Compressive Imaging Through Scattering Media

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ABSTRACT

The presence of scattering media (haze, dust, turbid water, or even diffuse wall surfaces) complicates a variety of defense/security imaging scenarios. Angular memory-effect imaging is one technique for imaging through scattering media; however, the general method has a number of highly-specific constraints which limit its applicability. We can understand those limitations as arising from an apparent loss of coherence. Here, I will discuss how coding and dictionary methods from the computational and compressive sensing domains are compatible with memory-effect methods and can be brought to bear to extract coherent channels from the apparently incoherent field, thereby overcoming some of the limitations of the memory-effect method. I will show experimental results that successfully reconstruct video and multispectral views of a scene from a single monochromatic frame acquired through an intervening scatterer.

1.0 INTRODUCTION

A wide variety of defense/security imaging scenarios are complicated by the presence of intervening scattering media. Although at first glance it may appear that the light arriving from a scattering medium is featureless and retains no information regarding the originating object, residual correlations remain. Angular memory-effect (ME) imaging is a method that uses these correlations to extract a diffraction-limited, infinite depth-of-field image of the object without the need for any prior information regarding the scatterer. This is a very powerful approach, but success of the method rests on the scenario complying with a number of very specific practical constraints.

A number of these practical constraints originate in the need to have a high degree of contrast (interference visibility) in the speckle image that is the acquired data. In the manuscript below we show that the introduction of computational and compressive sensing ideas allows us to overcome several these constraints and generalize the applicability of ME imaging. We are ultimately able to compressively reconstruct multidimensional image data from single acquisitions through scatter.

2.0 ANGULAR MEMORY-EFFECT IMAGING

In conventional ME imaging, narrowband light impinging on the scatterer as a plane wave from a given direction creates, post-scatterer, a *speckle pattern* on a subsequent screen or detector. If the impinging light arrives from a slightly different direction, to a first approximation the resulting speckle pattern is observed to not change, but rather undergo a *lateral shift*. The angular range over which this shifting behavior is maintained is known as the *angular memory-effect limit*. The scale of the ME limit depends on the details of the scatterer—for optical diffusers and white paint, the limit is on the order of 8–10°.

If we now consider a source object in the far-field, a given object point corresponds to a specific plane wave direction of arrival. If the entire object is within the ME limit as seen from the scatterer, then each point in the object gives rise to the same (but shifted) speckle pattern. In this case the speckle pattern acts as a *speckle point-spread-function* (PSF). The resulting intensity, *I*, at the detector or screen can then be written as the convolution of the object distribution, *O*, with the speckle PSF, *S*,

$$I = O * S$$

Conventional ME imaging utilizes this convolution relation to extract the object distribution O from a measurement of the intensity, I. Recovery of the object relies on the mathematical fact that the autocorrelation of a convolution is equal to the convolution of autocorrelations—specifically:

$$\begin{aligned} I \star I &= (O * S) \star (O * S) \\ &= (O \star O) * (S \star S) \\ &\approx (O \star O) * \delta \\ &\approx (O \star O) \end{aligned}$$

This result makes use of the fact that a speckle pattern is approximately delta-correlated. Thus we see that the autocorrelation of the measured intensity is approximately the same as the autocorrelation of the object, despite the presence of the intervening scatterer. Image recovery is then the mathematical problem of determining a function, *O*, given only knowledge of its autocorrelation. The Wiener-Khinchin theorem tells us this is equivalent to determining the phase of a function knowing only its Fourier magnitude—the *phase-retrieval problem*. While the phase-retrieval problem does not have a unique solution, in practice, one finds that a number of different algorithms can readily yield reasonable estimates of the object, *O*, given the autocorrelation of the measured intensity *I* [1].

A number of variants of angular ME imaging have been developed over the years. The earliest forebears are astronomical in origin [2] and required the collection of a temporal sequence of speckle images and the calculation of the autocorrelation of each. These multiple autocorrelations were then averaged together to yield a high-SNR estimate of the autocorrelation. In recent years, tabletop experiments have convincingly demonstrated that large-pixel-count digital cameras eliminate the need for multiple acquisitions, and conventional ME imaging can now be accomplished from a single speckle image acquisition [3].

3.0 EXPLICIT AND IMPLICIT CONSTRAINTS

Prior work in ME imaging identified a number of explicit constraints that needed to be met for the method to work:

- The angular extent of the object must lie within the ME limit
- The speckle pattern must be measured with at least Nyquist spatial sampling
- The detector must have a sufficient dynamic range and signal-to-noise (SNR) ratio to ensure stable, high-fidelity processing
- A sufficient number of speckle grains must be recorded (this constraint is what allows for single-shot operation)

The first constraint is a limitation on applications, while the others are limitations on optical system design. In addition to these constraints, however, we have identified another, implicit, constraint that is never explicitly discussed—*a sufficient degree of speckle contrast (visibility) must be maintained*.

4.0 LOSS OF COHERENCE AND SPECKLE CONTRAST

As the coherence of the optical field decreases, the contrast (visibility) of the resulting speckle pattern decreases. Goodman shows that the contrast, C, of a speckle field is given by

$$C \propto \frac{1}{\sqrt{N}}$$

where N is the number of independent *degrees-of-freedom* (DoF) that are being combined [4]. Here a DoF is any aspect of the system that leads to an independent speckle pattern contribution to the output—in essence, the number of independent speckle patterns that are being summed together. A variety of different system aspects can give rise to multiple DoFs: spectral breadth beyond the initial narrowband assumption, spatial extent outside the ME limit, temporal dynamics of the object within the detector acquisition time, etc. All give rise to distinct speckle patterns on the detector, which are then summed by the transduction process during acquisition and correspondingly reduce the contrast of the resulting speckle measurement and compromise the ability to perform ME imaging in these scenarios.

5.0 CODING AND DEMULTIPLEXING

Our key advance comes from a simple change in word-choice. By considering the combination of multiple independent speckle patterns not as *summing*, but rather as *multiplexing*, a solution becomes clear. Computational and compressive sensing approaches are fundamentally about how the introduction of known *coding* allows for the successful demultiplexing of signals. This suggests that if we are able to inject coding onto each independent speckle pattern, we can separate them post-transduction.

5.1 Dictionary learning

Compressive sensing algorithms for such signal demultiplexing problems exist (such as *orthogonal matching pursuit* (OMP)) [5], but tend to require a basis in which the signals are *sparse*. Naively, one would expect that speckle patterns have no sparse representation, as truly random signals are not compressible. However, as we are Nyquist sampling the speckle on the detector, there exists a finite spatial correlation length in the speckle and thus there can exist a sparse representation—however, it is not any of the typical sparse bases conventionally used in compressive sensing. We turn instead to a data-driven approach that learns the sparse representation from sample data—*dictionary learning*.

We collect a single speckle image from a point source and divide it into all possible (overlapping) 16x16 pixel patches. This is then used as the training set for the dictionary-learning process (we use beta-process factor analysis (BPFA)) [6]. Using BPFA, we then generate an overcomplete dictionary of 512 16x16 pixel patches. Any 16x16 pixel patch in a speckle image can then be represented as a linear combination of a small number of dictionary elements. Empirically, we observe that this dictionary representation is extremely effective (leading to high-fidelity representations using only a small number of elements per patch) and that it is also remarkably robust—a single learned dictionary remains effective even for significant changes in the underlying system geometry, SNR, scatterer, or wavelength. Thus, we need only learn a single dictionary for a wide-range of scenarios.

5.2 Signal separation and processing

Once we have the dictionary, we can then use the OMP algorithm (along with knowledge of the coding that is injected on different DoF) to separate the coded, multiplexed signal into independent speckle instantiations—one per DoF. These individual speckle patterns can then be processed individually by forming the autocorrelation and performing phase-retrieval. A general schematic of this process is shown below in Fig. 1.

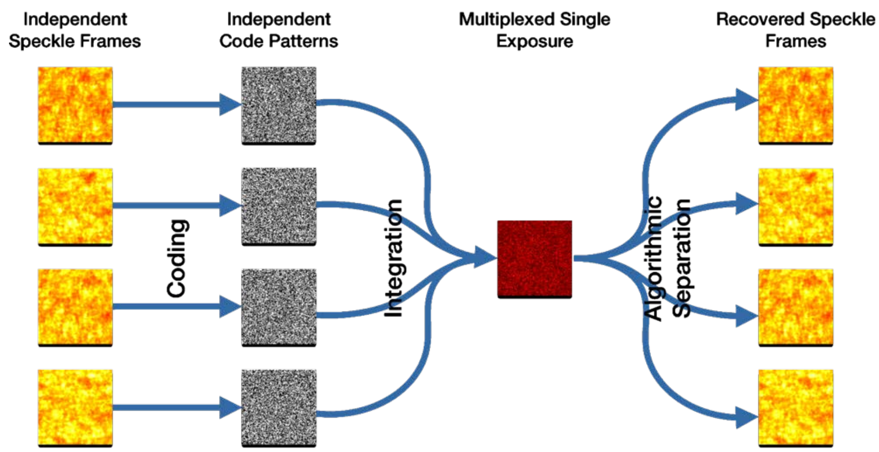

Figure 1: Generalized schematic of the separation and recovery process. Independent frames are multiplexed together with injected coding. The frames are then algorithmically separated and can be individually processed.

6.0 EXPERIMENTAL DEMONSTRATIONS

We have experimentally demonstrated the demultiplexing technique in two distinct scenarios: First, we applied the method to temporally-varying systems in which the object and/or scatterer evolved within the exposure time of the detector. Second, we used the technique with a spectrally-broadband object. In both cases, conventional ME imaging and processing fails, but our coding and demultiplexing technique allows for accurate multi-dimensional recovery.

6.1 Temporal coding

In our first demonstration of the demultiplexing method, we consider systems that undergo temporal dynamics during the acquisition time of the detector—either changes in the object, the scatterer, or both. Intuitively, we view this as evolution as creating a number of *instantaneous speckle frames*, which are multiplexed together by the transduction process of the detector. In the absence of coding, these frames cannot be separated and conventional ME imaging fails (leading to the conventional constraint of a *static* system). We modify the receiver as shown in Fig. 2 to allow for the injection of a temporally-varying spatial code onto the underlying speckle image at the detector.

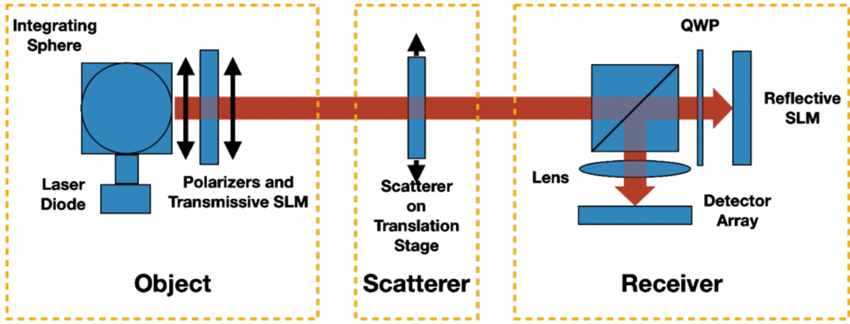

Figure 2: Schematic of the temporal demultiplexing experiment. Only the receiver section is required for the method. The other sections allow creation of a dynamic object and scatterer for the purposes of the experiment.

We then change this code at a frame-rate faster than the rate of the detector, and require that the system only be static on this shorter timescale. Given knowledge of the injected code, our dictionary, and the OMP algorithm, we can separate a single, coded acquisition into the underlying individual instantaneous speckle frames. We then compute the autocorrelation of each individual frame and perform phase-retrieval to extract an estimate of the object in that specific instantaneous frame. Experimental results for the case of simultaneous object and scatterer dynamics are shown in Fig. 3. We are able to successfully recover the underlying object dynamics from a single frame acquisition and are simultaneously robust against dynamics in the scatterer [7].

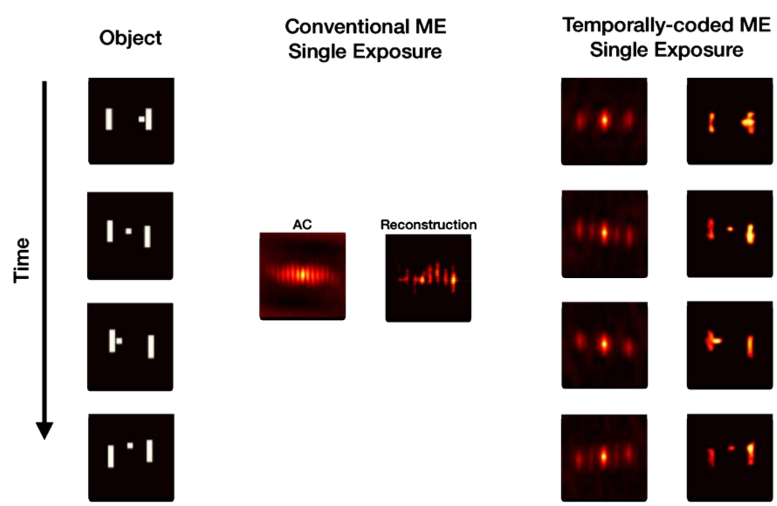

Figure 3: Experimental results of temporal demultiplexing in a scenario with both a dynamic object and scatterer. Conventional ME is unable to recover the object, while our method recovers the sub-acquisition temporal dynamics and is robust against dynamics in the scatterer.

6.2 Spectral coding

We then turned to applying the demultiplexing method to the situation of broadband illumination (specifically, multiband with RGB bands at 650, 550, and 450 nm, respectively). We view this scenario as consisting of a collection of *spectral frames*, each of which generates an independent speckle pattern at the detector, and which are multiplexed together during the transduction process. As before, in the absence of coding, these frames cannot be separated, leading to the failure of the conventional approach (and the imposition of the conventional constraint of *narrowband* illumination). To achieve separation of the frames, we require the ability to inject coding patterns that vary spectrally rather than temporally as in our prior demonstration. We replace the SLM of our temporal experiment with a coded-aperture snapshot spectral imaging (CASSI) spectrograph [8]. The CASSI spectrograph imposes a spectrally-shifting coded pattern onto the image received at the detector plane. A schematic of the experimental setup is shown below in Fig. 4.

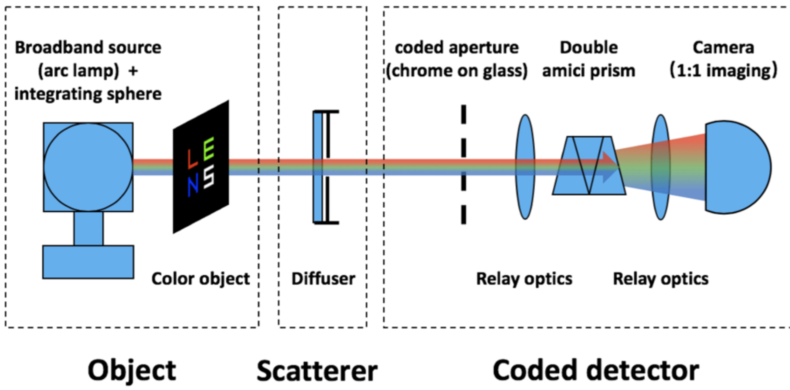

Figure 4: Schematic of the spectral demultiplexing experiment. Only the coded detector (receiver) section is required for the method. The other sections allow creation of a multispectral object for the purposes of the experiment.

Using knowledge of the spectrally-varying code, along with the same speckle dictionary, we once again use OMP to separate a single, monochromatic speckle acquisition into three independent speckle patterns, one for each spectral band. We then compute the autocorrelation of each and use phase-retrieval to generate an estimate of the underlying object structure in each spectral band. Experimental results are shown below in Fig. 5. We were able to successfully recover the spectral content of the scene from a single monochrome acquisition, while conventional methods recover a reasonable estimate of the spatial structure but lose all spectral information [9].

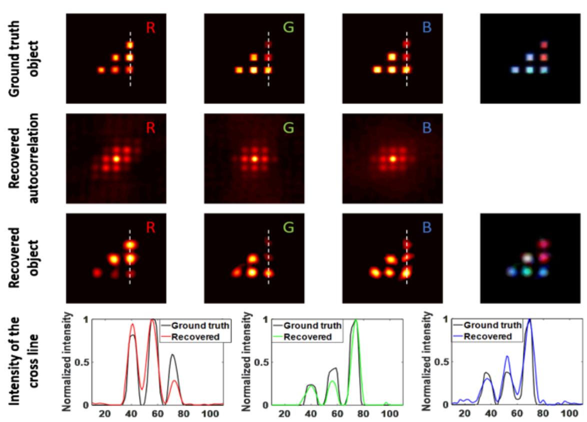

Figure 5: Experimental results of spectral demultiplexing in a scenario with RGB channels. We successfully recover the spatial and spectral content.

7.0 SUMMARY

We have successfully used computational and compressive sensing ideas to overcome implicit limitations on ME imaging that arise from the loss of coherence. By coding independent DoFs, we can separate the speckle patterns arising from each DoF and process them separately, allowing for the successful compressive recovery of multidimensional image data through a scattering medium. Key to this approach is the development of an overcomplete speckle dictionary that provides a sparse representation of speckle patterns. The dictionary is broadly general, and thus must be generated only once.

More generally, we have shown that individual coherent channels can be algorithmically extracted from an apparently incoherent sum provided coding can be injected into the system. This has profound implications for optical design of systems that rely on coherence, as current design methodologies specifically limit the modal content of the light in order to maintain high-contrast data. To the extent these constraints can be relaxed by post-acquisition separation, greater light throughput and hence SNR can be achieved.

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