ICML2023 rebuttal: Additional Results for "QCM-SGM+: Improved Quantized Compressed Sensing With Score-Based Generative Models for General Sensing Matrices"

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In this supplementary material, as per requested by the reviewers, we provide some additional results on some **other general matrices beyond ill-conditioned matrices**, such as **Fourier matrices, Hadamard matrices, i.i.d. nonzero-mean Gaussian matrices [1, 2], as well as correlated matrices [3].**

Figure 1 show the results of QCS-SGM+ and QCS-SGM on discrete cosine transform (DCT) and Hadamard matrices. It can be seen that, **since both DCT and Hadamard matrices are row-orthogonal matrices which satisfy the assumption of QCS-SGM, so that QCS-SGM+ performs the same as QCS-SGM**. Note that the reason why we consider discrete cosine transform (DCT) rather than Fourier matrix is that, the DCT matrix is a real matrix so that we do not have to modify our code, though QCS-SGM+ applies to complex-valued data with small modifications.

Figure 2 shows the comparison of QCS-SGM+ and QCS-SGM on i.i.d. nonzero-mean Gaussian sensing matrices and correlated matrices, respectively. Mathematically, for the i.i.d. nonzero-mean Gaussian matrices, each element follows $A_{ij} \sim \mathcal{N}(A_{ij}; \mu, \frac{1}{M})$ where μ is the mean value; for correlated matrices, $\mathbf{A}$ is constructed as $\mathbf{A} = \mathbf{R}_L \mathbf{H} \mathbf{R}_R$ [3], where $\mathbf{R}_L = \mathbf{R}_1^{\frac{1}{2}} \in R^{m\times m}$ and $\mathbf{R}_U = \mathbf{R}_2^{\frac{1}{2}} \in R^{n\times n}$, the (i,j)th element of both $\mathbf{R}_1$ and $\mathbf{R}_2$ is $\rho^{|i-j|}$ and ρ is termed as the correlation coefficient here, $\mathbf{H} \in R^{m\times n}$ is a random matrix whose elements are drawn i.i.d. from $\mathcal{N}(0,1)$.

It can be seen from Figure 2 that, as expected, since both two kinds of matrices no longer satisfy the row-orthogonal assumption of QCS-SGM, **the proposed QCS-SGM+ outperforms QCS-SGM for relatively large μ or ρ, demonstrating its robustness to general matrices**.

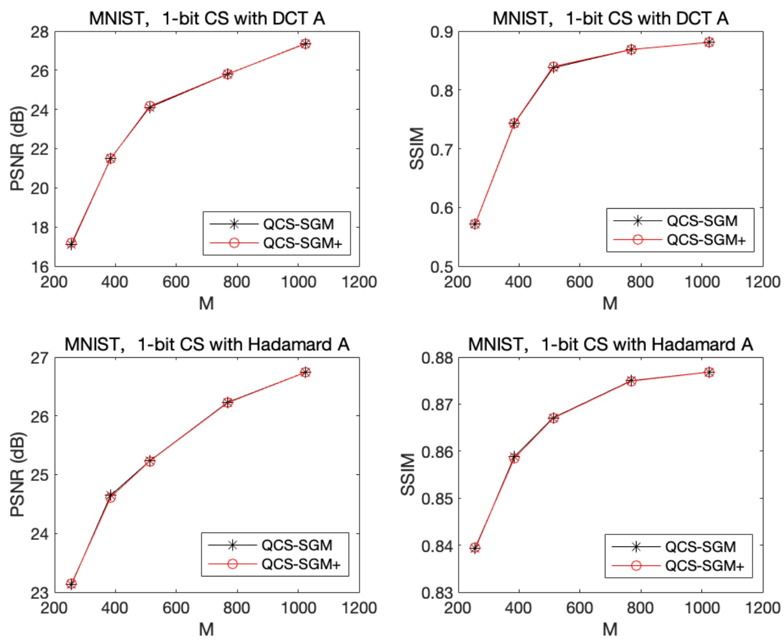

Figure 1: Quantitative comparisons of QCS-SGM+ (proposed) and the original QCS-SGM 1-bit CS for MNIST dataset on discrete cosine transform (DFT) and Hadamard matrices $\mathbf{A}$, respectively. As expected, since both DCT and Hadamard matrices are row-orthogonal matrices which satisfy the assumption of QCS-SGM, so that QCS-SGM+ performs the same as QCS-SGM. $\sigma = 0.05$

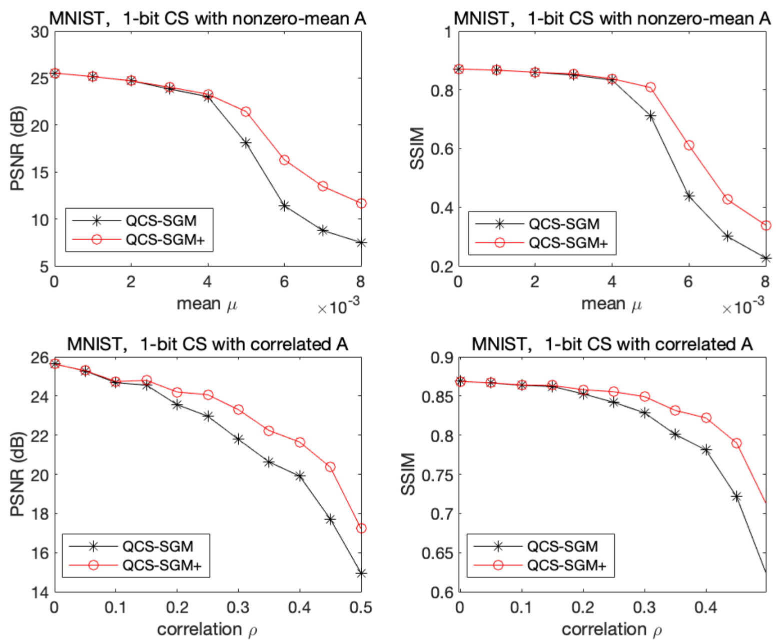

Figure 2: Quantitative comparisons of QCS-SGM+ (proposed) and the original QCS-SGM 1-bit CS on nonzero-mean Gaussian and correlated matrices $\mathbf{A}$ for MNIST dataset. As expected, since both two kinds of matrices no longer satisfy the row-orthogonal assumption of QCS-SGM, the proposed QCS-SGM+ outperforms QCS-SGM for relatively large μ or ρ. $M = 1024, \sigma = 0.05$

References

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