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Space Target Material Identification Based on Graph Convolutional Neural Network

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Abstract: Under complex illumination conditions, the spectral data distributions of a given material appear inconsistent in the hyperspectral images of the space target, making it difficult to achieve accurate material identification using only spectral features and local spatial features. Aiming at this problem, a material identification method based on an improved graph convolutional neural network is proposed. Superpixel segmentation is conducted on the hyperspectral images to build the multiscale joint topological graph of the space target global structure. Based on this, topological graphs containing the global spatial features and spectral features of each pixel are generated, and the pixel neighborhoods containing the local spatial features and spectral features are collected to form material identification datasets that include both of these. Then, the graph convolutional neural network (GCN) and the three-dimensional convolutional neural network (3-D CNN) are combined into one model using strategies of addition, element-wise multiplication, or concatenation, and the model is trained by the datasets to fuse and learn the three features. For the simulated data and the measured data, the overall accuracy of the proposed method can be kept at 85–90%, and their kappa coefficients remain around 0.8. This proves that the proposed method can improve the material identification performance under complex illumination conditions with high accuracy and strong robustness.



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Keywords: space target; material identification; complex illumination conditions; graph convolutional neural network

1. Introduction

Space target recognition is of great significance in the protection of the space environment as well as in the safe and sustainable development and utilization of space resources [1]. In a variety of space observation methods, spectra contain a large amount of information in the wavelength dimension, and they can provide a reliable basis for the identification of the space target surface materials, thereby meeting the needs for space security and determining space target behavior intention accurately [2,3]. Therefore, the development of spectra-based space target material identification research is an important topic in space target recognition.

The researchers hoped to identify materials by the difference in spectral reflectance and have developed a series of methods based on spectral features, including comparative analysis, statistical learning, deep learning, etc. The comparative analysis methods refer to the design of specific identification methods by directly comparing the features of the measurements and prior information. Abercromby et al. [4] used a short-wave infrared telescope to acquire spectral observations on two satellites and found that an absorption characteristic coincided with the absorption characteristic of the C-H bond in solar cell material; the authors inferred that the two satellites had solar cells. Vananti et al. [5]

proposed a preliminary classification using three different classes purely based on the shape and appearance of the spectra.

Statistical learning methods refer to the establishment of probabilistic and statistical models based on large amounts of data and are utilized to predict and analyze the data. Abercromby [6] and Deng [2] measured the visible spectra of geosynchronous orbit targets and made use of the partial least squares (PLS) method for material identification with high accuracy. Nie [7] proposed a method based on the Tucker decomposition (TD). Velez-Reyes et al. [8,9] applied the SVD-based column subset selection (SVDSS) and the constrained non-negative matrix factorization (CNMF) to identify simulated models.

Among the statistical learning methods, deep learning methods can mine the deep correlation of data and are suitable for processing massive hyperspectral data. Li et al. [10] applied the extreme learning machine (ELM), and Liu [11] applied the back-propagation neural network (BPNN); they measured the hyperspectral curves of the material samples under the solar simulator illumination in the experimental darkroom and demonstrated the good performances of these methods. Then, as the convolutional neural network (CNN) showed advantages in feature extraction, researchers turned their attention to the CNN [12] and proposed a variety of CNN-based identification methods. Deng et al. [13] and Gazak et al. [14] adopted a one-dimensional (1-D) CNN to deal with 1-D measured data, in which only spectral features played a role.

However, with the development of research on the influencing factors of material identification [15–18], it has been found that the applicability domain of methods using only spectral features may be narrow. These methods require consistent spectral features of the same material, but, because the space target materials are non-Lambertian objects, the spectra of the same material can become different when the target is exposed to complex illumination conditions consisting of sunlight and earthshine [19]. Many researchers have experimentally proved this phenomenon and discussed its properties. Bédard et al. [20] measured the photometric and spectral bidirectional reflectance distribution function (BRDF) of small Canadian satellites in a controlled environment and found that the spectral reflectance varied rapidly even with small changes in the light–object–sensor geometry. Then, Bédard et al. [21] measured the red/blue color ratios of geostationary satellites and proposed that spectral reflectance was dependent on the angle of the incident sunlight, the angle of measuring, and the inherent characteristics of the material. Augustine et al. [22] collected glint spectra of the geostationary satellite WildBlue-1 and found obvious differences in the relative intensities and profiles in the glint spectra between the two nights of collection. This supported the point that solar illumination angles played a major role in observed spectral features.

To solve this problem, the researchers subsequently proposed the use of a two-dimensional (2-D) CNN and a three-dimensional (3-D) CNN to extract spatial–spectral features of the space target for identification. Perez et al. [23] and Chen et al. [24] obtained hyperspectral images with obvious spatial features through semi-physical simulations or computer simulations and extracted the spatial–spectral features using Residual Network (ResNet), a regional-based CNN (R-CNN), and other CNN-based models. These methods reached high accuracies, but the spatial features applied are local and sensitive to imaging conditions, which may lead to poor performance in other application scenarios with different illumination conditions.

Therefore, to increase the accuracy and robustness of material identification, a method based on the improved graph convolutional neural network is proposed for the material identification problem under complex illumination conditions. The main contributions of the proposed method are presented as follows:

1. The global spatial features of the space target are introduced, and they refer to the position of a pixel in the global structure of the space target and the connection relationship with each component. The global spatial features are strongly associated with the materials.

2. A multiscale, joint global-structure topological-graph-building method is designed. The topological graphs generated from the superpixel segmentation results at different scales are joined together, highlighting the size differences between different components and improving the identification accuracy of materials on the small components.
3. The graph convolutional neural network (GCN) is introduced to learn the global spatial-spectral features of the space target and combined with a 3-D CNN that can learn local spatial-spectral features. They work together to improve the identification performance under complex illumination conditions.

The rest of this article is organized as follows. Section 2 describes the related work and our motivation. Section 3 describes the details of the proposed method. Section 4 describes the experimental data, the experimental results of the proposed method, and some common methods. Section 5 discusses the results, deficiencies, and possible improvements of the proposed method. Finally, Section 6 describes the conclusion and our future work.

2. Related Work

In this section, we will describe the application scenarios of the proposed method and introduce the relevant prior works related to complex illumination conditions. Then, the current development state of GCN will be introduced.

2.1. Complex Illumination Conditions of the Space Target

Early spectroscopic measurements of the space targets were made through ground-based telescopes [2,4–6], and the data obtained in this way were a single spectrum, so the material identification methods can only rely on spectral features. At present, researchers are gradually transitioning from ground-based detection to space-based detection [3,23,24], and the close detection distance in space-based detection enables hyperspectral images to show relatively rich spatial features. Existing material identification methods using spatial features are usually designed under ideal imaging scenarios, in which the detector and space target are relatively stationary during the measurement of hyperspectral images (e.g., the detector is executing a hovering operation [25] on the space target with three-axis stabilization). Our work is also conducted on this premise.

Sunlight [26] and earthshine [27,28] together constitute the illumination conditions of the space target, as shown in Figure 1. As the space target materials are non-Lambertian objects, the light reflected by the surface can generally be divided into a specular reflection component and a diffuse reflection component [29]. Because the specular component of sunlight can cause an image to be overexposed and unusable, in legible images, the spectrometer receives the diffuse component of sunlight on each surface of the target.

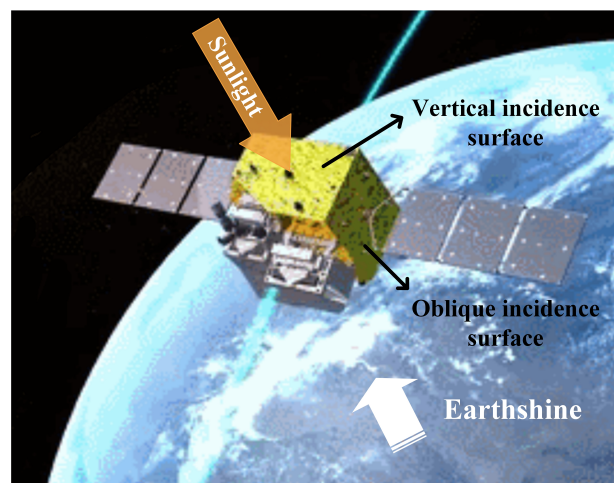


Figure 1. Schematic of the space target attitude and illumination.

As shown in Figure 2, commonly used materials for the space target exhibit the Fresnel effect, i.e., as the incidence angle of light on the surface increases, the specular component tends to be stronger, and the diffuse component tends to be weaker [30]. Therefore, when a surface has both sunlight and earthshine incidents at the same time, the greater the incidence angle of the sunlight, the more prominent the influence of the earthshine. In addition, mutual occlusion between the target components may cause spectral inconsistencies of the same material.

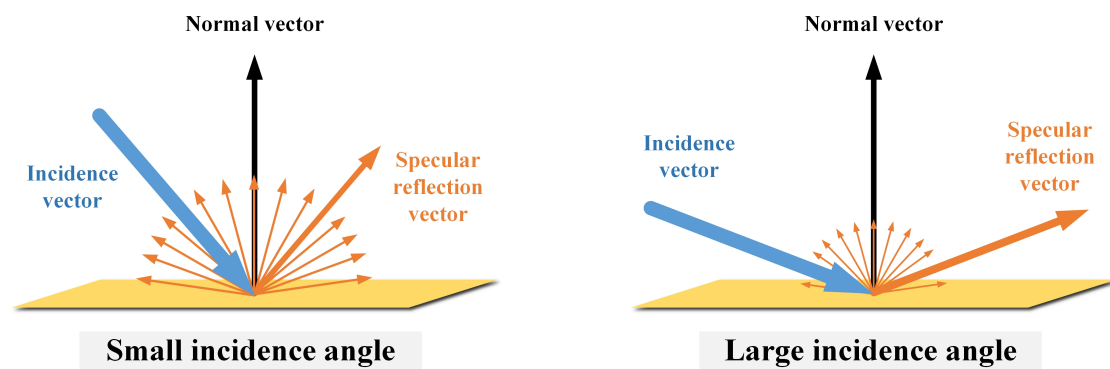


Figure 2. Schematic of the Fresnel effect. When the incidence angle of light on the surface is larger, the specular reflection component is stronger, and the diffuse reflection component is weaker.

In summary, in various illumination conditions, affected by the volume, structure, and attitude of the space target, spectral data distributions are sensitive to the direction of sunlight in the local coordinate system of the space target, and the spectral features of the same material may be inconsistent across the surfaces with different orientations. The local coordinate system is set as shown in Figure 3, where the origin is set at the center of the space target model body.

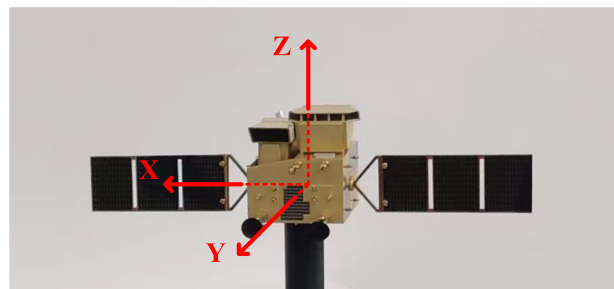


Figure 3. Local coordinate system of the space target model.

To verify the above contents, we placed a space target scale-down model and an imaging spectrometer (440–780 nm) in our laboratory and measured the hyperspectral images of the model under different illumination conditions by adjusting the direction of solar simulation light. The results show that there are indeed inconsistencies in the material spectra under complex illumination conditions, which are specifically expressed as:

1. Under the same illumination conditions, the spectral features of the same material can be very different, i.e., the gold mylar spectra on two surfaces with different orientations shown in Figure 4.
2. Under the same illumination conditions, the spectral features of different materials can be very similar, i.e., the spectra of the solar cell, antenna, and cooling area shown in Figure 4.
3. Under different illumination conditions, the spectral features of the same material can change dramatically, i.e., the gold mylar spectra in the two images shown in Figure 5.

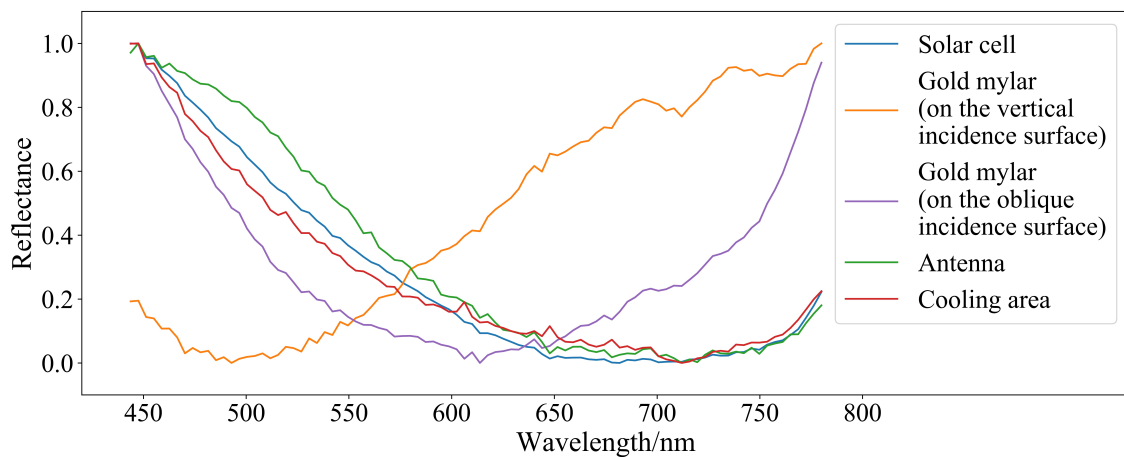
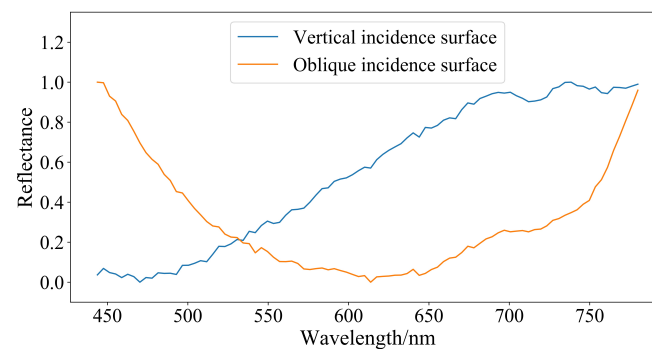
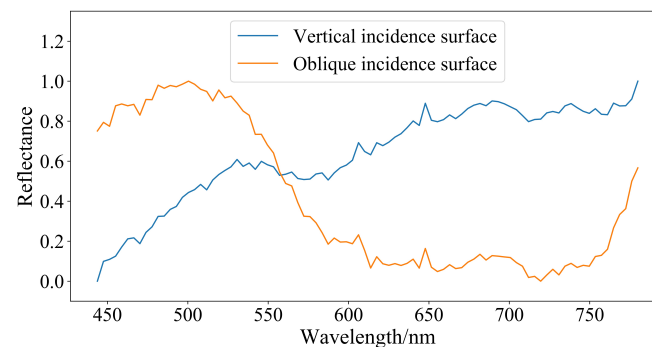


Figure 4. Normalized materials' spectra in the hyperspectral image of the space target model.



(a)



(b)

Figure 5. Normalized spectra of gold mylar in the images with different illumination conditions: (a) the first image; (b) the second image.

Because the spectral data distributions of the space target are no longer consistent, and because the local spatial features have poor robustness to the changes in detection distance, illumination conditions, and the target's attitude, the spectral features and local spatial features are no longer suitable as the only basis for material identification. We consider the structural features of the space target as the connection relationships of the components, and the connection relationship of two components means that the two components are spatially next to each other. The distribution of different materials on the space target is closely related to the structural features, and although under different relative attitudes of the target, the global spatial features reflect the structural features to different degrees; however, compared with the spectral features and local spatial features, the global spa-

tial features change more slowly and regularly with the relative attitude. Therefore, we decide to introduce the global spatial features of the space target as a powerful basis for material identification.

2.2. Graph Convolutional Neural Network

In order to achieve accurate and stable identification of the space target materials under complex illumination conditions, we introduce the GCN to learn the global spatial features. Recently, the GCN has been widely used in hyperspectral image classification [31] and achieved great success.

In hyperspectral image classification, early deep learning methods, such as the deep belief network (DBN) [32], the recurrent neural network (RNN) [33], and the 1-D CNN [34,35], only used the spectral features to effectively improve the classification performance, and the subsequently developed 2-D CNN [36,37] and 3-D CNN [38–43] used the local spatial–spectral features. However, researchers then noticed that the fixed-size convolution kernels would make the extracted local spatial–spectral features lack adaptability to changing scenarios, so some people chose to design the application strategies of the convolution kernels [44], and some people turned to GCN [45] hoping that the problem could be solved by applying global spatial features with the topological graph.

The topological graph $\mathcal{G}$ is an irregular data structure consisting of nodes, $\mathcal{V}$, and edges, $\mathcal{E}$. During computing, a topological graph $G = \{A, X\}$ is represented as a set of an adjacency matrix $A \in \mathbb{R}^{Nv \times Nv}$ and a node feature matrix $X \in \mathbb{R}^{Nv \times Nf}$, where Nv is the number of nodes, and Nf is the length of the node features. The GCN can learn from topological graphs, and the basic formulas of the GCN processing the topological graph $G = \{A, X\}$ are presented as:

$$d_{mm} = \sum_{n=0}^{Nv-1} a_{mn} \quad (1)$$

$$X' = \sigma(\tilde{A}XW) \quad (2)$$

where $\sigma(\cdot)$ is an activation function, Ch is the number of channels, $d_{mm} \in D$, $a_{mn} \in A$, D is the node degree matrix, $\tilde{A}$ is the normalized adjacency matrix, $\tilde{A}X$ is computed to propagate node features based on the node connection relationships and the normalized weights of $\tilde{A}$, and $W \in \mathbb{R}^{Nv \times Ch}$ is a trainable weight matrix.

The initial solution for applying the GCN to hyperspectral images was to treat each pixel as a node [46], but this brought an excessive amount of computation. So, the researchers turned to building topological graphs through image segmentation [47–50].

In addition, researchers have proposed a number of strategies to improve the GCN-based models. For instance, different types of features have been fused by integrating different networks (e.g., CNN+GCN) [49,51,52]; multiscale features have been learned through the construction of topological graphs of different scales or the application of graph attention (GAT) [48,53]; the lack of data labeling has been addressed by self-correlated learning and self-supervised learning [54,55]; and auto-regressive moving average (ARMA) filters have been utilized to avoid over-smoothing of the GCN [56]. Appropriately adjusting the structure and strategy of the model according to the application scenarios and needs has effectively improved performance.

3. Methodology

The proposed material identification method, based on an improved graph convolutional neural network, is proposed, as shown in Figure 6. First, we implement superpixel segmentation on the hyperspectral images and produce a global-structure topological graph with global spatial features. Next, the material identification datasets for each pixel are created based on global-structure topological graphs and pixel neighborhoods, and they are divided into the training set and test sets.

Then, the GCN and 3-D CNN are combined into one model, and it is trained by the training set. The model learns the fusion features of the global spatial features, local spatial

features, and spectral features to identify the material of each pixel. Finally, the test sets are used to evaluate the performance of the proposed method.

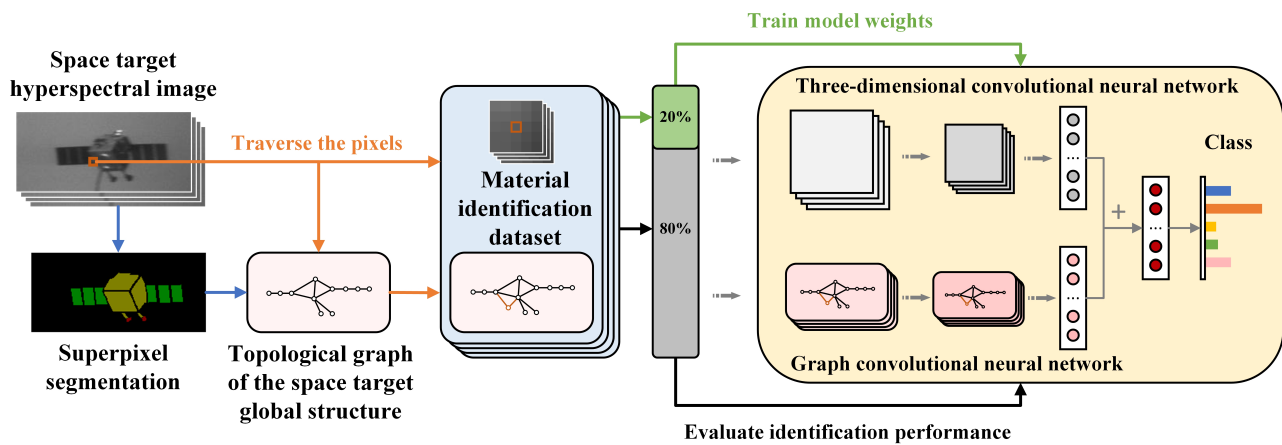


Figure 6. An overview of the proposed method.

3.1. The Topological-Graph-Building Method of the Space Target Global Structure

A global-structure topological-graph-building method of the space target based on superpixel segmentation is designed to extract the global spatial features. First, we need to perform image segmentation, dividing pixels belonging to a given material on the same surface into a cluster. Due to the large dispersion of the space target spectral data, the pixel-by-pixel segmentation methods (e.g., threshold segmentation) may be ineffective, so the superpixel segmentation method is adopted, and the distance and spectral features are together used as the basis for segmentation. The unsupervised segmentation algorithm Simple Linear Iterative Clustering (SLIC) [57] can obtain relatively regular superpixels and control the number of superpixels; it also has a high overall evaluation of efficiency and accuracy. Its simplicity and controllability facilitate the effective extraction of the global spatial features, so it is employed to perform the image segmentation step.

SLIC is executed on the hyperspectral image $I \in \mathbb{R}^{M \times N \times C}$, where $M \times N$ is the number of pixels in the image, and C is the number of bands. SLIC first sets an initial number of cluster centers, K_0 and then distributes the cluster centers evenly on the image; next, it completes the segmentation through multiple iterations to obtain q_0 superpixels $S_{0,i} = \{l_{0,0}, l_{0,1}, \dots, l_{0,p_{0,i}-1}\}$, $0 \leq i < q_0$. $S_{0,i}$ consists of $p_{0,i}$ pixels $l \in \mathbb{R}^{C \times 1}$ that are close to each other at a distance of D , where K_0 is the main parameter affecting $p_{0,i}$, and the larger K_0 is, the smaller $p_{0,i}$ is.

The distance D_{ij} between the two pixels l_i and l_j in SLIC is measured by Equations (3)–(5):

$$d_l = \frac{1}{C} [(l_j^0 - l_i^0)^2 + (l_j^1 - l_i^1)^2 + \dots + (l_j^{C-1} - l_i^{C-1})^2] \quad (3)$$

$$d_s = \frac{1}{2} [(x_j - x_i)^2 + (y_j - y_i)^2] \quad (4)$$

$$D_{ij} = \sqrt{\varepsilon_l d_l + \frac{2K_0}{MN} d_s} \quad (5)$$

where $l^0, l^1, \dots, l^{C-1}$ are the grayscale values of the spectral bands; the spectral distance d_l is the mean squared error of $l^0, l^1, \dots, l^{C-1}$, x, y are the location coordinates of pixels in the images; the spatial distance d_s is the mean squared error of x, y ; and the distance scale factor ε_l is utilized to adjust the emphasis on the spectral distance and the spatial distance. The spectral and spatial distances are both considered during segmentation.

After segmentation, a global-structure topological graph $G_0 = \{A_0, X_0\}$ is built according to $S_{0,i}$. $S_{0,i}$ is set as a node, and the superpixel average spectrum $\bar{l}_{0,i}$ is set as the

features of the node. Then, we search for superpixels with adjacency: A line is drawn on the image to connect the center points of two superpixels, $S_{0,m}$ and $S_{0,n}$, and it will pass through multiple pixels; of these pixels, if the proportion of the pixels belonging to $S_{0,m}$ and $S_{0,n}$ exceeds the threshold (e.g., 0.6), the two superpixels can be considered adjacent, and their nodes will be connected so that the spectral information of the components and the structural information of the space target is fully reflected in the global-structural topological graph G_0 .

To achieve spatial feature extraction of a small component structure, SLIC is executed twice with the initial number of cluster centers K_0 and K_1 ($K_1 > K_0$) to obtain the multi-level topological graphs $G_0 = \{A_0, X_0\}$ and $G_1 = \{A_1, X_1\}$. The spectral information and connection relationships of the large components are reflected in G_0 , and the spectral information and connection relationships of the small components are reflected in G_1 .

We combine G_0 and G_1 ; then, the superpixels with an overlapping relationship are searched for in turn, and their nodes are connected. Specifically, if the cluster center $l(\bar{x}_{1,j}, \bar{y}_{1,j})$ of $S_{1,j}$ belongs to $S_{0,i}$, i.e., $l(\bar{x}_{1,j}, \bar{y}_{1,j}) \in S_{0,i}$, $S_{1,j}$ and $S_{0,i}$ have an overlapping relationship, meaning that the small component represented by $S_{1,j}$ is on top of the large component represented by $S_{0,i}$, and their nodes are connected; thus, the multiscale, joint global-structure topological graph $G_2 = \{A_2, X_2\}$ is generated.

The building process of the multiscale, joint global-structure topological graph is given in Algorithm 1. In this process, the complexities of building graphs are much smaller than creating superpixels, so the computational complexity mainly depends on SLIC, i.e., $\mathcal{O}(M \times N)$, which is linear with the number of pixels in I .

Algorithm 1 Multiscale, Joint Global-Structure Topological Graph

Input:

- (1) Dataset: the hyperspectral image $I \in \mathbb{R}^{M \times N \times C}$;
- (2) Parameters: the initial number of cluster centers K_0 and K_1 ($K_1 > K_0$).

Procedure:

- (1) Execute SLIC on I with K_0 and (3)–(5) and obtain superpixels $S_{0,i}$, $0 \leq i < q_0$;
- (2) Build the first global-structure topological graph $G_0 = \{A_0, X_0\}$;
- (3) Execute SLIC on I with K_1 and (3)–(5) and obtain superpixels $S_{1,j}$, $0 \leq j < q_1$;
- (4) Build the second global-structure topological graph $G_1 = \{A_1, X_1\}$;
- (5) Combine G_0 and G_1 to obtain A_2 and X_2 ;
- (6) Connect $S_{1,j}$ and $S_{0,i}$, who have overlapping relationship;
- (7) Build the multiscale, joint global-structure topological graph $G_2 = \{A_2, X_2\}$;

Output:

The multiscale, joint global-structure topological graph $G_2 = \{A_2, X_2\}$.

After the building of G_2 , the topological graphs $G_l = \{A_l, X_l\}$ for each pixel l are generated according to G_2 . First, l is independently set as a superpixel S_l ; next, the nodes of S_l and $S_{0,i}$ are connected if they are adjacent, and the nodes of S_l and $S_{1,j}$ are connected under the same condition. The topological graph $G_l = \{A_l, X_l\}$ contains the spectral information of the pixel and reflects its global spatial features, such as its connection relationship with components of different scales, and its location on the space target.

Then, the fixed-size neighborhoods $Ne_l \in \mathbb{R}^{d_1 \times d_2 \times C}$ of each pixel are taken, where $d_1 \times d_2$ is the size of the region centered on pixel l . Ne_l contain the spectral information and local spatial features of the pixels. G_l and Ne_l of each pixel are collected to create material identification datasets, Ds , which can be represented as:

$$Ds = \{G_{l_0}, Ne_{l_0}; G_{l_1}, Ne_{l_1}; \dots; G_{l_{M \times N}}, Ne_{l_{M \times N}}\}. \quad (6)$$

At last, D_s are divided into training sets and test sets. Throughout the process of creating D_s for I , the computational complexity is also $\mathcal{O}(M \times N)$.

3.2. Identification Method Based on Fusion of GCN and 3-D CNN

The GCN is utilized to learn the spatial features of the space target global structure and integrated with the spectral features and spatial features of the pixel neighborhood learned by the 3-D CNN, breaking the bottleneck of a single model and solving the problem of material identification difficulties caused by inconsistent distributions of spectral data. The specific structure of the identification method is shown in Figure 7. The topological graph G_l and the fixed-size neighborhoods Ne_l of a pixel are input to the identification method, and a class confidence vector $Y^{Class} \in \mathbb{R}^{1 \times Cl}$ is output, where Cl is the total number of background and all material classes.

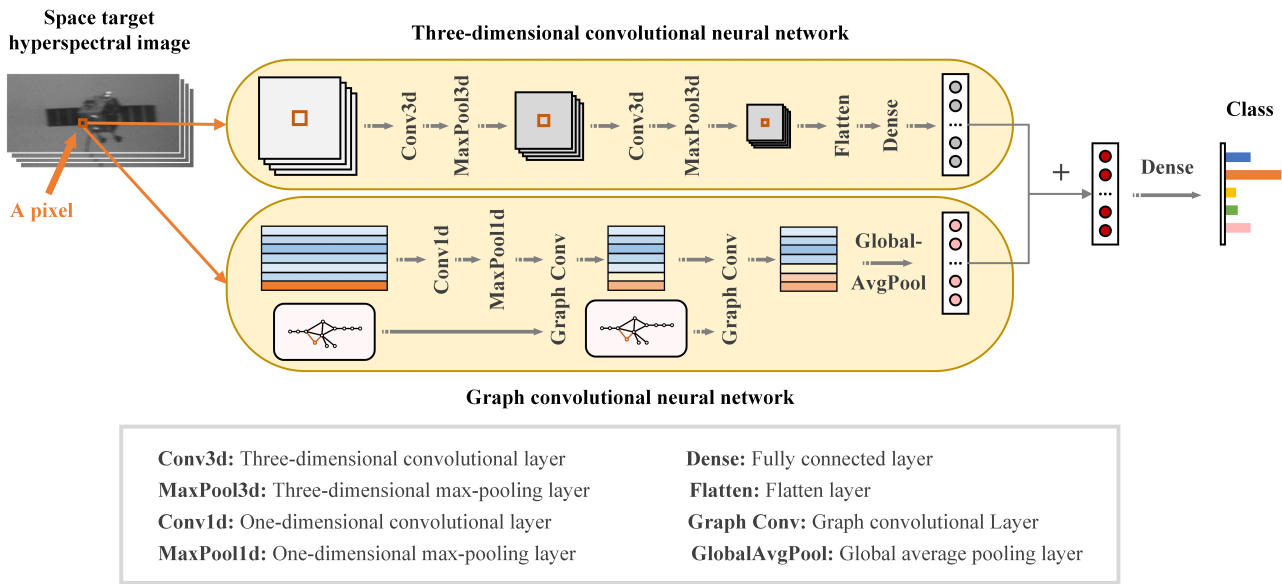


Figure 7. Flowchart for building the topological graph of the space target global structure.

In the 3-D CNN, Ne_l is input to the 3-D convolutional layer $f_{C3}(\cdot)$ and the 3-D max-pooling layer $f_{MP3}(\cdot)$ repeatedly to learn the local spectral-spatial features. N^{C3} convolution kernels $W_{C3,kn} \in \mathbb{R}^{L_{k1}^{C3} \times L_{k2}^{C3} \times L_{k3}^{C3}}$ ($0 \leq kn < N^{C3}$) slide for convolution on Ne_l in $f_{C3}(\cdot)$, and, then, the windows slide for max pooling on its output in $f_{MP3}(\cdot)$. The formulas are as follows:

$$Ne_{kn}^{C3} = \sigma[f_{C3,kn}(Ne_l)] \quad (7)$$

$$Ne_{kn}^P = f_{MP3}(Ne_{kn}^{C3}) \quad (8)$$

where $\sigma(\cdot)$ is the activation function ReLu, $Ne_{kn}^P \in Ne^P$, $Ne^P \in \mathbb{R}^{L_1^P \times L_2^P \times L_3^P \times N^{C3}}$. Immediately Ne^P is input to $f_{C3}(\cdot)$ and $f_{MP3}(\cdot)$ several times more, and $Ne^{CNN} \in \mathbb{R}^{L_1^C \times L_2^C \times L_3^C \times N^{C3}}$ is output. For the 3-D CNN, when the dimensions of the input and the parameters of the layers are determined, the number of calculations is determined. Therefore, the computational complexity of the 3-D CNN for an image $I \in \mathbb{R}^{M \times N \times C}$ is $\mathcal{O}(M \times N)$.

In the GCN, $G_l = \{A_l, X_l\}$ is taken as the input. First, $X_l = (l_0, l_1, \dots, l_{q_0+q_1})^T \in \mathbb{R}^{(q_0+q_1+1) \times C}$ is input to the one-dimensional (1-D) convolutional layers $f_{C1}(\cdot)$ and the 1-D max-pooling layers $f_{MP1}(\cdot)$ for extraction of the spectral features and a reduction in data dimension. A convolution kernel $W_{C1} \in \mathbb{R}^{1 \times L_k^{C1}}$ slides for convolution on $l_m \in X_l$ in $f_{C1}(\cdot)$, and, then, a window slides for max pooling on its output in $f_{MP1}(\cdot)$. The formulas are as follows:

$$l_m^{C1} = \sigma[f_{C1}(l_m)] \quad (9)$$

$$l_m^s = f_{\text{MP1}}(l_m^{C1}) \quad (10)$$

where $l_m^s \in X_l^s$, $X_l^s = (l_0^s, l_1^s, \dots, l_{q_0+q_1}^s)^T \in \mathbb{R}^{(q_0+q_1+1) \times L^s}$. Through $f_{C1}(\cdot)$ and $f_{\text{MP1}}(\cdot)$, the spectral features are extracted, and the number of elements in the node feature matrix X_l^s has been reduced to L^s/C of the original X_l . Meanwhile, the number of weights and the computational complexity of the next layer will decrease by the same proportion.

Next, X_l^s and A_l are input to the graph convolutional layer $f_G(\cdot)$ repeatedly to learn the global spectral-spatial features in the topological graph G_l . The calculation formulas for $f_G(\cdot)$ are expressed as:

$$\tilde{A} = D^{-1/2} A_l D^{-1/2} \quad (11)$$

$$X' = \sigma(\tilde{A} X_l^s W_1 + X_l^s W_2 + b) \quad (12)$$

where the number of channels is Ch ; D is the node degree matrix; and $\tilde{A}$ is the symmetric normalized adjacency matrix. $\tilde{A} X_l^s$ is computed to propagate node features based on node connection relationships and the normalized weights of $\tilde{A}$. Then, $\tilde{A} X_l^s$ and X_l^s are weighted and fused with two trainable weight matrices $W_1 \in \mathbb{R}^{L^s \times Ch}$, $W_2 \in \mathbb{R}^{L^s \times Ch}$ and a trainable bias matrix $b \in \mathbb{R}^{(q_0+q_1+1) \times Ch}$. Finally, a new node feature matrix $X' \in \mathbb{R}^{(q_0+q_1+1) \times Ch}$ is output. X' and A_l are input to $f_G(\cdot)$ several times more, and $X^{\text{GCN}} \in \mathbb{R}^{(q_0+q_1+1) \times Ch}$ is output. For the first $f_G(\cdot)$, its computational complexity is $\mathcal{O}((N_e + N_v) \times L^s \times Ch)$ [45], and, for the next several f_G , their computational complexity is $\mathcal{O}((N_e + N_v) \times Ch^2)$, where N_e and N_v are the numbers of edges and nodes in G_l . Although the scale of G_l is uncertain for different images, the numbers of edges and nodes in G_l are usually much smaller than the number of pixels in an image; therefore, the computational complexity of the GCN for an image can also be $\mathcal{O}(M \times N)$.

Ne^{CNN} , the output of the 3-D CNN, is input to the flattened layer $f_F(\cdot)$ and the fully connected layer $f_D(\cdot)$ with Ch nodes. X^{GCN} , the output of the GCN, is input to the global average pooling layer $f_{\text{GAP}}(\cdot)$. Then, they are fused using fusion strategies of addition (-A), element-wise multiplication (-M), or concatenation (-C) [46]. The processes can be formulated as:

$$Y^A = f_{\text{GAP}}(X^{\text{GCN}}) + \sigma[f_F(Ne^{\text{CNN}}) W_D] \quad (13)$$

$$Y^M = f_{\text{GAP}}(X^{\text{GCN}}) \otimes \sigma[f_F(Ne^{\text{CNN}}) W_D] \quad (14)$$

$$Y^C = f_{\text{GAP}}(X^{\text{GCN}}) \oplus \sigma[f_F(Ne^{\text{CNN}}) W_D] \quad (15)$$

where W_D is a trainable weight matrix in $f_D(\cdot)$, and $\otimes$ and $\oplus$, respectively, represent element-wise multiplication and concatenation. The function of W_D is to adjust the contribution ratio of the features extracted by the 3-D CNN and the GCN to the material identification.

At last, Y^F (i.e. Y^A , Y^M or Y^C) is input to the fully connected layer $f_S(\cdot)$ with Cl nodes and the activation function $\text{Softmax}(\cdot)$, and the formula can be written as:

$$Y^{\text{Class}} = \text{Softmax}(Y^F W_S) \quad (16)$$

where W_S is a trainable weight matrix in $f_S(\cdot)$, $y_i^{\text{Class}} \in Y^{\text{Class}}$, $\sum_{i=0}^{Cl-1} y_i^{\text{Class}} = 1$. If $y_k^{\text{Class}} \geq y_i^{\text{Class}}$ ($0 \leq i < Cl$), the result of the material identification is output as follows:

$$\text{result} = \begin{cases} \text{background}, & k = 0 \\ k_{\text{th}} \text{ material}, & 0 \leq k < Cl \end{cases} \quad (17)$$

and the identification methods are constructed completely. According to the three fusion strategies, the identification methods can be distinguished into the proposed method-A, the proposed method-M, and the proposed method-C. In the entire process of material

identification for an image, we can conclude that the computational complexity is $\mathcal{O}(M \times N)$, i.e., linear with the number of pixels in the image, and, therefore, there is no risk of a sudden explosion of the calculation volume.

After that, the model parameters are trained multiple times using the training sets and the cross-entropy loss function. To improve the accuracy while retaining the training speed, the decayed learning rate of exponential decay [58] is applied, and the learning rate is gradually reduced during the training as follows:

$$Lr = 0.001 \times 0.95^{Ct} \quad (18)$$

where Lr is the learning rate, and Ct is the cycle training time. The early stopping [59] is applied in the same manner as the stopping strategy of the training to avoid model parameters overfitting.

After training, the material class prediction for the test set is conducted using the proposed method-A, -M, and -C. Then, the identification performance is demonstrated, evaluated, and analyzed.

3.3. Data Quality Assessment

We chose spectral separability to describe the degree of data inconsistency. The higher the spectral separability, the lower the data inconsistency, and the less difficult it is to identify materials. The ratio of the inter-class distance to the intra-class distance is calculated to describe the spectral separability J of the materials in a dataset. The formulas are presented as:

$$\mathbf{m}^{(i)} = \frac{1}{N_i} \sum_{j=0}^{N_i-1} \mathbf{X}_j^{(i)} \quad (19)$$

$$\mathbf{m} = \frac{1}{M} \sum_{i=0}^{M-1} \mathbf{m}^{(i)} \quad (20)$$

$$P_i = \frac{N_i}{\sum_{k=0}^{M-1} N_k} \quad (21)$$

$$S_B = \sum_{i=0}^{M-1} P_i (\mathbf{m}^{(i)} - \mathbf{m})(\mathbf{m}^{(i)} - \mathbf{m})^T \quad (22)$$

$$S_W = \sum_{i=0}^{M-1} P_i \frac{1}{N_i} \sum_{j=0}^{N_i-1} (\mathbf{X}_j^{(i)} - \mathbf{m}^{(i)})(\mathbf{X}_j^{(i)} - \mathbf{m}^{(i)})^T \quad (23)$$

$$J = \frac{\text{tr}(S_B)}{\text{tr}(S_W)} \quad (24)$$

where M is the total number of the materials in the dataset, N_i is the total number of spectra for the i_{th} material, and $\mathbf{X}_j^{(i)} \in \mathbb{R}^{1 \times C}$ is the j_{th} spectra of the i_{th} material.

4. Results

4.1. Experimental Data

The experimental data include simulated data and measured data. The simulated data were space target spectral images created through computer simulation, and the measured data were acquired by measuring the satellite scale-down model in the laboratory. The satellite scale-down model is a simulation model whose materials are different from the real materials of the space targets, but it can be used to verify the effectiveness of the identification methods.

The simulated data and the measured data are used to evaluate the identification performance of the proposed method (-A, -M, and -C). In this field, researchers often use their own datasets, and these datasets have different qualities and different imaging conditions;

at the same time, there is a lack of benchmarks to uniformly compare the performances of all methods. Therefore, we applied several representative methods of different types as comparative methods, including the 3-D CNN [12–14,23,24], the CNMF [9], and the TD [7], wherein the proposed method and the 3-D CNN are fully supervised, the CNMF is semi-supervised, and the TD is unsupervised.

4.1.1. Simulated Data

We generated hyperspectral simulated data based on high-fidelity panchromatic simulated images of the “Tango” spacecraft released by the ESA, as shown in Figure 8. When computer simulating, a unique reflectance spectrum was set for each material, and changes in the illumination conditions were simulated by adjusting the proportion of sunlight and earthshine in incident light. The simulated model of the space target with different attitudes was labeled with material classes, and a spectrum was added to each pixel according to the label and set lighting conditions. Although different incidence spectra were used in different images, the incident spectra were the same for different surfaces on the target in an image. Then, the image was down-sampled to form simulated hyperspectral images with different illumination conditions and different spatial resolutions.

The band range of the simulated data is from 440 nm to 780 nm, and the spectral resolution is 10 nm. The material classes in the space target simulated images are solar cell, gold mylar, and antenna. The normalized materials’ spectra of these are shown in Figure 9, where the spectral features of the three materials are different from each other.



Figure 8. Examples of the simulated data: (a) example 1; (b) example 2.

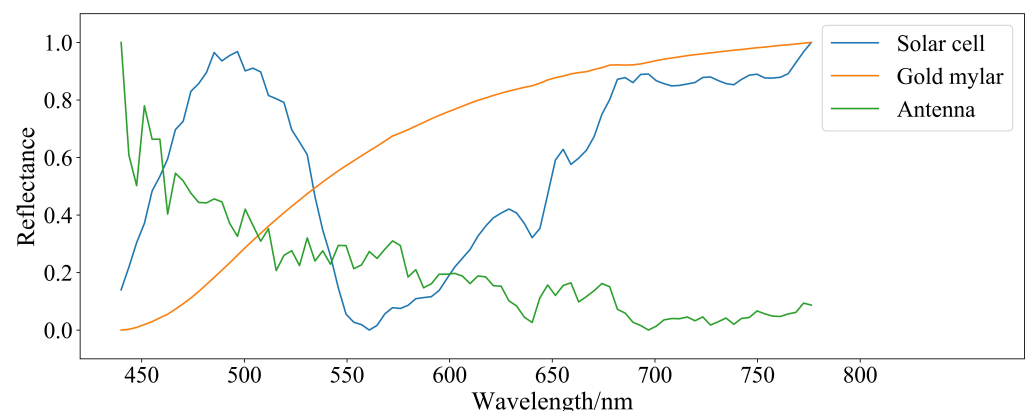


Figure 9. Examples of normalized materials’ spectra in the simulated data.

4.1.2. Measured Data

During the laboratory measurement, incandescent lamps were chosen to simulate earthshine, and a tungsten halogen lamp was aimed at the satellite model to simulate sunlight, as shown in Figures 10 and 11. The direction from the halogen tungsten lamp to the satellite model and the attitude of the satellite model together determined the angle of incidence of the tungsten halogen lamp to simulate the complex illumination situation of the space target in the space environment.



Figure 10. Laboratory measurement scene.

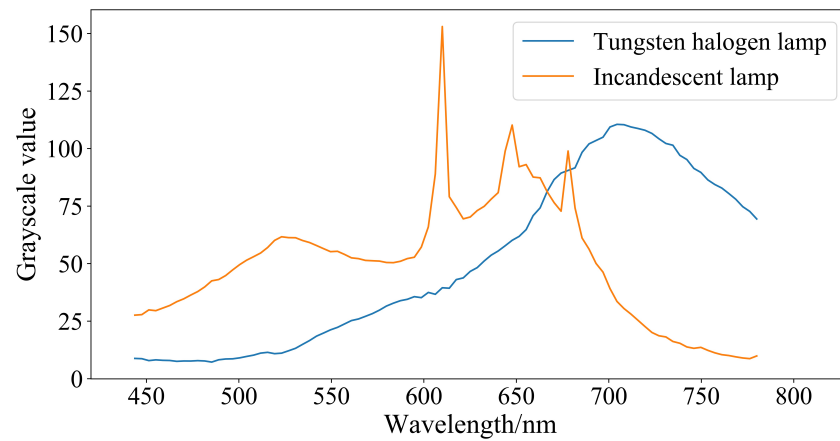


Figure 11. Spectra of the incandescent lamp and the tungsten halogen lamp.

The position and orientation of the tungsten halogen lamp and the attitude of the model were changed to simulate the changes in the spectral data distributions produced by different shooting times, attitudes of the space target, and other conditions, as shown in Figure 12. Then, the measured hyperspectral images of different illumination conditions and different spatial resolutions were obtained by adjusting the spatial resolution of the measuring instrument.

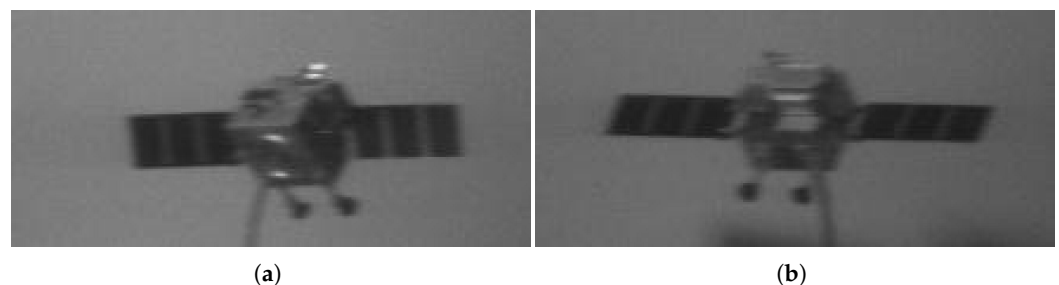


Figure 12. Examples of the measured data: (a) example 1; (b) example 2.

The measured data band range is from 440 nm to 780 nm, and the spectral resolution is 10 nm. The material classes in the measured data are solar cell, gold mylar, antenna, and cooling area. The normalized materials' spectra of these are shown in Figure 13, where the spectral features of the gold mylar on the vertical incidence surface and the oblique

incidence surface of the tungsten halogen lamp are quite different, and the spectral features of the other materials are similar.

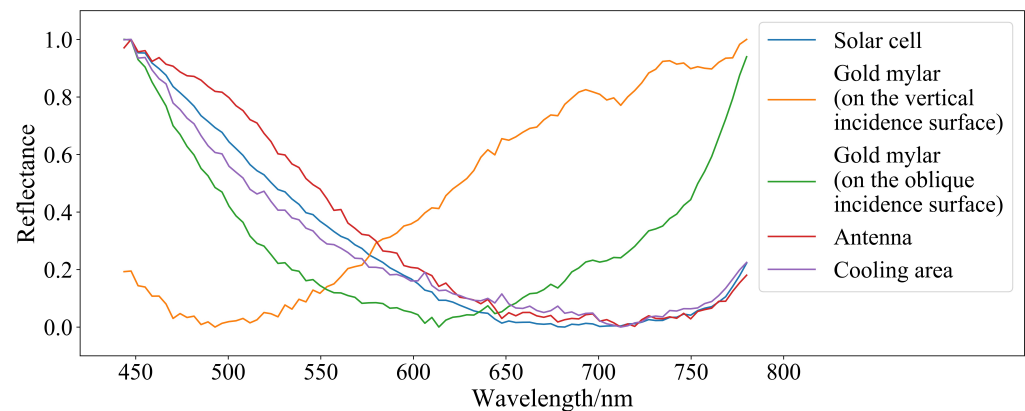


Figure 13. Examples of normalized materials' spectra in the measured data.

4.2. Analysis of Identification Results

The F1-measure [60], overall accuracy (OA), average accuracy (AA), and kappa coefficient [61] are applied as evaluation indexes. The F1-measure is calculated for each material.

4.2.1. Simulated Data

Five simulated hyperspectral images were generated; two of them were chosen for training, and three of them for testing. We divided the images into four datasets, which are the training set (T0), the test set 1 (T1), the test set 2 (T2), and the test set 3 (T3). Among these, the imaging conditions of T1 were the same as those of T0; the illumination conditions of T2 were changed compared with T0; and the spatial resolution of T3 was decreased compared to T0. Additionally, the parameter describing the illumination conditions is the ratio of the sunlight irradiance to the earthshine irradiance in the incident light, and the parameters of the simulated data are shown in Table 1.

Table 1. Simulation data parameters.

	T0	T1	T2	T3
Illumination conditions	10:1	10:1	20:3	10:1
Spatial resolution(cm/pixel)	3.2	3.2	3.2	6.4

The dimensions of the input data, the dimensions of the output data, and the parameters chosen in the proposed method are shown in Table 2. The material identification results of the simulated data are shown in Figure 14. Since the results of the proposed methods (-A, -M, and -C) are similar, and the proposed method-A performs best, only the results of it are shown.

In the simulated data, as shown in Table 3 and Figure 15, the identification performances of the solar cell and gold mylar in the proposed method and the comparative methods are always good, and the performance of the antenna in the proposed method is better than that in the comparative methods. Further, the results of the proposed method-A are better than the proposed method-M and the proposed method-C.

Table 2. The table of dimensions and parameters in the proposed method on the simulated data.

Steps	Dimensions and Parameters	
	Simulated Data	Measured Data
Inputs	1. The hyperspectral image $I \in \mathbb{R}^{150 \times 240 \times 90}$; 2. The topological graph $G_I = \{A_I, X_I\}$, $A_I \in \mathbb{R}^{q \times q}$, $X_I \in \mathbb{R}^{q \times 90}$, $16 \leq q \leq 22$; 3. The fixed-size neighborhoods $Ne_I \in \mathbb{R}^{5 \times 5 \times 90}$.	1. The hyperspectral image $I \in \mathbb{R}^{100 \times 220 \times 90}$; 2. The topological graph $G_I = \{A_I, X_I\}$, $A_I \in \mathbb{R}^{q \times q}$, $X_I \in \mathbb{R}^{q \times 90}$, $23 \leq q \leq 42$; 3. The fixed-size neighborhoods $Ne_I \in \mathbb{R}^{5 \times 5 \times 90}$.
SLIC	1. The initial number of cluster centers $K_0 = 30$, $K_1 = 60$; 2. The distance scale factor $\varepsilon_I = 9/40$.	1. The initial number of cluster centers $K_0 = 27$, $K_1 = 55$; 2. The distance scale factor $\varepsilon_I = 9/40$.
The Network	1. The 3-D convolutional layer $f_{C3}(\cdot)$ with $W_{C3, kn} \in \mathbb{R}^{3 \times 3 \times 3}$ ($0 \leq kn < 16$) and step sizes 1, 1, and 1; 2. The 3-D max-pooling layer $f_{MP3}(\cdot)$ with the windows of sizes $1 \times 1 \times 3$ and step sizes 1, 1, and 3; 3. The 1-D convolutional layers $f_{C1}(\cdot)$ with $W_{C1} \in \mathbb{R}^{1 \times 3}$ and step size 1; 4. The 1-D max-pooling layers $f_{MP1}(\cdot)$ with the window of size 3 and step size 3; 5. The graph convolutional layer $f_G(\cdot)$ with the number of channels $Ch = 32$; 6. The fully connected layer $f_D(\cdot)$ with the number of nodes $Ch = 32$;	
	7. The fully connected layer $f_S(\cdot)$ with the number of nodes $Cl = 4$.	7. The fully connected layer $f_S(\cdot)$ with the number of nodes $Cl = 5$.
Output	1. The class confidence vector $\mathbf{Y}^{Class} \in \mathbb{R}^{1 \times 4}$.	1. The class confidence vector $\mathbf{Y}^{Class} \in \mathbb{R}^{1 \times 5}$.

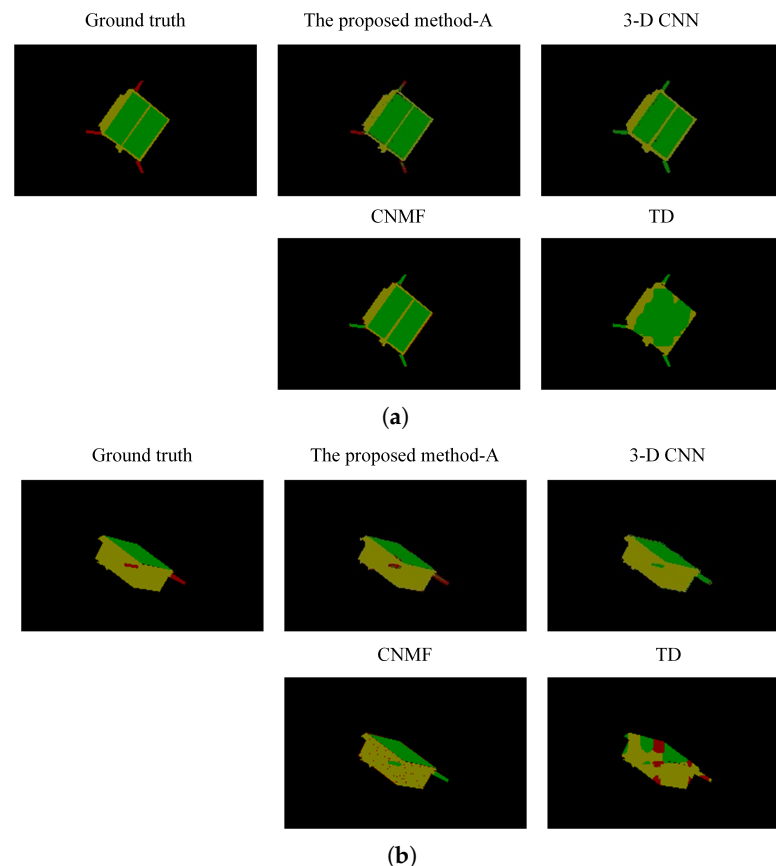
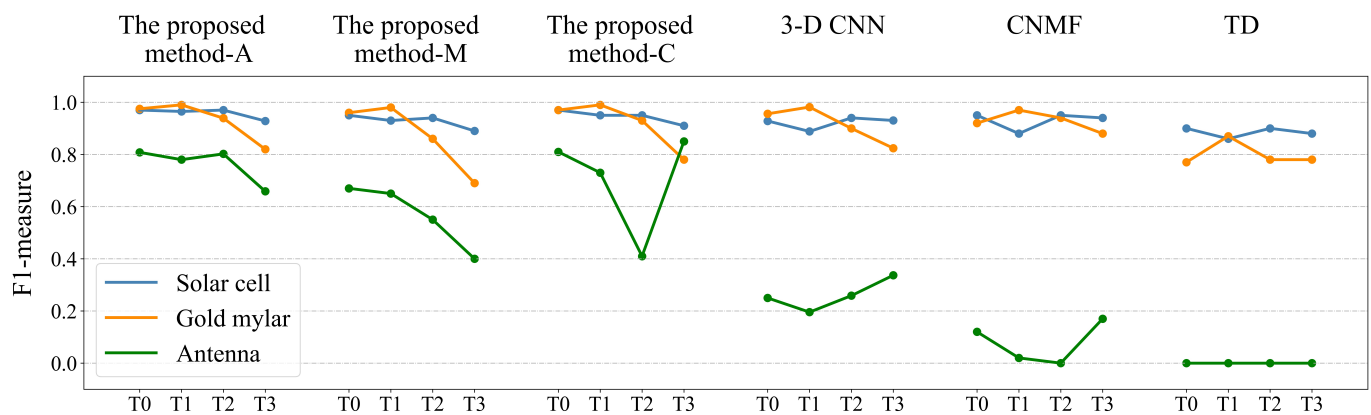
**Figure 14.** Examples of material identification results using the simulated data: (a) example 1; (b) example 2.

Table 3. F1-measure (%) table of the simulated data.

Class	The Proposed Method											
	-A				-M				-C			
	T0	T1	T2	T3	T0	T1	T2	T3	T0	T1	T2	T3
Solar cell	97	96	97	93	95	93	94	89	97	95	95	91
Gold mylar	97	99	94	82	96	98	86	69	97	99	93	78
Antenna	81	78	80	66	67	65	55	40	81	73	41	85

Class	3-D CNN				CNMF				TD			
	T0	T1	T2	T3	T0	T1	T2	T3	T0	T1	T2	T3
Solar cell	93	89	94	93	95	88	95	94	90	86	90	88
Gold mylar	96	98	90	82	92	97	94	88	77	87	78	78
Antenna	25	20	26	34	12	2	0	17	0	0	0	0

**Figure 15.** F1-measure chart of the simulated data.

As shown in Table 4 and Figure 16, the OAs of the proposed method and the comparative methods are close, but the AA and the kappa coefficient of the proposed method are basically higher than the comparative methods. This shows that the proposed methods, especially the proposed method-A, outperform the comparative methods on the identification performance of the material with small samples.

Table 4. Identification performance table of the simulated data (OA-AA-KAPPA).

Method		OA(%)				AA(%)				Kappa			
		T0	T1	T2	T3	T0	T1	T2	T3	T0	T1	T2	T3
The proposed method	-A	96.8	97.7	95.9	88.7	90.7	91.7	89.0	80.7	0.940	0.945	0.908	0.759
	-M	94.2	95.8	91.2	79.9	88.7	91.3	77.0	67.3	0.893	0.902	0.794	0.589
	-C	96.1	97.2	93.0	87.1	93.3	92.7	73.0	80.3	0.928	0.934	0.840	0.717
3-D CNN		92.0	93.9	92.5	86.9	70.1	69.3	70.7	68.0	0.849	0.850	0.826	0.737
CNMF		92.1	91.3	93.1	89.4	66.3	64.7	65.0	65.0	0.819	0.799	0.840	0.773
TD		84.4	80.2	84.6	83.0	56.3	58.7	57.0	56.3	0.632	0.628	0.641	0.633

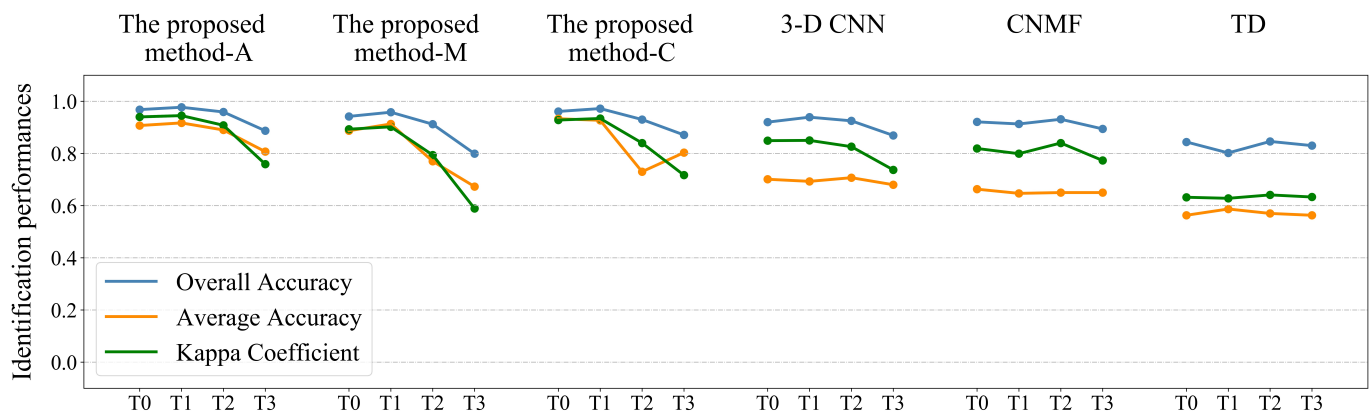


Figure 16. Identification performance chart of the simulated data (OA-AA-Kappa).

4.2.2. Measured Data

Four kinds of data were measured, including the training set (T0), the test set 1 (T1), the test set 2 (T2), and the test set 3 (T3). Among them, the imaging conditions of T1 were the same as those of T0; the illumination conditions of T2 were changed compared with T0; and the spatial resolution of T3 was decreased compared with T0. Additionally, the parameter describing the illumination conditions is the incidence direction of the tungsten halogen lamp in the local coordinate system of the space target model, and the parameters of the measured data are shown in Table 5.

Table 5. Measured data parameters.

	T0	T1	T2	T3
Illumination conditions	+ Y-axis; − Z-axis	− Z-axis	− X-axis	+ Y-axis
Spatial resolution (cm/pixel)	5.4	5.4	5.4	10.8

The dimensions of the input data, the dimensions of the output data, and the parameters chosen in the proposed method are shown in Table 2. The material identification results of the measured data are shown in Figure 17. For the same reason as the simulated data, among the proposed methods (-A, -M, and -C), only the results of the proposed method-A are shown.

In the measured data, as shown in Table 6 and Figure 18, the identification performances of the solar cell and gold mylar in the proposed method are always good and better than in the CNMF and the TD. In the 3-D CNN, the change in the illumination conditions and the reduction in the spatial resolution led to a significant decrease in the identification performances of the solar cell and gold mylar. The performances of the antenna and cooling area in the proposed method-A are better than those in the comparative methods. Additionally, the change in the illumination conditions and the reduction in the spatial resolution led to the reduction in the performances of the antenna and cooling area in the proposed method-M and the proposed method-C.

As shown in Table 7 and Figure 19, The performances of the OA, AA, and kappa coefficient on the measured data also show the advantage of the proposed method on the identification performance of the materials with small samples. The kappa coefficient of the proposed method stays around 0.8. The performances of the CNMF and the TD are poor, and the kappa coefficients are always below 0.6. The performance of the 3-D CNN is close to the proposed method on T0 and T1, but the changes in the illumination conditions and the reduction in the space resolution lead to a significant decrease in its performance on T2 and T3. This shows that the prediction results of the proposed methods are substantially consistent with the labels, and the 3-D CNN is more resistant to changes in the imaging conditions than the comparative methods, especially the proposed method-A.

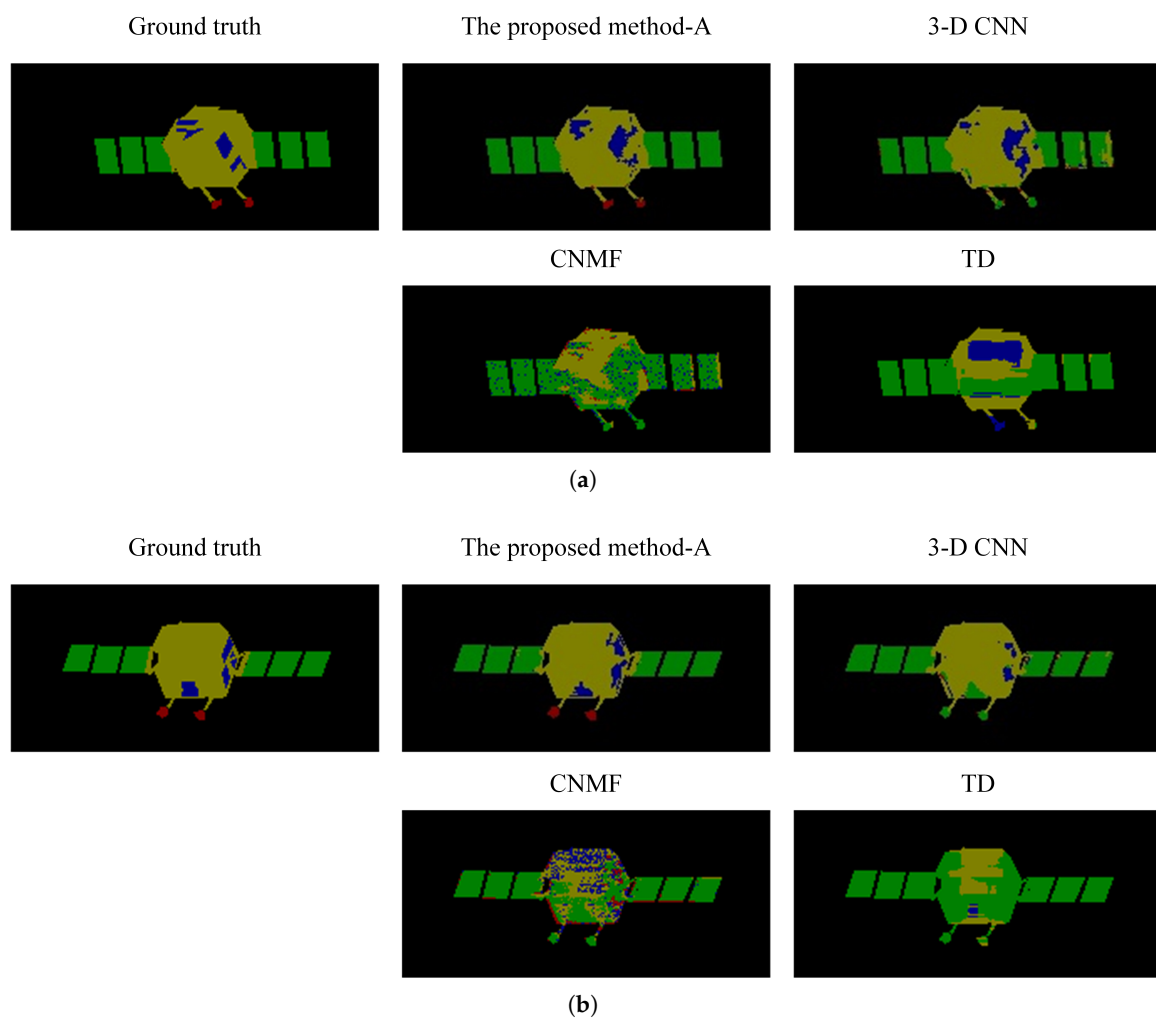


Figure 17. Examples of material identification results using the measured data (a) example 1; (b) example 2.

Table 6. F1-measure (%) table of the measured data.

Class	The Proposed Method											
	-A				-M				-C			
	T0	T1	T2	T3	T0	T1	T2	T3	T0	T1	T2	T3
Solar cell	98	98	95	96	97	96	91	88	97	96	86	95
Gold mylar	89	86	89	90	93	90	92	89	93	91	88	92
Antenna	79	64	66	76	83	55	54	38	79	57	0	46
Cooling area	67	53	42	40	61	42	2	28	63	40	0	29
Class	3-D CNN				CNMF				TD			
	T0	T1	T2	T3	T0	T1	T2	T3	T0	T1	T2	T3
Solar cell	94	97	65	42	84	66	60	82	91	87	88	75
Gold mylar	92	90	67	70	63	63	59	71	72	67	70	69
Antenna	14	17	0	32	7	1	2	1	0	0	0	0
Cooling area	41	22	18	11	25	18	13	6	19	0	12	0

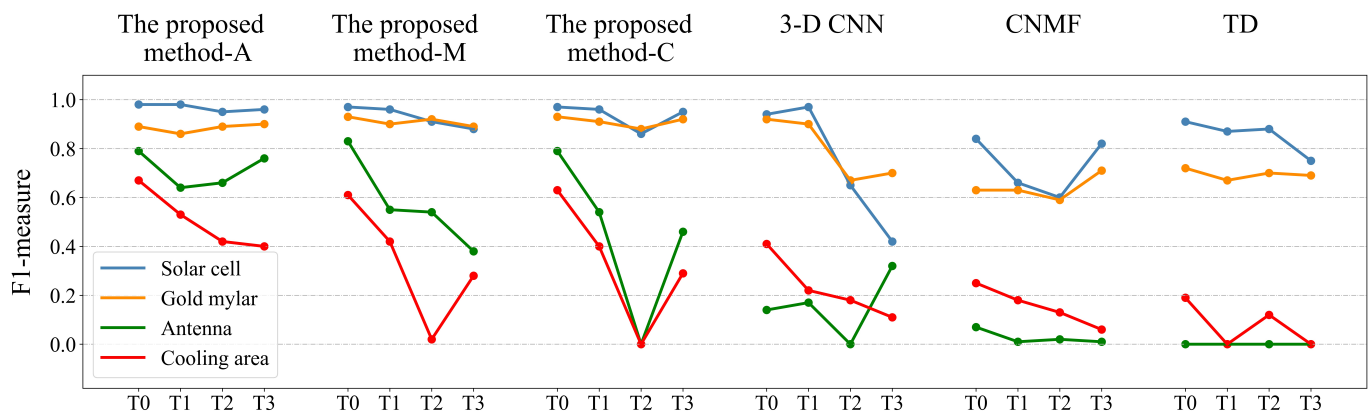


Figure 18. F1-measure chart of the measured data.

Table 7. Identification performance table of the measured data (OA-AA-KAPPA).

Method		OA(%)				AA(%)				Kappa			
		T0	T1	T2	T3	T0	T1	T2	T3	T0	T1	T2	T3
The proposed method	-A	89.9	87.7	87.4	89.4	86.3	81.3	76.8	72.8	0.837	0.799	0.791	0.817
	-M	92.2	89.3	87.6	84.3	92.8	79.0	58.0	71.5	0.864	0.813	0.774	0.722
	-C	92.8	90.5	85.0	90.3	91.8	74.3	44.8	71.0	0.875	0.830	0.715	0.825
3-D CNN		86.5	86.3	58.9	55.5	59.5	56.5	50.5	40.3	0.773	0.767	0.350	0.242
CNMF		71.8	56.3	53.8	69.4	49.5	40.8	37.0	41.5	0.500	0.331	0.232	0.492
TD		74.8	74.2	69.0	69.2	49.5	38.5	47.3	37.3	0.582	0.536	0.515	0.428

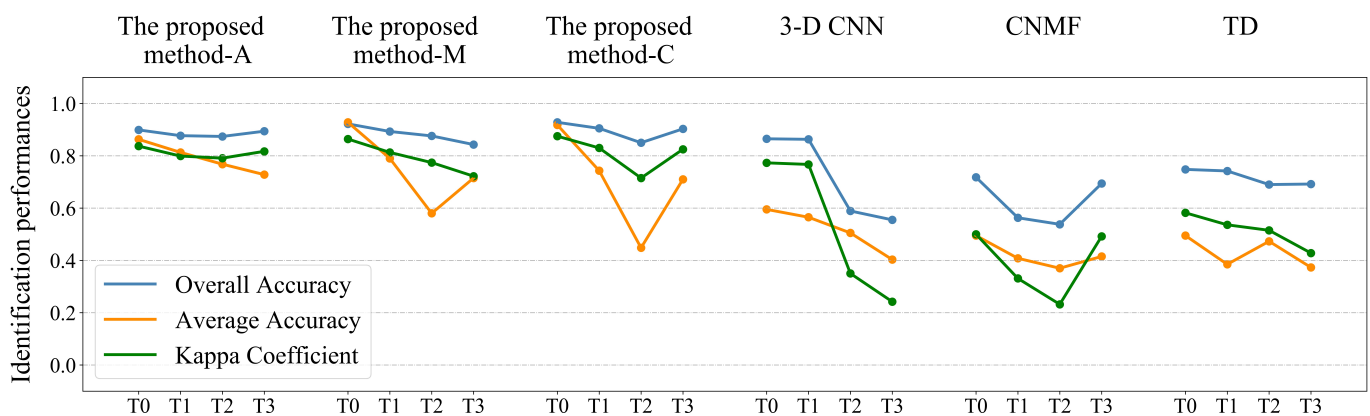


Figure 19. Identification performance chart of the measured data (OA-AA-Kappa).

4.3. Data Quality Assessment Results

We calculated the spectral separability of the two experimental data using Equations (19)–(24). The calculation results are shown in Table 8.

Table 8. The spectral separability of the materials.

	$tr(S_B)$	$tr(S_W)$	J
Simulated data	7.7473	1.6508	4.6930
Measured data	0.7777	2.4307	0.3199

5. Discussion

5.1. The Influence Analysis of Illumination Conditions on the Data Distributions

When measuring, the model attitude is adjusted to change the incidence angle of the tungsten halogen lamp, and the hyperspectral images are taken while the incidence relative direction is close to the negative X-axis, the positive Y-axis, and the negative Z-axis. The spectra of each material in the measured data are clustered by the k-means clustering algorithm, and the average grayscale values of the clusters are calculated. The grayscale values of the materials in different incidence directions and different spatial resolutions are shown in Figure 20.

From Figure 20, it is found that the gold mylar and solar cell on the space target model cover a wide area and high sample amounts, which can better reflect the influence of the incidence direction on the data distributions. The average spectra of the left solar cell, the right solar cell, and the gold mylar on the different surfaces of the model body in the datasets with different incidence directions are calculated and normalized, as shown in Figures 21–24.

It is observed that the spectral data distributions of the left solar cell and the right solar cell are relatively consistent, and there are differences in the spectra of the gold mylar on different surfaces. This is because the solar cells are always oriented in the same direction, while the gold mylar faces different directions on different surfaces. On the different surfaces of the model body, the incidence angles of the gold mylar are different, thus the problem of inconsistent distributions of the spectral data is clearly observed.

Additionally, because the distributions of the solar cell and gold mylar on the space target model are symmetrical along the X-axis, the spectral features are similar when the incidence direction is close to the YOZ plane, as shown in Figures 22–24. When the incidence relative direction is close to the negative X-axis, they change significantly, as shown in Figure 21. This indicates that the incidence direction of sunlight has a great influence on the spectral data distributions of hyperspectral images, and it is closely related to the structural features of the space target too.

5.2. Comparison of the Results between the Experimental Datasets

The simulated data are designed with simplified illumination and reflection models and contain hyperspectral images under ideal imaging conditions. Therefore, in the simulated data, the spectral data distributions of the same material in the same set are consistent. On the contrary, the illumination conditions and material reflection characteristics of the measured data are complex. According to the discussion in Section 5.1, in the measured data, the spectral data distributions of the same material in the same set are inconsistent.

As shown in the calculation results in Table 8, the separability of the simulated data is significantly greater than that of the measured data. Many methods can achieve good results on data with high separability, but only a method that performs equally well on data with low separability is really suitable for space target material identification.

The kappa coefficients of the proposed method-A, the 3-D CNN, the CNMF, and the TD on the simulated data and the measured data are compared, as shown in Figures 16 and 19. In the simulated data, the kappa coefficients of the four methods are all high, and there is a downward trend from the proposed method-A to the 3-D CNN to the CNMF to the TD. This shows that, under ideal conditions, these methods have good results, and the proposed method-A has only a slight advantage.

Compared with the simulated data, the kappa coefficients of each method in the measured data have decreased, and the proposed method-A has the smallest decrease. This indicates that the proposed method-A can achieve good identification performance under complex illumination conditions and has obvious advantages over the comparative methods.

In the global spatial features extraction of the space target, the global-structure topological graph was built by segmenting hyperspectral images, and it is insensitive to the changes in the data distributions caused by the spatial resolution and illumination conditions. By learning the global spatial features of the space target, the proposed method-A can

obtain high robustness, and it can better meet the requirements of the space target material identification with complex illumination conditions and spatial resolution changes.

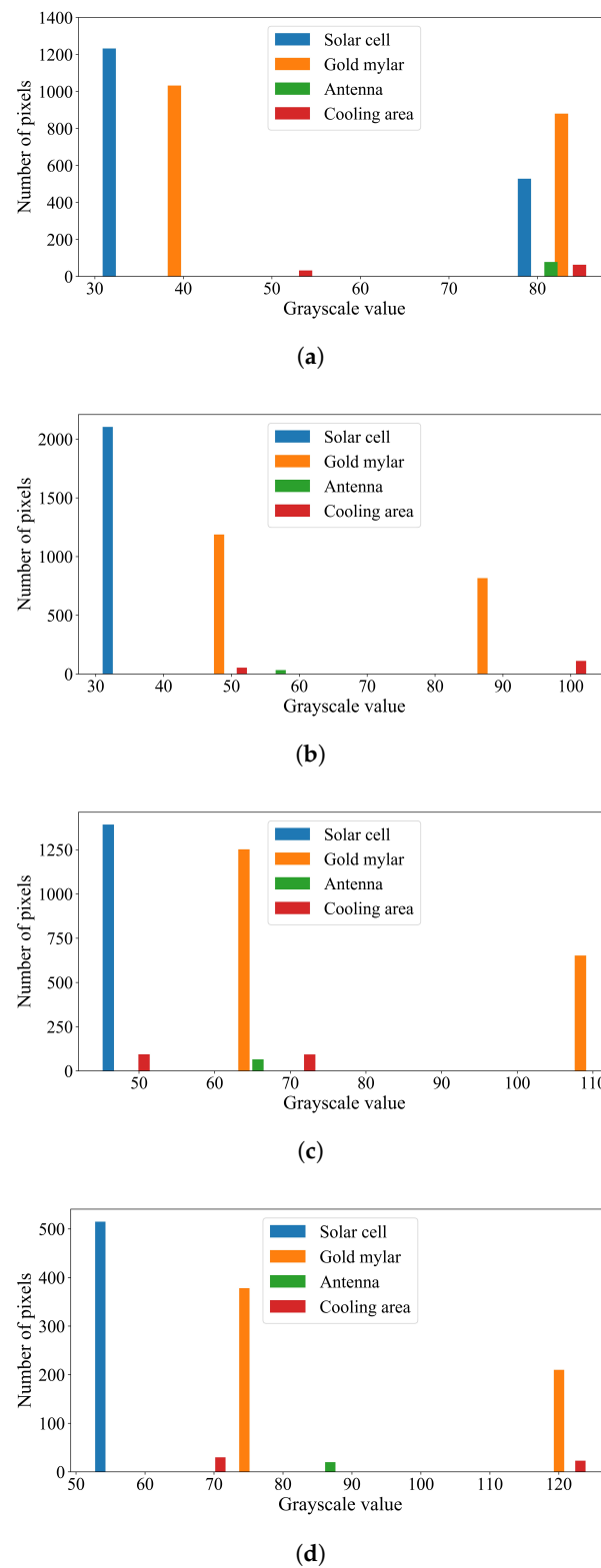


Figure 20. Distributions of grayscale values of different materials in different incidence directions and spatial resolutions: (a) high spatial resolution, negative X-axis; (b) high spatial resolution, positive Y-axis; (c) high spatial resolution, negative Z-axis; (d) low spatial resolution, positive Y-axis.

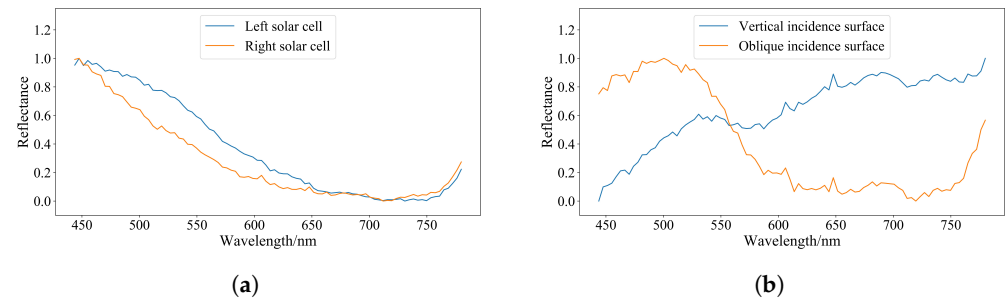


Figure 21. Spectral data distributions of high spatial resolution and negative X-axis incidence: (a) left and right solar cells; (b) gold mylar on different surfaces.

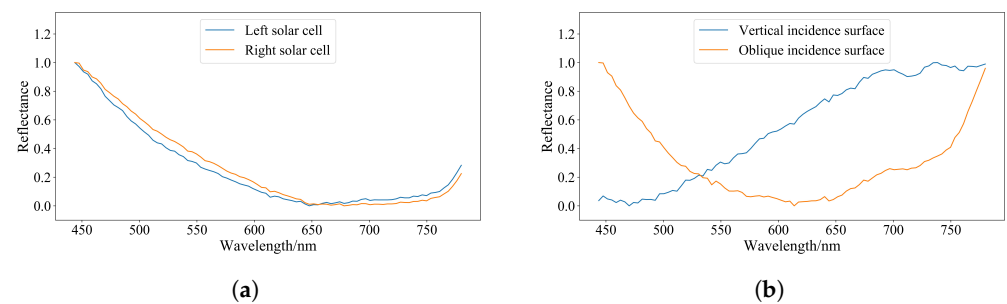


Figure 22. Spectral data distributions of high spatial resolution and positive Y-axis incidence: (a) left and right solar cells; (b) gold mylar on different surfaces.

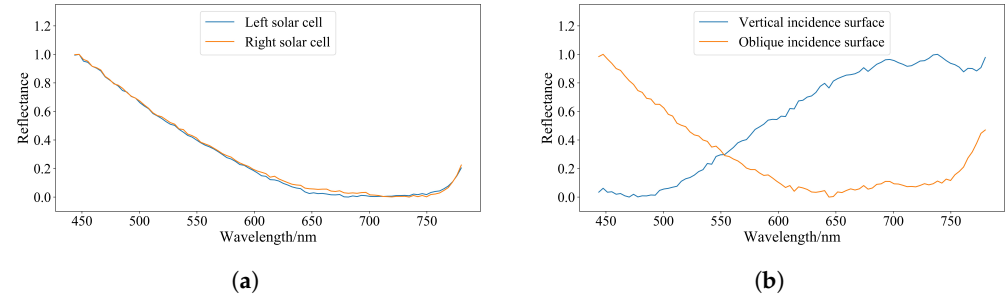


Figure 23. Spectral data distributions of high spatial resolution and negative Z-axis incidence: (a) left and right solar cells; (b) gold mylar on different surfaces.

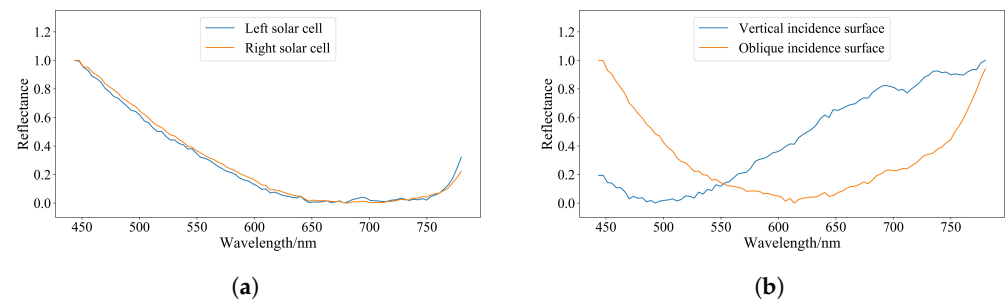


Figure 24. Spectral data distributions of low spatial resolution and positive Y-axis incidence: (a) left and right solar cells; (b) gold mylar on different surfaces.

5.3. Deficiencies and Improvements under Non-Ideal Imaging Conditions

The proposed method has the ability to handle the material identification of the space target with three-axis stabilization under complex illumination conditions when executing hovering operations. However, in fact, the imaging conditions of the space targets cannot

always be so ideal. We list the main factors that may affect the material identification performance during imaging and propose possible strategies to address these issues.

5.3.1. Image Degradation

Image degradation exists in the hyperspectral imaging system, resulting in the loss of spatial and spectral features of the space target, thereby reducing the accuracy of material identification. Our team has researched and developed staring imaging spectrometers based on an acousto-optic tunable filter (AOTF) and measured the linear diffusion function and spectral response function of the spectrometers [62]. Therefore, we plan to design image restoration methods using the degradation function of the spectrometer as prior knowledge.

5.3.2. Background Distractions

The background types for space target images include a space background, earth background, and limb background [63]. In addition to the space background with uniform low grayscale values, both the earth background and limb background have complex texture features and change frequently with the atmospheric environment. As the example image shows in Figure 25, it is conceivable that, without processing of the background, the earth background and limb background will interfere with the representation of the target structural features when building the space target topological graph.

Therefore, complete background removal is one of the requirements to ensure the performance of the proposed method. Additionally, because the grayscale values and texture features of the earth background and limb background are so variable, it is difficult to cover the backgrounds in all images with one method.

We recommend contrastive learning [64] to solve this problem. As shown in Figure 25, the pixels of the space target are set as positive samples, and the other pixels are set as negative samples. Each image is trained to differentiate the feature distance between positive and negative samples, making it easy to distinguish between positive and negative samples to accurately remove background pixels.

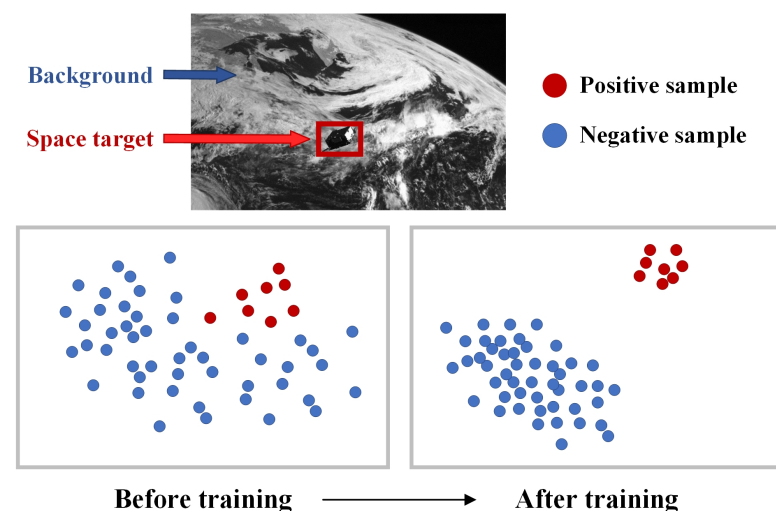


Figure 25. Increase the differences between target features and background features through contrastive learning.

5.3.3. Rapid Changes in Imaging Conditions

In some detection scenarios, imaging conditions may be in continuous high-speed changes, which cannot be ignored in hyperspectral imaging. For example, in rendezvous and proximity operations (RPO) [65], the imaging distance gradually decreases; in fly-around operations [66], the direction of imaging is constantly changed; and in accompanying flights [67], the rapid rotation of the space target leads to a constant change in its relative attitude to the detector.

In the above scenarios, the data acquired by scanning imaging spectrometers may become quite difficult to interpret. Additionally, the staring imaging spectrometer can intuitively acquire the spatial features of the target in each frame, as shown in Figure 26, so the structural features and spectral features can be extracted by operating on the image space for identification.

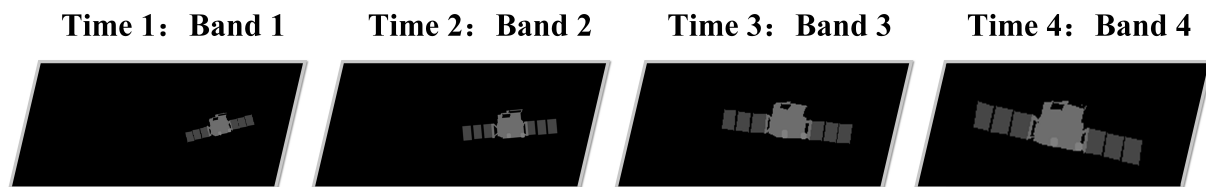


Figure 26. Schematic of staring hyperspectral images with decreasing imaging distance.

When processing staring hyperspectral images, we consider improving on the proposed method. On the one hand, when building topological graphs, every single frame image requires separate superpixel segmentation and topological graph building; then, all of the topological graphs will be connected selectively and merged together. On the other hand, the self-attention mechanism will be added to the GCN to enhance its ability to capture long-range interactions (LRI) [68] in graphs and learn the changes in structural features. In addition, we believe that it is possible to identify the motion status of the space target by the changes in structural features.

6. Conclusions

Under complex illumination conditions, the spectral features of materials in hyperspectral images become inconsistent. These phenomena are specifically expressed as obvious spectral feature differences of the same material, high spectral feature similarities of different materials, and intense changing of spectral features under different illumination conditions. Therefore, it is difficult to achieve accurate material identification only via spectral features and local spatial features.

Aiming at this problem, a material identification method based on an improved graph convolutional neural network is proposed. Superpixel segmentation is conducted on the hyperspectral images to build the multiscale, joint topological graph of the space target global structure. Based on this topological graph, material identification datasets including the topological graphs and neighborhoods of each pixel are obtained. These datasets contain the global spatial features, the local spatial features, and the spectral features. The proposed network model of the GCN and the 3-D CNN fusing with the strategies of -A, -M, or -C is constructed. Additionally, it is trained to learn the best weights of the three features. The simulated data and the measured data are used to demonstrate the performance of the proposed methods (-A, -M, and -C), and the 3-D CNN, the CNMF, and the TD are chosen as comparative methods. The overall accuracy of the proposed methods can be kept at 85–90%, and their kappa coefficients remain around 0.8, among which the proposed method-A has the best overall performance. Moreover, in the simulated data, the proposed methods and the comparative methods all perform well; in the measured data, the proposed methods perform more strongly than the comparative methods. This indicates that the proposed methods can improve the material identification performance under complex illumination conditions with high accuracy and strong robustness.

In future work, we plan to measure more hyperspectral images of the space target under different imaging conditions and verify the performances of the proposed method and other advanced methods on these images, determining the state-of-the-art (SOTA) methods and making the proposed method more convincing. Additionally, we will research the material identification of the space target under non-ideal imaging conditions to further improve the applicable scope and robustness of the proposed method, conduct space target status recognition, and pose estimation research.

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