A Survey on Image Fusion Technique forRemote Sensing Application

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Abstract**—** In last decades the hyperspectral (HS) imaging have been used vastly, as it provides very good temporal, spatial, and spectral resolutions of larger areas. The hyperspectral imaging provides accurate estimation similar objects with tolerable spectral signature and accurate estimation of complex surface physical properties; thus, HS imaging have been used in variety of remote sensing application such as military, crop monitoring, environmental study, and precision agriculture etc. The fusion of two images i.e., one with higher spectral information and other with higher spatial information provides huge scope in aforementioned application. This paper provides an extensive survey of various image fusion methodologies using statistical, machine learning (ML), and Deep learning methodologies for hyperspectral images. The survey shows the traditional panchromatic and multispectral (MS) image fusion techniquerequires high precision registration, which impose limitations in achieving high-quality fusion outcomes. Thus, fusion of MS and HS have been used in recent time for provisioning different remote-sensing application; thus, it prerequisite to minimize uncertainties for achieving better fusion enhancement. This paper provides present methodologies, problems, and possible solution of hyperspectral image fusion for remote sensing application.

Keywords—Deep learning, hyperspecral, image fusion, machine learning, multispectral, resolution enhancement.

I. INTRODUCTION

The remote sensing images have been collected using Unmanned aerial vehicle (UAV) and Satellites. Images captured by satellites are the primary source of global coverage information.

Many fields, including agricultural, forest, weather research, oceanography, and coastline science, make use of satellite imagery in this way. Most frequently, it is put to use in the context of highly precise agricultural as well as plant phenotypic [1], [2], [3]. Vegetation indices like the Normalized-Difference-Vegetation-Index (NDVI) [4] are often calculated by using the initial Unmanned Aerial Vehicle Multi-Spectral (MS) image for building the distribution mapping of NDVI. If the source multi-spectral images lack sufficient spatial resolution, the resulting NDVI distribution mapping could be inaccurate. High-Spectral-Resolution (HSR) and limited spatial resolution are typical of multi-spectral pictures. Panchromatic (PAN) and Hyper-Spectral (HS) images have good spatial resolution but low spectral resolution [5], [6]. Clearly, Multi-Spectral photos lose certain spatial details. This means that the spectral and spatial resolution of the combined Multi-Spectral, HS/PAN images could be enhanced simultaneously. The resulting Normalized-Difference-Vegetation-Index distribution mapping will have higher resolution. This improvement is the motivation of the present work.

One of the crucial necessities for such uses is high quality satellite images. Images taken using hyperspectral sensors have a lot of spectral data but not a lot of spatial data. In contrast, MS sensors are sensors which capture images with low spectral resolution but great spatial resolution. Image fusion is a preprocessing method that improves the spectral and spatial resolution of an image. Distance imaging, healthcare image visualization, as well as computer vision [7], [8]; bio-security, farm area categorization, variability classification, navigational assistance, practical surveillance, electronic imaging, satellite data as well as satellite imagery [9], [10]; automation vision; food microbes sensing [11], monitoring systems, and videography [12]; these are just a few of the many applications of image fusion techniques. The purpose of this paper is to investigate recent developments in the field of remote sensing data fusion and to illustrate the challenges and issues that arise when applying image fusion techniques to remote sensing data.

In process of image fusion technique, two given images of the same area captured by different sensors, the primary focus is on increasing the spatial resolution as well as spectral resolution inside a single image with maintaining the data quality. These methods all help to produce a higher-resolution merged image. Fused picture quality may also be affected by unwanted artefacts and noise contents in the source photos caused by poor registration. Depending on the task at hand and the original image, the resulting fused image's improved quality will seem very different. The most important aspect of learning the value of a fusion technique is evaluating its quality. Image fusion methods should be selected carefully, taking into account their intended usage of corresponding application. For a remote-sensing task, it can be difficult to settle on the best approach [13]. In this study, we outline the numerous image fusion methods, the procedures involved in image fusion, as well as the constraints that must be addressed.

Manuscript organization. In section II, various existing image registration, fusion, and object classification remote sensing application have been studied. The section III, provides problem statement and possible solution. Lastly, the research the concluded with future research direction.

II. LITTERATURE SURVEY

This section provides survey of different technique such as image registration and fusion technique for improving the quality satellite image for effective provisioning of remote sensing application.

A. *Registration technique:*

In this section different technique such as key-points, deep learning and hybrid combining key-point, clustering, and deep learning method for performing satellite image registration have been studied. According to [14], non-rigid distortions as well as poor overlapping ratios are caused by Low-Altitude-Aerial-Photography [15] taken utilizing Small-Unmanned-Aerial-Vehicles (SUAVs) involving significant perspective shifts. A technique for Low-Altitude Small-Unmanned-Aerial-Vehicles registration of image using non-rigid features was proposed. The core idea of their strategy was to keep the matched ratio higher across inliers when using outliers for dynamically change the distorting grids. Hence, one can achieve a decent estimate of the genuine transformation above the non-overlapping parts and exact image transformation across the overlapped portions. It was demonstrated throughout the [16] that ground level modification is a barrier to feature-point recognition in both quality and quantity. This is a typical problem that feature-based registering methods must deal with. It's possible that under extreme visual variance, the identified feature-points will have an excessive number of outliers as well as an unequal distribution of inliers. Two of their main innovations were the implementation of a Convolutional-Neural-Network (CNN) to construct reliable multi-scale feature descriptors, as well as the construction of a slowly rising selection of inliers for enhancing the reliability of feature-points registrations for multi-temporal remote-sensing images.

In [17], they have given a similarity measure called Rotationally-Invariant-Regional-Mutual-Information (RIRMI). The RIRMI measure is created by merging the mutual information along with a regional data that is dependent mostly on statistical link among rotationally stable center-symmetric localized binary sequences of the pictures. This construction leads to the creation of the RIRMI measure. The RIRMI-based similarity measure not only takes into account the spatial data, but also the impact of both the local grayscale changes as well as rotational variations for estimating the likelihood density function. In [18], an efficient method for reliable feature-matching of remotely sensed images was proposed; this method is known as Guided-Locality Preserving-Matching. The core of their method is indeed the simple concept of retaining the local structures of likely accurate matching among images. Furthermore, a mathematical method was developed to explain the phenomenon as well as a straightforward closed-form approach having linear time as well as space complexity was obtained. Hence, their technology can eliminate mismatches from hundreds of potential matches in a matter of milliseconds. They eventually devise a directed matching technique for dealing with exceptionally significant outlier fractions, which involves leveraging the matched outcome from a smaller presumptive group having a significant inlier ratio to direct the matching of a much larger presumptive group. By using this method, they have increased the number of accurate matches substantially.

Recent years have witnessed a rise in the use of High-Resolution-Remote-Sensing-Image registrations inside a wide range of applications, including agricultural, forests, as well as urban development, as explained in [19]. While a High-Resolution-Remote-Sensing-Image could provide a better accurate portrayal of said ground's textural characteristics, it moreover introduces new difficulties in the registration process, such as the requirement to account for textural similarities, limited storing capacity, as well as the potential for data leakage. Therefore, a Finite-State Chaotic-Compressed-Sensing (CS) Cloud Remote-Sensing Image-Registration methodology was developed to address the aforementioned issues. Initially, Chaotic-Compressed-Sensing having a finite state reduces the amount of storage every image needs to be stored and increases the image's confidentiality during communication. The next step is to put the image through processing in the cloud, which will speed up image analysis as well as make it easier to work with information in actual time. Last but not least, a methodology for registering High-Resolution-Remote-Sensing-Images using the Scale-Invariant-Feature-Transform (SIFT) which takes into account both Local as well as Global-Information (LG-SIFT) was developed.

In [20], the researchers offer a method for registering optically remote-sensing images that uses the concepts of Spatial-Consistency (SC) as well as Average-Regional-Information-Divergence (ARID), which they refer to as Spatial-Consistency as well as Average-Regional-Information-Divergence reduction utilizing Quantum-Behaved Particle-Swarm-Optimization (SC-ARID-QPSO). The core approach is to combine ARID minimization using SC for picking a group of spatially consistent characteristics having the lowest ARID value possible. Thereafter, a randomized tuning of the chosen consistency characteristic group produces a group of M registered characteristics that serve as preliminary particle inputs for the QPSO algorithm, allowing for the very last optimum registered characteristics to be obtained. QPSO uses the ARID as kind of a metric for picking a reliable group of characteristics, deciding over an initial group of characteristics, as well as determining the best fitness functions to employ. QPSO's iterative procedure ends when a user-defined automated stopping condition is met. For highly accurate UAV-based Fluvial-Hyperspectral-Imaging, [21] developed a feasible approach for effective image registration employing an optically flow algorithm. While pattern matching methods have become the most popular method of image registrations in RGB-based remote-sensing, these could be time-consuming as well as error-prone for some users due to the need for them to make several computations and choices about a wide range of parameters. However, since this method is not currently extensively used to hyperspectral imaging, its spatial precision remains unverified.

Very high resolution (VHR) satellite imagery has already been employed as a primary source of data in remote-sensing due to the findings of [22], which demonstrated that VHR imagery reliably carries a wide range of information over expansive regions. To make the most of the multi-temporal VHR satellite images, it is necessary to perform image registration.

In order to register images, Conjugate-Points (CPs) must be obtained from the exact same area in both images. Yet, when employed for image registration, CPs including outliers [23] inevitably lead to distortion. In this case, they used a deep learning-based method [24] to successfully filter out all the anomalous data. To improve registrations accuracy, a Siamese-Network was constructed and trained utilizing information based mostly on patched pairings centered on every CP [25], [26].

B. *Fusion Technique:*

In this section different technique such as key-points, deep learning, spatial-sparsity and hybrid method for performing satellite image fusion have been studied. The fusing of the High-Spatial-Resolution-Hyperspectral (HHS) image with the Low-Spatial-Resolution-Hyperspectral (LHS) as well as High-Spatial-Resolution-Multispectral (HMS) image is typically stated as a Spatially-Super-Resolution issue of said LHS image with the assistance of an HMS image, and this may result in the removal of precise structured data. [27] shown this. In order to address the aforementioned issue, a new Cluster-based Fusing methodology employing multi-Branch-BP-Neural-Networks (called CF-BPNNs) was suggested, having the goal of ensuring a much more appropriate spectrum mappings for every cluster. With in training phase, an unsupervised-clustering methodology is employed for dividing the spectrum of all down-sampled HMS images (labeled as LMS) into many clusters based to spectrum correlations. This is done by taking into consideration the underlying qualities that such spectrum is quite identical throughout every cluster compared to other clusters, along with the appropriate spectrum mapping. Also, this is done in consideration of the fact that such spectrum is generally identical throughout every cluster compared to throughout clusters. Finally, multi-branch BP-Neural-Networks (BPNNs) was trained using the spectrum-pairs first from clustered HMS image and then matching LHS image to determine the non-linear spectrum mappings for every cluster. The HMS image's spectrum are further clustered utilizing supervised clustering inside the fusing step, and then the resulting HHS image was rebuilt again from cluster HMS image utilizing the generated multi-branch BPNNs. As demonstrated in [28], current HSI-MSI fusing approaches generally require expert understanding of either the degradation mechanism or perhaps an insufficient amount of training information, which severely limits their applicability and readability. In this work, they have presented an unsupervised HSI-MSI fusing system known as UDALN [29], [30] that is equipped with the potential to engage in degradation adaptable learning. SpeDnet, SpaDnet and SpeUnet are the 3 components developed to directly encapsulate the spectral and spatial changes between resolutions. To ensure an accurate reconstruction of any required HSI, a well-constructed three-stage unsupervised learning technique allows the predicted system variables to reflect visible physical significance of degradation operations.

The purpose of image pan-sharpening during remote-sensing, the Deep-Convolutional-Neural-Network presented in [31] has two-stream inputs, one for MS images and other for the PAN images. The architecture begins by isolating characteristics gathered from the MS and PAN images, and then combines these characteristics into condensed feature mappings which can accurately capture the spectral and spatial details of both the MS and PAN images concurrently. Lastly, a decoding-encoding approach is employed to retrieve actual High-

Spatial-Resolution-MS image out from fused characteristics. A technique for improving images acquired using multi-spectral remote-sensing was developed in [32]. Features such as cloud identification as well as enhanced images were used to build an architecture. Inside the cloud identification phase, clouds are classified as either thin or thick based on their transmission ability using multi-spectral images, as well as a multi-layer cloud identification method is set up. In order to remove dense clouds, a bi-modal pre-detection method is built, which is based on the principles of standard image-processing. Thin cloud extraction is accomplished by modifying the MobileNet algorithm's architecture through a deep learning standpoint. Because there aren't enough data points for training upon, they really had to turn to something like a self-supervised system in order to identify clouds with acceptable accuracy and effectiveness, even with limited data. The initial step with in image-enhancement process is pinpointing the exact spot where ground objects are situated. The signal is next evaluated in both the frequency as well as the time domains as from point of view of compressed-sensing. This study applies the concept of compressed-sensing to the analysis of inter-frame data in hyper-spectral images in order to develop a sparse representational framework. After the above complete process, the desired image quality has been improved and the image has been enhanced.

High-Spectral-Resolution (HSR) as well as Low-Spatial-Resolution (LSR) are two characteristics of Hyper-Spectral (HS) images, as described in [33]. In contrast, the spectrum resolution of Multi-Spectral (MS) images is poor but the spatial-resolution is excellent. Combining these benefits is possible with HS-MS image fusing technique, that helps with precise feature classification. Yet, in practical circumstances, the HSR-HS as well as LSR-MS images from heterogeneous sensors invariably diverge in time, rendering the findings of standard fusing approaches useless. Here, they offer a fusing technique that use spectrum unmixing as well as an image masking to solve the issue. Initially, they took into account the dissimilarity among the 2 pictures by locating all constant areas of LSR-HS pictures and then extracting the end members and respective positions. With the assumption that LSR-MS images as well as the HSR-HS images represent the spatial and spectral degradation for HSR-HS images, respectively, they have obtained the HSR-MS images end-members. Two resultant matrices are combined to create the final fused image. Experimental findings both on synthetic as well as real-world datasets show statistical as well as visual proof of their method's effectiveness. According to [34], the goal of Multi and Hyper-Spectral Image-Fusing (MHIF) is always to re-create images through combining the spatial data from several spectrum images with the spectrum data from a single hyper-spectral image. It is challenging to employ the existing qualities and quantity of end-members for generating high fusion images because of the reason that perhaps the HS Canonical-Polyadic-Decomposition approach as well as the Tucker approach do not integrate the physiological understanding of the underlying variables further into architecture. Novel fusing method is proposed in this study. Estimation of the optimum High-Spatial-Resolution-Hyperspectral images is performed using a linked Non-Negative Block-Term-Tensor approach, with sparsity being characterized by the addition of a 1 norm as well as Total-Variation (TV) being included to express piece-wise smoothness. Finally, the piece-wise smoothness of the various operations in both directions is described and presented. To conclude, the approach is solved successively using the Alternating-Multiplier-Method (ADMM) as well as the Proximal-Alternating-Optimization (PAO) method. Experimental results on two benchmark datasets as well as three separate datasets demonstrate that the proposed strategy outperforms the current standard existing methods.

The fusing approaches are broken down into three groups in [35]: those that prioritize improving spatial-resolution, those that prioritize improving spectral-resolution, and those that prioritize improving temporal-resolution. Hyperspectral satellite sensors in particular have benefited from the increasing demand for higher resolution due to the proliferation of remote-sensing applications. Using the approach of CNN, this report suggests a way of information spectrum improvement approach frame to improve the spectrum resolution of Multi-Spectral information in order to gather sufficient Hyper-Spectral information. Several deep-learning-based approaches have been presented for the remote-sensing fusing technique. MDD (Multi-Dimensional Dataset) information structure was established by the author Zhang Lifu et al. depending on the features of multi-spectral information, multi-space and multi-temporal phase. Multi-dimensional data (MDD) can be stored in one of five distinct ways, depending on how the underlying dimensions are organized: temporally sequential in band, temporally sequential in pixel, temporally inter-leaved by band, temporally inter-leaved by pixel, as well as temporally inter-leaved by spectrum. The Harris-Corner technique as well as the Scale-Invariant-Feature-Transform (SIFT) operators are used for feature-point retrieval in [36] to get rich characteristics of satellite-borne optically imaging like multi-spectral as well as the panchromatic images. The K-Dimensional (K-D) tree is used in conjunction using the Best-Bin-Fit (BBF) approach to perform an approximate matching, with the nearest neighbor/second-nearest neighbor ratio serving as the similarity metric. After all other possibilities have been explored, a Triangle-Area-Representation (TAR) technique is used to filter out inaccurate matches and guarantee precise registration.

C. *Fusion method for Object and Crop Classification Approaches:*

This section studies recent fusion methodologies adopted for object and crop classification. In [37], they have proposed a model for the classification of the crop in the country, Brazil. The main aim of this work was to evaluate the spatial satellite-based characteristics for guiding the data collection of the crop. Further, they have tested the model by training the model using the data collected. They specifically have chosen the growing season of the crop for training. The accuracy of the model was examined using an early-season predictive method. Finally, the have developed a classification method to estimate the large-scale crop area. Crop type mapping is improved in [38] by combining optically as well as Synthetic-Aperture-Radar (SAR) information for a more complete image of the physiological as well as structural characteristics of targeted objects. Yet, high dimensional feature-space is typically a problem when attempting to fuse multi-sensor dense time-series data. First, the effect of using only optical information, solely SAR information, and a mix of the two on classification results has been studied. Second, the optimal combination of time-steps and feature-sets has been determined. Finally, misclassifications have been examined in relation to size of the parcel size, availability of the optical information, and cropping time-profiles. In this research, they took a look at features decision and stacking fusion, two different fusion methods, and evaluated them. Grouped-Forward-Feature-Selection (gFFS) was utilized to determine the most important subsets of features across time and across variables. Instead of analyzing and interpreting individual features, gFFS enables users to narrow in on selected features of relevance, such as spectrum bands, Vegetation-Indices (VIs), or information sensing time. Using this method of feature selection improves outcomes interpretability while drastically cutting down on computing costs. Most recently, it was demonstrated in [39] that fusion-based approaches get a lot of interest since they are viewed as a practical means of representing scene features. This research takes a fresh look at a well-established technique for remote-sensing picture scene classification: the fusion-based approach. To begin, they have divided the study into three distinct types: front side, middle side, and back side fusion mode. A variety of fusion modes are detailed, as are the associated techniques. Finally, the effectiveness of single-side fusion as well as hybrid-side fusion (a mixture of single-side fusion) is measured for classification [40], [41]. In [42], the authors summarized the most up-to-date applications of convolutional neural network (CNN)-based approaches to UAV-based remote-sensing image processing for crop/plant categorization, with the goal of assisting researchers as well as farmers in selecting the most appropriate algorithms for their specific crops and hardware. Combining data collected from unmanned aerial vehicles (UAVs) with deep learning techniques [43], [44], [45], and [46] has proven to be an effective method for accurately categorizing crops of varying sorts.

III. PROBLEM STATEMENT AND POSSIBLE SOLUTION

The extensive survey shows the current satellite image registration method failed to bring good tradeoffs between increasing inlier and reducing outlier during registration process of low and high dimensional satellite image [47]. Thus, effective registration technique combining multiple descriptors is needed for effective registration and fusion of satellite image.

Alongside, after performing registration of both low and high dimensional satellite images, the gradient sparse information must assure spectrum consistency considering both spatially and spectrally during fusion process [48], [49]. In general, there exist high gradient sparsity variance at the edges. Thus, it is spatial-spectral adaptive weight optimization mechanism is needed to assuring spectral consistency and minimize spectral distortion.

The spatial information composed of high similarities; especially at the smooth region; this, result in poor object/crop classification using ML or DL model. In addressing effective image feature fusion method that minimize redundant feature both spatially and spectrally to attain better classification performance [50].

The presence of feature and label noise have significant impact on classificaon accuracy; thus, an effective noise reduction technique retaining good quality fusion is needed for attaining better remote sensing object classification performance.

IV. CONCLUSION

The survey provides an insight of panchromatic, multi-spectral and hyperspectral image fusion; highlights the limitation of standard panchromatic and multi-spectral image fusion technique and shows multispectral and hyperspectral-based fusion can improve the spatial resolution if hyperspectral image. The work shows using prior regularization and optimization strategy for constructing statistical model can provide fusion process. However, it is time consuming; on the other side the spectral unmixing technique offers reduced reconstruction error with faster convergence. However, the traditional have not considered the impact of presence of noise within multispectral and hyperspectral imaging; how these feature and label noise affecting the remote sensing object classification. Further, the shadow element and object inherent feature and class imbalance issues must need to be considered for attaining better fusion and classificaon performance.

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