## Article

# Information Geometry of Randomized Quantum State Tomography 

Akio Fujiwara ${ }^{1, *}$ and Koichi Yamagata ${ }^{2}$<br>1 Department of Mathematics, Osaka University, Toyonaka, Osaka 560-0043, Japan<br>2 Graduate School of Informatics and Engineering, The University of Electro-Communications, Chofu, Tokyo 182-8585, Japan; koichi.yamagata@uec.ac.jp<br>* Correspondence: fujiwara@math.sci.osaka-u.ac.jp

Received: 29 June 2018; Accepted: 13 August 2018; Published: 16 August 2018


#### Abstract

Suppose that a $d$-dimensional Hilbert space $\mathcal{H} \simeq \mathbb{C}^{d}$ admits a full set of mutually unbiased bases $\left\{\left|1^{(a)}\right\rangle, \ldots,\left|d^{(a)}\right\rangle\right\}$, where $a=1, \ldots, d+1$. A randomized quantum state tomography is a scheme for estimating an unknown quantum state on $\mathcal{H}$ through iterative applications of measurements $M^{(a)}=\left\{\left|1^{(a)}\right\rangle\left\langle 1^{(a)}\right|, \ldots,\left|d^{(a)}\right\rangle\left\langle d^{(a)}\right|\right\}$ for $a=1, \ldots, d+1$, where the numbers of applications of these measurements are random variables. We show that the space of the resulting probability distributions enjoys a mutually orthogonal dualistic foliation structure, which provides us with a simple geometrical insight into the maximum likelihood method for the quantum state tomography.


Keywords: quantum state tomography; mutually unbiased bases; information geometry; dualistic foliation; mixed coordinate system

## 1. Introduction

Quantum state tomography is a method of estimating an unknown quantum state represented on some Hilbert space $\mathcal{H}$, consisting of a fixed set of measurements that provides sufficient information about the unknown quantum state, as well as a data processing that maps each measurement outcome into the quantum state space $\mathcal{S}(\mathcal{H})$ on $\mathcal{H}$ [1]. A set of measurements that fulfils this requirement is sometimes called a measurement basis. For mathematical simplicity, we restrict ourselves to Hilbert spaces of finite dimensions.

To elucidate our motivation, let us treat the simplest case when $\mathcal{H} \simeq \mathbb{C}^{2}$. It is well known that there is a one-to-one affine correspondence between the qubit state space

$$
\mathcal{S}\left(\mathbb{C}^{2}\right):=\left\{\rho \in \mathbb{C}^{2 \times 2} \mid \rho \geq 0, \operatorname{Tr} \rho=1\right\}
$$

and the unit ball (called the Bloch ball)

$$
B:=\left\{x=\left(x_{1}, x_{2}, x_{3}\right) \in \mathbb{R}^{3} \mid\|x\|^{2}:=\left(x_{1}\right)^{2}+\left(x_{2}\right)^{2}+\left(x_{3}\right)^{2} \leq 1\right\} .
$$

In fact, the correspondence is explicitly given by the Stokes parametrization

$$
x \longmapsto \rho_{x}=\frac{1}{2}\left(I+x_{1} \sigma_{1}+x_{2} \sigma_{2}+x_{3} \sigma_{3}\right),
$$

where $\sigma_{1}, \sigma_{2}$, and $\sigma_{3}$ are the standard Pauli matrices. Since $E_{\rho_{x}}\left[\sigma_{i}\right]:=\operatorname{Tr} \rho_{x} \sigma_{i}=x_{i}$ for $i \in\{1,2,3\}$, the set $\sigma=\left(\sigma_{1}, \sigma_{2}, \sigma_{3}\right)$ of observables is regarded as an unbiased estimator [2-4] for the Stokes parameter $x=\left(x_{1}, x_{2}, x_{3}\right)$. This is the basic idea behind the standard qubit state tomography, which runs as
follows: suppose that, among $N$ independent experiments, the $i$ th Pauli matrix $\sigma_{i}$ was measured $N / 3$ times, and outcomes +1 (spin-up) and -1 (spin-down) were obtained $n_{i}^{+}$and $n_{i}^{-}$times, respectively. Then a naive estimate for the true value of the parameter $x=\left(x_{1}, x_{2}, x_{3}\right)$ is

$$
\hat{x}=\left(\hat{x}_{1}, \hat{x}_{2}, \hat{x}_{3}\right):=\left(\frac{n_{1}^{+}-n_{1}^{-}}{N / 3}, \frac{n_{2}^{+}-n_{2}^{-}}{N / 3}, \frac{n_{3}^{+}-n_{3}^{-}}{N / 3}\right) .
$$

When the estimate $\hat{x} \in[-1,1]^{3}$ falls outside the Bloch ball $B$, it needs to be corrected so that the new estimate lies in the Bloch ball $B$. The maximum likelihood method is a canonical one to obtain a corrected estimate [2,5-10]. From the point of view of information geometry [11-13], the maximum likelihood estimate (MLE) is the orthogonal projection from the temporary estimate $\hat{x}$ onto the Bloch ball $B$ with respect to the standard Fisher metric along the $\nabla^{(m)}$-geodesic [14], (cf., Appendix A).

Now let us deal with a slightly generalized situation: suppose that the $i$ th Pauli matrix $\sigma_{i}$ was measured $N_{i}$ times and outcomes +1 and -1 were obtained $n_{i}^{+}$and $n_{i}^{-}$times, respectively, where $\left\{N_{i}\right\}_{i=1,2,3}$ were random variables. Such a situation arises in an actual experiment due to unexpected particle loss [15]. We shall call such a generalized estimation scheme a randomized state tomography. A naive estimate in this case is the following:

$$
\hat{x}=\left(\hat{x}_{1}, \hat{x}_{2}, \hat{x}_{3}\right):=\left(\frac{n_{1}^{+}-n_{1}^{-}}{N_{1}}, \frac{n_{2}^{+}-n_{2}^{-}}{N_{2}}, \frac{n_{3}^{+}-n_{3}^{-}}{N_{3}}\right) .
$$

One may invoke the maximum likelihood method when $\hat{x}$ falls outside the Bloch ball. It is then interesting to ask if there is also a useful geometrical picture for the MLE even when the numbers $N_{i}$ of measurements are random variables.

The above mentioned problem is naturally extended to quantum state tomography on an arbitrary Hilbert space that admits a full set of mutually unbiased bases [16,17]. In a $d$-dimensional Hilbert space $\mathcal{H} \simeq \mathbb{C}^{d}, k$ orthonormal bases

$$
\left\{\left|\alpha^{(1)}\right\rangle\right\}_{\alpha \in\{1, \ldots, d\}},\left\{\left|\beta^{(2)}\right\rangle\right\}_{\beta \in\{1, \ldots, d\}}, \ldots,\left\{\left|\gamma^{(k)}\right\rangle\right\}_{\gamma \in\{1, \ldots, d\}}
$$

are called mutually unbiased if they satisfy

$$
\left|\left\langle\alpha^{(a)} \mid \beta^{(b)}\right\rangle\right|^{2}=\frac{1}{d}
$$

for all $a, b \in\{1, \ldots, k\}$ with $a \neq b$, and $\alpha, \beta \in\{1, \ldots, d\}$. It is known that the number $k$ of mutually unbiased bases (MUBs) is at most $d+1$ [18]. If there are $d+1$ MUBs, the Hilbert space $\mathcal{H}$ is said to admit a full set of MUBs. For example, when the dimension $d$ of $\mathcal{H}$ is a power of a prime, $\mathcal{H}$ admits a full set of MUBs [19]. Whether or not any Hilbert space admits a full set of MUBs is an open question [16].

In what follows, unless otherwise stated, we assume that the Hilbert space $\mathcal{H} \simeq \mathbb{C}^{d}$ under consideration admits a full set of MUBs. As demonstrated in Appendix B (cf., $[17,20]$ ), each density operator $\rho \in \mathcal{S}(\mathcal{H})$ can be uniquely represented as

$$
\begin{equation*}
\rho=\rho(\xi):=\sum_{a=1}^{d+1}\left\{\sum_{\alpha=1}^{d-1} \xi_{\alpha}^{(a)} M_{\alpha}^{(a)}+\left(1-\sum_{\beta=1}^{d-1} \xi_{\beta}^{(a)}\right) M_{d}^{(a)}\right\}-I, \tag{1}
\end{equation*}
$$

where

$$
M^{(a)}:=\left\{M_{1}^{(a)}, \ldots, M_{d}^{(a)}\right\}=\left\{\left|1^{(a)}\right\rangle\left\langle 1^{(a)}\right|, \ldots,\left|d^{(a)}\right\rangle\left\langle d^{(a)}\right|\right\}
$$

is the projection-valued measure (PVM) associated with the $a$ th orthogonal basis in the MUBs, and

$$
\xi:=\left(\xi_{\alpha}^{(a)}\right)_{(a, \alpha) \in\{1, \ldots, d+1\} \times\{1, \ldots, d-1\}}
$$

is a $\left(d^{2}-1\right)$-dimensional real parameter that is chosen so that $\rho(\xi) \geq 0$. A simple calculation shows that, if the $a$ th measurement $M^{(a)}$ is applied to the state $\rho(\xi)$, one obtains each outcome $\alpha \in\{1, \ldots, d\}$ with probability

$$
p_{\alpha}^{(a)}=\operatorname{Tr} \rho(\xi) M_{\alpha}^{(a)}= \begin{cases}\xi_{\alpha}^{(a)}, & \text { for } \alpha=1, \ldots, d-1  \tag{2}\\ 1-\sum_{\beta=1}^{d-1} \xi_{\beta}^{(a)}, & \text { for } \alpha=d\end{cases}
$$

This implies that the parametrization $\xi \mapsto \rho(\xi)$ establishes an affine isomorphism between the quantum state space

$$
\mathcal{S}\left(\mathbb{C}^{d}\right):=\left\{\rho \in \mathbb{C}^{d \times d} \mid \rho \geq 0, \operatorname{Tr} \rho=1\right\}
$$

and the convex set

$$
B:=\left\{\xi \in \mathbb{R}^{d^{2}-1} \mid \rho(\xi) \geq 0\right\}
$$

Incidentally, the Stokes parametrization $x \mapsto \rho_{x}$ for the qubit state space $\mathcal{S}\left(\mathbb{C}^{2}\right)$ is regarded as a special case of the above parametrization $\xi \mapsto \rho(\xi)$ for $\mathcal{S}\left(\mathbb{C}^{d}\right)$. In fact, the eigenvectors of the Pauli matrices $\sigma_{1}, \sigma_{2}, \sigma_{3}$ form a full set of MUBs on $\mathbb{C}^{2}$, and the Stokes parametrization $x=\left(x_{1}, x_{2}, x_{3}\right)$ is related to the above parametrization $\xi=\left(\xi_{1}^{(1)}, \xi_{1}^{(2)}, \xi_{1}^{(3)}\right)$ as

$$
\tilde{\xi}_{1}^{(a)}=\frac{x_{a}+1}{2}, \quad(a=1,2,3)
$$

Now that a standard affine parametrization $\xi \mapsto \rho(\xi)$ has been established on an arbitrary Hilbert space $\mathcal{H} \simeq \mathbb{C}^{d}$ that admits a full set of MUBs, the scheme of randomized state tomography is naturally extended to $\mathcal{H}$ as follows. Suppose that the $a$ th measurement $M^{(a)}$ was applied $N^{(a)}$ times and the outcome $\alpha \in\{1, \ldots, d\}$ was obtained $n_{\alpha}^{(a)}$ times, where $\left\{N^{(a)}\right\}_{a=1, \ldots, d+1}$ were random variables. Then, due to (2), a naive estimate for the parameter $\xi_{\alpha}^{(a)}$ is

$$
\hat{\xi}_{\alpha}^{(a)}=\frac{n_{\alpha}^{(a)}}{N^{(a)}}
$$

When the estimate $\hat{\xi}:=\left(\hat{\tilde{\zeta}}_{\alpha}^{(a)}\right) \in[0,1]^{d^{2}-1}$ falls outside the parameter space $B$, one may invoke the maximum likelihood method to obtain a corrected estimate.

The objective of the present paper is to clarify that the $\nabla^{(m)}$-projection interpretation for the MLE is still valid for the randomized state tomography by changing the standard Fisher metric into a deformed one depending on the realization of the random variables $N^{(a)}$, which might as well be called a randomized Fisher metric. Such a novel geometrical picture will provide important insights into the quantum metrology.

The paper is organized as follows. In Section 2, we first introduce a statistical model on an extended sample space $\Omega$ that represents the randomized state tomography. We then clarify that the probability simplex $\mathcal{P}(\Omega)$ is decomposed into mutually orthogonal dualistic foliation by means of certain $\nabla^{(m)}$ - and $\nabla^{(e)}$-autoparallel submanifolds. In Section 3, we give a statistical interpretation of the above-mentioned dualistic foliation structure. In particular, we point out that the MLE is the $\nabla^{(m)}$-projection with respect to a deformed Fisher metric that depends on the realization of the random variables $N^{(a)}$. These results are demonstrated by several illustrative examples in Section 4. Finally, some concluding remarks are presented in Section 5 . For the reader's convenience, some background information is provided in Appendices A and B, including information geometry of the MLE and affine parametrization of a quantum state space $\mathcal{S}(\mathcal{H})$.

## 2. Geometry of Randomized State Tomography

We identify the randomized state tomography on $\mathcal{H} \simeq \mathbb{C}^{d}$ with the following scheme [21]: at each step of the measurement, one chooses a PVM $M^{(a)}$ at random with probability $s^{(a)},(a=1, \ldots, d+1)$, and applies the chosen PVM to yield an outcome $\alpha \in\{1, \ldots, d\}$. The sample space $\Omega$ for this statistical picture is

$$
\Omega=\{(a, \alpha) \mid a \in\{1, \ldots, d+1\}, \alpha \in\{1, \ldots, d\}\} .
$$

Suppose that the unknown state $\rho$ is specified by the coordinate $\xi \in B$ as (1). Then the corresponding probability distribution on $\Omega$ is represented by the $d(d+1)$-dimensional probability vector

$$
\begin{gathered}
p_{(s, \xi)}:=\left(s^{(1)}\left(\xi_{1}^{(1)}, \ldots, \xi_{d-1}^{(1)}, 1-\sum_{\alpha=1}^{d-1} \xi_{\alpha}^{(1)}\right), \ldots, s^{(d)}\left(\xi_{1}^{(d)}, \ldots, \xi_{d-1}^{(d)}, 1-\sum_{\alpha=1}^{d-1} \xi_{\alpha}^{(d)}\right)\right. \\
\left.\left(1-\sum_{a=1}^{d} s^{(a)}\right)\left(\xi_{1}^{(d+1)}, \ldots, \xi_{d-1}^{(d+1)}, 1-\sum_{\alpha=1}^{d-1} \xi_{\alpha}^{(d+1)}\right)\right)
\end{gathered}
$$

where the parameter $s:=\left(s^{(1)}, \ldots, s^{(d)}\right)$ belongs to the domain

$$
D:=\left\{s \in \mathbb{R}^{d} \mid s^{(a)}>0 \text { for } a \in\{1, \ldots, d\}, \text { and } \sum_{a=1}^{d} s^{(a)}<1\right\}
$$

Note that the family

$$
\left\{p_{(s, \xi)} \mid s \in D, \xi \in \Xi\right\}
$$

with

$$
\begin{gathered}
\Xi:=\left\{\xi \in \mathbb{R}^{d^{2}-1} \mid \xi_{\alpha}^{(a)}>0 \text { for }(a, \alpha) \in\{1, \ldots, d+1\} \times\{1, \ldots, d-1\}\right. \\
\text { and } \left.\sum_{\alpha=1}^{d-1} \xi_{\alpha}^{(a)}<1 \text { for } a \in\{1, \ldots, d+1\}\right\}
\end{gathered}
$$

forms a $\left(d^{2}+d-1\right)$-dimensional open probability simplex $\mathcal{P}(\Omega)$, and the parameters $(s, \xi)$ form a coordinate system of $\mathcal{P}(\Omega)$. Since we are only interested in estimating the parameter $\xi \in \Xi$, the remaining parameter $s \in D$ is understood as a set of nuisance parameters [2,12]. In what follows, we regard $\mathcal{P}(\Omega)$ as a statistical manifold endowed with the standard dualistic structure $\left(g, \nabla^{(e)}, \nabla^{(m)}\right)$, where $g$ is the Fisher metric, and $\nabla^{(e)}$ and $\nabla^{(m)}$ are the exponential and mixture connections [12].

Let us consider the following submanifolds of $\mathcal{P}(\Omega)$ :

$$
M(s):=\left\{p_{(s, \xi)} \mid \xi \in \Xi\right\}
$$

for each $s \in D$, and

$$
E(\xi):=\left\{p_{(s, \xi)} \mid s \in D\right\}
$$

for each $\xi \in \Xi$. Since $M(s)$ and $E(\xi)$ are convex subsets of $\mathcal{P}(\Omega)$, they are both $\nabla^{(m)}$-autoparallel. In addition, we have the following.

Proposition 1. For each $\xi \in \Xi$, the submanifold $E(\xi)$ is $\nabla^{(e)}$-autoparallel. Furthermore, for each $s \in D$ and $\xi \in \Xi$, the submanifolds $M(s)$ and $E(\xi)$ are mutually orthogonal with respect to the Fisher metric $g$.

Proof. Let us change the coordinate system $(s, \xi)$ into $\left(\eta_{\langle a\rangle}, \eta_{\langle b, \alpha\rangle}\right)$, where

$$
\eta_{\langle a\rangle}:=s^{(a)}
$$

for $a \in\{1, \ldots, d\}$, and

$$
\eta_{\langle b, \alpha\rangle}:=s^{(b)} \xi_{\alpha}^{(b)}
$$

for $(b, \alpha) \in\{1, \ldots, d+1\} \times\{1, \ldots, d-1\}$. With this coordinate transformation, the probability vector $p_{(s, \zeta)}$ is rewritten as

$$
\begin{equation*}
p_{\eta}=\bigoplus_{a=1}^{d+1}\left(\eta_{\langle a, 1\rangle}, \ldots, \eta_{\langle a, d-1\rangle}, \eta_{\langle a\rangle}-\sum_{\alpha=1}^{d-1} \eta_{\langle a, \alpha\rangle}\right) . \tag{3}
\end{equation*}
$$

Here, $\eta_{\langle d+1\rangle}$ is a function of $\left\{\eta_{\langle a\rangle}\right\}_{a \in\{1, \ldots, d\}}$ defined by

$$
\eta_{\langle d+1\rangle}:=1-\sum_{a=1}^{d} \eta_{\langle a\rangle}
$$

and is not a component of the coordinate system $\eta:=\left(\eta_{\langle a\rangle}, \eta_{\langle b, \alpha\rangle}\right)$. We see from the representation (3) that the coordinate system $\eta$ is $\nabla^{(m)}$-affine. The potential function for $\eta$ is given by the negative entropy

$$
\begin{aligned}
\varphi(\eta) & :=\sum_{\omega \in \Omega} p_{\eta}(\omega) \log p_{\eta}(\omega) \\
& =\sum_{a=1}^{d+1}\left\{\sum_{\alpha=1}^{d-1} \eta_{\langle a, \alpha\rangle} \log \eta_{\langle a, \alpha\rangle}+\left(\eta_{\langle a\rangle}-\sum_{\beta=1}^{d-1} \eta_{\langle a, \beta\rangle}\right) \log \left(\eta_{\langle a\rangle}-\sum_{\beta=1}^{d-1} \eta_{\langle a, \beta\rangle}\right)\right\}
\end{aligned}
$$

and the dual $\nabla^{(e)}$-affine coordinate system $\theta$ is given by

$$
\theta^{\langle a\rangle}=\frac{\partial \varphi}{\partial \eta_{\langle a\rangle}}=\log \frac{s^{(a)}}{\left(1-\sum_{b=1}^{d} s^{(b)}\right)}+\log \frac{\left(1-\sum_{\beta=1}^{d-1} \xi_{\beta}^{(a)}\right)}{\left(1-\sum_{\beta=1}^{d-1} \xi_{\beta}^{(d+1)}\right)}
$$

for $a \in\{1, \ldots, d\}$, and

$$
\theta^{\langle b, \alpha\rangle}=\frac{\partial \varphi}{\partial \eta_{\langle b, \alpha\rangle}}=\log \frac{\xi_{\alpha}^{(b)}}{\left(1-\sum_{\beta=1}^{d-1} \xi_{\beta}^{(b)}\right)}
$$

for $(b, \alpha) \in\{1, \ldots, d+1\} \times\{1, \ldots, d-1\}$. Thus, fixing $\xi$ is equivalent to fixing the coordinates $\left(\theta^{\langle b, \alpha\rangle}\right)_{(b, \alpha) \in\{1, \ldots, d+1\} \times\{1, \ldots, d-1\}^{\prime}}$ and the submanifold $E(\xi)$ is generated by changing the remaining parameters $\left(\theta^{\langle a\rangle}\right)_{a \in\{1, \ldots, d\}}$. This implies that $E(\xi)$ is $\nabla^{(e)}$-autoparallel, proving the first part of the claim.

To prove the second part, let us introduce a mixed coordinate system [11]

$$
\left(\eta_{\langle a\rangle} ; \theta^{\langle b, \alpha\rangle}\right)_{a \in\{1, \ldots, d\},(b, \alpha) \in\{1, \ldots, d+1\} \times\{1, \ldots, d-1\}}
$$

of $\mathcal{P}(\Omega)$. Since $\eta_{\langle a\rangle}=s^{(a)}$, the submanifold $M(s)$ is rewritten as

$$
M(s)=\left\{p_{(s, \xi)} \mid\left(\eta_{\langle a\rangle}\right)_{a \in\{1, \ldots, d\}} \text { are fixed and }\left(\theta^{\langle b, \alpha\rangle}\right)_{(b, \alpha) \in\{1, \ldots, d+1\} \times\{1, \ldots, d-1\}} \text { are arbitrary }\right\}
$$

On the other hand, the submanifold $E(\xi)$ is rewritten as
$E(\xi)=\left\{p_{(s, \xi)} \mid\left(\theta^{\langle b, \alpha\rangle}\right)_{(b, \alpha) \in\{1, \ldots, d+1\} \times\{1, \ldots, d-1\}}\right.$ are fixed and $\left(\eta_{\langle a\rangle}\right)_{a \in\{1, \ldots, d\}}$ are arbitrary $\}$.
Thus, the orthogonality of $M(s)$ and $E(\xi)$ is an immediate consequence of the orthogonality of the dual affine coordinate systems $\theta$ and $\eta$ with respect to the Fisher metric $g$.

Proposition 1 implies that the manifold $\mathcal{P}(\Omega)$ is decomposed into mutually orthogonal dualistic foliation based on the submanifolds $M(s)$ and $E(\xi)$, as illustrated in Figure 1. We shall exploit this geometrical structure in the next section.


Figure 1. Mutually orthogonal dualistic foliation of $\mathcal{P}(\Omega)$ based on $M(s)$ and $E(\xi)$. Each section $M(s)$ is affinely isomorphic to the parameter space $\Xi$. The greyish cylindrical area indicates the subset $\mathcal{B}=\left\{p_{(s, \xi)} \mid s \in D, \xi \in B\right\}$ of $\mathcal{P}(\Omega)$. In particular, for each $s \in D$, the intersection $M(s) \cap \mathcal{B}$ is affinely isomorphic to the physical domain $B$ that corresponds to the state space $\mathcal{S}(\mathcal{H})$.

## 3. Estimation of the Parameter $\xi$

Let us proceed to the problem of estimating the unknown parameter $\xi$ using the randomized tomography. Suppose that, among $N$ independent repetitions of experiments, the $a$ th measurement $M^{(a)}$ was applied $N^{(a)}$ times and outcomes $\alpha \in\{1, \ldots, d\}$ were obtained $n_{\alpha}^{(a)}$ times. Then temporary estimates $(\hat{s}, \hat{\xi})$ for the parameters $(s, \xi)$ are given by

$$
\hat{s}^{(a)}:=\frac{N^{(a)}}{N}
$$

for $a \in\{1, \ldots, d\}$, and

$$
\hat{\xi}_{\beta}^{(b)}:=\frac{n_{\beta}^{(b)}}{N^{(b)}}
$$

for $(b, \beta) \in\{1, \ldots, d+1\} \times\{1, \ldots, d-1\}$. If $\hat{\xi}$ has fallen outside the physical domain $B$, one may seek a corrected estimate by the maximum likelihood method. Observe that, due to (2), the empirical distribution $\hat{q}_{N} \in \mathcal{P}(\Omega)$ is represented as

$$
\begin{equation*}
\hat{q}_{N}=p_{(\hat{s}, \hat{\xi})} . \tag{4}
\end{equation*}
$$

On the other hand, the physical domain $B$ in the parameter space $\Xi$ corresponds to the subset

$$
\mathcal{B}:=\left\{p_{(s, \xi)} \mid s \in D, \xi \in B\right\}
$$

of $\mathcal{P}(\Omega)$, (see Figure 1). The MLE $p^{*}$ in $\mathcal{P}(\Omega)$ is then given by

$$
\begin{equation*}
p^{*}=\underset{p \in \mathcal{B}}{\arg \min } D\left(\hat{q}_{N} \| p\right), \tag{5}
\end{equation*}
$$

where $D(\cdot \| \cdot$ ) is the Kullback-Leibler divergence (cf., Appendix A). A crucial observation is the following.

Proposition 2. The minimum in (5) is achieved on $M(\hat{s}) \cap \mathcal{B}$.
Proof. Let us take a point $p_{(s, \xi)} \in \mathcal{B}$ arbitrarily. It then follows from the mutually orthogonal dualistic foliation of $\mathcal{P}(\Omega)$ established in Proposition 1 that

$$
\begin{aligned}
D\left(\hat{q}_{N} \| p_{(s, \xi)}\right) & =D\left(p_{(\hat{s}, \hat{\xi})} \| p_{(s, \tilde{\xi})}\right) \\
& =D\left(p_{(\hat{s}, \hat{\xi})} \| p_{(\hat{s}, \tilde{\zeta})}\right)+D\left(p_{(\hat{s}, \xi)} \| p_{(s, \xi)}\right) \\
& \geq D\left(p_{(\hat{s}, \hat{\zeta})} \| p_{(\hat{s}, \tilde{\zeta})}\right) .
\end{aligned}
$$

In the second equality, the generalized Pythagorean theorem was used. Consequently,

$$
\min _{\tilde{\xi} \in B} D\left(p_{(\hat{s}, \hat{\xi})} \| p_{(s, \tilde{\xi})}\right) \geq \min _{\tilde{\xi} \in B} D\left(p_{(\hat{s}, \hat{\xi})} \| p_{(\hat{s}, \xi)}\right)
$$

for all $s \in D$, and the right-hand side is achieved if and only if $s=\hat{s}$.
The geometrical implication of Proposition 2 is illustrated in Figure 2. The MLE $p^{*}=p_{\left(\hat{s}, 5^{*}\right)}$ is the $\nabla^{(m)}$-projection from the empirical distribution $p_{(\hat{s}, \hat{\xi})}$ to $\mathcal{B}$, and is on the section $M(\hat{s})$ specified by the temporary estimate $\hat{s}$.


Figure 2. The maximum likelihood method in the framework of randomized tomography. Given a temporary estimate $(\hat{s}, \hat{\zeta})$ with $\hat{\xi} \notin B$, we can restrict ourselves to the section $M(\hat{s})$ as the search space for the MLE $p^{*}$, and $p^{*}=p_{\left(\hat{s}, \zeta^{*}\right)}$ is the $\nabla^{(m)}$-projection from the empirical distribution $p_{(\hat{s}, \hat{\xi})}$ to $\mathcal{B}$ on the section $M(\hat{s})$.

Now we arrive at a geometrical picture behind the parameter estimation based on randomized state tomography. Suppose we are given a temporary estimate $(\hat{s}, \hat{\xi})$ with $\hat{\xi} \notin B$. Due to Proposition 2, we can restrict ourselves to section $M(\hat{s})$ as the search space for the MLE $p^{*}$. Since each section $M(\hat{s})$ is affinely isomorphic to the parameter space $\Xi$, we can introduce a dualistic structure $\left(\tilde{g}, \tilde{\nabla}^{(e)}, \tilde{\nabla}^{(m)}\right)$ on $\Xi$ in the following way. Firstly, we identify the metric $\tilde{g}$ with the Fisher metric $g$ restricted on $M(\hat{s})$, that is,

$$
\begin{aligned}
\tilde{g}_{(\hat{s}, \xi)}\left(\frac{\partial}{\partial \tilde{\xi}_{\alpha}^{(a)}}, \frac{\partial}{\partial \xi_{\beta}^{(b)}}\right) & =\left.\frac{\partial \eta_{\left\langle a^{\prime}, \alpha^{\prime}\right\rangle}^{(a)}}{\partial \tilde{\xi}_{\alpha}^{(a)}} \frac{\partial \eta_{\left\langle b^{\prime}, \beta^{\prime}\right\rangle}}{\partial \xi_{\beta}^{(b)}} g_{(s, \xi)}\left(\frac{\partial}{\partial \eta_{\left\langle a^{\prime}, \alpha^{\prime}\right\rangle}}, \frac{\partial}{\partial \eta_{\left\langle b^{\prime}, \beta^{\prime}\right\rangle}}\right)\right|_{s=\hat{s}} \\
& =\left.s^{(a)} s^{(b)} \frac{\partial^{2} \varphi(\eta)}{\partial \eta_{\langle a, \alpha\rangle} \partial \eta_{\langle b, \beta\rangle}}\right|_{s=\hat{s}} \\
& =\delta_{a b \hat{s}^{(a)}}\left(\frac{1}{\tilde{\xi}_{d}^{(a)}}+\frac{\delta_{\alpha \beta}}{\xi_{\alpha}^{(a)}}\right)
\end{aligned}
$$

for $a, b \in\{1, \ldots, d+1\}$ and $\alpha, \beta \in\{1, \ldots, d-1\}$, where $\hat{s}^{(d+1)}$ and $\xi_{d}^{(a)}$ are formally defined as

$$
\hat{s}^{(d+1)}:=1-\sum_{a=1}^{d} \hat{\mathcal{s}}^{(a)}, \quad \tilde{\xi}_{d}^{(a)}:=1-\sum_{\alpha=1}^{d-1} \tilde{\xi}_{\alpha}^{(a)}
$$

Secondly, the mixture connection $\tilde{\nabla}^{(m)}$ on $\Xi$ is defined through the natural affine isomorphism between $M(\hat{s})$ and $\Xi$. Finally, the dual connection $\tilde{\nabla}^{(e)}$ is defined by the duality

$$
\tilde{g}\left(\tilde{\nabla}_{X}^{(e)} Y, Z\right):=X \tilde{g}(Y, Z)-\tilde{g}\left(Y, \tilde{\nabla}_{X}^{(m)} Z\right)
$$

Thus, the MLE $\xi^{*}$ in the parameter space $\Xi$ is interpreted as the $\tilde{\nabla}^{(m)}$-projection from $\hat{\xi}$ to the physical domain $B$ with respect to the metric $\tilde{g}$.

## 4. Examples

In this section, we present some examples that demonstrate the implication of Proposition 2 as well as the general diagram given in Figure 2.

### 4.1. When $\operatorname{dim} \mathcal{H}=2$

Let us first study the simplest case when $\mathcal{H}=\mathbb{C}^{2}$. A full set of MUBs is given by

$$
\begin{aligned}
\left\{\left|1^{(1)}\right\rangle,\left|2^{(1)}\right\rangle\right\} & =\left\{\frac{1}{\sqrt{2}}\binom{1}{1}, \frac{1}{\sqrt{2}}\binom{1}{-1}\right\}, \\
\left\{\left|1^{(2)}\right\rangle,\left|2^{(2)}\right\rangle\right\} & =\left\{\frac{1}{\sqrt{2}}\binom{1}{-i}, \frac{1}{\sqrt{2}}\binom{1}{i}\right\}, \\
\left\{\left|1^{(3)}\right\rangle,\left|2^{(3)}\right\rangle\right\} & =\left\{\binom{1}{0},\binom{0}{1}\right\} .
\end{aligned}
$$

With these bases, the parameter representation (1) becomes

$$
\rho=\frac{1}{2}\left(\begin{array}{cc}
1+x_{3} & x_{1}-i x_{2} \\
x_{1}+i x_{2} & 1-x_{3}
\end{array}\right)
$$

where $x=\left(x_{1}, x_{2}, x_{3}\right)$ is the standard Stokes parameter, which is related to $\xi=\left(\xi_{1}^{(1)}, \xi_{1}^{(2)}, \xi_{1}^{(3)}\right)$ as $x_{a}=2 \tilde{\zeta}_{1}^{(a)}-1$ for $a=1,2,3$.

Figure 3 demonstrates how the $\tilde{\nabla}^{(m)}$-projection is realized. Here, the trajectories of $\tilde{\nabla}^{(m)}$-projections that gives the MLE $p^{*}$ are plotted only on the $x_{1} x_{2}$-plane. The left and right panels correspond to the cases when $N^{(1)}: N^{(2)}=1: 1$ and $N^{(1)}: N^{(2)}=5: 1$, respectively. The change of $\xi_{1}$-coordinate relative to the change of $x_{2}$-coordinate along each trajectory is less noticeable in the right panel than in the left panel. This is because a tomography with $N^{(1)} / N^{(2)}=5$ provides us with more information about $x_{1}$-coordinate, relative to $x_{2}$-coordinate, as compared with the case when $N^{(1)} / N^{(2)}=1$.


Figure 3. The trajectories of $\tilde{\nabla}^{(m)}$-projections on the Stokes parameter space when $N^{(1)}: N^{(2)}=1: 1$ (left) and $N^{(1)}: N^{(2)}=5: 1$ (right). The greyish disk represents the Bloch ball $B$.
4.2. When $\operatorname{dim} \mathcal{H}=3$

The space $\mathcal{H}=\mathbb{C}^{3}$ admits a full set of MUBs; for example,

$$
\begin{aligned}
& \left\{\left|1^{(1)}\right\rangle,\left|2^{(1)}\right\rangle,\left|3^{(1)}\right\rangle\right\}=\left\{\left(\begin{array}{l}
1 \\
0 \\
0
\end{array}\right),\left(\begin{array}{l}
0 \\
1 \\
0
\end{array}\right),\left(\begin{array}{l}
0 \\
0 \\
1
\end{array}\right)\right\}, \\
& \left\{\left|1^{(2)}\right\rangle,\left|2^{(2)}\right\rangle,\left|3^{(2)}\right\rangle\right\}=\left\{\frac{1}{\sqrt{3}}\left(\begin{array}{l}
1 \\
1 \\
1
\end{array}\right), \frac{1}{\sqrt{3}}\left(\begin{array}{c}
1 \\
\omega \\
\omega^{2}
\end{array}\right), \frac{1}{\sqrt{3}}\left(\begin{array}{c}
1 \\
\omega^{2} \\
\omega
\end{array}\right)\right\}, \\
& \left\{\left|1^{(3)}\right\rangle,\left|2^{(3)}\right\rangle,\left|3^{(3)}\right\rangle\right\}=\left\{\frac{1}{\sqrt{3}}\left(\begin{array}{c}
\omega \\
1 \\
1
\end{array}\right), \frac{1}{\sqrt{3}}\left(\begin{array}{c}
1 \\
\omega \\
1
\end{array}\right), \frac{1}{\sqrt{3}}\left(\begin{array}{c}
1 \\
1 \\
\omega
\end{array}\right)\right\} \\
& \left\{\left|1^{(4)}\right\rangle,\left|2^{(4)}\right\rangle,\left|3^{(4)}\right\rangle\right\}=\left\{\frac{1}{\sqrt{3}}\left(\begin{array}{c}
\omega^{2} \\
1 \\
1
\end{array}\right), \frac{1}{\sqrt{3}}\left(\begin{array}{c}
1 \\
\omega^{2} \\
1
\end{array}\right), \frac{1}{\sqrt{3}}\left(\begin{array}{c}
1 \\
1 \\
\omega^{2}
\end{array}\right)\right\}
\end{aligned}
$$

where $\omega=(-1+i \sqrt{3}) / 2$ is a primitive third root of unity. With these bases, the parameter representation (1) becomes

$$
\rho=\left(\begin{array}{ccc}
\xi_{1}^{(1)} & a_{12}-i b_{12} & a_{13}-i b_{13} \\
a_{12}+i b_{12} & \xi_{2}^{(1)} & a_{23}-i b_{23} \\
a_{13}+i b_{13} & a_{23}+i b_{23} & 1-\xi_{1}^{(1)}-\xi_{2}^{(1)}
\end{array}\right)
$$

where

$$
\begin{aligned}
& a_{12}=\frac{1}{2}\left(1+\xi_{1}^{(2)}-\xi_{1}^{(3)}-\xi_{2}^{(3)}-\xi_{1}^{(4)}-\xi_{2}^{(4)}\right) \\
& a_{13}=\frac{1}{2}\left(-1+\xi_{1}^{(2)}+\xi_{2}^{(3)}+\xi_{2}^{(4)}\right), \\
& a_{23}=\frac{1}{2}\left(-1+\xi_{1}^{(2)}+\xi_{1}^{(3)}+\xi_{1}^{(4)}\right), \\
& b_{12}=\frac{\sqrt{3}}{6}\left(1-\xi_{1}^{(2)}-2 \xi_{2}^{(2)}+\xi_{1}^{(3)}-\xi_{2}^{(3)}-\xi_{1}^{(4)}+\xi_{2}^{(4)}\right), \\
& b_{13}=\frac{\sqrt{3}}{6}\left(-1+\xi_{1}^{(2)}+2 \xi_{2}^{(2)}+2 \xi_{1}^{(3)}+\xi_{2}^{(3)}-2 \xi_{1}^{(4)}-\xi_{2}^{(4)}\right), \\
& b_{23}=\frac{\sqrt{3}}{6}\left(1-\xi_{1}^{(2)}-2 \xi_{2}^{(2)}+\xi_{1}^{(3)}+2 \xi_{2}^{(3)}-\xi_{1}^{(4)}-2 \xi_{2}^{(4)}\right)
\end{aligned}
$$

The physical domain $B$ that corresponds to the state space $\mathcal{S}\left(\mathbb{C}^{3}\right)$ is a compact convex subset of the parameter space $\Xi\left(\subset \mathbb{R}^{8}\right)$, and the extreme points of $B$ form an algebraic variety with respect to the parameters

$$
\xi=\left(\xi_{1}^{(1)}, \xi_{2}^{(1)}, \xi_{1}^{(2)}, \xi_{2}^{(2)}, \xi_{1}^{(3)}, \xi_{2}^{(3)}, \xi_{1}^{(4)}, \xi_{2}^{(4)}\right)
$$

A numerical example of a $\tilde{\nabla}^{(m)}$-projection that gives the MLE is illustrated in Figure 4, where no probe particle is lost, that is, when

$$
\hat{s}=\left(\frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4}\right) .
$$

In Figure 4, the dot laid outside the greyish region indicates the empirical distribution, i.e., the temporary estimate

$$
\hat{\xi}=(0.100,0.100,0.066,0.333,0.333,0.333,0.333,0.333)
$$

and the corresponding MLE is

$$
\xi_{*}=(0.122,0.122,0.108,0.329,0.299,0.327,0.327,0.299) .
$$



Figure 4. A trajectory of $\tilde{\nabla}^{(m)}$-projection displayed on randomly chosen two-dimensional affine subspaces of $\Xi$ to which both the empirical distribution (marked as a dot) and the MLE belong. The greyish region represents the physical domain $B$.

Furthermore, the greyish region represents the physical domain $B$ cut by a two-dimensional affine subspace of $\Xi$ specified by the equation

$$
\xi=(1-s) \hat{\xi}+s \xi_{*}+t v
$$

The vector $v$ was chosen randomly under the condition that

$$
v \perp \hat{\xi}-\xi_{*} \quad \text { and } \quad\|v\|=\left\|\hat{\xi}-\xi_{*}\right\|
$$

where the orthogonality $\perp$ and the norm $\|\cdot\|$ are understood relative to the standard Euclidean structure of $\mathbb{R}^{8}$. In Figure 4 , the vector $v$ was taken to be

$$
v_{1}=(-0.036,-0.038,0.012,-0.026,-0.038,0.011,0.002,0.005)
$$

in the left panel, and

$$
v_{2}=(0.028,0.000,-0.006,0.034,-0.024,-0.022,0.034,0.030)
$$

in the right panel.
Figure 4 also demonstrates that the sections of the physical domain $B$ show a variety of shapes. Unfortunately, due to this asymmetry of $B$, we were unable to find a (nontrivial) two-dimensional affine subspace on which every $\tilde{\nabla}^{(m)}$-projection runs. Such a difficulty is in good contrast to the simplest case $\mathcal{H} \simeq \mathbb{C}^{2}$, where the set $B$ is rotationally symmetric and the $\tilde{\nabla}^{(m)}$-projections can be displayed on any two-dimensional section of $B$ that passes through the origin of $B$ as Figure 3.

### 4.3. When $\operatorname{dim} \mathcal{H} \geq 4$

The space $\mathcal{H}=\mathbb{C}^{4}$ is also known to admit a full set of MUBs since $\operatorname{dim} \mathcal{H}=4$ is the second power of the prime number 2; for example [22],

$$
\begin{aligned}
& \left\{\left|1^{(1)}\right\rangle,\left|2^{(1)}\right\rangle,\left|3^{(1)}\right\rangle,\left|4^{(1)}\right\rangle\right\}=\left\{\left(\begin{array}{l}
1 \\
0 \\
0 \\
0
\end{array}\right),\left(\begin{array}{l}
0 \\
1 \\
0 \\
0
\end{array}\right),\left(\begin{array}{l}
0 \\
0 \\
1 \\
0
\end{array}\right),\left(\begin{array}{l}
0 \\
0 \\
0 \\
1
\end{array}\right)\right\}, \\
& \left\{\left|1^{(2)}\right\rangle,\left|2^{(2)}\right\rangle,\left|3^{(2)}\right\rangle,\left|4^{(2)}\right\rangle\right\}=\left\{\frac{1}{2}\left(\begin{array}{l}
1 \\
1 \\
1 \\
1
\end{array}\right), \frac{1}{2}\left(\begin{array}{c}
1 \\
1 \\
-1 \\
-1
\end{array}\right), \frac{1}{2}\left(\begin{array}{c}
1 \\
-1 \\
-1 \\
1
\end{array}\right), \frac{1}{2}\left(\begin{array}{c}
1 \\
-1 \\
1 \\
-1
\end{array}\right)\right\}, \\
& \left\{\left|1^{(3)}\right\rangle,\left|2^{(3)}\right\rangle,\left|3^{(3)}\right\rangle,\left|4^{(3)}\right\rangle\right\}=\left\{\begin{array}{l}
1 \\
\left.\frac{1}{2}\left(\begin{array}{c}
1 \\
-1 \\
-i \\
-i
\end{array}\right), \frac{1}{2}\left(\begin{array}{c}
1 \\
-1 \\
i \\
i
\end{array}\right), \frac{1}{2}\left(\begin{array}{c}
1 \\
1 \\
i \\
-i
\end{array}\right), \frac{1}{2}\left(\begin{array}{c}
1 \\
1 \\
-i \\
i
\end{array}\right)\right\}, \\
\left\{\left|1^{(4)}\right\rangle,\left|2^{(4)}\right\rangle,\left|3^{(4)}\right\rangle,\left|4^{(4)}\right\rangle\right\}
\end{array}\right\} \\
& \left.\frac{1}{2}\left(\begin{array}{c}
1 \\
-i \\
-i \\
-1
\end{array}\right), \frac{1}{2}\left(\begin{array}{c}
1 \\
-i \\
i \\
1
\end{array}\right), \frac{1}{2}\left(\begin{array}{c}
1 \\
i \\
i \\
-1
\end{array}\right), \frac{1}{2}\left(\begin{array}{c}
1 \\
i \\
-i \\
1
\end{array}\right)\right\}, \\
& \left\{\left\lvert\,\left(\begin{array}{c}
1 \\
-i \\
-1 \\
-i
\end{array}\right)\right., \frac{1}{2}\left(\begin{array}{c}
1 \\
-i \\
1 \\
i
\end{array}\right), \frac{1}{2}\left(\begin{array}{c}
1 \\
i \\
-1 \\
i
\end{array}\right), \frac{1}{2}\left(\begin{array}{c}
1 \\
i \\
1 \\
-i
\end{array}\right)\right\},
\end{aligned}
$$

It is straightforward to calculate the parameter representation (1) of a state $\rho \in \mathcal{S}\left(C^{4}\right)$; however, the corresponding density matrix is rather complicated, and we omit to display it here.

When $\mathcal{H}=\mathbb{C}^{6}$, or more generally, when $\operatorname{dim} \mathcal{H}$ is not a power of a prime, we do not know whether $\mathcal{H}$ admits a full set of MUBs. Let us touch upon a situation where a Hilbert space $\mathcal{H}$, if it exists, does not admit a full set of MUBs. In this case, there is no measurement basis $M^{(a)}$ that allows a parametrization $\xi$ of the state space $\mathcal{S}(\mathcal{H})$ having a direct connection to the probability distribution of the outcomes as (2). Such a situation could be comparable to the case when the Gell-Mann matrices [23] are used as the measurement basis for estimating an unknown state on $\mathcal{H}=\mathbb{C}^{3}$. A state $\rho \in \mathcal{S}\left(\mathbb{C}^{3}\right)$ is represented as

$$
\rho=\rho_{x}:=\frac{1}{3}\left(I+\sqrt{3} \sum_{i=1}^{8} x_{i} \lambda_{i}\right),
$$

where $\lambda_{1}, \ldots, \lambda_{8}$ are the Gell-Mann matrices, and $x=\left(x_{1}, \ldots, x_{8}\right)$ is a set of real parameters. The physical domain

$$
B=\left\{x \in \mathbb{R}^{8} \mid \rho_{x} \geq 0\right\}
$$

forms a compact convex subset of the unit ball in $\mathbb{R}^{8}$. With the state $\rho_{x}$, the probability distribution of obtaining the eigenvalues $(-1,0,1)$ of the observable $\lambda_{1}$ is

$$
\left(\frac{1-\sqrt{3} x_{1}+x_{8}}{3}, \frac{1-2 x_{8}}{3}, \frac{1+\sqrt{3} x_{1}+x_{8}}{3}\right)
$$

while the probability distribution of obtaining the eigenvalues $(-1,0,1)$ of the observable $\lambda_{2}$ is

$$
\left(\frac{1-\sqrt{3} x_{2}+x_{8}}{3}, \frac{1-2 x_{8}}{3}, \frac{1+\sqrt{3} x_{2}+x_{8}}{3}\right) .
$$

Note that the probability of obtaining the eigenvalue 0 of $\lambda_{1}$ is identical to that of $\lambda_{2}$. However, in a randomized estimation scheme in which $\lambda_{i}$ is measured $N_{i}$ times, the frequency of obtaining the eigenvalue 0 of $\lambda_{1}$ would be different from that of $\lambda_{2}$. Consequently, one cannot assign a consistent temporary estimate $\hat{x}_{8}$ for the parameter $x_{8}$ in that case. Put differently, the empirical distribution $\hat{q}_{N}$ on the extended outcome space $\Omega$ does not in general have a coordinate representation (4). Thus, the existence of a full set of MUBs is crucial in our analysis.

## 5. Concluding Remarks

In the present paper, we explored an information geometrical structure of the randomized quantum state tomography, assuming that the Hilbert space under consideration admits a full set of MUBs. We first introduced a classical statistical model $\left\{p_{(s, \xi)}\right\}_{s, \xi}$ on an extended sample space $\Omega$, and found that the probability simplex $\mathcal{P}(\Omega)$ was decomposed into mutually orthogonal dualistic foliation (Proposition 1). We then clarified that this geometrical structure had a statistical importance in estimating the coordinate $\xi$ of an unknown quantum state $\rho(\xi)$ under the existence of the nuisance parameter $s$ (Proposition 2). This result gave a generalized insight into the $\nabla^{(m)}$-projection interpretation for the MLE in that a similar interpretation was still valid for the randomized quantum state tomography by changing the standard Fisher metric into a deformed one. It also provided us with a new, convenient way of data processing in the actual quantum state tomography that may involve unexpected probe particle loss.

It should be noted that the existence of a full set of MUBs ensures the parametrization (1) of the quantum state space $\mathcal{S}(\mathcal{H})$. Such a parametrization is distinctive in that it enables a direct correspondence between the parameter space and the probability simplex, realizing the coordinate representation (4) of the empirical distribution $\hat{q}_{N}$. Thus, the use of a full set of MUBs is crucial in our analysis. Nevertheless, it is often the case that the Hilbert space under consideration takes the
form $\mathcal{H} \simeq\left(\mathbb{C}^{p}\right)^{\otimes n}$ for $p=2$ or 3 because qubits or qutrits are often regarded as building blocks of various quantum protocols. Therefore, the existence of a full set of MUBs would not be too strong a requirement in applications.

Author Contributions: The authors contributed equally to this work.
Funding: The present study was supported by JSPS KAKENHI Grant Numbers JP22340019 and JP17H02861.
Acknowledgments: The authors are grateful to Ryo Okamoto and Shigeki Takeuchi for helpful discussions.
Conflicts of Interest: The authors declare no conflict of interest.

## Abbreviations

The following abbreviations are used in this manuscript:
MUBs mutually unbiased bases
PVM projection-valued measure
MLE maximum likelihood estimate

## Appendix A. Information Geometry of MLE

Let $\mathcal{P}(\Omega)$ denote the set of probability distributions on a finite sample space $\Omega$, i.e.,

$$
\mathcal{P}(\Omega):=\left\{p: \Omega \rightarrow \mathbb{R} \mid p(\omega)>0 \text { for all } \omega \in \Omega, \text { and } \sum_{\omega \in \Omega} p(\omega)=1\right\}
$$

This set may be identified with the $(|\Omega|-1)$-dimensional (open) simplex, where $|\Omega|$ denotes the number of elements in $\Omega$, and thus it is sometimes referred to as the probability simplex on $\Omega$. The set $\mathcal{P}(\Omega)$ is also regarded as a statistical manifold endowed with the dualistic structure $\left(g, \nabla^{(e)}, \nabla^{(m)}\right)$, where $g$ is the Fisher metric, and $\nabla^{(e)}$ and $\nabla^{(m)}$ are the exponential and mixture connections [11-13].

Suppose that the state of the physical system at hand belongs to a (closed) subset $\mathcal{M}$ of $\mathcal{P}(\Omega)$, but we do not know which is the true state. We further assume that the probability distributions of $\mathcal{M}$ are faithfully parametrized by a finite dimensional parameter $\theta$ as

$$
\mathcal{M}=\left\{p_{\theta}(\omega) \mid \theta \in \Theta\right\}
$$

In this case, $\mathcal{M}$ is called a parametric model, and our task is to estimate the true value of the parameter $\theta$ that specifies the true state. Suppose that, by $n$ independent experiments, we have obtained data $\left(x_{1}, x_{2}, \ldots, x_{n}\right) \in \Omega^{n}$. This information is compressed into the empirical distribution, an element of $\mathcal{P}(\Omega)$ defined by

$$
\begin{aligned}
\hat{q}_{n}(\omega) & :=\frac{\text { Number of occurrences of } \omega \text { in data }\left(x_{1}, x_{2}, \ldots, x_{n}\right)}{n} \\
& =\frac{1}{n} \sum_{i=1}^{n} \delta_{x_{i}}(\omega)
\end{aligned}
$$

for each $\omega \in \Omega$, where $\delta_{x_{i}}(\omega)$ is the Kronecker delta. If $\hat{q}_{n}$ belongs to the model $\mathcal{M}$, then we have an estimate $\hat{\theta}_{n}$ that satisfies $p_{\hat{\theta}_{n}}=\hat{q}_{n}$. However, the empirical distribution $\hat{q}_{n}$ does not always belong to the model $\mathcal{M}$. When $\hat{q}_{n} \notin \mathcal{M}$, we need to find an alternative estimate from the data. A canonical method of finding an alternative estimate $p_{\hat{\theta}_{n}} \in \mathcal{M}$ is the maximum likelihood method, in which one seeks the maximizer of the likelihood function

$$
\theta \longmapsto p_{\theta}\left(x_{1}\right) p_{\theta}\left(x_{2}\right) \ldots p_{\theta}\left(x_{n}\right),
$$

within the domain $\Theta$ of the parameter $\theta$, so that

$$
\hat{\theta}_{n}:=\underset{\theta \in \Theta}{\arg \max }\left\{p_{\theta}\left(x_{1}\right) p_{\theta}\left(x_{2}\right) \cdots p_{\theta}\left(x_{n}\right)\right\}
$$

We can rewrite this relation as follows.

$$
\begin{aligned}
\hat{\theta}_{n} & =\underset{\theta \in \Theta}{\arg \max } \frac{1}{n} \sum_{i=1}^{n} \log p_{\theta}\left(x_{i}\right) \\
& =\underset{\theta \in \Theta}{\arg \max } \sum_{\omega \in \Omega} \hat{q}_{n}(\omega) \log p_{\theta}(\omega) \\
& =\underset{\theta \in \Theta}{\arg \min } \sum_{\omega \in \Omega} \hat{q}_{n}(\omega)\left\{\log \hat{q}_{n}(\omega)-\log p_{\theta}(\omega)\right\} \\
& =\underset{\theta \in \Theta}{\arg \min } D\left(\hat{q}_{n} \| p_{\theta}\right),
\end{aligned}
$$

where

$$
D(q \| p):=\sum_{\omega \in \Omega} q(\omega) \log \frac{q(\omega)}{p(\omega)}
$$

is the Kullback-Leibler divergence from $q$ to $p$. In other words, the maximum likelihood estimate (MLE) $p_{\hat{\theta}_{n}}$ is the point on $\mathcal{M}$ that is "closest" from the empirical distribution $\hat{q}_{n}$ as measured by the Kullback-Leibler divergence:

$$
p_{\hat{\theta}_{n}}=\underset{p \in \mathcal{M}}{\arg \min } D\left(\hat{q}_{n} \| p\right)
$$

Due to the generalized Pythagorean theorem, the MLE is geometrically understood as the $\nabla^{(m)}$-projection from $\hat{q}_{n}$ to $\mathcal{M}$ or its boundary, as illustrated in Figure A1.


Figure A1. The maximum likelihood estimate $p_{\hat{\theta}_{n}}$ is the minimizer of the function $p \mapsto D\left(\hat{q}_{n} \| p\right)$ with respect to $p \in \mathcal{M}$, and is also understood as the $\nabla^{(m)}$-projection from the empirical distribution $\hat{q}_{n}$ to $\mathcal{M}$ or its boundary.

## Appendix B. Parametrization of $\mathcal{S}(\mathcal{H})$

Suppose that the Hilbert space $\mathcal{H} \simeq \mathbb{C}^{d}$ under consideration admits a full set of MUBs

$$
\left\{\left|\alpha^{(a)}\right\rangle\right\}_{\alpha \in\{1, \ldots, d\}}, \quad(a=1, \ldots, d+1)
$$

For each $a \in\{1, \ldots, d+1\}$, let

$$
M^{(a)}:=\left\{M_{1}^{(a)}, \ldots, M_{d}^{(a)}\right\}=\left\{\left|1^{(a)}\right\rangle\left\langle 1^{(a)}\right|, \ldots,\left|d^{(a)}\right\rangle\left\langle d^{(a)}\right|\right\}
$$

Then, the operators

$$
\left\{M_{\alpha}^{(a)}-\frac{I}{d}\right\}_{(a, \alpha) \in\{1, \ldots, d+1\} \times\{1, \ldots, d-1\}}
$$

are linearly independent, spanning the space of selfadjoint operators with zero trace. This is easily seen from the orthogonality relation:

$$
\operatorname{Tr}\left(M_{\alpha}^{(a)}-\frac{I}{d}\right)\left(M_{\beta}^{(b)}-\frac{I}{d}\right)=\delta_{a b}\left(\delta_{\alpha \beta}-\frac{1}{d}\right)
$$

Thus, given $\rho \in \mathcal{S}(\mathcal{H})$, the operator $\rho-(I / d)$ is uniquely expanded as

$$
\rho-\frac{I}{d}=\sum_{a=1}^{d+1} \sum_{\alpha=1}^{d-1} x_{\alpha}^{(a)}\left(M_{\alpha}^{(a)}-\frac{I}{d}\right)
$$

where $x_{\alpha}^{(a)}$ are real numbers. We can regard $x_{\alpha}^{(a)}$ as a coordinate system of the state space $\mathcal{S}(\mathcal{H})$. When $d=2$, this is identical to the Stokes parametrization, up to a factor of 2.

Now, let us change the coordinate system $x_{\alpha}^{(a)}$ into $\xi_{\alpha}^{(a)}$ as

$$
x_{\alpha}^{(a)}=\xi_{\alpha}^{(a)}+\left(\sum_{\beta=1}^{d-1} \xi_{\beta}^{(a)}\right)-1
$$

We then arrive at the parametrization (1), i.e.,

$$
\rho=\sum_{a=1}^{d+1}\left\{\sum_{\alpha=1}^{d-1} \xi_{\alpha}^{(a)} M_{\alpha}^{(a)}+\left(1-\sum_{\beta=1}^{d-1} \xi_{\beta}^{(a)}\right) M_{d}^{(a)}\right\}-I
$$

This parametrization is useful in our analysis because it gives a direct connection to the probability distribution of outcomes of the measurement $M^{(a)}$ as

$$
p_{\alpha}^{(a)}:=\operatorname{Tr} \rho M_{\alpha}^{(a)}= \begin{cases}\xi_{\alpha}^{(a)}, & \text { for } \alpha=1, \ldots, d-1 \\ 1-\sum_{\beta=1}^{d-1} \xi_{\beta}^{(a)}, & \text { for } \alpha=d\end{cases}
$$

## References

1. Nielsen, M.A.; Chuang, I.L. Quantum Computation and Quantum Information; Cambridge University Press: Cambridge, UK, 2000.
2. Lehmann, E.L.; Casella, G. Theory of Point Estimation, 2nd ed.; Springer: New York, NY, USA, 1998.
3. Helstrom, C.W. Quantum Detection and Estimation Theory; Academic Press: New York, NY, USA, 1976.
4. Holevo, A.S. Probabilistic and Statistical Aspects of Quantum Theory; North-Holland: Amsterdam, The Netherlands, 1982.
5. Hradil, Z. Quantum-State Estimation. Phys. Rev. A 1997, 55, R1561-R1564. [CrossRef]
6. Banaszek, K.; D’Ariano, G.M.; Paris, M.G.A.; Sacchi, M.F. Maximum-likelihood estimation of the density matrix. Phys. Rev. A 1999, 61, 010304. [CrossRef]
7. Hradil, Z.; Summhammer, J.; Badurek, G.; Rauch, H. Reconstruction of the spin state. Phys. Rev. A 2000, 62, 014101. [CrossRef]
8. James, D.F.V.; Kwiat, P.G.; Munro, W.J.; White, A.G. Measurement of qubits. Phys. Rev. A 2001, 64, 052312. [CrossRef]
9. De Burgh, M.D.; Langford, N.K.; Doherty, A.C.; Gilchrist, A. Choice of measurement sets in qubit tomography. Phys. Rev. A 2008, 78, 052122. [CrossRef]
10. Blune-Kohout, R. Optimal, reliable estimation of quantum states. New J. Phys. 2010, 12, 043034. [CrossRef]
11. Amari, S.-I.; Nagaoka, H. Methods of Information Geometry; Translations of Mathematical Monographs 191; AMS and Oxford: Charles Street, RI, USA, 2000.
12. Amari, S.-I. Differential-Geometrical Methods in Statistics; Lecture Notes in Statistics 28; Springer: Berlin, Germany, 1985.
13. Murray, M.K.; Rice, J.W. Differential Geometry and Statistics; Chapman \& Hall: London, UK, 1993.
14. Fujiwara, A.; Yamagata, K. Data processing for qubit state tomography: An information geometric approach. arXiv 2016, arXiv:1608.07983.
15. Fraïsse, J.M.E.; Braun, D. Quantum channel-estimation with particle loss: GHZ versus W states. Quantum Meas. Quantum Metrol. 2016, 3, 53. [CrossRef]
16. Durt, T.; Englert, B.-G.; Bengtsson, I.; Życzkowski, K. On mutually unbiased bases. Int. J. Quantum Inf. 2010, 8, 535-640. [CrossRef]
17. Yuan, H.; Zhou, Z.; Guo, G. Quantum state tomography via mutually unbiased measurements in driven cavity QED systems. New J. Phys. 2016, 18, 043013. [CrossRef]
18. Wootters, W.K.; Fields, B.D. Optimal state-determination by mutually unbiased measurements. Ann. Phys. 1989, 191, 363-381. [CrossRef]
19. Bengtsson, I. Three ways to look at mutually unbiased bases. arXiv 2006, arXiv:quant-ph/0610216.
20. Ivonovic, I.D. Geometrical description of quantal state determination. J. Phys. A 1981, 14, 3241-3245. [CrossRef]
21. Yamagata, K. Efficiency of quantum state tomography for qubits. Int. J. Quantum Inform. 2011, 9, 1167-1183. [CrossRef]
22. Klappenecker, A.; Rötteler, M. Constructions of mutually unbiased bases. arXiv 2003, arXiv:quant-ph/0309120.
23. Gell-Mann, M. Symmetries of baryons and mesons. Phys. Rev. 1962, 125, 1067. [CrossRef]
© 2018 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http:/ /creativecommons.org/licenses/by/4.0/).
