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On Maximum-a-Posteriori estimation with Plug & Play priors and stochastic gradient descent

Rémi Laumont · Valentin De Bortoli ^{*} ·
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Abstract Bayesian methods to solve imaging inverse problems usually combine an explicit data likelihood function with a prior distribution that explicitly models expected properties of the solution. Many kinds of priors have been explored in the literature, from simple ones expressing local properties to more involved ones exploiting image redundancy at a non-local scale. In a departure from explicit modelling, several recent works have proposed and studied the use of implicit priors defined by an image denoising algorithm. This approach, commonly known as Plug & Play (PnP) regularisation, can deliver remarkably accurate results, particularly when combined with state-of-the-art denoisers based on convolutional neural networks. However, the theoretical analysis of PnP Bayesian models and algorithms is difficult and works on the topic often rely on unrealistic assumptions on the properties of the image denoiser. This paper studies maximum-a-posteriori (MAP) estimation for Bayesian models with PnP priors. We first consider questions related to existence, stability and well-posedness, and then present a convergence proof for MAP computation by PnP stochastic gradient descent (PnP-SGD) under realistic assumptions on the denoiser used. We report a range of imaging experiments demonstrating PnP-SGD as well as comparisons with other PnP schemes.

Keywords Plug & Play · Bayesian imaging · Stochastic Gradient Descent · Inverse Problems · Deblurring · Inpainting · Denoising

Mathematics Subject Classification (2020) 65K10 · 65K05 · 62F15 · 62C10 · 68Q25 · 68U10 · 90C26

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1 Introduction

Many inverse problems in imaging sciences consider the estimation of an unknown image $x \in \mathbb{R}^d$ from an observation y , related to x as follows

$$y = \mathbf{A}(x) + n, \quad (1)$$

where \mathbf{A} is an observation operator and n is additive noise. Equation (1) is commonly referred to as the forward model.

Recovering x from the observation y by inverting the observation model is usually an ill-posed or ill-conditioned problem, in the sense that the solution is not unique, or it is not stable w.r.t. perturbations of the observation y . To reduce estimation uncertainty and provide meaningful solutions it is necessary to use additional information about the unknown image x so that the estimation problem becomes well-posed¹.

The Bayesian statistical framework provides a powerful framework to formulate well-posed solutions to such imaging inverse problems. In this framework, the likelihood of the observation y given the unknown x is described by a statistical model with probability density function $p(y|x)$, and assumptions on the unknown x take the form of a marginal or prior density $p(x)$. These densities are usually specified explicitly, either directly or via their potentials $U(x) = -\log p(x)$ and $F(x, y) = -\log p(y|x)$. Observed and prior information are then combined by using Bayes' theorem to derive the posterior distribution of x given y , with probability density function given by

$$p(x|y) = \frac{p(y|x)p(x)}{\int p(y|\tilde{x})p(\tilde{x})d\tilde{x}}. \quad (2)$$

This model underpins our inferences about $x|y$ and provides the basis for deriving Bayesian estimates. While different Bayesian estimators can then be considered, the Bayesian imaging literature predominantly relies on the maximum-a-posteriori (MAP) estimator

$$\hat{x}_{\text{MAP}} = \arg \max_{x \in \mathbb{R}^d} p(x|y) = \arg \min_{x \in \mathbb{R}^d} \{F(x, y) + U(x)\}, \quad (3)$$

which is usually computationally cheaper than other estimators that require computing expectations w.r.t $x|y$, such as the Minimum Mean Square Error estimator (MMSE) $\hat{x}_{\text{MMSE}} = \mathbb{E}[x|y] = \int_{\mathbb{R}^d} \tilde{x}p(\tilde{x}|y)d\tilde{x}$.

Until recently, most approaches in Bayesian imaging relied on explicit priors such as Markov random fields [1] (with the fields based on the total-variation pseudo-norm and its approximations being particularly prominent examples [51, 13, 37]), priors expressing sparsity in a transformed domain [24], or learning-based priors like patch-based Gaussian mixture models [66, 62, 59]. Among these priors, log-concave models have been particularly favored for both computational and analytical reasons. With regards to computation, log-concavity leads to formulations for MAP estimation and uncertainty quantification which benefit from the full arsenal of convex optimization tools, scaling efficiently to high-dimensions, with

¹ A problem is said to be well-posed in the sense of Hadamard when a solution exists, is unique, and depends in a Lipschitz continuous manner w.r.t. the observed data y .

strong and well-known convergence guarantees [14, 43, 11, 4, 44, 49]. Similarly, log-concavity also enables the use of state-of-the-art Monte Carlo sampling algorithms (see, e.g., [25, 46]). Moreover, from an analytical viewpoint, log-concavity guarantees the well-posedness of $p(x|y)$, and that \hat{x}_{MAP} is formally a Bayesian estimator (as opposed to simply being the point with greatest density w.r.t. the Lebesgue measure, which is a significantly weaker result, see [45] for details).

Computation of the MAP solution. When the posterior density $p(\cdot|y)$ is proper and differentiable, with $\nabla \log p(\cdot|y)$ Lipschitz continuous, it is possible to use first-order optimisation methods to compute maximisers of $p(\cdot|y)$, *i.e.* MAP estimators. The simplest first order optimisation scheme to compute \hat{x}_{MAP} is arguably the gradient descent algorithm, given by an initial state $X_0 \in \mathbb{R}^d$ and the following recursion for all $k \in \mathbb{N}$

$$X_{k+1} = X_k - \delta_k \nabla F(X_k, y) - \delta_k \nabla U(X_k), \quad (4)$$

where $(\delta_k)_{k \in \mathbb{N}} \in (\mathbb{R}_+)^{\mathbb{N}}$ is a sequence of step-sizes. The sequence $(X_k)_{k \in \mathbb{N}}$ converges to critical points of $p(\cdot|y)$ under mild assumptions on the sequence $(\delta_k)_{k \in \mathbb{N}}$ [42] and $p(\cdot|y)$. Alternatively, the stochastic gradient descent (SGD) variant

$$X_{k+1} = X_k - \delta_k \nabla F(X_k, y) - \delta_k \nabla U(X_k) + \delta_k Z_{k+1}, \quad (5)$$

where $\{Z_k : k \in \mathbb{N}\}$ is a family of i.i.d Gaussian random variables with zero mean and identity covariance matrix, is more robust to local minima and saddle points and hence more suitable when $x \mapsto p(x|y)$ is not log-concave on \mathbb{R}^d [8, 6]. Of course, there are many optimisation schemes with better convergence properties than SGD (see, e.g., [42] in the convex case), as well as other dynamics to construct efficient optimisation algorithms [33, 67]. Nevertheless, SGD is straightforward to apply, robust, and has a detailed convergence theory, making it a valuable algorithm in the imaging scientist's toolbox.

Deep learning approaches. In the last few years, deep neural networks have become ubiquitous to solve inverse problems in imaging, showing unmatched performances for point estimation for some specific problems like image denoising. Deep networks can be trained without explicitly using the knowledge of the forward model (1) [23, 63, 65, 28, 53, 27] or on the contrary can use this model explicitly via unrolled optimization techniques [30, 16, 22, 29]. One disadvantage of using neural networks to solve imaging inverse problems is that in order to achieve state-of-the-art performance it is usually necessary to train the network for a specific problem configuration - the network must be retrained if the forward model or any model parameters change significantly. Also, imaging approaches based on neural networks struggle to support more advanced inferences, such as decision-theoretic procedures.

Plug & Play (PnP) approaches. PnP approaches strike a balance between an explicit and fully modular modelling paradigm that represents the likelihood $p(y|x)$ and the prior $p(x)$ explicitly (or the data-fidelity and regularisation terms in a variational formulation), and a purely data-driven approach that seeks to infer the model from data. More precisely, these methods usually combine an explicit likelihood density or data-fidelity term with a prior or regularisation term that is implicitly defined by an image denoising algorithm D_ϵ [3]. This construction takes place at the algorithmic level, as opposed to at an explicit modelling level, by using the

denoiser D_ε in lieu of the gradient ∇U (also called score in the literature) or the proximal operator prox_U within an iterative optimisation scheme to compute \hat{x}_{MAP} [38, 64, 15, 32, 52]. This strategy allows decoupling the data observation model from the regularisation (that can be represented by a neural network denoiser D_ε learnt from training data), and has been shown to deliver remarkably accurate results for a large panel of inverse problems, particularly when D_ε is chosen carefully. The question of the convergence of these PnP algorithms has been the focus of several papers in the recent years [52, 61, 56], but it has not been satisfactorily answered yet, especially with regards to the strong assumptions made on D_ε , on F , and on the algorithm parameters. All of these limitations will be detailed in Section 2.

Lastly, many other fundamental questions related to inference with PnP schemes remain largely unexplored, particularly in the context of the Bayesian paradigm. For example, questions related to the correct definition of the Bayesian models, to the existence and well-posedness of the estimators that the PnP scheme seeks to compute, and whether these are proper Bayesian estimators in the sense of decision theory.

Contributions. The aim of this paper is to significantly improve our theoretical understanding of MAP estimation with *Plug & Play* priors. We first study some fundamental questions related to the posterior density that are essential for meaningful MAP estimation. We establish easily verifiable conditions such that the PnP posterior density is proper, well-posed, Lipschitz continuously differentiable, and stable w.r.t. the parameter ε defining the strength of the denoiser D_ε . Following on from this, we investigate in detail the convergence of the Plug-and-Play Stochastic Gradient Descent (PnP-SGD) for MAP estimation. This iterative algorithm takes the following form: for $X_0 \in \mathbb{R}^d$ and any $k \in \mathbb{N}$

$$X_{k+1} = X_k - \delta_k \nabla F(X_k, y) - (\delta_k / \varepsilon)(X_k - D_\varepsilon(X_k)) + \delta_k Z_{k+1}, \quad (\text{PnP-SGD})$$

where $\{Z_k : k \in \mathbb{N}\}$ is a family of independent Gaussian random variables with zero mean and identity covariance matrix, $D_\varepsilon : \mathbb{R}^d \rightarrow \mathbb{R}^d$ is a denoiser operator and $(\delta_k)_{k \in \mathbb{N}}$ is a sequence of step-sizes. We establish convergence results for PnP-SGD under mild and realistic assumptions on D_ε that hold for several well-known denoisers, including state-of-the-art denoisers based on convolutional neural networks. We also provide extensive experiments on several canonical inverse problems, implementing PnP-SGD with the denoising neural network presented in [52], which satisfies our convergence guarantees. Using the same denoising network, we also implement other state-of-the-art Plug-and-Play methods, and show that all schemes provide close results (in terms of image quality) when they converge. Although PnP-SGD is often slower than schemes using D_ε to approximate a proximal operator, the conditions of convergence provided in this paper for PnP-SGD are less restrictive than those provided in the literature for other PnP schemes, and convergence is possible for any regularization parameter balancing the weights of the data and prior terms.

The paper is organized as follows. Section 2 presents an overview of previous works on *Plug & Play* approaches for MAP estimation. Following on from this, Section 3 describes the proposed theoretical framework for analysing MAP estimation with PnP priors, as well as a detailed convergence theory for MAP computation by PnP-SGD. Section 4 illustrates the behavior of PnP-SGD, along with other PnP schemes, on several classical imaging problems.

2 A survey of Plug & Play methods in imaging

In the context of imaging inverse problems, *Plug & Play* methods aim at using a carefully chosen denoiser $D_\varepsilon : \mathbb{R}^d \rightarrow \mathbb{R}^d$ to implicitly define an image prior. This is achieved by relating D_ε to a proximal operator or a gradient associated with the prior density. In the first case, D_ε replaces a MAP estimator for a denoising problem. In the second case, D_ε replaces a Minimum Mean Square Error (MMSE) estimator for a denoising problem, related to the gradient of a log-prior via Tweedie's identity²[26].

In what follows, we describe how these approaches have been widely used to compute solutions to inverse problems. In our discussion, we pay particular attention to questions related to algorithmic convergence, and to the interpretation of the computed solutions, as this has been an important focus of the literature.

2.1 Plug & Play MAP estimators using proximal splitting

Let D_ε^\dagger denote the MAP estimator to recover x from a noisy observation $x_\varepsilon \sim \mathcal{N}(x, \varepsilon \text{Id})$ under the assumption that x has marginal density $p(x) \propto \exp[-U(x)]$; that is, $D_\varepsilon^\dagger(x_\varepsilon) = \arg \min_{x \in \mathbb{R}^d} \{\frac{1}{2}\|x_\varepsilon - x\|^2 + \varepsilon U(x)\} = \text{prox}_{\varepsilon U}(x_\varepsilon)$. When we set the PnP denoiser D_ε such that $D_\varepsilon = D_\varepsilon^\dagger$, any optimization scheme making use of a proximal descent on the prior can be used to solve (3) via D_ε .

For instance, the alternating direction method of multipliers (ADMM) [7] writes the augmented Lagrangian of (3) as

$$E_\varepsilon(x, z, v) = F(x, y) + \|x - z\|^2 / (2\varepsilon) + v^\top (x - z) + U(z) .$$

The joint optimization of the augmented Lagrangian is given by

$$(\hat{x}_{\text{MAP}}, \hat{z}_{\text{MAP}}) = \arg \min_{x, z \in \mathbb{R}^d} \max_{v \in \mathbb{R}^d} E_\varepsilon(x, z, v) .$$

This provides the solution $\hat{x}_{\text{MAP}} = \hat{z}_{\text{MAP}}$ of (3) when $\varepsilon \rightarrow 0$. In practice, the joint optimization is solved by an alternate minimization scheme on x and z and a gradient ascent on $\mathbf{u} = \varepsilon v$,

$$x_{k+1} = \arg \min_x E_\varepsilon(x, z_k, \mathbf{u}_k / \varepsilon) = \text{prox}_{\varepsilon F(\cdot, y)}(z_k - \mathbf{u}_k) , \quad (6)$$

$$z_{k+1} = \arg \min_z E_\varepsilon(x_{k+1}, z, \mathbf{u}_k / \varepsilon) = \text{prox}_{\varepsilon U}(x_{k+1} + \mathbf{u}_k) = D_\varepsilon(x_{k+1} + \mathbf{u}_k) , \quad (7)$$

$$\mathbf{u}_{k+1} = \mathbf{u}_k + x_{k+1} - z_{k+1} . \quad (8)$$

Similarly, when $F(\cdot, y)$ is differentiable, the simpler Forward-backward splitting (FBS) scheme [18], which only requires to compute ∇F , can be written in a Plug-and-Play fashion as

$$x_{k+1} = \text{prox}_{\varepsilon U}(x_k - \varepsilon \nabla F(x_k, y)) = D_\varepsilon(x_k - \varepsilon \nabla F(x_k, y)) . \quad (9)$$

² Notice that although it is conceptually helpful to distinguish these two cases (in order to make a historical and practical survey of the subject), there are clear theoretical connections between the two approaches. Indeed, under regularity conditions on the Bayesian model involved, MAP denoisers can be expressed as MMSE denoisers under an alternative (albeit often unknown) Bayesian model [31]. However this equivalence can not always be exploited in practice and has been mostly ignored in the literature on *Plug & Play* methods until very recently with the work of Xu *et al.* [61] to be presented later.

A fully proximal version of this algorithm, called Backward-backward splitting (BBS) [18], writes

$$x_{k+1} = \text{prox}_{\varepsilon U}(\text{prox}_{\varepsilon F}(x_k)) = D_\varepsilon(\text{prox}_{\varepsilon F}(x_k)). \quad (10)$$

BBS aims at solving a slightly modified version of (3) where F is replaced by its Moreau envelope with parameter ε . The same algorithm can be derived using half-quadratic splitting to solve (3).

When U is convex, such splitting schemes and many variants (including primal-dual methods, ISTA or FISTA, etc.) are well understood and proved to converge to the global optimum [7]. They have also been successfully used for non-convex U like patch-based Gaussian mixture models (GMM) as pioneered for external learning by Zoran & Weiss in [66]. The use of splitting schemes with non-convex GMM priors was later refined with convergence guarantees for scene-adapted learning [58].

Following the seminal work [60], this kind of splitting schemes have become ubiquitous in cases where U (and hence D_ε^\dagger) are unknown and unspecified, but a denoiser D_ε is available and assumed to be a good approximation of $D_\varepsilon^\dagger = \text{prox}_{\varepsilon U}$. As popular and efficient these methods have become, their convergence properties have remained largely unknown. Indeed, for most denoisers D_ε , there is no guarantee that there exists a potential U such that $D_\varepsilon = \text{prox}_{\varepsilon U}$. In [54], Sreehari *et al.* establish some sufficient conditions for this to happen: D_ε must be differentiable, and its Jacobian J_{D_ε} should be symmetric with eigenvalues within the $[0, 1]$ interval to ensure non expansiveness. These assumptions hold for transform-domain thresholding denoisers and for variants of Non Local means [9] where symmetry is explicitly enforced [54]. However, the two assumptions are unfortunately false for most popular denoisers, including Non Local Means [9], BM3D [19], Non Local Bayes [35] and neural networks denoisers like DnCNN [63], as observed in [48].

Consensus equilibrium / fixed point interpretation. Since it remains difficult to show that PnP schemes converge to the MAP or even a critical point of (3), several authors have proposed to analyse these schemes from a consensus equilibrium point of view [12, 2], or similarly to consider and analyse these approaches as fixed-point algorithms [55, 52]. The fixed points attained by these algorithms cannot be interpreted as MAP estimators, but should be seen as solving a set of equilibrium equations involving both the denoiser and the data term. For instance, for PnP-FBS, the idea is to show convergence to the set of points x satisfying $x = D_\varepsilon(x - \varepsilon \nabla F(x, y))$. It can easily be shown that the fixed points of several of these PnP algorithms (in particular PnP-ADMM and PnP-FBS) coincide [38, 55].

In [55], assuming that such fixed points exist, Sun *et al.* show convergence of PnP-ISTA (which is equivalent to PnP-FBS above) under the assumptions that ∇F is L_y -Lipschitz, $\varepsilon L_y \leq 1$ and D_ε is θ -averaged, see [4, Definition 4.33] for a definition. This assumption on the denoiser is probably too strong, since most denoisers cannot be considered as averaged operators. In [56], Sun *et al.* reformulate PnP-ADMM with different convergence conditions, and still assume quite restrictive conditions on the denoiser D_ε ³.

³ In [56], the residual $\text{Id} - D_\varepsilon$ is assumed to be firmly non expansive, which is equivalent to say that D_ε is firmly non expansive, see [4, Proposition 4.4].

In [52], Ryu *et al.* propose a convergence analysis of PnP-ADMM, PnP-FBS and PnP-DRS (PnP Douglas-Rachford Splitting), based on the weaker assumption that the residual operator $D_\varepsilon - \text{Id}$ is L -Lipschitz with a Lipschitz constant which depends both on the data fitting term F and the denoiser D_ε . The proof also requires F to be μ -strongly convex (which excludes all cases where \mathbf{A} is not full rank and de facto excludes some of the applications considered in [52]) and it imposes quite restrictive assumptions on relative values of μ , ε and L .

In a similar direction, Xu *et al.* [61] very recently proposed a convergence study for PnP-ISTA, with the assumption that ∇F is L_y -Lipschitz with $\varepsilon L_y \leq 1$. However, they assume that D_ε is an exact MMSE denoiser, *i.e.* $D_\varepsilon(x_\varepsilon) = \mathbb{E}[x|x_\varepsilon]$, where $x \sim p$ and $x_\varepsilon \sim \mathcal{N}(x, \varepsilon \text{Id})$ conditionally to x . Therefore their theoretical results do not carry to many classical denoisers, such that those learned from training data and implemented by neural networks.

Assumptions on algorithm parameters. Most of the convergence proofs for PnP algorithms impose restrictive assumptions on the choice of parameters used in the iterative schemes. This may exclude interesting ranges of parameters for several inverse problems. For instance, for PnP-FBS, the parameter ε (which can be interpreted as the step of the proximal or gradient descents) and the Lipschitz parameter L_y of ∇F must typically be chosen such that $L_y \varepsilon \leq C$ with $C \in [1, 2]$ (see [52, 61], the exact value of C depends on the convergence proof). If $F(x, y) = \frac{1}{2\alpha\sigma^2} \|\mathbf{A}x - y\|^2$, with $\|\mathbf{A}\| \leq 1$, it implies that $\frac{1}{\alpha} \leq \frac{\sigma^2}{\varepsilon}$. The parameter ε is imposed by the denoiser D_ε (the denoiser is trained for a noise of variance ε), and σ is given by the quantity of noise in the forward model. If, for instance, the forward model involves a noise standard deviation σ which is 5 times smaller than the one used for the denoiser D_ε , it means that the penalty α (which balances the respective weights of the data and prior terms) should be chosen larger than 25, which implies that the algorithm will only converges for huge regularizations. We will see in the experimental section that for this kind of reason the PnP-FBS algorithm often fails to converge for classical imaging inverse problems, or converges only for values of α which are not interesting in practice. Fully proximal algorithms such as PnP-ADMM or PnP-BBS are much more robust in practice, even when the conditions of their theoretical convergence are not fully met. The PnP-SGD algorithm that we will introduce in the following does not suffer from the same convergence limitations.

AMP algorithms. It is worth mentioning at this point that the Plug-and-Play framework has also been shown to be very efficient with Approximate Message Passing algorithms [2]. These algorithms have excellent convergence properties for data terms of the form $\|\mathbf{A}x - y\|^2$ with \mathbf{A} belonging to specific classes of random matrices. This restriction on \mathbf{A} does not hold for the inverse problems considered in the current paper so we focus instead on classical optimization scheme such as the ones described above.

2.2 Plug & Play MAP estimators using gradient descent

Now, assume that $D_\varepsilon = D_\varepsilon^*$, where D_ε^* is the MMSE estimator to recover x from the noisy observation $x_\varepsilon \sim \mathcal{N}(x, \varepsilon \text{Id})$ when x has marginal density $p(x)$; that is,

$$D_\varepsilon^*(x_\varepsilon) = \mathbb{E}[x|x_\varepsilon] = \int_{\mathbb{R}^d} xp(x)G_\varepsilon(x_\varepsilon - x)dx / \int_{\mathbb{R}^d} p(x)G_\varepsilon(x_\varepsilon - x)dx, \quad (11)$$

where G_ε is a Gaussian kernel with variance ε . We introduce the following class of smooth approximations of $p(x)$, defined for any $x \in \mathbb{R}^d$ by

$$p_\varepsilon(x) = \int_{\mathbb{R}^d} p(\tilde{x}) G_\varepsilon(x - \tilde{x}) d\tilde{x}. \quad (12)$$

In this case, Tweedie's identity [26] establishes the following relationship between the MMSE denoiser D_ε^* and (12), for any $x \in \mathbb{R}^d$

$$\nabla U_\varepsilon(x) = -\nabla \log p_\varepsilon(x) = (x - D_\varepsilon^*(x))/\varepsilon, \quad (13)$$

where $U_\varepsilon = -\log(p_\varepsilon)$. This relation can be used to plug the MMSE denoiser D_ε^* in any gradient descent scheme involving ∇U_ε and it is at the core of the algorithm PnP-SGD presented in this paper. Similarly to the MAP denoiser D_ε^\dagger , the MMSE denoiser D_ε^* is usually not known, so PnP methods rely on other denoisers D_ε that are believed to be good approximations of D_ε^* . Observe that approximating D_ε^* for realistic image priors is precisely the goal of CNN denoisers, while it is much more complicated to approach corresponding MAP denoisers D_ε^\dagger . This makes approaches based on Tweedie's identity particularly attractive.

A similar relation is derived by Romano *et al.* in [50] where they present the Regularization by Denoising (RED) method, which proposes an insightful Bayesian formulation of denoiser-based priors as image-adaptive Laplacian regularisations. Instead of using Tweedie's identity, the RED method solves equation (3) via different optimization algorithms (including gradient descent and ADMM) with explicit regularization $U_\varepsilon(x) = (1/2)\langle x, x - D_\varepsilon(x) \rangle$. As shown in [48], under the assumptions that D_ε is locally homogeneous and has symmetric Jacobian, this implies that for any $x \in \mathbb{R}^d$, $\nabla U_\varepsilon(x) = x - D_\varepsilon(x)$, which is (up to a scaling factor $1/\varepsilon$) the same expression as Tweedie's identity in (13). Unfortunately, as pointed out before, these assumptions on D_ε are not strictly satisfied by most commonly used denoisers [48], although we note that Jacobian symmetry can be explicitly enforced [40]. The convergence of the RED algorithms for denoisers that do not verify the above-mentioned assumption remains unproven. As an alternative interpretation the RED algorithm can be seen as a way to approximate the score ∇U_ε by $(x - D_\varepsilon(x))/\varepsilon$ in the optimality equation $\nabla F + \nabla U_\varepsilon = 0$. Here the optimal MMSE denoiser D_ε^* is again replaced by some other denoiser.

More recently, [17] studies a projected RED estimator which seeks to minimise a data fidelity term subject to the constraint that the solution belongs to the set of fixed points $\{x \in \mathbb{R}^d : x = D_\varepsilon(x)\}$, thus sharing strong link with the consensus equilibrium interpretation of proximal-based PnP estimators. It is reported in [17] that when D_ε is a demi-contractive mapping, its fixed points define a convex set, which allows the construction of provably convergent algorithms for this alternative RED estimator. However, as pointed out in [47], verifying that a given denoising operator is demi-contractive is not easy and, to be the best of our knowledge, it is not yet clear what denoisers verify this property. Furthermore, from a Bayesian inference viewpoint, additional studies would be required in order to determine when this projected RED estimator defines or approximates a MAP estimator for a suitable Bayesian model - we leave this as a perspective for future work.

The PnP-SGD optimisation algorithm that will be presented in the next section is very close to the gradient descent version of RED presented in [50]. We will show that it converges to the vicinity of the solution of (3) under much milder conditions than previously assumed, and in particular when D_ε is not an exact

MAP or MMSE denoiser. Importantly, our convergence proof is valid for the neural network denoiser used in [52] (a variant of DnCNN [63] with a contractive residual) and also for the native Non Local Means [10].

3 PnP maximum-a-posteriori estimation: analysis and computation

3.1 Analysis of maximum-a-posteriori estimation with PnP priors

We are interested in MAP estimation for Bayesian models involving PnP priors that are defined implicitly by an image denoising algorithm D_ε . We pay special attention to the highly practically relevant case in which D_ε approximates the optimal MMSE denoiser D_ε^* associated to p , i.e., $D_\varepsilon^* = \mathbb{E}[x|x_\varepsilon]$ for $x_\varepsilon \sim \mathcal{N}(x, \varepsilon \text{Id})$ when x has marginal density p . As mentioned previously, state-of-the-art denoisers based on neural networks are often trained to approximate D_ε^* by using a sample of clean images $\{x_i\}_{i=1}^N$ from p , a corresponding noisy sample $\{x'_i\}_{i=1}^N$ with $x'_i \sim \mathcal{N}(x_i, \varepsilon \text{Id})$, and choosing D_ε to approximately minimize the empirical MSE loss $\sum_{i=1}^N \|D_\varepsilon(x'_i) - x_i\|^2$. Similarly, many state-of-the-art patch-based image denoisers are also designed to approximate D_ε^* .

The fact that D_ε is only an approximation of D_ε^* leads to several complications in the analysis and computation of MAP solutions. For example, unlike D_ε^* , D_ε does not define a gradient mapping in general, and key results such as Tweedie's identity [26] do not hold. Moreover, in the case of neural network denoisers trained from samples $\{x_i\}_{i=1}^N$ from p , the model is unknown as it is only available through $\{x_i\}_{i=1}^N$, making it difficult to check that basic regularity properties required for MAP estimation are satisfied.

Rather than imposing strong assumptions on D_ε , we address these difficulties by formulating our analysis in the *M-complete* Bayesian framework, in which we assume that the posterior $p(x|y)$ associated with the true prior $p(x)$ exists but remains largely unknown, and all inference on $x|y$ are conducted by using operational approximations of this true model [5]. In particular, we focus on the class of smooth approximations of $p(x|y)$ given for any $\varepsilon > 0$ and $x \in \mathbb{R}^d$ by

$$p_\varepsilon(x|y) = \frac{p_\varepsilon(x)p(y|x)}{\int_{\mathbb{R}^d} p_\varepsilon(\tilde{x})p(y|\tilde{x})d\tilde{x}}, \quad (14)$$

where $p_\varepsilon(x)$ is the smooth approximation of the prior $p(x)$ defined in (12). We will study MAP estimation for $p_\varepsilon(x|y)$ to establish that the procedure is well defined, well posed, amenable to efficient computation, and that it provides a useful approximation to MAP estimation with the true posterior $p(x|y)$. Following on from this, Section 3.2 will study the computation of MAP solutions for $p_\varepsilon(x|y)$ by using PnP SGD with a generic denoiser D_ε that approximates D_ε^* , where we will pay particular attention to the conditions on D_ε required to ensure convergence, as well as to the bias introduced by using D_ε instead of D_ε^* .

It is established in [34] that, under basic assumptions on the likelihood function $p(y|x)$ detailed in H1 below, the posterior approximation $p_\varepsilon(x|y)$ is well defined, proper, and can be made as close to the true posterior $p(x|y)$ as desired by reducing the value of ε , with the approximation error vanishing as $\varepsilon \rightarrow 0$. Crucially, [34] also establishes that, under H1 and mild assumptions on the optimal MMSE denoiser

D_ε^* (essentially, that the denoising problem underlying D_ε^* is well posed in the sense of Hadamard), then $x \mapsto p_\varepsilon(x|y)$ is differentiable with $x \mapsto \nabla \log p_\varepsilon(x|y)$ Lipschitz continuous. We conclude that the approximation $p_\varepsilon(x|y)$ is well defined and amenable to computation by first-order schemes, such as SGD to compute critical points of $p_\varepsilon(x|y)$ and perform MAP estimation.

H1 For any $y \in \mathbb{R}^m$, $\sup_{x \in \mathbb{R}^d} p(y|x) < +\infty$, $p(y|\cdot) \in C^1(\mathbb{R}^d, (0, +\infty))$. In addition, there exists $L_y > 0$ such that $\nabla \log p(y|\cdot)$ is L_y Lipschitz continuous and $x \mapsto \log p(y|x)$ is real-analytic^{4 5 6}.

With the above-mentioned properties of $p_\varepsilon(x|y)$ in mind, we wonder if computing a MAP solution for $p_\varepsilon(x|y)$ provides useful information about a MAP solution for $p(x|y)$. More precisely, we study if critical points for $p_\varepsilon(x|y)$ are stable w.r.t. variations in ε , and if they converge to critical points of $p(x|y)$ as $\varepsilon \rightarrow 0$. Proposition 1 below establishes that this is indeed the case. In words, MAP solutions computed with $p_\varepsilon(x|y)$ are in the neighbourhood of MAP solutions for $p(x|y)$, with ε controlling a trade-off between the computational efficiency of first-order schemes and the accuracy of the delivered solutions w.r.t. $p(x|y)$.

Formally, we investigate the dependency of the set of stationary points $S_{\varepsilon, \mathcal{K}} = \{x \in \mathbb{R}^d : \nabla \log p_\varepsilon(x|y) = 0\}$ w.r.t. $\varepsilon > 0$. We show that each cluster point (in the sense of the Hausdorff distance, see below) of the sequences of sets $(S_{\varepsilon_n, \mathcal{K}})_{n \in \mathbb{N}}$ with $\lim_{n \rightarrow +\infty} \varepsilon_n = 0$ is contained in the set of stationary points of $x \mapsto p(x|y)$, i.e. the true posterior, denoted by $S_{\mathcal{K}} = \{x \in \mathcal{K} : \nabla \log p(x|y) = 0\}$.

We start by recalling that for any compact set $C \subset \mathbb{R}^d$, we have that $\mathcal{K}_C = \{\mathcal{K} : \mathcal{K} \text{ is compact and } \mathcal{K} \subset C\}$. (\mathcal{K}_C, d_C) is a metric space where the metric d_C is called the Hausdorff distance d_C and is given for any $\mathcal{K}_1, \mathcal{K}_2 \in \mathcal{K}_C$ by

$$d_C(\mathcal{K}_1, \mathcal{K}_2) = \inf\{\varepsilon > 0 : \mathcal{K}_1 \subset \mathcal{K}_2 + \overline{B}(0, \varepsilon), \mathcal{K}_2 \subset \mathcal{K}_1 + \overline{B}(0, \varepsilon)\}, \quad (15)$$

where for any pair of sets $A, B \subset \mathbb{R}^d$ we have $A + B = \{x + y : x \in A, y \in B\}$.

Denote \mathbf{E} the set of sequences $(\varepsilon_n)_{n \in \mathbb{N}}$ such that for any $n \in \mathbb{N}$, $\varepsilon_n > 0$ and $\lim_{n \rightarrow +\infty} \varepsilon_n = 0$. For any sequence $e = (\varepsilon_n)_{n \in \mathbb{N}} \in \mathbf{E}$ denote $T_{e, \mathcal{K}}$ the set of cluster points of $(S_{\varepsilon_n, \mathcal{K}})_{n \in \mathbb{N}}$ with respect to the Hausdorff distance on \mathcal{K} , $d_{\mathcal{K}}$ defined in (15). We also define $T_{\mathcal{K}} = \bigcup_{e \in \mathbf{E}} T_{e, \mathcal{K}}$, i.e. the collection of the cluster points for all the sequences $(\varepsilon_n)_{n \in \mathbb{N}}$ such that $\lim_{n \rightarrow +\infty} \varepsilon_n = 0$. Finally, we define $S_{\mathcal{K}}^* = \bigcup_{S \in T_{\mathcal{K}}} S$ the union of all the cluster points.

Proposition 1 Assume H1 and that $p \in C^1(\mathbb{R}^d, (0, +\infty))$ with $\|p\|_\infty + \|\nabla p\|_\infty < +\infty$. Then for any compact set \mathcal{K} , $S_{\mathcal{K}}^* \subset S_{\mathcal{K}}$ with $S_{\mathcal{K}} = \{x \in \mathcal{K} : \nabla \log p(x|y) = 0\}$.

⁴ A function $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is said to be real-analytic if for any $x_0 = (x_0^1, \dots, x_0^d) \in \mathbb{R}^d$ there exists $(a_{n_1, \dots, n_d})_{n_1, \dots, n_d \in \mathbb{N}} \in \mathbb{R}^{\mathbb{N}^d}$ and $r > 0$ such that for any $x = (x^1, \dots, x^d) \in B(x_0, r)$

$$f(x) = \sum_{n_1 \in \mathbb{N}} \dots \sum_{n_d \in \mathbb{N}} a_{n_1, \dots, n_d} \prod_{j=1}^d (x^j - x_0^j)^{n_j}.$$

⁵ The assumption that $x \mapsto \log(p(y|x))$ is real-analytic is satisfied in all of our experiments since there exists $\mathbf{A} \in \mathbb{R}^{p \times d}$ and $\sigma > 0$ such that for any $x \in \mathbb{R}^d$ and $y \in \mathbb{R}^p$, $\log p(y|x) = \|\mathbf{A}x - y\|^2 / (2\sigma^2)$.

⁶ From Liouville's theorem one could think that the simultaneously verifying that $\nabla \log p(y|\cdot)$ is Lipschitz continuous and that $x \mapsto \log(p(y|x))$ is real-analytic restricts our analysis to models for which $\nabla^2 \log p(y|\cdot)$ is constant (i.e., Gaussian models), but this is not the case because Liouville's theorem applies entire functions, which are a subclass of the real-analytic class.

Proof Let $(\varepsilon_n)_{n \in \mathbb{N}} \in \mathbf{E}$ and \mathbf{S} a cluster point of $(\mathbf{S}_{\mathbf{K}, \varepsilon_n})_{n \in \mathbb{N}}$. Without loss of generality we assume that $\lim_{n \rightarrow +\infty} \mathbf{S}_{\mathbf{K}, \varepsilon_n} = \mathbf{S}$. Let $x^* \in \mathbf{S}$. For any $\eta > 0$ there exists $n_\eta \in \mathbb{N}$ such that for any $n \in \mathbb{N}$ with $n \geq n_\eta$, $\mathbf{S} \subset \mathbf{S}_{\mathbf{K}, \varepsilon_n} + \overline{\mathbf{B}}(0, \eta)$. Hence, for any $n \in \mathbb{N}^*$ there exist an increasing sequence $(k_n)_{n \in \mathbb{N}} \in \mathbb{N}^{\mathbb{N}}$ and $x_n \in \mathbf{S}_{\mathbf{K}, \varepsilon_{k_n}}$ and $z_n \in \overline{\mathbf{B}}(0, 1/n)$ such that $x^* = x_{k_n} + z_n$. Since $\lim_{n \rightarrow +\infty} z_n = 0$ we get that $\lim_{n \rightarrow +\infty} x_{k_n} = x^*$.

In what follows, we show that $\lim_{n \rightarrow +\infty} \nabla \log(p_{\varepsilon_{k_n}}(x_{k_n})) = \nabla \log p(x^*)$. First, we show that

$$\lim_{n \rightarrow +\infty} \max(|p - p_{\varepsilon_{k_n}}|_{\infty, \mathbf{K}}, \|\nabla p - \nabla p_{\varepsilon_{k_n}}\|_{\infty, \mathbf{K}}) = 0. \quad (16)$$

Indeed, let $f \in C(\mathbb{R}^d, \mathbb{R}^p)$ with $p \in \mathbb{N}$ such that $\|f\|_\infty < +\infty$ and denote $f_\varepsilon \in C(\mathbb{R}^d, \mathbb{R}^p)$ given for any $x \in \mathbb{R}^d$ by

$$f_\varepsilon(x) = \int_{\mathbb{R}^d} f(y) G_\varepsilon(x - \tilde{x}) d\tilde{x}, \quad (17)$$

where we recall that for any $\tilde{x} \in \mathbb{R}^d$, $G_\varepsilon(\tilde{x}) = (2\pi\varepsilon)^{-d/2} \exp[-\|\tilde{x}\|^2/(2\varepsilon)]$. For ease of notation, we define $G = G_1$. Let $\eta > 0$. Then, there exists $R > 0$ such that for any $\varepsilon > 0$ we have

$$\int_{\|\tilde{x}\| > R} \|f(x - \varepsilon^{1/2}\tilde{x}) - f(x)\| G(\tilde{x}) d\tilde{x} \leq 2\|f\|_\infty \int_{\|\tilde{x}\| > R} G(\tilde{x}) d\tilde{x} < \eta/2. \quad (18)$$

Let $\mathbf{K}' = \mathbf{K} + \overline{\mathbf{B}}(0, R)$. We have that \mathbf{K}' is compact and therefore f is uniformly continuous on \mathbf{K}' . Hence there exists $\xi > 0$ such that for any $x \in \mathbf{K}$, $\varepsilon \in (0, \xi]$ and $y \in \overline{\mathbf{B}}(0, R)$ we have

$$|f(x - \varepsilon^{1/2}y) - f(x)| \leq \eta/2. \quad (19)$$

Hence, combining (18) and (19) we get that for any $x \in \mathbf{K}$ and $\varepsilon \in (0, \xi]$

$$\|f_\varepsilon(x) - f(x)\| \leq \int_{\mathbb{R}^d} \|f(x - \tilde{x}) - f(x)\| G_\varepsilon(\tilde{x}) d\tilde{x} \quad (20)$$

$$\leq \int_{\mathbb{R}^d} \|f(x - \varepsilon^{1/2}\tilde{x}) - f(x)\| G(\tilde{x}) d\tilde{x} \quad (21)$$

$$\leq \int_{\overline{\mathbf{B}}(0, R)} \|f(x - \varepsilon^{1/2}\tilde{x}) - f(x)\| G(\tilde{x}) d\tilde{x} \quad (22)$$

$$+ \int_{\overline{\mathbf{B}}(0, R)^c} \|f(x - \varepsilon^{1/2}\tilde{x}) - f(x)\| G(\tilde{x}) d\tilde{x} \quad (23)$$

$$\leq \eta/2 + \int_{\overline{\mathbf{B}}(0, R)} \|f(x - \varepsilon^{1/2}\tilde{x}) - f(x)\| G(\tilde{x}) d\tilde{x} \leq \eta. \quad (24)$$

Hence $\lim_{\varepsilon \rightarrow 0} \|f - f_\varepsilon\|_{\infty, \mathbf{K}} = 0$. Therefore using this result and that $p \in C^1(\mathbb{R}^d, \mathbb{R})$ with $\|p\|_\infty + \|\nabla p\|_\infty < +\infty$ we get that

$$\lim_{n \rightarrow +\infty} \max(|p - p_{\varepsilon_{k_n}}|_{\infty, \mathbf{K}}, \|\nabla p - \nabla p_{\varepsilon_{k_n}}\|_{\infty, \mathbf{K}}) = 0. \quad (25)$$

Combining this result, the fact that $\lim_{n \rightarrow +\infty} x_{k_n} = x^*$ and that $p^* > 0$, we get that $\lim_{n \rightarrow +\infty} \nabla \log(p_{\varepsilon_{k_n}}(x_{k_n})) = \nabla \log p(x^*)$. Finally, we obtain that

$$\lim_{n \rightarrow +\infty} \{\nabla \log p(y|x_{k_n}) + \nabla \log p_{\varepsilon_{k_n}}(x_{k_n})\} = \nabla \log p(y|x^*) + \nabla \log p(x^*) = 0. \quad (26)$$

Hence, $x^* \in \mathbf{S}_{\mathbf{K}}$ and therefore $\mathbf{S}_{\mathbf{K}}^* \subset \mathbf{S}_{\mathbf{K}}$. \square

As a third and final point in our analysis, we study if MAP estimation for $p_\varepsilon(x|y)$ is a well-posed estimation procedure, which is an essential requirement for meaningful inference. One would ideally seek to establish the existence of a unique global maximiser that is Lipschitz continuous w.r.t. perturbations of the observed data y . Unfortunately, this is not possible without imposing very strong assumptions on the model. Instead, Proposition 2 below shows that, under some assumptions on the likelihood $p(y|x)$, the set of critical points of $p_\varepsilon(x|y)$ is locally Lipschitz continuous w.r.t. perturbations of y , which is a weaker form of well-posedness. Notice that the assumptions on the likelihood can be relaxed when D_ε^* is contractive, but this is usually unrealistic. This highlights a limitation of MAP estimation by comparison to other Bayesian estimators, namely MMSE estimation, which is shown in [34] to be well-posed under significantly weaker assumptions.

Proposition 2 *Assume H1, that $(x, y) \mapsto p(y|x) \in C^2(\mathbb{R}^d \times \mathbb{R}^p, \mathbb{R})$ and $p \in C(\mathbb{R}^d, \mathbb{R}_+)$. Let $y_0 \in \mathbb{R}^p$ denote some observed data and $x_{y_0}^* \in \mathbb{R}^d$ a maximiser of the posterior $x \mapsto p(x|y_0)$. In addition assume either that the Hessian matrix $\nabla_x^2 \log p(y_0|x_0^*)$ is positive definite, or that the Jacobian $\|dD_\varepsilon^*(x_{y_0}^*)\| < 1$. Then there exists an open set $V_0 \subset \mathbb{R}^p$ and a function $x^*(y) \in C^1(V_0, \mathbb{R}^d)$ such that $y_0 \in V_0$ and for any $y \in V_0$, $x^*(y)$ is a local minimizer of $x \mapsto p(x|y)$.*

Proof First, using that $p \in C(\mathbb{R}^d, \mathbb{R}_+)$ we have that for any $v \in \mathbb{R}^d$ and $c \in \mathbb{R}$ there exists $A \in \mathcal{B}(\mathbb{R}^d)$ such that $\int_A | \langle x, v \rangle - c | p(x) dx > 0$. Hence, we can apply [31, Lemma II.1] and $D_\varepsilon \in C^\infty(\mathbb{R}^d, \mathbb{R}^d)$.

Note that $(x, y) \mapsto p(x|y) \in C^2(\mathbb{R}^d \times \mathbb{R}^p, \mathbb{R}_+)$. Since $\nabla^2 \log p(x_{y_0}^*|x_0)$ is positive there exists $U_1 \subset \mathbb{R}^d$ open and $V_1 \subset \mathbb{R}^p$ open such that for any $x \in U_1$ and $y \in V_1$, $\nabla^2 \log p(y|x)$ is positive. Hence, for any $y \in V_1$, $x \in \mathbb{R}^d$ is a local minimizer if and only $\nabla \log p(y|x) = 0$.

Let $F \in C^1(U_1 \times V_1, \mathbb{R}^d)$ given for any $x \in \mathbb{R}^d$ and $y \in \mathbb{R}^p$ by

$$F(x, y) = \nabla_x \log p(x|y) = (x - D_\varepsilon^*(x))/\varepsilon + \nabla \log p(y|x) . \quad (27)$$

Using that either $\|dD_\varepsilon^*(x_{y_0}^*)\| \leq 1$ or that $\nabla^2 \log p(y_0|x_0^*)$ is positive, we get that $\nabla_x F(x_{y_0}^*, y_0)$ is invertible. Therefore using the implicit function theorem, there exists $\varphi \in C^1(V_0, \mathbb{R}^d)$ such that for any $y \in V_0$, $F(\varphi(y), y) = 0$, i.e. $\varphi(y)$ is a local minimizer of $x \mapsto \log p(y|x)$ which concludes the proof. \square

To conclude, a major challenge in understanding Bayesian inference with PnP priors and providing guarantees for the delivered solutions is that the underlying prior and posterior densities $p(x)$ and $p(x|y)$ are unknown. Also, the image denoiser D_ε used to construct PnP schemes is not usually directly related to the model. Instead, when it approximates the optimal MMSE denoiser D_ε^* , it is indirectly related to the model via Tweedie's identity and the smooth approximations $p_\varepsilon(x)$ and $p_\varepsilon(x|y)$. We establish that these operational approximations are useful for MAP inference for $x|y$, in the sense that they are well defined, proper, and MAP solutions for $p_\varepsilon(x|y)$ can be made arbitrarily close to the true MAP solutions through the choice of ε . Importantly, under some assumptions, MAP solutions for $p_\varepsilon(x|y)$ are well posed and amenable to efficient computation by first order optimisation methodology.

3.2 PnP-SGD and convergence

We are now ready to study the computation of MAP solutions for $p_\varepsilon(x|y)$ by using PnP SGD with a generic denoiser D_ε that approximates D_ε^\star . We pay particular attention to the conditions on D_ε required to ensure convergence, and to the bias introduced by using D_ε instead of D_ε^\star .

We begin by using Tweedie's identity to express SGD to compute critical points of $p_\varepsilon(x|y)$ as the following sequence: $X_0 \in \mathbb{R}^d$ and for any $k \in \mathbb{N}$

$$X_{k+1} = X_k - \delta_k \nabla F(X_k, y) - \delta_k / \varepsilon (X_k - D_\varepsilon^\star(X_k)) + \delta_k Z_{k+1}, \quad (28)$$

where $(\delta_k)_{k \in \mathbb{N}} \in (\mathbb{R}_+)^\mathbb{N}$ is a family of step-sizes, $\varepsilon > 0$, and $\{Z_k : k \in \mathbb{N}\}$ a family of i.i.d. Gaussian random variables with zero mean and identity covariance matrix. We recall that the sequences $(X_k)_{k \in \mathbb{N}}$ and $(Z_k)_{k \in \mathbb{N}}$ are defined on an underlying probability space $(\Omega, \mathcal{F}, \mathbb{P})$.

As mentioned previously, in most practically relevant cases D_ε^\star is an abstract quantity that cannot be computed. Instead, we have a different denoiser D_ε that can be assumed to be a good approximation of D_ε^\star . For example, when we have access to samples $\{x_i\}_{i=1}^N$ from p we can consider a noisy version of these samples $\{x'_i\}_{i=1}^N$ with level $\varepsilon > 0$ and train a neural network based denoiser D_ε to minimize the loss $\sum_{i=1}^N \|D_\varepsilon(x'_i) - x_i\|^2$. This loss corresponds to the empirical version of $\mathbb{E}[\|D_\varepsilon(x_\varepsilon) - x\|^2]$ (with $x \sim p$ and $x_\varepsilon \sim \mathcal{N}(x, \varepsilon \text{Id})$ conditionally to x) whose minimizer is the MMSE D_ε^\star .

Using a generic denoiser D_ε in our SGD scheme in lieu of D_ε^\star we obtain the Plug & Play SGD algorithm associated with following recursion: $X_0 \in \mathbb{R}^d$ and for any $k \in \mathbb{N}$

$$X_{k+1} = X_k + \delta_k (b_\varepsilon(X_k) + Z_{k+1}), \quad (29)$$

$$b_\varepsilon(x) = \nabla \log(p(y|x)) + \alpha (D_\varepsilon(x) - x) / \varepsilon, \quad (30)$$

where we note that we have introduced a regularization parameter $\alpha > 0$ that controls the amount of regularisation enforced by D_ε . The original SGD algorithm is recovered by setting $\alpha = 1$ and $D_\varepsilon = D_\varepsilon^\star$.

Algorithm 1 PnP-SGD

Require: $n, n_{\text{burnin}} \in \mathbb{N}$, $y \in \mathbb{R}^m$, $\varepsilon, \alpha, \delta > 0$

Initialization: Set $X_0 = \tilde{x}$ and $k = 0$.

for $k = 0 : N$ **do**

$Z_{k+1} \sim \mathcal{N}(0, \text{Id})$

if $k \leq n_{\text{burnin}}$ **then**

$X_{k+1} = X_k + \delta_0 \nabla \log(p(y|X_k)) + (\delta_0 \alpha / \varepsilon) (D_\varepsilon(X_k) - X_k) + \delta_0 Z_{k+1}$

end if

if $k \geq n_{\text{burnin}}$ **then**

$X_{k+1} = X_k + \delta_k \nabla \log(p(y|X_k)) + (\delta_k \alpha / \varepsilon) (D_\varepsilon(X_k) - X_k) + \delta_k Z_{k+1}$

$\delta_{k+1} = \delta_0 (k + 1 - n_{\text{burnin}})^{-0.8}$

end if

end for

return X_N

We now turn to the proof of convergence of PnP-SGD. The asymptotic estimates we derive in this work are only valid for sequences which remain in a

compact set K , which is a classical assumption in stochastic approximation [57, 21, 20, 39]. Under tighter conditions on $x \mapsto \log p_\varepsilon(x|y)$ this limitation can be circumvented using the global asymptotic results of [57, Theorem A1.1]. Another way to remove this restriction would be to consider an additive term of the form $x \mapsto (x - \Pi_{\mathsf{C}}(x))/\lambda$ in b_ε (where Π_{C} is the projection onto some compact convex set C and $\lambda > 0$ some hyperparameter) which ensures the stability of the numerical scheme. We leave this analysis for future work. In practice, we have not observed any stability issues for PnP-SGD provided that the stepsize is chosen appropriately see Section 4.3.

In what follows, we show that the bias of PnP-SGD depends on the distance between D_ε and the MMSE estimator D_ε^* , using recent results from [57].

H2 Assume that there exist $\varepsilon_0 > 0$, $\mathsf{L} \geq 0$ and a function $\mathsf{M} : \mathbb{R}^+ \rightarrow \mathbb{R}^+$ such that for any $\varepsilon \in (0, \varepsilon_0]$, $R \geq 0$, $x_1, x_2 \in \mathbb{R}^d$ and $x \in \overline{\mathsf{B}}(0, R)$ we have

$$\|D_\varepsilon(x_1) - D_\varepsilon(x_2)\| \leq \mathsf{L} \|x_1 - x_2\|, \quad \|D_\varepsilon(x) - D_\varepsilon^*(x)\| \leq \mathsf{M}(R), \quad (31)$$

where we recall that

$$D_\varepsilon^*(x_1) = \int_{\mathbb{R}^d} \tilde{x} g_\varepsilon(\tilde{x}|x_1) d\tilde{x}, \quad (32)$$

with $\tilde{x} \mapsto g_\varepsilon(\tilde{x}|x)$ the probability density of X given $X_\varepsilon = x$ where $X_\varepsilon \sim \mathcal{N}(X, \varepsilon \text{Id})$ conditionally to X and $X \sim p$.

The first part of (31) regarding the smoothness property of the denoiser can be explicitly verified for a certain class of neural networks by adding a spectral regularization term for each layer of the neural network, see [52, 41]. The second condition follows from carefully selecting the loss of the neural network as in the Noise2Noise network introduced in [36] and controlling the population error, see [34].

We are now ready to state Proposition 3 which ensures that stable PnP-SGD sequences are close to the set of stationary points of $x \mapsto \log p_\varepsilon(x|y)$ where $x \mapsto \log p_\varepsilon(x|y)$ is given in (14). The distance to this set of stationary points is controlled by the approximation error of the network D_ε .

Proposition 3 Assume H1, H2. Let $\alpha > 0$ and $\varepsilon \in (0, \varepsilon_0]$. Assume that $\lim_{k \rightarrow +\infty} \delta_k = 0$, $\sum_{k \in \mathbb{N}} \delta_k = +\infty$ and $\sum_{k \in \mathbb{N}} \delta_k^2 < +\infty$. Let $R > 0$, $\mathsf{K} \subset \overline{\mathsf{B}}(0, R)$ be a compact set, $X_0 \in \mathbb{R}^d$ and $\mathsf{A}_{\varepsilon, \mathsf{K}} \in \mathcal{F}$ given by

$$\mathsf{A}_{\varepsilon, \mathsf{K}} = \{\omega \in \Omega : \text{there exists } k_0 \in \mathbb{N} \text{ such that for any } k \geq k_0, X_k(\omega) \in \mathsf{K}\}, \quad (33)$$

where $(X_k)_{k \in \mathbb{N}}$ is given by (29). Then there exist $C_{\varepsilon, \mathsf{K}} \geq 0$ and $r_{\varepsilon, \mathsf{K}} \in (0, 1)$ such that $\limsup_{k \rightarrow +\infty} d(X_k(\omega), \mathsf{S}_{\varepsilon, \mathsf{K}}) \leq C_{\varepsilon, \mathsf{K}} \mathsf{M}(R)^{r_{\varepsilon, \mathsf{K}}}$ for any $\omega \in \mathsf{A}_{\varepsilon, \mathsf{K}}$, with

$$\mathsf{S}_{\varepsilon, \mathsf{K}} = \{x \in \mathsf{K} : \nabla \log p_\varepsilon(x|y) = 0\}, \quad (34)$$

where $x \mapsto p_\varepsilon(x|y)$ is given in (14).

Proof Let $\varepsilon > 0$ and $\omega \in \mathsf{A}_{\varepsilon, \mathsf{K}}$. For any $k \in \mathbb{N}$, let $\zeta_k = Z_{k+1}$ and $\eta_k = b_\varepsilon(X_k) - \nabla \log p(y|X_k) - \nabla \log p_\varepsilon(X_k)$. Using H2 we have for any $k \in \mathbb{N}$,

$$\|b_\varepsilon(X_k) - \nabla \log p(y|X_k) - \nabla \log p_\varepsilon(X_k)\| = \varepsilon^{-1} \|D_\varepsilon(X_k) - D_\varepsilon^*(X_k)\| \leq \mathsf{M}(R)/\varepsilon. \quad (35)$$

Hence, we obtain that [57, Assumption 2.1, Assumption 2.2] are satisfied. In what follows, we show that [57, Assumption 2.3.c] holds. First, we introduce $G_\varepsilon : \mathbb{R}^d \rightarrow \mathbb{R}$ given for any $x \in \mathbb{R}^d$ by

$$G_\varepsilon(x) = (2\pi\varepsilon)^{-d/2} \exp[-\|x\|^2/(2\varepsilon)]. \quad (36)$$

We have that for any $x \in \mathbb{R}^d$, $p_\varepsilon(x) = (p * G_\varepsilon)(x)$, where $*$ denotes the convolution product. Since $p, G_\varepsilon \in L^1(\mathbb{R}^d)$ we get that for any $\xi \in \mathbb{R}^d$, $\widehat{p * G_\varepsilon}(\xi) = \hat{p}(\xi)\hat{G}_\varepsilon(\xi)$. Since $p \in L^1(\mathbb{R}^d)$, $\|\hat{p}\|_\infty < +\infty$ using Riemann-Lebesgue theorem and in addition $\hat{G}_\varepsilon(\xi) = \exp[-\varepsilon\|\xi\|^2/2]$. Hence, $\widehat{p * G_\varepsilon} \in L^1(\mathbb{R}^d)$ and we obtain that for almost every $x \in \mathbb{R}^d$

$$p_\varepsilon(x) = \int_{\mathbb{R}^d} \hat{p}(\xi)\hat{G}_\varepsilon(\xi) \exp[i\langle x, \xi \rangle] d\xi. \quad (37)$$

In the rest of the proof, we denote $\bar{p}_\varepsilon : \mathbb{C}^d \rightarrow \mathbb{C}$ given for any $z = (z^1, \dots, z^d) \in \mathbb{C}^d$ by $\bar{p}_\varepsilon(z) = \int_{\mathbb{R}^d} \hat{p}(\xi)\hat{G}_\varepsilon(\xi) \exp[i\langle z, \xi \rangle] d\xi$ where for any $z_1, z_2 \in \mathbb{C}^d$ we have $\langle z_1, z_2 \rangle = \sum_{j=1}^d z_1^j \bar{z}_2^j$. We have that \bar{p}_ε is analytic using the dominated convergence theorem. Since for any $x \in \mathbb{R}^d$, $p_\varepsilon(x) > 0$ and $\bar{p}_\varepsilon \in C(\mathbb{C}^d, \mathbb{C})$, there exists an open set $U \subset \mathbb{C}^d$ such that for any $z \in U$, $\Re(\bar{p}_\varepsilon(z)) > 0$. Since $\log : \mathbb{C} \setminus (\{t \in \mathbb{C} : \Re(t) \leq 0\}) \rightarrow \mathbb{C}$ is analytic we obtain that $z \mapsto \log \bar{p}_\varepsilon(z)$ is analytic on U . Hence, $x \mapsto \log p(y|x) + \log p_\varepsilon(x)$ is real-analytic on \mathbb{R}^d . We conclude using [57, Theorem 2.1].

The proof can be extended to the case where $Z_k = 0$ using [57, Theorem 2.1]. In this case the assumption that $\sum_{k \in \mathbb{N}} \delta_k^2 < +\infty$ can be replaced by $\lim_{k \rightarrow +\infty} \delta_k = 0$.

The following experimental section demonstrates the PnP-SGD algorithm on three canonical imaging inverse problems, namely image deblurring, inpainting, and denoising, along with other standard PnP algorithms.

4 Experimental study

In this section, we study the behaviour of several PnP algorithms for three classical inverse problems: denoising, deblurring and inpainting. We recall that in each of these problems we consider a prior model $p(x) \propto \exp[-U(x)]$ which is unknown and that the inference $x|y$ is obtained by approximation of this model. For the deblurring and denoising problems, the log-posterior of the degradation model can be written for any $x, y \in \mathbb{R}^d$ as

$$-\log p(x|y) = \|\mathbf{A}x - y\|^2/(2\sigma^2) + \alpha U(x) + C, \quad (38)$$

where \mathbf{A} is a $d \times d$ matrix, $C \geq 0$ is a constant and the parameter $\alpha \geq 0$ balances the weights of the log-likelihood $F(x, y)$ and the log-prior U . In this case, we have for any $x, y \in \mathbb{R}^d$, $F(x, y) = \|\mathbf{A}x - y\|^2/(2\sigma^2)$. In our inpainting experiments, we change the likelihood so that pixels are either visible or hidden. In this case the log-posterior can be written for any $x \in \mathbb{R}^d$ and $y \in \mathbb{R}^m$ as

$$-\log p(x|y) = \iota_{\mathbf{Q}x=y} + \alpha U(x) + C, \quad \text{with } \iota_{\mathbf{C}}(x) = \begin{cases} 0 & \text{if } x \in \mathbf{C} \\ +\infty & \text{otherwise,} \end{cases} \quad (39)$$

with \mathbf{Q} a $m \times d$ matrix consisting of m random lines from the $d \times d$ identity matrix.

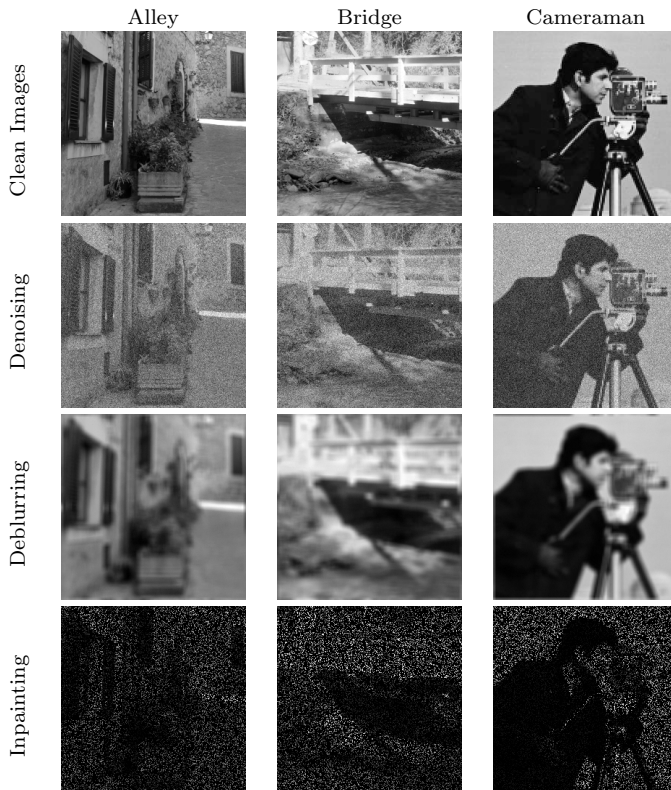


Fig. 1 *Dataset (part 1)*: First three images in our dataset, and examples of degraded images for the three inverse problems considered in this paper. For denoising, we add a Gaussian noise with variance $\sigma^2 = (30/255)^2$. For deblurring, the operator \mathbf{A} corresponds to a 9×9 uniform blur operator, and we add Gaussian noise with variance $\sigma^2 = (1/255)^2$. For inpainting, we hide 80% of the pixels.

4.1 Image dataset

In Figures 1 and 2 we present the 6 original images used in the experiments. These images contain both geometric structures, constant areas and textured regions. On the same figures, we display degraded versions of each image for each set of experiments. For the denoising experiment, the level of the Gaussian noise is fixed to $\sigma^2 = (30/255)^2$. In the case of deblurring, the operator \mathbf{A} corresponds to a 9×9 uniform blur operator, and we add Gaussian noise with variance $\sigma^2 = (1/255)^2$. Finally, in the context of inpainting, we hide 80% of the pixels.

4.2 Algorithms

In this section, we evaluate PnP-SGD (Algorithm 1) along with three other classical PnP algorithms: PnP-ADMM (Algorithm 2), PnP-FBS (Algorithm 3) and PnP-BBS (Algorithm 4). Note that in the case of inpainting the log-likelihood is

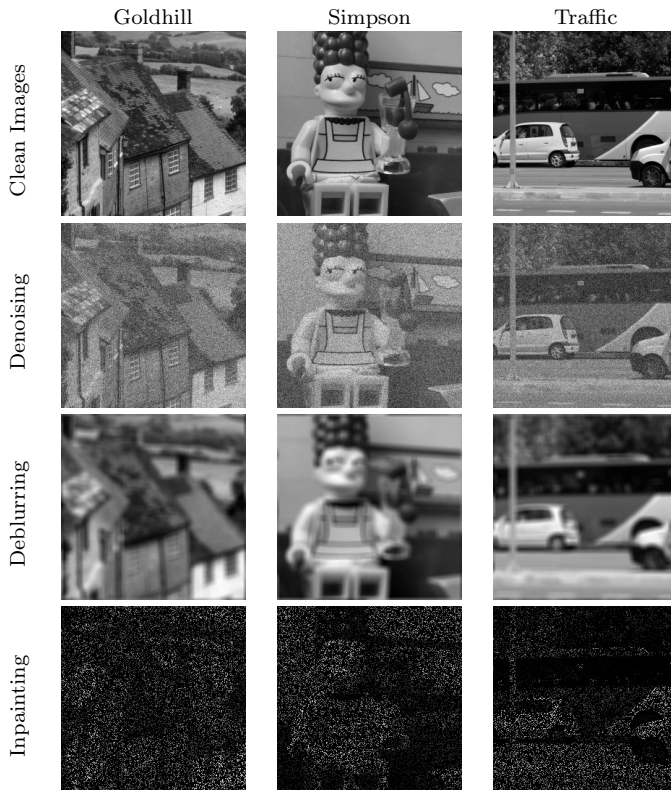


Fig. 2 *Dataset (part 2)*: Last three images in our dataset, and examples of degraded images for the three inverse problems considered in this paper. For denoising, we add a Gaussian noise with variance $\sigma^2 = (30/255)^2$. For deblurring, the operator \mathbf{A} corresponds to a 9×9 uniform blur operator, and we add Gaussian noise with variance $\sigma^2 = (1/255)^2$. For inpainting, we hide 80% of the pixels.

not differentiable, since ι_C is not differentiable. In Section 4.6 we will present an extension of these PnP algorithms to this setting using proximal operators.

In order to take into account the parameter $\alpha > 0$ into Algorithms 2-3-4, we slightly modify the target function. Instead of minimizing $x \mapsto -\log p(x|y)$ we aim at minimizing $x \mapsto -\log p(x|y)/\alpha$. Doing so the parameter $\alpha > 0$ can be included in the parameters of the log-likelihood which becomes $(x, y) \mapsto F(x, y)/\alpha$. All algorithms are implemented using Python and the PyTorch library. Our experiments are run on an Intel Xeon CPU E5-2609 server with a Nvidia Titan XP graphic card.

4.3 Parameters settings and convergence conditions

In this section, we recall and discuss the choice of the different parameters, as well as the convergence conditions for PnP-SGD. We also discuss the convergence properties of PnP-ADMM and PnP-FBS following the guidelines of [52,61].

Algorithm 2 PnP-ADMM

Require: $n \in \mathbb{N}$, $y \in \mathbb{R}^m$, $\varepsilon > 0$, $\alpha > 0$, $x_0 \in \mathbb{R}^d$
Initialization: Set $x_0 = z_0$, and $u_k = 0$.
for $k = 0 : N$ **do**
 $x_{k+1} = \text{prox}_{(\varepsilon/\alpha)F(\cdot, y)}(z_k - u_k)$
 $z_{k+1} = D_\varepsilon(x_{k+1} + u_k)$
 $u_{k+1} = u_k + (x_{k+1} - z_{k+1})$
end for
return x_{N+1}

Algorithm 3 PnP-FBS

Require: $n \in \mathbb{N}$, $y \in \mathbb{R}^m$, $\varepsilon > 0$, $\alpha > 0$, $x_0 \in \mathbb{R}^d$
for $k = 0 : N$ **do**
 $x_{k+1} = D_\varepsilon(x_k - (\varepsilon/\alpha)\nabla F(x_k, y))$
end for
return x_{N+1}

Algorithm 4 PnP-BBS

Require: $n \in \mathbb{N}$, $y \in \mathbb{R}^m$, $\varepsilon > 0$, $\alpha > 0$, $x_0 \in \mathbb{R}^d$
for $k = 0 : N$ **do**
 $x_{k+1} = D_\varepsilon(\text{prox}_{(\varepsilon/\alpha)F(\cdot, y)}(x_k))$
end for
return x_{N+1}

Recall that from (14), we denote L_y the Lipschitz constant of the log-likelihood gradient $x \mapsto \nabla F(\cdot, y)$. For $F(x, y) = \|\mathbf{A}x - y\|^2/(2\sigma^2)$, $L_y = \|\mathbf{A}^*\mathbf{A}\|/\sigma^2$, with \mathbf{A}^* the adjoint of \mathbf{A} . F is μ -strongly convex if and only if \mathbf{A} is invertible, in which case $\mu = \lambda_{\min}(\mathbf{A})^2/\sigma^2$, where $\lambda_{\min}(\mathbf{A})$ is the smallest singular value of \mathbf{A} . In our experiments we have $\lambda_{\min} = 1$ for denoising and $\lambda_{\min} = 0$ for deblurring and inpainting. In our experiments, the operator \mathbf{A} is always chosen such that $\|\mathbf{A}^*\mathbf{A}\| = 1$. Note that if F is replaced by F/α , as it the case in Algorithms 2-3-4, we have that L_y and μ are replaced by L_y/α and μ/α .

Denoiser. In all experiments, the denoising operator D_ε is chosen as the pretrained denoising neural network introduced in [52]. This denoiser is trained so that $\text{Id} - D_\varepsilon$ is L -Lipschitz with $L < 1$. Note that this corresponds to the first part of (31) in H2. In [52] three pretrained denoisers, at noise level $\varepsilon = (5/255)^2, (15/255)^2, (40/255)^2$ are proposed. In this work, we only use the first one in our denoising and deblurring experiments. The inpainting problem requires a more subtle strategy relying on a coarse to fine approach, described in Section 4.6.

PnP-SGD. In Algorithm 1, we consider a burn-in regime with a constant step δ_0 until some iteration n_{burnin} . After this initial phase, we set $(\delta_k)_{k \in \mathbb{N}}$ to be a decreasing sequence satisfying the conditions of Proposition 3. In the case of denoising or deblurring, δ_0 is given by

$$\delta_0 = \delta_{\text{stable}}/6, \text{ where } \delta_{\text{stable}} := 2/L_{\text{tot}}, \quad L_{\text{tot}} = 2/(\alpha L/\varepsilon + \|\mathbf{A}^*\mathbf{A}\|/\sigma^2), \quad (40)$$

where L_{tot} is the Lipschitz constant of $\nabla \log p(\cdot|y)$. Note that setting $\delta_0 = \delta_{\text{stable}}$ ensures that the deterministic scheme: $x_0 \in \mathbb{R}^d$ and for any $k \in \mathbb{N}$, $x_{k+1} = x_k +$

$\delta_0 \nabla \log p(x_k|y)$, satisfies that $(\log p(x_k|y))_{k \in \mathbb{N}}$ is non-decreasing. After the burn-in, we use a decreasing sequence of step-sizes $(\delta_k)_{k \in \mathbb{N}}$ such that for any $k \in \mathbb{N}$ we have

$$\delta_k := \delta_0 \times (k - n_{\text{burnin}})^{-0.8}, \quad (41)$$

which satisfies the conditions required in Proposition 3 for convergence. Note that contrary to existing work, any value of $\alpha > 0$ can be used in Algorithm 1 provided that δ_0 is defined accordingly using (40).

PnP-ADMM. The convergence results of [52] for PnP-ADMM require the strong convexity of F . In our experiments, this condition is met for denoising experiments (since $\mathbf{A} = \text{Id}$), but not for inpainting nor deblurring if the blur operator is not invertible (which is the case for a 9×9 uniform blur). In the denoising case, following [52], PnP-ADMM converges to a fixed point if $L \in [0, 1)$ and $L/(1 + L(1 - 2L)) < \varepsilon/(\alpha\sigma^2)$. In practice, this condition is not satisfied, see Section 4.4. However, Algorithm 1 experimentally converges to a fixed point with interesting visual properties. This suggests that it might be possible to prove the convergence of PnP-ADMM under weaker conditions than the ones of [52].

PnP-FBS. Similarly to PnP-ADMM the convergence results obtained by [52] for PnP-FBS are only valid in a strongly convex setting. In our case this corresponds to the denoising experiment here. The condition on the Lipschitz constant of the denoiser D_ε is $L/(1 + L) < \varepsilon/(\alpha\sigma^2) < (L + 2)/(L + 1)$. In Section 4.4, we show that these conditions are not met in our experiments. In practice, we still observe convergence of the algorithm for the denoising experiments. This is no longer case in non-strongly convex problems, see Section 4.5 and Section 4.6. In [61], convergence towards the set of stationary points of the log-posterior is established for PnP-FBS provided that $D_\varepsilon = D_\varepsilon^*$, *i.e.* D_ε is the optimal MMSE. In addition, [61] requires that $\varepsilon L_y \leq 1$. This condition implies that $\varepsilon \|\mathbf{A}^* \mathbf{A}\| \leq \alpha\sigma^2$. Since $\|\mathbf{A}^* \mathbf{A}\| = 1$ for all our experiments, this implies $\alpha \geq \varepsilon/\sigma^2$. In experiments with large noise level (as it is the case for our denoising setting), this leads to acceptable values of α . However, when σ is small in comparison to ε (which is the case for deblurring), the regularisation parameter α for which the convergence is ensured is too highlighted in Section 4.3.

4.4 Denoising

For these denoising experiments, we add a Gaussian noise of variance $\sigma^2 = (30/255)^2$ (see the second row of Figures 1 and 2 for examples of degraded images). In this experiment we use a denoiser D_ε trained for a noise level $\varepsilon = (5/255)^2$ on a dataset $\{x_i, x'_i\}_{i=1}^N$ with $x_i \sim p$ and $x'_i \sim \mathcal{N}(x_i, \varepsilon \text{Id})$ for any $i \in \{1, \dots, N\}$. Using this denoiser in Algorithms 1-4, we aim at denoising y with noise level σ^2 .

We run all algorithms for several values of the regularization parameter α and for two different initializations: first a TV-L₂ initialization, *i.e.* applying a simple TV-L₂ restoration to the noisy image following [51, 14], and second an oracle initialization (using the original image without degradation). Our goal here is to assess the dependency of the algorithm on initialization, since the log-posterior we study is highly non-convex.

For PnP-SGD, the initial step-size δ_0 and the sequence $(\delta_k)_{k \in \mathbb{N}}$ are defined as explained in Section 4.3. For these denoising experiments, the resulting value of δ_0 is already quite small, such that decreasing δ_k after the burn-in phase effectively stops the search for a better optimum and does not change the result. The number of iterations n_{burnin} for the burn-in was set between 5000 and 25000 for SGD. Within that range, we stop this phase as soon as $|\text{PSNR}(X_{k+1}) - \text{PSNR}(X_k)| < 0.1 \times \delta_0$. This conservative choice allows to make sure that the algorithm reaches its steady state, so that the oracle initialization (starting from an overestimated value of PSNR) does not overestimate the global maximum and the non-oracle initializations (starting from an underestimated value of PSNR) do not underestimate it. In practice, convergence is reached after a few hundreds of iterations in most cases and only rarely did the algorithm iterate beyond 5000. Increasing δ_0 to $\delta_0 = 0.9 \times \delta_{\text{stable}}$ also permits to achieve faster convergence, but in this case adding a decreasing phase for $(\delta_k)_{k \in \mathbb{N}}$ after the burn-in regime is important to achieve the same asymptotic results.

For the splitting-based algorithms (ADMM, BBS, FBS), practical convergence is very fast and 100 iterations are largely sufficient in all cases. Observe that since we use a denoiser trained for a noise level $\varepsilon = (5/255)^2$, and our denoising experiments are run for $\sigma^2 = (30/255)^2$, theoretical convergence of PnP-ADMM following [52] requires that $\alpha < (1 + L(1 - 2L))/36L$. The exact value of L for the denoising considered in [52] is not available, but our experiments suggest that $L \approx 1$. This implies that only drastically small values of α meet the previous condition. As a result, this condition is not satisfied with the choices of α that are experimentally optimal but does not prevent the algorithm to converge in practice. In the same way, provided that $L \in [0, 1)$, convergence of PnP-FBS following [52] implies that α is at least larger than 18, see Section 4.3. Yet, interesting values of α for this denoising experiment are far smaller. The condition provided in [61], $\alpha \geq \varepsilon/\sigma^2 = 1/3$ gives more realistic values for α but we remind that in this case we must assume that $D_\varepsilon = D_\varepsilon^*$.

Figure 3 summarizes the results of this denoising experiment on 10 independent random noise realizations on each of the 6 images in the dataset, for PnP-SGD, PnP-ADMM and PnP-BBS (PnP-FBS is not shown here for the sake of clarity, but it shows a very similar behavior). We first observe that initialization seems to play a very minor role for all the algorithms considered in this problem. A TV- L_2 initialization is sufficient to reach virtually the same reconstruction quality as the oracle initialization. This might be explained by the fact that denoising is a relatively simple inverse problem. Second, all algorithms produce very similar results, with an optimal value of α around 0.25, see Figure 3. Table 1 summarizes the denoising results of all algorithms (including PnP-FBS) obtained for this nearly optimal setting of $\alpha = 0.25$. In Figure 4 we display the results of the different algorithms for this denoising experiment. If the PSNR values are quite close, it seems that the algorithms make different compromises in terms of visual results. For example, the estimator obtained with PnP-ADMM seems to exhibit sharper edges. However, it also seems to hallucinate more false structures than other algorithms.

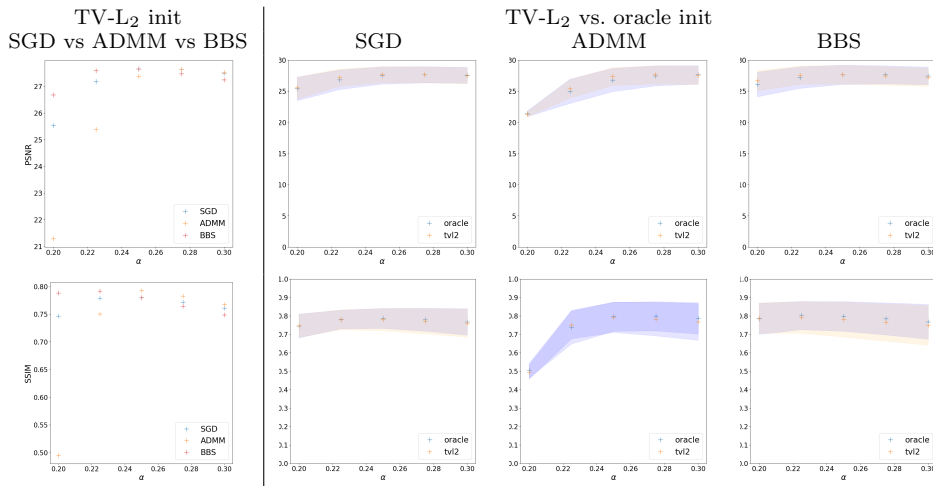


Fig. 3 Plug & Play denoising for $\sigma^2 = (30/255)^2$ with the prior implicit in D_ε for $\varepsilon = (5/255)^2$ and different values of the regularization parameter α . This table shows means and standard deviations for PSNR and SSIM values over $K=10$ independent noise realizations for each of the six images. Initialization plays a very minor role in this case and all algorithms achieve similar (nearly optimal) performance for $\alpha = 0.25$.

Denoising $\sigma^2 = (30/255)^2$, $\varepsilon = (5/255)^2$, TV- L_2 init, $\alpha = 0.25$				
	PnP-SGD	PnP-ADMM	PnP-BBS	PnP-FBS
Overall PSNR	27.65	27.37	27.65	27.56
Simpsons	30.04	30.10	30.41	30.35
Traffic	27.36	27.09	27.31	27.27
Cameraman	28.54	28.21	28.74	28.48
Alley	27.16	26.82	26.98	26.96
Bridge	26.28	25.83	26.18	26.03
Goldhill	26.55	26.18	26.30	26.30

Table 1 Plug & Play denoising for $\sigma^2 = (30/255)^2$ with the prior in D_ε for $\varepsilon = (5/255)^2$. This table shows mean PSNR values over $K=10$ independent noise realizations for each of the six images. The regularization parameter $\alpha = 0.25$ is nearly optimal for all algorithms.

4.5 Deblurring

We now turn to the deblurring problem. In this section, images are blurred with a uniform 9×9 kernel, and a small Gaussian noise of standard deviation $\sigma = 1/255$ is added in order to define the degradation model. We now compare the behavior of Algorithms 1-4.

Experiments with PnP-SGD follow the same rules as for the denoising problem and the same observations are valid. When running PnP-ADMM we use approximately 200 iterations to ensure the convergence whereas for PnP-FBS and PnP-BBS, we use approximately 500 iterations. Except for PnP-SGD (using Proposition 3), these PnP algorithms are not guaranteed to converge according to [52] since \mathbf{A} is not invertible. In practice PnP-FBS indeed converges only for very large values of the regularization parameter α , whereas other PnP algorithms converge for all our experiments. As highlighted in Section 4.3 this suggests that conver-

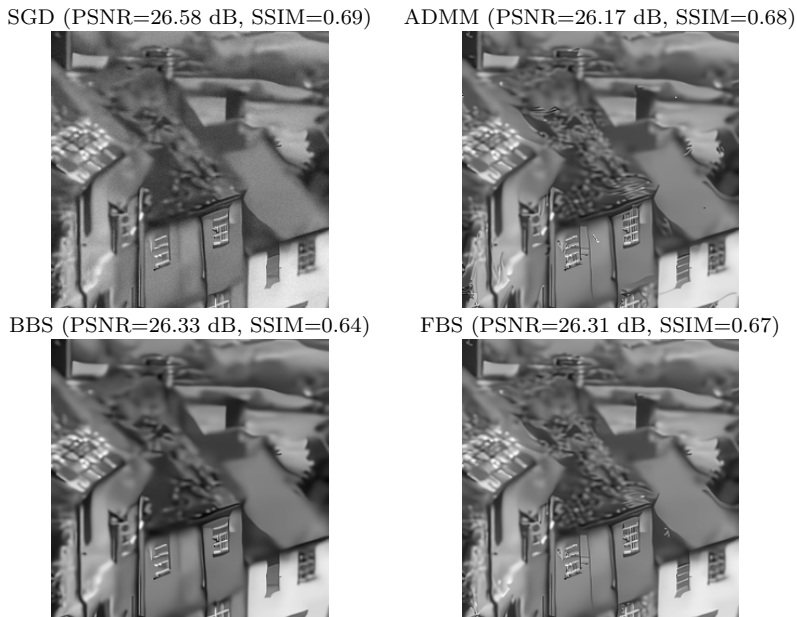


Fig. 4 Plug & Play denoising for $\sigma^2 = (30/255)^2$, $\varepsilon = (5/255)^2$ with $\alpha = 0.25$.

gence for PnP-ADMM and PnP-FBS occur under weaker conditions than the ones prescribed in [52].

Figure 5 summarizes the results of deblurring on 10 independent random noise realizations on each of the 6 images in the dataset, for PnP-SGD, PnP-ADMM and PnP-BBS (PnP-FBS is not shown here because it does not converge most of the time), for TV- L_2 and oracle initializations. Again, initialization appears to play a minor role in the final results.

Observe that all algorithms show very similar performances (when they converge) for these deblurring experiments. While PnP-SGD is slower to converge, it is ensured to approximate the MAP theoretically. Table 2 summarizes the deblurring results of all algorithms (including PnP-FBS) obtained for the nearly optimal setting of $\alpha = 0.3$. In Figure 4 we display the results of the different algorithms for this denoising experiment. Interestingly, we note that visual results for this deblurring problem are much more similar to each other than for denoising experiments.

4.6 Inpainting

The inpainting problem consists in trying to recover $x \in \mathbb{R}^d$ from a small proportion of its pixels, namely from the measurements vector $y = \mathbf{Q}x$, where \mathbf{Q} is a $m \times d$ matrix consisting of m random lines from the $d \times d$ identity matrix, and $m = qd \ll d$. In our experiments we set $q = 20\%$. In this case, since measurements are not affected by noise, the data-fitting term takes the form of a hard constraint, *i.e.*

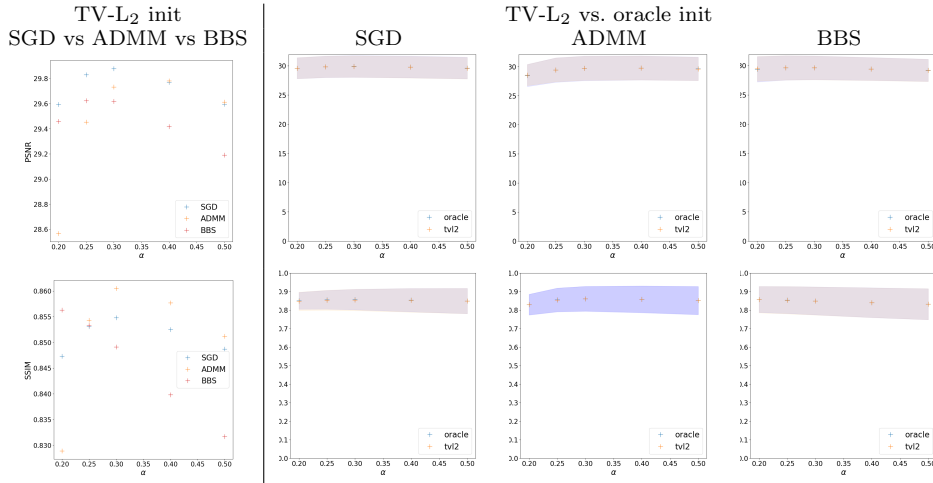


Fig. 5 Plug & Play deblurring. Image are blurred with a 9×9 uniform kernel, a Gaussian noise of standard deviation $\sigma^2 = (1/255)^2$ is added. The denoiser D_ε is trained at $\varepsilon = (5/255)^2$. The plots shows mean and standard deviation values of PSNR and SSIM over $K=10$ independent noise realizations for each of the six images and different values of the regularization parameter α . Initialization plays a very minor role in this case and all algorithms achieve similar (nearly optimal) performance for $\alpha = 0.3$, except for FBS which requires a larger (sub-optimal) α to converge.

Deblurring a 9×9 kernel with $\sigma^2 = (30/255)^2$, $\varepsilon = (5/255)^2$, TV-L ₂ init, $\alpha = 0.3$				
	PnP-SGD	PnP-ADMM	PnP-BBS	PnP-FBS
Overall PSNR	29.88	29.73	29.62	NaN
Simpsons	33.51	33.93	33.70	NaN
Traffic	29.41	29.27	29.10	NaN
Cameraman	30.68	30.43	30.39	NaN
Alley	29.26	28.99	28.90	NaN
Bridge	28.08	27.77	27.65	NaN
Goldhill	28.33	28.01	27.97	NaN

Table 2 Plug & Play deblurring. Image are blurred with a 9×9 uniform kernel, a Gaussian noise of standard deviation $\sigma = 1/255$ is added. The denoiser D_ε is trained at $\varepsilon^2 = (5/255)^2$. This table shows mean PSNR values over $K=10$ independent noise realizations for each of the six images. The regularization parameter $\alpha = 0.30$ is nearly optimal for all algorithms.



Fig. 6 Example of Plug & Play deblurring, for a 9×9 kernel, an additive Gaussian noise of standard deviation $\sigma^2 = (1/255)^2$, for $\varepsilon = (5/255)^2$ and for the nearly optimal value of $\alpha = 0.3$.

for any $x \in \mathbb{R}^d$ and $y \in \mathbb{R}^m$ we have

$$F(x, y) = \iota_{C_y}(x), \quad \text{where } C_y = \{x : y = \mathbf{Q}x\} .$$

The non-differentiability of F is not a problem when using ADMM and BBS since in this case the proximal operator of $\gamma F(\cdot, y)$ is not only defined but admits a closed-form (which is independent of $\gamma = \varepsilon/\alpha$). More precisely, we have for any $x \in \mathbb{R}^d$ and $y \in \mathbb{R}^m$, $\text{prox}_{\gamma \iota_C}(x) = \mathbf{P}^* \mathbf{P}x + \mathbf{Q}^* y$ in terms of the $(d-m) \times d$ matrix \mathbf{P} containing all the lines of the identity matrix which are not contained in \mathbf{Q} . However, SGD and FBS cannot be directly applied to this problem because they require F to be differentiable. Nevertheless we can apply these algorithms to an equivalent formulation in the reduced space \mathbb{R}^{d-m} of unknown pixels, as shown in the following subsection.

4.6.1 Adapting SGD to the non-differentiable inpainting problem

In what follows, we denote by $\tilde{x} := \mathbf{P}x \in \mathbb{R}^n$ the vector of $n = d - m$ unknown pixels in x . Given the unknown pixels $\tilde{x} = \mathbf{P}x$ and the measurements $y = \mathbf{Q}x$ we can reconstruct x via the affine mapping $f_y : \mathbb{R}^n \rightarrow \mathbb{R}^d$ defined for any $x \in \mathbb{R}^d$ and $y \in \mathbb{R}^m$ by $f_y(\tilde{x}) = \mathbf{P}^* \tilde{x} + \mathbf{Q}^* y$.

The solution of the original problem $x_{\text{MAP}} = \arg \min_x F(x, y) + U(x)$ can then be written as

$$x_{\text{MAP}} = \arg \min_{x \in C_y} U(x) = f_y(\arg \min_{\tilde{x}} U(f_y(\tilde{x}))) , \quad \tilde{x}_{\text{MAP}} = \arg \min_{\tilde{x}} U(f_y(\tilde{x})) , \quad (42)$$

and \tilde{x}_{MAP} can be found by gradient descent on $\tilde{U} = U \circ f_y$. Using the chain rule and Tweedie's formula, we have that the gradient of \tilde{U} is given for any $x \in \mathbb{R}^d$ and $y \in \mathbb{R}^m$ by

$$\nabla \tilde{U}(\tilde{x}) = \mathbf{P} \nabla U(f_y(\tilde{x})) = (1/\varepsilon) \mathbf{P}(\text{Id} - D_\varepsilon) \circ f_y(\tilde{x}) . \quad (43)$$

Finally, since the affine operators \mathbf{P} and f_y are 1-Lipschitz we have that $\tilde{\mathbf{L}} \leq (1/\varepsilon)$, where $\tilde{\mathbf{L}}$ is the Lipschitz constant of $\nabla \tilde{U}$.

4.6.2 Parameter settings and results

The inpainting problem we consider is extremely ill-posed since 80% of the pixels are only constrained by the image prior. Since our implicit prior $p_\varepsilon(x)$ is most likely far from log-concave, the posterior shows a particularly large number of local optima. For this reason all methods are extremely sensitive to the initial condition. The initial conditions used in the previous experiments may misguide both ADMM and SGD to a wrong local optimum.

To deal with this more difficult case, we consider a different approach, combining:

- A coarse to fine scheme where we start by solving the MAP problem for large values of ε , and then use the result of this coarse MAP as an initialization for the next smaller value of ε . In our experiments we used $\varepsilon = (40/255)^2, (15/255)^2, (5/255)^2$, both for ADMM and for SGD;
- For each value of ε , a burn-in phase of 2000 iterations with $\delta_0 = 2.5\delta_{\text{stable}}$, followed by a phase of 1000 decreasing steps, as defined in (41).

Method	PSNR		SSIM	
	mean	std dev	mean	std dev
Random initialization				
SGD $\varepsilon = (5/255)^2$	23.43	2.75	0.7715	0.0517
SGD $\varepsilon = (40/255)^2, (15/255)^2, (5/255)^2$	26.32	1.76	0.8074	0.0702
ADMM $\varepsilon = (5/255)^2$	19.34	3.09	0.6787	0.0629
ADMM $\varepsilon = (40/255)^2, (15/255)^2, (5/255)^2$	25.94	2.19	0.8292	0.0745
TV-L ₂ initialization				
SGD $\varepsilon = (5/255)^2$	26.01	1.53	0.8042	0.0684
SGD $\varepsilon = (40/255)^2, (15/255)^2, (5/255)^2$	26.34	1.80	0.8074	0.0699
ADMM $\varepsilon = (5/255)^2$	25.38	1.74	0.8216	0.0754
ADMM $\varepsilon = (40/255)^2, (15/255)^2, (5/255)^2$	25.87	2.13	0.8266	0.0764
Oracle initialization				
SGD $\varepsilon = (5/255)^2$	26.67	1.66	0.8116	0.0700
SGD $\varepsilon = (40/255)^2, (15/255)^2, (5/255)^2$	26.36	1.76	0.8079	0.0702
ADMM $\varepsilon = (5/255)^2$	26.16	2.18	0.8330	0.0742
ADMM $\varepsilon = (40/255)^2, (15/255)^2, (5/255)^2$	25.93	2.14	0.8269	0.0768

Table 3 Inpainting with $p = 0.8$, $\sigma = 0$ with random, TV-L₂ and oracle initialization. Mean and standard deviation of PSNR and SSIM measures computed on K=4 random tests for each of the 6 images. Note the effectiveness of the coarse-to-fine scheme with either random or TV-L₂ initialization: Coarse to fine SGD is only 0.33 dB away from the solution obtained with oracle init, which should be quite close to the global optimum. ADMM is only 0.22 dB away from the solution obtained with oracle init.

Table 3 summarizes the results of different algorithmic strategies to solve our inpainting problem, on our set of 6 images with $K = 4$ random realizations for each image, and Figure 7 shows an example of results on the *Simpsons* image.

We can observe in Table 3 that the coarse-to-fine scheme is beneficial to both SGD and ADMM, allowing to reach a reconstruction quality which comes very close to the oracle initialization. This benefit is also clear on the visual results shown on Figure 7. In the case of a random initialization, the coarse to fine strategy is needed to avoid the apparition of spurious geometric structure in the background. In the case of the TV – L₂ initialization, it yields better continuity in the fine black lines of the image. This holds both for ADMM and SGD.

In these inpainting experiments, we also observed that using larger initial step-sizes at the beginning and using the stochastic gradient descent instead of a simple gradient descent are important to obtain good MAP estimates. This could be explained by the highly non-convex nature of this problem: the stochastic term and the larger step sizes are required to avoid getting trapped in spurious local optima.

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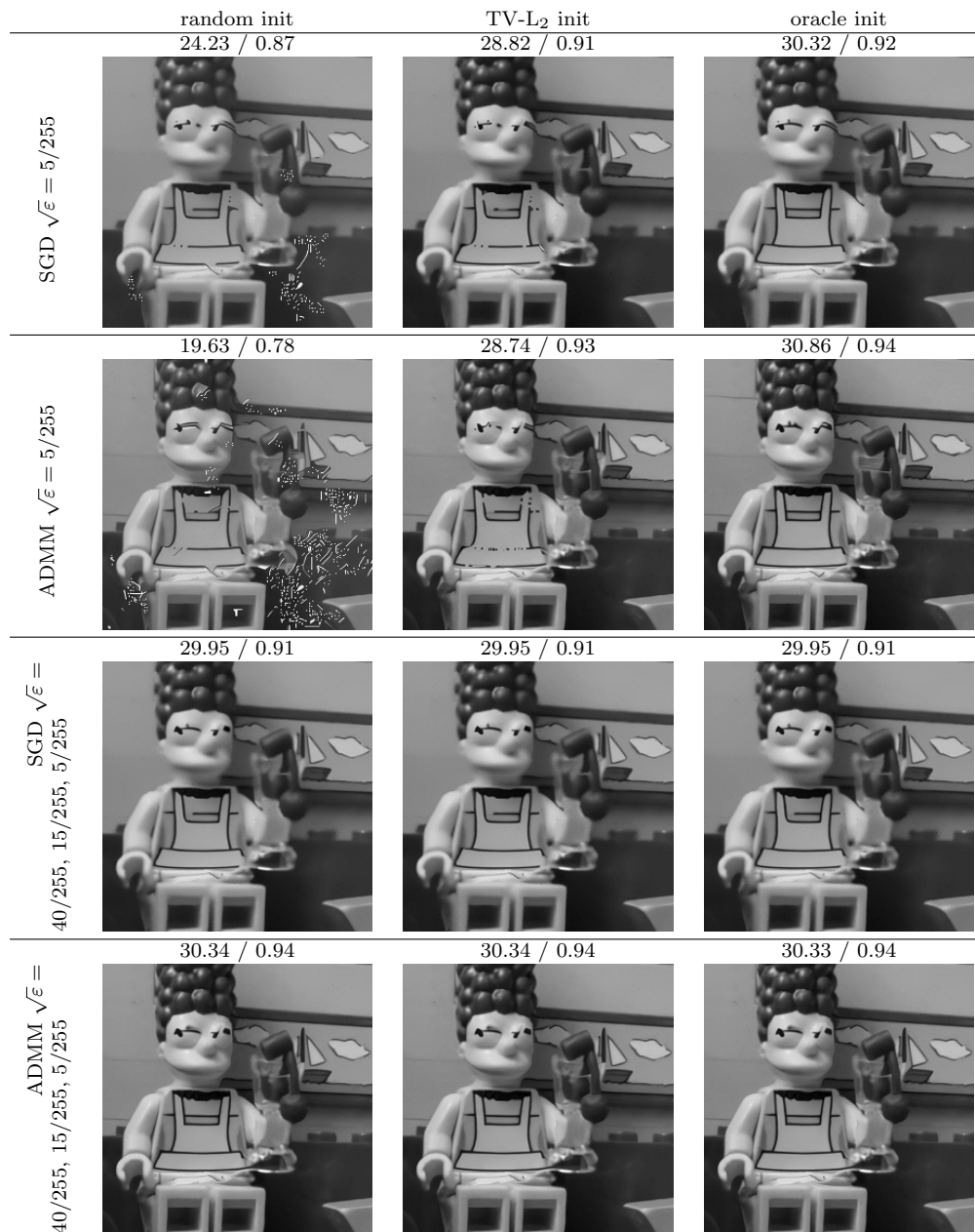


Fig. 7 Inpainting results for the Simpson's image with $p = 0.8$, $\sigma = 0$ each column corresponds to a different initial condition

References

1. Introduction to markov random fields. In: Markov Random Fields for Vision and Image Processing. The MIT Press (2011). DOI 10.7551/mitpress/8579.003.0001. URL <https://doi.org/10.7551/mitpress/8579.003.0001>
2. Ahmad, R., Bouman, C.A., Buzzard, G.T., Chan, S., Liu, S., Reehorst, E.T., Schniter, P.: Plug-and-play methods for magnetic resonance imaging: Using denoisers for image recovery. *IEEE signal processing magazine* **37**(1), 105–116 (2020)
3. Arridge, S., Maass, P., Öktem, O., Schönlieb, C.B.: Solving inverse problems using data-driven models. *Acta Numerica* **28**, 1–174 (2019). DOI 10.1017/S0962492919000059
4. Bauschke, H.H., Combettes, P.L., et al.: Convex analysis and monotone operator theory in Hilbert spaces, vol. 408. Springer (2011)
5. Bernardo, J., Smith, A.: Bayesian Theory, vol. 15 (2000). DOI 10.2307/2983298
6. Bottou, L., Curtis, F.E., Nocedal, J.: Optimization methods for large-scale machine learning. *Siam Review* **60**(2), 223–311 (2018)
7. Boyd, S., Parikh, N., Chu, E.: Distributed optimization and statistical learning via the alternating direction method of multipliers. Now Publishers Inc (2011)
8. Brandière, O., Duflo, M.: Les algorithmes stochastiques contourment-ils les pièges? *Ann. Inst. H. Poincaré Probab. Statist.* **32**(3), 395–427 (1996)
9. Buades, A., Coll, B., Morel, J.M.: A non-local algorithm for image denoising. In: 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’05), vol. 2, pp. 60–65. IEEE (2005)
10. Buades, A., Coll, B., Morel, J.M.: A review of image denoising algorithms, with a new one. *Multiscale Modeling & Simulation* **4**(2), 490–530 (2005)
11. Bubeck, S.: Convex optimization: Algorithms and complexity. arXiv preprint arXiv:1405.4980 (2014)
12. Buzzard, G.T., Chan, S.H., Sreehari, S., Bouman, C.A.: Plug-and-play unplugged: Optimization-free reconstruction using consensus equilibrium. *SIAM Journal on Imaging Sciences* **11**(3), 2001–2020 (2018)
13. Chambolle, A.: An algorithm for total variation minimization and applications. *Journal of Mathematical Imaging and Vision* **20**, 89–97 (2004). DOI 10.1023/B:JMIV.0000011325.36760.1e
14. Chambolle, A., Pock, T.: A first-order primal-dual algorithm for convex problems with applications to imaging. *Journal of mathematical imaging and vision* **40**(1), 120–145 (2011)
15. Chan, S.H., Wang, X., Elgendy, O.A.: Plug-and-play admm for image restoration: Fixed-point convergence and applications. *IEEE Transactions on Computational Imaging* **3**(1), 84–98 (2017). DOI 10.1109/TCI.2016.2629286
16. Chen, Y., Pock, T.: Trainable Nonlinear Reaction Diffusion: A Flexible Framework for Fast and Effective Image Restoration. *IEEE Transactions on Pattern Analysis and Machine Intelligence* **39**(6), 1256–1272 (2017). DOI 10.1109/TPAMI.2016.2596743
17. Cohen, R., Elad, M., Milanfar, P.: Regularization by denoising via fixed-point projection (red-pro) (2020)
18. Combettes, P.L., Pesquet, J.C.: Proximal splitting methods in signal processing. In: Fixed-point algorithms for inverse problems in science and engineering, pp. 185–212. Springer (2011)
19. Dabov, K., Foi, A., Katkovnik, V., Egiazarian, K.: Image denoising with block-matching and 3d filtering. In: Image Processing: Algorithms and Systems, Neural Networks, and Machine Learning, vol. 6064, p. 606414. International Society for Optics and Photonics (2006)
20. Delyon, B.: General results on the convergence of stochastic algorithms. *IEEE Transactions on Automatic Control* **41**(9), 1245–1255 (1996)
21. Delyon, B., Lavielle, M., Moulines, E.: Convergence of a stochastic approximation version of the em algorithm. *Annals of statistics* pp. 94–128 (1999)
22. Diamond, S., Sitzmann, V., Heide, F., Wetzstein, G.: Unrolled optimization with deep priors (2017)
23. Dong, C., Loy, C.C., He, K., Tang, X.: Learning a deep convolutional network for image super-resolution. In: European conference on computer vision, pp. 184–199. Springer (2014)
24. Donoho, D.L.: De-noising by soft-thresholding. *IEEE transactions on information theory* **41**(3), 613–627 (1995)

25. Durmus, A., Moulines, E., Pereyra, M.: Efficient bayesian computation by proximal markov chain monte carlo: when langevin meets moreau. *SIAM Journal on Imaging Sciences* **11**(1), 473–506 (2018)
26. Efron, B.: Tweedie’s formula and selection bias. *Journal of the American Statistical Association* **106**(496), 1602–1614 (2011)
27. Gao, H., Tao, X., Shen, X., Jia, J.: Dynamic scene deblurring with parameter selective sharing and nested skip connections. In: *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 3848–3856 (2019)
28. Gharbi, M., Chaurasia, G., Paris, S., Durand, F.: Deep joint demosaicking and denoising. *ACM Transactions on Graphics (TOG)* **35**(6), 191 (2016)
29. Gilton, D., Ongie, G., Willett, R.: Neumann networks for inverse problems in imaging (2019)
30. Gregor, K., LeCun, Y.: Learning fast approximations of sparse coding. In: *Proceedings of the 27th International Conference on International Conference on Machine Learning*, pp. 399–406. Omnipress (2010)
31. Gribonval, R.: Should penalized least squares regression be interpreted as maximum a posteriori estimation? *IEEE Transactions on Signal Processing* **59**(5), 2405–2410 (2011)
32. Kamilov, U.S., Mansour, H., Wohlberg, B.: A plug-and-play priors approach for solving nonlinear imaging inverse problems. *IEEE Signal Processing Letters* **24**(12), 1872–1876 (2017)
33. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980* (2014)
34. Laumont, R., de Bortoli, V., Almansa, A., Delon, J., Durmus, A., Pereyra, M.: Bayesian imaging using plug & play priors: when langevin meets tweedie (2021)
35. Lebrun, M., Buades, A., Morel, J.M.: A nonlocal bayesian image denoising algorithm. *SIAM Journal on Imaging Sciences* **6**(3), 1665–1688 (2013)
36. Lehtinen, J., Munkberg, J., Hasselgren, J., Laine, S., Karras, T., Aittala, M., Aila, T.: Noise2noise: Learning image restoration without clean data. *arXiv preprint arXiv:1803.04189* (2018)
37. Louchet, C., Moisan, L.: Posterior expectation of the total variation model: Properties and experiments. *SIAM Journal on Imaging Sciences* **6**(4), 2640–2684 (2013). DOI 10.1137/120902276
38. Meinhardt, T., Moller, M., Hazirbas, C., Cremers, D.: Learning proximal operators: Using denoising networks for regularizing inverse imaging problems. In: *(ICCV) International Conference on Computer Vision*, pp. 1781–1790 (2017). DOI 10.1109/ICCV.2017.198
39. Metivier, M., Priouret, P.: Applications of a kushner and clark lemma to general classes of stochastic algorithms. *IEEE Transactions on Information Theory* **30**(2), 140–151 (1984)
40. Milanfar, P.: Symmetrizing Smoothing Filters. *SIAM Journal on Imaging Sciences* **6**(1), 263–284 (2013). DOI 10.1137/120875843
41. Miyato, T., Kataoka, T., Koyama, M., Yoshida, Y.: Spectral normalization for generative adversarial networks. *arXiv preprint arXiv:1802.05957* (2018)
42. Nesterov, Y.: Lectures on convex optimization, *Springer Optimization and Its Applications*, vol. 137. Springer, Cham (2018). DOI 10.1007/978-3-319-91578-4. URL <https://doi.org/10.1007/978-3-319-91578-4>. Second edition of [MR2142598]
43. Parikh, N., Boyd, S.: Proximal algorithms. *Foundations and Trends in optimization* **1**(3), 127–239 (2014)
44. Pereyra, M.: Maximum-a-posteriori estimation with bayesian confidence regions. *SIAM Journal on Imaging Sciences* **10**(1), 285–302 (2017). DOI 10.1137/16M1071249. URL <https://doi.org/10.1137/16M1071249>
45. Pereyra, M.: Revisiting Maximum-a-Posteriori estimation in log-concave models. *SIAM Journal on Imaging Sciences* **12**(1), 650–670 (2019)
46. Pereyra, M., Vargas Mieles, L., Zygalakis, K.C.: Accelerating proximal Markov chain Monte Carlo by using an explicit stabilized method. *SIAM J. Imaging Sci.* **13**(2), 905–935 (2020). DOI 10.1137/19M1283719. URL <https://doi.org/10.1137/19M1283719>
47. Pesquet, J.C., Repetti, A., Terris, M., Wiaux, Y.: Learning maximally monotone operators for image recovery (2020)
48. Reehorst, E.T., Schniter, P.: Regularization by denoising: Clarifications and new interpretations. *IEEE Transactions on Computational Imaging* **5**(1), 52–67 (2018). DOI 10.1109/TCI.2018.2880326
49. Repetti, A., Pereyra, M., Wiaux, Y.: Scalable bayesian uncertainty quantification in imaging inverse problems via convex optimization. *SIAM Journal on Imaging Sciences* **12**(1), 87–118 (2019). DOI 10.1137/18M1173629

50. Romano, Y., Elad, M., Milanfar, P.: The little engine that could: Regularization by denoising (red). *SIAM Journal on Imaging Sciences* **10**(4), 1804–1844 (2017)
51. Rudin, L.I., Osher, S., Fatemi, E.: Nonlinear total variation based noise removal algorithms. *Physica D: Nonlinear Phenomena* **60**(1-4), 259–268 (1992). DOI 10.1016/0167-2789(92)90242-F
52. Ryu, E.K., Liu, J., Wang, S., Chen, X., Wang, Z., Yin, W.: Plug-and-play methods provably converge with properly trained denoisers. In: *Proceedings of the 36th International Conference on Machine Learning, ICML 2019, 9-15 June 2019, Long Beach, California, USA*, pp. 5546–5557 (2019). URL <http://proceedings.mlr.press/v97/ryu19a.html>
53. Schwartz, E., Giryes, R., Bronstein, A.M.: Deepisp: Toward learning an end-to-end image processing pipeline. *IEEE Transactions on Image Processing* **28**(2), 912–923 (2018)
54. Sreehari, S., Venkatakrishnan, S.V., Wohlberg, B., Buzzard, G.T., Drummy, L.F., Simons, J.P., Bouman, C.A.: Plug-and-Play Priors for Bright Field Electron Tomography and Sparse Interpolation. *IEEE Transactions on Computational Imaging* **2**(4), 1–1 (2016). DOI 10.1109/TCI.2016.2599778
55. Sun, Y., Wohlberg, B., Kamilov, U.S.: An online plug-and-play algorithm for regularized image reconstruction. *IEEE Transactions on Computational Imaging* (2019)
56. Sun, Y., Wu, Z., Wohlberg, B., Kamilov, U.S.: Scalable plug-and-play admm with convergence guarantees. *arXiv preprint arXiv:2006.03224* (2020)
57. Tadić, V.B., Doucet, A., et al.: Asymptotic bias of stochastic gradient search. *The Annals of Applied Probability* **27**(6), 3255–3304 (2017)
58. Teodoro, A.M., Bioucas-Dias, J.M., Figueiredo, M.A.: A convergent image fusion algorithm using scene-adapted gaussian-mixture-based denoising. *IEEE Transactions on Image Processing* **28**(1), 451–463 (2018)
59. Teodoro, A.M., Bioucas-Dias, J.M., Figueiredo, M.A.T.: Scene-Adapted Plug-and-Play Algorithm with Guaranteed Convergence: Applications to Data Fusion in Imaging (2018)
60. Venkatakrishnan, S.V., Bouman, C.A., Wohlberg, B.: Plug-and-play priors for model based reconstruction. In: *2013 IEEE Global Conference on Signal and Information Processing*, pp. 945–948. IEEE (2013)
61. Xu, X., Sun, Y., Liu, J., Wohlberg, B., Kamilov, U.S.: Provable Convergence of Plug-and-Play Priors with MMSE denoisers (4), 1–10 (2020). URL <http://arxiv.org/abs/2005.07685>
62. Yu, G., Sapiro, G., Mallat, S.: Solving inverse problems with piecewise linear estimators: From gaussian mixture models to structured sparsity. *IEEE Transactions on Image Processing* **21**(5), 2481–2499 (2011)
63. Zhang, K., Zuo, W., Chen, Y., Meng, D., Zhang, L.: Beyond a gaussian denoiser: Residual learning of deep cnn for image denoising. *IEEE Transactions on Image Processing* **26**(7), 3142–3155 (2017)
64. Zhang, K., Zuo, W., Gu, S., Zhang, L.: Learning Deep CNN Denoiser Prior for Image Restoration. In: *(CVPR) IEEE Conference on Computer Vision and Pattern Recognition*, pp. 2808–2817. IEEE (2017). DOI 10.1109/CVPR.2017.300
65. Zhang, K., Zuo, W., Zhang, L.: Ffdnet: Toward a fast and flexible solution for cnn-based image denoising. *IEEE Transactions on Image Processing* **27**(9), 4608–4622 (2018)
66. Zoran, D., Weiss, Y.: From learning models of natural image patches to whole image restoration. In: *2011 International Conference on Computer Vision*, pp. 479–486. IEEE (2011). DOI 10.1109/ICCV.2011.6126278. URL <http://people.csail.mit.edu/danielzoran/EPLLICVCameraReady.pdf>
67. Zou, F., Shen, L., Jie, Z., Zhang, W., Liu, W.: A sufficient condition for convergences of adam and rmsprop. In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 11127–11135 (2019)