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Compression at the Physical Interface

[The A-to-I and MONTAGE programs]

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A revolution is emerging in the theory and practice of analog-to-digital data conversion at fast and/or highly parallel physical interfaces. The revolution is based on the realization that data distributed over space and time (e.g., images and time series) is more efficiently and accurately sampled by nonlocal projections than by delta-function samples. Starting with this concept, creative multiplex sampling schemes, nonlinear signal inference algorithms, and statistical signal analysis strategies enable signal transduction at much higher effective bandwidths and over more channels than one would naïvely expect.

This article focuses on recent progress in physical compressive sampling under the Defense Advanced Research Agency's Analog-to-Information (A-to-I) and Multiple Optical Non-Redundant Aperture Generalized Sensors (MONTAGE) programs. A-to-I and MONTAGE focus on aggressive forms of generalized sampling under which

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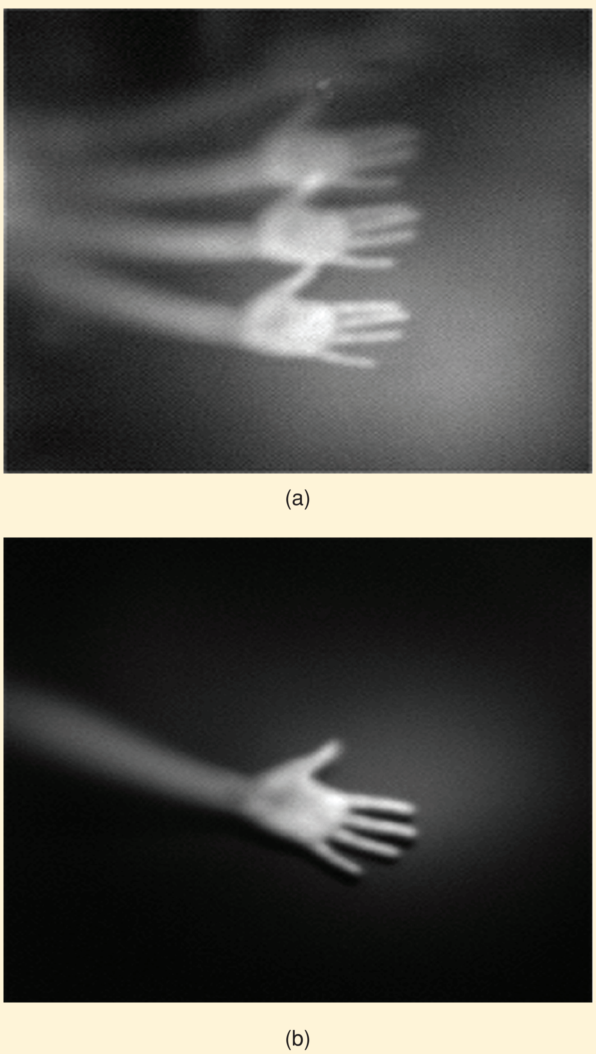
measurements consist of transformations, projections, or encodings of the signal onto discrete digital data. The central system design challenge is to select features, sampling strategies and hardware that enable high fidelity signal estimation from these features. The A-to-I and MONTAGE projects differ in application and implementation A-to-I seeks to revolutionize very high temporal bandwidth analog to digital signal conversion whereas MONTAGE seeks to revolutionize very high spatial bandwidth analog to digital signal conversion.

COMPRESSIVE IMAGING

MONTAGE applies generalized sampling and physical prefiltering to make digital cameras much thinner than the previous state of the art. Multiband sampling, as illustrated by the Osaka University TOMBO imaging system, was an initial motivator. The TOMBO system uses digital super-resolution to achieve high quality images from coarse multiaperture imaging systems [8]. For example, assuming that a digital camera subsamples an optical image by a factor of four, TOMBO uses a 4×4 array of apertures to synthesize a $4\times$ upsampled image. A TOMBO camera would make N^2 measurements to obtain an $N \times N$ image, but would make these measurements in an N times thinner package than a conventional camera. The Compressive Optical MONTAGE Photography Initiative (COMP-I), led by Duke University with support from Raytheon Company, Tessera, UNC Charlotte, the University of Delaware and Michigan Tech, focused on improving the TOMBO approach by increasing the diversity of images in such arrays, by dropping some of the subapertures in the array and by applying emerging decompressive image inference algorithms [4], [5].



[FIG1] (a) Superposition of frames from a single subaperture of a TOMBO-style visible imager. (b) Reconstruction of a temporally and spatially upsampled image from the 2×2 array of images. Image credit: Mohan Shankar.

Potential advantages of compressive measurement in optical systems include the following:

1) Power management. Battery weight and lifetimes are critical issues for mobile imaging devices. In typical systems, power demand is linearly proportional to the data acquisition and transmission volume. Reduced data acquisition rates can make the difference between a device that operates for an hour and a device that operates for a day. Of course, compressive measurement may increase image interpolation and exploitation energy costs, but these processes may be pushed downstream to data centers with ready access to power.

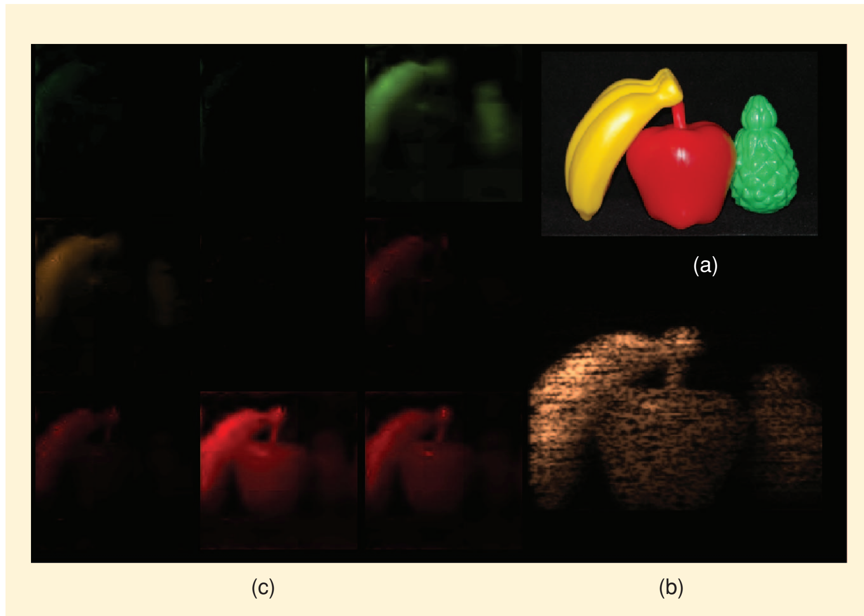
2) Physical layer feature extraction. As previously mentioned, autonomous exploitation of real-time image data is increasingly essential. Conventional systems measure image data on an arbitrary spatial structure that may be poorly matched to the underlying physical structure of target information. The classic scene analysis problem consists of two widely disconnected steps (capture an image, find Alice or Bob in the scene). Emerging feature specific compressive imaging systems bridge these steps using low-level physical sampling strategies that are not matched filters to Alice or Bob but which do enhance Alice and Bob discriminating features [3]. Feature specific imaging substantially reduces data and computational loads.

3) Multidimensional imaging. The classic optical image is a two-dimensional (2-D) projection of a three-dimensional (3-D) scene. One chooses to form 2-D images because the physical processing in lenses and conventional sampling make 2-D easy. Generalized sampling enable efficient multidimensional imaging, including spatial tomography, spectral and polarization imaging and wide field of view and multimodal image fusion.

Compressive measurement is implemented in optical systems by multiplexing pixel or voxel data at discrete detectors. Multiplexing may be implemented both in optical and in electronic components. Examples of electronic multiplexing might include design of the shape and distribution of focal plane pixels, implementation of spatial and temporal filters in focal plane readout, variations in pixel access and raster strategies and compressive projection in read-out integrated circuits. COMP-I focused optical multiplexing implemented by Fourier plane coding (the design of deliberate aberrations to shape the optical impulse response), image plane coding (direct optical modulation of focused pixel fields), and inteferometric coding (the use of thin film, plasmonic or photonic crystal filters to modulate spatial and spectral features in the field). The Rice single pixel camera [7] and the measurement efficient optical wavemeter [6] are examples of compression using image plane coding.

Demonstrations of compressive sampling under COMP-I included power management in multiaperture imaging systems and snapshot spectral imaging. As an example, Figure 1(a) shows a temporally integrated frame from a subaperture of a 2×2 lenslet camera. Each subaperture samples at one quarter of the full frame rate on an interstiched temporal sequence. Reconstruction of upsampled full frame data is implemented by combining least-squares inversion with an image constraint, such as sparcity or smoothness. We use a smoothness constraint to form the image shown in Figure 1(b). The objective of this multiplexing approach is to reduce the read data bandwidth by a 75% to same system power.

COMP-I has also demonstrated compressive imaging in spectral imaging systems by combining coded aperture spectroscopy with multiscale signal inference [2]. These systems enable snapshot multispectral image acquisition, corresponding to greater than $10\times$ compressive sampling of the spectral data cube. As illustrated in the Figure 2 these systems encode spectral data in spatial modulation of images acquired by spectrally insensitive focal planes. The reconstructed data cube shown at the left of Figure 2 is formed from the single frame of spatial-spectral data shown at lower left using the sparse representation strategy described in [11]. One can view spatial image estimation from this data as denoising, the spectral encoding is ideally uncorrelated to the image structure. Prior to denoising, however, the spatial encoding can be used to estimate the local color spectrum of the image.

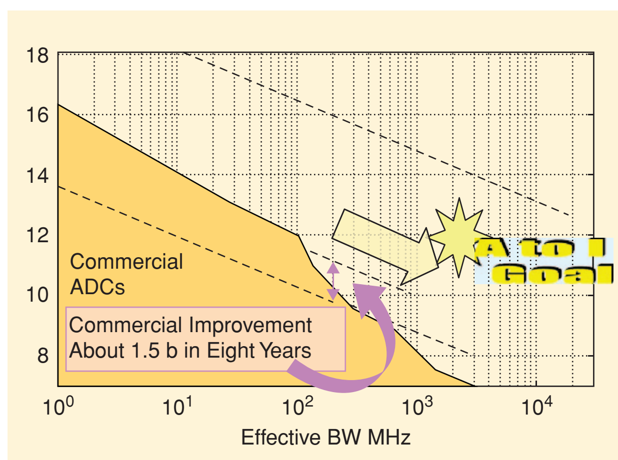


[FIG2] **Reconstruction of plastic fruit using a coded aperture snapshot spectral imaging system. An RGB image of the fruit is shown at upper right. The image at lower right is the single frame of data used to reconstruct the multispectral scene. The 3×3 array of color images at left show slices of the spectral data cube between 530 and 650 nm. Image credit: Ashwin Wagadarikar.**

A-TO-I PROGRAM

The A-to-I program complements MONTAGE's exploration of compressed physical and data volumes in highly parallel sampling interfaces through studies of compressed sampling on very high speed serial interfaces [e.g., analog-to-digital converters (ADCs)]. Current ADCs rely on the usual quantized Shannon representation, i.e., uniform discretized samples at the Nyquist rate or better. A-to-I attempts to get more information out of fewer measurements, easing the burden on both on the digital receiver's digitizing hardware as well as on the first levels of digital processing.

As illustrated in Figure 3, ADC implementations trade sampling frequency against dynamic range. Taken together, fast sampling and high resolution severely stress underlying electronic technology. Emerging applications require conversion of instantaneous bandwidths in the gigahertz range with dynamic range of up to 16 b. This translates to ADC sampling rates of



[FIG3] **Commercial ADCs (gray region) parameterized by sampling rate and dynamic range in effective number of bits. The A-to-I program seeks to rapidly make dramatic improvements in high bandwidth high dynamic range data conversion through the application of compressive sampling and related ideas.**

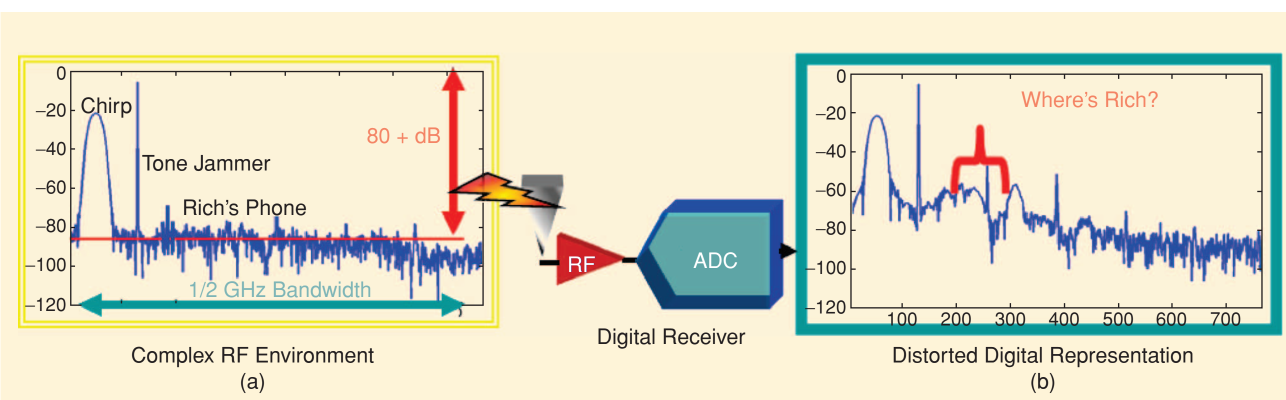
multiple gigasamples per second with a sample aperture jitter held to a tenth of a picosecond. Other implications for hardware include stringent limits on sources of noise and nonlinearities and extremely short settling time for comparators. Surveys of high speed ADC technology indicate that current capabilities fall well short of needs and are in fact advancing at a rather slow rate [9], [10].

Consider a simplified motivating example for the notion of A-to-I converters. Standard ADC strategies based on Shannon's representation exploit only minimal prior signal knowledge, namely the bandwidth. Consequently, standard digitization generally measures much more data than is actually useful. Suppose, for example, that a 500-MHz spectral range is surveyed to detect sporadic narrow band signals. In such a case we might know that at any time the signals of interest occupy at most 10% of a total search band. Standard converters play it safe, digitizing the search band at gigasample rates driven only by the known survey bandwidth. At this rate, the imperfections in technology mentioned above limit the effective dynamic range of the digitized bandwidth so that signals of interest may be lost (see Figure 4).

Most unfortunate! But we are not using all we know, namely the prior knowledge that only 10% of this is interesting. If we knew even more, i.e., where to look in the broad search band, we could use standard converters at 100 megasample rates, for which excellent high dynamic range commercial solutions are readily available. In the problem as stated, however, we do not know where to look. The fundamental question of the A-to-I program is whether our intermediate level of prior knowledge, that the signals of interest live somewhere within the 10% of the search band, buys anything over the minimal level knowledge of the survey bandwidth. Can this sort of intermediate level prior knowledge enable practical data conversion approaches to find the useful information content in complex RF environments and directly measure it in a more concentrated form than is possible in current practice? Can this confer a reduction overconventional approaches of the hardware challenges in capturing and converting information from broad band, high dynamic range RF environment, while simultaneously reducing downstream data burden, computational complexity, and improving inference through dimensionality reduction? In effect, A-to-I aims to intelligently combine sensing and processing to significantly simplify and improve both.

Several plausible mechanization concepts have been advanced for applying these ideas to reduce sampling in converters, including nonuniform sampling and various modulate-and-integrate schemes reminiscent of previous suggestions for different applications in parallel sigma-delta converters. As reported in this issue, early results with simulation and simple hardware implementations are extremely promising, but there remains significant research to be done. In particular, one must address the critical issue that in many applications the signal of interest is generally very small relative to interfering signals. Without modification, regular compression would likely disregard it. Analogously, a first look at restricted isometry property bounds in compressive sampling suggest a limit to dynamic range which may limit certain applications [1]. Another potentially difficulty for high dynamic range conversion arises from the folding of noise from the entire bandwidth of regard into the subsampled bandwidth. Recent work in the program reveals various cracks in this wall, as well as possible ways around or under. Exploiting these is a high priority for the A-to-I program.

Other relevant techniques pursued in the program include recent advances in real-time nonlinear system identification and signal processing. Like several of the implementations of compressive sampling, these techniques effectively encode the bandwidth of interest during the measurement process to improve the condition of the reconstruction of the folding incurred by subsampling. Some of these approaches



[FIG4] Spectral representation of a high dynamic range wideband RF environment (a) and the distorted view we get of it (b) looking through today's broadband converters providing low dynamic range Shannon sampling at the Nyquist rate for this bandwidth. Most of the techniques studied to date in analog to information can be characterized as coded sampling schemes, which fold the bandwidth of regard via sub-Nyquist sampling. However, rather than simply subsampling the signal, which generally creates irretrievable folding ambiguities, special encodings are applied first, creating distinctive signatures for the signals of interest which persist upon folding. This encoding enables in the reconstruction (decoding) of the signals of interest from the folded signal environment, an inversion regularized by various constraints including sparsity.

incorporate a fiducial tone into the nonlinear measurement process to purposefully couple energy into very weak signals and to aid in various deconvolved reconstructions of undersampled data, even offering some regularization against the effects of noise and interference relative to linear processing. There are strong indications that these approaches have very good dynamic range performance.

CONCLUSION

Novel approaches for reduced complexity sampling come from several related mathematical and signal processing advances discussed in the papers of this issue. For example, several studies apply and extend recent advances in information-based complexity to provide compressed data acquisition protocols that perform as if it were possible to directly acquire just the important information about the signals, in effect not acquiring that part of the data that would eventually just be "thrown away" by standard compression of a traditional converter's digital output. As space-time signals are essentially always significantly compressible in some representation, this promises huge benefits. These compressed sampling protocols are noteworthy for the relatively limited prior knowledge about the class of signal to be acquired: basically just the knowledge that the signal of interest would be compressible within a certain representation. These classes are quite large and, in principle, one compressive sampling protocol works for the whole class.

For implementation of compressive sampling theory, it is significant that one does not attempt to directly measure the signal's coefficients in a standard representation known to be compressive for signals of its class. In that case, one would typically need to measure a full set of coefficients before deciding which could be eliminated as insignificant for the particular signal. This would provide no real reduction of measurement. In contrast, compressive sampling shows that it is in principle possible to obtain a full description of the signal from a small number of projections onto a different fixed representation that is "incoherent" with the standard compressive representation. This reduces the number of measurements required for this representation to an amount on the order of that required for a standard compressed representation of the signal.

Rigorously determining the potential impact of these and other fundamental research concepts on practical imaging and data conversion approaches has been the focus MONTAGE and of the recently concluded initial study phase of the A-to-I program. These programs have uncovered significant opportunities and established various important bounds on the sampling required as a function of prior and ancillary information about the optical and RF environment and the particular task or application.

These bounds enable comparison of emerging strategies against the baseline of current Shannon sampling. Various standardized simulated and real signal sets have been collected and applied to such comparisons, revealing some significant advantageous prospects. We hope in the near future to take the next step, in which specific and practical mechanization strategies for reduced sampling protocols will be investigated in detail for their potential to provide breakthroughs in digitization techniques and hardware suitable for challenging Department of Defense imaging and data acquisition applications.

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