DIFFRACTION EFFICIENCY-AWARE RECONSTRUCTION FOR COMPRESSIVE SENSING IN THE MID-INFRARED

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ABSTRACT

Compressive sensing has established itself as a novel imaging paradigm. In this paper, we analyze the behavior of a a compressive instrument based on spatial light modulators (SLM), operating in the mid-infrared. We show that, contrary to the well-studied visible and near-infrared wavelengths, mid-infrared poses modeling challenges due to non-negligible SLM diffraction effects. We show a way to model such effect analytically and to account for them in the reconstruction process, leading to improved reconstruction quality.

Index Terms— Compressed sensing, mid-infrared, diffraction.

1. INTRODUCTION

Compressive sensing (CS) [1] has established itself as a novel approach to imaging, promising to overcome limitations of traditional instrument designs. CS is grounded in the fact that real images have a sparse nature, i.e., they can be compactly represented in some domain, and this allows to sample them at rates lower than what the Nyquist criterion would dictate. Imaging hardware exploiting CS principles may require much fewer detectors than conventional designs, as popularized by the single-pixel camera [2]. This has raised interest for the development of a novel generation of payloads for Earth observation missions [3]. Key to the CS theory is the acquisition of measurements of the light field obtained via spatial light modulation (SLM) with pseudorandom masks. Such modulation is typically implemented by programmable micromirror devices where the behavior of each micromirror follows the corresponding value of the pseudorandom mask. Most of the work on CS instruments has been focused on the visible and near-infrared spectrum [4], while mid-infrared has received relatively little attention [5].

In this paper, we analyze the problem of modeling the behavior of an SLM-based CS instrument operating in the mid-infrared and how the reconstruction algorithm needs to account for such model. In particular, we show that there are non-negligible diffraction effects due to the SLM, resulting in an efficiency term which is spatially-varying at sub-micromirror level and dependent on the state of a set of neighboring micromirrors (determined by the pseudorandom mask). While this effect is negligible in visible and near-infrared, it cannot be overlooked in the mid-infrared. In fact, not accounting for this phenomenon in the reconstruction process results in degraded image quality. We present a detailed equivalent mathematical model of the acquisition process which can be integrated in the reconstruction algorithm to make it aware of the phenomenon. We show that this leads to substantial improvements in the quality of the reconstructed images.

2. SYSTEM MODEL AND RECONSTRUCTION METHOD

2.1. SLM diffraction efficiency

In real optical systems, the finite size of the various optical elements implies the presence of a Point Spread Function (PSF) of finite size, even if there are no optical aberrations. The extent and distribution of the PSF is dependent on the characteristics of the optical system and, in any case, proportional to the wavelength. In the mid-infrared spectral region, the dimensions of the PSF are typically of the same order of magnitude, or larger, than those of the elements of commercially-avaiable, low cost SLMs. If the SLM consists of tilting micromirrors, the phase delay introduced by the micro-mirrors on the PSF wavefront should be considered.

In order to evaluate the diffractive optical efficiency, we have applied the basic principles of Fourier optics and implemented numerical simulations. In particular, took into account the main optical specifications of the CS instrumentation as described in [3, 6] and the configuration of the different states (ON/OFF) of the micromirrors, determined by the applied CS pseudorandom mask. In the simulations, and for each micropixel, i.e., pixel at the resolution of the mage to be reconstructed, constituted by 4×4 micromirrors as in the CS

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demonstrator of [3, 6], we considered all possible combinations of the state of the micropixels surrounding the one of interest. For each of these configurations, the diffractive efficiency was evaluated on a regular grid of 12×12 positions in order to take into account its variability and its dependance from the scene. The simulation results demonstrated that the diffractive efficiency varies up to 20% within the same micropixel and also depends on the specific configuration of the different states (ON/OFF) of micromirrors.

This results leads to the necessity to consider this effect in a numerical model of the acquisition process, so that it can be properly accounted for during reconstruction from compressive measurements.

2.2. Reconstruction algorithm

An equivalent model for SLM diffraction efficiency phenomenon introduced in Sec. 2.1 can be developed. In this equivalent description, the efficiency term is a scalar field modulating the scene to be acquired. We consider the scene at a higher spatial sampling rate, such as 12 times higher, than the SLM micromirrors due to the aforementioned submirror non-uniformity. Being the efficiency field dependent on the micromirrors state, this needs to be precomputed via simulation for each pseudorandom mask to be used in the acquisitions. In formulas, the i-the measurement value is modeled as:

$$y_i = \mathbf{\Phi}_i \mathrm{vec}\left([[\mathbf{U} \odot \varepsilon(\mathbf{\Phi}_i)] * \mathbf{H}_{\mathrm{PSF}} * \mathbf{B}_D]_{\downarrow D} \right) = \mathbf{A}\mathrm{vec}(\mathbf{U}) \tag{1}$$

where $\mathbf{\Phi}_i$ is the current SLM mask, $\mathbf{U}$ is the ideal scene under acquisition, $\varepsilon(\mathbf{\Phi}_i)$ is the SLM efficiency field as a function of the SLM mask, $\mathbf{H}_{\mathrm{PSF}}$ is the optics point spread function, $\mathbf{B}_D$ is a box function of size $D \times D$, $\downarrow D$ is 2D decimation by a factor D in each direction, vec is a vectorization operation and, finally, $\odot$ and $*$ denote elementwise product and convolution, respectively. Notice that the entire model is linear and can be expressed with operator $\mathbf{A}$. While this model needs to involve a super-sampled scene to account for the effect of SLM efficiency, we are only ultimately interested in estimating the image as it would be acquired by a detector placed on the SLM plane. The ground truth image we seek to reconstruct is therefore modeled as:

$$\mathbf{X} = [\mathbf{U} * \mathbf{H}_{\mathrm{PSF}} * \mathbf{B}_D]_{\downarrow D} \tag{2}$$

The reconstruction algorithm is based on total variation minimization and it accounts for the full model in Eq. (1) to properly include the efficiency term. The scene reconstruction is obtained as:

$$\hat{\mathbf{U}} = \arg\min_{\mathbf{U}} \|\mathbf{y} - \mathbf{A}\mathrm{vec}(\mathbf{U})\|_2^2 + \lambda \mathrm{TV}(\mathbf{U}). \tag{3}$$

The reconstructed image we are interested in is then obtained from the scene through the forward model in Eq. (2):

$$\hat{\mathbf{X}} = \left[\hat{\mathbf{U}} * \mathbf{H}_{\mathrm{PSF}} * \mathbf{B}_D\right]_{\downarrow D}. \tag{4}$$

It should be noted that due to the super-sampling factor D, solving Eq. (3) can be computationally expensive, especially for high target resolutions. It is also worth noting that, while for this preliminary investigation, we use total variation minimization, a number of physics-informed deep learning methods [7] could be used for reconstruction. However, this is left as future work since the large dynamic range and bimodal distributions typically encountered in real mid-infrared images can pose challenges in neural network designs.

3. EXPERIMENTAL RESULTS

The experimental setup simulates mid-infrared scenes and the acquisition process previously described in the previous section. The CS acquisition process uses binary random matrices with ± 1 entries with a block size of 32×32 pixels. We study three compression ratios, i.e., the number of measurements acquired for each block, namely 75%, 50%, 25% (768, 512, 256 measurements, respectively). In our setup, the super-sampling factor for the scene is $D = 21$. Table 1 reports some results in terms of relative error of the reconstructed image as function of the compression ratio, i.e., the ratio between the number of CS measurements and the number of image pixels. We first determine the performance under an ideal scenario in which efficiencies are negligible ($\varepsilon = 1$) to set the benchmark. For this benchmark, the variable of the optimization problem is directly the reconstructed image, so we do not attempt to reconstruct the scene and then apply the forward model. We then observe how the diffraction efficiency degrades reconstruction quality when naive reconstruction is performed, i.e., total variation minimization seeking to reconstruct $\mathbf{X}$ without knowing the existence of the diffraction efficiency model. We can however see how the efficiency-aware reconstruction of Eq. (3) is capable of improving reconstruction performance with respect to naive reconstruction. It is worth noting that at 25% compression ratio, efficiency-aware reconstruction improves upon the benchmark that had measurements without any diffraction efficiency. This can be explained by the more accurate modeling of the forward process generating the image with extra terms such as the optical PSF. However, we can also notice a performance floor due to diffraction, whereby increasing the number of measurements does not significantly improve performance. Finally, Fig. 1 shows a qualitative comparison of the reconstruction produced without correctly modeling diffraction efficiency and the efficiency-aware method.

Table 1. Reconstruction relative error

	Compression ratio		
	25%	50%	75%
Benchmark (efficiency=1)	10.75%	2.31%	1.54%
Naive reconstruction	11.72%	9.45%	8.76%
Efficiency-aware reconstruction	**6.97%**	**6.65%**	**6.21%**

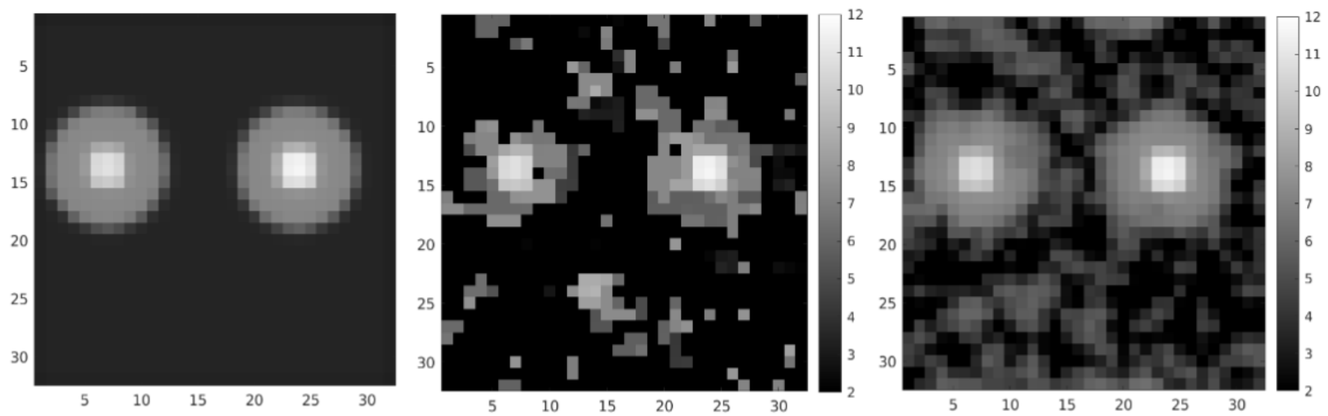

Fig. 1. Comparison between naive reconstruction without modeling SLM diffraction efficiency and efficiency-aware reconstruction. Left to right: ground truth, naive reconstruction, efficiency-aware reconstruction. Log scale.

4. CONCLUSIONS

This paper presented an investigation of a compressive instrument based on SLMs operating in the less-studied mid-infrared. We showed the importance of carefully modeling diffraction effects in order to improve reconstruction quality.

5. REFERENCES

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