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DATA FUSION FOR INDUSTRY 4.0: GENERAL CONCEPTS AND APPLICATIONS

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Abstract: More and more image data from airborne / satellite sensors have become available with the advancement of satellite and remote sensing techniques. In order to gain more inferences than can be made from a single sensor, multi-sensor image fusion attempts to integrate information from different images. In image-based application areas, since the end of the last century, image fusion has emerged as a promising research field. A summary of recent developments in multi-sensor satellite image fusion is provided in the paper. First, with focus on their recent developments, the most common current fusion algorithms are being introduced. Advances in the main fields of remote sensing applications, including object identification, classification, detection of changes and tracking of maneuvering targets, are described. The benefits and disadvantages of these apps are then addressed. Recommendations are discussed, including: (1) Improving fusion algorithms; (2) Designing methods for 'algorithm fusion'; (3) Implementing an automated quality evaluation scheme.

Keywords: Multi-Sensor, Data Fusion, Remote Sensing.

I INTRODUCTION

More and more data has become available for scientific research with the production of several types of biosensors, chemical sensors, and remote sensors on board satellites. When the data volume increases, so does the need to integrate data obtained from multiple sources in order to obtain the most valuable information. Data fusion is an efficient way for vast quantities of data from different sources to be optimally used. To achieve inferences that are not possible from a single sensor or source, multi-sensor data fusion attempts to integrate information from multiple sensors and sources. The fusion of sensor knowledge with different physical characteristics improves the perception of our environment and provides the basis for autonomous and intelligent machines planning, decision-making and control [1]. It has been implemented in various fields in the past decades, such as pattern recognition, visual enhancement, object detection and area surveillance [2].

There is extensive literature on data fusion in computer vision, artificial intelligence and medical imaging, but it will not be discussed here. In the satellite remote sensing area, this paper focuses on multi-sensor data fusion. By providing substantial coverage, mapping and classification of land cover features such as vegetation, soil , water and forests, remote sensing techniques have proven to be powerful tools for monitoring the Earth's surface and atmosphere on a global , regional and even local scale[3] The amount of remote sensing images continues to develop at an enormous rate due to advances in sensor technology As a consequence, there has been an growing volume of image data from airborne / satellite sensors, including multi-resolution images, multi-temporal images, images of multi-frequency / spectral bands and multi-polarization images. Multi-sensor data fusion is a method of merging images to create a composite image obtained from sensors of various wavelengths. The composite image is created to enhance the content of the image and to make it easier for the user to locate, recognise, and define goals and increase understanding of situations.

A general introduction to multi-sensor data fusion was provided by Hall and Llinas in 1997[1]. Another in-depth study paper on data fusion techniques for multiple sensors was published in 1998 [2]. As a contribution to multi-sensor integration focused data processing, this paper clarified the principles, methods and implementations of image fusion. Image fusion has gained growing attention since then. Further scientific papers on image fusion with a focus on improving the efficiency of fusion and seeking further application areas have been written. As a case in point, Simone et al. Define three typical remote sensing data fusion applications, such as obtaining elevation maps from interferometers of synthetic aperture radar (SAR), fusion of multi-sensor and multi-temporal images, and fusion of multi-frequency, multi-polarization and multi-resolution SAR images [3]. In remote sensing applications, Vijayaraj supplied the concepts of image fusion [4]. Recently, quite a few survey papers have been published providing overviews of the history, trends, and state of the art of image fusion in the fields of image-based application [5-7], but there has been no thorough discussion of recent developments in multi-sensor data fusion in the fields of remote sensing. The goal of this paper is to provide an overview of new developments in multi-sensor satellite image fusion, with a focus on its key fields of application in remote sensing. The paper is structured into four sections. Section 2 describes the categorization and the advance in algorithm; Section 3 describes advance in application, such as feature extraction, classification, change detection and maneuvering targets tracking; conclusions are drawn in Section 4.

II ADVANCES IN ALGORITHMS

2.1. Categorization of the algorithms

Depending on the point at which the fusion takes place, multi-sensor data fusion can be achieved at four different processing levels: signal level, pixel level, feature level, and decision level. The definition of four distinct degrees of fusion [8] is demonstrated in Figure

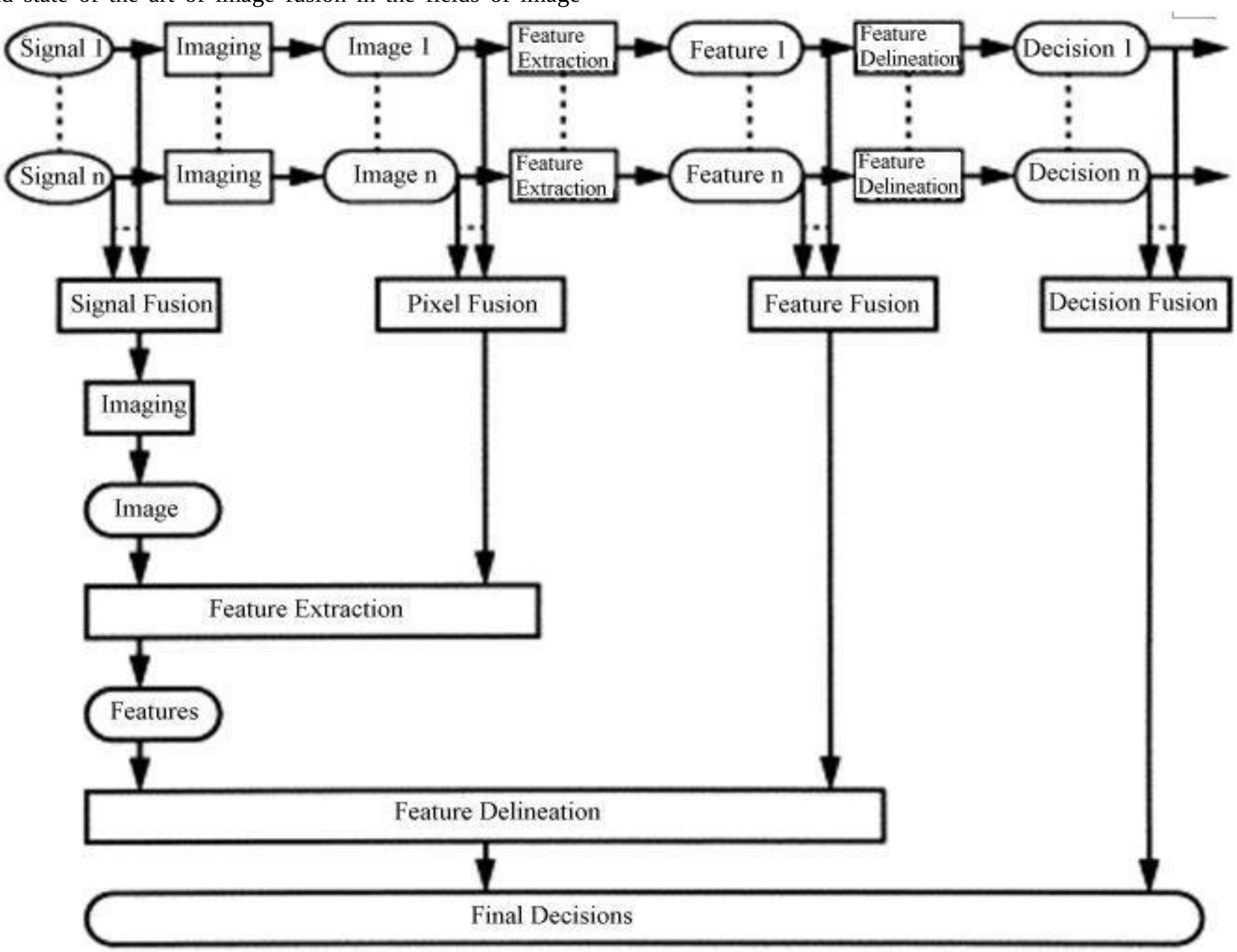

Figure 1. An overview of categorization of the fusion algorithms [8].

(1) Fusion at signal stage. Signals from various sensors are merged to create a new signal with a higher signal-to - noise ratio in signal-based fusion than the original signals.

(2) Fusion at the pixel level. On a pixel-by - pixel basis, pixel-based fusion is carried out. To improve the performance of image processing tasks such as segmentation, it produces a fused image in which information associated with each pixel is calculated from a collection of pixels in the source images.

(3) Fusion at the function stage. An extraction of objects recognized in the various data sources requires attribute-based fusion at the feature level. It involves the extraction of salient characteristics such as pixel intensities, edges or textures that depend on their setting. These comparable features are fused from input images.

(4) The fusion of the decision-level consists of integrating knowledge at a higher level of abstraction, incorporating the effects of several algorithms to generate a final fusion of decisions. For knowledge extraction, input images are individually processed. The data collected is then combined to strengthen standard understanding by applying decision rules.

2.2. Advances in fusion algorithms

The most common and efficient approaches include, but are not limited to, intensity-hue-saturation (IHS), high-pass filtering, main component analysis (PCA), different arithmetic combination (e.g., Brovey transform), multi-resolution analysis-based methods (e.g., pyramid algorithm, wavelet transform), and Artificial Neural Networks (ANN) among the hundreds of variations of image fusion techniques. The paper will provide a general introduction to the methods chosen, with a focus on recent developments in the field of remote sensing.

2.2.1. Standard fusion algorithms:

Inter-correlated multi-spectral (MS) bands are transformed into a new collection of uncorrelated components by the PCA transform. We have to get the key components of the MS image bands to do this approach first. After that, the panchromatic image is replaced by the first principal component that contains most of the image detail. Finally, to get the latest RGB (Red, Green , and Blue) multi-spectral image bands from the main components, the inverse PC transformation is carried out. The IHS fusion converts the colour MS image to the IHS colour space from the RGB space. It is replaced by a high-resolution PAN image in the fusion because the intensity (I) band resembles a panchromatic (PAN) image. On the PAN, together with the hue (H) and saturation (S) bands, a reverse IHS transform is then performed, resulting in an IHS fused image. For image fusion, various arithmetic combinations have been created. Some popular examples [9] are the Brovey transform, Synthetic Variable Ratio (SVR) and Ratio Enhancement (RE) techniques. The Brovey transform's basic method first multiplies each MS band by the PAN band of high resolution, and then divides each product by the number of the MS bands. The techniques of SVR and RE are similar, but provide more advanced calculations for better fusion efficiency for the MS sum.

The standard fusion algorithms described above have been widely used for fusion schemes that are relatively simple and time-efficient. Before their implementation, however, three problems must be considered: (1) Standard fusion algorithms produce a fused image from a collection of pixels from different sources. These pixel-level fusion methods are very sensitive to the accuracy of registration, so it is important to co-register input images at the sub-pixel level; (2) One of the key drawbacks of HIS and Brovey transformation is that the number of input multiple spectral bands should be equal to or less than three at a time; (3) Standard methods of image fusion also succeed in improving spatial resolution, h More recently, modern techniques such as wavelet transformation seem to reduce the issue of colour distortion and retain invariable statistical parameters.

2.2.2. Wavelet-based methods

Since the early 1980s, multi-resolution or multi-scale techniques, such as pyramid transformation, have been adopted for data fusion [11]. The methods of pyramid-based image fusion, including Palladian pyramid transformation, were all developed from Gaussian pyramid transformation, have been modified and commonly used, and in recent years have been replaced by the methods of wavelet transformation to some degree [12, 13]. Mallat put all wavelet construction methods into the framework of functional analysis in 1989 and described the rapid wavelet transformation algorithm and general wavelet orthonormal basis construction method. On the basis of this, it is very possible to apply wavelet transformation to image decomposition and reconstruction [14-16]. Wavelet transforms, with each level corresponding to a coarser resolution band, provide a framework in which an image is decomposed. For example, the Pan image is first decomposed into a collection of low-resolution Pan Images with corresponding wavelet coefficients (spatial details) for each level when fusing an MS image with a high-resolution PAN image with wavelet fusion. At the resolution level of the original MS image, individual bands of the MS image then replace the low-resolution Pan. By performing a reverse wavelet transformation on each MS band along with the corresponding wavelet coefficients, high resolution spatial information is inserted into each MS band (Figure 2).

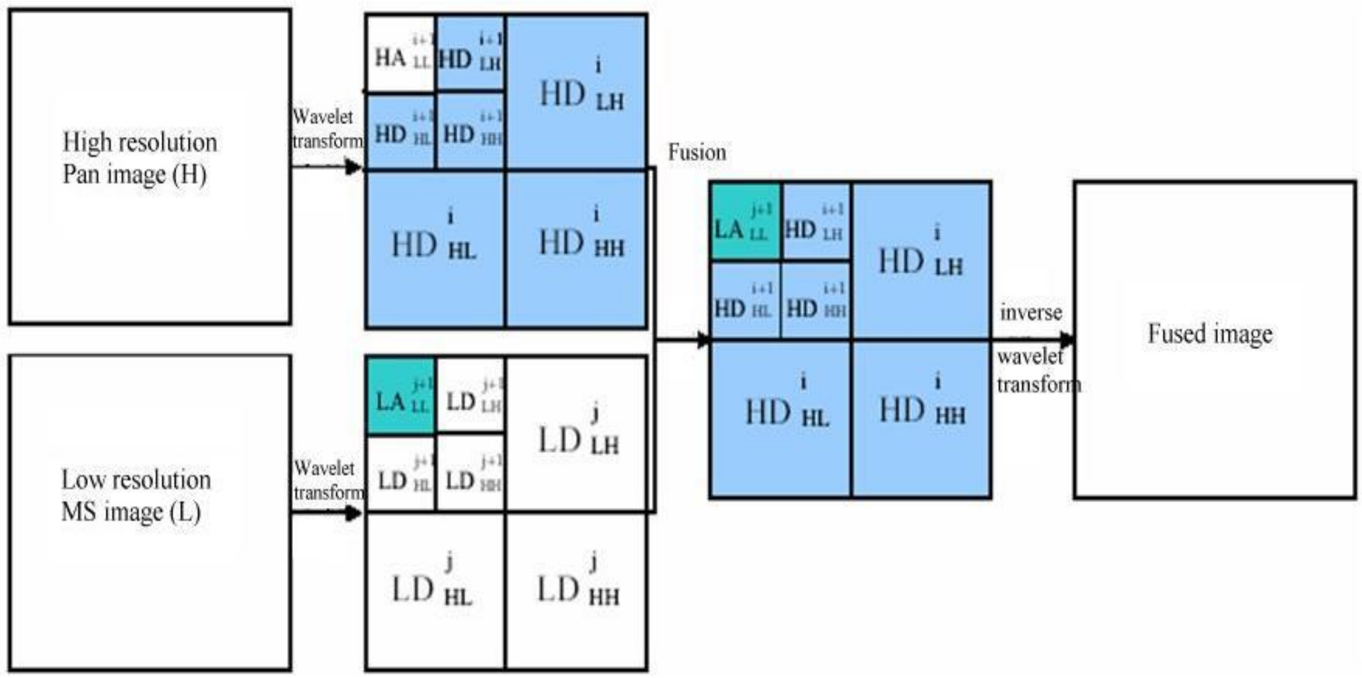

Figure 2. Generic flowchart of wavelet-based image fusion

Information is extracted from the PAN image using wavelet transforms in the wavelet-based fusion schemes and inserted into the MS image. Compared to the standard methods referred to in Section 2.2.1 [17], distortion of spectral information is reduced. Different wavelet-based fusion schemes have been studied by several researchers to achieve optimal fusion performance. Among these frameworks, many new concepts / algorithms have been implemented and discussed. Using the Curvelet transformation, Candes provided a method for fusing SAR and visible MS images. The method has been shown to be more powerful than wavelet transformation for detecting edge data and denoising [18]. In order to combine a Landsat ETM+ panchromatic and multiple-spectral image, Curvelet-based image fusion was used. Simultaneously, the proposed approach offers richer knowledge in spatial and spectral domains [19]. In order to solve the problem that wavelet transformation could not effectively represent the singularity of linear / curve in image processing, Donoho et al . Proposed a versatile multi-resolution, local, and directional image expansion using contour segments, the Contourlet transform [20, 21]. The Contourlet transformation offers a versatile number of directions and captures the image's inherent geometric structure. In general, wavelet-based fusion could obviously perform better than convenient methods in terms of reducing colour distortion and denoising effects, as a typical feature level fusion process. In recent years, it has become one of the most common fusion methods in remote sensing, and has been a standard module in many soft goods for commercial image processing, such as ENVI, PCI, and ERDAS. Problems and limitations associated with them include: (1) The computational complexity of small objects often lost in the fused images compared to standard methods; (2) Spectral content of small objects often lost in the fused images; The development of more advanced wavelet-based fusion algorithms (such as the transformation of Ridgelet, Curvelet, and Contourlet) might improve performance outcomes, but these new schemes through cause more difficulty in the computation and parameter setting processes.

2.2.3. Artificial neural network

Artificial neural networks (ANNs) have proven to be a more powerful and self-adaptive method of pattern recognition as compared to traditional linear and simple nonlinear analyses [22,23]. The ANN-based method employs a nonlinear response function that iterates many times in a special network structure in order to learn the complex functional relationship between input and output training data. The General schematic diagram of the ANN-based image fusion method can be seen in Figure 3. The input layer has several neurons, which represent the feature factors extracted and normalized from image A and image B. The hidden layer has several neurons and the output layer has one neuron (or more neuron). The ith neuron of the input layer connects with the jth neuron of the hidden layer by weight Wij, and weight between the jth neuron of the hidden layer and the tth neuron of output layer is Vjt (in this case t = 1). The weighting function is used to simulate and recognize the response relationship between features of fused image and corresponding feature from original images (image A and image B).

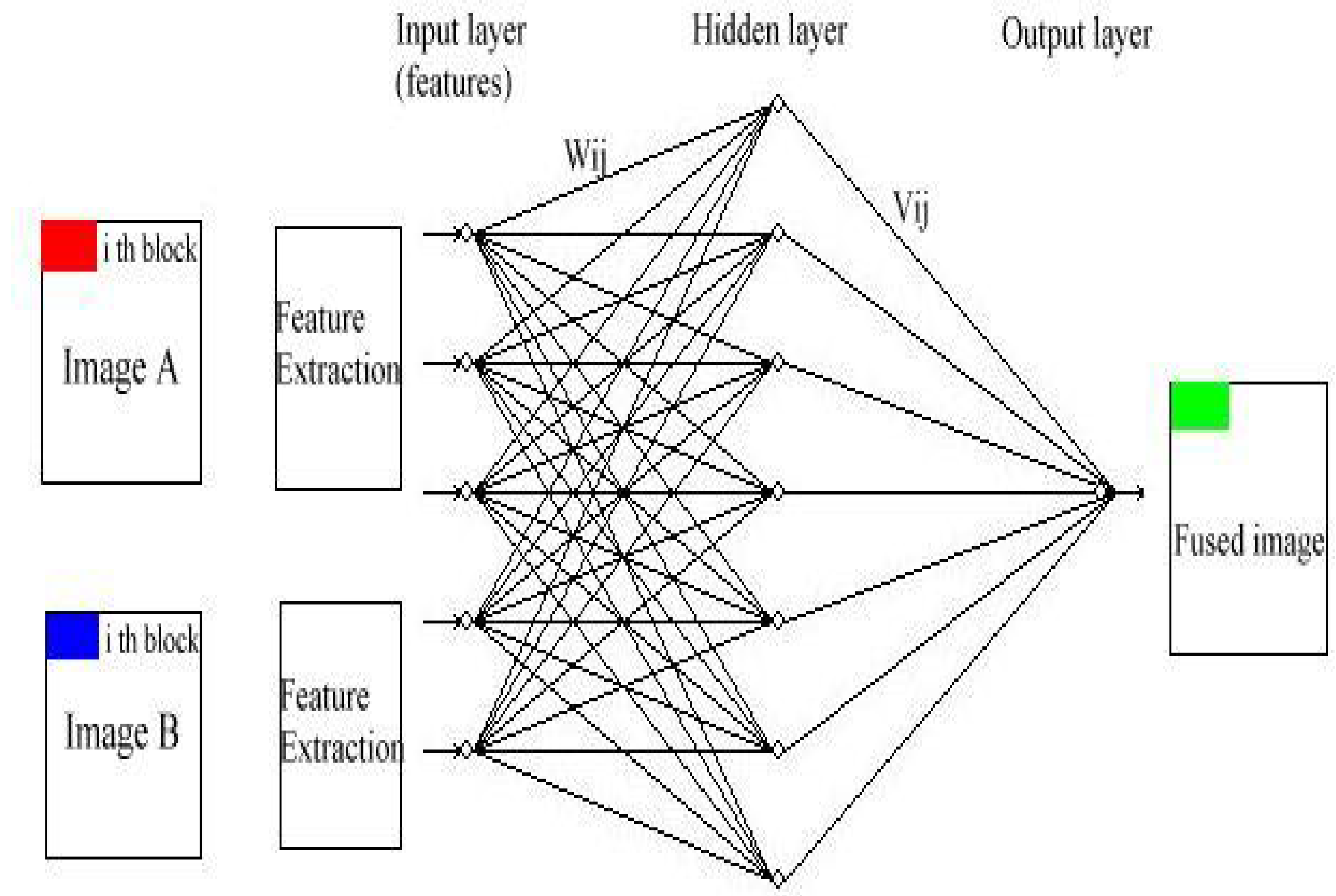

Figure 3. General schematic diagram of the ANN-based image fusion method.

Two recorded images are broken down into several blocks with the size of M and N as the first stage of the ANN-based data fusion (Figure 3). Then, in the two original pictures, characteristics of the corresponding blocks are extracted, and the normalized feature vector incident to neural networks can be constructed [24]. Normally, spatial frequency, visibility, and edge are the features used here to test the fusion effect. Selecting some vector samples to train neural networks is the next step. An ANN is a universal approximate of functions that adapts directly to any nonlinear function described by a representative set of training data. The ANN model, once learned, can remember a functional relationship and be used for additional calculations. For these purposes, in order to build highly nonlinear models for multiple sensor data fusion, the ANN principle has been adopted. The optimal fusion process of TV and infrared images using artificial neural networks [25] was discussed by Thomas et al. After that, several neural network models, such as BP, SOFM, and ARTMAP neural networks, were proposed for image fusion. The most widely used BP algorithm. However, the convergence of the BP networks is sluggish and it is not always possible to achieve the global minimum error space [26]. SOFM network clusters provide an input sample as an unsupervised network through competitive learning. However, before constructing a neural network model [27], the number of output neurons should be set. If sufficient hidden units are given, the RBF neural network can approximate objective function at any precise point. No iteration, few training parameters, elevated training speed, clear process and memory functions [28] are the advantages of RBF network training. Hong explored how to fuse the use of RBF neural networks in conjunction with the nearest neighbor clustering process and membership weighting. Experiments show that the best effect of cluster fusion with the correct width parameter [29] can be obtained by this approach. To form a fresh structure for self-organizing knowledge fusion, Gail et al. used Adaptive Resonance Theory (ART) neural networks. To extract hierarchical information structures from inconsistent training data, the ARTMAP neural network will act as a self-organizing expert system[30]. By assigning output groups to levels in a knowledge hierarchy, ARTMAP information fusion addresses obvious inconsistencies in input pixel labels [31]. A feature-level image fusion process based on the segmentation region and neural networks were proposed by Rong et al. According to the findings, this mixed fusion scheme was more successful than conventional methods [32]. The ANN-based fusion approach takes advantage of artificial neural networks' pattern recognition capabilities, while the learning power of neural networks makes it possible to customize the process of image fusion. Many of the applications showed that the fusion methods based on ANN had more advantages than conventional statistical methods, especially when multiple sensor data inputs were incomplete or with a lot of noise. For its self-learning characters, in particular in land use / land cover classification, it is also used as an effective decision level fusion method. Moreover, the multiple inputs-multiple outputs paradigm makes it possible to combine high-dimensional data, such as long-term time series data or hyper-spectral data, as an approach.

III ADVANCES IN APPLICATIONS

The aim of the fusion of multiple sensor data is to incorporate additional and redundant information to provide a composite image that could be used to better understand the whole scene. In several fields of remote sensing, such as object recognition, classification, and detection of change, it has been widely used. The following paragraphs explain in more detail the recent picture fusion accomplishments.

3.1. Object identification

In VIR / VIR combinations, the feature enhancement capability of image fusion is visually apparent, which often results in images that are superior to the original data. Useful products can be contained in fused images [2] in order to optimize the amount of information derived from satellite image data. In 2004, a Dumpster-Shafer fusion method was proposed for urban building detection. LIDAR data and multi-spectral aerial imagery were used for the first and last pulses. The groups "tree", "grass ground" and "bare soil" are also differentiated by a classification system based on the Dempster-Shafer data fusion principle, apart from houses. Identification of linear structures such as highways may also benefit from techniques of image fusion. In 2005, Jin et al. addressed an integrated framework for automated road mapping from high-resolution multi-spectral satellite imagery via information fusion [33]. With high-resolution PAN data, Andrea presents a solution to improve the spatial resolution of MS images. The proposed method takes advantage of the undecimated discrete wavelet transformation and the multi-scale vector Kalman philtre used to model the wavelet detail injection process. Fusion simulations on spatially degraded data and full-scale fusion experiments show that the proposed method[34] achieves accurate and efficient PAN-sharpening.

3.2. Classification

Classification is one of the key tasks of remote sensing applications. The classification accuracy of remote sensing images is improved when multiple source image data are introduced to the processing [2]. Images from microwave and optical sensors offer complementary information that helps in discriminating the different classes. As discussed in the work of Wang et al., a multi-sensor decision level image fusion algorithm based on fuzzy theory are used for classification of each sensor image, and the classification results are fused by the fusion rule. Interesting result was achieved mainly for the high speed classification and efficient fusion of complementary information [35]. Land-use/land-cover classification had been improved using data fusion techniques such as ANN and the Dempster-Shafer theory of evidence. The Dempster-Shafer theory of evidence method uses a limited number of prototypes as items of evidence and can be implemented in a modified FKCN with specific architecture consisting of one input layer, a prototype layer, a combination and output layer, and decision layer. The experimental results show that the excellent performance of classification as compared to existing classification techniques [36,37].

3.3. Change detection

Detection of change is the mechanism by which changes in the state of an entity or phenomenon are detected by observing it at different times [38]. In the monitoring and management of natural resources and urban growth, identification of change is an important process because it offers a quantitative overview of the spatial distribution of the population of interest [39]. The various configurations of the platforms carrying the sensors take advantage of image fusion for change detection. In the same region, the combination of these temporal images improves knowledge on changes that may have occurred in the area observed. To improve the changing knowledge of some ground objects, sensor image data with low temporal resolution and high spatial resolution can be fused with high temporal resolution data. For example (Figure 4), Spot 5 Spatial 2.5 m panchromatic band data from Yanqing Area, Beijing, China, was fused in 2005 with multiple Landsat TM spectral data bands (spatial resolution: 30 m) in 2007. A simple method of Brovey transformation fusion was used and TM's 3rd, 4th, 7th bands were chosen for calculation. The building areas remained grey-purple unchanged from 2005-2007, while the newly built buildings were highlighted in the composed picture (lime colour in Figure 4) and could be easily identified.

3.4. Maneuvering target tracking

A basic challenge in intelligent vehicle research is the manoeuvring of target detection. Automatic manoeuvring target monitoring can be done operationally with the advancement of sensor techniques and signal / image processing methods. Meanwhile, a effective method to enhance monitoring efficiency is found to be multi-sensor fusion. In the application areas of autonomous robots, military applications and mobile networks, the detection of objects using multiple distributed sensors is an important field of work[41]. In recent years , the numbers of papers based on the fusion issue between radar and image sensors in the detection of targets have appeared[42,43]. The fusion of radar data and infrared images could enhance the precision of positioning and narrow down the working area of the image[43,44]. The multi-target tracking issue for manoeuvring targets in cluttered environments was discussed by Vahdati-khajeh. In order to address the issue of clutter points and targets that have joint observation[45], the multiple scan joint probabilistic data association (MJPDA) algorithm was used. Chen et al . proposed a new multi-sensor data fusion algorithm for monitoring the large-scale manoeuvring target in order to resolve the defects of the existing statistical model on non-manoeuvring target tracking. For the large-scale manoeuvring target that extracts feature data from Kalman filtering processes to estimate the magnitude and time of manoeuvring, the fuzzy adaptive Kalman filtering algorithm with manoeuvring detection was used. The results of the simulation showed that the active and passive radar tracking device has greater accuracy than that of a single sensor for large-scale problems [42].

IV DISCUSSION AND CONCLUSIONS

In order to gain more inferences than can be made from a single sensor, multi-sensor image fusion attempts to integrate information from different images. It is widely recognized as an effective instrument for enhancing overall image-based application performance. The paper offers a state-of-the-art fusion of multi-sensor images in the remote sensing region. Some emerging issues are below, along with suggestions building on the discussion in the previous pages.

(1) Fusion Algorithm Enhancements. The most common and successful methods, such as IHS, PCA, Brovey transform, wavelet transform, and Artificial Neural Network (ANN), are among the hundreds of variations of image fusion techniques. The most important issue is colour distortion [9] for easy methods (e.g., HIS, PCA and Brovey transform), which have lower complexity and faster processing time. In terms of reducing colour distortion, wavelet-based systems perform better than convenient methods. Evidently, the development of more advanced wavelet-based fusion algorithms (such as transformation of Ridgelet, Curvelet, and Contourlet) might boost performance outcomes, but they also trigger greater computational and parameter setting complexity. The capacity to process hyper-spectral satellite sensor data would be another obstacle to current fusion techniques. One potential solution to handling the high-dimensional existence of hyper-spectral satellite sensor data appears to be an artificial neural network.

(2) Development of methods for "algorithm fusion." Each fusion method has its own set of benefits and limitations, as described above. The combination of many different fusion schemes has been authorized as a useful technique for improving the quality of results [9, 17]. As a case in point, quite a few researchers have concentrated on integrating the conventional IHS method into wavelet transformations, as the IHS fusion method performs well spatially, while the wavelet methods perform well spectrally[17,46]. The selection and arrangement of these candidate fusion systems is, however, very random and sometimes depends on the experience of the user. Therefore, an optimal combination strategy for various fusion algorithms, in another word, the "algorithm fusion" strategy, is urgently needed. For the following aspects, additional investigations are necessary:

1. Creation of a general structure for integrating various approaches to fusion;
2. Development of new approaches that can combine aspects of image fusion at the pixel / feature decision level;
3. Establishment of the automated quality assessment methodology, which is addressed as follows, for the evaluation of fusion effects.

(3) Creation of an automated scheme for quality evaluation: In order to analyses the potential benefits of fusion, to decide the optimal setting of parameters for a certain fusion scheme and to compare the results obtained with different algorithms, an automated quality evaluation is highly desirable[17]. In terms of improving spatial resolution while maintaining the spectral content of the data, mathematical methods have been used to assess the quality of merged imagery. For evaluation purposes, statistical indices, such as cross entropy, mean square error, signal to noise ratio, were used. Although a few quality measures of image fusion have been proposed recently, empirical studies of these measures have been missing. Yin et al. 's work centred on one common measure of quality based on shared knowledge and weighted average image fusion[47]. To evaluate the performance of the image fusion algorithm [48], Jiying presented a new metric based on image phase congruency. In general, however, no automated solution to reliably generate high-quality fusion for different data sets has been achieved [49]. The effect of fusing data from multiple independent sensors is expected to give the potential for better performance than either sensor can achieve and minimise vulnerability to sensor-specific countermeasures and deployment factors. We believe that future studies will discuss new requirements for performance evaluation and automated methods for quality evaluation.

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