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Review on Various Image Processing Techniques in Satellite Imagery Applications

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ABSTRACT
The classification of historical maps has become a crucial task in today's rapidly changing landscape. Changes to city and state boundaries, vegetation areas, water bodies and more can be monitored through satellite images. Therefore, a thorough understanding of satellite image processing is essential for the classification of historical maps. This paper evaluates the advantages and disadvantages of various satellite image processing methods. While many computational methods exist, they perform differently for different applications and choosing the wrong method can lead to subpar results. The paper highlights the appropriate methods forvarious satellite image processing applications, comparing them to provide insight into the bestsolution for each problem. This research will assist in the selection of effective techniques forsatellite image processing applications.

Keywords:- *Image processing, Image enhancement, Image segmentation, Image fusion Change detection, Satellite image compression, Image classification.*

INTRODUCTION

The combination of historical map classification and satellite images is a new approach to trackthe evolution of land and water features on Earth. By using satellite images taken at different times, it is possible to determine changes in the size of regions. This information is then used to produce precise maps for various purposes. Satellite image processing is a crucial computational method with applications in fields such as military, agriculture, disaster prevention, and resource identification. Despite its importance, processing satellite images is challenging due to their large size.

The quality of remote sensing images and the feature set used in image analysis can greatly impact the effectiveness of remote sensing applications. Visual interpretation of remote sensing images uses elements such as shape, color, tone, and texture, but manually analyzing multiple images at once is challenging and subjective. Automated image processing overcomes these limitations by analyzing multiple spectral bands and processing large data sets quickly. Image processing plays a crucial role in remote sensing applications. Remote sensing methods are also a valuable tool for covering a wide range of areas. The accuracy of the image processing techniques is key to the success of remote sensing applications. Understanding the performance of different image processing methods helps to determine the best approach for each specific application. The growing demand for near-real-time monitoring and visual images for emergency services during natural disasters has led to advancements in earth monitoring satellites. These developments aim to provide timely and accurate information to decision- makers and emergency services.

Access to a large amount of digital satellite and aerial imagery is abundant, but the challenge lies in accurately analyzing and extracting relevant information from raw images to be used in real-world applications. There are various image processing techniques, but it is important to evaluate conventional methods and understand image features. Advances in AI and machine learning have led to improved extraction of intricate features from high-resolution aerial imagery. Different layers are used to develop various image processing techniques.
Despite the various methods already available for processing satellite images, there is still room for improvement. A thorough understanding of conventional methods is crucial for developing new, automated systems for satellite image processing. This paper presents a comprehensive survey of various aspects and applications of satellite image processing. The benefits and limitations of each method are discussed, providing valuable insight into developing innovative solutions for current challenges in the field.

Image Processing in Remote Sensing
This paper highlights various methods and algorithms for satellite image processing, including enhancement, feature extraction, segmentation, fusion, change detection, compression, classification, and feature detection, depicted in Figure 1.

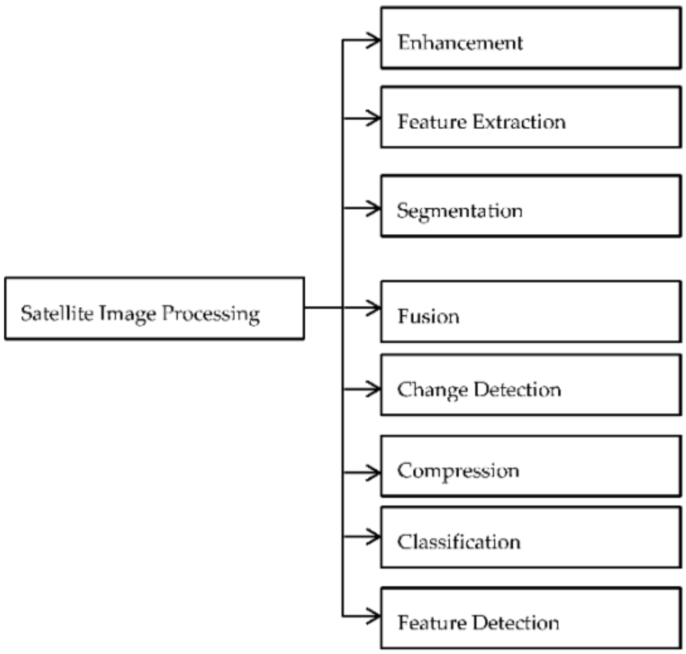

***Fig.1:-**Image Processing Framework*

IMAGE ENHANCEMENT
Image enhancement techniques such as histogram equalization, gamma correction, and local contrast enhancement are used to improve the contrast of images. These techniques increase the difference between the light and dark areas of the image, making it easier to distinguish between objects and the background. The goal is to improve the visual quality of the image while preserving its important details. However, care must be taken when enhancing the image to avoid over-enhancement, which can lead to loss of

important details and introduce noise into the image.

Image enhancement is an important pre-processing step in many computer vision and image processing applications. It is often the first step in a pipeline of image analysis because it makesit easier to detect objects and extract meaningful information from the image. Some common image enhancement algorithms include histogram equalization, adaptive histogram equalization, gamma correction, and local contrast enhancement. Each of these algorithms has its own strengths and weaknesses and the choice of algorithm depends on the specificrequirements of the application and the type of image being processed. Additionally, image enhancement algorithms can also be combined or modified to suit the needs of the application.

Image enhancement techniques categorized as spatial and frequency domain methods. Histogram Equalization is one of the widely used image enhancement methods which can be performed on the complete image or some parts in it. It can enhance the overall image quality. But HE has the limitation that it cannot retain the average intensity in an image. Several modifications were developed over the HE such as Bi-Histogram Equalization (BHE), Recursive Mean Separate HE (RMSHE) and so forth.

Here is a list of some commonly used image enhancement methods and their performance metrics:

- Histogram Equalization (HE):

Test Images: Low-contrast images with limited brightness range

Performance Metrics: Increase in global contrast, improvement in visual quality

- Adaptive Histogram Equalization (AHE):

Test Images: Images with non-uniform illumination and non-uniform contrast

Performance Metrics: Adaptive contrast enhancement that preserves details in both bright
and dark regions

- Gamma Correction:

Test Images: Underexposed or overexposed images

Performance Metrics: Correction of brightness and contrast, improved visual quality

- Local Contrast Enhancement (LCE):

Test Images: Images with non-uniform contrast

Performance Metrics: Enhancement of local contrast while preserving global contrast,improved visual quality

- Fourier Transform (FT):

Test Images: Images with complex patterns and textures

Performance Metrics: Enhancement of high-frequency components, improved visualquality

- Wavelet Transform (WT):

Test Images: Images with textures and small details

Performance Metrics: Enhancement of small details and textures, improved visual quality

The choice of image enhancement method and performance metric depends on the specific requirements of the application and the type of image being processed.

FEATURE EXTRACTION

Feature extraction is a crucial step in image classification as it determines the efficiency of theclassification process. The

features extracted from the image can be broadly categorized as general features and domain-specific features. General features include color, shape, and texture, which are basic and can be used in a wide range of image classification applications. On the other hand, domain-specific features are specific to a particular application or domain and may include conceptual features. The choice of features for extraction depends on the specific requirements of the image classification task, and the features that are most relevant to the task can be selected and used for classification. The features are then transformed into a compact representation, such as histograms or feature vectors, and fed into the classification stage for decision-making.
Here is a list of some commonly used feature extraction methods, the features they extract, andtheir performance metrics:

- Scale Invariant Feature Transform (SIFT):

Features Extracted: Scale-invariant local features

Performance Metrics: High accuracy, robust to affine transformations and image changes

- Speeded Up Robust Features (SURF):

Features Extracted: Scale and rotation-invariant local features Performance Metrics: High accuracy, fast detection speed

- ORB (Oriented FAST and Rotated BRIEF):

Features Extracted: Scale-invariant and rotation-invariant local features Performance Metrics: Fast detection speed, low memory usage

- Local Binary Patterns (LBP):

Features Extracted: Texture information

Performance Metrics: Simple and efficient, robust to uniform changes in intensity

- Harris Corner Detection:

Features Extracted: Corners and interest points

Performance Metrics: Robust to noise and illumination changes, sensitive to scale changes
The choice of feature extraction method depends on the specific requirements of the application, such as accuracy, speed, and robustness. The performance of the feature extractionmethod can be evaluated using metrics such as accuracy, processing speed, and robustness to changes in the image.

IMAGE SEGMENTATION

Image segmentation is a process of dividing an image into segments, with the goal ofidentifying objects and boundaries. The Cuckoo search (CS) algorithm is often used for color image segmentation. An improvement to the CS method, using McCulloch's method, has beensuggested in reference. This method incorporates the Levy flight method into the CS algorithm. Heuristic algorithms like Particle Swarm Optimization (PSO) and Artificial Bee Colony optimization (ABC) are commonly used, but they have a limitation of increasing computational time exponentially with an increase in the number of thresholds for segmentation. The use of McCulloch's method to produce stable random numbers sets this method apart from others. This approach can be expanded to include multi-level thresholding for better segmentation. In cases where remote sensing images are purely illuminated, pixel-based clustering is frequentlyused. One such method is the Hopfield Neural Network clustering strategy, which produces better results when a large number of clusters are

utilized.
Here are some commonly used image segmentation methods and a brief explanation of each:

- Thresholding: This is a simple and straightforward method where a threshold value is set and pixels with intensity values above the threshold are assigned to one class and pixels with intensity values below the threshold to another class.
- Watershed: This method is based on a "flood-fill" approach and considers the image as a topographical map, where the intensity values of the pixels represent elevations.
- K-means Clustering: This is an unsupervised learning method where the pixels are groupedinto K clusters based on their intensity values.
- Graph-based Segmentation: This method involves defining an adjacency graph for the image and then grouping the nodes in the graph into different clusters to form segments.
- Active Contours: Also known as Snake or Level Set methods, this involves using a curve that is initialized around the object of interest and then evolving the curve to minimize an energy function, resulting in the segmentation of the object.
- Convolutional Neural Networks (CNNs): This is a deep learning-based method where a neural network is trained to perform image segmentation.
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These are just a few examples of image segmentation methods and there are many other techniques that have been proposed. The choice of method depends on the specific requirements of the task and the nature of the images being processed.

The process of image segmentation involves dividing an image into multiple segments in order to identify objects and boundaries. One of the most widely used segmentation methods is histogram-based thresholding. This approach involves selecting a threshold for dividing the image into two classes using bi-level thresholding or multiple classes using multilevel thresholding. The method optimizes criteria such as maximum between class variance or minimum classification error to determine the threshold. Studies have shown that multilevel thresholding outperforms bi-level thresholding. Additionally, the classification results can be improved by using a Markov Random Field (MRF). The MRF uses fewer clusters for quantization, clustering and finding the likelihood, and has been found to enhance the minimum distance classification by considering local pixel interactions. Further improvements in classification can be achieved by applying the supervised Random Forest method to each of the extracted segments.
High-resolution satellite image segmentation is tackled through the use of Deep Convolution Neural Network (DCNN). A boundary detection and SEGNET encoder-based novel framework is introduced. SEGNET is a multi-class image segmentation network that utilizes encoder-decoder architecture. It achieves pixel-wise image segmentation, however, its size canbe quite large due to the large decoder, making it a challenging option for researchers. Additionally, the extracted boundaries tend to be blurred. Another method is using a firefly
algorithm based on fuzzy entropy function. The fuzzy entropy function measures the difference between adjacent entropies. Thresholds are determined by the minimum fitness function, resulting in regions with equal entropy values.

In the field of image segmentation, various techniques have been proposed and used. Histogrambased thresholding is one of the widely used techniques, which involves selection of thresholdlevels for classifying the image into multiple classes. Multilevel thresholding outperforms bi- level thresholding. The performance can be improved using Markov Random Field (MRF) that considers local pixel interactions for minimum distance classification. The classification performance is evaluated using Random Forest method.

Deep Convolution Neural Network (DCNN) is also used for high resolution satellite image segmentation by combining boundary detection and SEGNET encoder. However, it has the disadvantage of complexity and blurry extracted boundaries. Another approach is the firefly algorithm based on fuzzy entropy function, which computes the difference in adjacent entropies and forms the threshold levels based on the minimum fitness function.

In object based analysis, the technique used for image segmentation is crucial for determining the overall image performance. Image segmentation is followed by classification of thesegmented image. Supervised methods are commonly used for quantitative analysis, while qualitative analysis is subjective but easier. The performance evaluation can be done using Under Segmentation Error (USE) and Over Segmentation Error (OSE), which are calculated for each reference in the image and summed up to get the overall performance metric.

IMAGE FUSION

Image fusion is a technique that merges two or more images to form a new image. There are various methods of image fusion such as wavelet transform, High Pass Filter Additive Method (HPFA), High-Frequency-Addition Method (HFA), High Frequency Modulation Method (HFM), Local Mean Matching (LMM), Local Mean and Variance Matching (LMVM), Regression variable substitution (RVS), and Local Correlation Modeling (LCM). Image fusion can also be classified as probabilistic fusion, statistical fusion, unmixing-based fusion, semiphysical fusion, and hybrid fusion. Probabilistic fusion uses Bayesian and maximum likelihood methods, while statistical fusion involves pixel-based approaches. Unmixing-based fusion enhances the spatial resolution of coarse images. Semiphysical fusion models physical structures for image fusion. Hybrid fusion integrates different fusion techniques to improve accuracy. These methods are applied in various areas such as pan-sharpening, flood detection, water quality monitoring, and surface reflectance.

In summary, image fusion can be classified into different categories based on different methods such as probabilistic, statistical, unmixing based, semiphysical, and hybrid fusion. There are also different geometric analysis tools such as curvelet, contourlet, wedgelet, and Non-Subsampled Contourlet Transform (NSCT) used for image fusion. The Shift-Invariant Shearlet Transform (SIST) is a recent method that combines the advantages of wavelet transform and sparse representation for remote sensing image fusion.

The method involves fusing high frequency sub-bands and the quality of the fused image can be evaluated through metrics such as Spatial Correlation Coefficient (SCC) and mean gradient (G). The intensity components of multispectral images are first separated using IHS transform, then the wavelet transform is applied for multiscale representation, and finally different techniques are used for processing the low and high frequency sub-images.

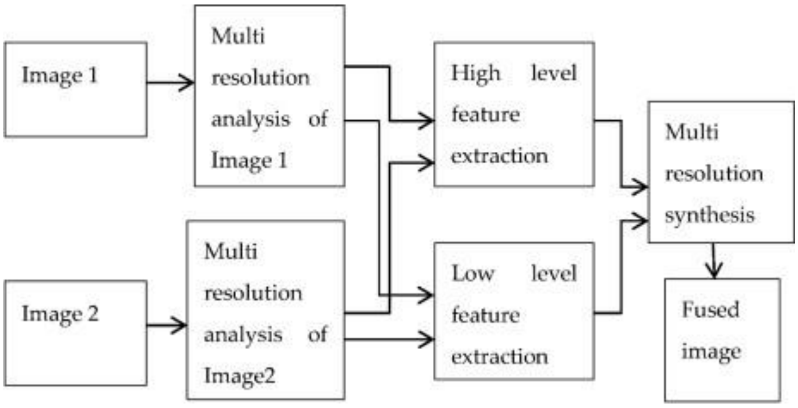

***Fig.2:-**Image Fusion block Diagram*

Here is a list of image fusion methods along with the test images they are commonly used with and the performance metrics used to evaluate their performance:

- Wavelet transform: commonly used for pan-sharpening, tested using multispectral and panchromatic images, evaluated using Mean Squared Error (MSE) and Structural Similarity Index (SSIM).
- High Pass Filter Additive Method (HPFA): tested using remote sensing images, evaluated using MSE, SSIM and the Normalized Cross Correlation (NCC).
- High-Frequency-Addition Method (HFA), High Frequency Modulation Method (HFM): tested using remote sensing images, evaluated using MSE and SSIM.
- Local Mean Matching (LMM), Local Mean and Variance Matching (LMVM), Regression variable substitution (RVS), and Local Correlation Modeling (LCM): tested using remote sensing images, evaluated using MSE and SSIM.
- Bayesian method: tested using multispectral and panchromatic images, evaluated using MSE and SSIM.
- Spatial and Temporal Adaptive Reflectance Fusion Method (STARFM): tested using remote sensing images, evaluated using MSE and SSIM.
- Spatial and Temporal Reflectance Unmixing Model (STRUM): tested using surfacereflectance images, evaluated using MSE and SSIM.
- Shift-Invariant Shearlet Transform (SIST): tested using remote sensing images, evaluatedusing Spatial Correlation Coefficient (SCC) and Mean Gradient (G).
- Intensity-Hue-Saturation (IHS) + wavelet transform: tested using multispectral images,evaluated using MSE and SSIM.

Note: The performance metrics used can vary depending on the specific application and the desired outcomes.

SAR images are often affected by speckle noise, but the NSCT method effectively captures the edges in the fused image and has a high efficiency in removing the noise components through Maximum A Posteriori estimation. The SAR image is then fused with the PAN image using an edge-based method. However, a common limitation of image fusion is the failure to capture smoothness across different contours.

It is important to analyze the correlation between satellite images for accurate fusion. This canbe done by evaluating the correlation coefficient on actual and synthetic time series images, followed by spatial and temporal fusion. However, this method's accuracy decreases when theland cover type changes. Another approach is to classify the scene by fusing local and global features in the image, using k-means clustering after dividing the image into dense regions.

Another fusion approach uses multilevel morphological decomposition to preserve the details in the source images. Fusion also has applications in radiometric normalization, such as using MODIS data to predict the Landsat reflectance for different viewing angles. A fusion approach using Spatial and Temporal Adaptive Reflectance Fusion Models is proposed to understand

landscape changes at spatiotemporal resolutions, but this method has the limitation of detecting changes in sub-pixel ranges.

There are several commonly used fusion algorithms, such as the Ehler method that enhances the spatial resolution of multispectral images using Intensity-Hue-Saturation (IHS) transform and adaptive filtering. The wavelet transform fusion algorithm combines high frequency components from the PAN image with the spectral information from the MS image. The University of New Brunswick fusion method uses the least square method to find the relationship of gray values in the PAN, MS, and fused images.

CHANGE DETECTION

Change detection is a process used to identify changes in a particular area using satellite data. There are several methods of change detection, including algebra-based, transform-based, GIS-based, and advanced model-based techniques. Algebra-based methods use mathematical operations to find changes in images, such as Image Differencing, Change Vector Analysis, and Principal Component Analysis. Transform-based methods use transforms to find image changes, such as Tasseled Cap Transformation. GIS-based methods integrate and analyze image data using a geographical information system. Advanced model-based methods use reflectance and spectral mixture models.

Initially, a maximum likelihood supervised classification technique is used to separate land cover types. Then, statistical change detection and image differencing are used to differentiate between past and present image changes. The mean and variance of the data are evaluated to calculate the probability of a pixel belonging to a particular class. However, this method has limitations such as misinterpretation of pixels and reduced overall efficiency.

An alternative method, Multi-Step Image Matching, uses fast clustering, image detection, and boundary matching to detect changes in disaster-prone areas. A graph-based method is also developed to detect spatial and temporal changes in satellite images using object-based analysis and the calculation of correlation coefficients. Classifier techniques are commonly used in change detection, but they may not provide enough information on temporal changes in images.

IMAGE COMPRESSION

Satellite image compression is necessary due to limited hardware resources onboard satellites and large image sizes. It helps reduce data storage and bandwidth requirements for transmitting images from the satellite to the ground station. The goal is to minimize the dependence on onboard resources without sacrificing image quality and information content that is critical for ground station analysis. The challenge of image compression is to maintain quality during reconstruction at the ground station without losing important information.

Image compression techniques used in satellite imaging:

- Lossless compression techniques: Huffman coding, Run Length Encoding, Arithmeticcoding
- Lossy compression techniques: Discrete Cosine Transform (DCT), Fractal compression, Vector quantization

Performance metrics used to determine

image compression quality:

- PSNR (Peak Signal to Noise Ratio)
- MSE (Mean Squared Error)
- SSIM (Structural Similarity Index)
- Compression Ratio
- Bit rate
- Visual Quality Assessment.

Fractal compression is a powerful technique for image compression, but it has its drawbacks in terms of computational complexity and image quality degradation. An alternative method isthe differential compression that predicts image pixels based on previous pixels and calculatesthe error. This method is simpler but has a lower compression ratio. To compress multispectral images, a method that removes sub-bands has been proposed in reference. The challenge in multispectral image compression lies in effectively storing and compressing different bands. The removed sub-bands are selected based on correlation coefficients between bands. Another lossless compression method decorrelates spatial and spectral domains, and recursively removes side information of the coefficients to improve compression. For the large aurora spectral images, they are transmitted as frames instead of a single image due to the limited transmission channel bandwidth. A Differential Pulse Code Modulation (DPCM) scheme is proposed for lossless compression. The Adaptive Spatial Dispersion Clustering (ASDC) method is used for spatial data compression, followed by a spatial prediction method called Fixed Rank Kriging, which uses only a subset of the data to reduce computation complexity. To further enhance compression and reduce complexity, a novel transform-based compression method called Discrete Tchebichef transform (DTT). DTT is an orthogonal transform that minimizes rounding errors by converting the DTT matrix into a single-row elementary matrix.

IMAGE CLASSIFICATION

Image classification is a pattern recognition technique for categorizing images or pixels based on similarity measures. It can be divided into supervised, unsupervised, and post-classificationmethods. Supervised methods use training data to recognize instances in an image and can be parametric (e.g. Bayesian and decision trees) or non-parametric (e.g. K-Nearest Neighbor and Logical Regression). Unsupervised methods group similar instances without class label information (e.g. hierarchical and partition clustering). Image classification in satellite images faces two main challenges: mixed pixels and large data handling. Random Forest Classifier is a popular approach for land use/cover classification. Spectral unmixing can address mixed pixels and is used to find the fractional abundances of various classes. Radial Basis Function Neural Network (RBFNN) is a prominent neural network with many tunable parameters. Post- classification algorithms can correct wrongly classified pixels. Deep feature learning is proposed for satellite image classification using spatial pyramid pooling. A Bayesian network classifier model is used to classify cloud presence. Evaluating the accuracy of the classificationmethod can be done using k-fold cross-validation and FSE-DST (integration of fuzzy evaluation and Dempster-Shafer theory). Object-based image classification is also important for developing more accurate results.

IMAGE FEATURE DETECTION

There has been an increase in the satellite images which helps to understand and analyze various applications. Feature recognition is gaining importance with the advancement in deeplearning.

- Harris Corner Detection: It is a popular method for detecting corner points in an image, which are considered to be distinctive features. The Harris corner detection algorithm works by looking for the areas in an image where the intensity changes rapidly in all directions. This algorithm uses the intensity gradients in both the x and y directions to identify these corners. The Harris corner detection method is often used in object recognition and computer vision applications.
- SIFT (Scale-Invariant Feature Transform): SIFT is a feature extraction method that is able to identify the distinctive features in an image, even when the image has undergone a change in scale or orientation. This is achieved by constructing a set of local descriptors around the detected features. The SIFT algorithm is robust to changes in lighting conditions and can be used in object recognition and tracking, among other applications.
- SURF (Speeded Up Robust Features): SURF is a feature extraction algorithm that is similar to SIFT, but is computationally faster. SURF uses an approximation of the SIFT algorithmto achieve faster processing times, while still maintaining good performance. SURF is commonly used in object recognition, image registration, and other computer visionapplications.
- ORB (Oriented FAST and Rotated BRIEF): ORB is a feature detection and description method that is based on the FAST (Features from Accelerated Segment Test) corner detector and the BRIEF (Binary Robust Independent Elementary Features) descriptor. ORB is designed to be computationally efficient and is commonly used in object recognition, image retrieval, and other computer vision applications.

Performance metrics for these feature detection methods can include the number of features detected, the accuracy of feature detection, and the computation time required to detect the features. Test images used to evaluate these methods can vary depending on the specific application, but they can include images of objects, landscapes, and other scenes.

The presence of jitter in an image can greatly impact its quality, so it's important to detect and compensate for it. A model based on displacement data is used to detect high altitude jitter in satellite images, and a bidirectional Kalman filter and smoothing filter are used to reduce its impact. To correct the image, a reimaging model is employed. Distinguishing between formal and informal settlements is done based on morphological characteristics and spatial information extracted using wavelet transforms.

For the efficient detection of oil spills in the sea, an International Maritime Organization employs feature selection using a machine learning algorithm. SAR images can provide clear images of oil spills on the ocean's surface with wide coverage. A novel transfer learning method is used for vehicle detection from aerial images and is based on a super resolution algorithm. A linear SVM based search technique is used to detect vehicle positions, but the matching performance is limited. This limitation is overcome using dictionary learning and sparse coding, which creates low-resolution sections using shared coefficients obtained through dictionary learning.

The efficiency of image processing techniques varies depending on the application, the type of noise in the image, and the type of image used. The accuracy of feature extraction, detection, fusion, and change detection all play a role in the quality of the segmentation and overall result. The type of noise present in the image influences which enhancement technique is used and, in turn, the final outcome. The complexity of satellite images, with their intricate edges, contours, and textures, highlights the need for general feature extraction. Choosing the right technique for the application can greatly improve the final outcome in image processing.

DISCUSSIONS

Remote sensing data includes spatial, spectral, and temporal resolution. Spectral statistics is widely used in remote sensing image classification. The accuracy of ground object recognition is largely dependent on the spatial resolution. Temporal resolution helps in generating land cover maps and detecting changes in land use, urban planning, and environmental planning.

Image enhancement is a crucial step in improving the quality and information content of an image before further processing is performed. Common techniques used include contrast enhancement and spatial filtering. Linear contrast enhancement is best applied to remote sensing images with Gaussian or near-Gaussian histograms where brightness values are concentrated in a single range. However, this technique may not be suitable for scenes with large land and water bodies. In such cases, non-linear contrast enhancement techniques like histogram equalization can be applied. Non-fusion based enhancement has low spatial information but high computational complexity, so fusion-based enhancement is used to overcome this limitation.

Remote sensing data contains spatial, spectral, and temporal resolution. Spectral statistics is widely used in remote sensing image classification. The accuracy of ground objects is mostly determined by spatial resolution, while temporal resolution is used for generating land cover maps, change detection, and urban planning. Image enhancement is used to improve image quality and information content before further processing, including contrast enhancement and spatial filtering. For remote sensing images with Gaussian or near-Gaussian histograms, linear contrast enhancement is suitable. Non-linear enhancement is used for low-contrast images with histogram equalization as a prominent technique. Pixel-based feature extraction extracts low- level features directly from raw pixels, while object-based approaches extract high-level features that represent shapes in images. Depending on the spatial resolution of the image, different segmentation algorithms are used, with multiresolution segmentation for high resolution and clustering for low to medium resolution. Integration of high spatial and spectral resolution enhances image capabilities for urban and environmental studies. Change detection is a challenging task that depends on various factors and selection of suitable technique varies based on the problem. Image classification is used to convert images into thematic maps, withdigital surface and terrain models being widely used. Recently, quantum image processing and quantum learning have been introduced to improve image processing efficiency and performance.

CONCLUSIONS

In this study, we aim to provide a comprehensive review of the various image processing techniques for satellite image analysis, and their applications in remote sensing. The increasing availability of satellite imagery has led to growing interest in image processing for remote sensing purposes. We explore different image processing techniques and the advantages and limitations associated with each method. The specific techniques for various remote sensing applications, including the performance measures, are discussed in detail.

One of the major challenges in image processing for remote sensing is the low contrast of satellite imagery, which can make it difficult to select the proper

threshold for image segmentation. Another challenge is the misinterpretation of image pixels in change detection, which can lead to inaccurate results. To overcome these difficulties, researchers are increasingly employing machine learning algorithms, which have the ability to make data-driven decisions effectively and learn and perform intelligently. The complexity of satellite images also requires the use of computationally intelligent paradigms like machine learning to achieve robust results in real-world classification applications.
The quality of the input image and the complexity of the features within it are two important factors that determine the appropriate image processing technique to be used. Researchers are now exploring hybridized image processing techniques to improve the robustness of existing techniques. The future of image processing for remote sensing holds great potential for the application of these techniques in practical areas, as well as the continued implementation of quantum algorithms for remote sensing applications.

In conclusion, this work provides an overview of the current state of image processing techniques for satellite image analysis, with a focus on their importance and applications in remote sensing. The study serves as a roadmap for further research activities in this area,highlighting the opportunities and challenges in the field of image processing for remotesensing.

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