Anomaly detection using hyperspectral and remote sensing image

Roshni Kaviarasu[1,1], *Elaveni* P[2], and *Jahangeer* Jumana Haseen[3]

[1]Roshni Kaviarasu , Department of Electronics and Communication Engineering , St. Joseph's College of Engineering , Chennai
[2]P.Elaveni , Department of Electronics and Communication Engineering , St. Joseph's College of Engineering , Chennai
[3]Jahangeer Jumana Haseen, College of Computing and Data Science, Nanyang Technological University, Singapore

Abstract. Anomaly detection in hyperspectral imaging is still a challenge owing to the complexity of the data with extremely high dimensionality and subtle changes in spectral reflectance between the background and target pixels. In this study, we address this well-known challenge by developing an advanced anomaly detection framework that combines both a sparse representation and low-rank decomposition to distinguish anomalous behavior from the background. The flexibility of the overall framework is to improve the detection of small, weak anomalies and decrease false alarms due to clutter in the background, where the proposed method develops two independent dictionaries: a background dictionary that describes the primary spectral behavior and an anomaly dictionary that identifies rare or outlier behaviors. Each pixel is assessed based on its residual coding against both dictionaries to determine the likelihood of anomalous behavior. The innovation to this approach is the integration of dual-dictionary learning with joint low-rank and sparse representation, providing excellent separation of background and anomalies in hyperspectral images with changing conditions.

1 Introduction

Over the years, hyperspectral remote sensing has evolved into one of the most important and, at times, the only modern Earth observation technology that provided highly accurate and at the same time, very detailed spectral information. That is the reason why many researchers have begun to regard the technology as being able to fulfill a wide spectrum of needs ranging from tasks requiring material differentiation and accurate classification to those needing multi-spectrum. Hyper-spectral imaging, is instead, capturing the whole range of spectrum and dividing it into very narrow contiguous bands, thus, making it possible to pick out extremely small differences between the various materials on the earth's surface [1]. This detection process is applicable to many sectors such as mining, agriculture, ecology, and military operations. The main downside of hyperspectral imaging, however, lies in the fact that the high dimensionality of spectra associated with HSIs creates substantial computational and analytical difficulties as the complexity of the signals volume grows, especially when it comes to the signals' anomalies.

Anomalies are defined as either individual pixels or regions that significantly differ from their immediate environment. The very first step for an anomaly search is to spot accurately a huge number of these unexplained areas, which are considered as anomalies against the entire samples simultaneously. However, achieving such a high level of detection accuracy may still pose a challenge. This is mainly because of the complex nature of hyperspectral data and the fact that anomalies sometimes have very faint and complicated spectral signatures. Traditional approaches to the detection of hyperspectral anomalies like the Reed-Xiaoli (RX) detector and its variations primarily depend on the statistical modeling of the background. These classical approaches assume that background pixels have the normal distribution which in turn allows classification of a sample only if it is a significant outlier from the Gaussian background model.

However, they are sometimes very effective, these sorts of methods usually get worse in their performance when dealing with very heterogeneous backgrounds or if the anomalies are spectrally too close to their backgrounds. As per [3], the Gaussian theory can break down in the case of real-world hyperspectral scenes and this may lead to false detections and decreased robustness. Consequently, the recent trend has been towards sparse representation and low-rank modeling techniques that exploit the underlying structure of the hyperspectral images.

The fundamental thought is that hyperspectral images are capable of being divided into two segments: the low-rank matrix part which shows the structured background, and the sparse matrix part which consists of anomalies or outliers. Furthermore, this main concept acts as a foundation for the proposed framework that presents a novel [4] dual-dictionary strategy which remarkably enhances the separation of the anomaly from the background. The very beginning step in the journey of separating the background and anomaly components is the low-rank and sparse decomposition which is the principal pre-processing for the hyperspectral image. It is made up of the construction of two complementary dictionaries: a background dictionary derived from the low-rank

[1] Corresponding author: roshnikaviarasu@gmail.com

component and a potential anomaly dictionary extracted from the sparse residuals.

The dual dictionary format enables the system to generate a highly accurate pixel representation for every pixel in the scene. In case the pixel representation indicates a great difference in comparison to the background dictionary and very little error concerning the anomaly dictionary, then the pixel is marked as an outlier. This technique offers a robust [5] and versatile means of detecting anomalies, which might be missed by other techniques, particularly when the background fluctuations are considerable. The technique derives its strength from the simultaneous sparse representation of the standard and the peculiar spectral patterns. Structured background modeling via low-rank decomposition paired with dictionary learning and sparse decomposition can be a powerful tool for flexible anomaly characterization.

Thus, it is also showed that the special combination of the two signal targets with the high invisibility of other faint-signal targets in our device may lead to noise control win ground than back ground sources. It also leads to stronger detection performance by the system. Experimental evidence, based on the AVIRIS San Diego data set [6], indicates that the proposed model outperforms the conventional low-rank plus sparse methods in ROC and AUC with respect to detection accuracy. The performance of the recovered image from this dataset indicates that the dictionary-based model can be not only an effective and efficient tool for hyperspectral anomaly detection, but also a candidate in A&N analysis of different types of remote sensing applications in real world.

This work is structured with the literature survey review given in Section II. Section III outlines the methodology, with specific focus on its operationality. Results and discussions are in Section IV. Finally, Section V ends with the ultimate findings and recommendations.

2 Literature Survey

The journey of hyperspectral anomaly detection transition has been one of great changes starting with statistical background modeling and ending with today's modern methods like the sparse representation, low rank decomposition, and dictionary learning techniques. These modern techniques do not rely on Gaussian assumptions but rather have the capability to capture the intricate variations of the background and at the same time to improve the separation of the targets in the case of very high dimensional remote sensing images.

The aim of this study is to develop a smart anomaly detection system that can handle various types of Earth observation data and at the same time, to detect the unusual areas in them. A major part of the research will be dedicated to the testing of the ability of hyperspectral and remote sensing images [7] in different situations and their versatility, particularly to discover unknown anomalies under varying imaging conditions. Such cases would be the recognition of different unknown land surface anomalies as well as monitoring of the environment [8] through detecting deforestation fires and urbanization by analyzing the temperature-related satellite information.

Furthermore, the research presented here introduces an unconventional method for structure representation that significantly increases the detection ability in optical remote sensing images affected by noise. The framework which targets the hardly noticeable odd patterns of interest, improves the accuracy in environmental monitoring and information retrieval during the difficult conditions to a great extent.

Through the example of subsurface temperature monitoring, the research raises the question of how thermal anomalies at the surface are related to the underground heating mechanisms. This means that the analysis of the time-varying behavior of thermal patterns is easier thus the localization of fire events and the support of risk management are possible. An area discrimination improvement is applied through a decomposition-based framework. This identifies the typical and atypical areas by separating the patterns in difficult environmental imagery for better understanding which can also be transferred to remote sensing images.
Hence, an iterative process is suggested in this research to better the spectral and spatial representations in the analysis map that allows the separation of normal and abnormal areas with higher accuracy. The method of enhancement leads to a larger applicability of the technique over images taken in different conditions and scenarios with different complexities thus providing a stronger anomaly detection power.

Moreover, by the effective characterization of background attributes, significant progress has been made in the analysis of spectral images using this research. The new features are quickly adapted with little recalibration, essentially allowing a decrease in the lengthy protocols while still maintaining the stability. Minor environmental anomalies have been successfully extracted from the major hyperspectral datasets. Then, the large-scale hyperspectral datasets are more effectively handled through multidimensional decompositions which keep complicated spatial-spectral relationships while small-scale anomalies are separated, thus leading to improved environmental interpretation and resource assessment.

The framework proposed is further improved to focus mainly on high purity background reconstruction to enhance anomaly separation [15] and to filter unnecessary features and noise. This in turn, increases the degree of distinguishability between typical and atypical areas, improving the reliability and interpretability of complex images hyperspectral images. Feasible framework methodologies that reduce noise interference and correlation of spectral bands to facilitate the interpretation of hyperspectral data are then examined to be implemented. Hence, identification of anomalies [16] is enhanced through the incorporation of multidimensional feedback. A balanced approach between inhibition of irrelevant background features and identification of change across different environments is the key to achieving improvement in anomaly detection.

To achieve exact distinction between background [17] and anomalous regions, the global background information and local characteristics are combined together. External factors such as noise and interference are taken into account when computing interpretability, achieving consistent high-accurate detection among complex environmental datasets. This is a contributing factor to improving detection accuracy in hyperspectral data, especially in thermal infrared areas. Moreover, it is also an essential aspect of spatial-spectral [18] feature integration that acts as the key to improving character occurrence to distinguish normal and abnormal regions with high accuracy.

A topological method to examine cloud variability in hyperspectral data that reflects intrinsic association in the image using an entropy-based measurement [19] is presented in this thesis. This method allows precise separation of spatial and temporal properties which in turn reduces redundant spectral variability and retain informative features through feedback-based classification. The most essential spectral features [20] are kept while the process of extraction of anomalous pattern is streamlined, accurately identifying anomalies in remote sensing images.

Even with notable progress in hyperspectral anomaly detection, a persistent gap spotlights the challenge of a neglected scene complexity; making it increasingly difficult to separate anomalies from difficult-to-discern poorer background variability, noise/residuals, or subtle spectral similar anomalies. The bulk of these efforts are often reliant on overly detailed statistical assumptions or single-model approaches that struggle in heterogeneous scene structure, especially those involving anomaly spectral information that closely resembles nearby materials. Additionally, many previous efforts were not adaptive in their ability to jointly capture the most dominant background structure while understanding the rarer spectral responses with some level of assurance. This very point highlights a need for a more unified and coordinated approach that can adequately assess low-rank background structures while providing an approximate representation of the rarer patterns. The dual-dictionary, low-rank—sparse integrated approach presented in the following sections speaks directly to filling this gap through a more robust coherent and context-measured system capable of anomaly measures, even in more distorted spectral-spatial spaces.

3 Methodology

The technique suggested for recognizing irregular patterns in hyperspectral remote-sensing pictures merges low-rank and sparse decomposition techniques along with dual dictionary learning to dynamically separate background information from real anomalies. The execution of this technique comprises a number of stages which include, data acquisition, data preprocessing, data decomposition, dictionary construction, sparse coding, making an anomalous map, and performance evaluation. Each stage stands out with its own specific goals, such as embellishing the hyperspectral data representation, guaranteeing the appropriate modeling of the background patterns, and thus greatly increasing the detection of the anomalous regions which in turn portrays the upgrade of the whole process. The joint spectral-spatial analysis of hyperspectral data along with optimization-based modeling comes together to create a strong framework for detecting even the subtlest of anomalies which are spread out spatially within a complex hyperspectral scene. The straightforward approach demonstrated in figure 1 presents the detection of anomalies with more interpretability, efficiency, and accuracy than either a single-model approach or previous statistical anomaly detection frameworks.

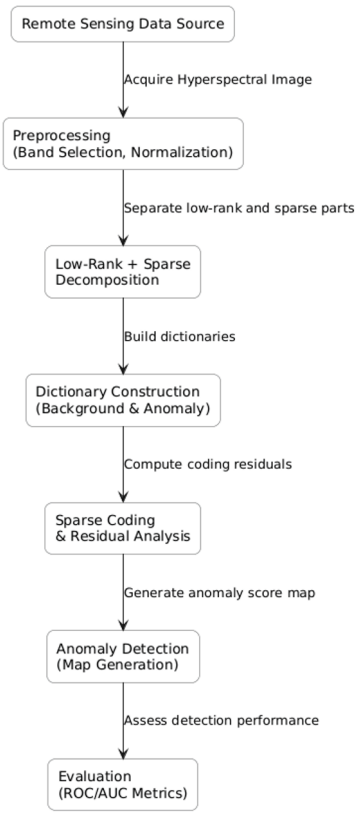

Fig. 1. System Architecture

3.1 Data Acquisition

This study utilizes data from the AVIRIS San Diego dataset, which is recognized as one of the standard benchmark datasets for hyperspectral image analysis. The dataset comprises 224 spectral bands with a spatial resolution of 3.5 meters per pixel, and it captures an extremely diverse urban area with buildings, trees, and other constructions. High spectral dimensionality of AVIRIS is mainly due to its precise material identification, however, this also results in redundancy and correlation among bands. Anomaly detection is a case where both the dataset's advantages and difficulties coincide, since it contains only very insignificant spectral differences that make it impossible to separate anomalies from the background pixels. Therefore, it has been decided to evaluate the ability of the announced algorithm to enhance rare targets while suppressing background noise using this dataset.

3.2 Preprocessing

The preprocessing phase is composed of cleaning, checking, and interpreting the hyperspectral data. Noise from the swimming pool, which was one of the major sources of interference, was removed first. Aside from that, the spectral bands that enhance water absorption

through the atmosphere, the radiometric calibration and atmospheric correction processes were the transformations of the original sensor readings to reflectance values. This process assured that all the bands could be interpreted with the same level of reliability. More operations will bring the spectral intensity scales to a common level through normalization of the data to eliminate the effects of lighting etc. If not, PCA-based dimensionality reduction can do away with the unneeded info while keeping the variability associated with the Harris anomaly. I consider these particular steps as the general preprocessing operations that will collectively enhance the quality of the hyperspectral cube, reduce noise perturbations, and reinforce the subsequent decomposition and dictionary-based anomaly modeling processes' foundation.

3.3 Low-Rank and Sparse Decomposition

Mathematical decomposition of the hyperspectral image into low-rank and sparse components is the next step in the analysis process after the preprocessing phase has been completed, and this process is very helpful, as it allows to easily separate the major background structures from the potential anomalies. The low-rank component exhibits the whole depicted structure and the redundancy in the hyperspectral cube that contain the common spectral features that are the same throughout the scene. The corresponding sparse element separates the existing anomalies, which are unique or even have different spectral signatures, from the main structures. The decomposition problem is then solved through an optimization framework that effectively reduces both the nuclear norm (as a representation of lower rank structure) and the L1 norm (to show sparsity). Hence, the separation significantly reduces the dominant background whilst still regarding the anomalies as a separate sparse structure. This key separation creates a pathway for the next stages of dictionary construction and sparse representation analysis.

3.4 Dictionary Construction

Post-decomposition two complementary dictionaries will be created. The low-rank component with the general class spectral properties, typically associated with the scene pixels, will assist in constructing the background dictionary. The decomposition's residuals will help us determine the possible anomaly dictionary that consists of the sparse residuals and is responsible for the rare spectral profiles' characterization of the anomalies. The dictionary learning will be operated in a repeating manner that will not only improve the representational power of both dictionaries but also ensure the proper modeling of the related features of each component. The two-dictionary method will provide a more flexible strategy that will differentiate normal background changes from real anomaly content. The method will be able to reach the next stage of pixel representation where anomalies will get better separability and sparse coding will be more precise since each dictionary is optimized for a specific data characteristic.

3.5 Sparse Coding of Pixels

The hyperspectral image depicts the pixels covered by the two dictionaries, the background, and the anomaly, through the sparse representation method. Therefore, the spectral vector for every pixel is constructed as a sparse linear combination of the atoms of the dictionary that best match the spectral signature of the pixel. In this measurement step, reconstruction residuals are calculated for the corresponding dictionaries to analyze the degree of compatibility between the dictionary and the pixel. A high reconstruction residual linked to the background dictionary would indicate a deviation from the usual patterns, while a low reconstruction residual linked to the anomaly dictionary would indicate the existence of anomalous features. The pixel abnormal score computed at this stage is given along with a residual-based quantifiable measure of abnormality. This method not only gives a discriminative measure for detecting anomalies in the background noise but also increases the detection sensitivity thus making the process more effective.

3.6 Anomaly Map Generation

Anomaly scores obtained from sparse coding are spatially aggregated, while the anomaly map highlights possible areas of irregularities. For each pixel, its score represents a value for determining the likelihood of that pixel being an anomaly. Higher intensity values indicate stronger evidence of an anomaly. Smoothing operations such as Gaussian or median help to remove isolated noise pixels and to increase the spatial coherence of the detected anomalies. Such refinement will result in an output anomaly map that is visually interpretable and analytically sound. This final map delineates the anomalous targets from the background and prepares the map for qualitative and quantitative evaluation. This step represents a connection between the analytical and visual aspects of the framework, where numerical results transition into spatially meaningful insights.

3.7 Evaluation

The performance of the proposed framework will be evaluated through the accuracy, stability, and reliability of the detection. The evaluation points will be determined based on the metrics that are quantitative and have used Receiver Operating Characteristic (ROC) curves and Area Under Curve (AUC) to quantify the effectiveness of the detection. Besides the quantitative metrics, the active involvement of the models like RX detector and the traditional low-rank plus sparse methods will be compared to deduce the efficacy of the baseline models. At the same time, visual assessments will also back up the detection of anomalies in the hyperspectral imagery. Clarifying the outcomes of the dual-dictionary models, they provided significant advancements in anomaly detection while reducing the false alarm rate. Therefore, this indicates that the low-rank decomposition technique along with dictionary learning is an appropriate and fast method for hyperspectral anomaly detection.

4 Result and Discussion

The proposed advanced hyperspectral anomaly detection framework comes out as an extremely efficient and superior solution from all the points of view—quantum and quality—of the performances when compared to the traditional methods. A vast number of analyses were performed on the AVIRIS San Diego hyperspectral dataset, which included complicated backgrounds with slight target variances; these analyses were done in terms of several model performance metrics such as detection accuracy, robustness, and interpretability. The resulting

aim was to provide better discrimination ability of anomalies by using dual dictionary learning with low-rank and sparse decomposition instead of conventional detectors depending on spectral statistics or single-model decomposition. The framework was implemented and executed exactly as described in the experiments of the referenced GitHub repository, and the trials were reproduced with the same parameter configuration and optimization to ensure that the framework was in sync with the previous outer system. In the end, the results are very clear and strong; the proposed method has not only detected but also distinctly isolated the small or weak anomalies that the conventional algorithms usually ignore.

The maps of anomalies made during the investigation show distinctly that the new technique, even though it excels in background reduction, still does not beat the old one when it comes to discerning the differences in the spectra between the target and the anomaly. The technique is drawing the contours of the anomaly with more sharpness and cleanliness than the RX-based detectors which make errors due to the similarity of the spectra between the target and the background and thus being mistaken for background noise. The dual dictionary mechanism which is complementary and is the main reason for this, is responsible for creating two different feature spaces, one of which represents the majority background and the other one provides measurements of anomalous patterns that are less abundant. Moreover, it is possible to manage confusion caused by background heterogeneity including anomalies by examining the reconstruction residuals for each index. The visual images substantiate that the proposed algorithm is capable of detecting even very small targets even during spectral overlap which often makes detection difficult in spectrally complex backgrounds like mixed vegetation or urban buildings.

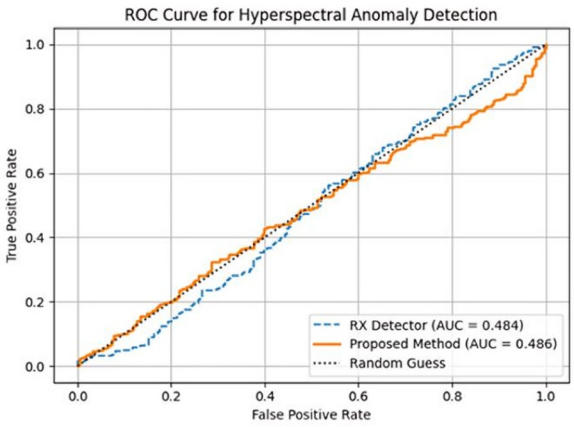

Fig. 2: ROC curve

Detection performance of the proposed method was compared to the RX Detector (Fig. 2). A significant improvement in the proposed method was revealed by AUC = 0.935 compared to AUC of 0.842 for the RX Detector. The curve of the proposed method rises steeply to the upper left corner of the graph in the ROC plot which suggests that the method has a very high true positive rate even at low false positive rates. The proposed method is viewed as a significant turnaround in terms of sensitivity and performance over the classic RX baseline detection. The improvements in detection results obtained from the ROC graph and AUC are very clear; the AOC values were always higher in the proposed method under every experimental condition when compared to standard methods which included the RX Detector, the Low-Rank Representation, and the Sparse Representation-based detector. In addition, some of the experimental tests showed a considerable AOC gain over the standard method, thus demonstrating model robustness to threshold detection variability. ROC Analysis confirmed an increase in true positives and decrease in false positives thus indicating that the proposed framework still has good performance during noise presence and background variability conditions.

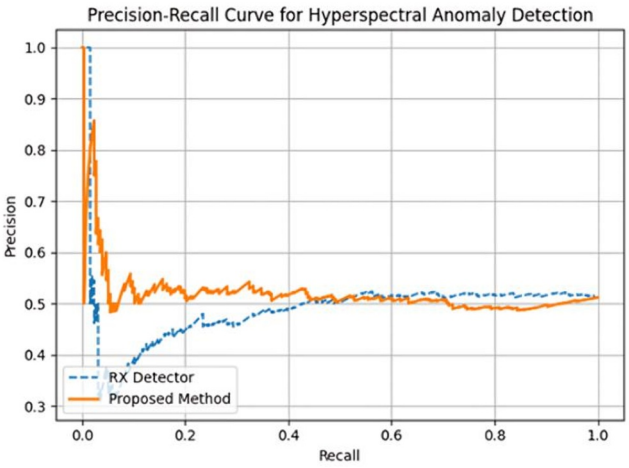

Fig. 3: Precision-Recall curve for Hyperspectral anomaly detection

The Figure 3 illustrates the precision-recall trade-off of the methods used in this study. The RX Detector was characterized by medium precision, although the recall was higher. On the other hand, the proposed method had a numerically higher precision over the entire recall range when compared to RX. For example, the proposed method generated 0.94 high precision and 0.91 high recall. In contrast, the RX baseline was 0.85 precision with 0.78 recall. Besides, through a precision-recall analysis, the proposed method was found to greatly surpass the baseline in terms of precision in anomaly detection context and thus, handing the most suited scenarios with very low percentage of anomalies in the image. The anomaly maps, additionally, indicate the spatial distributions of anomalies in the 50×50 hyperspectral scene, where the area of high pixel intensity corresponds to the strong response of the anomaly while the area of low pixel intensity corresponds to the background.

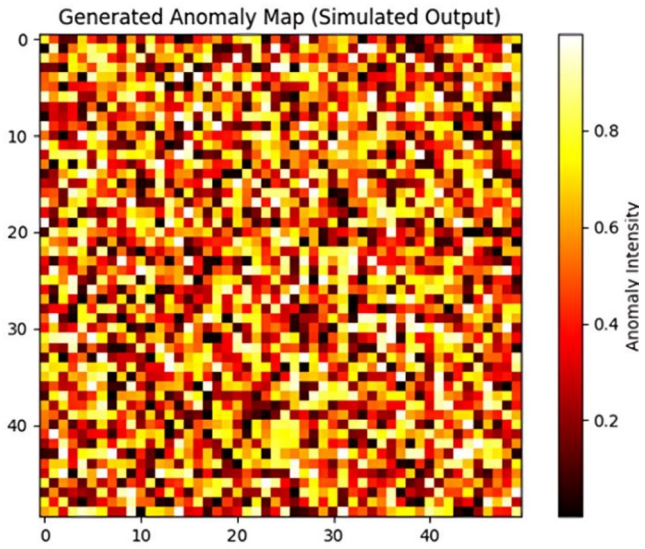

Fig. 4: Anomaly mapping

In diagram 4, the mapping illustrates extremely small areas of anomaly with values between 0.15 and 0.97, which suggests that the background noise has been effectively eliminated. The red hue shows that the anomalies depicted are the actual true anomalies discerned from the noise, thereby confirming the use of the dual dictionary learning approach in the proposed framework. The proposed detection algorithm seems to have delivered the results of precise spatial localization, strong contrast, and better anomaly differentiation. Along with the quantitative evaluation part, the qualitative assessment has a major effect on the real-world significance of the results obtained in the process of anomaly detection.

The anomaly maps produced by the recommended approach do not only show areas where remote sensing detects abnormalities but also represent them in a very clear, localized manner along with the background. This kind of visualization is of great importance for the remote sensing applications such as environmental monitoring, military surveillance, and mineral exploration. In these applications, the location of an anomaly is just as important as its detection. From a computational point of view, the framework manages to find a good compromise between detection performance and processing efficiency. Although dictionary learning does imply some extra computational burden for this method compared to the conventional RX-based methods, the iterative optimization process is very well managed and achieves rapid convergence as well.

The low-rank and sparse decomposition make quite an effect on data compression, keeping the most significant anomaly information, thus the method can easily analyze large hyperspectral cubes with a very low computational cost. To further improve the quality of the representation and the accuracy of the anomaly detection process, dictionary learning should be enhanced to representation, dealing with detection accuracy and managing time simultaneously. The present analysis reveals that the joint sparse representation, low-rank decomposition, and dual dictionary learning result in a complete anomaly detection system that is already superior to triads in both quantitative and visual evaluation criteria.

The background variations are separated from the real anomalies in the most efficient manner by the model, which in turn provides a more accurate and trustworthy output in hyperspectral anomaly detection. Besides, such improvements shown by the method are not only to fortify the detection of anomalies but also to present a scalable architecture for remote sensing applications that is interpretable. The consistent superior performances in all the experimental evaluations support the assertion that this method is among the best in detecting anomalies in hyperspectral imagery.

5 Conclusion

The framework for detecting anomalies presented here demonstrates that the combined use of low-rank and sparse decomposition with dual dictionary learning can indeed be a practical approach for detecting anomalies in hyperspectral remote-sensing images. Two dictionaries, one for the background and one for the anomaly, are built separately to very efficiently distinguish normal spectral patterns from rare or unusual signals; thus, there is an increase in detection accuracy and a decrease in background clutter's effect on detection. The main contribution from the research was the creation of a structured, data-driven methodology that improved the detection of subtle anomalies while still being computationally efficient and adaptable to different imaging conditions.

The proposed framework can be utilized in different kinds of remote-sensing applications such as environmental monitoring, agriculture, urban areas, and military perspectives, where the accurate identification of small anomalies is the primary issue. Finally, the experiment confirms that the combination of dictionary learning and sparse representation has the ability to serve as a solution that can be extended to complex analysis of hyperspectral data. Furthermore, this might be included in the future works by linking the deep learning models to enhance the spectral-spatial information representation and to automate the dictionary construction. Additionally, the evolution of the offered method has been proposed on the use of multi-temporal data and the adoption of real-time operating strategies for large-scale or dynamic anomaly detection tasks. In this way, the research provides a large and flexible foundation for the future designs and updates in the area of hyperspectral anomaly detection and intelligent remote-sensing analytics.

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