Adaptive uniform grayscale coded aperture design for high dynamic range compressive spectral imaging

Nelson Diaz[a], Hoover Rueda[b], and Henry Arguello[a]

[a]Department of Computer Science, Universidad Industrial de Santander, Bucaramanga, Colombia, 680002

[b]Department of Electrical and Computer Engineering, University of Delaware, Newark DE, USA, 19716

ABSTRACT

Imaging spectroscopy is an important area with many applications in surveillance, agriculture and medicine. The disadvantage of conventional spectroscopy techniques is that they collect the whole datacube. In contrast, compressive spectral imaging systems capture snapshot compressive projections, which are the input of reconstruction algorithms to yield the underlying datacube. Common compressive spectral imagers use coded apertures to perform the coded projections. The coded apertures are the key elements in these imagers since they define the sensing matrix of the system. The proper design of the coded aperture entries leads to a good quality in the reconstruction. In addition, the compressive measurements are prone to saturation due to the limited dynamic range of the sensor, hence the design of coded apertures must consider saturation. The saturation errors in compressive measurements are unbounded and compressive sensing recovery algorithms only provide solutions for bounded noise or bounded with high probability. In this paper it is proposed the design of uniform adaptive grayscale coded apertures (UAGCA) to improve the dynamic range of the estimated spectral images by reducing the saturation levels. The saturation is attenuated between snapshots using an adaptive filter which updates the entries of the grayscale coded aperture based on the previous snapshots. The coded apertures are optimized in terms of transmittance and number of grayscale levels. The advantage of the proposed method is the efficient use of the dynamic range of the image sensor. Extensive simulations show improvements in the image reconstruction of the proposed method compared with grayscale coded apertures (UGCA) and adaptive block-unblock coded apertures (ABCA) in up to 10 dB.

Keywords: Multispectral and hyperspectral imaging, imaging systems, adaptive imaging, computational imaging, coded aperture imaging.

1. INTRODUCTION

Imaging Spectroscopy (IS) has many applications: In surveillance, for instance, it is used for target acquisition when there is not prior knowledge of the target. IS can be used for recognizing a human physiological state such as that induced by stress or anxiety[1]. In remote sensing, IS is used to identify material in the unveil terrain. In addition, trees are characterized based on the chemical substances contained in the foliage[2]. In medicine IS is broadly used specially in disease diagnosis and image-guided surgery[3]. The spatially resolved spectral images are used in the diagnostic information of tissues because they are able to detect biochemical changes due to disease development. However, the disadvantage of the conventional imaging spectroscopy techniques is that they measure the whole datacube which is time consuming and expensive.

The datacube is a three dimensional signal, with two spatial and one spectral dimension. Recent research developed the coded aperture snapshot spectral imager (CASSI) which is a spectral compressive imager that captures

Further author information:
E-mail: nelson.diaz@correo.uis.edu.co.
E-mail: henarfu@uis.edu.co
E-mail: rueda@udel.edu

compressive spectral projections of the datacube[4]. The projections are the input of the convex optimization reconstruction algorithms that allow to reconstruct the whole datacube. Contrary to the conventional techniques, compressive spectral imager uses coded apertures to modulate the incoming light. The coded aperture determines the sensing matrix of the system. Traditionally, the CASSI architecture uses block-unblock coded apertures (BCA) to modulate the incoming light. The design of the coded apertures is critical in order to improve the quality of image reconstruction[5–8].

In CASSI the compressive measurements are subject to saturation when the illumination exceeds the dynamic range of the focal plane array (FPA). The errors that yield saturation are unbounded and compressive sensing recovery algorithms only provide solutions for bounded errors[9]. CASSI can be implemented with the most common sensor devices such as a charge-coupled device (CCD) or a complementary metal-oxide-semiconductor (CMOS). These sensors have a limited dynamic range, for instance, a detector with 8-bits is able to measure $2^8 = 256$ intensity levels. Accordingly, the design of the coded apertures should consider this limitation of the sensor.

Two approaches for dealing with saturated measurements are proposed in[9]. First, saturation rejection which discard saturated measurements and then perform signal recovery on those remaining. Second, constrained optimization, incorporating saturated measurements as constraints in the convex optimization problem. The methods that increase dynamic range also reduce the saturation, however they introduce modification directly in the sensor[10]. Other methods like temporal exposure change require post-processing algorithms[10].

In consideration of improving the dynamic range of CASSI the adaptive grayscale coded aperture (AGCA) was first introduced in[11] and[12]. AGCA is a CASSI architecture with two modifications. First, the BCA is replaced with a GCA in order to improve the modulation of the incoming light. Second, the adaptive system provides a feedback between FPA and the digital micromirror device (DMD), such that the next coded aperture is computed in a PC in real-time. Figure 1 shows an sketch of the AGCA. The proposed method reduces the saturation using an adaptive uniform grayscale coded aperture (AUGCA) that increases the dynamic range of the system. The modification of the architecture improves the adaptive system proposed in[11] and introduces the uniform grayscale coded aperture (UGCA).

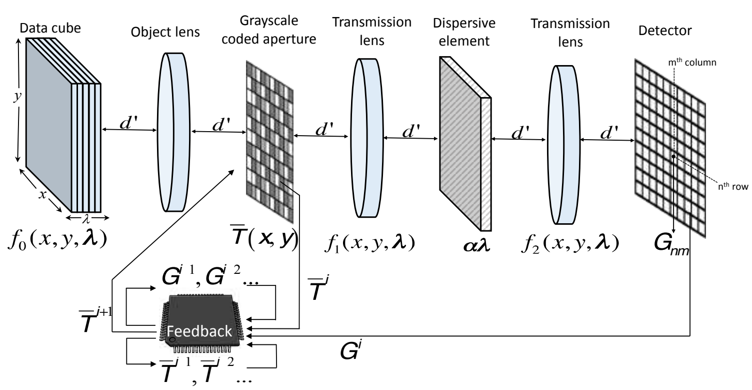
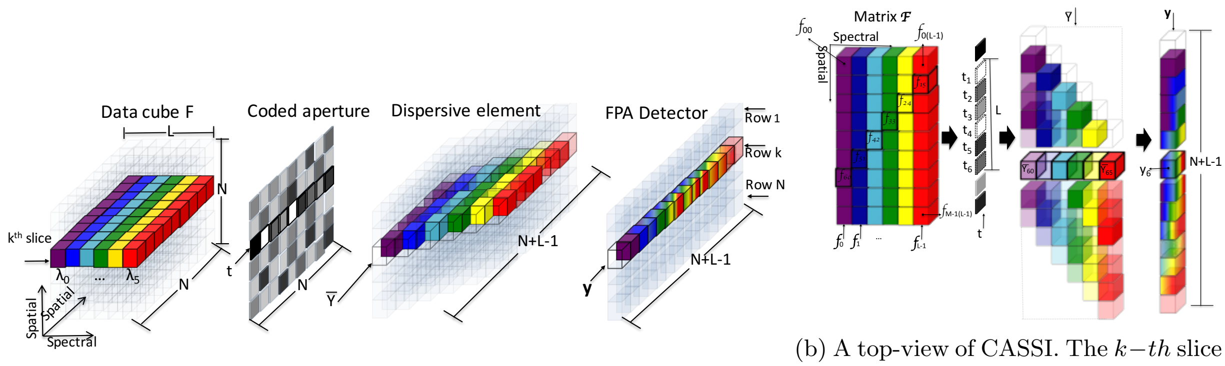


Figure 1: Sketch of the adaptive grayscale coded aperture (AGCA). The AGCA is composed of two modifications to the traditional CASSI. First, the BCA is replaced with the GCA in order to improve the modulation of the incoming light. On the other hand, an adaptive system allows the feedback between the focal plane array and the digital micromirror device. The adaptive system uses the compressive measurements to compute the next coded aperture.



(a) Sketch of the spectral data flow in CASSI.

(b) A top-view of CASSI. The $k-th$ slice of the data cube is represented by $\mathbf{F}$

Figure 2: Design of UGCA[11]

2. CASSI MATRIX MODEL

2.1 CASSI Model

A matrix model for the coded aperture apectral anapshot imaging (CASSI) has been developed in[5]. In this model, a compressive measurement of the $k-th$ slice can be represented by

$$\mathbf{y} = \sum_{j=0}^{V-1} \mathbf{P}_{V;j} \sum_{k=0}^{L-1} (\boldsymbol{\Theta}_{\boldsymbol{V}})^{\boldsymbol{k}} \bar{\mathbf{I}} \mathbf{R} \mathbf{F} \mathbf{P}_{L;k} \mathbf{C} (\boldsymbol{\Theta}_L^T)^{j+1} \mathbf{w}, \tag{1}$$

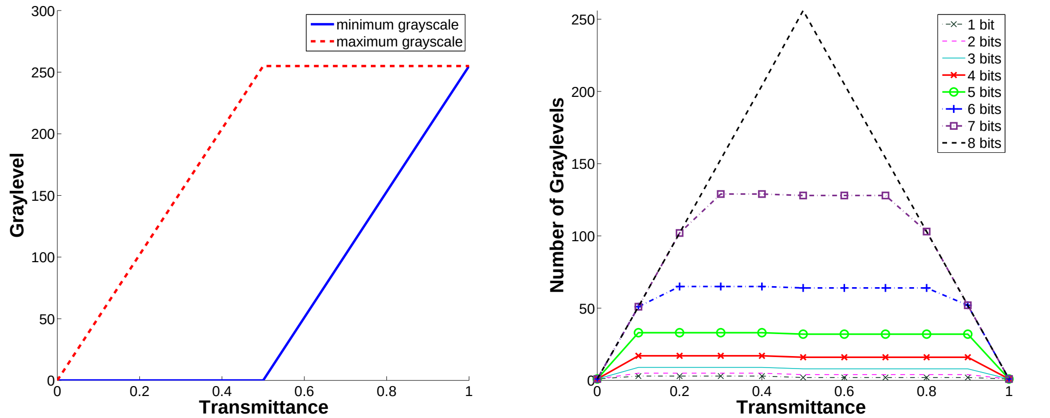
where $\mathbf{y} \in \mathbb{R}^V$ with V is $N + L - 1$, and each compressive measurement is composed by N slices. $\mathbf{P}_{V;j}$ is a $V \times V$ unique column/row matrix, $(\boldsymbol{\Theta}_{\boldsymbol{V}})^{\boldsymbol{k}}$ $V \times V$ is a cyclic permutation matrix, $\boldsymbol{\Theta}_L^T$ is the transpose of a $L \times L$ cyclic permutation matrix and $\mathbf{R} = diag(\tilde{\mathbf{r}})$. Figure 2a shows a sketch of the spectral data flow in CASSI with the $k-th$ slice highlighted. Figure 2b shows a top-view of CASSI in Fig. 2a. It shows the pixels of the coded aperture $t_1, ..., t_6$ that produce saturation in the y_6 position of the focal plane array.

2.2 Grayscale Boundary Function

The grayscale boundary function defines the intensity level of the uniform grayscale coded aperture (UGCA) according to the desired transmittance, which is the fraction of light that the coded aperture allows to pass in the CASSI system. The grayscale levels are generated following a uniform distribution across the GBF. The GBF is defined as follows

$$I_L = \begin{cases} [I_{min}, I_{max} * 2 * T_r] & 0 \leq T_r \leq 0.5 \\ [I_{max} * (2 * T_r - 1), I_{max}] & 0.5 < T_r \leq 1 \end{cases} \tag{2}$$

where I_L is the ordered pair that guarantees the desired transmittance T_r, $I_{min} = 0$ is the minimum grayscale level of a digital micromirror device (DMD), $I_{max} = 2^m - 1$ is the maximum grayscale level of the DMD where m is the number of bits. Figure 3a depicts the GBF. The dashed line corresponds to the maximum boundary of GBF and the straight line corresponds to the minimum boundary of the GBF. Figure 3b illustrates the optimal transmittance according to the number of bits. It means that all the intensity graylevels are used when T_r is 0.5. The design of uniform grayscale coded apertures (UGCA) is based on the grayscale boundary function (GBF). The GBF restricts the grayscale levels in order to achieve the desired transmittance. The vector $\tilde{\mathbf{r}} = [\tilde{r}_0, \tilde{r}_1, ..., \tilde{r}_{M-1}]$ represents the UGCA for the $k-th$ slice according to the matrix model from Eq. 1.



(a) Grayscale Boundary Function $\mathbf{I}_L$ defines the intensity level of the uniform grayscale coded aperture (UGCA), grayscale level is a function of desired transmittance

(b) Optimal Transmittance depends on number of bits of the digital micromirror device (DMD), when the number of bits is 8 the optimal transmittance is 0.5

Figure 3: Design of UGCA

2.3 Adaptive Matrix Model

The compressive measurement can not be directly used in the adaptive algorithm proposed in[10], due to the spatial difference between the compressive measurements $\mathbf{y} \in \mathbb{R}^V$ and the coded aperture $\tilde{\mathbf{t}} \in \mathbb{R}^N$. In order to adaptively design the coded aperture pattern for the next measurement, the the averaged intensity measurement (AIM) is defined as

$$I_j = \frac{1}{L}\sum_{\ell=0}^{L-1} y_{i+\ell}, \tag{3}$$

where I_j is the $j-th$ AIM, j is the index $j = \{1, ..., N\}$, L is the number of spectral bands, y_i is the $i-th$ compressive measurement of the $k-th$ slice, with $i = \{1, ..., (N+L-1)\}$. The $k-th$ row of AIM, $\mathbf{I}$, match with the entries of the $k-th$ slice of the coded aperture $\tilde{\mathbf{t}}$. The coded aperture is defined as

$$\tilde{\mathbf{t}} = \tilde{\mathbf{w}} \circ \bar{\mathbf{s}} + \tilde{\mathbf{r}} \circ \mathbf{s}, \tag{4}$$

where $\circ$ is the Hadamard product between the vectors $\tilde{\mathbf{w}}$ and $\bar{\mathbf{s}} \in \mathbb{R}^N$, and the vectors $\tilde{\mathbf{r}}$ and $\mathbf{s} \in \mathbb{R}^N$, $\mathbf{s}$ is a binary array whose entries are one if the position of coded aperture yields a saturated pixel in the compressive measurements in other case it is zero. $\bar{\mathbf{s}}$ is the complement of $\mathbf{s}$. $\tilde{\mathbf{w}}$ is the attenuation of the adaptive filter defined in[10], $\tilde{\mathbf{r}}$ is a uniform grayscale coded aperture.

The adaptive algorithm is based on[10]. The goal of the algorithm is try to bring all the irradiances values I_j between a "desirable range" which is $I_{jdes} \pm \Delta I_j$, avoiding the saturation I_{jsat}

$$\tilde{w}_j^{t+1} = \begin{cases} \alpha\dfrac{\tilde{w}_j^t}{2} + (1-\alpha)\tilde{w}_j^t & I_j \geq I_{jsat} \\ \alpha\tilde{w}_j^t\dfrac{I_{jdes}}{I_j} + (1-\alpha)\tilde{w}_j^t & I_{jsat} > I_j \geq I_{jdes} + \Delta I_j \\ \tilde{w}_j^t & I_{jdes} + \Delta I_j > I_j \geq I_{jdes} - \Delta I_j \\ \beta\tilde{w}_j^t\dfrac{I_{jdes}}{I_j} + (1-\beta)\tilde{w}_j^t & I_{jdes} - \Delta I_j > I_j \end{cases} \tag{5}$$

where $\tilde{w}_j^{t+1}$ is the attenuation of the $j-th$ pixel in the coded aperture in $t+1$, it is the next snapshot, $\tilde{w}_j^t$ is the attenuation of the $j-th$ pixel in the coded aperture in t, it is the current snapshot. In detail, if a pixel is saturated, its transmittance is reduced in a large fraction. If the irradiance is below the saturation level but above the desire range ($I_{jdes} \pm \Delta I_j$), then the transmittance is reduced. If it is below the desire range, the transmittance is increased. If the irradiance lies between the desire range the transmittance is kept unchanged. α and β are constants $\alpha = 1$ and $\beta = 0.5$ according to[10]. The measurements that persist saturated was discarded for AUGCA.

2.4 High dynamic range compressive spectral system

The dynamic range of a conventional CCD sensor is given by,

$$DR = 20 \log \frac{I_{max}}{I_{min}}, \tag{6}$$

where I_{max} and I_{min} are the maximum and minimum radiance values measure by the sensor, respectively. The minimum radiance value is set up to 1. For that reason, 8-bit CCD have a dynamic range of $20 \log(255) =$ dB. On the other hand, the adaptive dynamic range combines the dynamic range of the DMD and the CCD and it is given by

$$ADRC = 20 \log \frac{I_{max} Tr_{max}}{I_{min} Tr_{min}}, \tag{7}$$

where Tr_{max} and Tr_{min} are the maximum and minimum transmittance of the coded aperture, respectively. The ADRC system is the sum of the dynamic ranges of the attenuator and the CCD sensor. Particularly, an 8-bits CCD and attenuator with control of 8-bits of precision, i.e. $20 \log(255 \times 255) = 96.32$, are equivalent to a dynamic range of a 16-bit CCD.

3. RECONSTRUCTION

The two dimensional CASSI system requires to design N coded aperture rows $\tilde{\mathbf{t}}$ to calculate the compressive measurements $\tilde{\mathbf{y}}$. The set of all N rows of CASSI system can be written as,

$$\begin{bmatrix} \tilde{\mathbf{y}}_\mathbf{0} \\ \tilde{\mathbf{y}}_\mathbf{1} \\ \vdots \\ \tilde{\mathbf{y}}_\mathbf{N-1} \end{bmatrix} = \begin{bmatrix} \mathbf{H_0} & 0 & \cdots & 0 \\ 0 & \mathbf{H_1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \mathbf{H_{N-1}} \end{bmatrix} \begin{bmatrix} \tilde{\mathbf{f}}_\mathbf{0} \\ \tilde{\mathbf{f}}_\mathbf{1} \\ \vdots \\ \tilde{\mathbf{f}}_\mathbf{N-1} \end{bmatrix}. \tag{8}$$

Furthermore, all measurements can be arranged as $\tilde{\mathbf{y}} = [\tilde{\mathbf{y}}_0^T, \tilde{\mathbf{y}}_1^T, ..., \tilde{\mathbf{y}}_{N-1}^T]^T$ such that

$$\tilde{\mathbf{y}} = \mathbf{Hf}, \tag{9}$$

where $\mathbf{H}$ is the sensing matrix of each of the 2D slices of the CASSI model. According to CS theory $\mathbf{Hf}$ is expressed as a sparse representation as $\mathbf{f} = \mathbf{\Psi}\overline{\mathbf{\Theta}}$, where $\mathbf{\Psi}$ is a convenient representation basis and $\overline{\mathbf{\Theta}}$ is the coefficients vector. Then equation 9 can be rewritten as,

$$\tilde{\mathbf{y}} = \mathbf{H\Psi}\overline{\mathbf{\Theta}}. \tag{10}$$

The whole data cube can be recovered solving the convex optimization problem given by,

$$\overline{\mathbf{f}} = \mathbf{\Psi}^{-1}(\underset{\overline{\mathbf{\Theta}}}{\operatorname{argmin}} \|\mathbf{y} - \mathbf{H\Psi}\overline{\mathbf{\Theta}}\|_2 + \tau\|\overline{\mathbf{\Theta}}\|_1) \tag{11}$$

where τ is a parameter that stimulates sparse solutions. The compressive spectral reconstructions are realized with a compressive sensing based algorithm such as the gradient projection for sparse reconstruction (GPSR)[13].

4. RESULTS

In this section the uniform adaptive grayscale coded apertures (UAGCA) are compared against the adaptive block-unblock coded aperture (ABCA) and uniform grayscale coded aperture (UGCA). ABCA attenuate the coded aperture blocking all the light. A set of compressive measurements is simulated using equation 1. The dataset was captured using a CCD camera exhibiting 256×256 of spatial resolution.

The dataset used in the experiments is showed in figure 4. The size of the datacube is $256 \times 256 \times 16$. The regularization parameter is set to $\tau = 0.0001$. The simulations were realized with saturation levels between 0% and 10%. Noise was added to the UAGCA, ABCA and UGCA compressive measurements with $SNR = 10$ dB. The simulations with noise shows a behavior of the system close to the sytem implemented. The basis representation is $\boldsymbol{\Psi} = \boldsymbol{\Psi_1} \otimes \boldsymbol{\Psi_2}$ where $\boldsymbol{\Psi_1}$ playing the role of spatial sparsifier as the 2D-Wavelet Symmlet 8 basis, and $\boldsymbol{\Psi_2}$ the spectral sparsifier is the 1D-DCT basis.

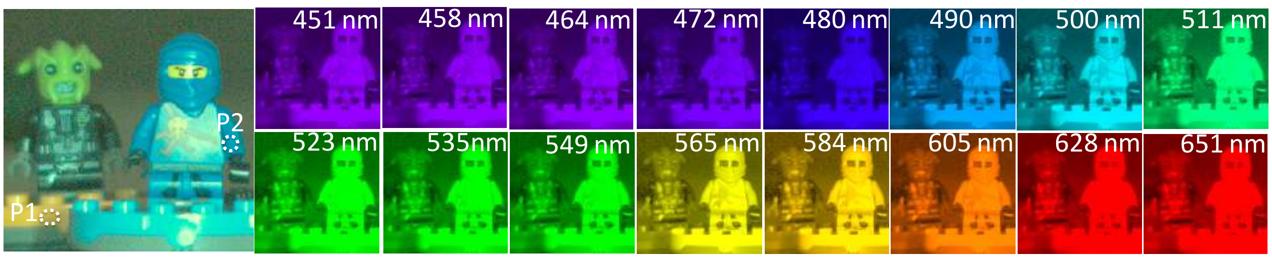


Figure 4: The datacube used for simulations with 256×256 pixels of spatial resolution and 16 spectral bands

Figure 5 shows the quality of reconstructions against the number of snapshots for 1%, 4%, 7% and 10% of saturation and the noise with $SNR = 10$ dB. The number of snapshots varies from 1 to 16. The quality of image reconstruction is improved in up to 10 dB when the number of shots is increased, that is in at least 5 shots are captured.

Figure 6 shows the quality of reconstruction as a function of the percentage of saturation for 2, 4, 8 and 12 snapshots and the noise with $SNR = 10$ dB. The percentage of saturation varies from 1% and 10%. In general, the quality of image reconstruction is improved in up to 10 dB when the percentage of saturation is increased.

Figure 7 shows the quality of reconstruction for the UGCA, ABCA and AUGCA, where the number of snapshots is 8 and noise with $SNR = 10$ dB. For UGCA the quality of reconstruction is PSNR=7.85 dB, ABCA is PSNR=12.85 dB and AUGCA is PSNR=25.15 dB.

5. CONCLUSIONS

The uniform adaptive grayscale coded apertures (UAGCA) have been introduced in CASSI system to replace the traditional block-unblock coded apertures. The proposed architecture permits to attenuate the effect of the saturation of the FPA sensors and increase the dynamic range of the system from 8-bits to 16-bits. The designed grayscale uniform coded apertures outperform the block-unblock adaptive coded apertures and grayscale coded aperture in up to 10 dB in the quality of the reconstructed images.

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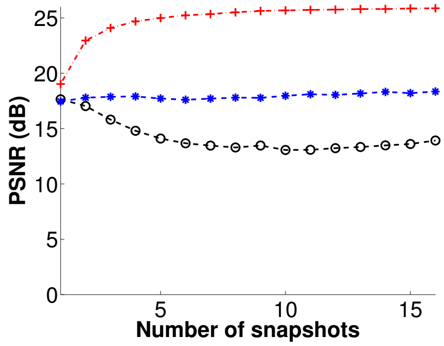
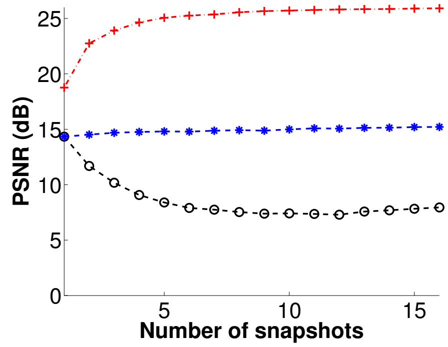
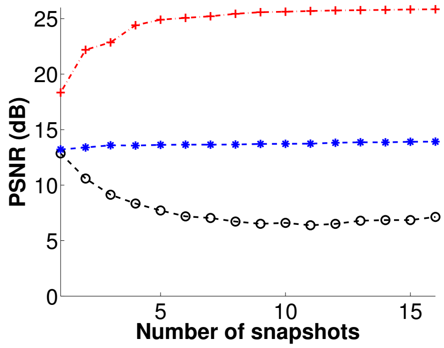


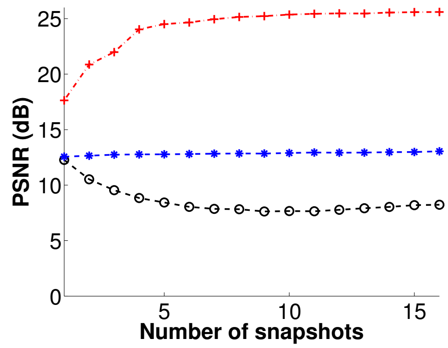
(a) Saturation 1%. For UGCA, ABCA and UAGCA



(b) Saturation 4%. For UGCA, ABCA and UAGCA



(c) Saturation 7%. For UGCA, ABCA and UAGCA



(d) Saturation 10%. For UGCA, ABCA and UAGCA

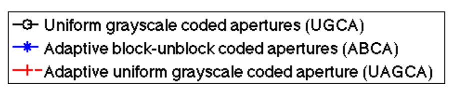


Figure 5: Quality of reconstruction as a function of the number of snapshots

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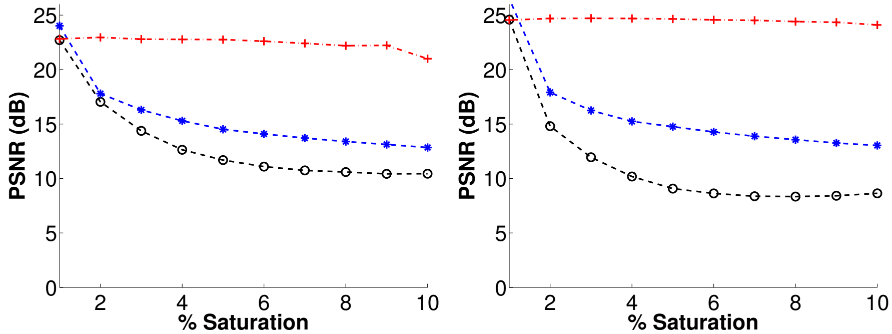
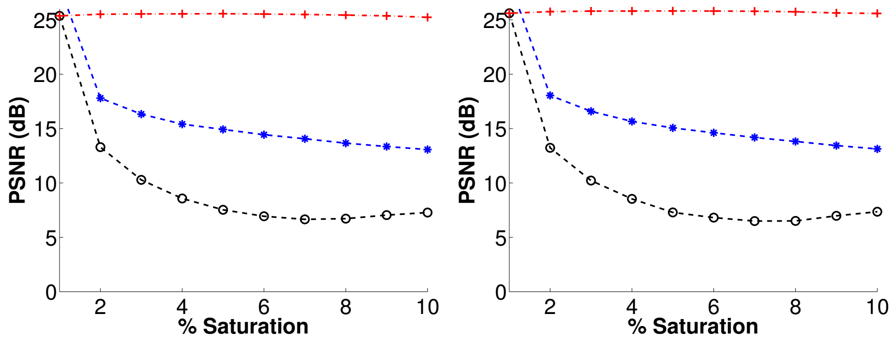


(a) 1 snapshot. For UGCA, ABCA and UAGCA

(b) 4 snapshots. For UGCA, ABCA and UAGCA



(c) 8 snapshot. For UGCA, ABCA and UAGCA

(d) 12 snapshots. For UGCA, ABCA and UAGCA

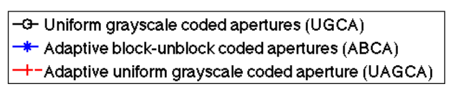


Figure 6: Quality of reconstruction as a function of the saturation

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(a)
Original

(b) Image reconstruction using UGCA, PSNR=7.85 dB

(c) Image reconstruction using ABCA, PSNR=12.85 dB

(d) Image reconstruction using UAGCA, PSNR=25.15 dB

Figure 7: Spatial reconstruction.