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Bayesian Deep Prior Denoising of XRF Maps Acquired Under Low Dose Constraints

Low-energy X-ray fluorescence (XRF) mapping at synchrotron radiation facilities [1, 2] is often limited by acquisition time and dose constraints [3], especially for sensitive samples such as biological specimens or cultural heritage objects. Compressive sensing strategies [3] offer a way to mitigate these limitations by enabling spatial undersampling or by triggering dynamical decisional mechanisms [3]. Still, reconstructions from these regimes are challenged by high noise, low photon counts, and incomplete data.
Traditional denoising, inpainting and reconstruction algorithms often fail under such low-count conditions, and iterative reconstruction pipelines require carefully tuned, handcrafted regularizers [4]. On the other hand, supervised deep learning methods - while powerful - pose risks of hallucinating details learned during training, which is especially problematic when ground truth is unavailable [5].
In this work, we propose a Bayesian Deep Image Prior (BDIP) framework for denoising and restoring XRF maps acquired at short dwell times [6, 7]. This method belongs to the class of unsupervised deep priors [5], requiring no pre-training, thus reducing the risk of introducing artificial features [7]. The approach [5] treats the reconstruction as an iterative optimisation problem, where a modified U-Net [8] fed with noise learns to generate a denoised image by progressively estimating the task-specific high-frequency content. Unlike conventional handcrafted priors that act as fixed filters or sparsity enforcers, the network learns a complex task-specific prior directly from the data.
A key advantage of the Bayesian formulation [7, 6] is its ability to estimate both epistemic uncertainty (reducible with more data) and aleatoric uncertainty (intrinsic to the noise) [9] via a variational method and Monte Carlo dropout [7, 10]. This results in pixel-wise uncertainty maps, providing insights into the reliability of the reconstructed signal [7]. Nonetheless, even if not fully immune to overfitting, BDIP provides more controlled convergence than conventional Deep Image Prior approaches [7].
We evaluated our method on XRF spectral maps measured at the TwinMic spectro-microscopy beamline [2] of the Elettra Synchrotron facility (Trieste) acquired from a 1 mm-thick sandstone sample treated with a nano-protective product [3, 11]. Due to the sample's opacity, localisation was guided using only visible light and back-scattering images. Dwell times of 3 s and 0.1 s were used to simulate high and low-count scenarios. From the detected emission lines (Na, Si, and Al), Na, the weakest emitter, posed the most significant denoising challenge. Comparative benchmarks were performed using state-of-the-art methods such as calibrated [12] non-local-means [13], total variation [14], and wavelet [15] denoisers under a j-invariant framework [12]. Our method consistently achieved the highest SSIM scores [16], particularly in recovering fine details in the noisy Na map. Pixelwise uncertainty maps further highlighted regions of reconstruction instability, aiding interpretation.

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Workshop topics

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Authors: Dr GUZZI, Francesco (Elettra Sincrotrone Trieste); Dr GIANONCELLI, Alessandra (Elettra Sincrotrone Trieste); Dr BILLÈ, Fulvio (Elettra Sincrotrone Trieste); Dr KOUROUSIAS, George (Elettra Sincrotrone Trieste)

Presenter: Dr GUZZI, Francesco (Elettra Sincrotrone Trieste)