A LAPLACE-INSPIRED DISTRIBUTION ON SO(3) FOR PROBABILISTIC ROTATION ESTIMATION

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ABSTRACT

Estimating the 3DoF rotation from a single RGB image is an important yet challenging problem. Probabilistic rotation regression has raised more and more attention with the benefit of expressing uncertainty information along with the prediction. Though modeling noise using Gaussian-resembling Bingham distribution and matrix Fisher distribution is natural, they are shown to be sensitive to outliers for the nature of quadratic punishment to deviations. In this paper, we draw inspiration from multivariate Laplace distribution and propose a novel Rotation Laplace distribution on $\mathrm{SO}(3)$. Rotation Laplace distribution is robust to the disturbance of outliers and enforces much gradient to the low-error region, resulting in a better convergence. Our extensive experiments show that our proposed distribution achieves state-of-the-art performance for rotation regression tasks over both probabilistic and non-probabilistic baselines.

1 INTRODUCTION

Incorporating neural networks to perform rotation regression is of great importance in the field of computer vision, computer graphics and robotics (Wang et al., 2019b; Yin et al., 2022; Dong et al., 2021; Breyer et al., 2021). To close the gap between the $\mathrm{SO}(3)$ manifold and the Euclidean space where neural network outputs exist, one popular line of research discovers learning-friendly rotation representations including 6D continuous representation (Zhou et al., 2019), 9D matrix representation with SVD orthogonalization (Levinson et al., 2020), etc. Recently, Chen et al. (2022) focuses on the gradient backpropagating process and replaces the vanilla auto differentiation with a $\mathrm{SO}(3)$ manifold-aware gradient layer, which sets the new state-of-the-art in rotation regression tasks.

Reasoning about the uncertainty information along with the predicted rotation is also attracting more and more attention, which enables many applications in aerospace (Crassidis & Markley, 2003), autonomous driving (McAllister et al., 2017) and localization (Fang et al., 2020). On this front, recent efforts have been developed to model the uncertainty of rotation regression via probabilistic modeling of rotation space. The most commonly used distributions are Bingham distribution (Bingham, 1974) on $\mathcal{S}^4$ for unit quaternions and matrix Fisher distribution (Khatri & Mardia, 1977) on $\mathrm{SO}(3)$ for rotation matrices. These two distributions are equivalent to each other (Prentice, 1986) and resemble the Gaussian distribution in Euclidean Space (Bingham, 1974; Khatri & Mardia, 1977). While modeling noise using Gaussian-like distributions is well-motivated by the Central Limit Theorem, Gaussian distribution is well-known to be sensitive to outliers in the probabilistic regression models (Murphy, 2012). This is because Gaussian distribution penalizes deviations quadratically, so predictions with larger errors weigh much more heavily with the learning than low-error ones and thus potentially result in suboptimal convergence when a certain amount of outliers exhibit.

Unfortunately, in certain rotation regression tasks, we fairly often come across large prediction errors, *e.g.* 180° error, due to either the (near) symmetry nature of the objects or severe occlusions (Murphy et al., 2021). In Fig. 1(left), using training on single image rotation regression as an example, we show the statistics of predictions on training data after achieving convergence, assuming matrix Fisher distribution (as done in Mohlin et al. (2020)). The blue histogram shows the population with different prediction errors and the red dots are the impacts of these predictions on learning, evaluated by computing the sum of their gradient magnitudes $\|\partial\mathcal{L}/\partial(\text{distribution param.})\|$ within each bin and then normalizing them across bins. It is clear that the 180° outliers dominate the gradient as well as the network training though their population is tiny, while the vast majority of

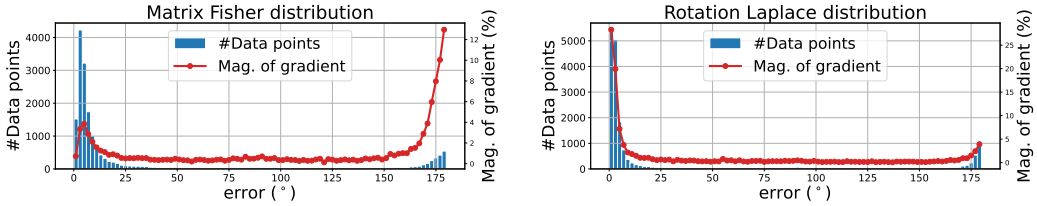

Figure 1: **Visualization of the results of matrix Fisher distribution and Rotation Laplace distribution after convergence.** The horizontal axis is the geodesic distance between the prediction and the ground truth. The blue bins count the number of data points within corresponding errors (2° each bin). The red dots illustrate the percentage of the sum of the gradient magnitude $\|\partial\mathcal{L}/\partial(\text{dist. param.})\|$ within each bin. The experiment is done on all categories of ModelNet10-SO3 dataset.

points with low error predictions are deprioritized. Arguably, at convergence, the gradient should focus more on refining the low errors rather than fixing the inevitable large errors (*e.g.* arose from symmetry). This motivates us to find a better probabilistic model for rotation.

As pointed out by Murphy (2012), Laplace distribution, with heavy tails, is a better option for robust probabilistic modeling. Laplace distribution drops sharply around its mode and thus allocates most of its probability density to a small region around the mode; meanwhile, it also tolerates and assigns higher likelihoods to the outliers, compared to Gaussian distribution. Consequently, it encourages predictions near its mode to be even closer, thus fitting *sparse* data well, most of whose data points are close to their mean with the exception of several outliers(Mitianoudis, 2012), which makes Laplace distribution to be favored in the context of deep learning(Goodfellow et al., 2016).

In this work, we propose a novel Laplace-inspired distribution on $\mathrm{SO}(3)$ for rotation matrices, namely Rotation Laplace distribution, for probabilistic rotation regression. We devise Rotation Laplace distribution to be an approximation of multivariate Laplace distribution in the tangent space of its mode. As shown in the visualization in Fig. 1(right), our Rotation Laplace distribution is robust to the disturbance of outliers, with most of its gradient contributed by the low-error region, and thus leads to a better convergence along with significantly higher accuracy. Moreover, our Rotation Laplace distribution is simply parameterized by an unconstrained 3×3 matrix and thus accommodates the Euclidean output of neural networks with ease. This network-friendly distribution requires neither complex functions to fulfill the constraints of parameterization nor any normalization process from Euclidean to rotation manifold which has been shown harmful for learning (Chen et al., 2022).

For completeness of the derivations, we also propose the Laplace-inspired distribution on $\mathcal{S}^3$ for quaternions. We show that Rotation Laplace distribution is equivalent to Quaternion Laplace distribution, similar to the equivalence of matrix Fisher distribution and Bingham distribution.

We extensively compare our Rotation Laplace distributions to methods that parameterize distributions on $\mathrm{SO}(3)$ for pose estimation, and also non-probabilistic approaches including multiple rotation representations and recent $\mathrm{SO}(3)$-aware gradient layer (Chen et al., 2022). On common benchmark datasets of rotation estimation from RGB images, we achieve a significant and consistent performance improvement over all baselines.

2 Related Work

Probabilistic regression Nix & Weigend (1994) first proposes to model the output of the neural network as a Gaussian distribution and learn the Gaussian parameters by the negative log-likelihood loss function, through which one obtains not only the target but also a measure of prediction uncertainty. More recently, Kendall & Gal (2017) offers more understanding and analysis of the underlying uncertainties. Lakshminarayanan et al. (2017) further improves the performance of uncertainty estimation by network ensembling and adversarial training. Makansi et al. (2019) stabilizes the training with the winner-takes-all and iterative grouping strategies. Probabilistic regression for uncertainty prediction has been widely used in various applications, including optical flow estimation(Ilg et al., 2018), depth estimation (Poggi et al., 2020), weather forecasting (Wang et al., 2019a), *etc.*

Among the literature of decades, the majority of probabilistic regression works model the network output by a Gaussian-like distribution, while Laplace distribution is less discovered. Li et al. (2021) empirically finds that assuming a Laplace distribution in the process of maximum likelihood estimation yields better performance than a Gaussian distribution, in the field of 3D human pose estimation. Recent work (Nair et al., 2022) makes use of Laplace distribution to improve the robustness of maximum likelihood-based uncertainty estimation. Due to the heavy-tailed property of Laplace distribution, the outlier data produces comparatively less loss and have an insubstantial impact on training. Other than in Euclidean space, Mitianoudis (2012) develops Generalized Directional Laplacian distribution in $\mathcal{S}^d$ for the application of audio separation.

Probabilistic rotation regression Several works focus on utilizing probability distributions on the rotation manifold for rotation uncertainty estimation. Prokudin et al. (2018) uses the mixture of von Mises distributions (Mardia et al., 2000) over Euler angles using Biternion networks. In Gilitschenski et al. (2019) and Deng et al. (2022), Bingham distribution over unit quaternion is used to jointly estimate a probability distribution over all axes. Mohlin et al. (2020) leverages matrix Fisher distribution (Khatri & Mardia, 1977) on $\mathrm{SO}(3)$ over rotation matrices for deep rotation regression. Though both bear similar properties with Gaussian distribution in Euclidean space, matrix Fisher distribution benefits from the continuous rotation representation and unconstrained distribution parameters, which yields better performance (Murphy et al., 2021). Recently, Murphy et al. (2021) introduces a non-parametric implicit pdf over $\mathrm{SO}(3)$, with the distribution properties modeled by the neural network parameters. Implicit-pdf especially does good for modeling rotations of symmetric objects.

Non-probabilistic rotation regression The choice of rotation representation is one of the core issues concerning rotation regression. The commonly used representations include Euler angles (Kundu et al., 2018; Tulsiani & Malik, 2015), unit quaternion (Kendall & Cipolla, 2017; Kendall et al., 2015; Xiang et al., 2017) and axis-angle (Do et al., 2018; Gao et al., 2018; Ummenhofer et al., 2017), *etc*. However, Euler angles may suffer from gimbal lock, and unit quaternions doubly cover the group of $\mathrm{SO}(3)$, which leads to two disconnected local minima. Moreover, Zhou et al. (2019) points out that all representations in the real Euclidean spaces of four or fewer dimensions are discontinuous and are not friendly for deep learning. To this end, the continuous 6D representation with Gram-Schmidt orthogonalization (Zhou et al., 2019) and 9D representation with SVD orthogonalization (Levinson et al., 2020) have been proposed, respectively. More recently, Chen et al. (2022) investigates the gradient backpropagation in the backward pass and proposes a $\mathrm{SO}(3)$ manifold-aware gradient layer.

3 Revisit Matrix Fisher distribution

3.1 Matrix Fisher Distribution

Matrix Fisher distribution (or von Mises-Fisher matrix distribution) (Khatri & Mardia, 1977) is one of the widely used distributions for probabilistic modeling of rotation matrices. It is defined as follows.

Definition 1. Matrix Fisher distribution. *The random variable* $\mathbf{R} \in \mathrm{SO}(3)$ *follows matrix Fisher distribution with parameter* $\mathbf{A}$*, if its probability density function is defined as*

$$p(\mathbf{R}; \mathbf{A}) = \frac{1}{F(\mathbf{A})} \exp\left(\mathrm{tr}(\mathbf{A}^T\mathbf{R})\right) \tag{1}$$

where $\mathbf{A} \in \mathbb{R}^{3\times 3}$ *is an unconstrained matrix, and* $F(\mathbf{A}) \in \mathbb{R}$ *is the normalization constant. Without further clarification, we denote* F *as the normalization constant of the corresponding distribution in the remaining of this paper. We also denote matrix Fisher distribution as* $\mathbf{R} \sim \mathcal{MF}(\mathbf{A})$.

Suppose the singular value decomposition of matrix $\mathbf{A}$ is given by $\mathbf{A} = \mathbf{U}'\mathbf{S}'(\mathbf{V}')^T$, *proper* SVD is defined as $\mathbf{A} = \mathbf{U}\mathbf{S}\mathbf{V}^T$ where

$$\mathbf{U} = \mathbf{U}' \,\mathrm{diag}(1, 1, \det(\mathbf{U}')) \qquad \mathbf{V} = \mathbf{V}' \,\mathrm{diag}(1, 1, \det(\mathbf{V}'))$$
$$\mathbf{S} = \mathrm{diag}(s_1, s_2, s_3) = \mathrm{diag}(s_1', s_2', \det(\mathbf{U}'\mathbf{V}')s_3')$$

The definition of $\mathbf{U}$ and $\mathbf{V}$ ensures that $\det(\mathbf{U}) = \det(\mathbf{V}) = 1$ and $\mathbf{U}, \mathbf{V} \in \mathrm{SO}(3)$.

The mode of matrix Fisher distribution is computed as $\mathbf{U}\mathbf{V}^T$. The columns of $\mathbf{U}$ specify the principle axes of rotations and the proper singular values $\mathbf{S}$ describe the concentration of the distribution along the principle axes.

3.2 Relationship between Matrix Fisher Distribution in $\mathrm{SO}(3)$ and Gaussian Distribution in $\mathbb{R}^3$

It is shown that matrix Fisher distribution is highly relevant with zero-mean Gaussian distribution near its mode. Denote $\mathbf{R}_0$ as the mode of matrix Fisher distribution, and define $\widetilde{\mathbf{R}} = \mathbf{R}_0^T\mathbf{R}$, the relationship is shown as follows. Please refer to supplementary for the proof.

Proposition 1. *Let $\mathbf{\Phi} = \log \widetilde{\mathbf{R}} \in \mathfrak{so}(3)$ and $\boldsymbol{\phi} = \mathbf{\Phi}^\vee \in \mathbb{R}^3$. For rotation matrix $\mathbf{R} \in \mathrm{SO}(3)$ following* matrix Fisher distribution*, when $\mathbf{R} \to \mathbf{R}_0$, $\boldsymbol{\phi}$ follows zero-mean* multivariate Gaussian distribution*.*

4 Probabilistic Rotation Estimation with Rotation Laplace Distribution

4.1 Rotation Laplace distribution

We get inspiration from multivariate Laplace distribution (Wikipedia, 2022), defined as follows.

Definition 2. Multivariate Laplace distribution. *If means $\boldsymbol{\mu} = \mathbf{0}$, the d-dimensional multivariate Laplace distribution with covariance matrix $\mathbf{\Sigma}$ is defined as*

$$p(\mathbf{x}; \mathbf{\Sigma}) = \frac{1}{F}\left(\mathbf{x}^T\mathbf{\Sigma}^{-1}\mathbf{x}\right)^{v/2} K_v\left(\sqrt{2\mathbf{x}^T\mathbf{\Sigma}^{-1}\mathbf{x}}\right)$$

where $v = (2-k)/2$ and K_v is modified Bessel function of the second kind.

We consider three dimensional Laplace distribution of $\mathbf{x} \in \mathbb{R}^3$, defined as

$$p(\mathbf{x}; \mathbf{\Sigma}) = \frac{1}{F}\frac{\exp\left(-\sqrt{2\mathbf{x}^T\mathbf{\Sigma}^{-1}\mathbf{x}}\right)}{\sqrt{\mathbf{x}^T\mathbf{\Sigma}^{-1}\mathbf{x}}}$$

In this section, we first give the definition of our proposed Rotation Laplace distribution and then shows its relationship with multivariate Laplace distribution.

Definition 3. Rotation Laplace distribution. *The random variable $\mathbf{R} \in \mathrm{SO}(3)$ follows Rotation Laplace distribution with parameter $\mathbf{A}$, if its probability density function is defined as*

$$p(\mathbf{R}; \mathbf{A}) = \frac{1}{F(\mathbf{A})}\frac{\exp\left(-\sqrt{\mathrm{tr}\left(\mathbf{S} - \mathbf{A}^T\mathbf{R}\right)}\right)}{\sqrt{\mathrm{tr}\left(\mathbf{S} - \mathbf{A}^T\mathbf{R}\right)}} \tag{2}$$

where $\mathbf{A} \in \mathbb{R}^{3\times 3}$ is an unconstrained matrix, and $\mathbf{S}$ is the diagonal matrix composed of the proper singular values of matrix $\mathbf{A}$, i.e., $\mathbf{A} = \mathbf{U}\mathbf{S}\mathbf{V}^T$. We also denote Rotation Laplace distribution as $\mathbf{R} \sim \mathcal{RL}(\mathbf{A})$.

Denote $\mathbf{R}_0$ as the mode of Rotation Laplace distribution and define $\widetilde{\mathbf{R}} = \mathbf{R}_0^T\mathbf{R}$, the relationship between Rotation Laplace distribution and multivariate Laplace distribution is shown as follows.

Proposition 2. *Let $\mathbf{\Phi} = \log \widetilde{\mathbf{R}} \in \mathfrak{so}(3)$ and $\boldsymbol{\phi} = \mathbf{\Phi}^\vee \in \mathbb{R}^3$. For rotation matrix $\mathbf{R} \in \mathrm{SO}(3)$ following* Rotation Laplace distribution*, when $\mathbf{R} \to \mathbf{R}_0$, $\boldsymbol{\phi}$ follows zero-mean* multivariate Laplace distribution*.*

Proof. Apply proper SVD to matrix $\mathbf{A}$ as $\mathbf{A} = \mathbf{U}\mathbf{S}\mathbf{V}^T$. For $\mathbf{R} \sim \mathcal{RL}(\mathbf{A})$, we have

$$p(\mathbf{R})\mathrm{d}\mathbf{R} \propto \frac{\exp\left(\sqrt{\mathrm{tr}(\mathbf{S}\text{-}\mathbf{A}^\mathrm{T}\mathbf{R})}\right)}{\sqrt{\mathrm{tr}(\mathbf{S}\text{-}\mathbf{A}^\mathrm{T}\mathbf{R})}}\mathrm{d}\mathbf{R} = \frac{\exp\left(\sqrt{\mathrm{tr}(\mathbf{S}\text{-}\mathbf{S}\mathbf{V}^\mathrm{T}\widetilde{\mathbf{R}}\mathbf{V})}\right)}{\sqrt{\mathrm{tr}(\mathbf{S}\text{-}\mathbf{S}\mathbf{V}^\mathrm{T}\widetilde{\mathbf{R}}\mathbf{V})}}\mathrm{d}\mathbf{R} \tag{3}$$

With $\boldsymbol{\phi} = (\log \widetilde{\mathbf{R}})^{\vee} \in \mathbb{R}^3$, $\widetilde{\mathbf{R}}$ can be parameterized as

$$\widetilde{\mathbf{R}}(\boldsymbol{\phi}) = \exp(\hat{\boldsymbol{\phi}}) = \mathbf{I} + \frac{\sin \|\boldsymbol{\phi}\|}{\|\boldsymbol{\phi}\|}\hat{\boldsymbol{\phi}} + \frac{1-\cos\|\boldsymbol{\phi}\|}{\|\boldsymbol{\phi}\|^2}\hat{\boldsymbol{\phi}}^2$$

and the Haar measure is given by

$$\mathrm{d}\widetilde{\mathbf{R}} = \frac{1-\cos\|\boldsymbol{\phi}\|}{4\pi^2\|\boldsymbol{\phi}\|^2}\mathrm{d}\boldsymbol{\phi} = \left(\frac{1}{8\pi^2} + O(\|\boldsymbol{\phi}\|)^2\right)\mathrm{d}\boldsymbol{\phi}. \tag{4}$$

Also, $\widetilde{\mathbf{R}}$ expanded at $\boldsymbol{\phi} = \mathbf{0}$ is computed as

$$\widetilde{\mathbf{R}} = \mathbf{I} + \hat{\boldsymbol{\phi}} + \frac{1}{2}\hat{\boldsymbol{\phi}}^2 + O(\|\boldsymbol{\phi}\|^3)$$

We have

$$\begin{aligned}\mathbf{V}^T\widetilde{\mathbf{R}}\mathbf{V} &= \mathbf{I} + \mathbf{V}^T\hat{\boldsymbol{\phi}}\mathbf{V} + \frac{1}{2}\mathbf{V}^T\hat{\boldsymbol{\phi}}^2\mathbf{V} + O(\|\boldsymbol{\phi}\|^3) = \mathbf{I} + \widehat{\mathbf{V}^T\boldsymbol{\phi}} + \frac{1}{2}\widehat{\mathbf{V}^T\boldsymbol{\phi}}^2 + O(\|\boldsymbol{\phi}\|^3) \\ &= \begin{bmatrix} 1-\frac{1}{2}(\mu_2^2+\mu_3^2) & \frac{1}{2}\mu_1\mu_2 - \mu_3 & \frac{1}{2}\mu_1\mu_3 + \mu_2 \\ \frac{1}{2}\mu_1\mu_2 + \mu_3 & 1-\frac{1}{2}(\mu_3^2+\mu_1^2) & \frac{1}{2}\mu_2\mu_3 - \mu_1 \\ \frac{1}{2}\mu_1\mu_3 - \mu_2 & \frac{1}{2}\mu_2\mu_3 + \mu_1 & 1-\frac{1}{2}(\mu_1^2+\mu_2^2) \end{bmatrix} + O(\|\boldsymbol{\phi}\|^3),\end{aligned} \tag{5}$$

where $(\mu_1, \mu_2, \mu_3)^T = \mathbf{V}^T\boldsymbol{\phi}$, and

$$\begin{aligned}\mathrm{tr}(\mathbf{S}\text{-}\mathbf{S}\mathbf{V}^{\mathrm{T}}\widetilde{\mathbf{R}}\mathbf{V}) &= \sum_{(i,j,k)\in I}\frac{1}{2}(s_j+s_k)\mu_i^2 + O(\|\boldsymbol{\phi}\|^3) \\ &= \frac{1}{2}\boldsymbol{\phi}^T\mathbf{V}\begin{bmatrix} s_2+s_3 & & \\ & s_1+s_3 & \\ & & s_1+s_2 \end{bmatrix}\mathbf{V}^T\boldsymbol{\phi} + O(\|\boldsymbol{\phi}\|^3)\end{aligned} \tag{6}$$

Considering Eq. 3, 4 and 6, we have

$$p(\mathbf{R})\mathrm{d}\mathbf{R} \propto \frac{\exp\left(\sqrt{\mathrm{tr}(\mathbf{S}\text{-}\mathbf{A}^{\mathrm{T}}\mathbf{R})}\right)}{\sqrt{\mathrm{tr}(\mathbf{S}\text{-}\mathbf{A}^{\mathrm{T}}\mathbf{R})}}\mathrm{d}\mathbf{R} = \frac{1}{8\pi^2}\frac{\exp\left(-\sqrt{2\boldsymbol{\phi}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\phi}}\right)}{\sqrt{2\boldsymbol{\phi}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\phi}}}\left(1+O(\|\boldsymbol{\phi}\|^2)\right)\mathrm{d}\boldsymbol{\phi} \tag{7}$$

When $\mathbf{R} \to \mathbf{R}_0$, $\widetilde{\mathbf{R}} \to \mathbf{0}$ and $\boldsymbol{\phi} \to \mathbf{0}$, so Eq. 7 follows the multivariate Laplace distribution with the covariance matrix as $\boldsymbol{\Sigma}$, where $\boldsymbol{\Sigma} = 4\mathbf{V}\,\mathrm{diag}(\frac{1}{s_2+s_3}, \frac{1}{s_1+s_3}, \frac{1}{s_1+s_2})\mathbf{V}^T$. □

Rotation Laplace distribution bears similar properties with matrix Fisher distribution. Its mode is computed as $\mathbf{U}\mathbf{V}^T$. The columns of $\mathbf{U}$ and the proper singular values $\mathbf{S}$ describe the orientation and the strength of dispersions, respectively.

4.2 Negative log-likelihood loss

Given a collection of observations $\mathcal{X} = \{\boldsymbol{x}_i\}$ and the associated ground truth rotations $\mathcal{R} = \{\mathbf{R}_i\}$, we aim at training the network to best estimate the parameter $\mathbf{A}$ of Rotation Laplace distribution. This is achieved by maximizing a likelihood function so that, under our probabilistic model, the observed data is most probable, which is known as maximum likelihood estimation (MLE). We use the negative log-likelihood of $\mathbf{R}_{\boldsymbol{x}}$ as the loss function:

$$\mathcal{L}(\boldsymbol{x}, \mathbf{R}_{\boldsymbol{x}}) = -\log p\left(\mathbf{R}_{\boldsymbol{x}}; \mathbf{A}_{\boldsymbol{x}}\right)$$

4.3 Discrete approximation of the normalizing constant

Efficiently and accurately estimating the normalization constant for distributions over $\mathrm{SO}(3)$ is non-trivial. Previous works introduce various methods to approximate this constant, including pre-computed lookup tables (Gilitschenski et al., 2019; Deng et al., 2022), polynomial approximation of integral over Bessel functions (Mohlin et al., 2020), *etc*. Inspired by Murphy et al. (2021), we approximate the normalization constant of Rotation Laplace distribution through equivolumetric discretization over $\mathrm{SO}(3)$ manifold. We employ the discretization method introduced in Yershova et al. (2010), which starts with the equal area grids on the 2-sphere (Gorski et al., 2005) and covers $\mathrm{SO}(3)$ by threading a great circle through each point on the surface of a 2-sphere with Hopf fibration. Concretely, the normalization constant of Laplace Rotation distribution is computed as

$$F(\mathbf{A}) = \int_{\mathrm{SO}(3)}\frac{\exp\left(-\sqrt{\mathrm{tr}\left(\mathbf{S}-\mathbf{A}^T\mathbf{R}\right)}\right)}{\sqrt{\mathrm{tr}\left(\mathbf{S}-\mathbf{A}^T\mathbf{R}\right)}}\mathrm{d}\mathbf{R} \approx \sum_{\mathrm{SO}(3)}\frac{\exp\left(-\sqrt{\mathrm{tr}\left(\mathbf{S}-\mathbf{A}^T\mathbf{R}\right)}\right)}{\sqrt{\mathrm{tr}\left(\mathbf{S}-\mathbf{A}^T\mathbf{R}\right)}}\Delta\mathbf{R}$$

Similar to matrix Fisher distribution, the normalization constant of Rotation Laplace distribution is only determined by the proper singular values $\mathbf{S}'$ of the parameter $\mathbf{A}$, i.e., $F(\mathbf{A})$ is merely a function of three parameters, which motivates us, for computational and memory efficiency, to further compute a lookup table wrt. the proper singular values for both the forward and backward pass. Experiments show that our approximation works well for rotation regression tasks.

4.4 QUATERNION LAPLACE DISTRIBUTION

In this section, we introduce our extension of Laplace-inspired distribution for quaternions, namely, Quaternion Laplace distribution.

Definition 4. Quaternion Laplace distribution. *The random variable $\mathbf{q} \in \mathcal{S}^3$ follows Quaternion Laplace distribution with parameter $\mathbf{M}$ and $\mathbf{Z}$, if its probability density function is defined as*

$$p(\mathbf{q}; \mathbf{M}, \mathbf{Z}) = \frac{1}{F(\mathbf{Z})} \frac{\exp\left(-\sqrt{-\mathbf{q}^T \mathbf{M}\mathbf{Z}\mathbf{M}^T \mathbf{q}}\right)}{\sqrt{-\mathbf{q}^T \mathbf{M}\mathbf{Z}\mathbf{M}^T \mathbf{q}}} \tag{8}$$

where $\mathbf{M} \in \mathbf{O}(4)$ is a 4×4 orthogonal matrix, and $\mathbf{Z} = \mathrm{diag}(0, z_1, z_2, z_3)$ is a 4×4 diagonal matrix with $0 \geq z_1 \geq z_2 \geq z_3$. We also denote Quaternion Laplace distribution as $\mathbf{q} \sim \mathcal{QL}(\mathbf{M}, \mathbf{Z})$.

Proposition 3. *Denote $\mathbf{q}_0$ as the mode of Quaternion Laplace distribution. Let π be the tangent space of $\mathbb{S}^3$ at $\mathbf{q}_0$, and $\pi(\mathbf{x}) \in \mathbb{R}^4$ be the projection of $\mathbf{x} \in \mathbb{R}^4$ on π. For quaternion $\mathbf{q} \in \mathbb{S}^3$ following* Bingham distribution / Quaternion Laplace distribution*, when $\mathbf{q} \to \mathbf{q}_0$, $\pi(\mathbf{q})$ follows zero-mean* multivariate Gaussian distribution / *zero-mean* multivariate Laplace distribution.

Both Bingham distribution and Quaternion Laplace distribution exhibit antipodal symmetry on $\mathcal{S}^3$, i.e., $p(\mathbf{q}) = p(-\mathbf{q})$, which captures the nature that the quaternions $\mathbf{q}$ and $-\mathbf{q}$ represent the same rotation on $\mathrm{SO}(3)$. For each distribution, the mode of the distribution is indicated by the first column of the matrix $\mathbf{M}$, and the remaining columns describe the orientation of dispersions. The corresponding $z_i (i = 1, 2, 3)$ describe the strength of dispersions.

Proposition 4. *Denote γ as the standard transformation from unit quaternions to corresponding rotation matrices. For rotation matrix $\mathbf{R} \in \mathrm{SO}(3)$ following* Rotation Laplace distribution*, $\mathbf{q} = \gamma^{-1}(\mathbf{R}) \in \mathbb{S}^3$ follows* Quaternion Laplace distribution.

Prop. 4 shows that our proposed Rotation Laplace distribution is equivalent to Quaternion Laplace distribution, similar to the equivalence of matrix Fisher distribution and Bingham distribution (Prentice, 1986), demonstrating the consistency of our derivations. Please see supplementary for the proofs to the above propositions.

The normalization constant of Quaternion Laplace distribution is also approximated by dense discretization and accelerated by the pre-computed lookup table.

$$F(\mathbf{Z}) = \oint_{\mathbf{q} \in \mathcal{S}^3} \frac{\exp\left(-\sqrt{-\mathbf{q}^T \mathbf{M}\mathbf{Z}\mathbf{M}^T \mathbf{q}}\right)}{\sqrt{-\mathbf{q}^T \mathbf{M}\mathbf{Z}\mathbf{M}^T \mathbf{q}}} \mathrm{d}\mathbf{q} \approx \sum_{\mathbf{q} \in \mathcal{S}^3} \frac{\exp\left(-\sqrt{-\mathbf{q}^T \mathbf{M}\mathbf{Z}\mathbf{M}^T \mathbf{q}}\right)}{\sqrt{-\mathbf{q}^T \mathbf{M}\mathbf{Z}\mathbf{M}^T \mathbf{q}}} \Delta\mathbf{q}$$

5 EXPERIMENT

Concerning the task of single image rotation regression, we find two kinds of independent research tracks with slightly different evaluation settings. One line of research focuses on probabilistic rotation regression with different parametric or non-parametric distributions on $\mathrm{SO}(3)$ (Prokudin et al., 2018; Gilitschenski et al., 2019; Deng et al., 2022; Mohlin et al., 2020; Murphy et al., 2021), and the other non-probabilistic track proposes multiple rotation representations (Zhou et al., 2019; Levinson et al., 2020; Peretroukhin et al., 2020) or improves the gradient of backpropagation (Chen et al., 2022). To fully demonstrate the capacity of our Rotation Laplace distribution, we leave the baselines in their original optimal states and adapt our method to follow the common experimental settings in each track, respectively.

5.1 DATASETS & EVALUATION METRICS

Datasets **ModelNet10-SO3** (Liao et al., 2019) is a commonly used synthetic dataset for single image rotation estimation containing 10 object classes. It is synthesized by rendering the CAD models of ModelNet-10 dataset (Wu et al., 2015) that are rotated by uniformly sampled rotations in $\mathrm{SO}(3)$. **Pascal3D+** (Xiang et al., 2014) is a popular benchmark on real-world images for pose estimation. It covers 12 common daily object categories. The images in Pascal3D+ dataset are sourced from Pascal VOC and ImageNet datasets, and are split into ImageNet_train, ImageNet_val, PascalVOC_train, and PascalVOC_val sets.

Table 1: Numerical comparisons with probabilistic baselines on ModelNet10-SO3 dataset averaged on all categories. Numbers in parentheses (·) are our reproduced results. Please refer to supplementary for comparisons with each category.

	Acc@3°↑	Acc@5°↑	Acc@10°↑	Acc@15°↑	Acc@30°↑	Med.(°)↓
Liao et al. (2019)	-	-	-	0.496	0.658	28.7
Prokudin et al. (2018)	-	-	-	0.456	0.528	49.3
Deng et al. (2022)	(0.138)	(0.301)	(0.502)	0.562 (0.584)	0.694 (0.673)	32.6 (31.6)
Mohlin et al. (2020)	(0.164)	(0.389)	(0.615)	0.693 (0.684)	0.757 (0.751)	17.1 (17.9)
Murphy et al. (2021)	(0.294)	(0.534)	(0.680)	0.719 (0.714)	0.735 (0.730)	21.5 (20.3)
Rotation Laplace	**0.446**	**0.613**	**0.714**	**0.741**	**0.770**	**12.2**

Evaluation metrics We evaluate our experiments with the geodesic distance of the network prediction and the ground truth. This metric returns the angular error and we measure it in degrees. In addition, we report the prediction accuracy within the given error threshold.

5.2 Comparisons with Probabilistic Methods

5.2.1 Evaluation Setup

Settings In this section, we follow the experiment settings of the latest work (Murphy et al., 2021) and quote its reported numbers for baselines. Specifically, we train one single model for all categories of each dataset. For Pascal3D+ dataset, we follow Murphy et al. (2021) to use (the more challenging) PascalVOC_val as test set. Note that Murphy et al. (2021) only measure the coarse-scale accuracy (e.g., Acc@30°) which may not adequately satisfy the downstream tasks (Wang et al., 2019b; Fang et al., 2020). To facilitate finer-scale comparisons (e.g., Acc@5°), we further re-run several recent baselines and report the reproduced results in parentheses (·).

Baselines We compare our method to recent works which utilize probabilistic distributions on $\mathrm{SO}(3)$ for the purpose of pose estimation. In concrete, **Prokudin et al. (2018)** models rotations in the form of Euler angle with the mixture of *von Mises* distributions. **Gilitschenski et al. (2019)** and **Deng et al. (2022)** incorporate *Bingham* distribution over unit quaternions as the probabilistic modeling of rotations. **Mohlin et al. (2020)** uses *matrix Fisher* distribution over rotation matrices. It is benefited from continuous representation and unconstrained parameterization. Recently, **Murphy et al. (2021)** proposes an implicit representation for non-parametric distributions. With dense sampling on $\mathrm{SO}(3)$, implicit-PDF better expresses arbitrary distributions. We also compare to the spherical regression work of **Liao et al. (2019)** to highlight the advantages of distribution-based methods, as Murphy et al. (2021) does.

5.2.2 Results

Table 1 shows the quantitative comparisons of our method and baselines on ModelNet10-SO3 dataset. From the multiple evaluation metrics, we can see that maximum likelihood estimation with the assumption of Rotation Laplace distribution significantly outperforms the other distributions for rotation, including matrix Fisher distribution (Mohlin et al., 2020), Bingham distribution (Do et al., 2018) and von-Mises distribution (Prokudin et al., 2018). Our method also gets superior performance than the non-parametric implicit-PDF (Murphy et al., 2021). Especially, our method improves the fine-scale Acc@3° and Acc@5° accuracy by a large margin, showing its capacity to precisely model the target distribution.

The experiments on Pascal3D+ dataset are shown in Table 2, where our Rotation Laplace distribution outperforms all the baselines. While our method gets reasonably good performance on the median error and coarser-scale accuracy, we do not find a similar impressive improvement on fine-scale metrics as in ModelNet10-SO3 dataset. We suspect it is because the imperfect human annotations of real-world images may lead to comparatively noisy ground truths, increasing the difficulty for networks to get rather close predictions with GT labels. Nevertheless, our method still manages to obtain superior performance, which illustrates the robustness of our Rotation Laplace distribution.

Table 2: Numerical comparisons with probabilistic baselines on Pascal3D+ dataset averaged on all categories. Numbers in parentheses (·) are our reproduced results. Please refer to supplementary for comparisons with each category.

	Acc@3°↑	Acc@5°↑	Acc@10°↑	Acc@15°↑	Acc@30°↑	Med.(°)↓
Tulsiani & Malik (2015)	-	-	-	-	0.808	13.6
Mahendran et al. (2018)	-	-	-	-	0.859	10.1
Liao et al. (2019)	-	-	-	-	0.819	13.0
Prokudin et al. (2018)	-	-	-	-	0.838	12.2
Mohlin et al. (2020)	(0.089)	(0.215)	(0.484)	(0.650)	0.825 (0.827)	11.5 (11.9)
Murphy et al. (2021)	(0.102)	(0.242)	(0.524)	(0.672)	0.837 (0.838)	10.3 (10.2)
Rotation Laplace	**0.150**	**0.298**	**0.566**	**0.711**	**0.876**	**9.4**

Table 3: Numerical comparisons with non-probabilistic baselines on ModelNet10-SO3 dataset. One model is trained for each category.

Methods	Chair			Sofa			Toilet			Bed		
	Mean↓	Med.↓	Acc@5↑	Mean↓	Med.↓	Acc@5↑	Mean↓	Med.↓	Acc@5↑	Mean↓	Med.↓	Acc@5↑
Euler angles	21.5	10.9	0.10	27.5	12.0	0.09	14.9	8.5	0.19	27.6	9.6	0.17
Axis-angle	25.7	14.3	0.07	30.3	14.6	0.06	20.3	13.0	0.08	36.3	16.7	0.04
Quaternion	25.8	15.0	0.06	30.0	15.7	0.06	20.6	13.0	0.08	34.1	15.5	0.05
6D	19.6	9.1	0.19	17.5	7.3	0.27	10.9	6.2	0.37	32.3	11.7	0.11
9D	17.5	8.3	0.23	19.8	7.6	0.25	11.8	6.5	0.34	30.4	11.1	0.13
9D-Inf	12.1	5.1	0.49	12.5	3.5	0.70	7.6	3.7	0.67	22.5	4.5	0.56
10D	18.4	9.0	0.20	20.9	8.7	0.20	11.5	5.9	0.39	29.9	11.5	0.11
RPMG-Quat	13.0	5.9	0.40	13.0	3.6	0.67	8.6	4.2	0.61	23.2	4.9	0.51
RPMG-6D	12.9	4.7	0.53	11.5	2.8	0.77	7.8	3.4	0.71	20.3	3.6	0.67
RPMG-9D	11.9	4.4	0.58	10.5	2.4	0.82	7.5	3.2	0.75	20.0	2.9	0.76
RPMG-10D	12.8	4.5	0.55	11.2	2.4	0.82	7.2	3.0	0.76	19.2	2.9	0.75
Rot. Laplace	**9.7**	**3.5**	**0.68**	**8.8**	**2.1**	**0.84**	**5.3**	**2.6**	**0.83**	**15.5**	**2.3**	**0.82**

5.3 Comparisons with Non-probabilistic Methods

5.3.1 Evaluation Setup

Settings For comparisons with non-probabilistic methods, we follow the latest work of Chen et al. (2022) to learn a network for each category. For Pascal3D+ dataset, we follow Chen et al. (2022) to use ImageNet_val as our test set. We use the same evaluation metrics as in Chen et al. (2022) and quote its reported numbers for baselines.

Baselines We compare to multiple baselines that leverage different rotation representations to directly regress the prediction given input images, including traditional **Euler angles**, **axis-angle**, **Quaternion** and later introduced **6D** (Zhou et al., 2019), **9D / 9D-Inf** (Levinson et al., 2020) and **10D** (Peretroukhin et al., 2020). We also include regularized projective manifold gradient series of methods, **RPMG-Quat**, **RPMG-6D**, **RPMG-9D** and **RPMG-10D** (Chen et al., 2022).

5.3.2 Results

We report the numerical results of our method and on-probabilistic baselines on ModelNet10-SO3 dataset in Table 3. Our method obtains a clear superior performance to the best competitor under all the metrics among all the categories. Note that we train a model for each category (so do all the baselines), thus our performance in Table 3 is better than Table 1 where one model is trained for the whole dataset. The results on Pascal3D+ dataset are shown in Table 4 where our method with Rotation Laplace distribution achieves state-of-the-art performance.

Table 4: Numerical comparisons with non-probabilistic baselines on Pascal3D+ dataset. One model is trained for each category.

Methods	Bicycle				Sofa			
	Acc@10↑	Acc@15↑	Acc@20↑	Med.↓	Acc@10↑	Acc@15↑	Acc@20↑	Med.↓
Euler angles	0.282	0.481	0.627	15.7	0.602	0.809	0.906	8.3
Axis-angle	0.053	0.081	0.101	79.7	0.450	0.709	0.851	11.0
Quaternion	0.208	0.388	0.546	18.7	0.343	0.608	0.735	13.2
6D	0.218	0.390	0.553	18.1	0.508	0.767	0.890	9.9
9D	0.206	0.376	0.569	18.0	0.524	0.796	0.903	9.2
9D-Inf	0.380	0.533	0.699	13.4	0.709	0.880	0.935	6.7
10D	0.239	0.423	0.567	17.9	0.502	0.770	0.896	9.8
RPMG-Quat	0.323	0.500	0.656	15.0	0.566	0.796	0.909	8.9
RPMG-6D	0.354	0.572	0.706	13.5	0.696	0.861	0.922	6.7
RPMG-9D	0.368	0.574	0.718	12.5	0.725	0.880	0.958	6.7
RPMG-10D	0.400	0.577	0.713	12.9	0.693	0.871	0.939	7.0
Rot. Laplace	**0.435**	**0.641**	**0.744**	**11.2**	**0.735**	**0.900**	**0.964**	**6.3**

Table 5: Numerical comparisons with our proposed Quaternion & Rotation Laplace distribution and baselines on ModelNet10-SO3 dataset. One model is trained for each category. Quaternion Laplace distribution clearly outperforms Bingham distribution (Deng et al., 2022).

	Chair			Sofa			Toilet			Bed		
	Mean↓	Med.↓	Acc@5↑	Mean↓	Med.↓	Acc@5↑	Mean↓	Med.↓	Acc@5↑	Mean↓	Med.↓	Acc@5↑
Deng et al. (2022)	16.5	7.2	0.31	16.5	4.9	0.52	9.6	4.2	0.59	22.0	5.1	0.49
Mohlin et al. (2020)	10.8	4.6	0.55	11.1	3.5	0.70	6.4	3.5	0.70	16.0	3.8	0.66
Quat. Laplace	12.6	5.2	0.49	13.1	3.7	0.67	5.9	3.4	0.69	17.7	3.4	0.69
Rot. Laplace	**9.7**	**3.5**	**0.68**	**8.8**	**2.1**	**0.84**	**5.3**	**2.6**	**0.83**	**15.5**	**2.3**	**0.82**

5.4 Implementation details

For fair comparisons, we follow the implementation designs of Mohlin et al. (2020) and merely change the distribution from matrix Fisher distribution to our Rotation Laplace distribution. For numerical stability, we clip $\mathrm{tr}(\mathbf{S} - \mathbf{A}^T\mathbf{R})$ by $\max(1\mathrm{e}-8, \mathrm{tr}(\mathbf{S} - \mathbf{A}^T\mathbf{R}))$ for Eq.2.

Specifically, we use pretrained ResNet-101 as our backbone, and encode the object class information (for single-model-all-category experiments) by an embedding layer that produces a 32-dim vector. We apply a 512-512-9 MLP as the output layer. The batch size is set as 32. We use the SGD optimizer and start with the learning rate of 0.01. For ModelNet10-SO3 dataset, we train 50 epochs with learning rate decaying by a factor of 10 at epochs 30, 40, and 45. For Pascal3D+ dataset, we train 120 epochs with the same learning rate decay at epochs 30, 60 and 90.

5.5 Ablation study

For the completeness of experiments, we also compare our proposed Quaternion Laplace distribution and Bingham distribution and report the performance in Table 5. As shown in the table, Quaternion Laplace distribution consistently achieves superior performance than its competitor, which validates the effectiveness of our Laplace-inspired derivations. However, its rotation error is in general larger than Rotation Laplace distribution, since its rotation representation, quaternion, is not a continuous representation, as pointed in Zhou et al. (2019), thus leading to inferior performance.

6 Conclusion

In this paper, we draw inspiration from multivariant Laplace distribution and derive two novel distributions for probabilistic rotation regression, namely, Rotation Laplace distribution for rotation matrices on $\mathrm{SO}(3)$ and Quaternion Laplace distribution for quaternions on $\mathcal{S}^3$. Extensive comparisons with both probabilistic and non-probabilistic baselines on ModelNet10-SO3 and Pascal3D+ datasets demonstrate the effectiveness and advantages of our proposed distributions.

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