Data Fusion and Remote Sensing – An Ever-Growing Relationship

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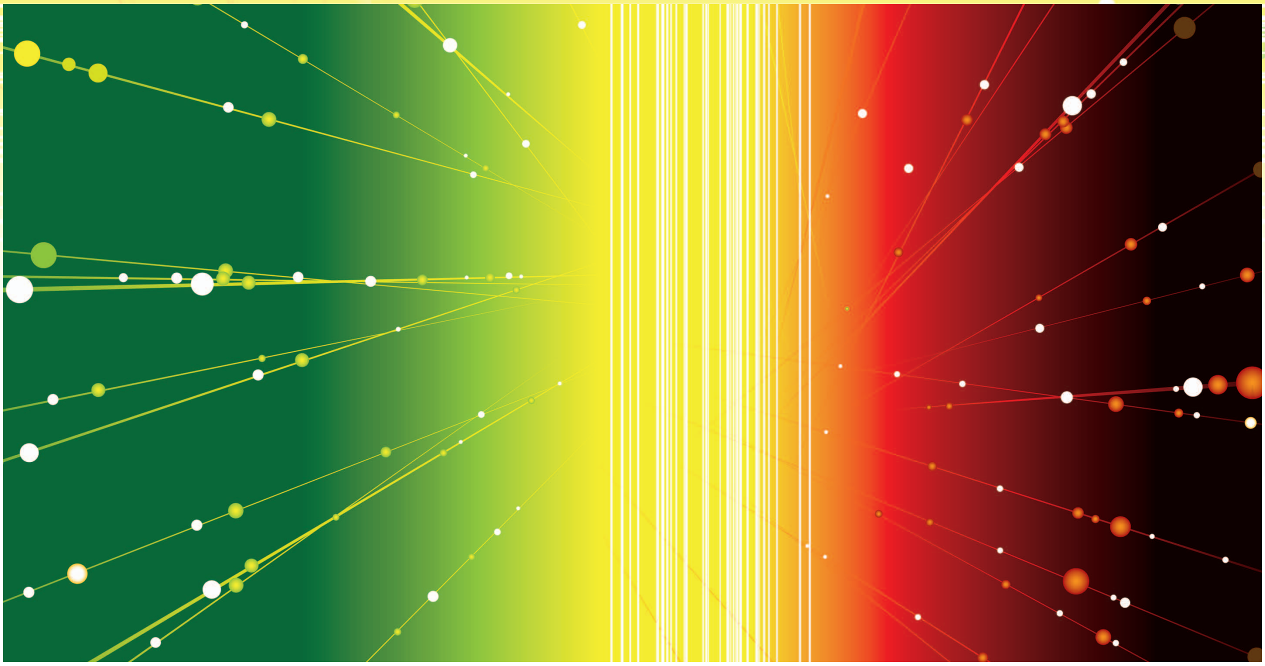

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Data Fusion and Remote Sensing

An ever-growing relationship

MICHAEL SCHMITT AND XIAO XIANG ZHU

Characterized by a certain focus on the heavily discussed topic of image fusion in its beginnings, sensor data fusion has played a significant role in the remote sensing research community for a long time. With this article, we aim to provide a short overview of established definitions, targeting a generalized understanding of the topic. In addition, a review of the state of the art of remote sensing data fusion research is given. By bringing together the conventional view expressed in the classical data fusion community and a review of current activities in the field of Earth observation, this article provides a holistic view of generic data fusion concepts and their applicability to the remote sensing domain.

KEY TERMINOLOGY

Data fusion, sensor fusion, information fusion, sensor data fusion, or simply fusion—no matter which specific term is used, the science of combining measurements, signals, or observations from different sources to obtain a result that is in some sense better than what could have been achieved without this combination is a widely discussed topic in many disciplines. Some scholars suggest that there is a subtle difference between the aforementioned terms. According to Gustafsson [55], information fusion is mostly used in information theory or artificial intelligence and aims at fusing information that cannot always be represented by real numbers. In contrast, sensor fusion combines data from different sensors on an intermediate level, and data fusion merges numerical data from multiple sources closer to the raw sensor data. In the context of remote sensing, the simple term data fusion is usually used, although sometimes this term extended to sensor data fusion if data from different sensor types are used, and sometimes this is termed *image fusion* if only two-dimensional images are combined. In any case, fusion is a crucial topic in a scientific field where the variety of exploited sensors ranges throughout most of the electromagnetic spectrum, includes both active and passive sensing technologies, comprises resolutions from the micrometer level to the kilometer level, and is used in applications from geological deformation monitoring to biomass estimation and urban-area reconstruction.

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As Figure 1 illustrates, the current trend is an ever-increasing versatility of sensor features, an ever-increasing number of available sensors, and, because of modern storage technologies, an ever-increasing amount of incoming data. Although each space-borne satellite mission, flight campaign, and field survey usually produces data for a specified goal, it is advisable to foster the development of data fusion techniques to enable the maximal utilization of what is available in the archives or of what can be acquired in the shortest possible time (e.g., in rapid mapping situations). In addition, current international space programs, such as the European Space Agency's *Copernicus*, are already designed to incorporate various sensor technologies. In this example, there will be six Sentinel satellites offering services based on radar, multispectral imagery, altimetric data, or thermal spectroscopy [40].

Data fusion has been a well-discussed research topic in the remote sensing community with the first review and discussion articles published more than 15 years ago [157]. For quite some time, a significant part of the scientific output was, and to a certain extent still is, dedicated to the topic of two-dimensional image fusion for either pan-sharpening or classification purposes. Because of the growing challenges introduced by the age of versatility and big data, this article intends to review the state of the art while providing a view beyond the current remote sensing horizon.

WHAT IS MEANT BY DATA FUSION? COMMON DEFINITIONS

Throughout the scientific literature, an abundance of data fusion definitions can be found. These come from diverse communities, such as information theory, computer science, signal processing, radar, tracking and surveillance, and, of course, remote sensing. An overview of different definitions published in recent decades is given in Table 1.

One of the most comprehensive surveys of data fusion definitions with a particular emphasis on the remote sensing context was provided by Wald [157]. In addition, he proposed his own definition, which he found to be better suited than most previous ones: "Data fusion is a formal framework in which […] means and tools for the alliance of data originating from different sources [are expressed]. It aims at obtaining information of greater quality; the exact definition of greater quality will depend upon the application." Although this is certainly a very good definition providing a comprehensive frame in a rather broad sense, there are many other definitions published before and after Wald's work that have their justifications. For example, a very similar definition was given by Ruser and Puente Leon [133], scientists from the field of classical metrology: "Information fusion denotes the process of combining data from different sensors or information sources to obtain new or more precise knowledge on physical quantities, events, or situations." This definition can easily and directly be applied to the remote sensing domain. In this definition, it is interesting to note the focus on a dynamic analysis to gain information not only about static objects but also about events and situations. Similar in meaning but aiming at a different level of interpretation is the definition suggested by Li et al. [76], which states that "fusion refers to the combination of a group of sensors with the objective of producing a single signal of greater quality and reliability."

More abstract definitions were provided by the U.S. Department of Defense [155], "Data fusion is a multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation, and combination of data and information from multiple sources," and the seminal article by Hall and Llinas [58], whose definition is based on the Joint Directors of Laboratories model: "Data fusion techniques combine data from multiple sensors, and related information from associated databases, to achieve improved accuracy and more specific inferences than could be achieved by the use of a single sensor alone." As in the previously mentioned definitions, the main motif is that data fusion is meant to provide better results than single-source data analysis.

Generalized definitions, such as the one provided by Khaleghi et al. [71], "Multisensor data fusion is a technology to enable combining information from several sources to form a unified picture," leave a great deal of room for interpretation and adaptation to certain application fields. In contrast, the remote sensing community has long relied on a more narrow rationale. In one of the most frequently cited articles on the topic, Pohl and van Genderen [106] claimed

FIGURE 1. The present—and, even more so, the future—is characterized by a large variety of available Earth observation sensors, ranging from satellites to aircraft to unmanned aerial vehicles (UAVs). (Background image courtesy of NASA/JPL/NIMA.)

TABLE 1. A SUMMARY OF DIFFERENT DEFINITIONS OF THE TERM *DATA FUSION* (AND OTHER TERMS WITH THE SAME OR SIMILAR MEANING).

ARTICLE	DEFINITION
Hackett and Shah, 1990 [57]	"Multisensor fusion deals with the combination of complementary and sometimes competing sensor data into a reliable estimate of the environment to achieve a sum that is better than the parts."
U.S. Department of Defense, 1991 [155]	"Data fusion is a multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation, and combination of data and information from multiple sources."
Li et al., 1995 [76]	"Fusion refers to the combination of a group of sensors with the objective of producing a single signal of greater quality and reliability."
Hall and Llinas, 1997 [58]	"Data fusion techniques combine data from multiple sensors and related information from associated databases to achieve improved accuracy and more specific inferences than could be achieved by the use of a single sensor alone."
Wald, 1999 [157]	"Data fusion is a formal framework in which [...] means and tools for the alliance of data originating from different sources [are expressed]. It aims at obtaining information of greater quality; the exact definition of 'greater quality' will depend upon the application."
Luo et al., 2002 [84]	"Multisensor fusion and integration refers to the synergistic combination of sensory data from multiple sensors to provide more reliable and accurate information."
Ruser and Puente Leon, 2007 [113]	"Information fusion denotes the process of combining data from different sensors or information sources to obtain new or more precise knowledge on physical quantities, events, or situations."
Dong et al., 2009 [37]	"Multisensor data fusion seeks to combine information from multiple sensors and sources to achieve inferences that are not feasible from a single sensor or source."
Sidek and Quadri, 2012 [127]	"Data fusion deals with the synergistic combination of information made available by different measurement sensors, information sources, and decision makers."
Gustafsson, 2012 [55]	"Sensor fusion is the combining of sensory data or data derived from sensory data from disparate sources such that the resulting information is in some sense better than what would be possible when these sources were used individually."
Castanedo, 2013 [22]	"[Data fusion is defined] as a combination of multiple sources to obtain improved information; in this context, improved information means less expensive, higher quality, or more relevant information."
Khaleghi et al., 2013 [71]	"Multisensor data fusion is a technology to enable combining information from several sources to form a unified picture."

that "image fusion is the combination of two or more different images to form a new image by using a certain algorithm." On the basis of image-centered reviews like this one or the work by Zhang [175], we see already that a certain emphasis in remote sensing data fusion is placed on image interpretation, either in the context of classification tasks or in the context of pan sharpening. In the context of classification, fusion applies to the combination of different images or image bands to extend the feature vector for every pixel or object to be classified. In the context of pan sharpening, a high-resolution image of one sensor can be used to improve the resolution of an image of lower resolution from the same or a different sensor.

From the broader view given by the more general definitions from other communities, a well-fitting, summarizing rationale can be found: the main objective of data fusion is either to estimate the state of a target or object from multiple sensors, if it is not possible to carry out the estimate from one sensor or data type alone, or to improve the estimate of this target state by the exploitation of redundant and complementary information. A nice description showing a similar direction was given in the early definition offered by Hackett and Shah [57], who claimed that the goal of multisensor fusion is to "achieve a sum, which is better than the parts." In that sense, the very core of data fusion is the estimation process itself. Data fusion is all about combining the observations from more than one sensor, position, or time (and ideally even from more than one sensor type) to infer unknown parameters about the object of interest. As Ruser and Puente Leon [113] explained, this is necessary because single sensors show the crucial disadvantage of being unable to cope with their inherent uncertainties during interpretation of the sensor signals, and only fusing information from different sources will enhance the reliability of the measurement task. Still, to do so, it is necessary beforehand to align the data and correlate them with the object of interest. In other words, the potentially heterogeneous information must be matched to each other and to the corresponding target object in both space and time and then transformed or coregistered to a joint reference frame [92]. Although this matching and coregistration step is therefore an inherent part of any data fusion task, sometimes little attention is paid to it in classical data fusion literature, mainly because sensor setups in typical surveillance or tracking tasks are usually well designed for their particular purpose [74]. In contrast, data matching and registration play a major role (and comprise a research field in their own right) in remote sensing because of the great range of heterogeneous sensor types with strongly different temporal, spatial, and radiometric resolutions [31].

MODELING THE DATA FUSION PROCESS

As explained in great detail by Hall and Llinas [58], multisensor data fusion can be organized into several levels, i.e., object refinement, situation refinement, and threat refinement. Coming from a military background, their theory, however, must be adapted to the remote sensing context [157]. In this regard, mainly the object refinement level is of interest, which itself is structured into the following tasks (Figure 2): data alignment, data/object correlation, attribute estimation, and identity estimation.

These four steps can be summarized into two core actions. Data alignment and data/object correlation together form what is commonly referred to as matching and coregistration in the remote sensing context. Their goal is to ensure that measurements are properly connected to each other and to the respective object of interest. The other two tasks, attribute estimation and identity estimation, constitute the actual fusion step, i.e., the combined exploitation of aligned and correlated measurement data in an estimation framework.

MATCHING AND COREGISTRATION

In general terminology, the data alignment step is about coordinate transformations and unit adjustments aimed at achieving a common representation of the heterogeneous measurements and observations describing the object of interest. In analogy, the data/object correlation stage is mainly about associating several multisensor measurements about the object of interest with each other. In other words, it is about letting the data fusion process know which particular measurements are supposed to be fused in the final estimation step.

In remote sensing, these two steps aim at the spatial and temporal matching and, if necessary, the coregistration, respectively, of different sensor data showing potentially very different radiometric, geometric, and other properties. When the alignment problem is solved and spatial, temporal, and/or semantic relationships among the individual data sources are established, a reference frame can be defined to which all available data can be transformed. This transformation may often require an additional resampling process, which may be necessary not only for the spatial domain but also for the temporal domain. In the end, the result of matching and potential coregistration is an exact determination of which measurements belong to the same geospatial object and/or were acquired at the same relevant point in time.

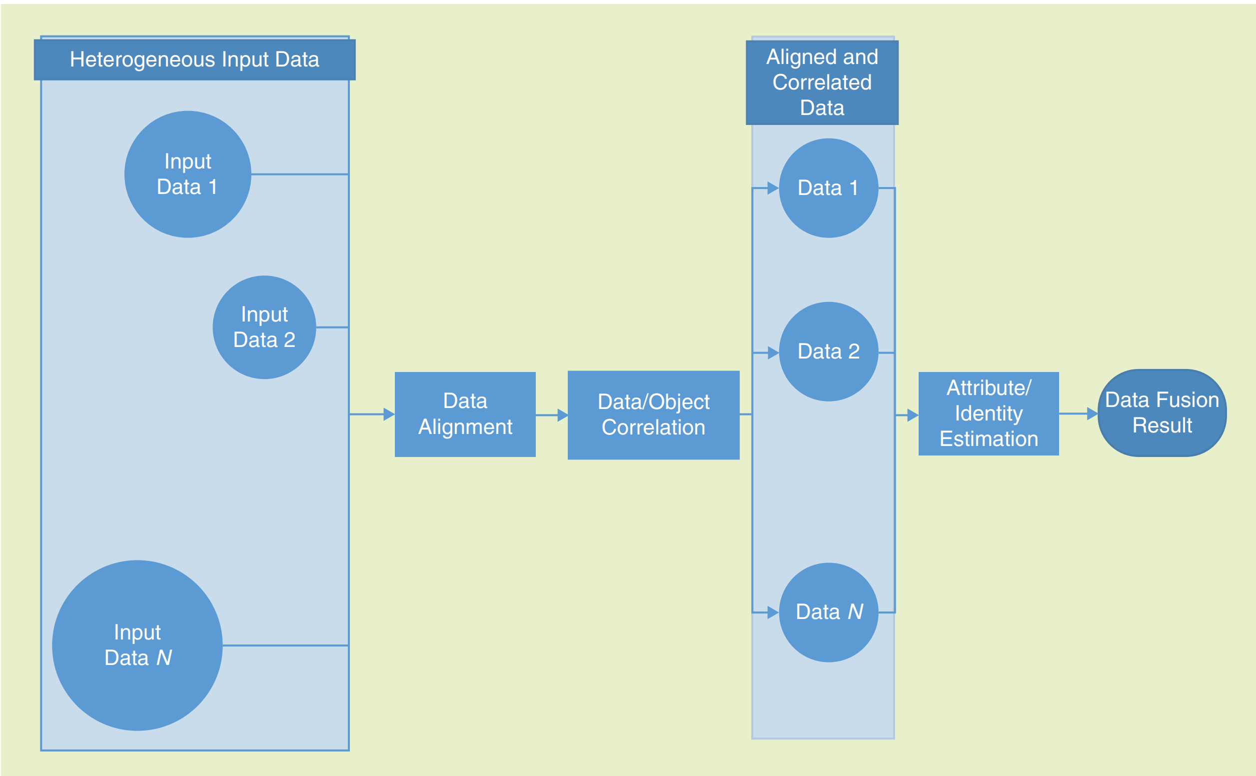

FIGURE 2. The flowchart shows the generalized data fusion process that starts with heterogeneous input data, potentially stemming from different sensors yielding different types of measurements and potentially acquired at different points in time. After the steps of data alignment and data/object correlation, the core step of data fusion (the attribute and identity estimation step) can be carried out, finally giving the desired information about the object of interest.

To provide some examples, Earth-observation data can be acquired by both airborne and space-borne missions, by optical cameras or line scanners, by synthetic aperture radar (SAR) sensors, or by spectrometers providing infrared or multi- or hyperspectral imagery. In addition, there might be information about atmospheric parameters [e.g., acquired by ultraviolet light detection and ranging (LiDAR)] or crowd-sourced optical imagery recorded by hand-held cameras or smartphones, global positioning system (GPS) coordinates, point clouds, or pre-existing geographic information system (GIS) data. All these data show great diversity in their information content, the amount of available metadata, and attributes such as spatial and temporal resolution, scale, and measurement accuracy, not to mention the difference between extensive observations (such as images) and point-wise measurements (such as GPS positions).

Therefore, the matching and coregistration of heterogeneous data comprise a core challenge in (remote sensing) data fusion. Although there have already been some investigations in this direction, aimed at specific registration tasks for image-like data, it is still an open field of research because massive data amounts require fully automated procedures for data registration, which in turn requires a preliminary automated matching of homologous data points. While this is rather simple to achieve for homogeneous sensor data such as mono-sensor images [31], [181], it is far more challenging for imagery from different sensors [42], [68], [70], [72], [137], [159], and it is still a largely undiscussed problem for strongly different data, such as airborne or space-borne imagery, crowd-sourced imagery [35], [160], or point clouds and image data [86], [163].

Furthermore, additional challenges arise if matching or coregistration cannot be carried out without external knowledge, such as pre-existing information about the three-dimensional (3-D) nature of the real-world object of interest. If this external knowledge corresponds to the desired entity, which actually is the goal of the whole data fusion process, it will be necessary to closely link the matching and coregistration steps to the actual fusion step and find a solution by jointly optimizing both the matching/coregistration and the estimation objective. Examples for such situations have been demonstrated for the joint registration and reconstruction of surfaces from different types of close-range imagery [23], [27] or for joint 3-D reconstruction and matching via object space in multiaspect multibaseline interferometric SAR (InSAR) data [121].

FUSION BY ESTIMATION

Like the first and second steps, the third and fourth steps of the data fusion process can be viewed together. Whether attribute estimation or identity estimation is needed for the object of interest, the goal is the same, i.e., the aligned and correlated measurements from heterogeneous sensor sources must be fused in a well-defined estimation framework to infer the desired information about the target in an optimal way. However, in the first case, only attributes describing the object are desired (e.g., 3-D coordinates, velocities, or parameters such as size or area); whereas, in the second case, a semantic identification of the object is the goal (e.g., building recognition or land-use classification). In this context, it is interesting to note that, generally, three different types of sensor integration are imaginable [113].

- Competitive integration is the fusion of homogeneous sensor data with similar information content to reduce uncertainties (e.g., by averaging). Example: The accumulation of images acquired under similar conditions for noise reduction.
- Complementary integration is the fusion of homogeneous sensor data with different information content to reduce information gaps. Example: The combination of sensors with different (complementary) measurement ranges, e.g., images with different cloud coverage or complementary spectral ranges.
- Cooperative integration means that the information content is distributed; i.e., all available measurements need to be exploited to receive the desired information about the target. Example: Stereo-imagery for 3-D reconstruction.

Independent of the type of sensor integration, this actual data fusion step can be categorized into three main types (Figure 3): 1) observation-level fusion, 2) feature-level fusion, and 3) decision-level fusion [58]. While observation-level fusion means that raw data are combined directly, feature-level fusion involves a preliminary extraction of representative features from the original sensor data. Finally, decision-level fusion is used only after a first determination of the target's attributes of interest by each sensor alone has already been achieved.

In any case, attribute and identity estimation are the very core of the data fusion domain and are mainly driven by different developments in statistical estimation theory and machine learning, respectively. In this context, the origins of data fusion can probably be found in the pioneering least-squares experiments of Carl Friedrich Gauss, who fused several observations of the orbit of the planetoid Ceres to estimate the corresponding orbit parameters [139]. Since then, many different estimation approaches, some more sophisticated and some less so, have been described in the literature for both Bayesian and non-Bayesian statistics, fuzzy measurements, and so forth [71]. Future research in data fusion, also within the field of remote sensing, will benefit from these developments. In particular, if strongly heterogeneous data must be fused, for which no convenient joint probability functions can be found, unconventional modeling may help provide closed-form solutions. Also, the availability of growing amounts of labeled data will further boost the importance of machine-learning techniques. More discussion on this topic is provided in the sections "An Excursion into Estimation Theory: Modeling the Actual Fusion Step" and "Integration of Machine Learning to the Data Fusion World."

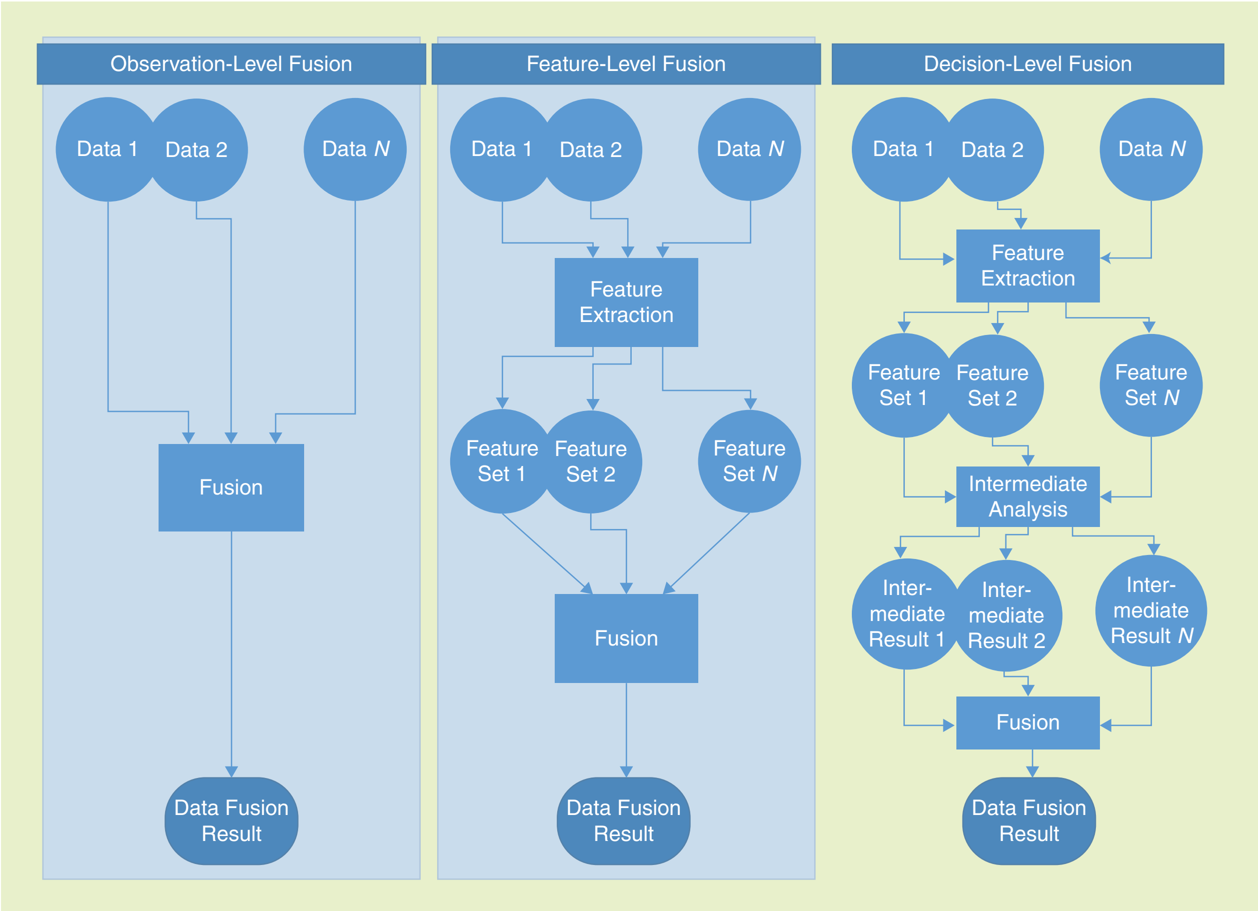

FIGURE 3. The three types of data fusion are compared side by side: observation level, feature level, and decision level.

A REVIEW OF THE STATE OF THE ART IN REMOTE SENSING

IMAGE FUSION—THE ROOTS OF REMOTE SENSING DATA FUSION

While a very general view of data fusion was described in the preceding sections, it is notable that a significant portion of the early literature about the fusion of remote sensing imagery is based on either image fusion for pan-sharpening purposes or feature fusion for the improvement of classification results [106]. For example, Ehlers et al. [39] provided a comprehensive overview of pan-sharpening methods based on well-known algorithms such as the Brovey transform [51], principal component transform [26], or modified intensity-hue-saturation transform [126], which are evaluated by the exemplary fusion of SPOT, Ikonos, and TerraSAR-X imagery. A similar comparison [98] added, among others, methods such as the wavelet transform [177] to the evaluation. Besides the manifold literature on optical pan sharpening, the enhancement of low-resolution SAR images with higher-resolution SAR images has been described [28]. Adding a critical view to the field of pan sharpening, Wald et al. [156] proposed a means to assess the quality of the resulting images, while Thomas et al. [145] gave a no less critical review, claiming the importance of proper consideration of the physical peculiarities of remote sensing. Another important development was the introduction of spectral-spatial fusion techniques, which paved the way for even better pan-sharpening techniques and improved classification results from multispectral data [64]–[66], [89], [109].

As the next natural step within the image fusion domain, much effort is currently put into the pan sharpening of hyperspectral data [81]. For example, methods based on nonnegative matrix factorization [173] or sparse representations [53], [168], [178] have been proposed for the optimized resolution enhancement of hyperspectral data with multispectral imagery. Furthermore, abundant examples of the fusion of hyperspectral imagery and other data for classification can be found throughout the literature [8], [15], [30], [158].

FUSION OF MULTIMODAL DATA—TAKING REMOTE SENSING DATA FUSION TO THE NEXT LEVEL

In addition to this basic view on remote sensing data fusion, a higher-level summary [175] specifically addressed work on the fusion of optical and SAR images for classification purposes (e.g., [135], [164], [165]); LiDAR data and imagery for object recognition (e.g., [56], [112], [161]) and biophysical parameter estimation (e.g., [54]); and optical images and GIS data for change detection (e.g., [169]). In addition, some publications have suggested the use of space-borne stereo imagery and digital surface models (DSMs) for change detection [146] or hyperspectral imagery and LiDAR for classification tasks [49]. Similar high-level approaches, aimed at the fusion of InSAR data and other data for improved image exploitation, have been summarized by Simone et al. [129], who even consider SAR interferometry itself a case of data fusion, as two images need to be exploited. More sophisticated data fusion tasks involving InSAR and external auxiliary data have been proposed by Thiele et al. [142], who discussed the potential of combining GIS and InSAR data for 3-D building reconstruction. In contrast, Wegner et al. [166] proposed carrying out this reconstruction task by fusing the InSAR data with just a single orthophoto. In [142], the ideas were taken a level lower by employing auxiliary GIS data already during the InSAR phase filtering step. In analogy, Zhu et al. [180] suggested incorporating auxiliary GIS data as prior knowledge into tomographic SAR processing for more accurate three- or even four-dimensional imaging of urban areas while significantly reducing the number of SAR images required.

Other reasons for data fusion in the SAR-optical fusion context are the sharpening of low-resolution optical images by very high-resolution SAR imagery [5], [111] or their exploitation for traffic monitoring [63]. Since the alignment of very high-resolution SAR and optical data is a nontrivial task because of strong radiometric and geometric differences [102], [137], recent fusion approaches have attempted to circumvent these problems by incorporating prior knowledge in the form of existing 3-D geodata and the simulation of reference data sets [138]. The resulting data set is then used for further information extraction, e.g., change detection or classification [103]. Interestingly, approaches for a stereogrammetric exploitation of SAR and optical data were suggested for low-resolution sensors and sparse matching situations two decades ago [13], [108], but these have lost the interest of the modern data fusion community until recently [184].

Urban areas lie at the center of interest for many remote sensing researchers. No wonder that a particularly visible application of data fusion is its support for urban mapping in a variety of scales. Comprehensive and recent reviews of the research activities in remote sensing data fusion with special regard for the mapping of urban areas are provided in [44] and [150]. Among others, an intensively discussed topic on local scale is the fusion of SAR and optical data for tasks such as urban surface model generation [147], [154], damage assessment [19], road network extraction [79], or building modeling [133], [153]. The latest developments in this area have extended the mapping of urban areas supported by data fusion even to the global scale [43], [45], [46], [116].

SINGLE-SENSOR DATA FUSION

Although most of the aforementioned examples aim at fusing data from different sensor types, there is some literature available about the fusion of single-sensor data from different viewing angles as well as at different resolutions or from different points in time. For example, so-called multiaspect SAR data acquired from flexible airborne platforms have been used for optimizing road extraction [59], [60], [118], [136], [152], 3-D reconstruction of urban surface models [119], [120], and semantic building recognition [14], [132], [140], [141], [143], [170]. The lessons learned from these investigations have already been transferred to the more limited case of ascending–descending data fusion using satellite-borne sensors, e.g., for building façade reconstruction [179]. However, the task of data alignment is also a prominent problem in this context, aimed either at the registration of multiangular SAR imagery directly [33], [93], [122] or of point clouds generated from multiaspect data sets [48], [162]. Another application of multiangular data is precise Stereo-SAR positioning [52]. While multiaspect approaches naturally have been investigated mostly within the context of SAR remote sensing because of its side-looking imaging geometry, multiangular data have also been used in optical remote sensing, e.g., for improving classification performance [83] or achieving superresolution [176].

Most of the literature on multiresolution single-sensor data fusion is found in the previously mentioned field of pan sharpening. There are, however, a few examples of multiresolution applications with different scopes, such as the fusion of multifrequency SAR imagery as a preprocessing step in scene interpretation [128], the exploitation of multiresolution SAR data for unsupervised change detection [94] and the mapping of urban areas [115], [116] or multiresolution staring spotlight and high-resolution spotlight data for SAR tomography [47]. Although the exploitation of multitemporal data is generally considered part of the data fusion theme complex, change detection techniques have long been a research direction in their own right within the remote sensing community and shall not be considered any further in this article [16], [67], [130].

Although not strictly (sensor) data fusion in the context of this review, a final group of decision-level-based fusion approaches must be mentioned. Here, the fusion task is not applied to the combination of data acquired by different sensors; instead, only a single input data set is used, and the fusion step is applied to several preliminary classification results obtained from this input. Examples of this type of fusion were presented by [151] for the interpretation of SAR images; by [9] for multispectral, elevation, and multiangular data; by [24] and [41] for Ikonos imagery; and by [172] for hyperspectral images.

WHAT'S NEXT? FUSION OF STRONGLY HETEROGENEOUS DATA

Among the most sophisticated fusion tasks is the combination of strongly heterogeneous space-borne, airborne, and terrestrial data for the development of seamless multiview and multiresolution Earth-observation systems. In this context, e.g., the automatic georeferencing of satellite images can be realized by exploiting existing orthophotos made from aerial images [50] or by registering them to accurately geocoded SAR data [110]. Additional examples are the fusion of aerial imagery and terrestrial photos for the reconstruction of building models [69], [160], the fusion of aerial imagery and vehicle-borne sensor data (e.g., omnidirectional optical imagery, LiDAR measurements, and GPS tracks) for semantic mapping purposes [105], or the fusion of airborne and terrestrial imagery for the support of road management tasks [96]. Another application can be found in the field of atmospheric remote sensing, where InSAR data, global navigation satellite system signals, and other information sources can be fused to determine information about atmospheric water vapor [3], [4], [61], or geostatistical fusion can be applied for the combination of remote sensing and ground-based observations for measuring aerosol contents [25], [97]. Only a handful of contributions in the literature have addressed one of the most recent challenges, i.e., the fusion of remote sensing and social media data. The few existing examples address the joint classification of aerial and social media images [11], the monitoring of people dynamics using airborne sensor and mobile phone data [62], [99], or the mapping of flood damage using governmental and crowd-sourced information [123]. Handling the massive, unstructured, and strongly heterogeneous data delivered by remote sensing sensors and social media will be one of the major challenges of future data fusion research.

CURRENT SCIENTIFIC ACTIVITIES IN THE REMOTE SENSING DATA FUSION COMMUNITY

Publications are among the best measureable entity to assess current scientific activities of a certain discipline. For this reason, Figure 4 summarizes the distribution of the publications in which articles referenced in this review were published. Although such reviews and their corresponding statistics are always biased to some extent, the distribution certainly gives a first hint regarding the most relevant outreach organs in remote sensing data fusion. Whereas the prevalence of *IEEE Transactions on Geoscience and Remote Sensing* and *IEEE Journal of Selected Topics of Applied Earth Observations in Remote Sensing* is not really surprising, it is interesting to note that *International Journal of Image and Data Fusion*, founded in 2010 and issued by the renowned publishing group Taylor & Francis, is the third most active journal in the field, although it is currently still waiting to be included in the Science Citation Index.

Concerning scientific associations, data fusion is mainly institutionalized within the remote sensing community by two consortia in the framework of the two major professional organizations (Table 2). On one hand, there is currently the working group ISPRS WG VII/6 "Remote Sensing Data Fusion" of the International Society for Photogrammetry and Remote Sensing (ISPRS), which names the promotion of *International Journal of Image and Data Fusion* as one of their goals. (In the previous sentence, "currently" refers to the beginning of 2016. Since then, the technical commissions and working groups of the ISPRS were rearranged at ISPRS Congress 2016, so data fusion might now be represented in a different frame.) On the other hand, there is the Image Analysis and Data Fusion Technical Committee (IADFTC) of the IEEE Geoscience and Remote Sensing Society (IEEE GRSS). This group is very active in the field, mainly via the annual IEEE GRSS Data Fusion contests, which they've hosted since 2006. From the summary of the past contest topics given in Table 3, it can be seen that, whenever a specific goal was provided, it was about either classification or pan sharpening, which seems to prove the hypothesis of the section "Modeling the Data Fusion Process," which is that remote sensing data fusion has long put a certain emphasis on these topics. Although many participants consistently work on the same issues, different topics are more often addressed whenever the contest encourages the submission of creative ideas rather than specifying tasks. For example, participants in 2011 exploited the multiangular WorldView-2 imagery provided in the contest for the tracking and velocity estimation of moving objects [90], [114]. In 2012, the winning groups used LiDAR and SAR data in combination with image simulation techniques for change detection, fused multispectral and LiDAR data to create a new measure for the intensity of urban development (urban density), and exploited multispectral and LiDAR data for the retrieval of reflectance values in complex illumination environments [10]. In 2015, shared feature representations of LiDAR and optical images using sparsity and neural networks were discussed [20], and, in the recently finished 2016 contest, a convolutional neural network

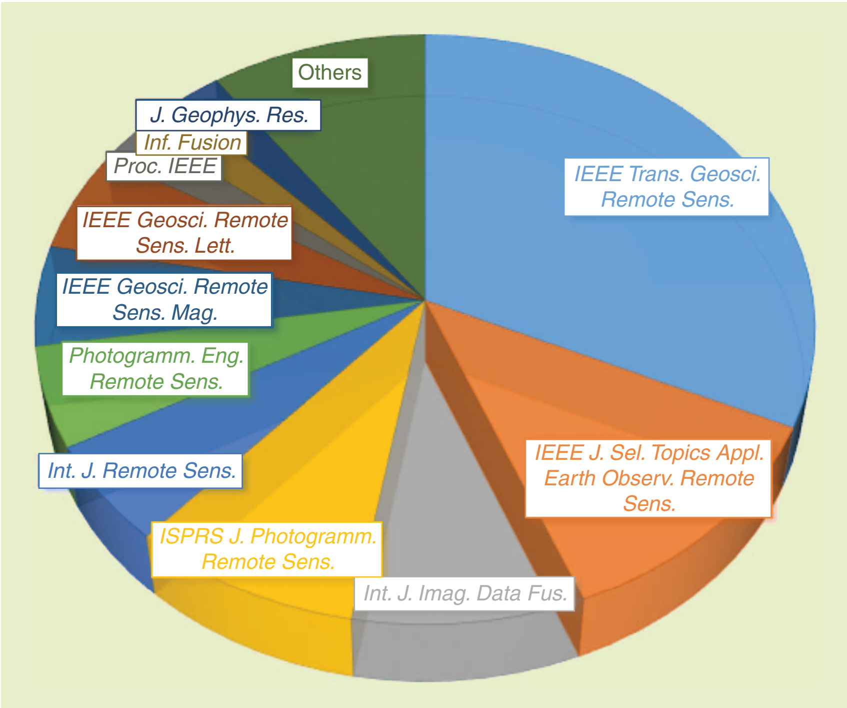

FIGURE 4. This chart shows the distribution of publications in which the articles referenced in this review were published.

TABLE 2. AN OVERVIEW OF DIFFERENT DATA FUSION RESOURCES.

RESOURCE	ISSUES	INTERNET
Societies and Working Groups		
ISPRS WG VII/6, "Remote Sensing Data Fusion"	Automatic registration; fusion algorithms; integration of space-borne, airborne, and terrestrial measurements; data fusion applications in the field of mapping; and high-performance computing	http://www2.isprs.org/commissions/comm7/wg6.html
IEEE GRSS Technical Committee, "Image Analysis and Data Fusion"	Geospatial data fusion, image fusion, and organization of the annual GRSS Data Fusion Contest	http://www.grss-ieee.org/community/technical-committees/data-fusion/
ISIF	Umbrella organization of information fusion researchers, host of the annual International Conference on Information Fusion	http://isif.org/
Conferences and Workshops		
International Conference on Information Fusion	Annual three-day eight-track conference hosted by ISIF; topics include multitarget tracking, sensor registration, signal processing, data mining, and machine learning	http://fusion2016.org/
Data Fusion and Target Tracking Conference	Biannual two-day workshop hosted by IET; topics include multitarget tracking, particle and Kalman filters, and exploiting information from imaging sensors	http://conferences.theiet.org/target/about/scope/index.cfm
Sensor Data Fusion: Trends, Solutions, and Applications	Annual three-day workshop hosted by FKIE, cosponsored by IEEE Aerospace and Electronic Systems Society and ISIF; topics include localization, pattern recognition, tracking, estimation theory, and simultaneous localization and mapping	https://www.fkie.fraunhofer.de/de/veranstaltungen/2015/sensor-data-fusion-trends-solutions-applications.html
Signal Processing, Sensor/Information Fusion, and Target Recognition	Part of massive annual SPIE Defense and Security Conference; topics include object recognition, image data fusion, map/photo fusion, and vision-based target tracking	http://spie.org/SID/conferencedetails/signal-processing-sensor-fusion-target-recognition
IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems	Three-day, three-track conference hosted by IEEE; topics include tracking, navigation, vision-based fusion, and point cloud registration	http://mfi2016.org/
Scientific Journals		
International Journal of Image and Data Fusion	Published by Taylor & Francis; everything about image and sensor data fusion, including a certain emphasis on remote sensing	http://www.tandfonline.com/loi/tidf20
Information Fusion	Published by Elsevier; aimed at general higher-level information fusion	http://www.journals.elsevier.com/information-fusion/
ISIF Journal of Advances in Information Fusion	Open-access flagship journal of ISIF	http://isif.org/journals/all
ISIF Perspectives on Information Fusion	New ISIF journal (first articles scheduled to appear in 2016) that will serve as a magazine-style publication composed of review/survey articles, interdisciplinary discussion, and classroom notes on established topics	http://isif.org/publications/isif-perspectives-information-fusion

Notes: ISIF: International Society of Information Fusion; IET: Institution of Engineering and Technology; FKIE: Fraunhofer Institute for Communication, Information Processing and Ergonomics.

for spatiotemporal scene interpretation using space videos was presented [185]. This confirms the quickly broadening horizon of the remote sensing data fusion research community. For further information on the organization of the classical data fusion community, see "Excursion: A View Beyond the Remote Sensing Horizon."

LESSONS TO BE LEARNED—FUTURE CHALLENGES IN REMOTE SENSING DATA FUSION

From the general definitions and categorizations and the review of current research activities, it can be seen that data fusion is a long-established topic in the field of remote sensing. While the beginnings were mostly image centered, many more applications exploiting heterogeneous data sources for a wide variety of tasks have found their way into the literature. Nevertheless, the future will bring even greater amounts of even more heterogeneous data, thus introducing the need to learn from other communities related to data fusion research. Therefore, the authors of this article believe that the main challenges of data fusion in the remote sensing context can be summarized as follows.

AUTOMATIC MATCHING AND COREGISTRATION OF HETEROGENEOUS DATA

It is obvious that our future will be characterized by massive amounts of data waiting for proper extraction of information. While the term *big data* is already on everyone's lips and influencing all parts of modern life [80], [87], this will also emerge in the field of remote sensing and spatiotemporal Earth observation. As mentioned earlier and supported by

TABLE 3. TOPICS OF THE IEEE GRSS DATA FUSION CONTESTS FROM 2006 TO 2016.

YEAR	DATA SETS	GOAL	ARTICLE
2016	Very high temporal resolution imagery and video from space	Open for creative ideas	Not available yet
2015	Extremely high-resolution LiDAR and optical data	Open for creative ideas	Moser et al., 2015 [95]
2014	Coarse resolution thermal/hyperspectral data and VHR color imagery	Classification	Liao et al., 2015 [77]
2013	Hyperspectral imagery and LiDAR-derived DSMs	Classification	Debes et al., 2014 [32]
2012	VHR optical, SAR, and LiDAR data	Open for creative ideas	Berger et al., 2013 [10]
2011	Multiangular optical images	Open for creative ideas	Pacifici and Du, 2012 [101]
2009–2010	Multitemporal optical and SAR images	Change detection	Longbotham et al., 2012 [82]
2008	VHR hyperspectral imagery	Classification	Licciardi et al., 2009 [78]
2007	Low-resolution SAR and optical data	Classification	Pacifici et al., 2008 [100]
2006	Multispectral and panchromatic images	Pan sharpening	Alparone et al., 2007 [1]

VHR: very-high-resolution.

the foreword to *IEEE Geoscience and Remote Sensing Magazine*'s special issue on data fusion [149], an abundance of data from heterogeneous vehicle-borne, UAV-borne, airborne, and space-borne sensors will be available, providing optical, multispectral, hyperspectral, and radar imagery and exploiting a great variety of wavelengths. These will be complemented by point-wise measurements, such as conventional laser scanning or GPS points, and by the ever-growing availability of pre-existing geodatabases. In addition, there will be unforeseeable amounts of crowd-sourced data, e.g., GPS tracks, manually edited maps, or smartphone photographs. As an example, mobile phone data have already been used to map population dynamics down to intraday scale [36].

Moreover, as explained in the section "Matching and Coregistration," data alignment and data/object correlation generally are crucial steps in any data fusion undertaking. Therefore, one of the most important research tasks is to enable the fully automatic matching and/or coregistration of sensor data, which are strongly heterogeneous from both a geometric and a radiometric perspective as well as from a temporal point of view.

For this task, new and innovative joint models for the representation of homologue information of heterogeneous sources are needed (see also the "Integration of Machine Learning to the Data Fusion World" section), e.g., beginning with the problem of matching optical imagery and SAR data, point clouds, range data and images, or imagery from strongly varying views and scales. In addition, sophisticated methods for data assimilation and interpolation are required to incorporate observations acquired at strongly different time scales or highly deviating intervals. Examples for upcoming challenges are described here.

SIMULTANEOUS MATCHING AND 3-D RECONSTRUCTION

Similar to the situations discussed in the section "Matching and Coregistration," in which the coregistration problem is

Excursion: A View Beyond the Remote Sensing Horizon

Outside the field of remote sensing, data fusion is an active community in its own right, drawing scientists and engineers from fields such as information theory, radar engineering, and signal processing. The community is mainly represented by the International Society of Information Fusion (ISIF), which annually hosts the three-day, eight-track International Conference on Information Fusion and publishes two journals. Topics such as multitarget tracking, sensor registration, data mining, and machine learning are discussed in great depth. In addition, there are several smaller workshops (see Table 2):

- the Data Fusion and Target Tracking Conference, hosted by the Institution of Engineering and Technology (IET)
- Sensor Data Fusion: Trends, Solutions, and Applications, organized by the Fraunhofer Institute for Communication, Information Processing and Ergonomics (FKIE) and supported by the IEEE Aerospace and Electronic Systems Society and ISIF
- Signal Processing, Sensor/Information Fusion, and Target Recognition within the SPIE Defense and Security Conference
- the IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems.

Although attending these scientific events may be a good opportunity for remote sensing researchers to look beyond the community's horizon and achieve some external outreach, some of the topics discussed there are only partially relevant. In particular, works related to target tracking for the generation of military situation overviews or sensor fusion for autonomous navigation, which both belong to the core of classical data fusion research, are not directly transferable to current remote sensing applications.

Although data fusion is a multifaceted problem in remote sensing and classical data fusion research aims at different (mainly military or navigation related) applications, much can still be learned from the greater information/data fusion community, both concerning more exact terminology (e.g., many remote sensing articles using the term "data fusion" in the title deal with registration or simple data combination problems without even incorporating a proper fusion step) and sophisticated estimation theoretical solutions.

solved simultaneously with a surface reconstruction problem, one potential approach for a solution to the nontrivial matching problem for data acquired from different viewing angles or by sensors with different viewing geometries is to combine the matching and the 3-D modeling steps in a joint estimation procedure. Relevant approaches have until now mainly come from the field of computer vision, e.g., for solving the multiview stereo problem within an optimization framework [29], [131]. It must be mentioned, however, that, in these examples, the alignment of the measurements is already solved because the camera positions are known.

MATCHING OF CONVENTIONAL REMOTE SENSING OBSERVATIONS AND OTHER DATA

Another major challenge in the field of matching and coregistration is the joint exploitation of classical remote sensing data (e.g., images, range measurements, depth maps, and point clouds) and data from other domains, such as texts, point-wise observations, or vector data. The coregistration of point-wise and extensive observations is relatively easy to achieve if the data are provided in geocoded form (e.g., [167] and [183]). Far more challenging examples are the fusion of text and image data, which has recently been demonstrated for the detection of events based on the analysis of Twitter messages [2]. In this case, the matching of geospatial information with the semantic content of the social media data is certainly the main problem, whereas coregistration can be achieved by the exploitation of geolocation information provided by the social media services [134].

In any case, these preliminary examples from other disciplines must be transferred and adapted to the remote sensing context to enable a maximally flexible alignment of the different data types to be expected. Without this alignment and the proper correlation of measurements and the object of interest, any subsequent data fusion request will fail. There will be cases where a 100% alignment might not be possible, e.g., if small-scale nadir-view (e.g., containing only the roofs of some buildings) and oblique-view (containing only the buildings' facades) imagery are fused. Such a situation might be interesting in the sense of complementary integration (see the "Fusion by Estimation" section); but, depending on the application, it might be reasonable to exclude the nonmatchable observations from further processing and instead focus on other retrievable parameters (e.g., the roof or ground parts visible in both images).

AN EXCURSION INTO ESTIMATION THEORY: MODELING THE ACTUAL FUSION STEP

Although most data acquired during space-borne Earth-observation missions or well-planned airborne flight campaigns will always be well documented and contain sufficient metadata, most of the potentially available crowd-sourced data (e.g., GPS tracks or smartphone images) will not provide any additional information. It will therefore be necessary to create sophisticated fusion approaches that go beyond classical Bayesian estimation and can incorporate fuzzy, imprecise, or incomplete data without losing the ability to deliver statistically optimal estimates including stochastically sound quality and reliability measures. Khaleghi et al. [71] provided an extensive review of different fusion approaches in a broad, general sense. They extended the well-known probabilistic formulation of data fusion problems by evidential belief reasoning, fuzzy reasoning, possibilistic fusion, and rough or random set-based fusion. While classical probabilistic fusion relies on probability distribution functions and Bayesian estimation, ranging from least-squares estimation via Kalman filter to particle filter and Markov chain Monte Carlo algorithms, evidential belief reasoning is mainly based on the Dempster–Shafer theory, which introduces the notion of assigning beliefs and plausibilities rather than probability distributions to measurement hypotheses [34], [125]. In combination with suitable rules for the fusion step, this can be considered a generalization of Bayesian theory dealing with probability mass functions. An exemplary remote sensing application of the Dempster–Shafer theory has been presented for the fusion of high-resolution optical and SAR imagery for updating building databases [107].

Fuzzy set theory, then, is another example of a theoretical reasoning scheme for imperfect data and introduces the notion of partial set membership that enables imprecise reasoning [174]. In contrast to probability and evidence theories, fuzzy set theory is well suited to model the fuzzy membership of an object in an ill-defined class, so it is a powerful theory to represent vague data. In the remote sensing context, it has already been applied for the fusion of displacement measurements derived from both amplitude image correlation and differential SAR interferometry [171].

Fuzzy theory can also be integrated with probabilistic and Dempster–Shafer-based fusion algorithms in a complementary manner. Possibilistic fusion is based on fuzzy set theory but was designed to represent incomplete data [38]. In that sense, it is similar to the Dempster–Shafer theory but uses a different quantification approach.

Finally, rough set theory is a framework to model imprecise data, ignoring uncertainty at different granularity levels [104], whereas random set theory models target states and measurements as random sets of finite size instead of conventional vectors [85]. Priors and likelihood functions that are capable of modeling a wide range of different phenomena are constructed.

While most of the mentioned estimation frameworks are aiming at the attribute estimation step, another possibility, which is particularly interesting in the context of identity estimation, is the utilization of machine-learning methods (see the "Integration of Machine Learning to the Data Fusion World" section) such as random forests [18] or neural networks [12] for bootstrap aggregating, which provides improvements for unstable procedures and some variance reduction and furthermore helps to avoid overfitting [17]. One example from the remote sensing context suggested learning relevant features to improve multisensor classification results [148].

This summary shows that many frameworks exist for the final step of data fusion based on different estimation theories. The choice of framework depends on the desired fusion level. For example, fuzzy set theory might be better suited for decision-level fusion tasks, such as semantic building recognition, than for observation-level tasks such as 3-D coordinate estimation from multiview data. Furthermore, the type of the available data or sensor information will also determine the particular estimation theory best suited for the task. In the case of conventional Earth-observation measurements, certainly enough metainformation is available to formulate precise probability distributions and employ well-established Bayesian estimators. However, for unconventional observation measures such as crowd-sourced imagery to be exploited, it can often be the case that no information about sensor type, acquisition time, or other factors is provided; so a framework allowing fuzzy information may be needed.

ROBUST ESTIMATION FOR OUTLIER MITIGATION

Another point to consider during the final fusion step is the introduction of robust estimation techniques for outlier mitigation. Because of the massive amounts of data that can be expected from modern Earth-observation missions, flight campaigns, and crowd-sourced geodatabases, it will often be the case that the data fusion process will have to deal with correlated, spurious, or disparate data. While highly correlated data may lead to positively biased estimation results and artificially high confidence levels, spurious data contain outliers that also bias the estimation process. In addition, disparate data might also lead to conflicting information. Therefore, it is necessary to include robust estimation strategies to the data fusion process that guarantee optimal estimation results in the case of highly erroneous input data [182].

INTEGRATION OF MACHINE LEARNING TO THE DATA FUSION WORLD

The discipline of machine learning has generally met growing interest in many other scientific communities in recent years. Among those communities, there certainly is a noticeably strong connection to the field of computer vision, which already has led to a number of textbooks (e.g., [124]). The connection to remote sensing is likewise active and becoming ever more fruitful [21]. In a sense, every machine-learning procedure can potentially be interpreted as an instance of data fusion if the data used in the training and/or prediction step come from different sources and the learned or predicted parameters are seen as a result of an attribute or identity estimation step. But, apart from this interpretation, machine-learning techniques can serve as invaluable tools for larger remote sensing data fusion frameworks. Thus, the third major challenge for the future of remote sensing data fusion research will be an even more thorough integration of machine-learning concepts to the data fusion domain. This will help to find solutions for difficult problems that might not be solvable in closed form but will become solvable if sufficient training data are available. In particular, neural networks [73] and ensemble-learning methods [91] can provide promising perspectives for the fusion of heterogeneous data at the decision level.

Considering frequently faced challenges in remote sensing, we believe that one of the most promising applications of machine learning for the fusion of strongly heterogeneous data will take place at the feature level. Big data from heterogeneous sensors or other resources has introduced the need to learn invariant features for tasks such as matching, semantic labeling, or automatic interpretation of available data. In this regard, significant insights can be drawn from results in the current research field of deep learning and convolutional neural networks [75]. Although this working package is of a general nature and relevant to many different tasks, it is of particular interest for the identity estimation step (often dealing with object recognition or land-cover classification) but also for the matching and coregistration problem described in the "Automatic Matching and Coregistration of Heterogeneous Data" section if, for example, similarities between strongly different data sets are to be determined [6], [7], [88].

CONCLUSION

This article has given an overview of the long-standing and ever-growing relationship between data fusion and remote sensing. By recalling the general definitions from the classical data fusion community and summarizing the state of the art within the field of remote sensing, we have shown that remote sensing researchers continuously broaden their view of data fusion applications. The future trend is thus going far beyond the early horizon described by the combination of images for pan sharpening or classification purposes. On the other hand, it was also shown that data fusion becomes much more than just a special field of estimation theory or target tracking when applied in the context of remote sensing. Besides the general challenges, some additional aspects often overlooked in classical data fusion research arise, e.g., the important geometric modeling of multiple sensors and the well-known matching and coregistration problem.

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