Unleashing High-Quality Image Generation in Diffusion Sampling Using Second-Order Levenberg-Marquardt-Langevin

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Abstract

The emerging diffusion models (DMs) have demonstrated the remarkable capability of generating images via learning the noised score function of data distribution. Current DM sampling techniques typically rely on first-order Langevin dynamics at each noise level, with efforts concentrated on refining inter-level denoising strategies. While leveraging additional second-order Hessian geometry to enhance the sampling quality of Langevin is a common practice in Markov chain Monte Carlo (MCMC), the naive attempts to utilize Hessian geometry in high-dimensional DMs lead to quadratic-complexity computational costs, rendering them non-scalable. In this work, we introduce a novel Levenberg-Marquardt-Langevin (LML) method that approximates the diffusion Hessian geometry in a training-free manner, drawing inspiration from the celebrated Levenberg-Marquardt optimization algorithm. Our approach introduces two key innovations: (1) A low-rank approximation of the diffusion Hessian, leveraging the DMs' inherent structure and circumventing explicit quadratic-complexity computations; (2) A damping mechanism to stabilize the approximated Hessian. This LML approximated Hessian geometry enables the diffusion sampling to execute more accurate steps and improve the image generation quality. We further conduct a theoretical analysis to substantiate the approximation error bound of low-rank approximation and the convergence property of the damping mechanism. Extensive experiments across multiple pretrained DMs validate that the LML method significantly improves image generation quality, with negligible computational overhead.

1. Introduction

The emerging diffusion models (DMs) [30, 74, 76, 77], generating samples of data distribution from initial noise, have been proven to be an effective technique for modeling complex distribution, especially in generating high-quality images [13, 31, 58, 62, 67, 70]. Training DMs can be viewed as using a neural network to match the (Stein) score function of the target distribution corrupted by different levels of noise. The sampling of DMs can be seen as running Langevin dynamics [65] using the learned diffused score and simultaneously slowly decreasing the noise level, which is called annealed Langevin dynamics [76].

Recently, many sampling methods have been proposed to enhance the quality of generated samples of pretrained DMs. The majority of these efforts focus on refining the denoising scheme, as seen in works such as DDIM [75], DPM-Solvers [51, 52], PNDM [50], and others [7, 85, 91–94]. Some also propose to select more critical denoising timesteps to enhance sampling quality [23, 35, 87, 88]. These efforts are primarily based on the analysis along the denoising path, yet they still perform first-order Langevin using the learned score within a specific noise level.

In the Langevin sampling area, it is common to employ additional second-order Hessian geometry to enhance the sampling quality. The additional second-order information can guide Langevin dynamics to take more accurate steps [12, 54], which is called Newton-Langevin [73]. A natural idea is that we can also leverage the Hessian geometry of DMs within each noise level to enhance the quality of diffusion sampling results. However, it is extremely challenging to calculate the Hessian geometry within the context of high-dimensional DMs [3], cause it requires quadratic-complexity computations. Current methods on diffusion Hessian either require auxiliary networks [15, 84] or maintain memory-intensive states [64], making them inefficient for enhancing DM sampling.

In this paper, we introduce a novel method for approximating the diffusion Hessian within a specific noise level. Notably, our approach is the first to approximate the diffusion Hessian and apply it to enhance the sampling quality of pretrained commercial-level DMs. Our method, inspired by the celebrated Levenberg-Marquardt method in optimization [45, 53, 68], is referred to as the Levenberg-Marquardt-Langevin (LML) method. Our approach introduces two key

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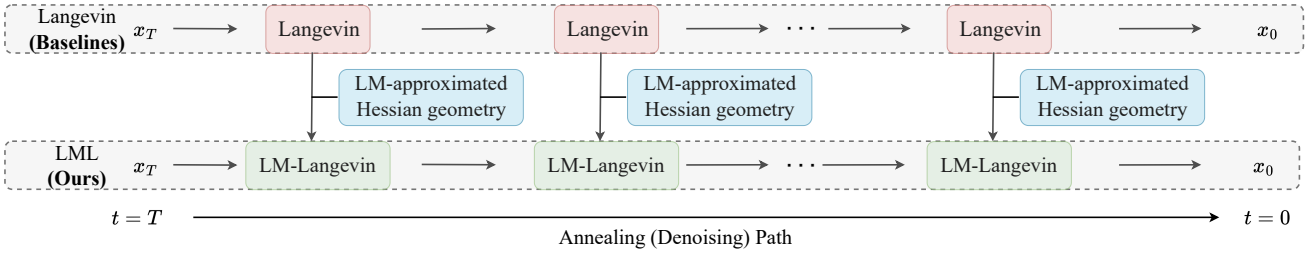


Figure 1. Schematic comparison between our LML method and baselines. While previous works mainly focus on intriguing designs along the annealing path to improve diffusion sampling, they leave operations at specific noise levels to be first-order Langevin. Our approach proposes to leverage the Levenberg-Marquardt approximated Hessian geometry to guide the Langevin update to be more accurate.

innovations: Initially, we derive a computationally tractable low-rank approximation of the diffusion Hessian by emulating the Gauss-Newton transformation, avoiding explicit quadratic-complexity computations. This approach capitalizes on the inherent structure of DMs to construct a low-rank approximation that captures critical geometric information. Following this, we stabilize the approximated Hessian using the damping mechanism, which addresses its ill-conditioning, and acquire its inverse for geometric guidance. Our method uses this LML-approximated Hessian geometry to enable the Langevin dynamics to take more accurate steps and improve image generation quality.

We also conduct comprehensive theoretical analyses for our low-rank approximation and damping mechanism. First, we establish the error bound for the low-rank approximation of the diffusion Hessian. Subsequently, we prove that the damping mechanism preserves an unbiased stationary measure and exhibit exponentially fast convergence in terms of χ^2-divergence.

Extensive experiments on multiple pretrained DMs, including CIFAR-10, CelebA-HQ, SD-15, SD2-base, SD-XL and PixArt-α, validate that the LML method significantly improves image generation quality with negligible computational overhead.

2. Preliminaries

Notation. The Euclidean norm over $\mathbb{R}^d$ is denoted by $\|\cdot\|$. Throughout, we simply write $\int g$ to denote the integral with respect to the Lebesgue measure: $\int g(x)\mathrm{d}x$. When the integral is with respect to a different measure μ, we explicitly write $\int g\mathrm{d}\mu$. The expectation and variance of $g(X)$when $X \sim p$ are respectively denoted $\mathbb{E}_\mu g = \int g\mathrm{d}\mu$ and $\mathrm{var}_\mu g := \int (g - \mathbb{E}_\mu g)^2 \mathrm{d}\mu$. When clear from context, we sometimes abuse notation by identifying a measure μ with its Lebesgue density. We use $\boldsymbol{I}_d$ to denote the d-dimensional identity matrix; when clear from context, we sometimes simply write $\boldsymbol{I}$. $\boldsymbol{H}_f$ and $\boldsymbol{J}_f$ denote the Hessian and Jacobian of f respectively.

2.1. Langevin Dynamics and Gradient Descent

In statistics, the *(Stein) score* of a distribution $p(\boldsymbol{x})$ is defined to be $\nabla_{\boldsymbol{x}} \log p(\boldsymbol{x})$. Given an initial value $\boldsymbol{x}_0 \sim \pi(\boldsymbol{x})$ with π being a prior distribution, Langevin dynamics (LD) can produce samples from $p(\boldsymbol{x})$ using only the score function $\nabla_{\boldsymbol{x}} \log p(\boldsymbol{x})$ following the SDE,

$$\mathrm{d}\boldsymbol{x}_t = \nabla_{\boldsymbol{x}} \log p\left(\boldsymbol{x}_t\right) \mathrm{d}t + \sqrt{2}\mathrm{d}B_t, \tag{1}$$

where B_t is the standard d-dimensional Brownian Motion (BM). The distribution of $\boldsymbol{x}_t$ equals $p(\boldsymbol{x})$ when $T \to \infty$, in which case $\boldsymbol{x}_t$ becomes an exact sample from $p(\boldsymbol{x})$ under some regularity conditions [86]. Strictly speaking, a Metropolis-Hastings adjustment is needed, but it can often be ignored in practice [9]. There is a deep connection involving the distribution of $\boldsymbol{x}_t$ in LD to the renowned Gradient Descent method (GD) [56] in optimization. The marginal distribution of a Langevin process $(\boldsymbol{x}_t)_{t\geq 0}$ evolves according to a GD, over the Wasserstein probability space, that minimizes the Kullback-Leibler (KL) divergence $D_{\mathrm{KL}}(\cdot \| \pi)$[2, 36, 81].

2.2. Diffusion Models and Annealed Langevin

Suppose that we have a d-dimensional random variable $\boldsymbol{x}(0) \in \mathbb{R}^d$ following an unknown target distribution $p_0(\boldsymbol{x}_0)$. Diffusion Models (DMs) define a forward process $\{\boldsymbol{x}(t)\}_{t\in[0,T]}$ with $T > 0$ starting with $\boldsymbol{x}(0)$, such that the distribution of $\boldsymbol{x}(t)$ conditioned on $\boldsymbol{x}(0)$ satisfies

$$p_{t|0}(\boldsymbol{x}(t)|\boldsymbol{x}(0)) = \mathcal{N}(\boldsymbol{x}(t); \alpha(t)\boldsymbol{x}(0), \sigma^2(t)\mathbf{I}), \tag{2}$$

where $\alpha(\cdot), \sigma(\cdot) \in \mathcal{C}([0, T], \mathbb{R}^+)$ have bounded derivatives, and we denote them as α_t and σ_t for simplicity. The choice for α_t and σ_t is referred to as the noise schedule of a DM.

DMs, both SMLD [76] and DDPM [30], can be seen as learning a network to match the score of the diffused distribution $\log p_t(\boldsymbol{x}_t)$ at different noise levels. In practice, DMs usually use $\boldsymbol{\varepsilon}_\theta(\boldsymbol{x}(t), t)$ to estimate $-\sigma(t)\nabla_{\boldsymbol{x}(t)} \log p_t(\boldsymbol{x}(t), t)$ via optimizing the following denoising score matching objective:

$$\mathbb{E}_t \left\{ \lambda_t \mathbb{E}_{x_0, x_t} \left[\| s_\theta(x_t, t) - \nabla_{x_t} \log p_(x_t, t|x_0, 0) \|^2 \right] \right\}. \tag{3}$$

The sampling process of diffusion models can be seen as annealed Langevin dynamics [76], which executes Langevin updates at each noise level while progressively reducing the noise scale.

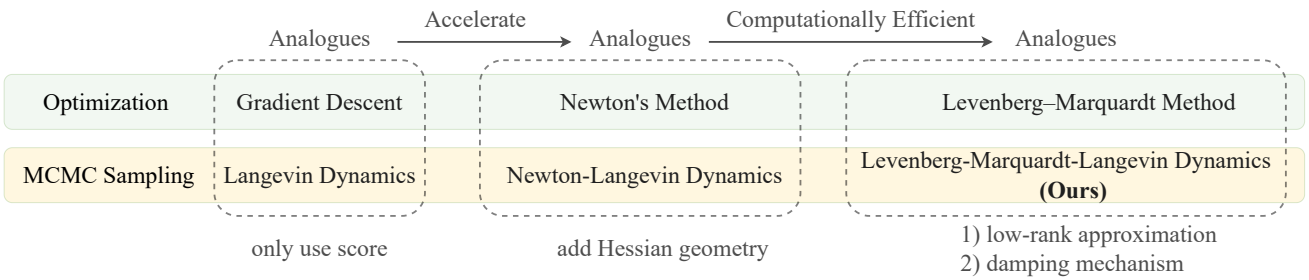


Figure 2. The relation between optimization algorithms and MCMC sampling algorithms. We initially wanted to develop a diffusion sampler utilizing Hessian geometry, following the path of Newton-Langevin dynamics [73]. However, this approach proved to be highly computationally expensive within the DM context. Drawing inspiration from the Levenberg-Marquardt method used in optimization, our method incorporates low-rank approximation and damping techniques. This enables us to obtain the Hessian geometry in a computationally affordable manner. Subsequently, we use this approximated Hessian geometry to guide the Langevin updates.

2.3. Langevin Guided by Hessian Geometry

Newton's method (also called Newton–Raphson) [60] is a famous optimization method that utilizes the second-order Hessian geometry to improve the GD. Developed as an analogy to Newton's method, the Newton-Langevin dynamics [54] utilize Hessian geometry to generate samples that adhere to the SDE

$$\mathrm{d}\boldsymbol{x}_t = \left[\nabla^2_{\boldsymbol{x}} \log p\left(\boldsymbol{x}_t\right)\right]^{-1} \nabla_{\boldsymbol{x}} \log p\left(\boldsymbol{x}_t\right) \mathrm{d}t + \sqrt{2}\mathrm{d}B'_t, \quad (4)$$

where the B'_t is the BM scaled by the square-rooted Hessian geometry. Calculating the Hessian geometry of high-dimensional distributions poses a significant challenge. Some studies have attempted to alleviate this issue through the Quasi-Newton technique [22, 73]. However, these approaches fail to address the problem in the context of DM-scale dimensional data. For instance, the Stable Diffusion-v1.5 model [67] features a latent dimension of 16384, resulting in a Hessian matrix of 16384×16384. Current methods on diffusion Hessian either require auxiliary networks training [15, 84] or maintain memory-intensive states [64]. To the best of our knowledge, there is currently no effective method available to access the diffusion Hessian of advanced commercial-level DMs like SD-XL.

2.4. Levenberg-Marquardt Method

In the field of optimization, the Levenberg-Marquardt (LM) method [68] is proposed as a computationally friendly and stabilized analogue to Newton's method. Specifically, it modifies the computation of Hessian geometry in Newton's method in two key aspects:

- **Low-rank approximated Hessian** In the context of least squares problems, the Levenberg-Marquardt method often constructs a low-rank estimation of the Hessian geometry. Specifically, when $f(\boldsymbol{x}) = \sum_{i=1}^{m} r_i(\boldsymbol{x})^2$, the Levenberg-Marquardt method approximates the Hessian into the following form, which is constructed from the Jacobians $\boldsymbol{J}_f(\boldsymbol{x})$.

$$\boldsymbol{H}_f(\boldsymbol{x}) \approx 2\boldsymbol{J}_f(\boldsymbol{x})^\top \boldsymbol{J}_f(\boldsymbol{x}). \quad (5)$$

  This low-rank approximation technique is also referred to as the Gauss-Newton method in some literature [16]. However, it is still unclear how to obtain a Levenberg-Marquardt-type low-rank estimation of the Hessian in the context of diffusion models.
- **Damping mechanism** The Levenberg-Marquardt Method introduces an additional damping identity matrix to the Hessian geometry. That is, it replaces the pure Hessian geometry $[\boldsymbol{H}_f(\boldsymbol{x}_k)]^{-1}$ in Newton's method with a combination expressed as $[\boldsymbol{H}_f(\boldsymbol{x}_k) + \lambda \boldsymbol{I}]^{-1}$. Consequently, the Levenberg-Marquardt Method with damping is expressed as:

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k - \eta \left[\boldsymbol{H}_f(\boldsymbol{x}_k) + \lambda \boldsymbol{I}\right]^{-1} \nabla_{\boldsymbol{x}} f(\boldsymbol{x}_k). \quad (6)$$

  Empirical evidence suggests that the damping mechanism contributes to numerical stabilization [41], since $\lambda \boldsymbol{I}$ can resolve the ill-conditioning of the Hessian. While the damping mechanism can be perceived as a trust region approach, it is more intuitive to view $\boldsymbol{H} + \lambda \boldsymbol{I}$ as a geometrical interpolation between $\boldsymbol{H}$ and $\boldsymbol{I}$.

3. Methodology

3.1. Low-rank Approximation of Diffusion Hessian

Inspired by the low-rank estimation technique of the Hessian in the Levenberg-Marquardt method, we derive a similar low-rank estimation for the diffusion Hessian. Specifically, we follow the intuition of the Levenberg-Marquardt method to approximate the diffusion Hessian by simplifying the second-order partial derivatives. The low-rank approximate Hessian of diffusion models that we obtained is shown below. It is important to note that it includes noise schedule related coefficients, which distinguishes it from the least squares problem case in Eq. 5.

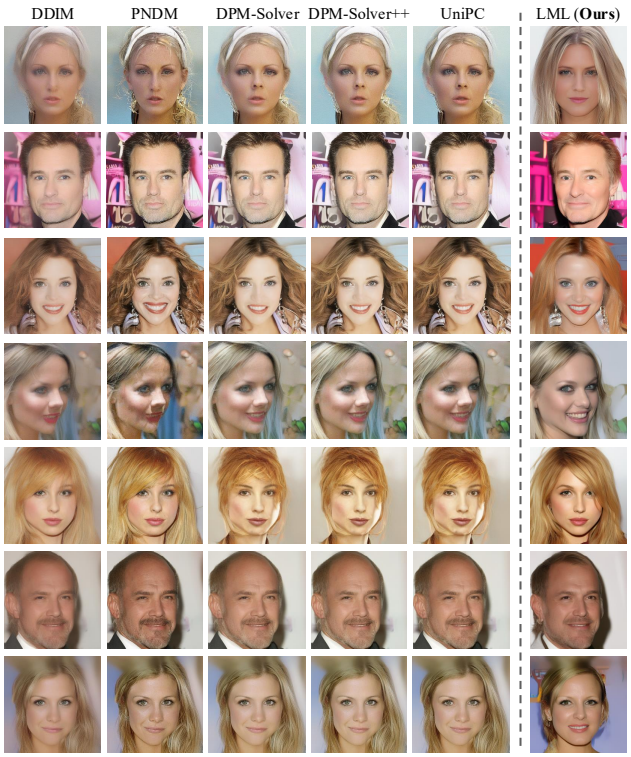


Figure 3. **Visual comparison** of images generated by our LML method and other methods, using the pre-trained LDM on CelebA-HQ 256×256 [39] with the same seeds. It shows that our LML method contributes to more vivid and detailed generated images.

Proposition 1. *Let p_t be the diffused marginal distribution at time t of the diffusion process, Eq. 2 and ε_θ is learned via Eq. 3, then the Hessian derivative of its log-density function $\nabla^2_{\boldsymbol{x}_t} \log p_t(\boldsymbol{x}_t)$ has a low-rank approximation form of $\frac{1}{\sigma(t)^2\|\varepsilon_\theta\|^2}\varepsilon_\theta\varepsilon_\theta^\top$.*

Notice that this approximation form is a scaled outer-product of the score. The detailed derivation can be found in the Supplementary A.2. For here and for the remainder of the paper, we will denote $\varepsilon_\theta(\boldsymbol{x}(t), t)$ as ε_θ, provided there is no risk of ambiguity. In section 4.1, we will show that this low-rank approximation possesses an error bound, ensuring that our approximation does not generate excessive errors.

3.2. Damping Mechanism

Similar to the scenario in the Levenberg-Marquardt method, we have obtained an accessible approximation of the diffusion Hessian as presented in Proposition 1. However, this form is significantly ill-conditioned, making its inverse impossible to calculate. Specifically, the outer-product Hessian in Proposition 1 has an infinite condition number [32]; hence, its inverse strictly does not exist in mathematical terms. To address this issue, we propose adopting the damping mechanism used in the LML method. We introduce an additional damping identity matrix to the approximate Hessian as shown in Proposition 1. This damped Hessian geometry is used in place of the full Hessian in the Newton Langevin in Eq. 4, we consequently derive the following damping dynamics:

$$\mathrm{d}\boldsymbol{x}_t = \left[\nabla^2_{\boldsymbol{x}} \log p\left(\boldsymbol{x}_t\right) + \lambda \boldsymbol{I}\right]^{-1} \nabla_{\boldsymbol{x}} \log p\left(\boldsymbol{x}_t\right) \mathrm{d}t + \sqrt{2}\mathrm{d}B'_t, \tag{7}$$

where the B'_t is the BM scaled by the square-rooted LM approximated Hessian geometry. Drawing inspiration from the Levenberg-Marquardt method, we refer to this damping Hessian Langevin in Eq. 7 as the Levenberg-Marquardt-Langevin dynamics (LML dynamics). Similar to the Levenberg-Marquardt method, the damping coefficient λ in Eq. 7 can be interpreted as an interpolation coefficient between the Hessian geometry and Identity geometry. Specifically, as $\lambda \to \infty$, Eq. 7 would degenerate to the standard Langevin with normalization on the geometry. We observe that by adding the Levenberg-Marquardt damping identity matrix to the outer-product form of the Hessian in Equation Proposition 1, its inverse can be conveniently computed using the Sherman-Morrison formula [72].

$$\begin{aligned}
\boldsymbol{H}^{-1}_{LM}(\boldsymbol{x}_t, \lambda) &= \left[\nabla^2_{\boldsymbol{x}} \log p\left(\boldsymbol{x}_t\right) + \lambda \boldsymbol{I}\right]^{-1} \\
&\approx \left[\frac{1}{\sigma(t)^2\|\varepsilon_\theta\|^2}\varepsilon_\theta\varepsilon_\theta^\top + \lambda \boldsymbol{I}\right]^{-1} \\
&= \frac{1}{\sigma(t)^2\|\varepsilon_\theta\|^2}\left[\varepsilon_\theta\varepsilon_\theta^\top + \lambda' \boldsymbol{I}\right]^{-1} \\
&= \frac{1}{\lambda'\sigma(t)^2\|\varepsilon_\theta\|^2}\left[\boldsymbol{I} - \frac{\varepsilon_\theta\varepsilon_\theta^\top}{\lambda' + \|\varepsilon_\theta\|^2}\right],
\end{aligned} \tag{8}$$

where $\lambda' = \sigma(t)^2\|\varepsilon_\theta\|^2\lambda$. We also point out that the coefficients $\frac{1}{\lambda'\sigma(t)^2\|\varepsilon_\theta\|^2}$ will be absorbed in the discretizing stepsize of the LML dynamics and only affect the norm. The geometry direction essence is in the $\left[\boldsymbol{I} - \frac{\varepsilon_\theta\varepsilon_\theta^\top}{\lambda'+\|\varepsilon_\theta\|^2}\right]$ part. In the remainder of this paper, we will slightly abuse notation by not distinguishing between λ and λ'. This simplification should not lead to any confusion.

3.3. Annealed Levenberg-Marquardt-Langevin

To utilize the LML for diffusion sampling, we perform the discretization of Eq. 7 at each nose level, and gradually decrease the noise level. We called this annealed LML, and point out that its continuous-time form would converge to the following SDE:

$$\mathrm{d}x_t = \left[f_t\boldsymbol{x}_t - g_t^2\boldsymbol{H}^{-1}_{LM}\nabla_x \log p_t(\boldsymbol{x}_t)\right]\mathrm{d}t + g_t\mathrm{d}B'_t. \tag{9}$$

Similar to the connection of the reverse SDE and diffusion ODE [77], the LM reverse SDE in Eq. 9 also has an associated ODE, which is a deterministic process that shares the

Algorithm 1 Levenberg-Marquardt-Langevin (LML) diffusion sampler

1: **Input**: pretrained diffusion model noise predictor $\boldsymbol{\varepsilon}_\theta$, number of timesteps N, noise schedule $\{\alpha_t\}$ and $\{\sigma_t\}$, Levenberg-Marquardt damping coefficient $\lambda > 0$, EMA coefficient κ.
2: Initiate $\boldsymbol{x}_{\text{list}} = []$, $\widetilde{\boldsymbol{H}}_{N+1}^{-1} = \boldsymbol{I}$
3: Sample $\boldsymbol{x}_N \sim \mathcal{N}(0, \sigma_{t_N} I)$.
4: **for** $i = N, N-1, ..., 1$ **do**
5: $\quad \boldsymbol{\varepsilon}_i = \boldsymbol{\varepsilon}_\theta(\boldsymbol{x}_i, i)$
6: $\quad$ **if** $i \neq N$ **then**
7: $\quad\quad \widetilde{\boldsymbol{\varepsilon}}_i = \kappa * \boldsymbol{\varepsilon}_{i+1} + (1-\kappa) * \boldsymbol{\varepsilon}_i$
8: $\quad$ **else**
9: $\quad\quad \widetilde{\boldsymbol{\varepsilon}}_i = \boldsymbol{\varepsilon}_i$
10: $\quad$ **end if**
11: $\quad \widetilde{\boldsymbol{H}}_i^{-1} = \boldsymbol{I} - \frac{\widetilde{\boldsymbol{\varepsilon}}_i \widetilde{\boldsymbol{\varepsilon}}_i^\top}{\lambda + \|\widetilde{\boldsymbol{\varepsilon}}_i\|^2}$ {Levenberg-Marquardt approximate Hessian geometry}
12: $\quad \boldsymbol{\varepsilon}_i^{LM} = \widetilde{\boldsymbol{H}}_i^{-1} \boldsymbol{\varepsilon}_i$ {Apply the approximate Hessian geometry}
13: $\quad \boldsymbol{\varepsilon}_i^{LM} = \frac{\|\boldsymbol{\varepsilon}_i\|}{\|\boldsymbol{\varepsilon}_i^{LM}\|} \boldsymbol{\varepsilon}_i^{LM}$ {Geometrical normalization}
14: $\quad \boldsymbol{x}_{i-1} = \text{DPM-Solver}(\boldsymbol{x}_{\text{list}}, \boldsymbol{\varepsilon}_i^{LM}, i)$
15: $\quad \boldsymbol{x}_{\text{list}} = \boldsymbol{x}_{\text{list}}.\text{append}(\boldsymbol{x}_{i-1})$
16: **end for**
17: **Output**: $\boldsymbol{x}_0$

same single-time marginal distribution:

$$\mathrm{d}x_t = \left[f_t \boldsymbol{x}_t - \frac{1}{2} g_t^2 \boldsymbol{H}_{LM}^{-1} \nabla_{\boldsymbol{x}} \log p_t(\boldsymbol{x}_t) \right] \mathrm{d}t. \tag{10}$$

The following section will develop a practical LML sampler based on this deterministic LML ODE.

Remark 1. *Our LM process can be viewed as the Legendre dual of the classical diffusion process with a transform map of* $\nabla \log p_t(\cdot) + \lambda \|\cdot\|$. *See discussions in Supp. D.3.*

3.4. Levenberg-Marquardt-Langevin Sampler

We implement a diffusion sampler based on the LML diffusion ODE in Eq. 10, because it is suggested that deterministic diffusion samplers are far more efficient than the stochastic ones [40]. Our approach is generally consistent with the practices outlined in [76]. The scheme for our LML diffusion sampler is illustrated in Algorithm 1. Primarily, our sampler substitutes the first-order Langevin dynamics with LML at each noise level. At each noise level, we initially compute the LM low-rank approximated and damping Hessian geometry, $\widetilde{\boldsymbol{H}}_i^{-1}$, as detailed in step 11 of Algorithm 1. We incorporate the network output from previous steps, as shown in step 7, following studies suggesting that this mixture is closer to the underlying true score due to the manifold's curvature [50]. We then apply this approximate Hessian geometry to our initial gradient, $\boldsymbol{\varepsilon}_i$, to obtain

Figure 4. **Qualitative comparison** of our LML method and other methods in text-guided image generation. The evaluation was performed on SD-15 [67], using 10 NFEs and the same seeds.

the Hessian-guided gradient, $\boldsymbol{\varepsilon}_i^{LM}$, as detailed in step 12. In terms of the stepsize for our LML sampler, in contrast to some sophisticated ways of choosing the stepsize of second-order methods [25, 43], we follow the approach of [20] to ensure that the Hessian geometry has a unit spectrum, which can be easily implemented through a normalization operation on the Hessian guided gradient $\boldsymbol{\varepsilon}_i^{LM}$ as illustrated in step 13. The rescaling of BM in Eq. 7 can also be absorbed into this normalization operation. Once the Hessian-guided gradient, $\boldsymbol{\varepsilon}_i^{LM}$, is obtained, we adopt the DPM-Solver as our denoising scheme to calculate the next state, $\boldsymbol{x}_{i-1}$, as shown in step 14.

It is worth noting that our LML does not require additional training, components, or network access. Instead, we only need several additional tensor arithmetic operations.

4. Theoretical Analysis

In this section, we present rigorous theoretical analyses to substantiate the correctness and efficacy of our LML.

4.1. Analysis on Low-rank Approximation

Here, we establish the error bound of the low-rank approximation of the diffusion Hessian in Proposition 1, thereby ensuring that our approximation does not introduce exces-

Figure 5. **Qualitative comparison** of our LML method and other methods in text-guided image generation. The evaluation was performed on SD2-base [67], using 10 NFEs and the same seeds.

sive errors. Given that we are evaluating the accuracy of a matrix-valued approximation, we choose to use the Hilbert-Schmidt norm [24] as a criterion.

Proposition 2. *Assume that the norm of $\boldsymbol{x}_t$ is bounded by δ_1, the approximation error on $\boldsymbol{\varepsilon}_\theta(\boldsymbol{x}_t, t)$ is denoted as δ_2, δ_3 denote the bound on the second partial derivative of δ_1 w.r.t. $\boldsymbol{x}_t$, and $\mathcal{D}_y$ denote the dataset diameter. The approximation error of the LM low-rank Hessian, as referenced in Proposition 1, is at most $(\delta_1 + \alpha_t\delta_2 + \alpha_t\mathcal{D}_y)\left(2 + \delta_3 + 2\frac{\alpha_t^2}{\sigma_t^2}\mathcal{D}_y^2\right)$ when measured in terms of the Hilbert–Schmidt norm.*

Our analysis relies on the analytical form diffusion Fisher [84]. The detailed proof can be found in Supp. A.6.

4.2. Analysis on Damping Mechanism

Subsequently, we demonstrate the unbiased, exponentially fast convergence property of the damping mechanism.

4.2.1. Stationary Measure

We confirm that the stationary measure of the damping dynamics, as defined in Eq. 7, aligns with the target diffused distribution. This ensures that the damping updates still guide samples towards the correct data distribution.

Proposition 3. *Under mild regularity conditions, the stationary distribution of the damping dynamics in Eq. 7 exists and is unique, which also coincides with the marginal distribution $p_t(\boldsymbol{x}_t)$ at every noise level.*

We achieve this analysis by the Fokker-Planck equation [63]. The detailed proof can be found in Supp. A.7.

4.2.2. Ergodic Convergence Rate

We also want to determine the speed at which our damping dynamics converge. We demonstrate that our damping dynamics exhibit a satisfyingly fast, exponential convergence rate towards the target distribution.

Proposition 4. *Let μ_t be the evolving distribution of the damping dynamics in Eq. 7. We have that μ_t converges to the stationary distribution at an exponential ergodic convergence rate in terms of χ^2-distance at every noise level, under certain regularity conditions.*

We achieve this analysis by determining the relationship between Eq. 7 and the Mirror-Langevin [12]. The formal version and detailed proof can be found in Supp. A.8.

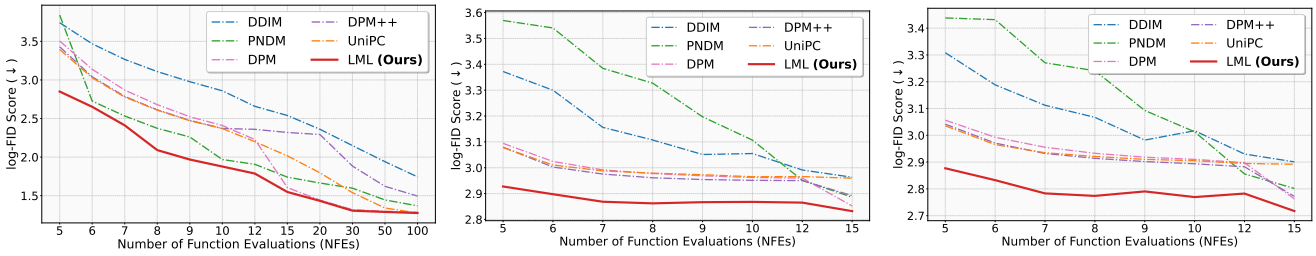
Remark 2. *Once we establish the exponential ergodic convergence rate in terms of χ^2-distance, The exponential convergence results for total variation distance [80], Hellinger distance [28], KL divergence [44] as illustrated in [4, §2.4]. And the exponential convergence results on Wasserstein distance [81] can also be established with a log-Sobolev assumption, as illustrated in [14].*

5. Experiments

In this section, we validate the enhanced sampling quality of our LML method across various pretrained DMs. We evaluate in both pixel-space, latent-space, and text-guided conditional generation scenarios. We select several most commonly-used and advanced sampling methods such as DDIM [77], PNDM [50], DPM-Solver [51], DPM-Solver++ [52] and UniPC [92] as baselines. We will also demonstrate the computational efficiency of our LML method. All experiments are executed using open-source, pretrained DMs, with the datatype set to float32 and the timestep scheme as uniform. More experimental details and results are deferred to Supp. B and C.

5.1. Pixel-Space Image Generation

We initially compare the unconditional sampling quality of our LML method with baselines on the CIFAR-10 dataset [1]. For each sampler, we generate 50,000 samples for FID evaluation. As illustrated in Table 1 and Figure 6a, our approach improves the sampling performance of the baseline Langevin methods in most NFE scenarios.



(a) CIFAR-10 (b) SD-15 on MS-COCO (c) SD2-base on MS-COCO

Figure 6. This line chart compares the log-FID scores (↓) on (a) CIFAR-10, (b) MS-COCO with SD-15 and (c) MS-COCO with SD2-base.

Table 1. Comparison of different samplers on FID score(↓) on CIFAR-10 unconditional generation. Best results are **bolded** and the second best results are underlined. The FID scores were obtained by generating 50,000 samples, and all samplers were tested using the same seeds on the same checkpoint. It is shown that our LML always achieves the best or second best FID across all different NFEs.

Methods	FID (↓) on CIFAR-10 generation											
	5 NFEs	6 NFEs	7 NFEs	8 NFEs	9 NFEs	10 NFEs	12 NFEs	15 NFEs	20 NFEs	30 NFEs	50 NFEs	100 NFEs
DDIM [75]	42.17	32.09	26.21	22.38	19.64	17.45	14.27	12.67	10.60	8.58	6.96	5.72
PNDM [50]	46.56	15.27	12.59	10.73	9.59	7.16	6.73	5.70	5.28	4.94	4.24	3.93
DPM-Solver [51]	33.26	23.06	17.61	14.58	12.47	11.13	9.28	4.98	4.23	3.74	3.66	3.62
DPM-Solver++ [52]	30.87	20.92	16.22	13.63	11.89	10.71	10.59	10.17	9.90	6.58	5.06	4.46
UniPC [92]	29.81	20.64	16.10	13.59	11.84	10.70	9.02	7.51	6.03	4.66	3.82	**3.58**
LML **(Ours)**	**17.28**	**14.18**	**11.15**	**8.09**	**7.16**	**6.54**	**5.97**	**4.70**	**4.19**	**3.69**	**3.63**	**3.58**

Table 2. Comparison of different samplers on CelebA-HQ unconditional generation. Best results are **bolded** and the second best results are underlined.

Methods	Colorful	Face Quality		Aesthetic		
	ColorS(↑)	FS(↑)	DFIQA(↑)	PicS(↑)	EAT(↑)	Laion(↑)
DDIM [75]	34.13	4.85	0.539	19.85	4.61	5.24
PNDM [50]	38.29	4.89	0.553	19.70	4.28	5.11
DPM [51]	34.85	5.06	0.566	20.00	4.51	5.29
DPM++ [52]	35.08	5.08	0.560	19.97	4.46	5.26
UniPC [92]	35.95	5.09	0.568	19.97	4.47	5.26
LML**(Ours)**	**40.53**	**5.24**	**0.607**	**20.98**	**4.75**	**5.37**

5.2. Latent-Space Image Generation

We evaluated our LML on the LDM [67] that was trained on CelebA-HQ [39] at a resolution of 256×256. In Table 2, we employed five metrics spanning three aspects to demonstrate the superiority of LML. These aspects include colorfulness [26], face quality (FS [46] and DFIQA [10]), and human-preference-aesthetic scores (PicS [42], EAT [27] and Laion-Aes [71]). Additionally, we present a visual comparison in Figure 3. All these experiments were carried out with a NFE of 10. The results were tested by averaging over 1000 samples and the same seeds.

5.3. Text-guided Image Generation

5.3.1. Qualitative Comparison

Qualitative comparison on SD-15 and SD2-base generation is provided in Figure 4 and 5, clearly indicating that our LML method enhances the quality of image details under the same seed and prompt with a NFE of 10.

Table 3. Comparison of FID score (↓) for the task of text-guided conditional generation of SD on randomly selected 30,000 MS-COCO prompts. Best results are **bolded** and the second best results are underlined.

Methods \NFEs	FID (↓) on MS-COCO-14 prompts							
	5	6	7	8	9	10	12	15
	SD-1.5							
DDIM [75]	29.14	27.11	23.48	22.36	21.14	21.22	19.91	19.36
PNDM [50]	35.50	34.49	29.50	27.86	24.46	22.35	19.13	17.92
DPM [51]	22.07	20.58	19.92	19.64	19.47	19.34	19.30	17.32
DPM++ [52]	21.75	20.14	19.60	19.32	19.19	19.13	19.11	18.03
UniPC [92]	21.72	20.30	19.84	19.67	19.55	19.40	19.41	19.29
LML **(Ours)**	**18.68**	**18.13**	**17.61**	**17.50**	**17.58**	**17.60**	**17.55**	**16.98**
	SD2-base							
DDIM [75]	27.34	24.25	22.47	21.48	19.73	20.43	18.73	18.19
PNDM [50]	31.13	30.93	26.33	25.56	22.04	20.35	17.39	16.47
DPM [51]	21.25	19.94	19.21	18.78	18.51	18.36	18.13	15.84
DPM++ [52]	20.94	19.51	18.77	18.43	18.21	18.06	17.86	15.99
UniPC [92]	20.81	19.40	18.82	18.56	18.36	18.27	18.08	18.03
LML **(Ours)**	**17.76**	**16.99**	**16.17**	**16.02**	**16.29**	**15.95**	**16.16**	**15.14**

5.3.2. FID on MS-COCO Benchmark

Following the approach in [69, 90], we randomly selected 30,000 prompts from the MS-COCO dataset [47] and generated images conditioned on these prompts. We tested our sampler in terms of FID on the SD-1.5 and SD2-base models with resolutions of 512×512 and a CFG scale 7.0. Table 3 shows that our LML sampler surpasses the baseline methods on SD models across different NFEs.

Table 4. Comparison of different samplers in text-guided image generation task on the T2I-BC benchmark [34]. The metrics are Color, Shape, and Texture. Best results are **bolded** and the second best results are underlined.

Metrics	T2I Benchmark on SD-1.5 [67]			T2I Benchmark on SD2-base [67]			T2I Benchmark on SD-XL [59]			T2I Benchmark on PixArt-α [8]		
	Color$_{(\uparrow)}$	Shape$_{(\uparrow)}$	Texture$_{(\uparrow)}$	Color$_{(\uparrow)}$	Shape$_{(\uparrow)}$	Texture$_{(\uparrow)}$	Color$_{(\uparrow)}$	Shape$_{(\uparrow)}$	Texture$_{(\uparrow)}$	Color$_{(\uparrow)}$	Shape$_{(\uparrow)}$	Texture$_{(\uparrow)}$
DDIM [75]	0.3864	0.3791	0.4231	0.5111	0.4182	0.4822	0.5670	0.4712	0.5076	0.2933	0.3746	0.4045
PNDM [50]	0.3810	0.3761	0.4331	0.5067	0.4190	0.4863	0.5682	0.4772	0.5085	**0.4035**	0.3996	0.4225
DPM [51]	0.3877	0.3945	0.4294	0.5162	0.4307	0.5002	0.5795	0.4841	0.5194	0.3263	0.3895	0.4349
DPM++ [52]	0.3881	0.3958	0.4307	0.5202	0.4326	0.5020	0.5798	0.4858	0.5201	0.3136	0.3882	0.4364
UniPC [92]	0.3892	0.3889	0.4306	0.5146	0.4337	0.4995	0.5828	0.4910	0.5234	0.3187	0.3880	0.4266
LML (**Ours**)	**0.4335**	**0.4252**	**0.4746**	**0.5640**	**0.4792**	**0.5330**	**0.5908**	**0.4938**	**0.5363**	0.3801	**0.4265**	**0.4684**

Figure 7. LML integrates seamlessly with ControlNet.

5.3.3. T2I-CB Benchmark

To further validate the enhanced sampling quality of LML in text-to-image generation, we carried out tests on diverse commercial-level DMs (SD-1.5 [67], SD2-base [67], SD-XL [59], and PixArt-α [8]) using the T2I-CB [34] benchmark. This benchmark is designed for open-world text-to-image generation evaluation. For each model, we evaluated three metrics (color, shape, and texture) to assess the visual quality of the samplers. Each assessment was based on 30,000 images with a NFE of 10. As shown in Table 4, our LML always achieves the best or second best scores on T2I-BC across these models.

5.3.4. Application on ControlNet

Our model can seamlessly integrate with existing diffusion model plugins, such as ControlNet [89]. The results in Fig 7 demonstrate that our method is fully compatible with ControlNet and generates high-quality samples.

5.4. Time-costs Comparison

Table 5 presents the average wall-clock time costs for LML across different image generation tasks. These time-cost experiments were conducted on a single NVIDIA RTX 4090 chip and averaged over 200 tests with a batchsize of 1. The results suggest that the additional computational cost incurred by our LML technique is virtually negligible, making LML as time-efficient as DDIM [75].

Table 5. Average wall-clock time costs for LML and DDIM.

Models	Methods \NFEs	Time-costs (s)						
		5	10	15	20	30	50	100
CIFAR-10	DDIM	0.13	0.20	0.27	0.34	0.52	0.81	1.49
	LML (**Ours**)	0.13	0.21	0.27	0.37	0.48	0.82	1.51
CelebA	DDIM	0.20	0.28	0.39	0.47	0.66	1.03	1.95
	LML (**Ours**)	0.20	0.31	0.38	0.48	0.67	1.10	2.08
SD-1.5	DDIM	0.45	0.73	1.03	1.31	1.87	3.01	5.85
	LML (**Ours**)	0.45	0.74	1.04	1.32	1.89	3.03	5.89
SD-2base	DDIM	0.45	0.71	1.00	1.25	1.80	2.87	5.53
	LML (**Ours**)	0.46	0.72	0.98	1.27	1.81	2.88	5.60
SD-XL	DDIM	2.32	4.25	6.23	8.12	12.06	19.82	39.48
	LML (**Ours**)	2.32	4.30	6.23	8.21	12.11	19.99	39.55
PixArt	DDIM	0.66	1.08	1.49	1.92	2.74	4.31	8.45
	LML (**Ours**)	0.67	1.08	1.51	1.92	2.75	4.28	8.49

5.5. Hyperparameters

Our LML introduces two robust hyperparameters with clear high-level interpretations: the damping coefficient λ and the mixture coefficient κ. The damping coefficient λ determines the degree to which our approximated Hessian is interpolated with the identity matrix. A larger λ value results in the dominance of the identity matrix, leading the LML to degenerate into Langevin. Conversely, a smaller λ value allows more guidance from the Hessian geometry, but a minimal value could lead to ill-conditioning issues. The κ controls the EMA rate of previous information. A small κ would make the LML close to the identity map, but LML contributes to obvious image quality enhancement in practice. More discussions on hyperparameter tuning scheme, setup, and ablation experiments are provided in Supp. B.2.

6. Conclusions

In this paper, we propose a training-free method termed Levenberg-Marquardt-Langevin (LML) for improving sampling quality, which uses a low-rank approximated damping Hessian geometry to guide the Langevin update. We provide a theoretical analysis of the approximation error for low-rank approximation, the stationary measure, and the convergence rate for damping dynamics. We conduct extensive experiments to demonstrate that our LML method can contribute to significant improvement in sampling quality, with negligible computational overhead. The code is available at https://github.com/zituitui/LML-diffusion-sampler.

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