Theoretical Simulation of Streak-Tube-Based Compressed Ultrafast Imaging System

Authors: Liu Junkai, Deng Xuan, Yang Kaizhi, Luo Qiuyan, Niú Lìhóng, Zhang Jingjin, Liu Jinyuan, Houzhi Cai, Xiang Lijuan, Cai Houzhi, Xiang Lijuan

Date: 2024-01-31T16:32:21+00:00

Abstract

Simulations were performed on a compressed ultrafast imaging system based on compressed sensing and streak cameras. The original three-dimensional image I(x-y-t) undergoes encoding modulation via digital micromirror devices (DMD), and is then transmitted to a streak tube with fully open slit. Under the action of a deflection electric field, multiple images at different times are superimposed, and the final integrated image is output on a CCD. The CCD integrated image is reconstructed into multiple original images I(x-y-t) using a total variation reconstruction algorithm. The image acquisition process and reconstruction algorithm of the compressed ultrafast imaging system were simulated, yielding 8 dynamic two-dimensional images of laser propagation in air medium, with each image having an exposure time of 12.5 ps, and a similarity of 92% between the reconstructed signal and the original signal.

Full Text

Theoretical Simulation of a Compression Ultrafast Imaging System Based on Streak Tube

LIU Junkai, DENG Xuan, YANG Kaizhi, LUO Qiuyan, NIU Lihong, ZHANG Jingjin, LIU Jinyuan, CAI Houzhi*, XIANG Lijuan*

Key Laboratory of Optoelectronic Devices and Systems of Ministry of Education and Guangdong Province, College of Physics and Optoelectronic Engineering, Shenzhen University, Shenzhen 518060, Guangdong Province, China

Abstract

This paper presents a simulation of a compressed ultrafast imaging system that integrates compressed sensing with a streak camera. The original three-dimensional image I(x-y-t) undergoes encoding and modulation via a digital micromirror device (DMD) before transmission to a slit-full-open streak image converter tube. Under the influence of a deflection electric field, multiple images from different time points superimpose onto each other, producing a final integrated image on the CCD. A total variation restoration algorithm reconstructs multiple original images I(x-y-t) from this CCD-integrated image. We simulate both the image acquisition process and the restoration algorithm of the compressed ultrafast imaging system, obtaining eight dynamic two-dimensional images of a laser pulse propagating through air. Each image has an exposure time of 12.5 ps, and the reconstructed signal achieves a similarity of 92% compared to the original signal.

Keywords: ultrafast diagnosis; streak camera; compressed sensing; temporal resolution

Introduction

In 1948, American telecommunications engineer H. Nyquist proposed the Nyquist sampling theorem in signal processing research. At the beginning of the 21st century, mathematician Terence Tao serendipitously discovered during image signal restoration research that perfect reconstruction of the original signal is possible even when the sampling frequency falls below the Nyquist requirement. This led Tao and colleagues to introduce compressed sensing theory in 2006. By exploiting the sparsity of signals, this theory enables the acquisition of discrete samples through random sampling at rates far below the Nyquist criterion, with subsequent signal reconstruction achieved through specialized algorithms.

Since its inception, compressed sensing theory has found widespread applications across information technology, imaging, biology, optics, and computer science. Ultrafast imaging is a technique for capturing extremely rapid processes, enabling real-time observation and recording of dynamic scenes at nanosecond to femtosecond timescales. Its development originated with the emergence of ultrafast laser technology in the 1980s, when advances in high-energy, high-power lasers motivated researchers to pursue real-time observation of ultrafast dynamic processes. As laser technology has become increasingly prevalent, the field of ultrafast imaging has demanded ever-faster and more sensitive detectors.

Streak image converter tubes represent one of the mainstream devices in ultrafast imaging, offering picosecond-level temporal resolution and commonly employed in inertial confinement fusion (ICF) diagnostics. Integrating compressed sensing technology with streak cameras significantly expands their capabilities, enabling applications such as femtosecond pulsed laser experiments for studying electrons in atoms, molecules, and condensed matter; investigations of spin dynamics in magnetic materials; and pharmaceutical research on drug absorption, distribution, and metabolism kinetics. Compressed ultrafast imaging systems combining these technologies can play crucial roles in these scenarios.

In 2014, Professor Lihong Wang' s team proposed an efficient compressed ultrafast imaging methodology with advanced data acquisition and reconstruction algorithms that addressed key challenges in observing ultrafast dynamic processes. Their approach substantially surpassed conventional ultrafast diagnostic imaging speeds while delivering excellent image quality, further advancing the application of compressed ultrafast imaging technology and providing valuable references for related research. However, current compressed ultrafast imaging technology still faces challenges, including reconstruction accuracy in complex or high-noise environments and demands for even faster imaging speeds and higher temporal resolution. This study addresses these issues by simulating the working principle of streak cameras, reconstructing signals using restoration algorithms, and comparing the results with original signals. Our findings demonstrate that the compressed ultrafast imaging system can accurately record the trajectory of picosecond laser pulses with extremely high temporal resolution.

1.1 Compressed Sensing Theory

In compressed sensing theory, the sampling rate for target signals is substantially lower than that required by the traditional Nyquist sampling theorem. However, accurate reconstruction imposes specific conditions: the original signal must satisfy sparsity requirements. For an N-dimensional original signal x (x ^N), it can be represented in a particular transform domain using a sparse basis Ψ (Ψ ^(N×N)) with relatively few non-zero coefficients s (while remaining coefficients are zero or near-zero). This property makes x s-sparse in the transform domain.

[Figure 1: see original paper]

In practice, signals rarely exhibit perfect sparsity. Nevertheless, if a signal is approximately sparse—meaning most values in a transform domain are near-zero with only a small number of significant non-zero values—it can be considered sufficiently sparse to meet the basic conditions for compressed sensing sampling and reconstruction.

After identifying a sparse domain that renders the signal sparse, we construct an observation matrix Φ that is incoherent with the sparse basis Ψ. The selection of Φ is critical, as it controls signal sampling by projecting the target signal from a high-dimensional space to a low-dimensional space while preserving effective information and enabling accurate reconstruction through restoration algorithms.

[Figure 2: see original paper]

To achieve precise reconstruction, the observation matrix Φ must satisfy the restricted isometry property (RIP) with respect to the sparse basis Ψ. The RIP requires that every subset of M column vectors extracted from the observation matrix forms a non-singular matrix. The product $\Phi\Psi$ defines the sensing matrix :

$$= \Phi\Psi$$

[Figure 3: see original paper]

The reconstruction problem thus becomes a mathematical model of solving for s given y and . Once s is determined, the original signal x can be recovered through the relationship $x = \Psi s$. The projection from high-dimensional to low-dimensional space inevitably loses some information, resulting in an underdetermined system with far fewer equations than unknowns—a problem that is NP-hard to solve directly. Tao and colleagues proved that when signals satisfy sparsity conditions and observation matrices meet restricted isometry properties, s can be accurately determined, enabling original signal reconstruction.

1.2 Compressed Ultrafast Imaging System

The original image signal I(x-y-t) must first be modulated by a DMD before entering the streak camera. The DMD is a spatial light modulator that controls light reflection direction through numerous microscopic mirrors, functioning as an optical switch.

The DMD has two stable mirror states (+12°/-12°). In compressed ultrafast imaging systems, a controller at the DMD base adjusts the micro-mirror angles: when the memory unit contains "1," the aluminum mirror tilts to +12°, corresponding to an open pixel state; when the memory unit contains "0," the mirror tilts to -12°, corresponding to a closed state. The spatial encoding of the original image signal by the DMD can be represented as C, producing an encoded signal CI(x-y-t).

The system employs a streak camera with picosecond temporal resolution for signal detection and imaging. Figure 4 illustrates the working principle of the streak camera, which consists of an image converter tube (including a photoelectric conversion system, scanning deflection system, and multiplication/electro-optical conversion system) and scanning circuits.

[Figure 4: see original paper]

To diagnose ultrafast scene signals I(x-y-t) using compressed ultrafast imaging, the slit must be fully opened to eliminate the one-dimensional spatial sampling limitation of conventional streak cameras. The encoded image signal enters the streak camera without slit restrictions. The photocathode inside converts the incoming optical signal into corresponding electrical signals while linearly transforming characteristic parameters. Simultaneously, a scanning ramp pulse electrical signal varies linearly with time, deflecting the encoded signal. This deflection operation can be represented as S, yielding a deflected encoded signal SCI(x-y-t), which we denote as I' (x' -y' -t):

SCI(x-y-t) = I' (x' -y' -t)

This electron image exists inside the streak tube before bombarding a phosphor screen to convert into a visible light image, which is then captured by a CCD image sensor. During the CCD' s single exposure time T, noise n affects the signal, producing the final measured signal M(x' -y'):

M(x' -y') = TSC I' (x' -y' -t) + n

For computational convenience, we represent TSC as O:

M = OI' + n

[Figure 5: see original paper]

Reconstructing the original signal from the measured signal requires solving this equation inversely to recover the ultrafast scene I(x-y-t) from M(x' -y'). This underdetermined problem cannot be solved directly for an exact solution. Compressed sensing theory enables transformation of this problem into an unconstrained optimization using total variation regularization with prior knowledge of the encoding matrix:

arg min_I ||M - OI||_2^2 + $\lambda\phi$(I)

where λ is the regularization parameter and ϕ is the regularization function. This unconstrained problem can be further transformed into a constrained optimization:

arg min_I ||M - OI||_2^2 subject to ϕ(I) $\leq$

Through gradient descent iterations updating I and auxiliary variables P, a locally optimal solution can be obtained, yielding the original signal I(x-y-t).

2.1 Simulation of Compressed Ultrafast Imaging Acquisition

To evaluate the diagnostic capability of the compressed ultrafast imaging system for original three-dimensional image signals I(x-y-t), we simulated the acquisition process in MATLAB. The simulation performs encoding, deflection, and superposition operations on the original 3D image signal, as shown in Figure 6, with subsequent reconstruction using compressed sensing algorithms.

[Figure 6: see original paper]

A random 0-1 matrix generated by MATLAB' s built-in functions serves as the encoding matrix C, which remains fixed after generation with 50% of elements being 1, corresponding to a 50% sampling rate for the compressed ultrafast imaging system. Figure 7 illustrates the encoding process, where element-wise multiplication between the encoding matrix and image signal simulates DMD encoding.

[Figure 7: see original paper]

The electric field strength in the streak camera’ s deflection region varies linearly and uniformly. Image signals entering at different times experience different deflection fields, imaging at different vertical positions on the CCD.

[Figure 8: see original paper]

The simulation employs streak camera parameters: ultimate temporal resolution of 10 ps, scanning speed of 2 mm/ns, full-screen scanning time of 20 ns, and an effective phosphor screen diameter of 40 mm.

The ultrafast scene simulates a single laser pulse propagating through a medium and reflecting off two plane mirrors, following a Z-shaped trajectory. This 3D image signal spans 100 ps and comprises 8 frames, each 256$$\times 256 pixels : I(256, 256, 8). After encoding and deflection, these eight original images overlap to produce a 2D measurement sign

[Figure 9: see original paper]

2.2 Reconstruction of Original Images from Compressed Ultrafast Imaging System

Reconstructing the original scene from measured signals requires solving Equation (8) using prior knowledge of the random encoding matrix C. The Two-Step Iterative Shrinkage/Thresholding (TWIST) algorithm can minimize the objective function through multiple iterations to obtain an optimal solution. Each iteration applies weighted soft-thresholding to produce a sparser signal, followed by weighted back-projection to generate a reconstruction that updates weights and thresholds for the next iteration. While TWIST offers rapid convergence and high reconstruction accuracy, it suffers from low efficiency and may converge to local rather than global optima.

This work employs the Plug-and-Play Total Variation (PnP-TV) algorithm, widely used in video compression and image processing. Compared to traditional TWIST, PnP-TV demonstrates superior reconstruction quality and efficiency. Combining compressed sensing with total variation regularization for image restoration and denoising, PnP-TV offers simplicity, efficiency, and flexibility when applied to compressed ultrafast imaging systems.

The PnP-TV approach transforms image reconstruction into an optimization problem with two components: a data fidelity term measuring the difference between observed and reconstructed data, and a regularization term quantifying image smoothness using total variation. The method involves: (1) projecting observed data into image space using nonlinear operators to obtain projection data for the fidelity term; (2) applying total variation regularization to constrain image smoothness and promote structured reconstructions (total variation being the L1 norm of differences between adjacent pixels); (3) formulating a combined optimization problem solved via iterative algorithms like alternating direction method of multipliers; and (4) iteratively updating the image until convergence.

PnP-TV’ s primary advantage lies in enabling state-of-the-art denoising algorithms to solve sub-problems without specifying explicit priors, greatly enhancing flexibility. For instance, inserting a total variation denoising algorithm allows flexible processing. Compared to the parameter-intensive and time-consuming TWIST algorithm, PnP-TV demonstrates superior reconstruction quality and efficiency.

The reconstruction algorithm successfully recovered eight original 2D images from the compressed ultrafast imaging measurements, each with 12.5 ps exposure time.

[Figure 10: see original paper]

Reconstruction quality can be analyzed using Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). The reconstruction process required 13 seconds, achieving an average PSNR of 32 dB and SSIM of 0.92. As an emerging signal sampling and reconstruction theory, compressed sensing enables high-quality signal acquisition at sub-Nyquist rates. In compressed ultrafast imaging systems, reconstruction quality depends critically on sparse representation and measurement matrices. The sparse prior term in our objective function uses the L1 norm, promoting sparsity but limiting detail and texture recovery, resulting in some blur and noise. Simulation results demonstrate that the compressed ultrafast imaging system can accurately reconstruct dynamic images of ultrafast scenes at imaging speeds of 80 billion frames per second.

3 Conclusion

Using MATLAB, we simulated the compressed ultrafast imaging system, performing encoding, deflection, and superposition operations on original 3D image signals to obtain measurement data. The PnP-TV reconstruction algorithm successfully recovered the original ultrafast image signals by selecting locally optimal solutions during each iteration to progressively approach the original signal, thereby improving PSNR and SSIM. Simulation results demonstrate that the compressed ultrafast imaging system achieves picosecond-level temporal resolution and 80 billion frames per second imaging speed, with PSNR exceeding 30 dB and structural similarity coefficient surpassing 0.91. This system can be applied to diagnostic applications involving ultrafast two-dimensional dynamic processes.

References

[1] Zhao X, Feng W, Liu L, et al. Optimization of compressive 4D-spatio-spectral snapshot imaging[C]//AOPC 2017: 3D Measurement Technology for Intelligent Manufacturing. Beijing, China: SPIE, 2017, 10458: 295-303.

[2] Cai H, Liu J, Peng X, et al. Note: Non-gain microchannel plate gated framing camera[J]. Review of Scientific Instruments, 2011, 82(5): 056102.

[3] Liu J, Niu L, Peng W, et al. Application of a fast electrical pulse in gated multichannel plate camera[J]. Review of Scientific Instruments, 2007, 78(5): 055104.

[4] Gao L, Liang J, Li C, et al. Single-shot compressed ultrafast photography at one hundred billion frames per second[J]. Nature, 2014, 516(7529): 74-77.

[5] Yao J, Qi D, Yao Y, et al. Total variation and block-matching 3D filtering-based image reconstruction for single-shot compressed ultrafast photography[J]. Optics and Lasers in Engineering, 2020, 139: 106475.

[6] Shen Q, Tian J, Pei C. A Novel Reconstruction Algorithm with High Performance for Compressed Ultrafast Imaging[J]. Sensors, 2022, 22(19): 7372.

[7] Liang J, Wang P, Zhu L, et al. Single-shot stereo-polarimetric compressed ultrafast photography for light-speed observation of high-dimensional optical transients with picosecond resolution[J]. Nature Communications, 2020, 11(1): 5252.

[8] Donoho D L. Compressed sensing[J]. IEEE Transactions on Information Theory, 2006, 52(4): 1289-1306.

[9] Lei X, Shahid H, Wu S. A novel algorithm to improve image reconstruction quality for 2D streak camera[J]. Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, 2021, 991: 165023.

[10] Lu Y, Wong T, Chen F, et al. Compressed Ultrafast Spectral-Temporal Photography[J]. Physical Review Letters, 2019, 122(19): 193904.

[11] Wang Q. Theoretical and Experimental Research on Femtosecond Time-resolved Fringe Camera[D]. Graduate University of Chinese Academy of Sciences: Xi' an Institute of Optics and Fine Mechanics, 2014.

[12] Liang J, Gao L, Hai P, et al. Encrypted three-dimensional dynamic imaging using snapshot time-of-flight compressed ultrafast photography[J]. Scientific Reports, 2015, 5(1): 15504.

[13] Lai Y, Xue Y, Côté C Y, et al. Single-Shot Ultraviolet Compressed Ultrafast Photography[J]. Laser & Photonics Reviews, 2020, 14(10): 2000122.

[14] Dong C, Loy C C, He K, et al. Image super-resolution using deep convolutional networks[J]. IEEE Transactions on Pattern Analysis and Machine Intelligence, 2015, 38(2): 295-307.

[15] Zhao Y, Zheng S, Yuan X. Deep equilibrium models for video snapshot compressive imaging[J]. arXiv preprint arXiv, 2022, 2201.06931.

[16] Zhang Y, Shen B, Wu T, et al. Ultrafast and hypersensitive phase imaging of propagating internodal current flows in myelinated axons and electromagnetic pulses in dielectrics[J]. Nature Communications, 2022, 13(1): 5247.

[17] Zhao Fuli, Zhang Heling, Xing Jingting, et al. Realization and digital reconstruction of computer-generated hologram based on Matlab[J]. Journal of

Applied Optics, 2009, 30(6): 953-957.

[18] Wang P, Liang J, Wang L V. Single-shot ultrafast imaging attaining 70 trillion frames per second[J]. Nature Communications, 2020, 11(1): 2091.

[19] Qi D, Zhang S, Yang C, et al. Single-shot compressed ultrafast photography: a review[J]. Advanced Photonics, 2020, 2(1): 014003-014003.

[20] Yuan X, Liu Y, Suo J, et al. Plug-and-play algorithms for large-scale snapshot compressive imaging[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020: 1447-1457.

[21] Yang C, Qi D, Cao F, et al. Improving the image reconstruction quality of compressed ultrafast photography via an augmented Lagrangian algorithm[J]. Journal of Optics, 2019, 21(3): 035703.

Funding: National Natural Science Foundation of China (11775147, 62001301); Guangdong Basic and Applied Basic Research Foundation (2019A1515011474, 2019A1515110130); Shenzhen Science and Technology Program (JCYJ20190808115605501, JCYJ20200109105201936, JCYJ20210324095007020, JCYJ20220814133504001).

Author Information: LIU Junkai (1998-), male, master' s student. Research focus: ultrafast optoelectronic information detection and imaging. E-mail: 2110456025@email.szu.edu.cn

CAI Houzhi and XIANG Lijuan are co-corresponding authors.

Corresponding Author 1: CAI Houzhi (1983-), male, Ph.D., researcher. Research focus: ultrafast optoelectronic information detection and imaging. E-mail: hzcai@szu.edu.cn

Corresponding Author 2: XIANG Lijuan (1989-), female, Ph.D., associate researcher. Research focus: ultrafast optoelectronic information detection and imaging, intelligent control, and wireless charging. E-mail: xianglijuan@szu.edu.cn