Compressive light field spectral imaging in a single-sensor device by using coded apertures.

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Outline

1. Light field imaging
2. Compressive spectral imaging using microlens
3. Discrete model
   - 3.1 Data structures
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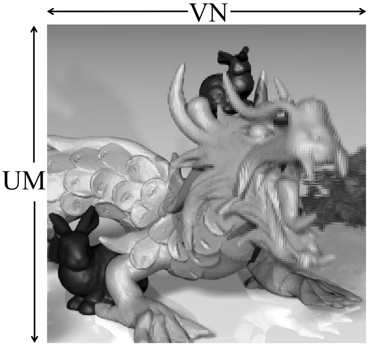
4. Simulation results
5. Conclusions



Ways to collect plenoptic function

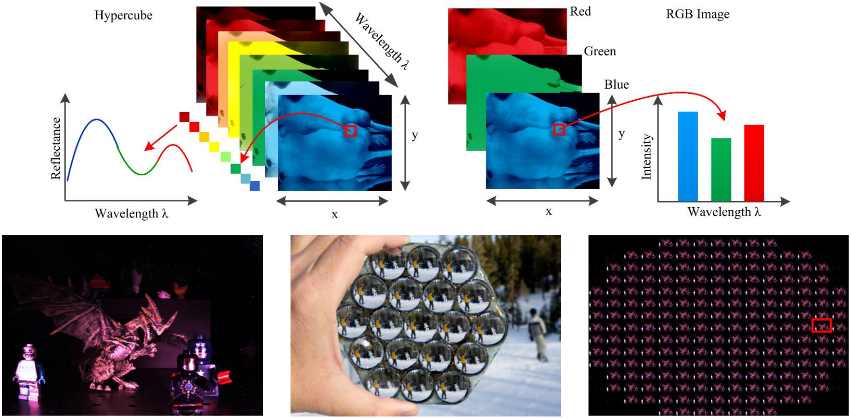


Figure 2: Way to collect the plenoptic function.

Ways to collect plenoptic function

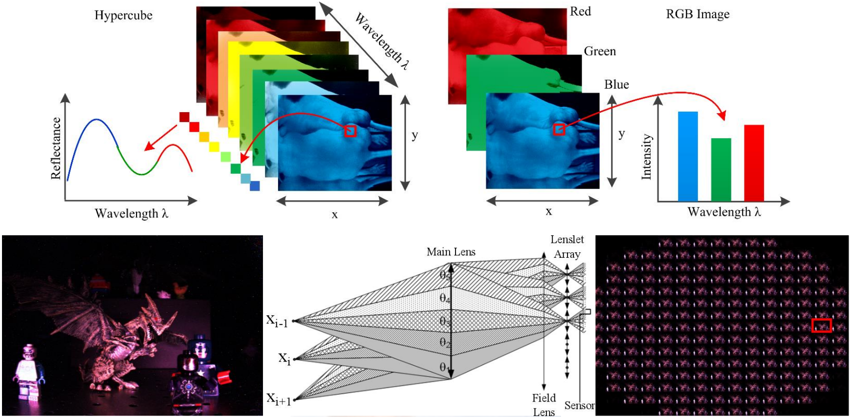


Figure 3: Way to collect the plenoptic function.

State of art: light field unarranged structure

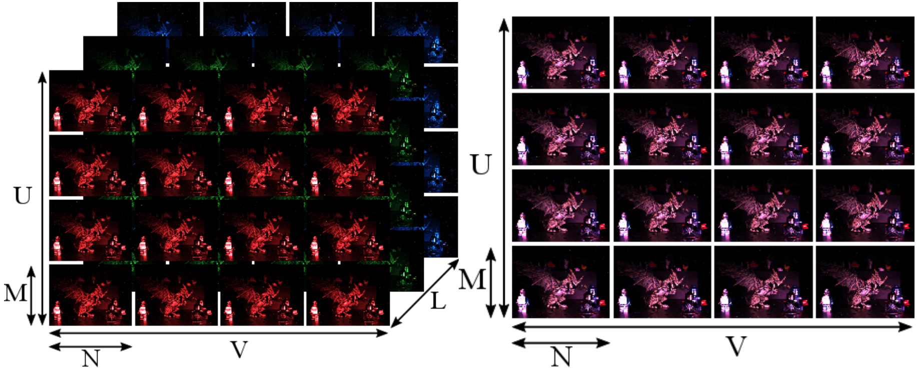
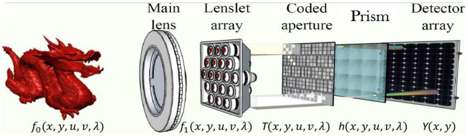


Figure 4: Light field matrix representation

Contribution

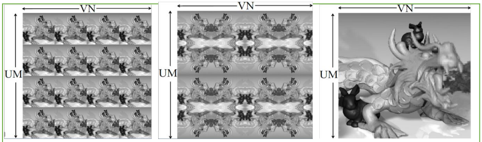
1. It is compressive spectral imaging light field.
2. The discrete mathematical model for the proposed architecture.
3. The design of three data structures.
4. The design and testing sparsifiers.



Proposed architecture

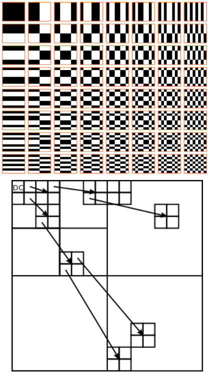
Mathematical model

$$\widehat{\mathbf{f}} = \boldsymbol{\Psi}\{\arg\min_{\boldsymbol{\theta}} \|\mathbf{y} - \mathbf{H}\boldsymbol{\Psi}\boldsymbol{\theta}\|_2 + \tau\|\boldsymbol{\theta}\|_1\}$$

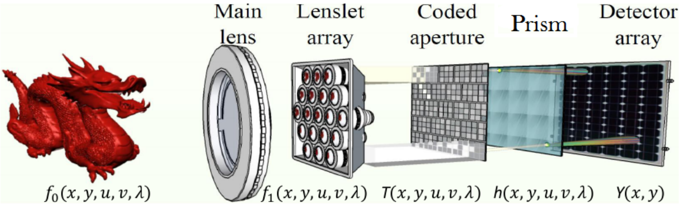


Data structures

Sparsifiers



Compressive spectral integral imaging with microlens



$$f_1(x,y,u,v,\lambda) = \int\int f_0(x,y,u,v,\lambda)A(u,v)\cos^4\beta du dv, \quad (1)$$

$$Y(x,y) = \int_\Lambda \int_{\Delta x} \int_{\Delta y} (T(x,y,u,v)f_1(x,y,u,v,\lambda)) * h(x,y,u,v,\lambda)\, \mathrm{d}\lambda \mathrm{d}\widehat{x} \mathrm{d}\widehat{y}, \quad (2)$$

- $A(u,v)$ is the aperture function.
- $\beta \in \mathbb{R}$ is the angle subtended by the microlens.
- $T(x,y,u,v,\lambda)$ is the coded aperture.
- $h(x,y,u,v,\lambda)$ is the dispersion system.
- $Y(x,y)$ are compressive measurements.

Discrete mathematical model

The energy captured on the detector that comes from the (m, n)-th angle, can be written as

$$(Y_{i,j})_{m,n} = \sum_k F_{i,(j-k),k,m,n} T_{i,(j-k),m,n} + w_{(m,n,i,j)}, \quad (3)$$

where $T_{i,j,m,n}$ be the discretized coded aperture. In general, Eq. (3) can be expressed in vector form as

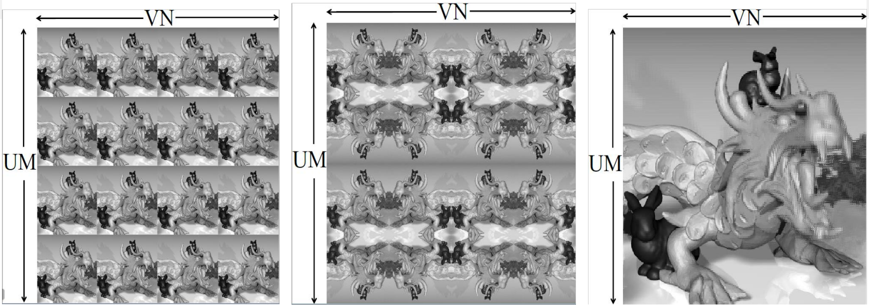
$$\mathbf{y} = \mathbf{H}\mathbf{f} + \mathbf{w}, \quad (4)$$

where $\mathbf{w} \in \mathbb{R}^{KM(N+L-1)UV}$ represent the noise in the detector. This requires solving the optimization problem

$$\widehat{\mathbf{f}} = \boxed{\boldsymbol{\Psi}} \{\arg\min_{\boldsymbol{\theta}} \|\mathbf{y} - \mathbf{H} \boxed{\boldsymbol{\Psi}} \boldsymbol{\theta}\|_2 + \tau \|\boldsymbol{\theta}\|_1\} \quad (5)$$

where $\boldsymbol{\theta}$ is an S-sparse representation of $\mathbf{f}$ on the basis $\boldsymbol{\Psi}$, and τ is a regularization constant.

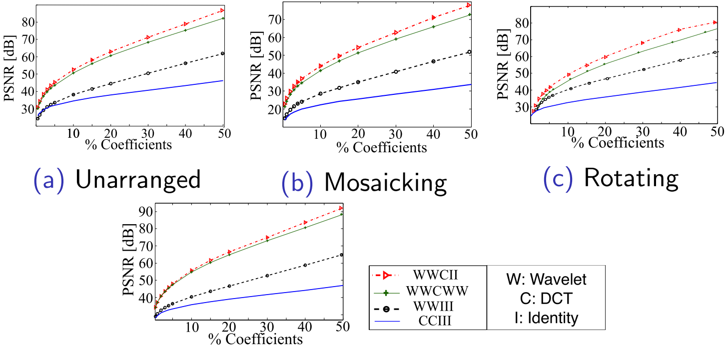
Data structure



Mosaicking Rotating Macro

- **Mosaicking:** Spatio-spectral images concatenate along the angular dimension.
- **Rotating:** Similar to mosaicking, but favoring the continuity of spatial patterns.
- **Macro:** Pixels in the same spatial and spectral position are concatenated along the angular dimension.

Data structures and representation basis.



(a) Unarranged (b) Mosaicking (c) Rotating

(d) Macro

Figure 6: PSNR of the reconstructed image as a function of the percentage of coefficients for its representation. Here, W:wavelet, C:cosine, I:identity.

Analysis of the data structures

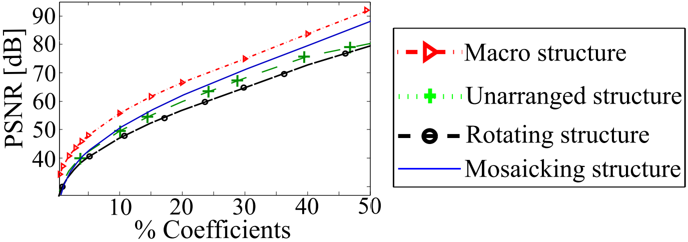


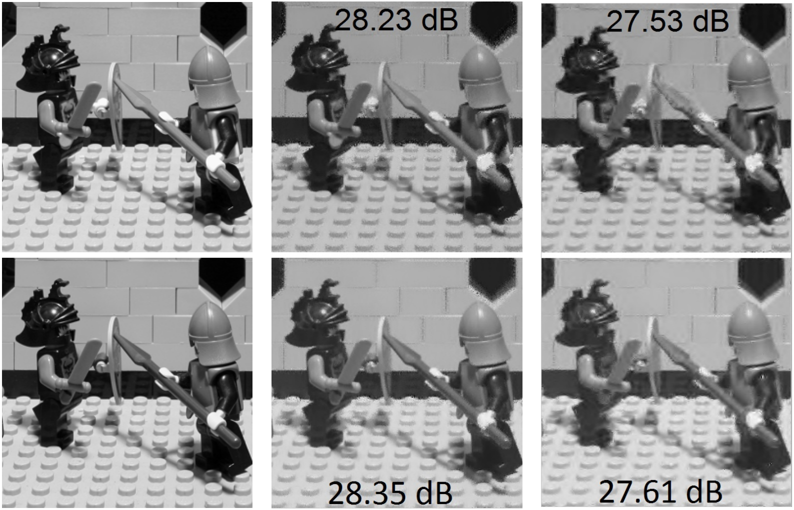
Figure 7: PSNR reconstructed images as a function of the percentage of coefficients in the *WWCII* representation base, and the macro structure.

Light field reconstruction: Scene 1

(a) Original (b) Macro (c) Unarranged

Figure 8: Reconstruction of light-field images with noise ($SNR = 10$) using the proposed architecture. The reconstruction using the macro and unarranged structure with WWCII base are 33.75 [dB] and 29.91 [dB], respectively.

Light field reconstruction: Scene 2



(a) Original (b) Macro (c) Unarranged

PSNR against number of spectral bands

Image	Data structure	Numbers of spectral bands [L]			
		3	4	6	8
Scene 1	Macro	**26.83**	**30.73**	**31.16**	**33.75**
	Unarranged	23.21	27.45	28.74	29.91
Scene 2	Macro	**25.35**	**29.99**	**31.54**	**33.50**
	Unarranged	25.08	29.60	31.12	32.46

Table 1: Mean reconstruction PSNR in dB for two multispectral images with spectral bands of $L = 3, 4, 6, 8$, and numbers of shots $Q = \lfloor L/2 \rfloor$, respectively.

PSNR against number of snapshots, including noise

SNR [dB]	Data structure	Numbers of shots [Q]			
		1	2	3	4
10	Macro	**24.45**	**26.05**	**27.17**	**28.79**
	Unarranged	20.33	23.99	24.83	25.83
15	Macro	**24.84**	**28.01**	**30.64**	**32.54**
	Unarranged	22.13	24.83	26.76	28.34
20	Macro	**26.04**	**29.22**	**31.47**	**33.44**
	Unarranged	22.42	25.08	27.44	29.71

Table 2: Mean reconstruction PSNR in dB with spectral bands of $L = 8$, numbers of shots $Q = 1, 2, 3, 4$, and three different noise levels ($SNR = 10, 15, 20$ dB), respectively.

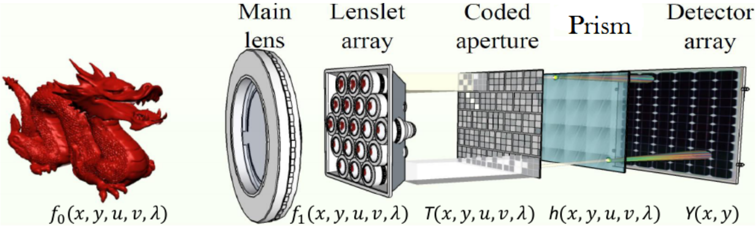
PSNR against number of snapshots for the two scenes

Image	Data structure	Numbers of shots [Q]			
		1	2	3	4
Scene 1	Macro	**26.33**	**29.36**	**31.78**	**33.75**
	Unarranged	22.48	25.24	27.90	29.91
Scene 2	Macro	**24.68**	**28.35**	**31.34**	**33.50**
	Unarranged	23.88	27.61	30.62	32.46

Table 3: Mean reconstruction PSNR in dB with spectral bands of $L = 8$, and numbers of shots $Q = 1, 2, 3, 4,$ respectively.

Conclusions

- It has been proposed the **compressive light field spectral imaging in a single-sensor using coded apertures and microlens**.
- Four sparsifying basis are studied studies to determine the best sparsest representation is obtained with **Wavelet-Wavelet-Cosine**.
- Different structures are tested the best results are obtained with the **macrostructure** up to **3 dB** with respect to the unarranged.



Any Question?

Thanks for your attention!