Restoration of Remote Satellite Sensing Images using Machine and Deep Learning: A Survey

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Abstract. Remote sensing satellite images are affected by different types of degradation, which poses an obstacle for remote sensing researchers to ensure a continuous and trouble-free observation of our space. This degradation can reduce the quality of information and its effect on the reliability of remote sensing research. To overcome this phenomenon, the methods of detecting and eliminating this degradation are used, which are the subject of our study. The original aim of this paper is that it proposes a state of art of recent decade (2012-2022) on advances in remote sensing image restoration using machine and deep learning, identified by this survey, including the databases used, the different categories of degradation, as well as the corresponding methods. Machine learning and deep learning based strategies for remote sensing satellite image restoration are recommended to achieve satisfactory improvements.

Key words: image restoration, remote sensing images, Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Convolutional Neural Network (CNN).

1. Introduction

Remote sensing images are used to obtain a variety of data, including spying on enemy territories for the military purposes (the main purpose of building satellites), climate prediction and control, which has been one of the main civilian activities of remote sensing (Meteosat satellites), disaster prevention, measuring the ozone layer, detecting and controlling forest fires or oil slicks, mapping, etc. In other words, the general aim of remote sensing is to record and recognize the globe. Although satellites have made progress, researchers often encounter problems when taking satellite images, in terms of sensor malfunctions or the presence of clouds that prevent optimal exploitation of the data. In order to solve this problem, restoration treatments are frequently required to restore the polluted parts of these images and to exploit them afterwards. This document aims to present the studies carried out during the last decade (2012-2022) and their techniques for reconstructing satellite images based on automatic and deep learning, the different kinds of noise and the databases used. The papers consulted for our study were taken from references, publications and conferences relevant to our topic. This paper is structured as follows: Section 2 presents the databases used, Section 3 describe the main sources of degradation, Section 4 describe various techniques to detect and reduce them. Section 5 presents applications of these techniques. Section 6 concludes the paper.

2. Databases

As of April 30, 2018, the United States was leading the space launches; indeed, it has successfully launched 859 satellites in orbit. China launched 250, Russia 146, while in the rest of the world launched 631 satellites. In 2021, interestingly, the Chinese space industry has surpassed that of the United States, in terms of satellite launches, , while in Africa there was no rocket fired [1]. In turn, China has planned to organise more than 40 space expeditions in the coming months [2], where the Chinese super administrator China Aerospace Science and Technology Corporation (CASC), said in early 2022.

The remote sensing images were collected in several databases. Where, in this section, we will present the different satellites used in the work done according to the continents. In the United States, the Geostationary Operational Environmental Satellite (GOES) series [3] is the main group of meteorological satellites moving in geostationary orbit to provide frequent images of the Earth's surface and cloud cover to the National Weather Service, such as Meteosat [4] and [5]). The GOES satellites were planned by the National Aeronautics and Space Administration (NASA) [6].

In America, Land Satellite (Landsat) is widely used, and it is the main space program of Earth observation for non-military purposes. It was created by the American space agency NASA. Landsat was initially known under the acronym Earth Resources Technology Satellite (ERTS-1) [7] and its program is a technical and scientific success. This type of satellite is employed in [8]-[20]. In California, Vandenberg AFB launched QuickBird which is a commercial high resolution Earth Observation Satellite. QuickBird is used in [21]. PatternNet dataset has been suggested since 2017; it is composed of a large number of high-resolution and large-scale remote sensing images collected for remote sensing image databases. These images are collected from Google Maps (GMA) and Google Earth Imagery (GEI) for cities in the United States (US). PatternNet is utilized in [22]. National Oceanic and Atmospheric Administration (NOAA) is the American agency responsible for the investigation of the ocean and the atmosphere. On board of NOAA there is the primary sensor named Advanced Very High Resolution Radiometer (AVHRR), valuable for monitoring weather and vegetation on the surface of the globe, sea surface temperature, storms, etc. NOAA-AVHRR is applied in [23]. Space Plug-and-play Architecture Research Cubesat (SPARC) is a military research nano satellite shared by the United States and Sweden. SPARC is applied in [20].

In Europe, the system (satellite for Earth observation, SPOT) is a family of French civilian remote sensing satellites for earth observation. It was designed and launched by the French National Centre for Space Studies (CNES) [24], in a joint effort with Belgium and Sweden. It is used to acquire remote sensing information for commercial purposes. SPOT images have some applications in areas that require continuous imagery, such as guard service and agriculture. In addition, the Sentinel satellites are a family of European Earth observation satellites, focused on the environment and security [25]. Meteosat is a European meteorological satellite placed in geostationary orbit [26]. These satellites are developed under the supervision of the European Space Agency (ESA) on behalf of the European meteorological satellite operator (EUMETSAT). The European satellites Meteosat, Spot and Sentinel are used in [4, 5], [27, 28], and in [29, 31], respectively.

In Asia, the Indian Remote Sensing (IRS) satellite series includes all Earth observation satellites launched and operated by the Indian Space Research Organization (ISRO) [32]. The Indian space agency is responsible for the planning and operation of satellites and launchers. In China, China National Space Administration (CNSA) is the space agency responsible for the Chinese Space Program. Gaofen is a family of Chinese earth observation satellites for civilian use. Its objective is to provide near real-time data for natural disaster prevention and treatment, climate change monitoring, mapping, resource and environmental monitoring, and agricultural support. Ziyuan (meaning Resources) is a Chinese Earth observation satellite. It is a high-resolution imaging satellite operated by the Ministry of Land and Resources (MLR) of the People's Republic of China. The satellite is utilized to provide imagery to monitor resources, land use and ecology, and for use in urban planning and disaster management. GaoFen is applied in [18, 33, 34, 35, 36, 37] and ZiYun-3 is used in [18, 33, 37] and [38]. In addition, Yaogan (meaning remote sensing satellite) is a complete Chinese platform of earth observation and remote sensing satellites for military use. Officially, the Chinese authorities consider them as observation satellites designed for crop evaluation, disaster prevention, urban planning and scientific experimentation. But it is generally accepted that, given their orbit, payload and launch rate, they are in fact military satellites [22]. UC Merced is the Google image dataset of the University of California, Merced (UC Merced) or (UCM). Its images were extracted in a manual way from large images from the database of The United States Geological Survey (USGS), which is a U.S. government agency responsible for monitoring the seismic phenomenon. UC Merced is applied in [22]. WHU-RS19 is a set of remote sensing satellite images exported from Google Earth, and it was released by Wuhan University responsible for providing high-resolution satellite images [22]. As for the aerial image dataset (AID) [39], it is a new large-scale dataset, obtained by collecting sample images from Google Earth. RSSCN7 is a satellite image database collected from the private research company Remote Sensing Systems (RSS) that processes microwave data from a variety of NASA satellites. RSSCN7 is utilized in [39].

3. Sources of image degradation

The main sources of degradation can be divided into several categories: physical degradation, linked to the imperatives of physics, notably the radiative nature of sunlight and air turbulence. Mechanical degradation linked to the camera (the impacts of photographic grain), electronic degradation linked to errors in information transmission (transmission in the camera to the radio device), and optical degradation linked to the properties of the imaging system (the lenses), and so on. For each type of degradation, the image processing operations that can be applied to reduce its effects depend on the source of the degradation [40]. This is why image restoration processing is often essential to correct the distortions introduced and thus improve the quality of these images, so that they can be used later.

The presence of degradation is the major problem of images obtained from satellites. It can take various forms such as: clouds [4, 5, 10, 12, 13, 14, 17, 18, 20, 21, 23, 28, 31, 33, 35, 41], the cloud and its shadow [8, 19, 34, 37], haze [9, 11, 39, 42], thin cloud [15], thick cloud [16,23,38], thick cloud and cloud shadow [29], cloud and snow [30], noise [36,43,44], shadow [45], noise and blur [46] and jitter [22].

4. Techniques used

With the rapid development of remote sensing image acquisition technology, there are often degraded regions in these images due to poor atmospheric conditions or internal malfunction of satellite sensors that cause the loss of collected information and also make target detection, object recognition and other post-processing tasks very difficult, generating erroneous results. Detection and elimination of degradation can therefore improve the efficiency of remote sensing image interpretation. Image restoration involves restoring missing data from the original image from the degraded image. The considerable number of application areas of image restoration techniques demonstrates the importance of this operation in the field of image processing, from cosmic and astronomical images to medical images [47] and police investigations. In this section, the bibliography surveyed the different detection and removal techniques employed by researchers to restore remote sensing images.

4.1. Classification of restoration techniques

Relevant approaches to remote sensing image restoration can be divided into two broad categories: approaches based on classical algorithms and approaches based on Artificial Intelligence [48]. Some examples of approaches based on classical algorithms are:

- Clear-Sky Background Differencing (CSBD) algorithm based on image characteristics [50, 51].
- Automatic Cloud Cover Assessment (ACCA) based on the relationship between objects of cloud and cloud shadow [52].
- Background Subtraction Adaptive Threshold (BSAT) method [53].
- Spectral indices method-cloud index (CI) and clod shadow index (CSI) [54].
- Himawari-8 Cloud and Haze Mask (HCHM) algorithm [55].
- Fmask algorithm (Cloud Displacement Index) CDI [56].

Regarding the approaches based on Artificial Intelligence here are some types:

- Multi-Scale Residual Convolutional Neural Network (MRCNN) [11].
- Simple Linear Iterative Cluster (SLIC), Deep Convolutional Neural Networks (CNNs) [21].
- Multiple Convolutional Deep Neural Networks (ConvNets), Conditional Random Field (CRF) [45].
- Image Despeckling Convolutional Neural Network (ID-CNN) [57].

4.2. Techniques based on classical algorithms

Classical algorithms are considered as the methods that have specific known steps to follow for a specific input image. The output of cloud removal and detection depends on the input image and the algorithms employed (input + program = output); moreover, in classical techniques there is no learning. In contrast, machine learning is a field of Artificial Intelligence that allows systems to learn automatically based primarily on the input image and existing data (input + output = program).

4.3. Artificial intelligence based techniques

Artificial Intelligence (AI) is a term used in 1956 by John McCarthy. It is the science and engineering of making intelligent machines, it is a thought that suggests that hardware can learn and think on its own, without being coded with commands [49]. AI has offered promising solutions to the problem of image processing, especially the restoration of remote sensing images, allowing greater flexibility which makes it more robust than traditional techniques. Machine learning (ML) is a field of study in AI, its basic idea is the study of computer algorithms that can improve automatically through experience and the use of data. AI has two phases: the first is learning or training where the ML must first be trained by processing a large number of input patterns and their associated reference output patterns, once trained, the ML is able to recognize similarities when presented with a new input pattern, resulting in a predicted output pattern presented by the second phase. Deep learning (DL) is the sub-domain of ML derived from AI.

Machine and deep learning is about creating huge neural network models capable of making accurate choices based on data, DL is suitable for situations where the data is complex. DL algorithms have been progressing day by day for a very long time in the improvement of image processing algorithms and have developed in many fields. Notably, space research, intelligent robots, security and surveillance, autonomous vehicles, voice, facial and fingerprint recognition, social networks where Facebook uses it to break down the message in online discussions, financial forecasting, automated commerce, identification of defective parts and localization of malware or false statements. In the health field, DL algorithms analyze information extracted from wearable watches, artificial pacemakers and various monitoring sensors placed in the human body. DL elements have made it possible to detect many diseases including epilepsy, hypoglycemia and atrial fibrillation. As for the gaming industry, the Xbox uses DL. to detect body movements and respond by exciting game fans. In addition, in language processing, DL can understand speech, convert it into written form and translate one language into another. Likewise, all the intelligent computer systems that are equipped with DL, have contributed to the enormous success, which we are currently witnessing [51].

5. Application of machine and deep learning for remote sensing restoration

Restoration of remote sensing images using machine and deep learning is the objective of our paper. However, considerable research is available in the literature to provide noise-free images or at least images with reduced degradation impacts, in particular, due to the arrival of new satellite images. This leads us to classify these algorithms in three categories as follows: Some of them deal with suppression, others with detection, while the last ones deal with both at the same time. The bibliography survey has reviewed different techniques.

5.1. Detection techniques

Noise frequently exists in remote sensing images, diminishing the quality of the image and leading to erroneous or inaccurate interpretations and thus causing many obstacles to remote sensing image applications. To remedy this, it is essential to first detect this noise and then remove it. Recently, several new studies have appeared for this type of technique, we present them below:

- Multilayer Perceptron (MLP) [4].
- Fuzzy Logic, Neural Network [5].
- Fully Convolutional Neural Networks Fully Convolutional Network (CloudFCN) [10].
- Multiscale Features-Convolutional Neural Network (MF- CNN) [12].
- Spectral Rationing + Fuzzy C-Means Clustering (FCM) [17].Cloud Detection Neural Network (CDnet), Deep Convolutional Neural Network (DCNN) [18].
- Deep Convolutional Neural Networks, SegNet, Remote Sensing Network (RS-Net) [20].
- Adaptive Simple Linear Iterative Clustering (A-SCLI), Multiple Convolutional Neural Networks (MCNNs) [33].
- Machine Learning and Multi-Feature, Multilevel Feature Fused Segmentation Network (MFFSNet) [34].
- Linear Stripe Noise Detection (LSND)[34].Convolutional Neural Network -3D Multiscale (3D-CNN) [37].

The paper [4] adopted the Multilayer Perceptron (MLP) approach which is a multilayer perceptron neural network to detect clouds in the Meteosat second generation Spin Enhanced Visible and Infrared Imager (MSG SEVIRI) images with the CLoud Mask

(CLM) provided by EUMETSAT. The MLP model is a feed forward artificial neural network classifier. The connections between the perceptrons in an MLP are direct and each perceptron is connected to all the perceptrons in the next layer, except for the output layer which gives the result. This approach is useful in cases where there is not enough auxiliary data. Furthermore, it is believed that the multilayer perceptron can be improved by increasing the size and diversity of the training and test sets, and by systematically testing other types of artificial neural networks and training algorithms. This proposed model was able to detect not only thick and bright clouds but also thin or less bright clouds. In addition, the execution time is about 20 s, which gives a significant impact on reducing the computational load when large data sets need to be processed.

Automatic detection of daytime land and marine clouds from Meteosat second generation rotationally enhanced visible and infrared imager (MSG SEVIRI) images based on fuzzy logic and neural networks was the proposed topic of the authors of [5]. They used the threshold mechanism and auxiliary data such as numerical weather prediction (NWP) for the development of the model. The analysis of the results obtained by the neural network compared to fuzzy logic also demonstrates its high accuracy and the usefulness of using artificial intelligence techniques in remote sensing imagery applications. This approach was not only able to detect thick clouds but also thin and less bright clouds.

Correct detection of cloudy pixels in Landsat 8 remote sensing images that relies on deep learning using fully Convolutional neural networks named FCN and CloudFCN are developed by [10] and [13] respectively. The deep learning process aims at extracting local and global semantic features at the pixel level of cloudy areas in an image. In addition, a gradient-based total identification is designed to perceive and exclude snow/ice areas in ground truths from the training set. The proposed techniques provide distinct and diverse detailed performance tests, which confirm that fully Convolutional network architectures are indeed a powerful and effective tool for cloud detection in remote sensing images, and can outperform previous techniques. Although these designs have become a standard deep learning approach for image segmentation, a direct deficiency of this work is the coverage of cloud shadows, fog and haze.

The Multiscale Features Convolutional Neural Network (MF-CNN) method described in the paper [12] is based entirely on a neural network and aims to solve the problem of reliably detecting thin clouds at the pixel level, while providing excessive accuracy for detecting thick clouds and non-cloudy pixels in remote sensing images. The design consists of first stacking the visible near- infrared, shortwave, cirrus, and thermal infrared bands of Landsat 8 imagery to obtain the combined spectral information. To learn the global multiscale features of the stacked images, the MF-CNN model is then used. The high-level semantic information acquired in the feature learning procedure is integrated with the low-level spatial information to classify the imagery into thick, thin, or cloud-free regions. The proposed method leads to the identification of complex cloud types and shapes. Experimental comparison of the results of the MF-CNN model with those of traditional machine learning, deep learning, and the classical Fmask and F_Score method of thick and thin clouds are needed to further evaluate the performance of the proposed model.

The authors of [17] have automatically detected clouds in Landsat ETM+ images without any manual intervention. The proposed approach is to conduct a color transformation on the input image. Then, by using the spectral image rationing technique a report image will be produced. Finally, it gathers the report image using Fuzzy C-Means clustering (FCM) to detect the clouds in an automatic way. The spectral rationing technique uses the value of the ratio between croma and luma to build the report image to detect clouds in satellite images. This method is effective in detecting thick clouds and thin clouds in average time.

The topic addressed by [18] is to detect clouds through a neural network of (CDnet) with an encoder-decoder structure, a feature pyramid module (FPM) and a boundary refinement block (BR) used for cloud mask extraction via ZY-3, GF-1 WFV and Landsat-8 satellite vignettes. The objective of this paper is threefold: First, the FPM module extracts multi-scale contextual data without lack of resolution and coverage. Second, the BR block refines object boundaries by exploiting high-level semantic capabilities and mid-level visual properties for category recognition of image areas. Finally, the encoder-decoder network structure recovers the segmentation results step by step with a size equivalent to the input image. Experimental results show its efficiency and robustness using only three bands of the multi-spectral images, but its drawback is the localization of boundaries for thin clouds.

The authors of [19] proposed a deep Convolutional Neural Network (CNN) to surface clouds and their shadows in Landsat 7 and Landsat 8 images. The authors performed a detailed CNN-based semantic segmentation named SegNet for extracting multi-level spatial and spectral features computed on the full input image to identify pixels as clouds, thin clouds, cloud shadows or bright areas. According to the extensive qualitative and quantitative analysis compared to FCMask, the adapted SegNet technique achieves promising performance in terms of overall accuracy for cloud and cloud shadow detection.

A formula for cloud detection in satellite imagery using deep learning and a remote sensing network (RS-Net) based on the U-net structure employing a fusion of spatial and spectral models has been planned by the authors of [20]. The model is trained using Landsat 8 Biome and SPARCS datasets. The high performance of this approach, which uses only the RGB and RGBI (Red/Green/Blue/Infrared) bands, outperformed the Fmask algorithm.

The author of [28] evaluated the performance of the proposed algorithm to automatically detect clouds from panchromatic SPOT5-HRS multi-temporal satellite images. This algorithm is designed by a regional growth procedure. The sheaths that correspond to the cloud are picked by a pixel-to-pixel comparison between existing images based on a strong change in reflection between two images. Although this method works on images with a single panchromatic channel and no longer requires a thermal band, the drawback is the false positive detection of many clouds which requires improved post-processing.

Multi-level cloud detection is a challenge for high-resolution remote sensing images based on a deep learning framework, this was the topic proposed by the authors of [21, 23]and [30]. First, the image is segmented into good quality super-pixels using the Simple Linear Iterative Clustering (SLIC) method. Then, a pair of image patches is extracted from each super-pixel and fed into a two-branch deep Convolutional Neural Network (CNN) designed to extract the multi-scale features of each super-pixel which effectively predicts the class of that super-pixel. Finally, the final cloud detection result is obtained using the predictions of all super-pixels. Through qualitative and quantitative analysis, and by evaluating the approach used with those previously performed, it was found that the performance of the approach used not only detects clouds at multiple levels, but also distinguishes between thin and thick clouds in [21] and [23] and between clouds and snow in [30].

The article [33] adopted the same techniques as the previous articles [21, 23, 30]. Because it performs multilevel cloud detection by applying the Adaptive Simple Linear Iterative Clustering (A-SCLI) algorithm to segment the satellite image into superpixels. Except that the CNN used by the authors of [21, 23] and [30] is replaced by a Multiple Convolutional Neural Network (MCNNs) which has the same task. The proposed method performed on GF-1, GF-2 and ZY-3 databases to distinguish between thin clouds, thick clouds and cloud shadows. Cloud and cloud shadow detection using multi-level feature fusion segmentation network (MFFSNet) for automatic training is performed by the authors in [34]. First, they used a fully convolutional network for training the cloud features and their shadows. Then, the extraction of the contextual relationship between the cloud and its shadow is performed by a new pyramid. Finally, to combine the semantic and spatial information of different levels to achieve better multi-scale object management and produce detailed segmentation boundaries, a special multi-level feature fusion structure is designed. The experimental aspect shows that MFFSNet outperforms the latest methods and achieves a high level of accuracy.

The authors of [35] investigated the machine learning strategy and fusion of several features, based on a comparative analysis of spectral, textural, and other typical variations between clouds and backgrounds in the images for cloud detection. By processing the Gao Fen-1 and Gao Fen-2 image database selected in southern China, object-oriented post-processing was applied using rectangles and a length-to-width ratio shape index, which further minimizes the classification errors of highly reflective images, thus increasing the accuracy. The proposed algorithm can be applied to totally different varieties, sizes and densities of clouds, and to any image source. Despite the reliability shown by this approach, the training samples must necessarily be selected manually. This analysis is intended to meet the requirements of the Chinese disaster reduction project, which focused on drought and flooding in southern China.

The authors of [36] have developed a new approach for band noise detection in GaoFen-2 high resolution remote sensing images using a deep learning technique called Linear Stripe Noise Detection (LSND). First, through linear transformations a large scale dataset is generated by simulating a wide variety of remote sensing images with band noise. Then, the target recognition of the band noise was performed using Deep Convolutional Neural Networks. On the experimental basis the LSND algorithm indicated its validity in terms of accuracy and time.

The basic concept of the paper [37] focuses on a multi-scale (3D-CNN) network of high- resolution multi-spectral imagery for the detection of clouds and their shadows in GF-1 WFV and ZY-3 data sets. The extraction of contextual data of clouds and their shadows at various levels was performed by a multi-scale learning module. In addition, a joint spectral-spatial information of the 3D convolution layer developed to discover the joint spatial-spectral correlations in the input data. The proposed network significantly improved the accuracy of shadow and cloud detection and could even distinguish between high-albedo objects (snow and ice) and low-albedo objects (water and mountain shadow).

In the paper [39] the researchers combined wavelet transform and deep learning technology to remove deep haze in remote sensing images where the haze was not evenly distributed in the image. First, the input image information is extracted from the first-order low-frequency Subband of its 2D stationary wavelet transform. Then, the network learns the more abundant image features and improves the overall ability to detect non-uniform haze in remote sensing images. Qualitatively and quantitatively, the proposed approach has superior advantages over traditional methods for removing non-uniform haze in remote sensing images.

The techniques for detecting noise in satellite images are summarized in Table 1, where the techniques used, the databases, the form of noise as well as the reference of each article and its year of publication are described.

5.2. Elimination techniques

Remote sensing images are frequently degraded, which minimizes the efficiency and accuracy of image interpretation. The removal of degradation from satellite images is an essential task after its detection. For this reason, many research efforts have been directed towards the removal of degradation from satellite images such as:

- Spatial Procedures for the Automated Removal Cloud and cloud Shadow (SPARCS) [8].
- Multi-Scale Residual Convolutional Neural Network (MRCNN) [11].
- Convolutional Neural Network (CNN) [15]. Progressively Spatio-Temporal Patch Group Deep Learning [29].
- Sentinel-1/2 Cloud Removal Time Series (SEN12MS-CR-TS) [31].

Tab. 1. Summary of detection techniques

Techniques used	**Databases**	**Forms of noise**	**Ref.**	**Year**
• Multilayer Perceptron Neural Networks (MLP)	Meteosat Second Generation Spinning Enhanced Visible and Infrared Imager (MSG-SEVIRI)	Cloud	[4]	2015
• Fuzzy Logic • Neural Network	Meteosat Second Generation Spinning Enhanced Visible and Infrared Imager (MSG SEVIRI)	Cloud	[5]	2018
• Fully Convolutional Neural Networks (FCN)	Landsat 8	Cloud	[10]	2018
• Multiscale Features Convolutional Neural Network (MF-CNN)	Landsat 8	Cloud	[12]	2018
• Fully Convolutional Network (CloudFCN)	Carbonite-2 Landsat 8	Cloud	[13]	2018
• Spectral Rationing • Fuzzy C-Means Clustering (FCM)	Landsat ETM+	Cloud	[17]	2013
• Cloud Detection Neural Network (CDnet) • Deep Convolutional Neural Network (DCNN)	ZY-3 GF-1 WFV Landsat 8	Cloud	[18]	2019
• Deep Convolutional Neural Network • SegNet	Landsat 7 Landsat 8	Cloud and cloud shadow	[18]	2019
• Remote Sensing Network (RS-Net) • Deep Learning	Landsat 8 Biome, SPARCS	Cloud	[20]	2019
• Simple Linear Iterative Clustering (SLIC) • Deep Convolutional Neural Networks (CNNs)	Quickbird	Cloud	[21]	2016
• Simple Linear Iterative Clustering (SLIC) • Convolutional Neural Networks (CNN)	NOAA/AVHRR	Cloud	[23]	2017
• Automatic method	SPOT5-HRS	Cloud	[28]	2012
• Simple Linear Iterative Clustering (SLIC) • Convolutional Neural Networks (CNN)	Sentinel-2A	Cloud and snow	[30]	2018
• Adaptive Simple Linear Iterative Clustering (A-SCLI) • Multiple Convolutional Neural Networks (MCNNs)	GF-1 GF-2 ZY-3	Cloud	[33]	2018
• Multilevel Feature Fused Segmentation Network (MFFSNet)	GF-1	Cloud and cloud shadow	[34]	2018
• Machine Learning • Multi-Features	GF-1 GF-2	Cloud	[35]	2016
• Linear Stripe Noise Detection (LSND)	GF-2	Noise	[36]	2022
• Convolutional Neural Network • 3D Multiscale (3D-CNN)	GF-1 WFV ZY-3	Cloud and cloud shadow	[37]	2020
• Wavelet Transform • Deep Learning	AID RSSCN7 BH	Haze	[39]	2021

- Wavelet Transform, Deep Learning [39].
- Reliable Cloudy Image Synthesis Model [41].
- Hyper Spectral Image denoising by Network (HSI-DeNet), Convolutional Neural Network (CNN) [43].

Spatial Procedures for Automated Removal of Cloud and Shadow (SPARCS) was the methodology proposed by the paper [8] using Landsat TM and ETM+ single date satellite images. This approach firstly uses a neural network to determine the membership of each pixel of an image scene to the classification of clouds, cloud shadow, water, snow/ice and clear sky. Then, it applies a series of spatial procedures to determine pixels with questionable membership using data, e.g., membership values of adjacent pixels and an estimate of the location of cloud shadows from solar geometry. For this approach to be applicable, it must meet the following rules: SPARCS uses only single-date images, and does not depend on auxiliary data sets. Furthermore, this strategy is fully computerized and does not require the determination of new boundaries for different scenes. The usefulness of the SPARCS method is demonstrated by comparing it to a state-of-the-art method used, FMask.

In the articles [9] and [11] the authors were able to efficiently remove haze in each band of Landsat 8 OLI (Operational Land Imager) multi-spectral images using a combination of a Convolutional Neural Network (CNN) with Residual and Multi-Scale Residual Convolutional Network (MRCNN) architecture respectively. These two techniques are similar. The basic idea of these algorithms is as follows. Starting with, haze removal based on Convolutional Neural Network (CNN), where different CNN individuals are connected to each other to learn the correspondence between the hazy image and the clear image, and a fusion unit is used to adaptively integrate the outputs of these individuals to generate the restored image. Then, through multi-scale convolutional the multi-scale features of the haze are extracted and the residual architecture to minimize the learning difficulty is adopted. Finally, the haze as a function of wavelength to generate a haze very close to the real conditions is simulated, thus training the designed network. The experimental results showed the validity of the proposed algorithm compared to the existing algorithms, to remove the haze in each band of multi-spectral images under different scenes with remarkable accuracy.

The paper [15] focuses on thin cloud removal in multi-spectral remote sensing images using Convolutional Neural Network (CNN) and a traditional imaging model. U-Net is used to estimate the reference thin cloud thickness map, while, the Slope-Net is used to estimate the thickness coefficient of each band. Thus, the cloud thickness maps of different bands are obtained. Finally, using the traditional thin cloud imaging model, the thin cloud thickness maps are subtracted from the cloud image. In order to evaluate the reliability and credibility of this experiment, a qualitative and quantitative analysis was performed on synthetic and real Landsat 8 OLI satellite images. The results showed that the suggested method can keep a better color quality by removing thin clouds in multi-spectral images with various land cover types.

The fundamental concept of the paper [29] is the combination of global and local spatiotemporal information from remote sensing images with the nonlinear learning capability of the Deep Neural Network for the removal of thick clouds and their shadows in multi-temporal images from the Sentinel-2 MSI and Landsat 8 OLI satellites. The significant advantages of this method over previous methods are: thick cloud coverage over large-scale areas, all temporal images have clouds or shadows and the deficient use of a single temporal image. A global-local DCNN network provided to optimize the formation model across cloudy and non-cloudy regions, taking into account global consistency and local particularity. The proposed system applied a global-local loss function in the supervised learning technique to optimize the training model across cloud-covered and non-cloud regions. In addition, weighted aggregation and progressive generation are used to reconstruct the holistic results. Experimental analysis proved the accuracy of removing thick clouds and their shadows from single and multi-temporal images of small/large scale scenes.

The authors of [31] designed an algorithm known as SEN12MS-CRTS for the reconstruction of Sentinel-1 and Sentinel-2 optical satellite images and the removal of multi-modal and multi- temporal clouds. The validity and efficiency of SEN12MS-CRTS has been proven by considering two methods: first, a 3D multi-modal and multi-temporal Convolutional Neural Network that predicts a cloud-free image from a time series covered with clouds. Second, a network for sequence-to-sequence cloud removal which is the first case where a model preserving temporal information has been predicted in the context of cloud removal. Both strategies take advantage of the presence of co-registered and matched SAR (Synthetic Aperture Radar) measurements contained in the data set. Interestingly, the benefits of using multi-modal and multi-temporal data to reconstruct noisy data have highlighted the contribution of the dataset to the remote sensing community. The reliable model for cloudy image synthesis is the Convolutional Neural Network (CNN) based cloud removal approach in satellite images was proposed in reference [41]. First, the extraction of cloud masks from real cloud images by the layer separation method and the dark channel selection method. Second, the refinement of cloud masks by reflecting the color of the background surface as a function of cloud thickness. Finally, using the synthesized cloud images the hierarchical cloud suppression network is trained with a multi-scale scheme. An experimental evaluation indicated the validity of the proposed technique compared to state-of-the-art methods for accurate cloud removal in satellite images.

To improve the quality of multi-spectral remote sensing images contaminated by haze, the authors of [42] developed an efficient and reliable haze removal algorithm based on a learning framework. A linear regression model with relevant haze features was established, and the gradient descent methodology applied to the training model. From a hazy image, a correct transmission map was obtained by learning the coefficients of the linear model. Similarly, this algorithm estimated the atmospheric light in order to limit the influence of highlighting surfaces on the acquisition of atmospheric light. This method has shown its reliability to obtain a better image quality in the context of removing fine haze while preserving colors compared to the traditional strategies. The authors of [43] performed noise removal in hyper-spectral images (HSI), including random noise, structural stripe noise and dead pixels/traces, based on the deep Convolutional Neural Network (CNN) through the (HSI-DeNet) approach. The objective of this algorithm has overcome the problems faced by researchers of the same concern, which are the following. First, the proposed HSI-DeNet technique can be taken as a tensor method using filter learning in each layer without destroying the spectral and spatial structures. Secondly, the HSI-DeNet can take into account both different forms of noise in the HSI. Furthermore, this approach can be adapted for single and multiple images by slightly changing the filter channels of the first and last layer. Finally, the excessive speed of this method for testing, made it more practical for real applications. The quantitative and qualitative evaluation of HSI-DeNet on different types of simulated and real HSI images proved its high performance and extreme restoration runtime compared to the compared methods.

The methods for noise removal in satellite images are summarized in Table 2, where the techniques used, the datasets, the form of noise and the reference of each paper and its year of publication are indicated.

5.3. Detection and suppression techniques

As degradation detection and removal are exceptionally interrelated and complementary, there is a need for an integrated framework that handles both tasks simultaneously. Another rich family of techniques to solve the remote sensing image detection and removal problem using machine and deep learning is described below:

- Cloud Detection Network (CDN), Cloud Removal Network (CRN) [14].
- Spatial-Temporal-Spectral based on a Deep Convolutional Neural Network (STS-CNN) [16].
- Image Restoration Based on Generative Adversarial Networks (RestoreGAN) [22].
- Deep PnP Low-Rank Tensor Approximation (DPLRTA) [44]. Multiple Convolutional Deep Neural Networks (ConvNets), Conditional Random Field (CRF) [45].
- Image restoration via deep learning (RestoreNet-Plus) [46].

The technique of detecting and removing clouds and cloud shadows simultaneously in Landsat-8 remote sensing bitemporal images through cascaded convolutional neural network (CNN) has been the proposed topic by [14]. Its design is organized as follows: the cloud images and the corresponding temporal images are processed by two fully convolutional networks (FCN) in cascade that structure the fundamental body of the system. The first FCN with multi-scale aggregation and channel attention mechanism,

Tab. 2. Summary of removal techniques

Techniques used	Databases	Forms of noise	Ref.	Year
• Spatial Procedures for Automated Removal of Cloud and Shadow (SPARCS)	Landsat TM Landsat ETM+	Cloud and cloud shadow	[8]	2014
• Convolutional Neural Network (CNN) • The residual structure	Landsat 8 OLI	Haze	[9]	2018
• Multi-Scale Residual Convolutional Neural Network (MRCNN)	Landsat 8 OLI	Haze	[11]	2018
• Convolutional neural network (CNN) combined with an imaging model	Landsat 8 OLI	Thin cloud	[15]	2021
• Progressively Spatio-Temporal Patch Group Deep Learning	Sentinel-2 MSI Landsat 8 OLI	Thick cloud and cloud shadow	[29]	2020
• Sentinel-1/2 Cloud Removal Time Series (SEN12MS-CR-TS)	Sentinel-1 Sentinel-2 Landsat 8 OLI	Cloud	[31]	2022
• Convolutional Neural Network (CNN) • Reliable Cloudy Image Synthesis Model	Satellite images	Cloud	[41]	2019
• Learning Framework	Remote Sensing Multispectral Images	Haze	[42]	2019
• Hyperspectral Image denoising byNetwork (HSI-DeNet) • Convolutional Neural Network (CNN)	Hyperspectral Images	Noise	[43]	2018

aims to detect clouds and shadows using the Cloud Detection Network (CDN), while the second FCN with the detected cloud and shadow masks, the cloud image and a temporal image, is used for cloud removal and reconstruction of missing data provided by the Cloud Removal Network (CRN). The restoration was accomplished by a methodology of self-training designed to learn the correspondence between pairs of clean pixels of bitemporal images, thus avoiding the need for manual labels. The experimental aspect showed that the suggested algorithm was able to simultaneously detect and remove clouds and shadows from remote sensing images, thus outperforming traditional methods in all indicators, with a significant margin.

A pioneering work is done in the paper [16]. In this paper, the author adopts the Spatial- Temporal-Spectral (STS-CNN) method based on Deep Convolutional Neural Network, which reconstructed the missing data in a Landsat ETM + (Enhanced Thematic Mapper Plus) remote sensing image through a unified spatial-temporal-spectral (STS) framework based on a deep convolutional neural network (CNN). The basic idea of this paper is to use the unified framework to solve the following three problems: first, recovering deadlines in the Aqua Moderate Resolution Imaging Spectroradiometer (MODIS) band 6, second, correcting the scan lines (SLC) of Landsat ETM+, and third, removing thick clouds. Although existing methods can only handle a single task of reconstructing missing information, the proposed strategy was found to be effective in recovering deadlines in Aqua MODIS band 6, solving the SLC problem and removing thick clouds. The STS-CNN approach had some shortcomings such as, spectral distortion and blurring appeared during the removal of thick clouds by using temporal information.

The paper [22] proposed RestoreGAN architecture for jitter detection and restoration of remote sensing image, based on a Generative Adversarial Network (GAN) to learn and correct in an automatic way the features of the contaminated scene from a single remote sensing image. While two Convolutional Neural Networks (CNN) are designed, the first one serves to separate the inputs and the second one to adjust the distortions. After the validation and verification proofs of the RestoreGAN method on PatternNet, UC Merced, WHU-RS19 and Yaogan-26 databases respectively, the proposed system demonstrated its performance in terms of Deformation Metric (DM) compared to UnrollingCNN, GenCNN and ContGAN methods.

The topic of [38] presents a deep learning based method for the detection and removal of thick clouds from optical images of the ZY-3 satellite. For the first task convolutional neural network (CNN) architecture is used, while for the second one which is the recovery of image information under the clouds, content, texture and spectrum generation (CTS) networks based on classical CNN are used. It should be noted that the framework of the proposed CNN structure can use multi-source data (content, texture and spectrum) as a unified input. Although, the experimental results on simulated and real images have shown the effectiveness is robustness of the approach to remove particular types of thick, thin and shadow clouds. But it stands helpless in front of the changing land cover.

For hyper-spectral image recovery (HSI), the authors of [44] treated the Plug-and-Play (PnP) framework, due to its scalability and flexibility, as a bridge between traditional HSI restoration techniques and deep noise removal networks. The proposed approach, Deep PnP Low-Rank Tensor Approximation (DPLRTA), is a three-step process: Tensor Modeling, Low-Rank Tensor Decomposition, and Noise Removal by Implicit Convolutional Neural Network (ICNN) by regularization. PnP is a bridge that connects these three steps. Simulation and real experiments on Pavia City Centre and HYDICE Urban data respectively proved that DPLRTA can effectively preserve the detail, fundamental shape and texture data of HSI.

The authors of [45] automatically detected and removed shadows in real-world scenes from a single image using a fusion of Convolutional Deep Neural Networks (ConvNets) and a Conditional Random Field (CRF). The approach aims to automatically learn the most relevant features in a supervised manner for shadow detection based on multiple networks (ConvNets). Properties were also learned at the super-pixel level and on the dominant boundaries of the image. Posterior predictions based on the learned features introduced in a field model (CRF) to obtain shadow masks. With the help of the detected shadow masks, a Bayesian formulation that constitutes the concept of this shadow elimination process was used to appropriately extract the shadow matte with the recovered image, and then eliminate it. The proposed framework proved its performance

Tab. 3. Summary of detection and suppression techniques

Techniques used	**Databases**	**Forms of noise**	**Ref.**	**Year**
• Cloud Detection Network (CDN) • Cloud Removal Network (CRN)	Landsat 8	Cloud and cloud shadow	[14]	2020
• Spatial-Temporal-Spectral based on a Deep Convolutional Neural Network (STS-CNN)	Landsat ETM+	Thick Cloud	[16]	2018
• Image Restoration Based on Generative Adversarial Networks (RestoreGAN)	PatternNet UC Merced WHU-RS19 Yaogan-26	Jitter	[22]	2021
• Detection: Convolutional Neural Network (CNN) • Removal: Content-Texture-Spectral (CTS-CNN)	ZY-3	Thick Cloud	[38]	2019
• Deep PnP Low-Rank Tensor Approximation (DPLRTA) • Convolutional Neural Network (CNN)	Pavia City Centre (data simulation) HYDICE Urban (data real)	Noise	[44]	2020
• Multiple Convolutional Deep Neural Networks (ConvNets) • Conditional Random Field (CRF)	UCF CMU UIUC	Shadow	[45]	2015
• Image restoration via deep learning (RestoreNet-Plus)	Optical Synthetic Aperture Imaging (OSAI)	Noise and Blur	[46]	2021

on various databases (UCF shadow, CMU shadow and UIUC shadow) unlike previous research.

The paper [46] suggested an improved RestoreNet-Plus network for image restoration of a synthetic aperture optical imaging system based on deep learning. To establish a hidden nonlinear correspondence between the output and input without analytical expression, a neural network is used. While learning, the neural network is able to fit an input model to an output model that approximates the inverse problem process. Analysis of the experimental results indicated that RestoreNet-Plus is a better alternative compared to other methods in terms of noise suppression and restoration of synthetic aperture optical imaging.

The strategies for detecting and suppressing or removing noise in satellite images are summarized in Table 3, which shows the approaches used, the databases, the form of noise as well as the reference of each paper and its year of publication.

6. Conclusion

The bibliographic survey carried out between 2012 and 2022 on the techniques of restauration of satellite imagery data by machine and deep learning is analyzed. The satellites used in each work, the recognition of different forms of degradation, including clouds, haze and shadows are examined. The type of technique suitable for their treatment;

detection, elimination and algorithms that process both are studied. The study of the literature shows that the most used databases are, in descending order, the American satellites (Landsat), the Asian satellites (GF-1/2 and ZY-3), then the European satellites (Spot, Sentinel, Meteosat). In terms of the most processed type of degradation, clouds come first, followed by clouds and their shadows, and haze. The most widely used techniques are primarily the simple iterative linear cluster (SLIC) with convolutional neural networks (CNN) and fully convolutional neural networks (FCN). In addition, we note that the methods that deal with detection are more than those of suppression. It should be noted that, despite the great success and wide dissemination of American databases, there has recently been competition between Asia and America in terms of launching remote sensing satellites. Although AI-based strategies are pioneering in all areas compared to traditional algorithms, complementary efforts are needed to achieve promising results and performance in terms of reliability and calculation time. The accuracy of degradation detection and suppression can be increased by integrating special zones and time conditions according to various weather models. In addition, to overcome the constraints and disadvantages of current algorithms, it is crucial to combine atmospheric parameters with the artificial neural networks.

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