LED-BASED COMPRESSIVE SPECTRAL TEMPORAL IMAGING

by

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ABSTRACT

A new compressive spectral temporal imaging system is proposed to obtain a four dimensional (4D) spectral and temporal image cube. A multi-spectral Light-Emitting Diode (LED) array is applied for target illumination and spectral modulation while a digital micromirror device (DMD) encodes the temporal image frames. High frame-rate spectral video is recovered from successive compressed measurements captured on a RGB sensor. Computer simulations are performed based on the developed forward model. The imaging system is optimized through the design of the DMD patterns. A laboratory implementation is further conducted to validate the performance of the proposed imaging system.

Chapter 1 INTRODUCTION

High frame-rate video recording poises challenging hardware requirements such as faster acquisition, larger memory buffers, and broader bandwidths. These demands are only amplified if, in addition, the spectral content in the video scenes are also of interest. Multi-spectral sensing usually requires spatial or spectral scanning thus temporal resolution is seriously sacrificed. Compressive sensing (CS) has recently been used to overcome these limitation without increasing the system volume or power requirements [1]. Compressive sampling is based on the a-priori knowledge that the underlying signals are sparse or compressible in some transform domain, allowing the entire signal to be reconstructed from relatively few measurements. Spectral video streams not only exhibit strong inter-voxel correlation in space and time but along the spectral dimension as well and thus are amenable to compressive sampling.

Fundamental to the principles of CS are coded projections where high-dimensional data streams are coded and projected onto detectors spanning lower dimensions. Coding strategies, as such, play a key role in any CS imaging system. Several coding mechanisms have been proposed to sample video signals including spatial light modulators [2] that enable dynamic coded apertures, strobe shutters [3] to temporally code the incoming optical field, and dispersive elements [4, 5] used in concert with coded apertures to code spectral data cubes.

Compressive measurements for dynamic imaging, record a coded dynamic scene into a sequence of detector array snapshots, from which many more video frames can be recovered. The coded aperture compressive temporal imager (CACTI) [6] was introduced recently which uses a harmonically driven binary coded aperture during the exposure of a video capture. In this way, each temporal frame in the video sequence is modulated by a shifted version of the code. Decoding of the signal is subsequently done using one of many reconstruction algorithms available in compressive sensing where multiplexed temporal frames are separated from the compressed measurements [1, 5, 7, 8, 9]. CACTI can be generalized by using a dispersive element to spectrally modulate the optical source. Spectral coding is done by a coded aperture and a dispersive element placed after coded aperture modulation. The detection integrates the coded spectral planes. The video stream can be recovered by isolating each spectral plane based on its local code structure.

Given that optical coding is at the heart of CACTI and its multi-spectral camera extension, one may ask if there are other efficient approaches to realize optical coded projections of spectral video streams, in addition to mechanical movement of coded apertures. This is in fact the case if one exploits light emitting diode (LED) structure illumination. In this case, the coding builds on the concepts used in LED illumination multi-spectral cameras which sequentially capture images of a scene under n different color LED lights, thus producing an n-band spectral image of the scene. The multi-spectral data cube is thus built by sequentially scanning the cube along the spectral dimension.

In this thesis, a novel compressive spectral temporal imaging system is proposed, optimized, and implemented for the high speed acquistion spectral temporal images. Different from traditional compressive spectral imaging systems [5, 10, 11], the newly proposed LEDbased imaging systems [12, 13, 14] employ an active multi-spectral LED array without the use of any dispersive element or spatially varying color filters. Multi-spectral LED has been successfully implemented in spectral imaging systems for static scenes. Without dispersive elements, each pixel in the sensor integrates the whole spectral range of the same pixel without dispersive limitation. In [7], the spectral resolution is limited by the LED illumination types. We compare the use of traditional discrete cosine transform (DCT) [5, 6, 10] spectral basis and trained Munsell principal component analysis (PCA) [15] spectral basis. With the help of Munsell PCA training, better reconstruction results can be achieved. Multi-spectral LEDs, spectral-video was used to capture a reduced frame-rate sequence in [13]. To increase the temporal resolution for dynamic scenes, a DMD is adopted in our system for spatial temporal coding. The proposed imaging architecture consists of an active multi-spectral LED illumination, a DMD on the focal plane, an objective lens, a relay lens and a Bayer RGB sensor. During a measurement snapshot, multi-spectral LEDs are selectively turned on for spectral illumination, while the DMD rapidly alters its pattern for temporal coding. The RGB sensor then compresses multiple coded temporal images into a single 2D projection. Compressive sensing theory is then used to recover a high frame-rate spectral video from a set of successively collected low-rate measurement frames.

This sensing process is studied through the development of a forward model and its corresponding sensing matrix. Based on the forward model, computer simulations with laboratory measured data cube is then performed where random block-unblock DMD patterns and random LED selections are applied. To improve the reconstruction quality, a good design on DMD and LED coding is necessary. Several DMD coding patterns are compared in [2] for their performances in compressive temporal imaging systems. We further propose the use of multi-frame blue noise patterns [16] for DMD coding in this spectral temporal imaging system. Compared with traditional Bernoulli random coding patterns, the blocking and unblocking pixels on the multi-frame blue noise binary patterns are more evenly distributed [17]. All the coding frames are complementary to each other which generates a better conditioned sensing matrix [18]. The LED illumination pattern selection is then optimized based on the spectral distribution of each type of LED. The synchronization of the LEDs, the DMD, and the camera sensor is then performed for a laboratory testbed implementation. High frame-rate spectral video is then recovered from these testbed measurements. With the proposed imaging system, high temporal resolution spectral video can be recovered with a common RGB video camera, aided by the DMD and the muti-spectral LEDs. This enables several possible applications [14, 19, 20].

The main contributions of this thesis are summarized below: First, a novel compressive spectral temporal imaging system is proposed to acquire a 4D spectral temporal image cube. Second, the performance of different types of spectral sparse representations are compared under the proposed imaging design. Third, the performance of the proposed system is analyzed through computer simulations and improved via the optimization on DMD coding patterns and the selection on LED types combinations. Finally, the synchronization of field-programmable gate array (FPGA) controller is built to capture the continuous moving target with a dynamic multi-spectral LED array, a multi-dimensional coding DMD and a RGB camera. With the synchronization system, the newly proposed imaging system is implemented in the optical testbed. Compressive sensing reconstruction is performed from the raw measurement data.

Chapter 2

SYSTEM FORWARD MODEL

2.1 Imaging via compressive sensing

Natural scenes usually have correlation between neighborhood spectral bands and among video frames. As such it is possible to represent spectral and temporal images in some given bases, with only a small number of non-zero coefficients are needed. The sparsity of the spectrum and the redundancy on temporal domain enables the applications of compressive sensing in spectral and temporal imaging systems. The sensing procedure can be written as:

$$\mathbf{g} = \mathbf{H}\mathbf{f},\tag{2.1}$$

where **H** is the forward matrix of the imaging system. Denote the vector **f** as the collection of the desired image cube, and **g** as the vector formed by the CCD measurements. With a fine selected basis Ψ , **f** can be represented as

$$\mathbf{f} = \boldsymbol{\Psi}\boldsymbol{\theta},\tag{2.2}$$

where the coefficients vector θ is sparse. The imaging process can be rewritten as

$$\mathbf{g} = \mathbf{H}\boldsymbol{\Psi}\boldsymbol{\theta} = \mathbf{A}\boldsymbol{\theta},\tag{2.3}$$

where, the sensing matrix $\mathbf{A} = \mathbf{H} \boldsymbol{\Psi}$.

To solve the inverse problem in Eq. (2.3), many reconstruction algorithms [1, 5, 7, 8, 9] can be applied.

Since LED illumination is used in the proposed imaging system, we will introduce the LED array at Chapter 2.2. Then the forward sensing process of LCSTI is described Chapter 2.3. The sparse representations are illustrated in Chapter 2.4. Finally, the system resolution is discussed in Chapter 2.5.



Figure 2.1: LED spectral distributions varying over wavelength. The spectra of LEDs overlap in the 420-680 nm wavelength range.

2.2 LED illumination

To obtain the spectral information of a scene, a multi-spectral LED array is applied as illumination patterns in the imaging system. The LED illumination we prototyped consists of 8 different types of LED with different visible spectral distributions. Thus, the LEDs not only provides illumination, but also produces the spectral modulation. There are totally thirty LED evenly distributed on a printed circuit board (PCB). Figure 2.1 shows the spectral intensity distributions of 8 types of distributions.

The LED illumination is controlled by a FPGA controller. The intensity can be changed through voltage level change for each type of LED. In our system, the LED control unit turns on certain types when each image frame is sensed.

2.3 System model

The proposed compressive imaging architecture is described below. LED illumination provides the illumination on the target with the spectral modulations. The spectral modulation is created through random selection of few types of LEDs. The reflections of a scene reach the DMD through the objective lens. The DMD projections modulate each



Figure 2.2: The testbed of LCSTI system.

temporal frame with a different set of block-unblock coding patterns. The DMD reflection is then collected by a RGB sensor. In the testbed of Fig. 2.2, a monochrome sensor is used. Thus, Red, Green and Blue filters are placed sequentially before imaging lens to simulate a Bayer filter. Through the whole sensing process, the system compresses a 4D scene onto a 2D Bayer measurement.

In the sensing process, shown in Fig. 2.3, we denote the 4D scene as data cube $f(x, y, \lambda, t)$, where x and y are the dimensions on spatial domain, λ is the dimension on spectral domain and t represents time. As the LED illumination and DMD patterns change over time, the LED illumination can be modeled as $S(\lambda, t)$, while the DMD coding is represented as C(x, y, t). $B(x, y, \lambda)$ is the Bayer filter distribution for the RGB sensor. The DMD and RGB sensor shares the same pixel size in our system. A compressed measurement on the sensor is given by

$$g(x,y) = \int_t \int_\lambda f(x,y,\lambda,t) S(\lambda,t) C(x,y,t) B(x,y,\lambda) \,\mathrm{d}\lambda \,\mathrm{d}t.$$
(2.4)

The discrete representation of the 4D data cube can be written as

$$f_{mnkj} = \int_{t_j}^{t_{j+1}} \int_{\lambda_k}^{\lambda_{k+1}} \iint_{\Omega_{mn}} f(x, y, \lambda, t) \, \mathrm{d}x \, \mathrm{d}y \, \mathrm{d}\lambda \, \mathrm{d}t, \tag{2.5}$$

where m and n show the coordinate of the sensor. Ω_{mn} is the pixel size at sensor (m, n), while k indicates the spectral bands, and j represents temporal frame. The LED modulation can be written as

$$s_{kj} = \int_{t_j}^{t_{j+1}} \int_{\lambda_k}^{\lambda_{k+1}} S(\lambda, t) \,\mathrm{d}\lambda \,\mathrm{d}t.$$
(2.6)

Similarly, the DMD coding is represented in discrete form as

$$c_{mnj} = \int_{t_j}^{t_{j+1}} \iint_{\Omega_{mn}} C(x, y, t) \,\mathrm{d}x \,\mathrm{d}y \,\mathrm{d}t.$$

$$(2.7)$$

Additionally, the discrete form of the Bayer filter is written as

$$b_{mnk} = \int_{\lambda_k}^{\lambda_{k+1}} \iint_{\Omega_{mn}} B(x, y, \lambda) \, \mathrm{d}x \, \mathrm{d}y \, \mathrm{d}\lambda.$$
(2.8)

Based on Eq. (2.5) - (2.8), the Eq. (2.4) can be discretized as

$$g_{mn} = \iint_{\Omega_{mn}} \int_{\lambda} B(x, y, \lambda) \int_{t} S(\lambda, t) C(x, y, t)$$

$$f(x, y, \lambda, t) dt d\lambda dx dy$$

$$= \iint_{\Omega_{mn}} \sum_{k} \int_{\lambda_{k}}^{\lambda_{k+1}} B(x, y, \lambda) \sum_{j} \int_{t_{j}}^{t_{j+1}} f(x, y, \lambda, t) S(\lambda, t) C(x, y, t) dt d\lambda dx dy$$

$$= \sum_{j}^{F} \sum_{k}^{L} f_{mnkj} s_{kj} c_{mnj} b_{mnk},$$
(2.9)

where g_{mn} represents the sensing data collected by the sensor. F and L indicate the number of spectral bands in our system and number of frames per measurement respectively.

After vectorizing the data cube and the measurement data as f and g, the sensing process in one measurement can be written in the form of Eq. (2.1). Here the forward matrix H represents the effects of the LED, DMD and Bayer modulations. The vector form of the DMD coding is represented as

$$\mathbf{c_j} = [c_{11j}, c_{21j}, ..., c_{12j}, ..., c_{MNj}]^T.$$
(2.10)

Similarly, the vector form of the Bayer filter is written as

$$\mathbf{b}_{\mathbf{k}} = [b_{11k}, b_{21k}, \dots, b_{12k}, \dots, b_{MNk}]^T.$$
(2.11)



Figure 2.3: Compressive sensing process with spectral modulation, binary coding and Bayer filter. The scene is modulated in its spectral and temporal dimensions from t_1 to t_4 and compressed onto the Bayer sensor.

Then, the matrix **H** is written as

$$\mathbf{H} = [s_{11}diag(\mathbf{c_1} * \mathbf{b_1}), s_{21}diag(\mathbf{c_1} * \mathbf{b_2}), \dots, s_{LF}diag(\mathbf{c_F} * \mathbf{b_L})],$$
(2.12)

where c_j is vectorized spatial coding for a temporal frame j, and b_k is the Bayer filter distribution on a spectral band k. $c_j * b_k$ represents the element-wise product of c_j and b_k . M, N are the spatial resolution of sensor and DMD, and L, F are the number of bands and number of frames. Let $V = M \times N$, then H has the dimensions of $V \times VLF$. In order to visualize the matrix H, a test data cube with 6×6 (M = 6, N = 6) pixels, three spectral bands (L = 3) and two temporal frames (F = 2) is used. The corresponding H matrix is shown in Fig. 2.4. The values in this figure are between 0 and 1. The Bayer filter arrangement can be found in Fig. 2.3. The LED modulations vary by spectral bands and frames. The spatial codings for each frame are changed by the DMD.

2.4 Sparse representations and data cube recovery

As discussed in Chapter 2.1, the data cube f can be represented as $f = \Psi \theta$. Here we apply a Kronecker basis $\Psi = \Psi_1 \otimes \Psi_2 \otimes \Psi_3 \otimes \Psi_4$, where $\Psi_1 \otimes \Psi_2$ provides the 2D Wavelet basis in spatial domain, Ψ_3 and Ψ_4 represent discrete cosine transform (DCT) in the temporal domain and Munsell PCA in the spectral domain.

While many compressive spectral imaging systems use the DCT basis for spectral sparse representations, a spectral sparse basis trained by PCA is used here to reach higher resolution and spectral precision. The PCA spectral basis can be trained by color sets in the



Figure 2.4: Forward matrix **H** for a 6 by 6 spatial area with 3 spectral bands and 2 temporal frames. In a forward matrix, a 6 by 6 spatial modulation at a temporal frame, with 3 bands spectral modulations by a LED pattern and a Bayer filter, is vectorized and diagonalized in a 36×36 area. In a temporal frame, all three bands share the same spatial coding, but with different spectral modulations. The first and second frame show different spatial modulations and different LED modulations.

visible range [15]. The Munsell color with 1269 color chips shown in Fig. 2.5(a) [15] and its spectral distributions are shown in Fig. 2.5(b). The Munsell spectra set [21] is used for PCA calculation. The spectral mean μ and the sparsity basis Ψ_4 are generated from the training data set. μ is used for centering the spectrum of targets. After the employment of PCA, the representation of f in Eq. (2.2) can be rewritten as

$$\mathbf{f} = \boldsymbol{\mu} + \boldsymbol{\Psi}\boldsymbol{\theta}.\tag{2.13}$$

Substituting Eq. (2.13) in Eq. (2.3),

$$\mathbf{g} = \mathbf{H}\boldsymbol{\mu} + \mathbf{A}\boldsymbol{\theta}.\tag{2.14}$$

The sensing process expressed in Eq. (2.14), can be solved inversely as

$$\hat{\theta} = \arg\min_{\theta} ||\mathbf{y} - \mathbf{H}\boldsymbol{\mu} - \mathbf{A}\boldsymbol{\theta}||^2 + \lambda |\boldsymbol{\theta}|_1, \qquad (2.15)$$

where θ is recovered to minimize this $l_1 - l_2$ cost function, λ is a regularization constant. We applied the gradient projection sparse reconstruction (GPSR) [8] algorithm to solve the equation above in our system.

2.5 Discussion on the system resolution

Compressive imaging systems usually capture dimensionality reduced measurements. In these imaging systems, the capability of resolution reconstruction becomes critical. For



Figure 2.5: (a) The Munsell 1269 color chips. (b) The reflection spectra of 1269 colors. The spectral mean is generated by the average of these 1269 color spectra, and the principal components are calculated and used as spectral sparse basis Ψ_4 .

example, DMD based compressive imaging systems [3, 22] have their spatial resolution limited by the resolution of DMD and sensor. In our system, the digital devices play a more important role since they also control the temporal coding speed, and the detail timing sequences are shown in Chapter 5.2. Thus, the temporal resolution, or called the frame-rate in video system, is limited by the control system's frequency speed, sensor speed, LED speed and DMD speed. If we assume the frame-rate of the sensor is R_s , From Eq. (2.9) we know that the system frame-rate

$$R = R_s \times F. \tag{2.16}$$

In dispersive element-based imaging systems, the continuous spectrum is divided into spectral bands, according to the dispersion onto sensor pixels. Multi-spectral LED-based imaging systems sense the whole spectrum in each pixel. Several approaches using a small number of LED types reconstructed a large number of spectral bands [13, 12], relying on the smoothness of spectrum. To further verify the spectral recovery capability of the multi-spectral LED system, we compare the Munsell PCA spectral basis with DCT in Chapter 3.4.

Chapter 3

SIMULATION

3.1 Data cube acquisition process

To study the performance of the LCSTI system, a 4D data cube was acquired by illuminating the scene with a visible monochromator. Figure 2.1 shows the multi-spectral LED illumination distributions from 420 to 680 nm wavelength. Therefore, twenty-seven spectral image bands are captured from 420 to 680 nm central wavelength at 10 nm interval on a 9.9 μ m monochrome CCD camera. In the temporal domain, the dynamics of the scene are simulated by smoothly moving a toy with a nanopositioner for 32 frames. The resulting data cube has 256×256 pixels of spatial resolution, 27 spectral bands and 32 temporal frames. In this way, a $256 \times 256 \times 27 \times 32$ data cube is obtained. Figure 3.1(a)-(c) show three images, in the same temporal frame and selected spectral bands. The central wavelength is used to represent each band. Figure 3.1(d)-(f) show 520 nm spectral band images in three different frames.

3.2 Simulated process

The simulated measurements are constructed by employing random DMD mask patterns with 50% transmittance. Four different types of multi-spectral LEDs illuminate the scene at each temporal frame. The Bayer RGB sensor captures measurements at video rate from 15 frames per second (fps). Note that the Bayer sensor is simulated using real RGB curves [23]. Since all L spectral bands are integrated on the focal plane array (FPA), the spectral compression is L : 1. From each snapshot, F temporal frames are recovered. Then the compression rate in the temporal domain is F : 1. Thus, the imaging system has a compression of LF : 1. In the simulations, if K = 4 snapshots were applied to recover $N_{ft} = 32$



Figure 3.1: (a)-(c) Selected 3 spectral band images from total of 27 spectral bands at 18th temporal frame. Colors have different intensity at different bands. (d)-(f) Selected 3 images at 570 nm spectral band of different temporal frames. The Lego figure moves from left to right in an uniform speed.

temporal frames in L = 27 spectral bands, the compression is then $N_{ft}/K * L : 1 = 216 : 1$. Figure 3.2 illustrates 2 measurement snapshots captured on the FPA.

3.3 Reconstruction

Reconstruction results are shown in Fig. 3.3 with selected spectral bands and selected temporal frames. Four snapshots are applied for 32 temporal frames. The scene is assumed being measured at 15 fps, with random LED selections and random DMD codings. The average PSNR for the reconstruction is 26.66 dB with 120 fps. The system can achieve a higher frame-rate of 240 fps with higher compression 432:1, when setting F = 16. This provides an average PSNR 24.19 dB. With further compression to 864:1, 480 fps spectral video is recovered at 22.56 dB average PSNR. Both spectral and temporal image bands are successfully separated. However, spatial blur can be observed on the edges of the moving targets. To overcome these blurring artifacts, complementary blue noise aperture coding is further proposed in Chapter 4.



Figure 3.2: Two selected FPA measurement snapshots. The clear Bayer coding texture can be observed. The Lego figure shows blur, because of several temporal frames are compressed in a measurement, but the still background targets show clear edges.

3.4 Comparation of different spectral sparse bases

To test the capability of spectral reconstruction, Munsell PCA basis compares with DCT spectral basis with a data cube having a peak at 490 nm. The comparisons are conducted with frame-rate F = 8, with same LED selections and DMD codings. The reduced spectral resolution data cube is created by averaging neighbor spectral bands. Two points P1, P2 in Fig. 3.4 of the 4th temporal frame image are selected to compare the results for spectral responses, one is at the moving target of the Lego helmet, another one is at the still target of the toy sun. Spectrum responses of these two points are compared in Fig. 3.5 with basis, DCT, Munsell PCA and peak added Munsell PCA. The peak is added in Munsell spectra data by the same method as in the data cube to train the spectral basis. According to the spectral responses in Fig. 3.5(b), Munsell PCA basis can relative recognize the added peak, when only 8 bands are reconstructed. However, the peak can be reconstructed with higher spectral resolution trained by the peak added Munsell data set. In Fig. 3.5(d), peak only can be reconstructed by the spectral basis trained by the peak added Munsell data set. Thus, the PCA basis can achieve better spectral responses when the spectra are smooth. Second, if the training data is similar enough with spectrum in the scenes, a much better result can be achieved. In visible spectral range, Munsell color set is sufficient to train the spectral basis.



Figure 3.3: Selected 6 spectral bands, 4 temporal frames images from 27 spectral bands 32 temporal frames 4D image reconstruction, and corresponding 4 temporal RGB images merged by reconstruction image cube to compare with 4 temporal RGB images merged by original image cube. The scene is successfully measured by LCSTI system.



Figure 3.4: Two selected points for spectral comparisons.



Figure 3.5: The spectral response comparisons for different spectral sparse bases, DCT, Munsell PCA, and Peak added trained PCA. (a) The comparison of the spectral responses with 8 bands. The capability of Munsell PCA as good as DCT. (b) The comparison of the spectral responses with peak added 8 bands data cube. Munsell PCA basis with peak add data training best reconstructed on spectral. (c) The comparison of the 27 bands spectral responses. Munsell PCA basis gives us higher precision than DCT. (d) The comparison of peak added data cube with 27 bands. Munsell PCA basis with peak add data training perfectly reproduce the spectral response.

Chapter 4 DMD CODING DESIGN

In Fig. 3.3, the recovered results show strong blur on the edge of the moving target. It is because that, in Fig. 4.1(a), the spatial coding with large clusters fail to distinguish the sharp changes between neighbor pixels in a single compressed snapshot, resulting in poor edge reconstruction.

Blue noise coding is one kind of high frequency coding and well recognized for its use in halftoning [24]. In coded aperture compressive imaging systems, efforts have been made on designing aperture coding with fewer clusters. In compressive temporal imaging, the normalized aperture codings are proposed against random codings [25]. These normalized codings guarantee uniform sensing for each spatial pixel, however they do not maximize the power of high frequency information. On the other hand, blue noise binary patterns reserve both randomness and high frequency properties, making them as a good alternative to the random white noise aperture coding. Pixel sensing uniformity is achieved through the application of multi-layer blue noise [16]. These blue noise binary patterns were applied in the design of spatial-polarization and spatial-spectral coding patterns [26, 27] to outperform the random coding in different compressive spectral imaging systems. The comparison of a 50% white coding and a blue noise coding are shown in Fig. 4.1. In the Fig. 4.1(b), the clusters are obviously reduced. Furthermore, the implementation of multi-layer blue noise produces complementary blue noise codings. For instance, if there are 8 temporal frames compressed in a snapshot, 8 unique and not overlapped blue noise codings with 12.5% transmittance are produced.

One compressed snapshot is simulated with blue noise aperture coding to compare with the random ones. The reconstruction results with complementary blue noise coding gives us 1.94 dB better PSNR compared with 50% white coding ones. To further show the



Figure 4.1: The comparison of (a) a 50% white coding and (b) a complementary blue noise coding. Compare (b) to (a), instead of crowing together, the opening points are even distributed.

benefit of blue noise coding, the 4th temporal frame's mean-square error (MSE) is compared between 50% white noise coding and complementary blue noise coding in Fig. 4.2. Compare Fig. 4.2(d) to Fig. 4.2(c), the error around the edge of moving target is significantly reduced by using complementary blue noise coding.



Figure 4.2: (a) The 4th temporal frame reconstruction with 50% white noise codings. . Motion blur occurs in the zoomed part. (b) The 4th temporal frame reconstruction with complementary blue noise codings. And the motion blur is highly reduced in the zoomed part. The comparison of (c) MSE of white noise coding between (d) MSE of complementary blue noise coding shows the error reduced around edges.

Chapter 5

EXPERIMENT

5.1 Experimental testbed setup

The experimental testbed setup is shown in Fig. 2.2. LUXEON[®] Rebel Color LEDs are used in our system. The PCB boards in Fig. 5.1(a) are designed to align the LEDs, giving the system illumination with spectral modulations. The DMD model is LC4500, from Keynote PhotonicsTM. The monochrome sensor is BOBCAT B2021M from IMPERXTM Inc., supporting synchronization control. The color filters are the common RGB color filters. To repeat experiments with different filters, an accurate rotating rotor from Thorlabs Inc. is adopted in the system as a target, which is shown in Fig. 5.1(b).

5.2 The synchronized sensing

The LCSTI system relies on several electrical controllable devices listed in Chapter 5.1. To capture a continuous moving target, a synchronization system needs to accurately control the devices on time. Hence, a high speed FPGA controller is used to send spectral coding patterns (a binary code) to the LEDs, to send raising and falling sync signals to the DMD, the sensor and the target. The devices start to work at the raising signal and stop working at the falling signal. The timing sequences for one snapshot having 4 temporal frames are shown in Fig. 5.2. Before starting the procedure, binary spatial codings need to download in DMD. First, all signals from the controller to the devices are set to 0, and the LED pattern coding 0 means, no LEDs are lighted. Then, the rotating target is commanded to move, and the sensor starts to collect light. The LED illumination controls the exposure time T_e and idling time T_i , resulting in a reconstructed frame rate of $1/T_f = 1/(T_e + T_i)$. In each temporal frame, LEDs illuminate a different pattern. To avoid the refreshing noise, DMD loads a new coding by the raising signal, before the LED illumination start and clear



Figure 5.1: (a) The designed LED illumination board with even distributed LEDs. (b) A color target mounted on a precision rotation platform.

current coding with falling signal after LED illumination closed. The loaded coding was downloaded before the measuring. At last, the sensor is closed after last temporal frame exposure of a measurement ending. Then, the sensor will process the sensing data and save the data in disks. The target will be closed, after all the measurements are finished. To easily control the system, a Windows interface is built for sending configuration parameters to the controller.

5.3 Lab measurements and reconstruction

In an experiment, the exact measuring procedure needs to repeat 3 times with different RGB filters. Then the combined measurement with Bayer modulation is used as the input of the reconstruction algorithm described in Chapter 3.

The experiments are only performed for the compressive temporal imaging currently. High frame-rate video is recovered from reduced frame-rate measurements. The selected measurements measured in the Lab are shown in Fig. 5.3. The selected frames of reconstruction are shown in Fig. 5.4. In this experiment, 8 temporal frames are compressed in a snapshot and 10 snapshots are captured sequentially.



Figure 5.2: Timing sequences of signals from controller to devices for one snapshot with 4 temporal frames. With the rising signal, the target starts to rotate, while the DMD loads a new coding, and the sensor starts the integration. With the falling signal, the target stops moving, the DMD clears current coding, and the sensor stops collecting the light. Corresponding spectral patterns P1 to P4 are sent to LEDs in different temporal frame exposure time. T_e is exposure time and T_i is the idling time.



Figure 5.3: Two Lab measurement snapshots captured using the compressive temporal imaging system. The spatial modulation texture can be observed in each measurement.



Figure 5.4: 80 temporal frame images are reconstructed, from which 12 frame images are shown. Different frames are successfully separated.

Chapter 6 CONCLUSION

A LED-based compressive spectral temporal imaging system was developed, analyzed and tested in this thesis. A 4D scene (spatial, spectral and temporal) was measured by a 2D compressive measurement onto the FPA. A detailed mathematical model of the imager was presented, and $l_1 - l_2$ norm algorithm was implemented for reconstruction. Moreover, a comparison between DCT and Munsell PCA is conducted for their performance as the sparsity basis in spectrum. Then a complementary blue noise coding was designed to enhance the edges pixels reconstruction base on simulations. The laboratory experiments demonstrate accurate reconstruction in spatial, spectral, and temporal domains.

Future study may concentrate on quality improving and faster reconstruction algorithm. In the experiment, spectral information need be added in the compressive system, to further verify the system capability.

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