, cautious, etc.), providing different properties in order to match the user’s expectations. Kallel et al. [69] address the analysis of vegetation index and propose a cautious-adaptive combination rule based on belief functions.

III. CONCLUSION

New research fields are emerging, and new forces are working toward new data-fusion algorithms, architectures, and solutions. This Special Issue was meant to give them an option to discuss their achievements and set a further milestone in the DFTC’s history.

The overwhelming response to the call for papers (more than 45 submitted papers) showed that we were right. The strong selection procedure provided us with an excellent table of content. It sets the scene for the next years, but we already forecast a new issue in the near future. For the moment, enjoy your reading!

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