CYBERNETICS AND PHYSICS, VOL. 14, NO. 4, 2025, 342–349

PARAMETER ESTIMATION USING COMPRESSED SENSING UNDER UNKNOWN-BUT-BOUNDED NOISE

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Article history:
Received 30.11.2025, Accepted 20.12.2025

Abstract

Standard compressed sensing (CS) theory typically assumes that noise is bounded in ℓ_2-norm (e.g., Gaussian). In practice, noise can be unknown-but-bounded (for example, in low-light imaging or MRI artifacts). In this work a new CS recovery algorithm for parameter estimation under unknown-but-bounded noise is proposed. Experiments on images with various non-Gaussian noises demonstrate that proposed method outperforms classical ℓ_2-constrained recovery.

Key words

Compressed sensing, parameter estimation, randomized algorithms, unknown-but-bounded noise, sparse reconstruction.

1 Introduction

Dynamic systems, such as power grids, robot swarms, and IoT systems, are actively researched. scie[Krejčí et al., 2025; Habib and Chukwuemeka, 2025; Madakam et al., 2015; Varabin, 2019; Granichin and Sergeev, 2020].

One of the most popular problem is noise filtering and adapting control methods under different types of noise and limited number of observations [Vapnik, 1979; Fomin, 1976; Stepanov, 2010]. Mathematical models are represent processes with measurement errors and external disturbances. Sometimes the available observation number is few or sparse. Traditional methods that rely on common statistical assumptions may not work well in these cases or may require too much computational effort to provide good results.

One of the popular method which works with sparse data is *compression sensing* (CS) and randomization methods. Compression recognition allows to recover sparse signals from significantly fewer measurements than required by the Nyquist-Shannon theorem [Candes et al., 2006b; Donoho, 2006; Baraniuk, 2007].

Compressive sensing (CS) has evolved from theoretical guarantees for sparse signal recovery to practical applications in medical imaging and image processing [Upadhyaya and Gupta, 2025]. Random Gaussian and binary sensing matrices remain the standard due to their restricted isometry property (RIP), ensuring stable recovery with minimal measurements. Recent approaches focus on structured designs: equiangular tight frame (ETF)-based optimization minimizes coherence with sparsity dictionaries, improving PSNR by 2–4 dB, while MIMO radar matrices are designed based on coherence of sensing matrix and signal-to-interference ratio criteria. Structured matrices incorporating side information require 20–30% fewer measurements [Mousavi et al., 2019; Rani et al., 2018].

Turning to recovery methods, convex optimization via ℓ_1-minimization provides theoretical stability guarantees. Bregman iterative algorithms [Yin et al., 2008] demonstrate fast convergence for large-scale problems. Greedy algorithms (OMP, CoSaMP) [Goklani et al., 2017] select matrix columns based on residual correlation; OMP-Net implements soft-sorting for differentiability, enabling end-to-end training. Submodular matching pursuit achieves a $(1 - e^{-1})$ approximation guarantee. Iterative hard thresholding (IHT) combines gradient descent with projection onto sparse vector sets, yielding logarithmic complexity with respect to signal-to-noise ratio [Blumensath and Davies, 2009].

Classical methods exhibit linear error dependence on noise level under Gaussian noise. For heavy-tailed noise and outliers, Median-of-Means with generative models provides ε-contamination robustness. One-bit CS (preserving only measurement signs) [Huang and Tran, 2020] employs GAMP with adaptive posterior estimation; quantization necessitates oversampling, with Sigma-Delta modulation improving quantization noise control [Jalal et al., 2020].

Unrolling iterative algorithms into neural networks has revolutionized CS [Sandino et al., 2020; Uzhva et al., 2022]. Variational networks (VN) automatically tune regularization, eliminating under-/over-regularization artifacts in MRI [Hammernik et al., 2018]. TVINet unrolls proximal dual gradient descent with total variation regularization. Scalable deep unrolling integrates learnable sensing matrices into EAMP networks, operating across compression ratios [Hu et al., 2024]. DEIL combines external dataset training with internal per-image learning.

Pre-trained generative models (VAE, GAN) require 5–10 times fewer measurements than Lasso. Structured-covariance VAEs model pixel correlations, competing with VNs in MRI. One-bit CS with generators (2025) substantially improves quality. Diffusion models solve CS as degradation process inversion: DiracDiffusion ensures data consistency across iterations, balancing PSNR vs. LPIPS trade-offs, while Shortcut Sampling Diffusion achieves 10 times acceleration with comparable quality [Bora et al., 2017; Duff et al., 2022; Kafle et al., 2025].

In this article the new signal recover method in CS that works under unknown-but-bounded noise.

2 Compressive Sensing

When modeling a data processing task, one of the main issues is the formalization of the observation model, which will most accurately display significant and/or hidden system parameters within the simulation. For example, when modeling the operation of magnetic resonance imaging (MRI) or shooting in low light conditions, it is important to take into account not only the value of the real signal, but also additional characteristics that appear during the use of different devices that read this signal.

In particular, it is necessary to works with the error of the measuring device and other noise that may occur during measuring the device. For example, during long-term shooting, the noise on the matrix increases, which in low light makes a serious correction in the formation of the final image.

In signal processing, the Kotelnikov (Nyquist-Shannon) sampling theorem [Kotel'nikov, 2006] is fundamental, but it requires storing large amounts of data for accurate signal reconstruction. An alternative approach is Compressed Sensing (CS) [Candes et al., 2006a; Donoho, 2006; Granichin and Pavlenko, 2010], which enables the recovery of a signal from a relatively small number of measurements, given that the signal is sparse.

2.1 Observation Model

First of all it's need to clarify what the observation model will look like for the compression-based recognition problem. Since most measuring instruments operate on discrete signals, without loss of generality, we will consider a real-valued, one-dimensional discrete signal f of finite length N. For the compression-based recognition problem, it is important to introduce the following definitions.

Definition 1 (s-sparse signal). *A discrete signal f is called an s-sparse signal if it admits the representation*

$$f = \Psi x = \sum_{j=1}^{N} x_j \psi_j, \tag{1}$$

where $\Psi = (\psi_1, \psi_2 ... \psi_N) \in \mathbb{R}^{N \times N}$ is an orthonormal basis ($\{\psi_1\}$ is a basis vector of dimension $N \times 1$) in which the signal has an s-sparse representation, that is, among the components of the vector $x = (x_1, \dots, x_N)^T$ there are at most s nonzero components.

Definition 2 (s-compressible signal). *A signal is called s-compressible if it can be represented in the form of a formula (1) that contains no more than s distinct components. That is, s components are sufficiently large, while the rest are small.*

Usually, a signal $f \in \mathbb{R}^N$ is recorded by some physical instruments, so mathematically it is represented by applying some operator $A : \mathbb{R}^N \to \mathbb{R}^m$, where m is the dimension (number) of the recorded data. Ideally, the observation model would look like this:

$$y = Af. \tag{2}$$

However, each instrument has measurement error and some potential external disturbances, which, under fairly general assumptions, allows us to write the observation model as follows:

$$y = Af + v, \tag{3}$$

where v is the measurement noise, including the instrument error and potential external disturbances affecting the observation process.

It is generally assumed that the noise v has useful statistical properties. For example, it is random, independent, identically distributed, centered, has a finite second moment, etc.

However, in many practical cases, verifying these assumptions is quite difficult. Therefore, this paper will consider not only classical noise cases, but also more general noise, such as arbitrary unknown-but-bounded sequences.

2.2 The Problem of Recognition by Compression

Consider a linear discrete measurement process of an s-sparse signal $f \in \mathbb{R}^N$. For this process, the observation model will look as follows:

$$y_k = \langle a_k, f \rangle,\ k = 1..m \tag{4}$$

or

$$y = Af = A\Psi x = \Phi x \tag{5}$$

where $y = y_k$ is the observation, $m \ll N$ is the number of recorded observations, $a_k \in \mathbb{R}^N$ are the known weights at the time of the observation, denoted by $\Phi = A\Psi \in \mathbb{R}^{m\times N}$.

To solve the problem of recognition by compression, it is necessary to design the following two important things:

- a universal measurement matrix A such that, when reducing the dimensionality from $f \in \mathbb{R}^N$ to $y \in \mathbb{R}^m$, the essential information about any s-sparse (or s-compressible) signal is not damaged;
- a reconstruction algorithm that, given $m \sim s$ measurements, allows us to reconstruct x (and, accordingly, f).

Let's consider each of these problems separately.

2.3 Designing the matrix A

The matrix A is chosen such that it can be used to reconstruct the signal $f \in \mathbb{R}^N$ from a significantly smaller number of dimensions $y \in \mathbb{R}^m$. However, when working with such a small number of values, the location of those s nonzero components is unknown, so we must take $m : s \leq m \ll N$ dimensions in the sparse matrix. Since $y = \Phi x$, $\Phi = A\Psi$, then, by construction, Φ will have the same properties as A. Therefore, we can limit ourselves to checking that Φ preserves the lengths of these s-sparse vectors. To ensure this, the matrix is checked for the Restricted Isometry Property (RIP)[Candes and Tao, 2005].

Definition 3 (RIP). *We introduce the following notation: Let $\Phi_G, G \subset 1, ..., N$ be an $m \times |G|$ submatrix obtained by extracting the columns of Φ by indices from G. Then there exists a constant s-restricted isometry δ_s of Φ such that:*

$$(1-\delta_s)||c||^2_{\ell_2} \leq ||\Phi_T \cdot c||^2_{\ell_2} \leq (1+\delta_s)||c||^2_{\ell_2} \tag{6}$$

for all subsets of $G : |G| \leq s$ and coefficient $(c_j)_{j\in G}$.

This essentially means that every set of columns with cardinality less than s behaves approximately like an orthonormal system.

In [Candes and Wakin, 2008], it was proved that to reconstruct an s-sparse signal with noisy observations, it is sufficient to check the satisfiability of the RIP($\delta, 3s$) condition in the sense that the reconstruction result will differ from the true value according to the following relation:

$$||x - \hat{x}||_1 \leq const||x - x^*||_1, \tag{7}$$

where $\hat{x}$ is the reconstruction result of x, and the vector x^* is obtained by zeroing out all components of x except those with the largest absolute value, s.

In directly constructing a matrix A such that the matrix Φ obtained with it satisfies the RIP condition, it would be necessary to check the condition (6) $\frac{N!}{s!(N-s)!}$ times for all possible positions of s nonzero components in the vector $z \in \mathbb{R}^N$. However, research in this area has shown that the RIP property is achieved using a randomly generated matrix A. For example, in [Candes et al., 2006a], the matrix $A : a_{i,j} \sim \mathcal{N}\left(0, \frac{1}{m}\right)$ of independent and identically distributed (i.i.d.) elements has the following useful properties:

> A satisfies RIP(δ, m) with probability $\geq 1 - 2e^{c_2 m}$ if $\delta \in (0,1)$ and $m \geq c_1 s \log(N/s)$, small constants $c_1, c_2 > 0$ (depending on δ);
> A is universal: essential information about the s-sparse signal will be preserved, and the matrix $\Phi = A\Psi$ will also be a random matrix with normally distributed independent and identically distributed elements.

The first property allows us to reconstruct signals from $m \ll N$ dimensions, and the second means that, regardless of the choice of the orthonormal basis Ψ, the matrix Φ will also have the RIP(δ, m) property. This result makes it possible to simply construct the matrix A for signal reconstruction.

2.4 Designing a Signal Reconstruction Algorithm

To reconstruct a signal $f \in \mathbb{R}^N$ from the given m dimensions, matrix A, and basis Ψ, a reconstruction algorithm must be constructed. In a series of papers, E. J. Candes and D. L. Donoho et al. presented results on signal reconstruction within the framework of the compression recognition paradigm. It turned out that, given the observation model (5), to reconstruct signal x, it suffices to solve the following convex optimization problem:

$$(P_1) \qquad \min ||x||_{\ell_1} : \ \Phi x = y, \tag{8}$$

where the matrix $\Phi \in \mathbb{R}^{m\times N}$ corresponds to the uniform uncertainty principle [Candes et al., 2006b], according to which the measurement matrix Φ must satisfy the property of bounded isometry. In the article [Candes and Tao, 2005], it was proved that if s is such that:

$$\delta_s + \delta_{2s} + \delta_{3s} < 1 \tag{9}$$

then the solution to problem (P_1) reconstructs any sparse signal x based on at most s measurements.

However, the above formulation is often unrealistic, since in practice, signal measurements are noisy, and the signal itself is not entirely sparse, making it impossible to claim that Φx is known with arbitrary precision. Therefore, it is necessary to extend the observation model by adding a perturbation $v : ||v||_{\ell_2} < \epsilon$ (similar to (3)):

$$y = \Phi x + v. \quad (10)$$

The following nuance must be taken into account in the recovery procedure: since an important property of the recovery procedure is the stability of the recovery, when introducing small changes to the observations, the recovered value will also contain small changes.

Consider a convex optimization problem, as in [Donoho et al., 2005], in which the goal is to find a signal that, among all signals and corresponding observations y, has the minimum ℓ_1 norm:

$$(P_2) \qquad \min ||x||_{\ell_1} : \ ||\Phi x - y||_{\ell_2} \leq \epsilon. \quad (11)$$

According to the results of the article, the solution (P_2) recovers the value with an error that does not exceed the noise level.

The article [Candes et al., 2006b] presents theorems that describe the principle of selecting a constant depending on the constant of the s-restricted isometry δ_S.

Theorem 1. *[Candes et al., 2006b] Let $s : \delta_{3s} + 3\delta_{4s} < 2$, then for any s-sparse x and any noise $v : ||v||_{\ell_2} \leq \epsilon$, the solution $\hat{x}$ of problem (P_2) is such that:*

$$||\hat{x} - x||_{\ell_2} \leq C_s \cdot \epsilon, \quad (12)$$

where C depends only on δ_{4s}.

For important values of δ_{4s}, the constant C_s is easily computed. For example, $C_s \approx 8.82$ for $\delta_{4s} = 1/5$ and $C_s \approx 10.47$ for $\delta_{4s} = 1/4$ (see [Candes et al., 2006b]).

Theorem 2. *[Candes et al., 2006b] $x \in \mathbb{R}^N$ is an arbitrary vector, and let x_s be the truncated vector corresponding to the s largest absolute values of x. Given the assumptions of Theorem 1, the solution $\hat{x}$ of system (P_2) satisfies:*

$$||\hat{x} - x||_{\ell_2} \leq C_{1,s} \cdot \epsilon + C_{2,s} \cdot \frac{||x - x_s||_{\ell_1}}{\sqrt{s}}. \quad (13)$$

For important values of δ_{4s}, the constants (12) are easily calculated. For example, $C_{1,s} \approx 12.04$ and $C_{2,s} \approx 8.77$ with $\delta_{4s} = 1/5$ (see [Candes et al., 2006b]).

The proposed formulation is more realistic; however, the perturbation, bounded by the ℓ_2 norm to a small ϵ, precludes the application of the compression-based recognition approach to problems where the noise does not satisfy this assumption. Suppose that in the observation model $v \in \mathbb{R}^m : |v_i| < c_v, \forall i = 1..m$ (i.e., unknown but bounded):

$$y = \Phi x + v. \quad (14)$$

These noise constraints do not satisfy the conditions for solving problem (P_2). In problem (P_2), ϵ becomes equal to $\sqrt{m}c_v$, which prevents this value from being considered sufficiently small. For example, the problem of photographing in low-light conditions with a relatively high level of dark noise, as in the EMVA 1288 standard, was discussed above. In the case of shooting in low-light conditions, the value of ϵ becomes comparable in size to the signal level.

We multiply the observation model (14) on the left by $(\Phi^T\Phi)^\dagger\Phi^T$, where $\cdot^T$ is the transpose sign and $\cdot^\dagger$ is the Moore-Penrose pseudoinverse[Penrose, 1955]. We rewrite the observation model as:

$$\tilde{y} = (\Phi^T\Phi)^\dagger\Phi^T y = (\Phi^T\Phi)^\dagger\Phi^T\Phi x + (\Phi^T\Phi)^\dagger\Phi^T v. \quad (15)$$

The article [Candes et al., 2006b] proves that the matrix Φ can be chosen to be a matrix of independent identically distributed elements with a normal distribution density with zero mean and variance $1/m$. By construction, the matrix Φ is independent of x and v.

Since in formula (15) the mathematical expectation of the error satisfies the condition $\mathbf{E}((\Phi^T\Phi)^\dagger\Phi^T v) = 0$ then under these conditions for noise v, signal recovery can be achieved by solving the following optimization problem:

$$(P_3) \min ||x||_{\ell_1} : \ ||(\Phi^T\Phi)^\dagger\Phi^T\Phi x - (\Phi^T\Phi)^\dagger\Phi^T y||_{\ell_2} \leq \epsilon. \quad (16)$$

Randomization introduced into the observation model with subsequent normalization "removes the bad properties" of the error, i.e., in the new observation model, the residual is highly likely to become small in the ℓ_2 metric, as in the model considered in problem P_2, subject to Assumption 3.

Assumption 3. The noise v in the observations (15) is independent of the choice of the measurement matrix Φ.

2.5 Experiments

The experiments described below were performed using Python 3, utilizing the numpy, cvxpy, and scipy libraries.

2.5.1 Sinusoidal Signal Consider a signal that initially consists of a weighted sum of 5 sinusoids with noise v [Granichin and Pavlenko, 2010]:

$$f(t) = \sum_{i=0}^{s-1} a_i \sin(2\pi \cdot \omega_i t) + v, \quad t \in [0; 1) \quad (17)$$

where s is the unknown number of frequencies, $a_i \in \mathbb{R}, \omega_i \in [0; 500]$ are the parameters of the i-th frequency, and v is the signal measurement error. It is worth noting that the unknown frequencies do not necessarily have to be integers.

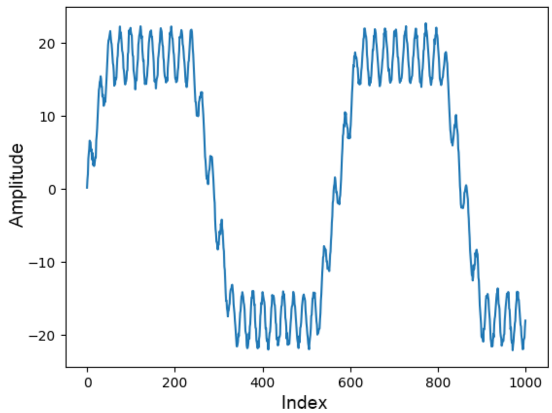

Figure 3. Noise distribution graph.

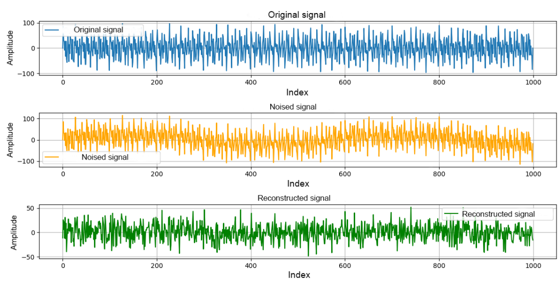

Figure 4. Signals with noise distributed as in Fig.3.

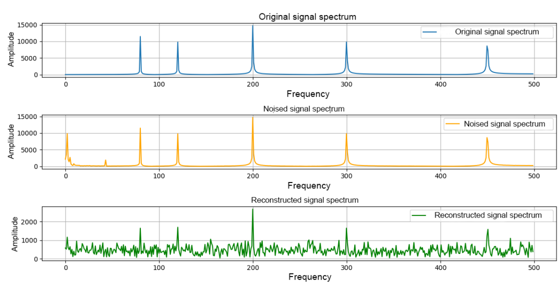

Figure 5. Spectral representation of signals with noise distributed as in Fig. 3.

Knowing the bandwidth $[0; 500]$ and relying on the Kotelnikov (Nyquist-Shannon) theorem [Kotel'nikov, 2006; Nyquist, 1928], to work with the signal, it is necessary to obtain at least 1000 values on the interval $[0; 1)$ to find the original frequencies.

For the signal model in the experiment, active frequencies $\omega = [80, 120, 200, 300, 450]$ and amplitudes $a = [23.1,\ 20,\ 31.5,\ 23,\ 25]$ were chosen. To reconstruct the signal using compression recognition, $m = 4s\log(N/s) \approx 153$ observations were chosen.

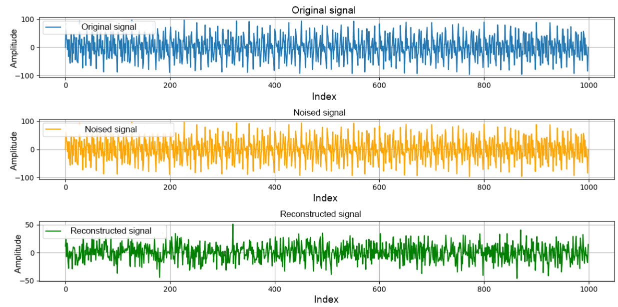

Figure 1. Signals with normally distributed noise.

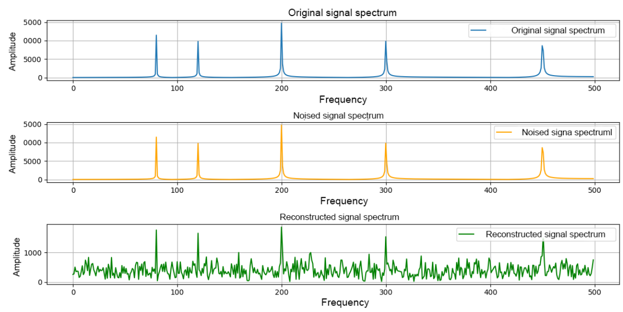

Figure 2. Spectral representation of signals with normally distributed noise.

To begin, an experiment was conducted with normally distributed noise. Figures 1 and 2 show images of the original, noisy, and reconstructed signals using compression-based recognition in their original and spectral representations. The spectral representation helps confirm that the reconstruction was successful, as the peak frequencies match.

Next, the noise shown in Figure 3 was chosen as an example of poor noise.

The experimental results, shown in the 4 and 5 graphs, show that "extra" peak values appear in the spectral representation for a noisy observation. However, the spectrum of the reconstructed signal retains the original peak frequencies.

As a result, using the compression-based recognition approach, we were able to reconstruct the original signal while preserving significant spectral values using only 153 measurements instead of 1000.

2.5.2 Image with Circles Let's consider another experiment. Let's assume we have a black image with two white-gray circles of different diameters, $s = (2r_1)^2$, where r_1 is the radius of the larger sphere in the image. The following noise categories were considered: Gaussian noise, uniform centered noise, heavy-tailed noise, fat-tailed noise, intermittent noise with varying intensities across regions (step-like).

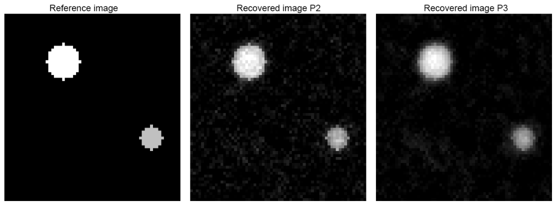

Figure 6. Gaussian noise, 64 by 64 pixels.

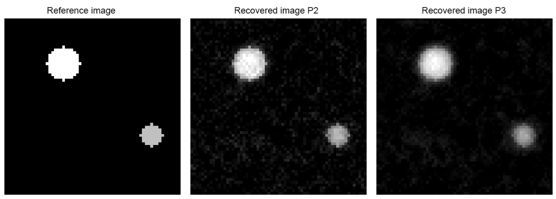

Figure 7. Uniform noise, 64 by 64 pixels.

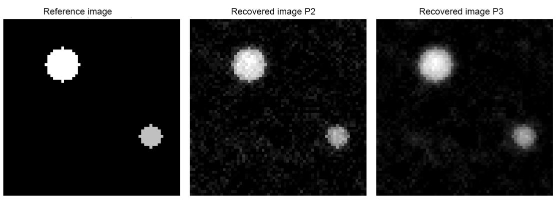

Figure 8. Fat tails, 64 by 64 pixels.

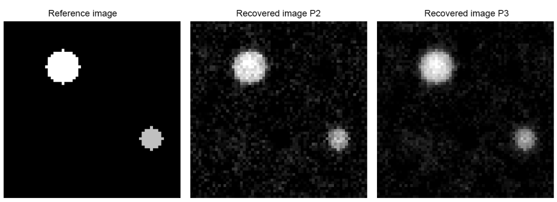

Figure 9. Heavy tails, 64 by 64 pixels.

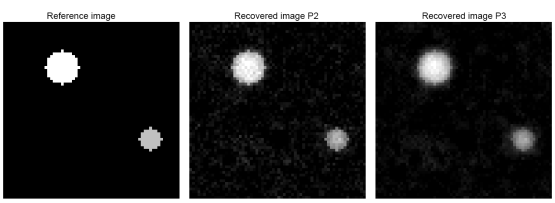

Figure 10. Stepped noise, 64 by 64 pixels.

Fig. 6-10 shows the original image, reconstructed using task P_2, and reconstructed using task P_3 for a 64x64 pixel image. The figures show that reconstruction using task P_3 produces a smoother image with less graininess, which was not present in the original image.

Metric comparisons of restoration using the P_2 and P_3 tasks were conducted using the mean squared error (MSE) and peak signal-to-noise ratio (PSNR). The results are presented for 32x32 and 64x64 pixel images in Tables 1 and 2, respectively. The tables demonstrate that the P_3 restoration algorithm outperforms the P_2 task for all types of noise. The P_3 algorithm demonstrated the greatest qualitative gain for heavy-tailed noise.

Table 1. MSE and PSNR results for different noise types (32 x 32 pixel image)

	MSE		PSNR	
Noise Type	P_2	P_3	P_2	P_3
Gaussian	0.0137	**0.0125**	18.64	**19.02**
Uniform	0.0126	**0.0117**	19.00	**19.32**
Heavy-tailed	0.0303	**0.0242**	15.19	**16.15**
Fat tails	0.0142	**0.0126**	18.46	**19.00**
Staggered	0.0141	**0.0127**	18.50	**18.98**

Table 2. MSE and PSNR results for different noise types (64x64 pixel image)

	MSE		PSNR	
Noise Type	P_2	P_3	P_2	P_3
Gaussian	0.0059	**0.0058**	22.33	**22.39**
Uniform	0.0056	0.0056	22.53	**22.55**
Heavy-Tailed	0.0097	**0.0077**	20.15	**21.16**
Fat-Tailed	0.0067	**0.0062**	21.72	**22.07**
Stepped	0.0058	0.0058	22.34	**22.38**

3 Conclusion

This paper proposes an approach within the compression-based recognition paradigm for the case of unknown-but-bounded noise. A comparison of signal recovery quality for the P_2 problem and the new P_3 problem is conducted, where recovery using the latter approach demonstrated its advantage, particularly for heavy-tailed noise.

Acknowledgements

This work was supported by the grant of the state program of the “Sirius” Federal Territory “Scientific and technological development of the “Sirius” Federal Territory” (Agreement №33-03 dated 01.08.2025).

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