Single-pixel neutron imaging with artificial intelligence: Breaking the barrier in multi-parameter imaging, sensitivity, and spatial resolution

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Different from X-rays, neutrons mainly interact with atomic nuclei and magnetic moments in materials. This makes neutron imaging a complementary contrast mechanism to X-ray imaging. Neutron imaging aims to infer the internal material information of the object by measuring the changes in neutron beam parameters, such as the intensity attenuation, polarization, scattering, and matter wave interference. It has a wide range of applications in industry such as the inspection of batteries, magnetic structure analysis, and strain mapping in alloys.¹ Although the imaging technique has been developed, there is a trade-off in multi-parameter imaging, spatial resolution, and sensitivity due to the following reasons: (1) a high-sensitivity imaging system needs to increase the thickness of the sensor (typically consists of scintillator) to capture more energy, but this usually will reduce the spatial resolution of the detector; (2) it is difficult to focus polychromatic neutrons and thus hard to develop scanning probes with high-spatial resolution; (3) high-resolution neutron microscopy is difficult to build due to a limited availability of ideal sources, the lack of appropriate detectors and lens; (4) nuclear reactor and spallation neutron sources only provide limited neutron flux, and (5) neutrons are ionizing radiation and the dose must be limited.² In a nutshell, it is extremely challenging to obtain neutron images of high-spatial and multi-parameter resolutions (energy, polarization, etc.) with low flux illumination using ordinary position-sensitive detectors. This challenge has recently been addressed using the technique of single-pixel imaging or ghost imaging (GI) with neutrons.³,⁴ Moreover, by using the recent advances of artificial intelligence (AI), a deep convolutional neural network (CNN) can improve the quality of the reconstructed image from neutron GI significantly under low neutron flux illumination. This beautiful work was recently done by the scientists from the China Spallation Neutron Source and Institute of Physics, Chinese Academy of Sciences.¹ With the breakthroughs in GI and AI, neutron imaging is coming to a new era, which may lead to non-invasive biological applications and non-destructive inspections in industry. In this commentary, we briefly review the key technologies of neutron GI developed in He and co-workers¹,² and discuss some future research directions of integrating AI and GI.

The key technique leading to this breakthrough in the hardware is GI³ (Figure 1, left), which uses a single-pixel bucket detector to perform the sampling, and then obtains the image of the object by conducting the correlation between these detected signals (without spatial resolution) and a reference light-field ("reference beam" in Figure 1) that does not pass through the object. GI was originally developed in the context of visible light quantum, initially named by the thought of an action of quantum entangled photons. It was later recognized that only the correlation property of the photons is required, and classical forms of GI started to emerge.¹ The main advantage of GI is to decouple the detection and imaging modules. Since a bucket detector does not require any spatial resolution, it is easy to resolve the parameters, such as energy and polarization of the beam passing through the object. Therefore, GI enables multi-parameter imaging via investigating the correlation between the reference light field and the signal detected by the bucket sensor with energy and polarization resolution that is difficult in conventional imaging. Because the bucket detector collects all the radiations passing through the object in each measurement, the signal is larger and thus GI can improve the signal-to-noise ratio of detection, and requires much less flux illumination compared with conventional imaging with an ordinary array detector; this can also reduce the dose during imaging with radioactive sources. Inspired by these gains, GI has been successfully performed with visible light, terahertz waves, microwaves, X-rays, atoms, and electrons. In the meantime, Fourier transform, holographic, and phased-contrast GI systems have also been proposed.

The underlying principle of GI is to spatially modulate the signal, usually during light illumination or propagation, before being captured by the sensor. The modulation needs to be changed per measurement shown by the "variant mask" in Figure 1A. Although only a single-pixel bucket detector is used, each measurement captured by the bucket detector contains
information from all pixels in the image. Given these modulation patterns and the captured measurements, the desired image can be reconstructed. The vital component in GI is the modulation. For a long time, it has been difficult to realize GI with neutrons because of the lack of suitable modulation. The modulation devices have recently been developed using Hadamard patterns made of cadmium in He et al., and using cylindrical shell random masks filled by grains of iodized table salt (NaCl) or gadolinium oxide (Gd₂O₃) as in Kingston et al., and thus paved the way for single-pixel neutron GI. This lays the foundation of using neutron GI for vast applications, such as in vivo biological observations.

As a parallel but strongly related research into GI, single-pixel imaging (SPI) based on compressive sensing (CS) has also been developed during the same time, which similarly uses a single-pixel sensor to capture the image. In addition to the correlation property of photons, SPI using CS is usually modeled as an ill-posed problem and, by using the priors of the desired signal, the measurement number can be much smaller than the number of pixels in the desired image. This has significantly reduced the number of required measurements and it is, therefore, extremely beneficial when radioactive sources such as neutrons and X-rays are used. CS has inspired computational GI, where the reconstruction algorithms developed for CS are widely used in GI reconstruction to improve the image quality. This has significantly reduced the number of required measurements and it is, therefore, extremely beneficial when radioactive sources such as neutrons and X-rays are used. CS has inspired computational GI, where the reconstruction algorithms developed for CS are widely used in GI reconstruction to improve the image quality.

In the following, we briefly introduce the forward model and reconstruction process of GI. Let \( f(x, y) \) denote the ensemble illumination introduced by the modulation mask as shown in Figure 1A. The desired signal is the neutron intensity transmission function of the sample (shown as the “N” in Figure 1A), denoted by \( T(x, y) \), where \( 0 \leq T(x, y) \leq 1 \). Assuming a uniform spatial distribution of the neutrons arriving at the plane of the object when no mask is present, the captured measurement of the bucket detector \( g_j \) for the \( j \)th illumination pattern \( I_j(x, y) \) is

\[
g_j = \int \int I_j(x, y) T(x, y) dx \, dy. \tag{1}
\]

By taking \( N \) measurements, the desired image \( f(x, y) \) in GI, is usually obtained by the correlation of the intensity fluctuations via

\[
f(x, y) = \frac{1}{N} \sum_{j=1}^{N} (g_j - \langle g \rangle)(I_j - \langle I \rangle), \tag{2}
\]

where \( \langle g \rangle = E(g) \), with \( E \) denoting the expectation value and similar for \( I \). This is also called ensemble average when \( N \) approaching infinity.

To connect GI with CS, we use the discrete formulation of Equation (1) as

\[
g = Hf + \epsilon. \tag{3}
\]

Here, we consider a more general case with \( g \in \mathbb{R}^M \) being the captured measurements, with \( M \leq N \); \( f \in \mathbb{R}^N \) is the vectorized image and \( \epsilon \in \mathbb{R}^N \) denotes the measurement noise. The sensing matrix \( H \in \mathbb{R}^{MN} \) corresponds to the mask, i.e., each row denotes one modulating pattern. Equation (3) is usually an ill-posed problem, i.e., there are more unknowns than knowns due to \( M > N \) in most cases. The reconstruction is given by

\[
\hat{f} = \text{argmin}_f \| g - Hf \|_2^2 + \tau R(f), \tag{4}
\]

where \( R(f) \) is the prior to be used. In the literature, widely used image priors include sparsity, piece-wise constants, such as total variation, and low rankness.

Equation (4) plays a significant role in computational GI with a 2-fold contribution: (1) speeding up the sampling process due to a smaller number of measurements and (2) improving the quality of the reconstructed image with priors. Equation (4) is usually solved by an iterative algorithm, and one drawback is the slow reconstruction speed due to iterations. Therefore, there is a trade-off between the imaging speed and the reconstruction speed. Thanks to the recent advances of AI, the CNN has been employed to solve the reconstruction problems in GI, which can achieve high-quality results instantly after training. This has also been used in single-pixel neutron GI, where we can see, from Figure 1E, that the result of CNN is much better than that of conventional GI obtained by Equation (2) shown in Figure 1C. This strongly verified that, by integrating GI with AI, high-quality energy-resolved neutron images can be obtained in a high-speed manner even under a low radiation flux environment. Therefore, the long-term barrier in multi-parameter imaging, sensitivity, and spatial resolution in high-penetration imaging systems such as neutrons can be conquered.

Looking forward, the inexpensive, low-intensity implementation of neutron GI has potential extensions of neutron ghost tomography, neutron ghost microscopy, dark-field neutron ghost imaging, scattering ghost imaging, and isotope-resolved color neutron ghost imaging via prompt gamma-ray bucket detection as discussed by He and co-workers. Meanwhile, with the powerful learning property of deep neural networks, AI can extract extensive useful high-dimensional features in tomography and microscopy and thus can further reduce the required measurements in these new systems to speed up the imaging process and to conduct multi-parameter imaging. On the other hand, Fourier transform GI (FGI) is an important research direction in addition to the GI developed by He and co-workers. The spatial resolution of FGI is determined by the maximum spatial frequency of the Fourier transform diffraction pattern and, theoretically, FGI can provide a higher spatial resolution than GI developed in He and co-workers. From this perspective, the development of neutron GI will also inspire the implementation of neutron FGI and furthermore to apply AI to solve the challenges in FGI.

Although the current integration of GI and AI is still in the preliminary stage, it has been demonstrated clearly in He et al. that AI can significantly improve the quality of the reconstructed image. This has paved the way of obtaining neutron images of high-spatial and multi-parameter resolutions, with low flux illumination using ordinary position-sensitive detectors. Therefore, the barrier in multi-parameter imaging, sensitivity, and spatial resolution, is breaking by taking the advantages of GI and AI. Taking one step further, inspired by the recent explosive growth of AI, a deep integration of GI and AI can perform classification and recognition directly from the raw multi-parameter imaging measurements without reconstruction. The integration with AI is not limited to neutron GI but can be used in other kinds of GI and more broadly any computational imaging systems because images are not necessarily the ultimate goal in real applications. Computational imaging along with AI will break more barriers in conventional imaging to provide more useful information that cannot be captured before. We are coming to a new era of imaging that leads to a revolution in signal capture, transmission and analysis.

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