EPLL: An Image Denoising Method Using a Gaussian Mixture Model

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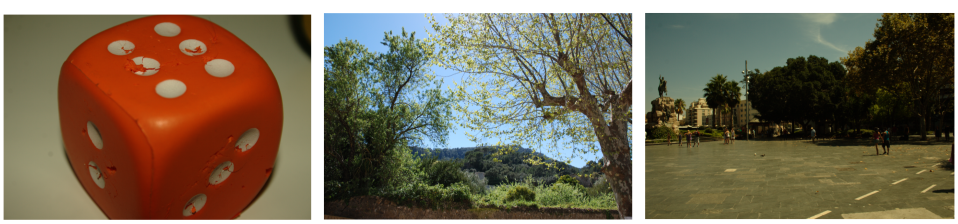
1 Introduction

The Expected Patch Log-Likelihood (EPLL) is a patch-based image denoising method that leverages Gaussian Mixture Models (GMMs) learned on a large set of patches. By estimating the prior distributions of clean patches, EPLL reconstructs denoised images from their noisy counterparts. This report evaluates the performance and parameter sensitivity of EPLL on various images and discusses its strengths and limitations.

2 Experiments on Denoising Performance

We tested the EPLL method on three images: a simple image with fewer details (*Dice*), a textured image (*Natural*), and a complex image with diverse structures (*Plaza*) as shown in the following figure 1:



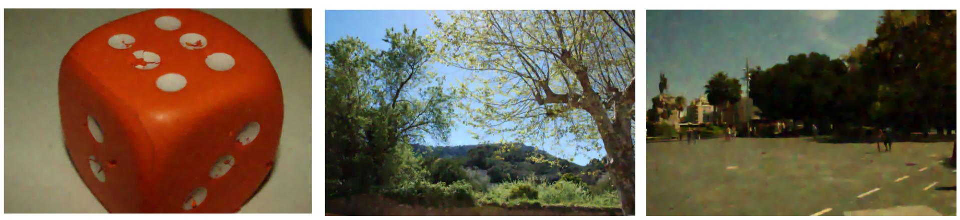
(a) Dice (b) Natural (c) Plaza

Figure 1: Clean images used in the experiments

The parameters were set to `sigma=30`, `steps=3`, `rank=75%`, and `number` `of scales=1`. Figures 2 and 3 display the noisy and denoised images, respectively. The PSNR values for each image are presented in Table 1.

(a) Dice (Noisy) (b) Natural (Noisy) (c) Plaza (Noisy)

Figure 2: Noisy images used in the experiments



(a) Dice (Denoised) (b) Natural (Denoised) (c) Plaza (Denoised)

Figure 3: Denoised images using EPLL

Image	PSNR (dB)
Dice	37.22
Natural	24.74
Plaza	30.21

Table 1: PSNR results for the denoised images

2.1 Interpretation

The results demonstrate that EPLL performs well on simpler and less structured images (e.g., *Dice*) but struggles with highly textured and detailed images (e.g., *Natural*). The method's inability to differentiate between fine textures and noise can lead to artifacts in regions with high detail or texture:

in fact, the denoised image for the *Plaza* omits basically completely the lines in the ground not to mention the introduction of distorsions in the form of small blob in the ground as well as a little bit in the sky.

3 Parameter Sensitivity Analysis

3.1 Effect of Noise Level

We studied the influence of noise level (`sigma`) on the Plaza image, keeping other parameters constant (`steps=3`, `rank=75%`, `number of scales=1`). Figure 4 displays the results, and Table 2 shows the PSNR values.

(a) $\sigma = 30$ (b) $\sigma = 45$ (c) $\sigma = 60$

Figure 4: Denoised Plaza images using EPLL with noise level variation.

`Sigma`	PSNR (dB)
30	30.21
45	28.65
60	27.62

Table 2: PSNR values for varying noise levels.

Interpretation Increasing noise levels degrade PSNR and introduce more artifacts. For higher `sigma` values, the method's performance diminishes as it struggles to reconstruct fine details. We highlit the degradation is considerably big!

3.2 Effect of Step Size

The impact of step size was analyzed on the Plaza image with `sigma=30`, `rank=75%`, and `number of scales=1`. Results are shown in Figure 5 and Table 3.

(a) $s = 3$ (b) $s = 5$ (c) $s = 7$

Figure 5: Denoised Plaza images using EPLL with number of steps variation.

`Step`	PSNR (dB)
3	30.21
5	30.05
7	29.82

Table 3: PSNR values for varying step sizes.

Interpretation Larger step sizes reduce PSNR as fewer patches overlap during denoising. Smaller steps yield better results but increase computational cost as we notice in IPOL demo. We highlight that the PSNR degradation is mediocre, roughly 0.4 dB!

3.3 Effect of Number of Scales

The Plaza image was denoised with different scales, keeping `sigma=30`, `step=3`, and `rank=75%`. Figure 6 and Table 4 summarize the results.

(a) $\#scales = 1$ (b) $\#scales = 2$ (c) $\#scales = 3$

Figure 6: Denoised Plaza images using EPLL with number of scales variation.

`Number of Scales`	PSNR (dB)
1	30.21
2	30.19
3	30.22

Table 4: PSNR values for varying scales.

Interpretation Varying the number of scales has minimal impact on PSNR, though computational complexity increases with more scales.

3.4 Effect of Maximum Rank

We investigated the effect of varying maximum rank on the denoising performance of the *Dice* image since it shows a time limit exceeded error when trying with the *Palza* image or the *Natural* image. By changing the rank parameter while keeping `sigma=30`, `step=3`, and `number of scales=1`, the impact on PSNR was evaluated. Figure 7 shows the denoised images, and Table 5 provides the corresponding PSNR values.

(a) $Rank = 50\%$ (b) $Rank = 75\%$ (c) $Rank = 100\%$

Figure 7: Denoised *Dice* images for varying maximum ranks

`Rank`	PSNR (dB)
50%	37.15
75%	37.22
100%	37.34

Table 5: PSNR values for varying maximum ranks.

Interpretation Increasing the maximum rank improves PSNR for the *Dice* image, as higher ranks allow for better preservation of structural details. However, this comes at the cost of increased computational complexity what we saw with the time limit exceeded error with *Palza* and *Natural* images. Nevertheless, let us highlight that this improveemnt is rather mediocre, just about 0.2 dB.

4 Zoran-Weiss GMM Commentary

The Gaussian Mixture Model proposed by Zoran and Weiss comprises 200 components, each meticulously trained on a vast collection of image patches. These components represent a wide spectrum of structures, from simple edges to intricate textures. Some Gaussian components exhibit highly sparse patterns, characteristic of less complex regions such as smooth surfaces or edges, while others embody rich, detailed textures that capture high-frequency details. This diversity underscores the flexibility and capability of the GMM in modeling the complex statistical properties of natural images, making it a powerful tool in tasks such as denoising and image reconstruction.

5 Conclusion

The EPLL method demonstrates robust denoising capabilities, particularly for low-texture images. Parameter tuning significantly impacts performance, with trade-offs between quality and computational cost. While effective, the method struggles with high-detail regions and introduces artifacts in textured areas.