Experimental Results of the Balloon-Borne Spectral Camera Based on Ghost Imaging via Sparsity Constraints

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ABSTRACT The spectral camera based on ghost imaging via sparsity constraints (GISC spectral camera) is a phase modulated compressive snapshot spectral imager. It makes use of the second-order intensity correlation of the light field to resolve the spatial and spectral information. In this paper, an optical design for GISC spectral camera which aims to obtain the desired spatial and spectral resolution is presented. A system calibration strategy based on few-mode optical fiber and monochrometer is developed. The snapshot spectral imaging experiments for the test targets and natural scenes are conducted using the prototype of GISC spectral camera loaded on the tethered balloon. The result of the spatial resolution, linearity, and spectra reconstruction error of the prototype is quantitatively evaluated. The distinguishable size at the distance of 1 km is around 0.34 m. The linearity is higher than 0.99 among the wavelength channels from 410 to 640 nm. The reconstructed spectra of eight color targets are compared with those measured by a commercial spectroradiometer. The average relative root mean squared error of the reconstructed spectra is 0.65.

INDEX TERMS Ghost imaging, snapshot spectral imaging, compressive imaging.

I. INTRODUCTION

Compared with scanning spectral imager, snapshot spectral imager [1] collects the entire (x, y, λ) 3D data cube in a single integration period. Its advantages include high light collection efficiency and the absence of scanning artifacts for dynamic objects [2]. With the development of compressed sensing theory [3], compressive snapshot spectral imaging has been proposed [4]. It first encodes the spectral image data cube with random codes and then reconstructs the spectral image by algorithm. Compared with the traditional snapshot spectral imaging, it can overcome the limitation of the pixel number on the spectral image’s resolution remarkably via sparsity constraints or other prior information [5], [6]. Most of the existing compressive snapshot spectral imaging systems are based on amplitude modulation using occultation masks [7]—[12]. Due to this mask, about one half or more of the optical energy received by the object lens is sacrificed [2]. To increase the light collection efficiency, researchers have proposed the phase modulated snapshot spectral imaging in recent years. Wang and Menon [13] used the transparent diffractive-filter array to demonstrate snapshot hyperspectral imaging and absorption-free color imaging with high sensitivity. However, the cross talk in the spatial domain affects the spatial resolution of their system. Liu et al. [14] proposed the spectral camera based on ghost imaging via sparsity constraints (GISC spectral camera); it prevents the problem of cross talk via the second order intensity correlation of light field in both spatial and spectral domain. For the phase modulated snapshot spectral imager, the design for the phase modulator is crucial. Golub et al. [15] proposed a design method for the phase modulator based on the one-dimensional sawtooth function for a compact compressive snapshot spectral imager. As they didn’t provide the relation between the system’s resolution and the parameter for the phase modulator, quantitative design for the system was difficult. In this paper, we build a design model for the
phase modulator based on Gaussian correlation random surface [16] in GISC spectral camera. The design procedure for GISC spectral camera to reach the desired spatial and spectral resolution is presented. The calibration strategy for GISC spectral camera is proposed. And a prototype of GISC spectral camera is developed to conduct the field experiments of snapshot spectral imaging on a tethered balloon. The result of the spatial resolution, linearity and spectral fidelity for the prototype of GISC spectral camera is quantitatively evaluated by test targets.

This paper is organized as follows: the optical design for the GISC spectral camera prototype is elaborated in Section II and the calibration for the sensing matrix, the sparse reconstruction algorithm, and the field test results of snapshot spectral imaging on the tethered balloon are described successively.

![FIGURE 1. Schematic for the GISC spectral camera: a. object plane b. initial image plane c. speckles plane d. detection plane; 1. objective lens 2. spatial phase modulator 3. relay lens 4. detector.](image1.png)

**II. OPTICAL DESIGN FOR THE PROTOTYPE OF GISC SPECTRAL CAMERA**

The physical principle for GISC spectral camera has been elaborated in the literature [14]. As shown in Fig. 1, the GISC spectral camera is basically composed of three modules: the initial imaging module, the speckles modulation module and the relay imaging module. Based on this model, we set up a GISC spectral camera prototype and show its optical layout in Fig. 2. The beamsplitter 1 splits 10% light energy to the inspection camera CCD5 and transmits 90% light energy to the spectral imaging system. The front and rear surfaces of it are coated so that only the light ranging from 410nm to 900nm is highly transmitted. The edge wavelength of 1# dichroic mirror 2 is 640nm which means the light fields with wavelength longer than 640nm are transmitted and those shorter than 640nm are reflected. The edge wavelengths of 2# dichroic mirror 3 and 3# dichroic mirror 4 are 500nm and 780nm. Added with four shortpass filters whose cutoff wavelengths are 500nm, 640nm, 780nm and 900nm, the whole system is divided into four subsystems covering the spectral band ranging from 410nm to 500nm, from 510nm to 640nm, from 650nm to 780nm, from 790nm to 900nm respectively. Each one is composed of the initial imaging module a, the speckles modulation module b and the relay imaging module c which are only marked for the subsystem from 510nm to 640nm. And the fore lens of the initial imaging module is shared by the four subsystems. In the following, the optical design method for the prototype is put forward taking example of the subsystem from 510nm to 640nm. The method for designing the other three subsystems is just the same.

The initial imaging module is designed to image the scene 1km away. The aperture size $D_0$ and focal length $f$ for the objective lens are 31mm and 100mm respectively. The diameter of the field stop is 3.1mm, so the system’s field of view angle is about $1.8^\circ$. The relay imaging module is used to image the speckles distribution in the speckles plane to the CCD’s detection plane. Its magnification factor is 5.2. The models for CCD1, CCD2, CCD3 are all ALTA F47, Apogee, Oxford Instruments. And the model for CCD4 is DU-934N-BRD, Andor, Oxford Instruments. The pixel sizes for the four CCDs are all 13 $\mu$m. Both these two modules belong to classical imaging system and their optical design can be done by common software for optical system design.

While the speckles modulation module is an imaging system based on ghost imaging principle which means that its spatial resolution and spectral resolution is determined by the second- order correlation of the optical intensity. The spatial phase modulator 10 is the main component of this module. It transforms each narrow banded point light source of different location in the initial image plane to one frame of speckles in the speckles plane by diffraction. The main task of the design is to determine the height distribution $h(r)$ for the spatial phase modulator, the distance $z_1$ from the spatial phase modulator to the initial image plane, and the distance $z_2$ from the spatial phase modulator to the speckles plane as shown in Fig. 1.

According to the literature [14], if the spatial phase modulator is Gaussian correlation random surface e.g. the
autocorrelation function of the height distribution is

\[ R_h (r_0, r_0') = \langle h(r_0) h(r_0') \rangle = \omega^2 \exp \left\{ - \left( \frac{r_0 - r_0'}{\zeta} \right)^2 \right\} = R_h (\Delta r_0) \] (1)

the spatial correlation function denoting the intensity correlation between two frames of speckles produced by the narrow-banded point source at \( r'_{i1} \) and \( r'_{i2} \) in the initial image plane can be approximated as

\[ g^{(2)}_{c} (r'_{i1}, \lambda_1; r'_{i2}, \lambda_2; r'_{i}) = \left\{ \frac{E_{c}^{*} (r; r'_{i1}, \lambda_1) E_{c} (r; r'_{i2}, \lambda_2)}{I_{c} (r; r'_{i1}, \lambda_1)} \right\}^2 = \exp \left\{ -2 \left[ 2\pi (n - 1) / \lambda_1 \right]^2 \right\} \times \omega^2 \left\{ 1 - \exp \left\{ - \left( \frac{z_2}{z_1 + z_2} (r'_{i1} - r'_{i2})^2 / \zeta^2 \right) \right\} \right\} \]

(2)

According to the principle of ghost imaging, the spatially distinguishable size \( \Delta r'_{i} \) equals to the FWHM for the spatial correlation function, thus

\[ g^{(2)}_{c} \left( \frac{\Delta r'_{i}}{2}, \lambda_1 \right) = 1/2 \] (3)

Suppose that the distinguishable size for the whole imaging system is \( r_s \), it is obvious that the inequality

\[ \Delta r'_{i} \leq r_s \] (4)

should be satisfied. By (2), (3) and (4), we can choose one of the initial solutions for \( \omega, \zeta \) and \( z_1, z_2 \). Then the height distribution \( h(r) \) for the spatial phase modulator can be generated by the algorithm in [16]. The phase retardation by the phase modulator \( \phi(r) \) can then be obtained according to the following equation

\[ \phi(r) = \frac{2\pi}{\lambda} \left( 1 - n \right) h(r) \] (5)

where \( n \) is the refractive index for the spatial phase modulator. By the Fresnel diffraction formula, we can calculate the optical intensity distribution in the speckles plane generated by the narrow-banded point source in the initial image plane. And the spectral correlation function [14] defined by (6) can be obtained from two frames of speckles with different center wavelength.

\[ g^{(2)}_{c} (\lambda_1, \lambda_2; r'_{i}) = \left\{ \frac{E_{c}^{*} (r; r'_{i}, \lambda_1) E_{c} (r; r'_{i}, \lambda_2)}{I_{c} (r; r'_{i}, \lambda_1)} \right\}^2 = \left\{ \frac{E_{c}^{*} (r; r'_{i}, \lambda_1) E_{c} (r; r'_{i}, \lambda_2)}{I_{c} (r; r'_{i}, \lambda_1)} \right\}^2 \] (6)

As the spectral resolution \( \Delta \lambda \) equals to the FWHM of the spectral correlation function, by setting

\[ g^{(2)}_{c} (\lambda_1, \lambda_2, r'_{i}) \approx g^{(2)}_{c} (\lambda_1 - \lambda_2, r'_{i}) = \frac{1}{2} \] (7)

we obtain the spectral resolution \( \Delta \lambda = 2(\lambda_1 - \lambda_2) \) for a certain set of \( \omega, \zeta \) and \( z_1, z_2 \) with \( r'_{i} \) and \( \lambda_1 \) given. Then the calculated spectral resolution should be compared with the desired spectral resolution. If the former is larger than the latter, \( \zeta \) is decreased with \( \omega \) fixed. Otherwise, \( \zeta \) is increased with \( \omega \) fixed. The spectral correlation function is calculated repeatedly with a new \( \zeta \) according to the steps above until it reaches the desired value. In general, when \( z_1 \) is changed slightly, the spectral resolution for the speckles modulation module is barely changed while the spatial resolution is significantly changed. So the spatially distinguishable size can be adjusted by changing \( z_1 \) to get the desired value.

The design parameter for the speckles modulation module covering the spectral band from 510nm to 640nm is at last produced to be \( \omega = 1.5 \mu m, \zeta = 20 \mu m, z_1 = 7.6 \mu m, z_2 = 2 \mu m \). With \( \omega, \zeta \) known, the height distribution \( h(r) \) for the spatial phase modulator is generated [16].

To make the speckles’ envelopes generated by different point light source overlap in the speckles plane, a field lens is placed in the focal image plane of the initial imaging module. It images the exit pupil of the initial imaging module to the speckles plane. As its object distance equals to the focal length \( f \) of the initial imaging objective lens, the image distance is the sum of \( z_1 \) and \( z_2 \), the magnification of the field lens is

\[ K = \frac{z_1 + z_2}{f} = \frac{7.6 + 2}{100} = 0.096 \] (8)

As the object diameter of the field lens equals to the aperture diameter \( D_0 \) of the initial imaging system, the image diameter in the speckles plane is

\[ D_1 = D_0 \cdot K = 31 \times 0.096 \approx 2.98 \mu m \] (9)

Thus the size of the spatial phase modulator is designed as \( 5mm \times 5mm \) including allowance. Then the spatial phase modulator can be made from fused silica glass by photoetching method.

**FIGURE 3.** The spatial correlation function at 590nm.

The spatial and spectral correlation functions at the wavelength of 590nm are shown in Fig. 3 and Figure 4. From Fig. 3, the FWHM of the spatial correlation function is \( l_1 \approx 12.5 \mu m \) which means that the spatially distinguishable size in the initial image plane is 12.5\( \mu m \). As the focal length of the initial imaging system is 100mm, the angle
resolution for the system is 125 µrad. This corresponds to the distinguishable size of 0.13m at the distance of 1km. From Fig. 4, the FWHM of the spectral correlation function is Δλ ≈ 40.9nm. This means that the spectral resolution at 590nm is 40.9nm.

III. CALIBRATION FOR THE PROTOTYPE OF THE GISC SPECTRAL CAMERA

The sensing matrix \( A \) [14] for the GISC spectral camera prototype is calibrated before imaging. As mentioned above, the elements of each column in \( A \) correspond to one frame of speckles generated by one narrow-banded point source \( I(x, y, \lambda) \) which is located in the object plane \((x, y)\). We set up a calibration system as shown in Fig. 5.

The broadband light field generated by the 300W xenon light source (Newport Corporation, 66984-300XF-R1) is at first focused into the monochrometer (BeiJing Optical Century Instrument Co., LTD) and the output narrow-banded light is then coupled into a few-mode optical fiber (Fiber-Home Telecommunication Technologies Co., Ltd.) whose core diameter is about 20 µm. The output end of the optical fiber is fixed onto a motorized high-precision two dimensional translation stage (Shanghai Lianyi optical fiber and laser instrument Co., LTD). And the output facet of the optical fiber is situated in the focal plane of a telephoto lens (Olympus Corporation, M.Zuiko Digital ED 40-150mm F2.8 PRO). Therefore the narrow-banded light emitting from the optical fiber is collimated by the telephoto lens. The effective focal length of the telephoto lens is set as 210mm by adding a converter lens. The focal plane of the telephoto lens is the effective object plane for an object infinitely far away. The interval between two adjacent pixels in the focal plane is set as 20.9 µm. Therefore the size of the calibrated pixel in the object plane is about 0.1m at the distance of 1km. According to the Nyquist sampling theorem, the smallest distinguishable size for the system should be no smaller than 0.2m at the distance of 1km. When the GISC spectral camera is exposed to the collimated narrow-banded light, the detector records one frame of speckles which correspond to one column of elements in the sensing matrix. By translating the optical fiber or adjusting the center wavelength, a different column of elements can be acquired. Taking advantage of the spatial shift-invariant characteristic of the system, the optical fiber is translated every eight pixels both in row and column direction, the speckles corresponding to each skipped pixel are interpolated by the speckles of the four measured pixels surrounding the skipped one. Thus the number of the frames of speckle to be measured is significantly reduced.

IV. SPARSE RECONSTRUCTION ALGORITHM FOR GISC SPECTRAL CAMERA

With the spectral image of the target denoted as a column vector \( X \), and the corresponding data image collected by the GISC spectral camera as \( Y \), one may have the following equation

\[
Y = AX + n
\]

where \( A \) is the fore-mentioned calibrated sensing matrix and \( n \) is the additive noise.

The theory of snapshot compressive hyperspectral imaging has been developed in [17], which states that,

**Theorem 1** [17]: Assume that \( \forall x \in Q, \|x\|_{\infty} \leq \frac{\delta}{2} \). Further assume the rate-\( r \) code achieves distortion \( \delta \) on \( Q \). Moreover, for \( i = 1, \ldots, B, D_i = \text{diag}(D_{i1}, \ldots, D_{in}) \), and
\( \{ D_y \}_{y=1}^{n} \overset{\text{i.i.d.}}{\sim} N (0, 1) \). For \( x \in Q \) and \( y = \sum_{i=1}^{B} D_i x_i \), let \( \hat{x} \) denote the solution of compressible signal pursuit optimization. Assume that \( \epsilon > 0 \) is a free parameter, such that \( \epsilon \leq \frac{16}{\pi} \).

Then,

\[
\frac{1}{n} \| x - x \|_2^2 \leq \delta + \rho^2 \epsilon
\]

with a probability larger than \( 1 - 2^{nB+1} \epsilon^{-n(\frac{\pi}{2})^2} \).

Details of this theory can be found in [17]. This theoretical finding strongly encourages our snapshot spectral imaging experiments by the spectral camera based on ghost imaging via sparsity constraints. Various algorithms have been developed to reconstruct the spectral cube from the measurement [18]—[21]. To exploit the sparse properties of the spectral image \( X \), we take into account its total variation (TV) [20] and nuclear norm (NN) [21] in the reconstruction process.

To define the TV of \( X \), first we rewrite it in a matrix form:

\[
X \overset{\text{mat}}{=} \begin{bmatrix} X_1 & \cdots & X_L \end{bmatrix}
\]

(12)

where \( X_i \) is the matrix corresponding to the narrow-banded image component of the spectral image with a center wavelength of \( \lambda_i \). Then we write the TV of \( X \) as:

\[
\| X \|_{TV} = \sum_{l=1}^{L} \| X_l \|_{TV}
\]

(13)

with

\[
\| X_l \|_{TV} = \sum_{0 \leq i,j,i-1,j-1 \leq N} \left( | x_{ij} \left( i,j \right) - x_{ij} \left( i-1,j \right) |^2 + | x_{ij} \left( i,j \right) - x_{ij} \left( i,j-1 \right) |^2 \right)^{1/2}
\]

(14)

where the summation should be interpreted in such a way that whenever \( 0 \leq i,j,i-1,j-1 \leq N \) is not satisfied the corresponding squared terms vanish.

To define the NN of \( X \), we need to use the vector form of \( X_i \), denoted as \( X_i^{vec} \). Then one may have the singular decomposition

\[
U^\dagger \begin{bmatrix} X_1^{vec} & \cdots & X_L^{vec} \end{bmatrix} V = \Sigma,
\]

(15)

where \( U, V \) are unitary matrices, \( \Sigma \) diagonal and \( U^\dagger \) is the conjugate transpose of \( U \). The NN of \( X \), denoted as \( \| X \|_s \), is defined as the sum of the diagonal elements \( \sigma \left( k \right) \), \( k = 1, \ldots, L \) of \( \Sigma \):

\[
\| X \|_s = \sum_{k=1}^{L} \sigma \left( k \right)
\]

(16)

Based on the above description, we may formulate the reconstruction as the following optimization problem:

\[
X = \arg \min_{\tilde{x}} \| Y - A \tilde{x} \|_2^2 + \mu_1 \| X \|_{TV} + \mu_2 \| X \|_s,
\]

s.t. \( x \geq 0 \)

(17)

where \( \mu_1, \mu_2 \) are non-negative real parameters. The problem generally has to be solved using an iterative algorithm. We here adopted the gradient projection algorithm [22], [23].

\section*{V. THE EXPERIMENTAL RESULTS ON TETHERED BALLOON}

The prototype of GISC spectral camera is loaded on the tethered balloon via a stable platform to conduct snapshot spectral imaging. Fig. 7(a) and Fig. 7(b) respectively shows the distant view and close view for the GISC spectral camera prototype. In Fig. 7(b), the white rectangle box is the GISC spectral camera prototype and the grey instrument connected to it is the stable platform. The GISC spectral camera prototype is set to look towards the ground 45° downward. To evaluate the spatial resolution, the linearity of response and the accuracy of the reconstructed spectra, several test targets are laid on the ground. They include one three-line target 1, one sector target 2, six grey scaled targets 3 and eight color targets 4 as shown in Fig. 8 and Fig. 9. Fig. 8 is obtained on the tethered balloon by the inspection camera which shares the objective lens with the GISC spectral camera on the ground. Fig. 9 is captured by the mobile phone camera. Among all the test targets, only the sector target is laid 45° upward so that the prototype can look at it perpendicularly.

\section*{FIGURE 8. The monochrome image for the test targets.}

After the targets are photographed by the prototype, the spectral images are reconstructed by the sparse reconstruction algorithm. The spectral images of three spectra bands ranging from 410nm to 500nm, from 510nm to 640nm, from 650nm to 780nm are reconstructed independently. The result is shown in Fig. 10. The spectral intervals for all spectra bands are 10nm. The pixel number of one reconstructed image for a certain wavelength channel is 337 × 337. Together with the wavelength channel numbers, the dimensions of \( X \) in (8) for these spectra bands are 1,135,690;
1,589,966 and 1,589,966 respectively. The detection pixel numbers of the CCDs e.g. the dimensions of $Y$ in (8) are all 640,000. And the corresponding dimensions of $A$ in (8) are 640, 000 × 1, 135, 690; 640, 000 × 1, 589, 966 and 640, 000 × 1, 589, 966 respectively. The performance of the subsystem from 790nm to 900nm are degraded by some dirts on the surface of the filed lens. So the reconstructed spectral images in this spectra band are not so good and they are omitted here. Fig. 11 shows the synthesized color image by choosing three spectral channel 440nm, 550nm, 700nm representing the three basic color.

To evaluate the spatial resolution, the sector target and three- line target are imaged alone. The reconstructed image for the sector target at 590nm is analyzed as an example. As shown in Fig. 12, plot several arcs at the different arc radius on the sector target image and the arc length is chosen as to cover five consecutive bright stripes. Plot the intensity distribution along the arcs and count the number of peaks which represent the number of bright stripes distinguishable. As shown in Fig. 13, when the arc radius decrease from length of 13pixels to 12pixels the number of peaks declines from five to three. Choose five arcs with the same arc radius at different start point. The arc radius that five bright stripes can just be distinguished is 12.1 pixels by average. As the angle between the center lines of the two adjacent bright stripes for the sector target is $16^\circ$, the corresponding arc length at the arc radius of 12.1pixels is 3.4 pixels. According to the calibration result, the size of one pixel in the reconstructed image corresponds to 0.1m at the distance of 1km. So the distinguishable size at the distance of 1km for the prototype at 585nm is 0.34m. Recalling that the designed distinguishable size at 1km is 0.13m and the distinguishable size limited by the size of the calibrated pixel is 0.2m, the actual distinguishable size result of 0.34m tested by sector target is determined more by the size of the calibrated pixel.
The same analysis procedure for the reconstructed images of sector targets at other bands is conducted. The largest distinguishable size is 0.35m and the smallest one is 0.32m among all the bands. The linearity is tested by six grey scaled targets with different reflectance. In Fig. 8, the nominal reflectance for the chosen five grey scaled targets labeled with a to f is 0.7, 0.6, 0.6, 0.4, 0.2, 0.05 respectively. As the signal to noise ratio (SNR) for the data of the grey target with the nominal reflectance of 0.05 is not high enough, this data is not included in the calculation of the linearity of the system response. In experiment, the actual spectral distributions for these grey scaled targets are tested by the spectrometer on the ground. From these detected spectral data, the spectral irradiance luminance $L(\lambda)$ at the input aperture of the prototype can be calculated by the software Modtran (MODerate resolution atmospheric TRANsmission). Denotes the digital value of the pixels in the corresponding reconstructed image as $DN(\lambda)$. With $L(\lambda)$ set as the input for the prototype and $DN(\lambda)$ chosen as the system response, the correlation coefficient $C$ which denotes the linearity of the system response can be acquired by the following equation

$$C_k = \frac{\sum_{i=1}^{n} (L_{i,k} - \bar{L})(DN_{i,k} - \bar{DN})}{\sqrt{\sum_{i=1}^{n} (L_{i,k} - \bar{L})^2} \sqrt{\sum_{i=1}^{n} (DN_{i,k} - \bar{DN})^2}}$$  \hspace{1cm} (18)$$

where $k$ denotes different wavelength, $i$ denotes different grey sector and $n = 5$ corresponds to the five grey sectors with the nominal reflectance of 0.7, 0.6, 0.6, 0.4, 0.2. It can be seen from Fig. 14 that the linearity is higher than 0.99 for the band ranging from 410nm to 500nm and the band ranging from 510nm to 640nm. The linearity is relatively lower in the band ranging from 650nm to 780nm. This is probably because the signal to noise in this band is lower as is evaluated from Fig. 10.

To test the accuracy for the spectral reconstruction, the reconstructed spectra for the color targets is compared with the spectra measured by a commercial spectroradiometer (Spectra Vista Corporation, HR-1024i). The radiometric calibration accuracy for the instrument is about ±5% in the spectral band ranging from 400nm to 750nm. The spectral resolution of it is superior to 3.5nm. The comparison result for the spectral distributions is shown in Fig. 15(a-h).

To quantitatively evaluate the spectra reconstruction error, we calculate the RRMSE of spectral distribution for a certain color target

$$RRMSE = \sqrt{\frac{\sum_{i=1}^{N} (R(i) - \bar{R}(i))^2}{N}}$$  \hspace{1cm} (19)$$

where $R$ denotes the spectra reconstructed by the GISC spectral camera and $R'$ denotes the spectra measured by the spectroradiometer, $i$ denotes different wavelength and $N = 38$ denotes the whole number of wavelengths reconstructed. Fig. 16 shows the RRMSE result for eight color targets. The average RRMSE for the eight color targets is 0.65.
The spectra reconstruction error is probably resulted from the low signal to noise ratio for the raw data, the calibration error and the error brought about by the algorithm.

In addition to the artificial test targets, the prototype of GISC spectral camera has also imaged many natural scenes. For example, Fig. 17 shows one scene including vehicles, concrete ground and trees captured by the inspection camera. Fig. 18 shows its spectral images reconstructed by the GISC spectral camera. It indicates that the prototype has the capability of snapshot spectral imaging for natural scenes.

VI. CONCLUSION AND OUTLOOK
FOR THE FUTURE WORK

As a phase modulated compressive snapshot spectral imager, the GISC spectral camera makes use of the second-order intensity correlation of the light field to resolve spatial and spectral information. It has the advantage of high throughput of light energy and high information acquisition efficiency. In this paper, the method of the optical design for the GISC spectral camera is proposed especially for the speckles modulation module. It designs the random phase modulator as a Gaussian correlation random surface characterized by two statistical parameters $\omega$ and $\zeta$ where the former denotes the spatial correlation size and the latter denotes the height fluctuation intensity. The spatial resolution and spectral resolution for the speckles modulation module can be adjusted incorporating $\omega$, $\zeta$ with $z_1$, $z_2$. For example, the angle resolution of $125\mu$rad and the spectral resolution of 40.9nm at 590nm have been obtained when $\omega = 1.5\mu$m, $\zeta = 20\mu$m, $z_1 = 7.6mm$, $z_2 = 2mm$.

The strategy of calibration for the GISC spectral camera is introduced. A few-mode optical fiber generating uniform point-shaped light is selected to increase the calibration accuracy. A monochrometer is used to offer the freedom of choosing the center wavelength and the linewidth.

The prototype of GISC spectral camera is set up and the snapshot spectral imaging experiment for the test targets and natural scenes is conducted with the prototype loaded on the tethered balloon. By analysis for the spectral image of the test targets, the distinguishable size at the distance of 1km is around 0.34m for most bands. The linearity is higher than 0.99 for the band ranging from 410nm to 500nm and that from 510nm to 640nm. The reconstructed spectral distributions are compared with the data measured by the commercial spectroradiometer. The RRMSE of the reconstructed spectral distributions for eight different color targets are analyzed. The average RRMSE for the eight color targets is 0.65. The spectral imaging result for natural scenes verifies the feasibility of remote sensing for this kind of snapshot spectral imager. Next we will try to improve the spectra reconstruction accuracy.

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