Spatio-Spectro-Temporal Coded Aperture Design for Multiresolution Compressive Spectral Video Sensing

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***Abstract*—Colored coded apertures (CCA) have been introduced in compressive spectral imaging (CSI) systems entailing richer coding strategies. CCA incorporate a wavelength-dependent coding procedure, which not only achieves spatial but also spectral coding in a single step. Even though the use of the CCA offers significant advantages and could also be applied to compressive spectral video sensing, this later application still exhibits diverse challenges originated by the temporal variable. The scene motion during the acquisition yields to motion artifacts such that these artifacts get aliased during the video reconstruction, damaging the entire data. As a result, multiresolution approaches have been proposed in order to alleviate the aliasing and enhance the video reconstruction. In this paper, it is proposed an algorithm to generate temporal colored coded aperture patterns that allow to sense the spatial, spectral and temporal information in an uniform way such that each spectral frame is spatially sensed at least once. In addition, it is proposed a multiresolution approach in the spectral multiplexing system allowing to extract optical flow estimates to address a higher quality reconstruction. Simulation results show an improvement up to 6 dB in terms of peak-signal to noise ratio (PSNR) in the reconstruction quality with the multiresolution approach using the designed patterns with respect to traditional random structures.**

***Keywords*—Spectral video, compressive spectral video, coded aperture design, optical flow, optical filter**

I. Introduction

Compressive spectral imaging (CSI) is an undersampling framework having faster data cube acquisition than full sampling techniques [1]. CSI exploits the fact that spectral images are sparse, or highly compressible, in some basis representation, i.e, most of the energy of the signal is concentrated in a small number of coefficients [2]. Formally, a spectral image is denoted by $\mathcal{F} \in \mathbb{R}^{N\times N\times L}$, with $N \times N$ spatial pixels and L spectral bands. Then, the vectorized form $\mathbf{f} \in \mathbb{R}^{N\cdot N\cdot L}$ of $\mathcal{F}$ is K-sparse on a given basis $\mathbf{\Psi}$, such that $\mathbf{f} = \mathbf{\Psi}\boldsymbol{\theta}$ can be estimated by a linear combination of just K vectors of $\mathbf{\Psi}$. CSI sensors that measure the spectral information in a single shot have been developed based on undersampling and constrained reconstruction. Snapshot cameras as the coded aperture snapshot spectral imager (CASSI) [3], its three-dimensional version named colored coded aperture snapshot spectral imager (C-CASSI) [4], [5], the prism-mask video imaging spectrometry (PMVIS) [6], the snapshot colored compressive spectral imager (SCCSI) [7], and the single pixel camera spectrometry (SPCS) [8] are examples of CSI systems. There are other snapshot systems designed to capture spectral video, or spectral dynamic scenes, in a compressive format such as the single dispersive CASSI extended to video (video-CASSI) [9], the hybrid spectral video imaging system (HVIS) [10] and the high-speed hyperspectral (HSHS) [11] video acquisition. Furthermore, snapshot spectral systems such as C-CASSI, using random-colored coded apertures, have been extended to capture spectral images at video rates [12]. The advantage of C-CASSI relies on the colored coded apertures (CCA) that improve the quality of the reconstruction in terms of peak-signal to noise ratio (PSNR) while reducing the number of snapshots. Basically, snapshot systems are composed by the encoding and dispersion elements. Particularly, an encoding element such as the CCA incorporates a wavelength-dependent coding procedure that exhibits a spectrally richer optical system. The CCAs are composed by a set of optical filters that modulate the light with a specific spectral response [4], [5]. However, the CCAs have been designed and optimized just for static spectral images.

On the other hand, in the recover step, compressive spectral video entails diverse challenges originated by the temporal variable. The scene motion during the acquisition yields to motion artifacts, and these artifacts get aliased during the video reconstruction damaging the entire data [13]. As a result, multiresolution approaches have been proposed in order to alleviate the aliasing and enhance the video reconstruction. This work presents an algorithm to design temporal coded apertures based on a finite set of optical filters for compressive spectral video. The designed patterns allow sensing the spatial, spectral and temporal information in an uniform way such that each spectral frame is spatially sensed at least once. In addition, the designed patterns permit the reconstruction of a low spatial resolution version, or preview, using few iterations of a $\ell_2 - \ell_1$-norm recovery algorithm. Then, the temporal

ISBN 978-0-9928626-7-1

correlation between frames is estimated from the preview in a similar way as in the spatial (Compressive Sensing Multi-scale Video, CS-MUVI)[14] and temporal (Programmable Pixel Compressive Camera, P2C2)[15] multiplexing approaches. Thereby, the temporal correlation is imposed to restrict the inverse problem of the high resolution video reconstruction. Simulations show an improvement of up to 6 dB of PSNR with the multiresolution approach using the designed patterns.

II. Compressive spectral video sensing

A. Mathematical sampling model

In discrete form, a spatio-spectral video can be expressed as $\mathcal{F} \in \mathbb{R}^{N\times N\times L\times D}$, with $N \times N$ spatial pixels, L spectral bands and D frames. Mathematically, the sensing process of $\mathcal{F}$ using video-CASSI can be modeled as the linear projection of the vectorized form of the source $\mathbf{f} \in \mathbb{R}^n$, with $n = N^2LD$, onto a sensing matrix $\mathbf{H}$ as

$$\underbrace{\begin{bmatrix} \mathbf{g}_0 \\ \vdots \\ \mathbf{g}_d \\ \vdots \\ \mathbf{g}_{D-1} \end{bmatrix}}_{\mathbf{g}} = \underbrace{\begin{bmatrix} \mathbf{H}_0 & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ & \ddots & & & \\ \vdots & & \mathbf{H}_d & & \vdots \\ & & & \ddots & \\ \mathbf{0} & \mathbf{0} & \cdots & & \mathbf{H}_{D-1} \end{bmatrix}}_{\mathbf{H}} \underbrace{\begin{bmatrix} \mathbf{f}_0 \\ \vdots \\ \mathbf{f}_d \\ \vdots \\ \mathbf{f}_{D-1} \end{bmatrix}}_{\mathbf{f}}, \quad (1)$$

and $d = 0, ..., D-1$, where $\mathbf{g}_d$, $\mathbf{H}_d$ and $\mathbf{f}_d$ represent the measurements, the sensing matrix and the vectorized-form of the spectral video for the d-th frame, respectively. Then, Eq.(1) can be succinctly expressed as

$$\mathbf{g} = \mathbf{Hf} = \mathbf{PTf}, \quad (2)$$

being $\mathbf{g} \in \mathbb{R}^m$ with $m = (N + L - 1)ND$ the compressive measurements, and $\mathbf{H} \in \mathbb{R}^{m\times n}$ the sensing matrix that models the spectral multiplexing system. Notice that the compression is just performed in the spectral component, i.e, for each measured spectral frame $\mathbf{g}_d$ are obtained $(N + L - 1)N$ pixels. The matrix $\mathbf{H}$ accounts for dispersion ($\mathbf{P} \in \mathbb{R}^{m\times n}$) and coding ($\mathbf{T} \in \mathbb{R}^{n\times n}$) effects [5]. More precisely, the dispersion matrix $\mathbf{P}$ is an $m \times n$ rectangular matrix composed by 1-valued $N^2 \times N^2$ diagonal matrices. The $\mathbf{T}$ matrix is a block-diagonal matrix that can be expressed as $\mathbf{T} = \text{blckdiag}\{(\tilde{\mathbf{T}}^0)^T, ..., (\tilde{\mathbf{T}}^{D-1})^T\}^T$, where $\text{blckdiag}\{\cdot\}$ denotes a block-diagonal concatenation and $\tilde{\mathbf{T}}^d$ is given by

$$\tilde{\mathbf{T}}^d = \left(\begin{array}{c|c|c|c} \text{diag}(\mathbf{t}_0^d) & \mathbf{0}_{N^2\times N^2} & \cdots & \mathbf{0}_{N^2\times N^2} \\ & \text{diag}(\mathbf{t}_1^d) & \cdots & \\ & & \cdots & \\ & & \ddots & \\ \mathbf{0}_{N^2\times N^2} & \mathbf{0}_{N^2\times N^2} & \cdots & \text{diag}(\mathbf{t}_{L-1}^d) \end{array}\right)_{N^2L\times N^2L}, \quad (3)$$

where $\text{diag}(\mathbf{t}_k^d)$ is a $N^2 \times N^2$ diagonal matrix whose entries are the coded aperture values for $k = 0, ..., L-1$. Traditionally, the coded aperture entries are selected at a random Gaussian or Bernoulli distribution, and the entries satisfy $\mathbf{t}_0^d = \mathbf{t}_1^d =, ..., = \mathbf{t}_{L-1}^d$ for $\mathbf{t}_k^d \in \{0, 1\}$. As a result, all the spectral pixels are blocked ($\mathbf{t}_k^d = 0$) or pass through ($\mathbf{t}_k^d = 1$) for each spatial position of the coded aperture. This class of coded apertures is known as block-unblock coded apertures. On the other hand, in the wavelength-dependent colored coded apertures, the CCA pixels correspond to a filter which can operate on the spectral axis as frequency-selective filters, i.e. as low pass ($\mathcal{L}$), band pass ($\mathcal{B}$) or high pass ($\mathcal{H}$) optical filters.

Observe that in Eq. (2), $\mathbf{f}$ can be expressed as $\mathbf{f} = \mathbf{\Psi}\theta$ where $\mathbf{\Psi}$ is the representation basis. Specifically, for spectral video, the basis $\mathbf{\Psi}$ can be constructed as a Kronecker product between different basis as $\mathbf{\Psi} = \mathbf{\Psi}_1 \otimes \mathbf{\Psi}_2 \otimes \mathbf{\Psi}_3 \otimes \mathbf{\Psi}_4$, such that the four dimensional basis exploits the correlation between the spatial, the spectral and the temporal information of the spectral video [2]. Commonly used bases include Wavelet, Cosine, Curvelet transforms and trained dictionaries [16], [17].

B. Multiresolution approach

Compressive video reconstruction exhibits a lot of challenges that compressive "static" imaging does not. The scene motion during the acquisition yields motion artifacts such that these artifacts get aliased during the video reconstruction damaging the entire data [13]. Multiresolution approaches have been proposed in order to alleviate the aliasing and enhance the video reconstruction. Therefore, the idea of interpret data at multiple resolutions have been entailed as a "chicken-and-egg" problem, which states that reconstructing a high-quality CS video could be obtained adding temporal correlation as motion compensation, and computing motion compensation requires the knowledge of the full video. Previous works have proposed to compute a preview reconstruction to estimate the motion field in the video such that it can be used to achieve a high quality reconstruction. Specifically, approaches as the spatial multiplexing system known as CS-MUVI (Compressive Sensing Multi-scale Video) and the temporal multiplexing system known as P2C2 (Programmable Pixel Compressive Camera) have been proposed. However, these frameworks have been focused to compressive video, disregarding the spectral component of the scene. Thereby, in this paper, the preview reconstruction strategy is addressed in a spectral multiplexing system by obtaining an enhancement in the high-resolution reconstructed spectral video.

III. Temporal Colored Coded Apertures

Colored coded apertures (CCA) have been developed to compress and sense "static" spectral images using a single or multiple shots. Opposed to traditional block-unblock coded apertures, CCA have shown a remarkable improvement in the spatial and spectral quality reconstruction in real and simulated scenarios [4], [5]. A CCA is designed based on a set of optical filters with ideal responses, more specifically, on a large set of cut-off wavelengths. Then, the optimized design of a CCA relies on the minimization of the correlations of the spectral responses of the L optical filters ensemble. Further, since multiple shots set the CCA pixels to be complementary, the correlation between multiple shots is reduced as well. Thus, in order to achieve a low spatio-spectral correlation, the CCA design allows to block or unblock pixels of the scene [4].

A. Design criteria for temporal CCA

Aiming to extend the CCA design criteria from spectral static images to spectral dynamic scenes, an algorithm using a finite set of optical filters is proposed. Algorithm 1 generates the structure for the coded aperture for spatial, spectral and temporal modulation. The inputs of the algorithm are the set of optical filters ξ, the number of filters F_N of the set ξ, and the dimensions of the spectral video N, L, D. Algorithm 1 starts with a vector of F_N values ordered in a random way, i.e. for some value γ_{Ω_i} and γ_{Ω_j} of the random vector, $\boldsymbol{\gamma} = [\gamma_{\Omega_1}, \gamma_{\Omega_2}, ..., \gamma_{\Omega_i}, ..., \gamma_{\Omega_j}, ..., \gamma_{\Omega_{F_N}}]$, it is satisfied that $\Omega_i \neq \Omega_j, i \neq j$. This random vector represents the index of each optical filter in ξ. Then, Algorithm 2 generates a distribution of filters with the aforementioned parameters.

Algorithm 1 Generate the Temporal Colored Coded Apertures

Input: F_N, N, L, D, ξ
Output: Temporal CCA, $\mathbf{T}$

$\boldsymbol{\gamma} \leftarrow [\gamma_{\Omega_1}, \gamma_{\Omega_2}, ..., \gamma_{\Omega_i}, ..., \gamma_{\Omega_j}, ..., \gamma_{\Omega_{F_N}}]$, $\Omega_i \neq \Omega_j, i \neq j$
$\mathbf{A} \leftarrow$ FILTERSDISTRIBUTION$(N, F_N, \xi, \boldsymbol{\gamma})$
$\mathbf{T} \leftarrow \mathbf{A}(\xi_r)$ with $r = 1, ..., F_N$

Iteratively, Algorithm 2 spatially allocates the optical filters of the given set ξ, taking into account the minimum correlation between adjacent filters. The minimum correlation obeys the ℓ_2 norm between two optical filters selected. In other words, if an optical filter Γ_i, chosen from the given optical filters set ξ, is allocated in pixel 1, then the next optical filter Γ_{i+1} must satisfy

$$\Gamma_{i+1} = \underset{r}{\operatorname{argmin}} \|(\Gamma_i)\xi_r^T\|_2 \tag{4}$$

for $r = 1, ..., F_N$, being F_N the total number of filters of the set ξ. Briefly, the algorithm 2 includes three *for* loops; in the first two loops, the variables i, j go over the $M \times N$ matrix Γ spatially allocating the index filters $\hat{r}$ that satisfy Eq. (4). The third loop realizes a modulo repetition of the filters distribution $\mathbf{\Gamma}$ by the temporal dimension i.e. $d = 0, ..., D-1$. Then, algorithm returns a matrix $\mathbf{A}$ which contains the spatial filters distribution for D spectral frames. Finally, the $\mathbf{T}$ matrix contains the spatio-spectro-temporal distribution generated following algorithm 1. The designed coded apertures are called temporal colored coded apertures (temporal CCA).

It is important to highlight that with the temporal CCA, using the set of optical filters of Fig. 1, each spectral frame is spatially sensed at least once, which means that for each frame the motion, or frames changes, must be sensed. Particularly, the selected set of optical filters have a complementary distribution (Fig.1). Notice that the distance between the unblock elements is maximum providing a minimal spectral correlation.

IV. SIMULATIONS AND RESULTS

In order to test the temporal CCA, two datasets of spectral videos were sensed simulating the model in Eq. 2. The first

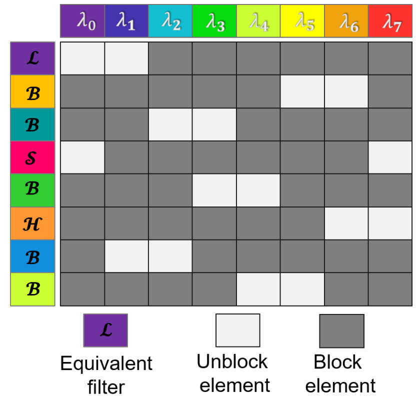

Figure 1: Illustration of the spectral responses of the set of optical filters. A maximal distance between unblock elements provides a minimal spectral correlation

Algorithm 2 Spatial distribution of the set of optical filters

function FILTERSDISTRIBUTION$(N, F_N, \xi, \boldsymbol{\gamma})$
  $\delta = 0$
  for $i \leftarrow 1$ to N **do**
    $\Gamma_{i,1} = \xi_{\gamma_{\Omega_1}}$ ▷ Initial guess
    for $j \leftarrow 2$ to N **do**
      $\hat{r} = \underset{r}{\operatorname{argmin}}(\|(\Gamma_{i,j-1})\xi_r^T\|_2 + \delta \cdot \|(\Gamma_{i-1,j})\xi_r^T\|_2)$ with $r = 1, ..., F_N$
      $\Gamma_{i,j} \leftarrow \hat{r}$
    end for
    $\delta = 1$
  end for
  for $d \leftarrow 0$ to $D-1$ **do** ▷ Temporal modulo loop
    $\mathbf{A}_d \leftarrow \mathbf{\Gamma}$
    $\mathbf{\Gamma} \leftarrow (\mathbf{\Gamma} \bmod F_N) + 1$
  end for
  return$(\mathbf{A})$
end function

dataset is a cropped section of a spectral video [18]. The second dataset is a synthetic spectral video of a moving object over a spectral static scene [19]. Both databases were acquired with a CCD camera and a VariSpec Liquid Crystal Tunable Filter (LCTF) in wavelengths from 400nm to 700nm at 10nm steps. A spatial section of $M = 128$, $N = 128$, $L = 8$ spectral bands and $D = 8$ frames was used for simulations. Figure 2 presents an RGB profile of the test spectral videos.

The 4D basis representation selected was composed as the Kronecker product of three transforms as follows: $\mathbf{\Psi}_1$ and $\mathbf{\Psi}_2$ are a 2D-wavelet Symmlet 8 basis for the spatial dimensions, $\mathbf{\Psi}_3$ is a 1D-Discrete Cosine basis (DCT) for the spectral dimension, and $\mathbf{\Psi}_4$ is a 1D-DCT basis for the temporal dimension. The reconstruction quality for each reconstructed spectral-frame is evaluated in terms of the PSNR and the structural similarity index (SSIM). Furthermore, a preview reconstruction of the spectral video is obtained by using few iterations of a $\ell_2 - \ell_1$-norm recovery algorithm. Then, based on

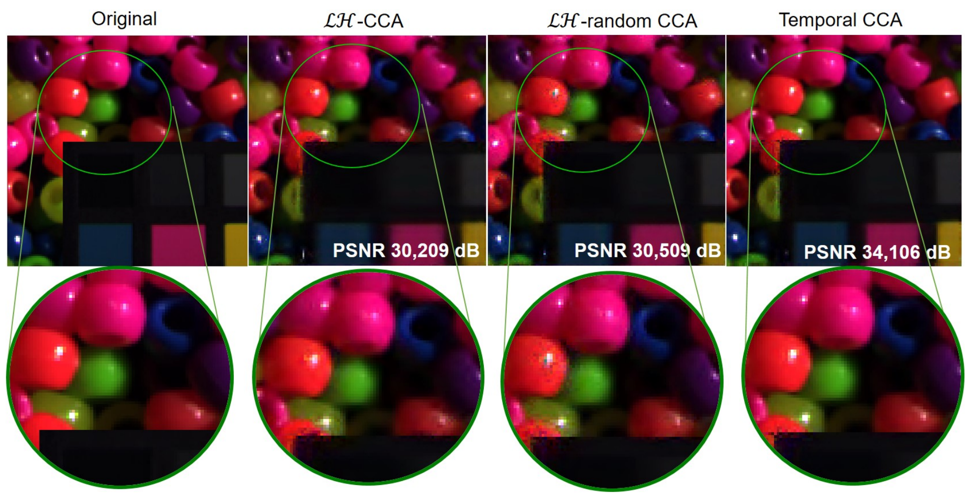

Figure 3: RGB representation of the original fifth frame of the spectral video 2 and the reconstructed frame using $\mathcal{LH}$-CCA, the $\mathcal{LH}$-random CCA and the temporal CCA.

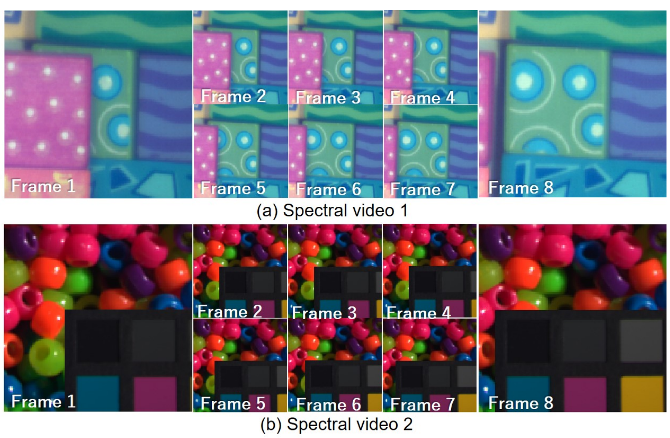

Figure 2: RGB profile of eight frames of the two test spectral videos. (a) a cropped section of a spectral video [18]. (b) a synthetic spectral video of a moving object over a spectral static scene [19].

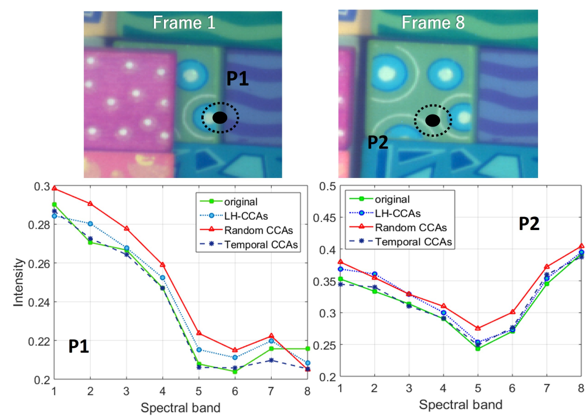

Figure 4: Spectral signature comparison for points P1 (frame 1) and P2 (frame 8) of the spectral video 1 using the $\mathcal{LH}$-CCA, the $\mathcal{LH}$-random CCA and the temporal CCA.

the preview, the motion is obtaining following an optical flow estimation. The Gradient Projection for Sparse Reconstruction (GPSR) algorithm with an optical flow restriction was used to recover the underlying signal in high resolution. Thereupon, in order to compare the temporal CCA against to CCA, a realization with an ensemble of high and low pass filters with an optimal set of cut-off wavelengths ($\mathcal{LH}$-CCA) is presented [4]. In addition, a CCA based on a random selection of the filters above ($\mathcal{LH}$-random CCA) is also included. For each tested dataset and coded aperture a preview version was computed. Figure 3 shows the RGB ground truth representation and reconstructed video 2 for the fifth frame using $\mathcal{LH}$-CCA, $\mathcal{LH}$-random CCA, and the proposed temporal CCA. The zoomed section for the reconstructions in Fig. 3 shows that there is a spatial quality improvement using the temporal CCA. Figure 4 shows the spectral signature comparison for two points of two different frames of the spectral video 1. It can be seen that the spectral signature sampled with the temporal CCA is more accurate than the $\mathcal{LH}$-CCA and the $\mathcal{LH}$-random CCA. The performance of the multiresolution approach can be demonstrated by comparing the average reconstruction quality of the reconstructed videos sampled with the $\mathcal{LH}$-CCA, the $\mathcal{LH}$-random CCA and the temporal CCA. In the multiresolution approach, the preview version is obtained to measure the optical flow in the spectral video. Thereby, a comparison adding the optical flow restriction and without the restriction is included. Figure 5 shows the eight band of the preview reconstruction by using the three coded apertures. Table 1 summarizes the reconstructions results for the two spectral videos.

The results are shown with and without the optical flow (OF) restriction. Further, if the restriction is added, the metrics for the preview version reconstruction are also included. It can be observed that a better reconstruction in terms of PSNR is

ISBN 978-0-9928626-7-1

Table 1: SUMMARY OF RESULTS IN TERMS OF PSNR AND SSIM MEAN FOR THE TWO SPECTRAL VIDEOS.

• $\mathcal{LH}$-CCA : Low/High pass filters CCA. • $\mathcal{LH}$-random CCA : Random CCA. • **Temporal CCA**: Designed Coded Apertures

Spectral video 1	*Without the Optical Flow Restriction*		*With the Optical Flow Restriction*			
	PSNR	**SSIM**	**PSNR**	**SSIM**	**PSNR preview**	**SSIM preview**
LH-CCA	31,600	0,942	33,451	0,962	29,78	0,95
R-CCA	31,603	0,942	33,583	0,959	27,47	0,92
Temporal CCA	32,717	0,952	**34,855**	0,970	**31,19**	0,96
Spectral video 2	*Without the Optical Flow Restriction*		*With the Optical Flow Restriction*			
	PSNR	**SSIM**	**PSNR**	**SSIM**	**PSNR preview**	**SSIM preview**
LH-CCA	26,685	0,885	30,526	0,938	28,87	0,94
R-CCA	26,410	0,871	30,093	0,944	27,84	0,93
Temporal CCA	27,981	0,895	**33,243**	0,966	**29,12**	0,94

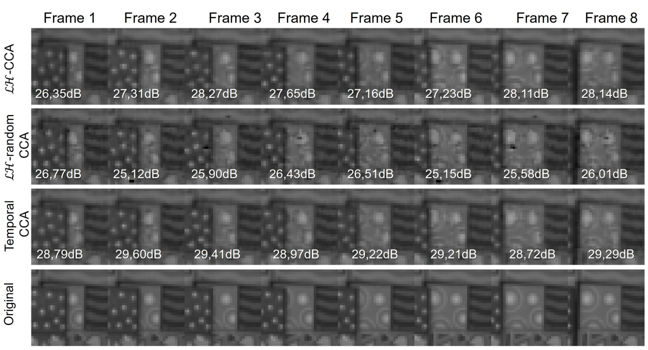

Figure 5: Preview reconstruction of the eight band by using the three coded apertures. Notice that the designed apertures achieves better quality reconstruction in terms of PSNR

obtained for the preview version with the temporal CCA.

V. Conclusion

In this paper, an algorithm to design spatio-spectro-temporal coded apertures based on a finite set of optical filters for compressive spectral video was proposed. The designed patterns allow to sense the spatial, spectral and temporal information in an uniform way such that each spectral frame is spatially sensed at least once. The mathematical procedure of the proposed algorithm has been presented. Further, aiming to alleviate the temporal artifacts of the video reconstruction a multiresolution approach is used. The results show that using the designed coded apertures the reconstruction quality improves even without adding the optical flow. In general, the multiresolution approach using the designed coded apertures improves up to 6 dB of PSNR with respect to the traditional random patterns structures.

Acknowledgment

The authors gratefully acknowledge the Vicerrectoría de Investigación y Extensión of Universidad Industrial de Santander for supporting this work registered under the project titled “Diseño y simulación de un sistema adaptativo de sensado compresivo de secuencias de video espectral”.

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