Hyperspectral image reconstruction for spectral camera based on ghost imaging via sparsity constraints using V-DUnet

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Abstract—Spectral camera based on ghost imaging via sparsity constraints (GISC spectral camera) obtains three-dimensional (3D) hyperspectral information with two-dimensional (2D) compressive measurements in a single shot, which has attracted much attention in recent years. However, its imaging quality and real-time performance of reconstruction still need to be further improved. Recently, deep learning has shown great potential in improving the reconstruction quality and reconstruction speed for computational imaging. When applying deep learning into GISC spectral camera, there are several challenges need to be solved: 1) how to deal with the large amount of 3D hyperspectral data, 2) how to reduce the influence caused by the uncertainty of the random reference measurements, 3) how to improve the reconstructed image quality as far as possible. In this paper, we present an end-to-end V-DUnet for the reconstruction of 3D hyperspectral data in GISC spectral camera. To reduce the influence caused by the uncertainty of the measurement matrix and enhance the reconstructed image quality, both differential ghost imaging results and the detected measurements are sent into the network’s inputs. Compared with compressive sensing algorithms, such as PICHCS and TwIST, it not only significantly improves the imaging quality with high noise immunity, but also speeds up the reconstruction time by more than two orders of magnitude.

Index Terms—Convolution neural network, Deep learning, Ghost imaging, Hyperspectral image reconstruction.

I. INTRODUCTION

GHOST imaging (GI) obtains the image information through intensity correlation of optical fields between the object path and the reference path [1]–[6]. It can restore the high-dimensional information from the low-dimensional detecting measurements by encoding the image information into the intensity fluctuations of light fields, thus providing a new solution for high dimensional image sensing [7]–[10]. As a typical case, spectral camera based on ghost imaging via sparsity constraints (GISC spectral camera) modulates the 3D hyperspectral information into a 2D spatial intensity fluctuations of light fields, which enables capturing the 3D hyperspectral image information in a single shot [11], [12]. Combined with compressive sensing [13]–[15], it can realize compressive sensing of the information during the acquisition process with improved efficiency. However, the image reconstruction process is full of challenges. Conventional GI reconstruction algorithms, such as differential GI (DGI) [16], suffer from the low reconstruction quality in the case of low sampling rate and low signal to noise ratio. Though Compressive sensing algorithms can contribute to obtain higher reconstruction quality by utilizing prior information of the object, the time-consuming interactive process makes it difficult to reconstruct the image in real time. With recent explosive growth of artificial intelligence, deep learning (DL) has provided new opportunities and tools for computational imaging [17]–[26]. In recent years, DL has also been applied in ghost imaging and has achieved good performance [27]–[33]. Many excellent works set the detected measurements as the net input [27], [30], [33], and the sufficient sampling rate for high quality image goes down to a cheerful level. However, these works require that the measurement matrix must be the same during the training and imaging process. Zhu [28] proposes a novel dynamic decoding deep learning framework called Y-net, which introduces the statistical characteristics of the random reference measurements into the net and works well under both fixed and unfixed measurement matrix. Hu [29] and Lyu [31] have also reduced the sensibility of the measurement matrix by setting the conventional ghost imaging results as the network’s input.

Compared to the 2D reconstruction in GI, introducing deep learning into the reconstruction of 3D hyperspectral information in GISC spectral camera faces the following challenges. Firstly, large-size data need to be processed due to its high dimensional property. Secondly, how to reduce the sensibility of the random reference measurements also plays an important role in the generalization ability of the network. What’s more, the reconstruction quality of 3D hyperspectral information has also to be ensured. In this paper, we propose an end-to-end V-DUnet to reconstruct 3D hyperspectral images of GISC spectral camera. Owing to the encoder and decoder architecture of the Unet [34], it can effectively deal with large-
Fig. 1. The schematic of GISC spectral camera. The system is composed of three modules: (1) A front imaging module (a conventional imaging system), which projects the 3D hyperspectral data cube $x(m_x, n_x, \lambda)$ onto the first imaging plane, (2) Modulation module (a spatial random phase modulator), which modulates the light fields in the first imaging plane, (3) Detection module (CCD), which records the speckle patterns in the measurement plane $y(m_y, n_y)$. A monochromatic point source on the object plane. Thus, 3D hyperspectral images can be obtained by calculating the intensity correlation between the calibrated speckle patterns and imaging speckle patterns [12]. Meanwhile, the imaging process can be written into a matrix form as

$$Y = \Phi X + \epsilon, \quad (1)$$

in which $X \in \mathbb{R}^{M_x \times N_x \times L}$ is reshaped from the HSI data cube $x(m_x, n_x, \lambda) \in \mathbb{R}^{M_x \times N_x \times L}$ where $1 \leqslant m_x \leqslant M_x$, $1 \leqslant n_x \leqslant N_x$ and $1 \leqslant \lambda \leqslant L$, $Y \in \mathbb{R}^{M_y \times N_y}$ is reshaped from the measurement image $y(m_y, n_y) \in \mathbb{R}^{M_y \times N_y}$ where $1 \leqslant m_y \leqslant M_y$ and $1 \leqslant n_y \leqslant N_y$ in the CCD detector. $\epsilon$ represents the noise of the system. The pre-determined random measurement matrix $\Phi \in \mathbb{R}^{M_y \times M_x \times N_x \times L}$ is obtained after $M_x \times N_x \times L$ calibration measurements, each column vector in $\Phi$ presents a calibrated speckle intensity pattern corresponding to one pixel in HSI.

In order to have an intuitive view of our GISC spectral camera sensing matrix $\Phi$, we choose a tiny HSI data cube
$x_e \in \mathbb{R}^{2 \times 2 \times 3}$ as an example and set the $y_e \in \mathbb{R}^{2 \times 2}$ to give an illustration. What’s more, we suppose the system is noise-clean for simplicity. First, the tiny HSI data’s flow in GISC spectral camera is particularly illustrated in Fig. 3 each pixel in HSI data cube $x_e$ produces a random speckle pattern on the CCD plane after the interaction of the conventional imaging system and the spatial random phase modulator. In our selected tiny HSI data cube $x_e$, it has total 12 ($M_x = 2$, $N_x = 2$ and $L = 3$, $2 \times 2 \times 3 = 12$) pixels $x_1^{(1)}$, $x_2^{(1)}$, $x_3^{(1)}$, $x_4^{(1)}$, $x_1^{(2)}$, $x_2^{(2)}$, $x_3^{(2)}$, $x_4^{(2)}$, and $x_1^{(3)}$, $x_2^{(3)}$, $x_3^{(3)}$, $x_4^{(3)}$, thus the corresponding 12 random speckle patterns are $y_e(x_1,1)$, $y_e(x_2,1)$, $y_e(x_3,1)$, $y_e(x_4,1)$, $y_e(x_1,2)$, $y_e(x_2,2)$, $y_e(x_3,2)$, $y_e(x_4,2)$, and $y_e(x_1,3)$, $y_e(x_2,3)$, $y_e(x_3,3)$, $y_e(x_4,3)$, respectively. $y_e$ is the superposition of those total 12 random speckle patterns, namely

$$y_e = y_e(x_1,1) + y_e(x_2,1) + y_e(x_3,1) + y_e(x_4,1) + y_e(x_1,2) + y_e(x_2,2) + y_e(x_3,2) + y_e(x_4,2) + y_e(x_1,3) + y_e(x_2,3) + y_e(x_3,3) + y_e(x_4,3)$$

(2)

Second, the calibration measurement process of the sensing matrix $\Phi_e$ in HSI data cube $x_e$ to 1 in sequence. As the same data flow process illustrated in Fig. 2, 12 corresponding random speckle patterns $\tilde{y}(x_1,1)$, $\tilde{y}(x_2,1)$, $\tilde{y}(x_3,1)$, $\tilde{y}(x_4,1)$, $\tilde{y}(x_1,2)$, $\tilde{y}(x_2,2)$, $\tilde{y}(x_3,2)$, $\tilde{y}(x_4,2)$, and $\tilde{y}(x_1,3)$, $\tilde{y}(x_2,3)$, $\tilde{y}(x_3,3)$, $\tilde{y}(x_4,3)$ are generated, respectively. And the sensing matrix $\Phi_e$ is finally obtained by reshaping all those patterns to column vectors and placing them in order, as is shown in Fig. 3 and Eq. (3). Finally, we let $X_e \in \mathbb{R}^{12}$ represent the column vector reshaped from $x_e$, $Y_e \in \mathbb{R}^{2}$ represent the column vector reshaped from $y_e$, thus the formula between $X_e$ and $Y_e$ can be written as

$$Y_e = \Phi_e X_e,$$

(4)

in which $Y_e = [y_1^{(e)} \ y_2^{(e)} \ y_3^{(e)} \ y_4^{(e)}]^T$, $X_e = [x_1^{(1)} \ x_2^{(1)} \ x_3^{(1)} \ x_4^{(1)} \ x_1^{(2)} \ x_2^{(2)} \ x_3^{(2)} \ x_4^{(2)} \ x_1^{(3)} \ x_2^{(3)} \ x_3^{(3)} \ x_4^{(3)}]^T$.

### III. THE PROPOSED FRAMEWORK

Inspired by the DAttNet [27], Unet [33], Attention Unet [35] and DenseNet [36], we propose a framework V-DUnet. As illustrated in Fig. 4, it is composed of two parts, the first part is the V part and the second part is the DUnet part. There are two inputs in V-DUnet, one is the measurement image $y$ with $256 \times 256$ pixels recorded by the CCD, the other is the reconstructed DGI result with size $128 \times 128 \times 15$. 

![Fig. 3. Structure of the matrix $\Phi_e$ for $M_x = 2$, $N_x = 2$, $L = 3$ and $M_y = 2$, $N_y = 2$.](image-url)

\[
\Phi_e = \begin{bmatrix}
\Phi_e^{(A)} & \Phi_e^{(B)} & \Phi_e^{(C)}
\end{bmatrix}
\]

\[(3)\]
The input $y$ is firstly reshaped into four channels with size $128 \times 128 \times 4$, then the reshaped result and DGI result pass through two convolutional block respectively and finally concatenated as one block (this process is corresponding to the V part of V-DUnet) and feeds into the DUnet part of V-DUnet. DUnet part is mainly designed based on DenseNet and Unet. DenseNet have four compelling advantages: (1) alleviate the vanishing-gradient problem, (2) strengthen feature propagation, (3) encourage feature reuse, and (4) substantially reduce the number of parameters [36]. The Dense block used in V-DUnet is displayed in Fig. 5. The architecture of the Dense block. Each layer connects to every other layer in a feed-forward fashion.

Additionally, we apply dropout layers to prevent overfitting [37], and batch normalization (BN) layers to speed up the convergence of loss function [38]. The attention gate (AG) is also used to eliminate the irrelevant and noisy responses in Unet skip connections process, and enhance the salient features which pass through the skip connections [34], [35]. Here we introduce the FFDNet [39] in the training process as the denosing part of V-DUnet. It can deal with a wide range of noise levels and easily remove spatially variant noise by specifying a non-uniform noise level map with a single network.

The random sensing matrix $\Phi$ [18], [22] and the structural similarity (SSIM) [25], [40] between the ground truth and the reconstructed results are introduced into the loss function. Therefore, the loss function of our V-DUnet can be finally expressed as

$$\text{Loss} = \alpha \|X - \hat{X}\|_1 + \beta \|Y - \Phi \hat{X}\|_1 + \gamma [1 - \text{ssim}(X, \hat{X})],$$  \hspace{1cm} (5)

where $\alpha = 50$, $\beta = 1$ and $\gamma = 50$. $X$ represents the ground truth of the original HSI while $\hat{X}$ is the corresponding reconstructed HSI from the net. $\text{ssim}(X, \hat{X})$ represents the SSIM between $X$ and $\hat{X}$, and it is formulated as

$$\text{ssim}(X, \hat{X}) = \frac{(2\bar{w}_X\bar{w}_{\hat{X}} + C_1)(2\sigma_{w_X w_{\hat{X}}} + C_2)}{(\bar{w}_X^2 + \bar{w}_{\hat{X}}^2 + C_1)(\sigma_{w_X}^2 + \sigma_{w_{\hat{X}}}^2 + C_2)},$$  \hspace{1cm} (6)

where $w_X(w_{\hat{X}})$ represents the region of image $X(\hat{X})$ within window $w$ while $\bar{w}_X(\bar{w}_{\hat{X}})$ is the mean of $w_X(w_{\hat{X}})$. $\sigma_{w_X}(\sigma_{w_{\hat{X}}})$ is the variance of $w_X(w_{\hat{X}})$, $\sigma_{w_X w_{\hat{X}}}$ represents the co-variance between $w_X$ and $w_{\hat{X}}$. $C_1$ and $C_2$ are constants (experimentally set as $1 \times 10^{-4}$ and $9 \times 10^{-5}$), the window $w$ is set to 11 [25].
### TABLE I
The average evaluation results on the ICVL, CAVE and Minho datasets. 225 ICVL HSIs, 279 CAVE HSIs and 201 Minho HSIs are used to average evaluate PSNR, SSIM and SAM, respectively.

| Net     | Input          | ICVL(225) | CAVE(279) | Minho(201) |
|---------|----------------|-----------|-----------|------------|
|         | PSNR | SSIM | SAM | PSNR | SSIM | SAM | PSNR | SSIM | SAM |
| U-Net   | only y | 19.5750 | 0.4791 | 0.3698 | 16.9264 | 0.4189 | 0.4939 | 17.9258 | 0.3917 | 0.4207 |
|         | only DGI | 25.1347 | 0.7557 | 0.1793 | 21.5853 | 0.6683 | 0.3068 | 21.5046 | 0.6676 | 0.2739 |
|         | y+DGI | 25.5148 | 0.7720 | 0.1707 | 21.7931 | 0.6789 | 0.3034 | 21.6336 | 0.6852 | 0.2676 |
| Proposed | only y | 20.9977 | 0.6002 | 0.2969 | 18.2602 | 0.5476 | 0.4119 | 19.0723 | 0.4986 | 0.3671 |
|         | only DGI | 25.7483 | 0.7635 | 0.1744 | 22.8264 | 0.7007 | 0.2919 | 22.8366 | 0.7037 | 0.2429 |
|         | y+DGI | 26.9447 | 0.7978 | 0.1565 | 23.4499 | 0.7303 | 0.2799 | 23.1362 | 0.7234 | 0.2403 |

### TABLE II
Six different scenes reconstructed by different algorithms.

| Algorithm | Ours | PICHCS | TwIST | DGI |
|-----------|------|--------|-------|-----|
|           | PSNR | SSIM | SAM | PSNR | SSIM | SAM | PSNR | SSIM | SAM | PSNR | SSIM | SAM |
| Scene 1   | 30.5125 | 0.8827 | 0.1239 | 25.4607 | 0.5704 | 0.2668 | 20.3763 | 0.2691 | 0.3766 | 14.4801 | 0.3471 | 0.5073 |
| Scene 2   | 30.7070 | 0.9010 | 0.0969 | 24.8118 | 0.4440 | 0.2174 | 19.5310 | 0.1943 | 0.4372 | 14.8900 | 0.4787 | 0.2908 |
| Scene 3   | 32.2708 | 0.8778 | 0.1659 | 25.4932 | 0.6471 | 0.3537 | 24.5597 | 0.4074 | 0.4046 | 14.8006 | 0.3795 | 0.4141 |
| Scene 4   | 31.3115 | 0.8861 | 0.1897 | 25.9568 | 0.5729 | 0.3253 | 27.4102 | 0.6281 | 0.3992 | 12.2076 | 0.2326 | 0.5289 |
| Scene 5   | 32.2683 | 0.8678 | 0.1899 | 25.3419 | 0.4434 | 0.3360 | 23.7993 | 0.3571 | 0.4654 | 16.7134 | 0.5047 | 0.3587 |
| Scene 6   | 31.1425 | 0.8922 | 0.1437 | 21.3948 | 0.4542 | 0.3170 | 20.5054 | 0.2671 | 0.5294 | 14.4138 | 0.4230 | 0.4168 |
| Average   | 31.3688 | 0.8846 | 0.1523 | 24.7432 | 0.5220 | 0.2961 | 22.6970 | 0.3538 | 0.4354 | 14.6509 | 0.3943 | 0.4194 |

### TABLE III
Anti-noise performance comparisons on the ICVL, CAVE and Minho datasets for the cases with SNR 30 dB and SNR 10 dB. 225 ICVL HSIs, 279 CAVE HSIs and 201 Minho HSIs are used to average evaluate PSNR, SSIM and SAM, respectively.

| SNR     | ICVL(225) | CAVE(279) | Minho(201) |
|---------|-----------|-----------|------------|
|         | PSNR | SSIM | SAM | PSNR | SSIM | SAM | PSNR | SSIM | SAM |
| 30 dB   | 26.9447 | 0.7978 | 0.1565 | 23.4499 | 0.7303 | 0.2799 | 23.1362 | 0.7234 | 0.2403 |
| 10 dB   | 26.8888 | 0.7890 | 0.1526 | 23.2716 | 0.7157 | 0.2814 | 22.5408 | 0.7058 | 0.2421 |

### IV. Simulation Results
Three public HSI datasets are used to evaluate our method, including the ICVL dataset [41], CAVE dataset [42], and the Minho dataset [43]. The ICVL dataset consists of 201 HSIs (1024 × 1392 × 31) and the CAVE dataset consists of 32 images (512 × 512 × 31), the spectral bands of both the ICVL and CAVE datasets are ranged from 400 nm to 700 nm with 10 nm intervals. The Minho dataset consists of 30 HSIs (820 × 820 × 31), the wavelength range of 410 nm−720 nm was sampled at 10 nm intervals. We choose 15 channels with spectral range from 560 nm to 700 nm in those datasets.

To eliminate the overfitting effect, we manually exclude 91 HSIs with similar background or contents and selected 110 HSIs in ICVL dataset. Then we randomly select 101 HSIs in the subsets for training and thus use the rest 9 HSIs for testing. To formulate the training and validation datasets, HSI patches with the size of 128 × 128 × 15 are uniformly extracted with the stride of 128 from the above 101 HSIs in ICVL dataset. We randomly select 90% patches for training and 10% patches for validation. As for the CAVE and Minho dataset, none of them has been included in the training dataset, they are only used for testing. We randomly crop 225 HSI patches from the rest 9 HSIs in ICVL dataset, 279 HSI patches from the CAVE dataset and 201 HSI patches from the Minho dataset for testing. All the models are only trained on ICVL dataset and another input y for training is obtained by Eq [1] where the detected Signal to Noise Ratio (SNR) is 30 dB and Φ is obtained by the calibration of GISC spectral camera.

Three quantitative image quality metrics, including peak signal-to-noise ratio (PSNR), SSIM and spectral angle mapping (SAM) [44], are used to evaluate the performance of all methods. Larger PSNR, SSIM and the smaller SAM values
Fig. 6. Exemplar reconstructed images by 4 algorithms for three scenes (from left to right: Scene 1, Scene 2, Scene 3). The upper figures are the synthetic RGB and the image \( y \) respectively. Three (560 nm, 630 nm and 700 nm) out of 15 spectral channels are shown to compare with the ground truth.

Fig. 7. Exemplar reconstructed images by 4 algorithms for three scenes (from left to right: Scene 4, Scene 5, Scene 6). The upper figures are the synthetic RGB and the image \( y \) respectively. Three (560 nm, 630 nm and 700 nm) out of 15 spectral channels are shown to compare with the ground truth.
DGI and the net reconstruction result is unsatisfactory for neither Unet. When the net input is only y, as shown in TABLE I, it is obvious that when only y is used as input, the net reconstruction result is unsatisfactory for neither Unet nor DUnet. When the net inputs are DGI and y, the average improvement in PSNR of reconstructed result has greatly achieved about 6 dB compared with the case when the net input is only y, and about 1 dB compared with the case when the net input is only DGI. As shown in TABLE I, compared with the case when only basic Unet is used in the second part of the net, DUnet which is mainly designed by Dense block and Unet obtains better reconstruction performance.

To verify the performance of our proposed method, we compare it with several representative reconstruction methods including DGI, TwIST [45], and PICHCS [46]. We have made great effort to achieve the best results of all those competitive methods. To visualize the experimental results for all methods, we compare it with several representative reconstruction methods including DGI, TwIST [45], and PICHCS [46]. We have made great effort to achieve the best results of all those competitive methods. To visualize the experimental results for all methods, including DGI, TwIST [45], and PICHCS [46].

![Fig. 8. Spectral curves of the Scene 3 and Scene 6.](image)

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