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Accelerating GMM-based patch priors for image restoration: Three ingredients for a 100$\times$ speed-up

Shibin Parameswaran, Charles-Alban Deledalle, Loïc Denis and Truong Q. Nguyen

Abstract—Image restoration methods aim to recover the underlying clean image from corrupted observations. The Expected Patch Log-likelihood (EPLL) algorithm is a powerful image restoration method that uses a Gaussian mixture model (GMM) prior on the patches of natural images. Although it is very effective for restoring images, its high runtime complexity makes EPLL ill-suited for most practical applications. In this paper, we propose three approximations to the original EPLL algorithm. The resulting algorithm, which we call the fast-EPLL (FEPLL), attains a dramatic speed-up of two orders of magnitude over EPLL while incurring a negligible drop in the restored image quality (less than 0.5 dB). We demonstrate the efficacy and versatility of our algorithm on a number of inverse problems such as denoising, deblurring, super-resolution, inpainting and devignetting. To the best of our knowledge, FEPLL is the first such algorithm that can competitively restore a 512$\times$512 pixel image in under 0.5s for all the degradations mentioned above without specialized code optimizations such as CPU parallelization or GPU implementation.

Index Terms—Image restoration, image patch, Gaussian mixture model, efficient algorithms

I. INTRODUCTION

Patch-based methods form a very popular and successful class of image restoration techniques. These methods process an image on a patch-by-patch basis where a patch is a small sub-image (e.g., of 8$\times$8 pixels) that captures both geometric and textural information. Patch-based algorithms have been at the core of many state-of-the-art results obtained on various image restoration problems such as denoising, deblurring, super-resolution, defogging, or compression artifact removal to name a few. In image denoising, patch-based processing became popular after the success of the Non-Local Means algorithm [2]. Subsequently, continued research efforts have led to significant algorithmic advancements in this area [1], [8], [39], [11], [27], [37], [24]. Other inverse problems such as image super-resolution and image deblurring have also benefited from patch-based models [9], [16], [30], [34], [14], [25].

Among these various patch-based methods, the Expected Patch Log-Likelihood algorithm (EPLL) [39] deserves a special mention due to its restoration performance and versatility. The EPLL introduced an innovative application of Gaussian Mixture Models (GMMs) to capture the prior distribution of patches in natural images. Note that a similar idea was introduced concurrently in [37]. The success of this method is evident from the large number of recent works that extend the original EPLL formulation [35], [26], [4], [29], [31], [18]. However, a persistent problem of EPLL-based algorithms is their high runtime complexity. For instance, it is orders of magnitude slower than the well-engineered BM3D image denoising algorithm [8]. However, extensions of BM3D that perform super-resolution [10] and other inverse problems [20] require fundamental algorithmic changes, making BM3D far less adaptable than EPLL. Other approaches that are as versatile as EPLL [33], [5], [19] either lack the algorithmic efficiency of BM3D or the restoration efficacy of EPLL.

Another class of techniques that arguably offers better runtime performance than EPLL-based methods (but not BM3D) are those based on deep learning. With the advancements in computational resources, researchers have attempted to solve some classical inverse problems using multi-layer perceptrons [3] and deep networks [6], [13], [21]. These methods achieve very good restoration performance, but are heavily dependent on the amount of training data available for each degradation scenario. Most of these methods learn filters that are suited to restore a specific noise level (denoising), blur (deblurring) or upsampling factor (super-resolution), which makes them less attractive to serve as generic image restoration solutions. More recently, Zhang et al. [38] demonstrated the use of deep residual networks for general denoising problems, single-image super-resolution and compression artifact removal. Unlike earlier deep learning efforts, their approach can restore images with different noise levels using a single model which is learned by training on image patches containing a range of degradations. Even in this case, the underlying deep learning model requires retraining whenever a new degradation scenario different from those considered during the learning stage is encountered. Moreover, it is much harder to gain insight into the actual model learned by a deep architecture compared to a GMM. For this reason, even with the advent of deep learning methods, flexible algorithms like EPLL that have a transparent formulation remain relevant for image restoration.

Recently, researchers have tried to improve the speed of EPLL by replacing the most time-consuming operation in the EPLL algorithm with a machine learning-based technique of their choice [36], [32]. These methods were successful in accelerating EPLL to an extent but did not consider tackling all of its bottlenecks. In contrast, this paper focuses on accelerating EPLL by proposing algorithmic approximations to all the prospective bottlenecks present in the original algorithm.
proposed by Zoran et al. [39]. To this end, we first provide a complete computational and runtime analysis of EPLL, present a new and efficient implementation of original EPLL algorithm and then finally propose innovative approximations that lead to a novel algorithm that is more than 100× faster compared to the efficiently implemented EPLL (and 350× faster than the runtime obtained by using the original implementation [39]).

Contributions: The main contributions of this work are the following. We introduce three strategies to accelerate patch-based image restoration algorithms that use a GMM prior. We show that, when used jointly, they lead to a speed-up of the EPLL introduced by Zoran and Weiss [39]. To this end, we first provide a complete computational and runtime analysis of EPLL, present a new and efficient implementation of original EPLL algorithm and can be easily adapted for vector quantization techniques that use a dictionary. For reproducibility purposes, we release our software on GitHub along with a few usage demonstrations (available at https://goo.gl/xqJKUA).

II. EXPECTED PATCH LOG-likelihood (EPLL)

We consider the problem of estimating an image \( x \in \mathbb{R}^N \) (\( N \) is the number of pixels) from noisy linear observations \( y = Ax + w \), where \( A : \mathbb{R}^N \to \mathbb{R}^M \) is a linear operator and \( w \in \mathbb{R}^M \) is a noise component assumed to be white and Gaussian with variance \( \sigma^2 \). In a standard denoising problem \( A \) is the identity matrix, but in more general settings, it can account for loss of information or blurring. Typical examples for operator \( A \) are: a low pass filter (for deconvolution), a masking operator (for inpainting), or a projection on a random subspace (for compressive sensing). To reduce noise and stabilize the inversion of \( A \), some prior information is used for the estimation of \( x \). The EPLL introduced by Zoran and Weiss [39] includes this prior information as a model for the distribution of patches found in natural images. Specifically, the EPLL defines the restored image as the maximum \( \text{a posteriori} \) estimate, corresponding to the following minimization problem:

\[
\begin{align*}
\arg\min_x \quad P \frac{1}{2\sigma^2} \|Ax - y\|^2 + \beta \sum_{i \in I} \log p(P_i; x)
\end{align*}
\]

where \( I = \{1, \ldots, N\} \) is the set of pixel indices, \( P_i : \mathbb{R}^N \to \mathbb{R}^P \) is the linear operator extracting a patch with \( P \) pixels centered at the pixel with location \( i \) (typically, \( P = 8 \times 8 \)), and \( p(.) \) is the \( \text{a priori} \) probability density function (i.e., the statistical model of noiseless patches in natural images). While the first term in eq. (1) ensures that \( Ax \) is close to the observations \( y \) (this term is the negative log-likelihood under the white Gaussian noise assumption), the second term regularizes the solution \( x \) by favoring an image such that all its patches fit the \( \text{prior} \) model of patches in natural images. The authors of [39] showed that this prior can be well approximated (upon removal of the DC component of each patch) using a zero-mean Gaussian Mixture Model (GMM) with \( K = 200 \) components, that reads for any patch \( z \in \mathbb{R}^P \), as

\[
p(z) = \sum_{k=1}^{K} w_k \left( \frac{1}{(2\pi\sigma^2)^{P/2}} \right) \exp \left( -\frac{1}{2} z^T \Sigma_k^{-1} z \right),
\]

where the weights \( w_k \) (such that \( w_k > 0 \) and \( \sum_k w_k = 1 \)) and the covariance matrices \( \Sigma_k \in \mathbb{R}^{P \times P} \) are estimated using the Expectation-Maximization algorithm [12] on a dataset consisting of 2 million “clean” patches extracted from the training set of the Berkeley Segmentation (BSDS) dataset [28].

Half-quadratic splitting: Problem (1) is a large non-convex problem where \( A \) couples all unknown pixel values \( x \) and the patch prior is highly non-convex. A classical workaround, known as half-quadratic splitting [15], [23], is to introduce \( N \) auxiliary unknown vectors \( z_i \in \mathbb{R}^P \), and consider instead the penalized optimization problem that reads, for \( \beta > 0 \), as

\[
\begin{align*}
\arg\min_{x, z_1, \ldots, z_N} \quad & P \frac{1}{2\sigma^2} \|Ax - y\|^2 + \beta \sum_{i \in I} \|P_i x - z_i\|^2 - \sum_{i \in I} \log p(z_i). 
\end{align*}
\]

When \( \beta \to \infty \), the problem (3) becomes equivalent to the original problem (1). In practice, an increasing sequence of \( \beta \) is considered, and an alternating optimization scheme is used:

\[
\begin{align*}
\hat{z}_i &\leftarrow \arg\min_{z_i} \frac{\beta}{2} \|P_i \hat{x} - z_i\|^2 - \log p(z_i) \\
\hat{x} &\leftarrow \arg\min_x \frac{P}{2\sigma^2} \|Ax - y\|^2 + \frac{\beta}{2} \sum_{i \in I} \|P_i x - \hat{z}_i\|^2.
\end{align*}
\]

Algorithm: Subproblem (5) corresponds to solving a linear inverse problem with a Tikhonov regularization, and has an explicit solution often referred to as Wiener filtering:

\[
\hat{x} = \left( A^T A + \frac{\beta \sigma^2}{P} \sum_{i \in I} P_i^T P_i \right)^{-1} \left( A^T y + \frac{\beta \sigma^2}{P} \sum_{i \in I} P_i^T \hat{z}_i \right),
\]

where \( P_i^T P_i \) is a diagonal matrix whose \( i \)-th diagonal element corresponds to the number of patches overlapping the pixel.
of index $i$. This number is a constant equal to $P$ (assuming proper boundary conditions are used), which allows to split the computation into two steps: *Patch reprojection* and *Image estimation* as shown in Alg. 1. Note that the step *Patch reprojection* is simply the average of all overlapping patches. In contrast, subproblem (4) cannot be obtained in closed form as it involves a term with the logarithm of a sum of exponentials. A practical solution proposed in [39] is to keep the solution of (4) is also given by Wiener filtering, and the reprojection step can be performed using conjugate gradient (CG) method, as done in [39]. In any case, as shown in the next section, this step has a complexity independent of $P$ and $K$ and is one of the faster operations in the image restoration problems considered in this paper.

### Table I

<table>
<thead>
<tr>
<th>Step</th>
<th>Without accelerations</th>
<th>With the proposed accelerations</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Gaussian selection)</td>
<td>43.35s</td>
<td>0.23s</td>
</tr>
<tr>
<td>(Patch estimation)</td>
<td>0.95s</td>
<td>0.05s</td>
</tr>
<tr>
<td>(Patch extraction)</td>
<td>0.46s</td>
<td>0.03s</td>
</tr>
<tr>
<td>(Patch reprojection)</td>
<td>0.23s</td>
<td>0.01s</td>
</tr>
<tr>
<td>Others</td>
<td>0.52s</td>
<td>0.03s</td>
</tr>
<tr>
<td>Total</td>
<td>45.69s</td>
<td>0.35s</td>
</tr>
</tbody>
</table>

**COMPARISON OF THE EXECUTION TIME OF OUR IMPLEMENTATION OF EPLL WITH AND WITHOUT PROPOSED ACCELERATIONS. EXPERIMENT CONDUCTED ON A 481 \times 321 IMAGE DENOISING PROBLEM. PROFILING WAS CARRIED OUT USING MATLAB (R2014b) ON A PC WITH INTEL(R) CORE(TM) i7-4790K CPU @4.00GHz AND 16 GB RAM. EXECUTION TIMES ARE REPORTED IN SECONDS (S) AND AS A PERCENTAGE OF THE TOTAL TIME (%).**

### Table II

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**THE THREE KEY INGREDIENTS**

To uncover the practical computational bottlenecks of EPLL, we have performed the following computational analysis. To identify clearly which part is time consuming, it is important to make the algorithm implementation as optimal as possible. Therefore, we refrain from using the MATLAB code provided by the original authors [39] for speed comparisons. Instead, we use a MATLAB/C version of EPLL based on the eigenspace implementation described above, where some steps are written in C language and interfaced using mex functions. This version, which we refer to as EPLLc, provides results identical to the original implementation while being 2-3 times faster. The execution time of each step for a single run of EPLLc is reported in the second column of Table I. Reported times fit our complexity analysis and clearly indicate that the Step *Gaussian selection* causes significant bottleneck due to $O(NP^2K)$ complexity.

In the next section, we propose three independent modifications leading to an algorithm with a complexity of $O(NP^2\log K/s^2)$ with two constants $1 \leq s^2 \leq P$ and $1 \leq \tilde{r} \leq P$ that control the accuracy of the approximations introduced. The algorithm, in practice, is more than 100 times faster as shown by its runtimes reported in the third column.

### III. FAST EPLL: THE THREE KEY INGREDIENTS

We propose three accelerations based on (i) scanning only a (random) subset of the $N$ patches, (ii) reducing the number of mixture components matched, and (iii) projecting on a smaller subspace of the covariance eigenspace. We begin by describing this latter acceleration strategy in the following paragraph.
A. Speed-up via flat tail spectrum approximation

To avoid computing the $P$ coefficients of the vector $\tilde{c}_k^i$ in eq. (7), we rely on a flat-tail approximation. The $k$-th Gaussian model is said to have a flat tail if there exists a rank $r_k$ such that for any $j > r_k$, the eigenvalues are constant: $[S_k]_{j,j} = \lambda_k$. Denoting by $U_k \in \mathbb{R}^{P \times r_k}$ (resp. $U^T_k \in \mathbb{R}^{P \times r_k}$) the matrix formed by the $r_k$ first rows and columns of $U_k$, we have $U^T_k(U_k^T)^t = Id_P - U_kU_k^T$. It follows

$$
\begin{align*}
(\Sigma_k + \frac{1}{2}Id_P)^{-1} &= U_k(\tilde{S}_k + \frac{1}{2}Id_{r_k})^{-1}U_k^T \\
&\quad + (\lambda_k + \frac{1}{2})^{-1}(Id_P - U_kU_k^T), \quad (11)
\end{align*}
$$

$$
\begin{align*}
(\Sigma_k + \frac{1}{2}Id_P)^{-1}\Sigma_k &= U_k(\tilde{S}_k + \frac{1}{2}Id_{r_k})^{-1}S_kU_k^T \\
&\quad + \lambda_k(\lambda_k + \frac{1}{2})^{-1}(Id_P - U_kU_k^T), \quad (12)
\end{align*}
$$

where $
\tilde{S}_k \in \mathbb{R}^{r_k \times r_k}$ is the diagonal matrix formed by the $r_k$ first rows and columns of $S_k$. Steps Gaussian selection and Patch estimation can thus be rewritten as

$$
\begin{align*}
\{c_i^k \leftarrow \tilde{U}_k^T\tilde{z}_i\}_{k=1, \ldots, K} & \quad \mathcal{O}(NKPF) \quad (13) \\
\{k_i^* \leftarrow \arg\min_{1 \leq k \leq K} \nu_k + \frac{r_k}{\nu_k} \log \nu_k + \frac{\|\tilde{z}_i\|^2}{\nu_k^2}\} & \quad \mathcal{O}(NK\bar{r}) \quad (14) \\
\left\{\tilde{c}_i^k \leftarrow (\nu_k^* - \nu_i^k) \frac{\tilde{c}_i^k}{\nu_k^*} \right\}_{j=1 \ldots, N}^{k_i^*} & \quad \mathcal{O}(NP\bar{r}) \quad (15) \\
\{\tilde{z}_i \leftarrow \tilde{U}_{k_i^*}\tilde{c}_i + \gamma_{i}^{k_i^*}\tilde{z}_i\} & \quad \mathcal{O}(NP\bar{r}) \quad (16)
\end{align*}
$$

where $\nu_k^* = \lambda_k + \frac{1}{2}$, $\gamma_{i}^{k_i^*} = \lambda_k/\nu_k^*$. As $\|\tilde{z}_i\|^2$ can be computed once for all $k$, the complexity of each step is divided by $P/\bar{r}$, where $\bar{r} = \frac{1}{K} \sum_{k=1}^{K} r_k$ is the average rank after which eigenvalues are considered constant.

In practice, covariance matrices $\Sigma_k$ are not flat-tail but can be approximated by a flat-tail matrix by replacing the lowest eigenvalues by a constant $\lambda_k$. To obtain a small value of $\bar{r}$ (hence a large speed-up), we preserve a fixed proportion $\rho \in (0, 1)$ of the total variability and replace the smallest eigenvalues accounting for the remaining $1 - \rho$ fraction of the variability by their average (see Fig. 1): $r_k$ is the smallest integer such that $\text{Tr}(\tilde{S}_k) \geq \rho \text{Tr}(S_k)$. Choosing $\rho = 0.95$ means that 5% of the variability, in the eigendirections associated to the smallest eigenvalues, is assumed to be evenly spread in these directions. In practice, the choice of $\rho = 0.95$ leads to an average rank of $\bar{r} = 19.6$ (for $P = 8 \times 8$) for a small drop of PSNR as shown in Fig. 4. Among several other covariance approximations that we tested, for instance, the one consisting in keeping only the $r_k$ first directions, the flat tail approximation provided the best trade-off in terms of acceleration and restoration quality.

B. Speed-up via a balanced search tree

As shown in Table I, the step Gaussian selection has a complexity of $\mathcal{O}(NP^2K)$, reduced to $\mathcal{O}(NPK\bar{r})$ using the flat tail spectrum approximation. This step remains the biggest bottleneck since each query patch has to be compared to all the $K$ components of the GMM. To make this step even more efficient, we reduce its complexity using a balanced search tree. As described below, such a tree can be built offline by repeatedly collapsing the original GMM to models with fewer components, until the entire model is reduced to a single Gaussian model.

We progressively combine the GMM components from one level to the level above, by clustering the $K$ components into $L < K$ clusters of similar ones, until the entire model is reduced to a single component. The similarity between two zero-mean Gaussian models with covariance $\Sigma_1$ and $\Sigma_2$ is measured by the symmetric Kullback-Leibler (KL) divergence

$$
\text{KL}(\Sigma_1, \Sigma_2) = \frac{1}{2} \text{Tr}(\Sigma_2^{-1}\Sigma_1 + \Sigma_1^{-1}\Sigma_2 - 2Id_P). \quad (17)
$$

Based on this divergence, at each level $n$, we look for a partition $\Omega^n$ of the $K$ Gaussian components into $L$ clusters (with about equal sizes) minimizing the following optimization problem

$$
\arg\min_{\Omega^n} \sum_{l=1}^{L} \sum_{k_1, k_2 \in \Omega^n} \text{KL}(\Sigma_{k_1}, \Sigma_{k_2}). \quad (18)
$$
such that $\bigcup_{l=1}^{L} \Omega_{l}^n = [K]$ and $\Omega_{l1}^n \cap \Omega_{l2}^n = \emptyset$, where $\Omega_{l}^n$ is the $l$-th set of Gaussian components for the GMM at level $n$. This clustering problem can be approximately solved using the genetic algorithm of [22] for the Multiple Traveling Salesmen Problem (MTSP). MTSP is a variation of the classical Traveling Salesman Problem where several salesmen visit a unique set of cities and return to their origins, and each city is visited by exactly one salesman. This attempts to minimize the total distance traveled by all salesmen. Hence, it is similar to our original problem given in eq. (18) where the Gaussian components and the clusters correspond to $K$ cities and $L$ salesmen, respectively. Given the clustering at level $n$, the new GMM at level $n-1$ is obtained by combining the zero-mean Gaussian components such that, for all $1 \leq l \leq L$:

$$w_{l}^{n-1} = \sum_{k \in \Omega_{l}^n} w_{k}^{n} \quad \text{and} \quad \Sigma_{l}^{n-1} = \frac{1}{w_{l}^{n-1}} \sum_{k \in \Omega_{l}^n} w_{k}^{n} \Sigma_{k}^{n}, \quad (19)$$

where $\Sigma_{l}^{n}$ and $w_{l}^{n}$ are the corresponding covariance matrix and weight of the $k$-th Gaussian component at level $n$. Following this scheme, the original GMM of $K=200$ components is collapsed into increasingly more compact GMMs with $K=64$, $32$, $16$, $8$, $4$, $2$ and $1$ components. The main advantage of using MTSP compared to classical clustering approaches, is that this procedure can be adapted easily to enforce approximately equal sized clusters, simply by enforcing that each salesman visits at least $3$ cities for the last level and $2$ for the other ones.

We also experimented with other clustering strategies such as the hierarchical kmeans-like clustering in [17] and hierarchical agglomerative clustering. With no principled way to enforce even-sized clusters, these approaches, in general, lead to unbalanced trees (with comb structured branches) which result in large variations in computation times from one image to another. Although they all lead to similar denoising performances, we opted for MTSP based clustering to build our Gaussian tree in favor of obtaining a stable speed-up profile for our resulting algorithm.

In Fig. 2 we show that the tree obtained using MTSP-based clustering is almost a binary tree (left) and also display the types of patches it encodes along a given path (right). Such a balanced tree structure lets one avoid testing each patch against all $K$ components. Instead, a patch is first compared to the two first nodes in level 1 of the tree, then the branch providing the smallest cost is followed and the operation is repeated at higher levels until a leaf has been reached. Using this balanced search tree reduces the complexity of step Gaussian selection to $O(NP^{2}\log K)$.

**C. Speed-up via the restriction to a random subset of patches**

The simplest and most effective proposed acceleration consists of subsampling the set $\mathcal{I}$ of $N$ patches to improve the complexity of the four most time-consuming steps, see Table I. One approach, followed by BM3D [8], consists of restricting the set $\mathcal{I}$ to locations on a regular grid with spacing $s \in [1, \sqrt{P}]$ pixels in both directions, leading to a reduction of complexity by a factor $s^2$. We refer to this approach as the regular patch subsampling. A direct consequence is that $|\mathcal{I}| = N/s^2$ and the complexity is divided by $s^2$. However, we observed that this strategy consistently creates blocky artifacts revealing the regularity of the extraction pattern. A random sampling approach, called "jittering", used in the computer graphics community [7] is preferable to limit this effect. This procedure ensures that each pixel is covered by at least one patch. The location $(i_0, j_0)$ of a point of the grid undergoes a random perturbation, giving a new location $(i, j)$ such that

$$i_0 - \left\lceil \frac{\sqrt{P} - s}{2} \right\rceil \leq i \leq i_0 + \left\lceil \frac{\sqrt{P} - s}{2} \right\rceil,$$

$$j_0 - \left\lceil \frac{\sqrt{P} - s}{2} \right\rceil \leq j \leq j_0 + \left\lceil \frac{\sqrt{P} - s}{2} \right\rceil,$$

where $\lceil \cdot \rceil$ denotes the flooring operation. We found experimentally that independent and uniform perturbations offered the best performance against all other tested strategies. In addition, we also resample these positions at each of the $T$ iterations and add a (random) global shift to ensure that all pixels have the same expected number of patches covering them.

Figure 3 illustrates the difference between a regular grid and a jittered grid of period $s=6$ for patches of size $P=8 \times 8$. In both cases, all pixels are covered by at least one patch, but the stochastic version reveals an irregular pattern.

Nevertheless, when using random subsampling, a major bottleneck occurs when $A^t A$ is not diagonal because the inversion involved in eq. (6) cannot be simplified as in Alg. 1. Using a conjugate gradient is a practical solution but will negate the reduction of complexity gained by using subsampling. To the best of our knowledge, this is the main reason why patch subsampling has not been utilized to speed up EPLL. Here, we follow a different path. We opt for approximating the solution of the original problem (involving all patches) rather than evaluating the solution of an approximate problem (involving random subsample of patches). More precisely, we speed up Alg. 1 by replacing the complete set of indices by the random subset of patches. In this case, step Patch reprojection consists of averaging only this subset of overlapping restored patches. This novel and nuanced idea avoids additional overhead and attains dramatic complexity improvements compared to the standard approach.
with a linear separator in order to decide if the recursion should continue on the left or right child given by

$$\langle a_k^n, \tilde{z}_i \rangle + b_k^n \geq 0$$  \hspace{1cm} (21)$$

where \((a_k^n, b_k^n)\) are the parameters of the hyperplane for the \(k\)-th node at level \(n\). These separators are trained offline on all pairs of \((\tilde{z}_i, k_i^n)\) obtained after the first iteration of EPLL for a given \(\beta\) and noise level \(\sigma\). Once a leaf has been reached, its index provides a first estimate for the index \(k_i^n\). To reduce errors due to large variations among the neighboring pixels, this method further employs a Markov random fields on the resulting map of Gaussian components which runs in \(O(NK)\) complexity. Hence, their overall approach reduces the complexity of step Gaussian selection from \(O(NKP^2)\) to \(O(NPD + K)\), where \(D = 12\) is the depth of the learned decision tree.

In [32], the authors approximate the Gaussian selection step, by using a gating (feed-forward) network with one hidden layer

$$\tilde{z}_i \mapsto \tilde{c}_i^k = \sum_{j=1}^{Q} \left( \frac{1}{\bar{\nu}_j} \right)$$

where \(Q\) is the size of the hidden layer. The matrix \(V \in \mathbb{R}^{p \times Q}\) encodes the weights of the first layer, \(\omega_j\) corresponds to the weights of the hidden layer and they are learned discriminatively to approximate the exact posterior probability:

$$\tilde{z}_i \mapsto \tilde{c}_i^k = \sum_{j=1}^{p} \left( \log \nu_j^k + \frac{(\tilde{c}_i^k)^2}{\nu_j^k} \right)$$

that we encounter in eq. (7) and (8). Theoretically, a new network will need to be trained for each type of degradations, noise levels and choices of \(\beta\) (recall that \(\nu_j^k = (S_k)_{j,j} + \frac{1}{\beta}\)). However, the findings of [32] indicate that applying a network learned on clean patches and with \(\frac{1}{\beta} = 0\) is effective regardless of the type of degradation or the value of \(\beta\). Their main advantage can be highlighted by comparing eq. (22) and (23) where complexity is reduced from \(O(NKP^2)\) to \(O(NQ(K + P))\). The authors utilize this benefit by choosing \(Q = 100\).

Unlike these two approaches, our method does not try to learn the Gaussian selection rule directly (which depends on both the noise level through \(1/\beta\) and the prior model through the GMM). Instead, we simply define a hierarchical organization of the covariance matrices \(\Sigma_k\). In other words, while the two other approaches try to infer the posterior probabilities (or directly the maximum \(a posteriori\)), our approach provides an approximation to the prior model. During runtime, this approximation of the prior is used in the posterior for the Gaussian selection task. Please note that the value of \(\beta\) does not play a role in determining the prior. This allows us to use the same search tree independently of the noise level, degradations, etc. Given that the main advantage of EPLL is that the same model can be used for any type of degradations, it is important that this property remains true for the accelerated version. Last but not least, the training of our search tree takes a few minutes while the training steps for the above mentioned approach take from several hours to a few days [36].

In the next section, we show that our proposed accelerations produce restoration results with comparable quality to competing methods while requiring a smaller amount of time.
In this section, we present the results obtained on various image restoration tasks. Our experiments were conducted on standard images of size 512 × 512 such as Barbara, Boat, Couple, Fingerprint, Lena, Mandrill and on 60 test images of size 481 × 321 from the Berkeley Segmentation Dataset (BSDS) [28] (the original BSDS test set contains 100 images, the other 40 was used for validation purposes while setting parameters \(\rho\) and \(s\). For denoising, we compare the performance of our fast EPLL (FEPLL) to the original EPLL algorithm [39] and BM3D [8]. For the original EPLL, we have included timing results given by our own MATLAB/C implementation (EPLLc) and the MATLAB implementation provided by the authors (EPLlm). We also compare our restoration performance and runtime against other fast restoration methods introduced to achieve competitive trade-off between runtime efficiency and image quality. These methods include RoG [32] (a method accelerating EPLL based on feedforward networks described in Sec. IV), and CSF [33] (a fast restoration technique using random field-based architecture).

For deblurring experiments, we additionally compare with field-of-experts (FoE)-based non-blind deconvolution [5] denoted as iPiano. We contacted the corresponding author of [36] and got confirmation that the implementation of their algorithm (briefly described in IV) is not publicly available. Due to certain missing technical details, we were unable to reimplement it faithfully. However, the results reported in [36] indicate that their algorithm performs in par with BM3D in terms of both PSNR and time. Hence, BM3D results can be used as a faithful proxy for the expected performance of Wang et al.’s algorithm [36].

To explicitly illustrate the quality vs. runtime tradeoff of FEPLL, we include results obtained using a slightly slower version of FEPLL referred to as FEPLL\(^{\prime}\), that does not use the balanced search tree and uses a flat tail spectrum approximation with \(\rho = 0.98\). Please note that FEPLL\(^{\prime}\) is not meant to be better or worse than FEPLL, it is just another version running at a different PSNR/runtime tradeoff which allows us to compare our algorithm to others operating in different playing fields.

Finally, to illustrate the versatility of FEPLL, we also include results for other inverse problems such as devignetting, super-resolution, and inpainting.

**Parameter settings:** In our experiments, we use patches of size \(P = 8 \times 8\), and the GMM provided by Zoran et al. [39] with \(K = 200\) components. The 200-components GMM is progressively collapsed into smaller GMMs with \(K=64,32,16,8,4,2\) and 1, and then all Gaussians of the tree are modified offline by flat-tail approximations with \(\rho = 0.95\). The final estimate for the restored image is obtained after \(5\) iterations of our algorithm with \(\beta = 1\), and the GMM provided by Zoran et al. [39]. For inverse problems, \(\lambda = \min\{N^{-1}A^2\boldsymbol{A}^2,|\lambda|^{-1}\}\) where \(\lambda = \min\{N^{-1}A^2\boldsymbol{A}^2,|\lambda|^{-1}\}\) and \(N\) is the number of Gaussians we include in the tree.

\(\lambda = 1\) which boils down to the setting used by Zoran et al. [39]. For inverse problems, we found that the initialization \(\hat{x} = (A^2 + 0.2\sigma^2|\lambda|^{-1}A^2)^{-1}y\), with \(\nabla\) the image Laplacian, provides relevant solutions whatever the linear operator \(\Lambda\) and the noise level \(\sigma^2\). While the authors of [39] do not provide any further direction for setting \(\beta\) and the initialization in general inverse problems, our proposed setting leads to competitive solutions irrespective of \(\Lambda\) and \(\sigma^2\).
BM3D [8], EPLLm [39], RoG [32], CSF [33] and iPiano [5] we use the implementations provided by the original authors and use the default parameters prescribed by them.

**Denoising:** Table II shows the quantitative performances of FEPLL on the denoising task compared to EPLLm [39], EPLLc (our own MATLAB/C implementation), RoG [32] BM3D [8] and CSF [33]. We evaluate the algorithms under low-, mid- and high-noise settings by using Gaussian noise of variance $5^2$, $20^2$ and $60^2$, respectively. The result labeled “Berkeley” is an average over 60 images from the BSDS testing set [28]. Figures 6 provide graphical representations of these performances in terms of PSNR/SSIM versus computation time for the BSDS images for the noise variance setting $\sigma^2 = 20^2$.

On average, FEPLL results are 0.5dB below regular EPLL and BM3D; however, FEPLL is approximately 7 times faster than BM3D, 170-200 times faster than EPLLc and over 350 times faster than EPLLm. FEPLL outperforms the faster CSF algorithm in terms of both PSNR and time. In this case, FEPLL is even faster than the GPU accelerated version of CSF (CSFgpu). Our approach is 4 times faster than RoG with a PSNR drop of 0.1-0.3dB. Nevertheless, if we slow down FEPLL to FEPLL', we can easily neutralize this quality deficit while still being faster than RoG. Note that these accelerations are obtained purely based on the approximations and no parallel processing is used. Also, in most cases, a loss of 0.5dB may not affect the visual quality of the image. To illustrate this, we show a sample image denoised by BM3D, EPLL and FEPLL in Fig. 5.

**Deblurring:** Table III shows the performance of FEPLL when used for deblurring as compared to RoG [32], iPiano [5] and CSF [33]. For these experiments, we use the blur kernel provided by Chen et al. [5] along with their algorithm implementation. The results under the label “Berkeley” are averaged over 60 images from the BSDS test dataset [28]. The results labeled “Classic” is averaged over the six standard images (Barbara, Boat, Couple, Fingerprint, Lena and Mandrill). FEPLL consistently outperforms its efficient competitors both in terms of quality and runtime. Although the GPU version of CSF is faster, the restoration quality obtained by CSF is 2-3dB lower than FEPLL. The proposed algorithm outperforms RoG by 1-1.8dB while running 3 and 5 times faster on “Berkeley” and “Classic” datasets, respectively.

The superior qualitative performance of FEPLL is demonstrated in Fig. 7. For brevity, we only include the deblurring results obtained from the top competitors of FEPLL algorithm in terms of both quality and runtime. As observed, FEPLL provides the best quality vs. runtime efficiency trade-off. In contrast, a deblurring procedure using the regular EPLL is around 350 times slower than FEPLL with the original implementation [39]. Specifically, on the sample image shown in Fig. 7, EPLL provides a qualitatively similar result (not shown in the figure) with a PSNR of 32.7 dB and SSIM of 0.922 in 142 seconds.

**Other inverse problems:** Unlike BM3D, EPLL and FEPLL are more versatile and handle a wide range of inverse problems.
without any change in formulation. In Fig. 8, we show the results obtained by FEPLL on problems such as (a) denoising, which involves a progressive loss of intensity, (b) super-resolution and (c) inpainting. To show the robustness of our method, the input images of size 481×321 were degraded with zero-mean Gaussian noise with $\sigma=2$. All of the restoration results were obtained within/under 0.4 seconds and with the same set of parameters explained above (cf. Parameter settings).

VI. CONCLUSION

In this paper, we accelerate EPLL by a factor greater than 100 with negligible loss of image quality (less than 0.5dB). This is achieved by combining three independent strategies: a flat tail approximation, matching via a balanced search tree, and stochastic patch sampling. We show that the proposed accelerations are effective in denoising and deblurring problems, as well as in other inverse problems such as super-resolution and devignetion. An important distinction of the proposed accelerations is their generlicity: the accelerated EPLL prior can be applied to many restoration tasks and various signal-to-noise ratios, in contrast to existing accelerations based on learning techniques applied to specific conditions (such as image size, noise level, blur kernel, etc.) and that require an expensive re-training to address a different problem.

Since the speed-up is achieved solely by reducing the algorithmic complexity, we believe that further inclusion of accelerations based on parallelization and/or GPU implementations will allow for real-time video processing. Moreover, the acceleration techniques introduced in this work are general strategies that can be used to speed up other image restoration and/or related machine learning algorithms. For reproducibility purposes, the code of FEPLL is made available on GitHub\(^1\).

REFERENCES


\(^1\)https://goo.gl/xjKJUA
Fig. 8. FEPLL on various inverse problems. All inputs contain Gaussian noise with $\sigma = 2$. Top row: (a) the observation in a devignetting problem, (b) the bi-cubic interpolation and the actual low-resolution size image (inset) in a $\times 3$ super-resolution problem and (c) the observation in an inpainting problem with 50% of missing pixels shown in red. Bottom row: respective FEPLL results all obtained in less than 0.4s.