Ming Yan

Assistant Professor, CMSE; Department of Mathematics
yanm@math.msu.edu | 517.353.8492 | 619 Red Cedar Rd., Room C301

BIO SKETCH

Ming Yan joined the MSU faculty in July 2015 with joint appointments in the Department of Computational Mathematics, Science, and Engineering, and the Department of Mathematics.

Prior to arriving at MSU, Dr. Yan was with the UCLA Department of Mathematics—first as a Postdoctoral Scholar (2012–13) and then as an assistant adjunct professor (2014–15). In 2012, he was a Postdoctoral Fellow in the Rice University Department of Computational and Applied Mathematics, in Houston, TX.

He received his Ph.D. in mathematics in 2012 from the University of California, Los Angeles (UCLA) under Prof. Luminita A. Vese. His dissertation was *Image and Signal Processing with Non-Gaussian Noise: EM-Type Algorithms and Adaptive Outlier Pursuit*. He previously earned both his B.S. (2005) and M.S. (2008) in mathematics from the University of Science and Technology of China (USTC), Hefei, Anhui, China.

RESEARCH INTERESTS

Image and signal processing, machine learning, computational optimization, parallel and distributed optimization for large problems

WEBSITE

www.math.msu.edu/~yanm

CURRENT RESEARCH FOCUS

My research focuses on developing fast, robust algorithms with provable convergence for solving inverse problems arising in image processing, sparse signal recovery, statistical regression, etc.

Non-Gaussian noise removal. The removal of non-Gaussian noise is important since non-Gaussian noise is common in applications. Different types of non-Gaussian noise follow different distributions, and they are usually more difficult to remove than Gaussian noise.

Poisson noise is unavoidable in photon-counting data such as astronomy, Positron Emission Tomography (PET), Computed Tomography (CT), and fluorescence microscopy. We developed a parameter-free and general convergent EM-type algorithm for image recovery when the measurements are contaminated by Poisson noise. A method named EM+TV is proposed for image reconstruction in CT. It uses much fewer projections than the traditional filtered back-projection employed by commercial CT scanners, thus reduces the radiation dose received by patients. It has been implemented on Graphics Processing Units (GPUs) and Field-Programmable Gate Arrays (FPGAs) for acceleration and applied on real patient data for lung cancer screening.

Sparse random noise is another common type of noise in signal and image processing (e.g., impulse noise in images and outliers in measurements). We introduced an accurate model based on the nonconvex L_0 "norm." The algorithm is shown to converge to a local minimum in finitely many steps. It performs better than other algorithms based on convex optimization and other nonconvex optimization models in many applications, including impulse noise removal, robust one-bit compressive sensing, robust matrix completion, and robust evaluation of quality of experience.

Nonconvex sparse optimization. In sparse optimization applications, nonconvex regularization terms are more favorable than convex ones because they are able to obtain better recovery results with even fewer measurements. The challenge is how to choose the nonconvex regularization term and develop efficient algorithms with provable convergence results. Nonconvex optimization problems with the previous proposed L_p terms are generally difficult to solve. We proposed a new nonconvex model called nonconvex sorted L_1 minimization that performs better than other nonconvex models and has rigorous convergence analysis. At present, we are applying this regularization term to more challenging problems.

Parallel and distributed sparse optimization. Parallel and distributed computing is crucial to many modern applications of inverse problems involving data of much larger scales than standard optimization packages can handle. The challenge is that inverse problems usually have dense data and nonsmooth objective functions, and its traditional algorithms do not lend themselves for distributed implementations. We developed GRock, which solves gigantic sparse recovery problems in minutes by massive parallel computing. Instead of greedily updating just one variable or randomly updating several variables, GRock greedily updates several variables independently and reduces its total time as a result of both cheaper per-iteration cost and fewer iterations.

Asynchronous parallel computing. Synchronous parallel iterative algorithms have the following disadvantages comparing to asynchronous approaches: When multiple cores execute a synchronous parallel iterative algorithm, all the cores must wait until the slowest core has finished its iteration before they can start the next iteration. In addition, all the cores simultaneously make congestion-inducing communication and memory-access requests. However, it is more difficult to analyze asynchronous algorithms and ensure their convergence. There is no longer a sequence of iterations where the output of one iteration determines that of the next

FIGURE 1. (a) Image with 25% random-valued impulse noise, (b) denoised image.

iteration. We developed ARock—an algorithmic framework for asynchronous parallel coordinate updates—and showed its convergence with minimum assumptions. As special cases of ARock, novel algorithms for linear systems, convex optimization, machine learning, distributed and decentralized optimization are introduced with provable convergence.

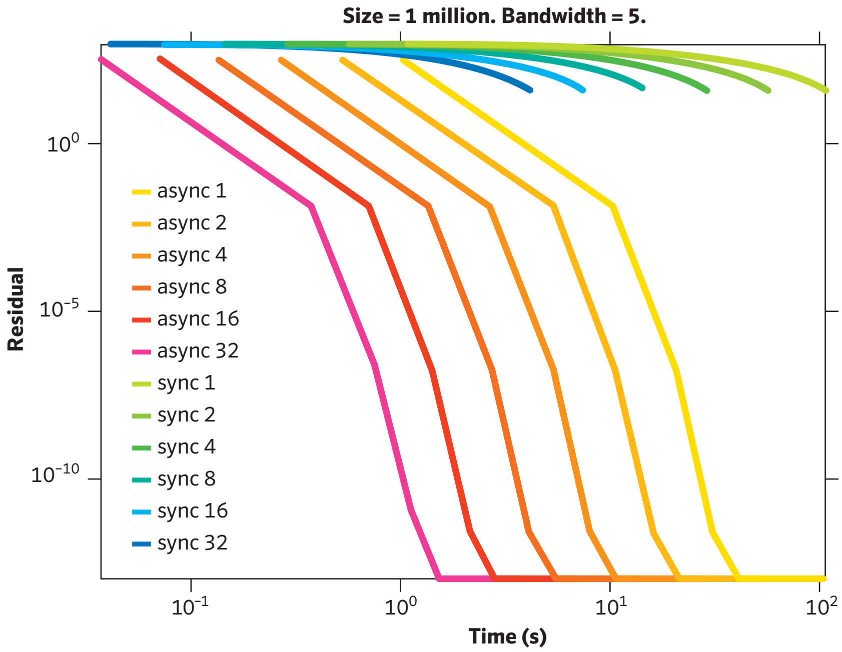

FIGURE 2. Residual versus wall-clock time for synchronous parallel Jacobi and ARock (asynchronous parallel) for solving linear equations on different cores at the same number of epoches.

RECENT PUBLICATIONS

X. Huang, L. Shi, M. Yan, "Nonconvex sorted L1 minimization for sparse approximation," *Journal of Operations Research Society of China*, 3, 207–229 (2015).

Z. Peng, M. Yan, W. Yin, "Parallel and distributed sparse optimization," in *Proceedings of IEEE Asilomar Conference on Signals Systems and Computers*, 659–664 (2013).

M. Yan, A. Bui, J. Cong , L.A. Vese, "General convergent expectation maximization (EM)-type algorithms for image reconstruction," *Inverse Problems and Imaging*, 7, 1007–1029 (2013).

M. Yan, "Restoration of images corrupted by impulse noise and mixed Gaussian impulse noise using blind inpainting," *SIAM Journal on Imaging Sciences*, 6, 1227–1245 (2013).