DTA095A - Lab 3 Report

PnP-ADMM vs PnP-Forward-Backward (Deterministic vs DRUNet Denoiser) / Matching Pursuit (MP) vs Orthogonal Matching Pursuit (OMP)

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1 Introduction

This lab compares Plug-and-Play (PnP) methods like ADMM and Forward-Backward with different denoisers, and evaluates sparse approximation algorithms Matching Pursuit (MP) and Orthogonal Matching Pursuit (OMP) for image reconstruction. Performance is measured using metrics such as PSNR and LPIPS.

2 Experimental Setup

The experiments have been carried out using **Python** within a **Jupyter Notebook** environment. Core libraries included **NumPy** for numerical operations, **Torch** for tensor-based computations and GPU acceleration, and **scikit-image** for image manipulation. All scripts and functions used for **noise generation**, **filtering**, and **metric evaluation** are provided in Appendix A.1.

3 Results and Analysis

3.1 PnP-ADMM vs PnP-Forward-Backward

In the first experiment, two PnP (Plug and Play) frameworks have been compared: ADMM (Alternating Direction Method of Multipliers) and FB (Forward and Backward splitting). They are two different approaches that lead to an effectively decoupling of the data fidelity term from the image prior.

3.1.1 Hyperparameters tuning

The Plug-and-Play (PnP) algorithms were evaluated through a grid search over key parameters to balance data fidelity and denoising strength. The following ranges were explored:

- **Denoisers:** `median`, `bilateral`, `nlm`, `drunet`
- **ADMM regularization weights** (ρ): $\{0.1, 0.3, 1.0\}$
- **FB step sizes** (τ): $\{0.5, 1.0\}$
- **Denoising strengths**: $\{0.02, 0.05, 0.10\}$

For each denoiser, all parameter combinations were tested and the configuration yielding the highest PSNR and lowest LPIPS was selected. Fixed noise level ($\sigma = 0.03$) and blur kernel characteristics (size = 15, $\sigma = 3$) have been used.

3.1.2 Results and analysis

The results in Tables 1 and 2 highlight the different behaviors of deterministic and learned denoisers within the PnP-ADMM and PnP-FB frameworks. Among the deterministic methods, Non-Local Means (NLM) achieves the best balance between fidelity and perceptual quality, showing the lowest LPIPS and competitive PSNR values. The bilateral and median filters tend to oversmooth or leave residual artifacts, especially at higher denoising strengths. In contrast, the learned DRUNet denoiser attains the highest PSNR scores in both schemes, particularly for moderate strengths (0.05–0.10), effectively reducing noise without over-smoothing. Sweeping the regularization parameters confirms that smaller values of ρ provide more stable convergence and fewer artifacts, while larger ones cause over-smoothing. A value of τ around 1.0 led to the best results for FB framework. Overall, DRUNet delivers the best quantitative and perceptual performance, whereas deterministic denoisers yield smoother but less accurate reconstructions.

Table 1: PnP-ADMM results (PSNR / LPIPS) for different denoisers, ρ, and denoising strengths. The median filter does not include a strength parameter. Best PSNR and LPIPS for each denoiser are highlighted in bold.

	Bilateral			**DRUNet**			**NLM**			**Median**		
Metric	ρ=0.1	ρ=0.3	ρ=1.0	ρ=0.1	ρ=0.3	ρ=1.0	ρ=0.1	ρ=0.3	ρ=1.0	ρ=0.1	ρ=0.3	ρ=1.0
Strength 0.02 (PSNR)	**22.23**	22.06	21.83	22.84	22.99	22.95	22.83	22.81	22.67	**22.92**	22.84	22.62
Strength 0.02 (LPIPS)	0.323	0.352	0.396	0.439	0.352	0.318	**0.222**	0.233	0.260	0.303	**0.289**	0.290
Strength 0.05 (PSNR)	21.41	21.20	20.79	23.11	23.11	23.00	22.93	22.82	22.55	–	–	–
Strength 0.05 (LPIPS)	**0.301**	0.329	0.379	0.290	**0.286**	0.307	0.234	0.254	0.289	–	–	–
Strength 0.10 (PSNR)	21.02	20.68	20.04	**23.14**	23.07	22.82	**23.29**	22.94	22.16	–	–	–
Strength 0.10 (LPIPS)	0.326	0.366	0.429	0.288	0.308	0.337	0.263	0.296	0.348	–	–	–

Table 2: PnP-FB results (PSNR / LPIPS) for different denoisers, τ, and denoising strengths. The median filter does not include a strength parameter. Best PSNR and LPIPS for each denoiser are highlighted in bold.

	Bilateral		**DRUNet**		**NLM**		**Median**	
Metric	τ=0.5	τ=1.0	τ=0.5	τ=1.0	τ=0.5	τ=1.0	τ=0.5	τ=1.0
Strength 0.02 (PSNR)	22.38	**22.78**	24.66	**25.11**	23.17	**23.67**	23.58	**24.03**
Strength 0.02 (LPIPS)	0.396	0.375	0.328	0.304	0.274	**0.254**	0.282	**0.264**
Strength 0.05 (PSNR)	20.90	21.48	24.51	25.08	22.25	22.84	–	–
Strength 0.05 (LPIPS)	0.402	**0.371**	0.326	**0.297**	0.301	0.277	–	–
Strength 0.10 (PSNR)	19.38	20.40	23.93	24.66	21.61	22.04	–	–
Strength 0.10 (LPIPS)	0.466	0.424	0.355	0.323	0.368	0.338	–	–

The parameters ρ (in ADMM) and τ (in FB) balance data fidelity and prior strength. Smaller values preserve detail but may leave noise artifacts, while larger values enforce stronger regularization and risk over-smoothing.

A visual comparison of the best results in terms of LPIPS from DRUNet and NLM denoisers can be found in Figure 3 and 2.

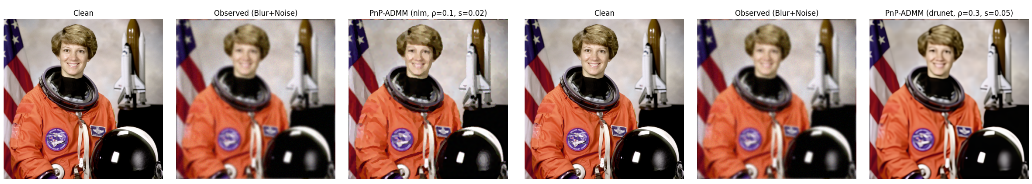

Figure 1: PnP-ADMM best results: nlm vs. DRUNet

3.1.3 Early stopping

Both PnP-ADMM and PnP-FB iterations were capped at 50 steps, with convergence monitored through a tolerance of 10^{-4} on the relative change of successive estimates. An early stopping criterion with a patience of 5 iterations was employed, terminating optimization when no further improvement in PSNR was observed within this window. This strategy prevented unnecessary computations and mitigated over-smoothing effects that may occur with excessive iterations.

3.2 Matching Pursuit (MP) vs Orthogonal Matching Pursuit (OMP)

This experiment compares two greedy sparse approximation algorithms, Matching Pursuit (MP) and Orthogonal Matching Pursuit (OMP), on a small-scale image reconstruction task. Both methods are evaluated using an orthogonal DCT dictionary and a non-orthogonal, overcomplete dictionary derived from linear combinations of DCT atoms. The goal is to analyze how dictionary structure and sparsity level affect reconstruction quality, measured in PSNR.

3.2.1 Hyperparameters tuning

The reconstruction performance was analyzed across different image resolutions and sparsity levels. The image size was varied among $\{16, 32, 64\}$ to study scalability effects, while the number of selected atoms was swept over $T \in \{5, 10, 40, 80, 200, 400, 600, 1000\}$. Both orthogonal and non-orthogonal dictionaries were tested for

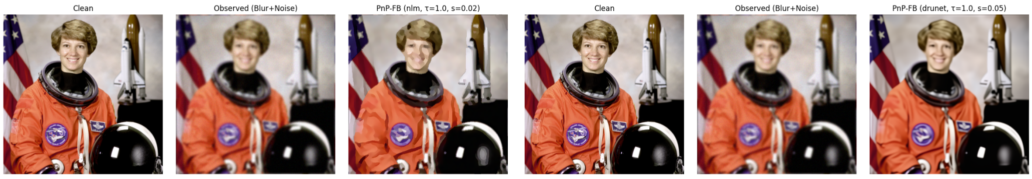

Figure 2: PnP-FB best results: nlm vs. DRUNet

each configuration to assess their impact on MP and OMP behavior. These settings allowed assessing the trade-off between sparsity, reconstruction accuracy, and computational cost.

3.2.2 Results and analysis

The PSNR results show that both MP and OMP achieve nearly perfect reconstruction for orthogonal dictionaries. In this case, MP and OMP produce identical results because the dictionary atoms are mutually orthogonal, so selecting an atom and updating its coefficient one at a time (MP) is equivalent to solving the full least-squares problem over the selected atoms (OMP). When the dictionary is non-orthogonal, however, differences between MP and OMP appear. OMP tends to outperform MP at moderate T because it solves a least-squares problem over the selected atoms at each iteration, effectively optimizing the coefficients to better fit the signal. MP, on the other hand, updates one coefficient at a time without global optimization, which can be suboptimal when atoms are highly correlated.

TOY_SIZE = 32

T	MP (o)	OMP (o)	MP (n-o)	OMP (n-o)
5	12.77	12.77	12.87	12.87
10	14.12	14.12	14.32	14.32
40	18.06	18.06	18.37	18.37
80	20.59	20.59	21.08	21.08
200	25.77	25.77	26.39	26.52
400	32.21	32.21	33.50	33.91
600	39.08	39.08	40.25	41.62
1000	80.85	80.85	59.11	85.68

TOY_SIZE = 64

T	MP (o)	OMP (o)	MP (n-o)	OMP (n-o)
5	11.78	11.78	11.85	11.85
10	12.98	12.98	13.11	13.11
40	15.88	15.88	16.08	16.08
80	17.78	17.78	17.99	18.02
200	20.75	20.75	20.99	21.05
400	23.64	23.64	24.13	24.21
600	25.87	25.87	26.45	26.57
1000	29.50	29.50	30.24	30.49

TOY_SIZE = 16

T	MP (o)	OMP (o)	MP (n-o)	OMP (n-o)
5	14.71	14.71	14.92	14.92
10	16.48	16.48	16.92	16.92
40	22.56	22.56	23.01	23.22
80	27.37	27.37	28.80	29.07
200	46.96	46.96	45.39	50.24

Table 3: PSNR comparison for MP and OMP (orthogonal (o) vs non-orthogonal (n-o)) for different toy sizes and target sparsities T.

Regarding image size, larger images tend to have lower PSNR for the same target sparsity because the number of coefficients grows quadratically with size, making it harder for a fixed T to capture the full signal. For the smallest image size (16×16), the results have been truncated at $T = 200$ because selecting more atoms than the number of pixels would produce an underdetermined least-squares system in OMP, leading to an ill-posed problem and potentially causing numerical instability and large reconstruction errors (see Appendix A.2

Overall, OMP generally achieves higher PSNR than MP for the same sparsity when using non-orthogonal dictionaries, especially at moderate T, because it better exploits correlations among atoms.

4 Conclusion

The experiments demonstrate that learned denoisers, particularly DRUNet, consistently outperform deterministic methods in PnP frameworks, achieving higher PSNR and better perceptual quality. In sparse approximation, OMP proves superior to MP when using non-orthogonal dictionaries, especially at moderate sparsity levels, due to its global coefficient optimization. These findings highlight the importance of selecting appropriate algorithms and parameters based on the problem structure, whether for image restoration or sparse reconstruction, to balance accuracy, efficiency, visual quality and computational resources.

A Appendix 1a

A.1 Source code

The complete code of Lab 3 session and all the images processed can be found here.

A.2 MP and OMP

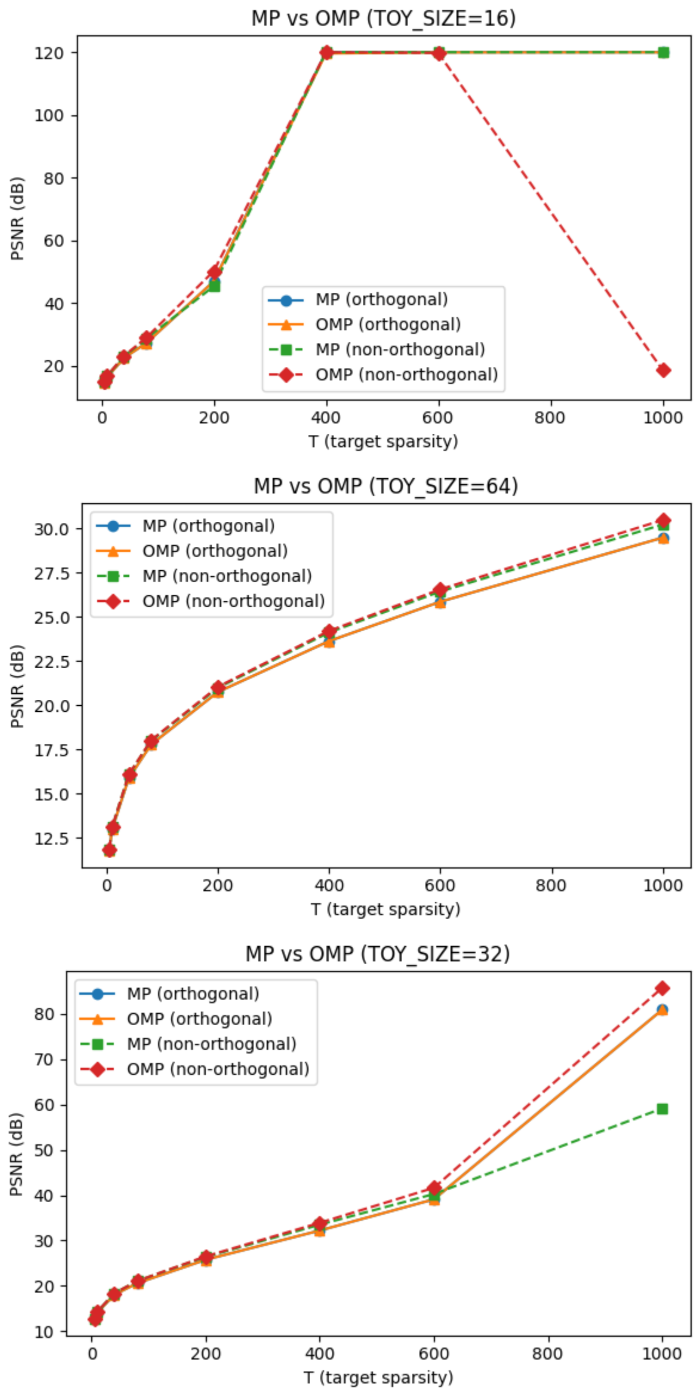

Figure 3: PSNR convergence for MP and OMP. Note the saturation after $T = 200$ and numerical instability for $TOY\_SIZE = 16$

Figure 4: Image reconstruction for $TOY\_SIZE = 32$