

# Parameter estimation for different quantum systems

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# Introduction

# State of a quantum system

- A finite quantum state  $\rho \in M_n(\mathbb{C})$  can be described with the following properties:

$$\text{Tr}(\rho) = 1, \quad \rho \geq 0$$

- Let  $\sigma_i$  be generalized Pauli-matrices: orthonormal basis with respect to the Hilbert-Schmidt inner product:

$$\langle A, B \rangle = \text{Tr}(A^* B)$$

- We use the Bloch parametrization

$$\rho(\theta) = \sum_{i=0}^{n^2-1} \theta_i \sigma_i.$$

# State of a quantum system II.

$$\rho(\theta) = \sum_{i=0}^{n^2-1} \theta_i \sigma_i,$$

- $\text{Tr}(\rho) = 1 \iff \theta_0 = \frac{1}{\sqrt{n}}.$

State space can be parametrized with  $\theta \in \mathbb{R}^{n^2-1}$

- $\rho \geq 0 \implies \sum_{i=0}^{n^2-1} \theta_i^2 \leq 1.$

Note that if  $n = 2$  (qubit case) this is also a sufficient condition, so in that case we have the so-called Bloch ball as state space.

# Measurements

- $(E_1, E_2, \dots, E_k)$  forms a positive operator valued measurement (POVM) if

$$\forall i : E_i \geq 0 \quad \text{and} \quad \sum_i E_i = I.$$

- For  $k = 2$ :  $(P, I - P)$  are projections (von Neumann meas.).
- The probability of observing an outcome related to  $E_i$  is

$$p_i = \text{Tr}(\rho E_i).$$

- E.g.,  $A = \sum \lambda_i P_i$ . Then  $E_i := P_i$ , while the outcome is  $\lambda_i$ .
- State after measurement:

$$\rho'_i = \frac{E_i \rho E_i}{\text{Tr} E_i \rho E_i}$$

# Quantum tomography

- The state estimation process has the following steps:
  - Choose a set of measurements
  - Measure multiple times on identical copies of a quantum state
  - Construct an estimator from the measurement data
- Our choices:
  - Measurements
  - Estimator
  - Figure of merit for estimation efficiency

# Standard method

- We measure in the 3 axis directions:  $P_i = \frac{I+\sigma_i}{2}$ , ( $i = 1, 2, 3$ )
- The probability of an outcome related to  $P_i$ :

$$p_i = \frac{1}{2}(1 + \theta_i)$$

- $m$  measurements are performed in each direction

$$\nu_i := \frac{m_i}{m}, \text{ where } m_i \text{ is the number of outcomes related to } P_i$$

- Then the estimation on  $\theta$ :

$$\Phi_m(\nu_1, \nu_2, \nu_3) = \begin{bmatrix} 2\nu_1 - 1 \\ 2\nu_2 - 1 \\ 2\nu_3 - 1 \end{bmatrix}$$

# Standard method II.

- $\Phi_m$  is unbiased:  $E(\Phi_m) = \theta$ .
- Its covariance matrix is

$$\text{Var}(\Phi_m) = \frac{1}{m} \begin{bmatrix} 1 - \theta_1^2 & 0 & 0 \\ 0 & 1 - \theta_2^2 & 0 \\ 0 & 0 & 1 - \theta_3^2 \end{bmatrix}$$

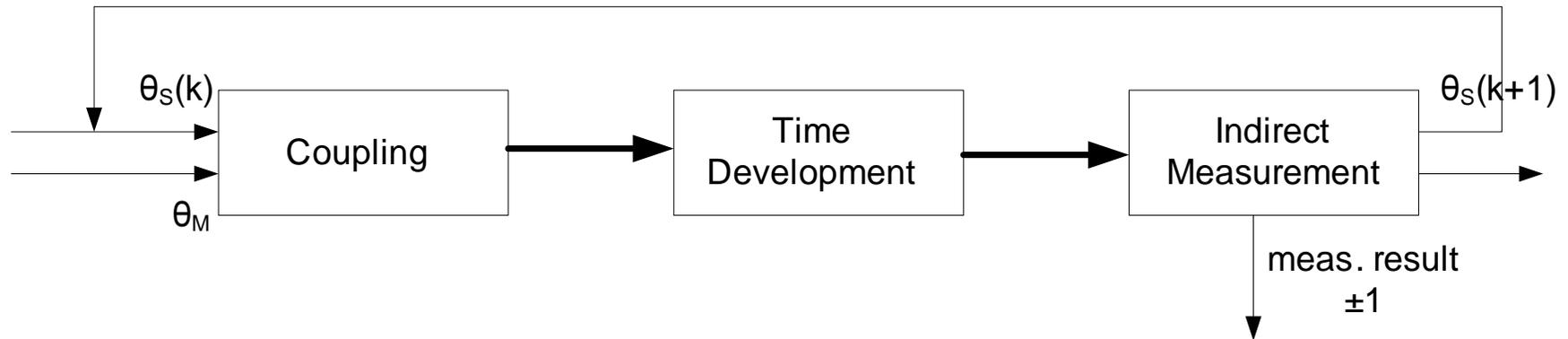
- If  $\Psi_m$  is an unbiased estimator, the Cramér-Rao inequality says

$$\text{Var}(\Psi_m) \geq I_m(\theta)^{-1}.$$

For  $\Phi_m$  we have equality, so  $\Phi_m$  is efficient.

# Weak measurements

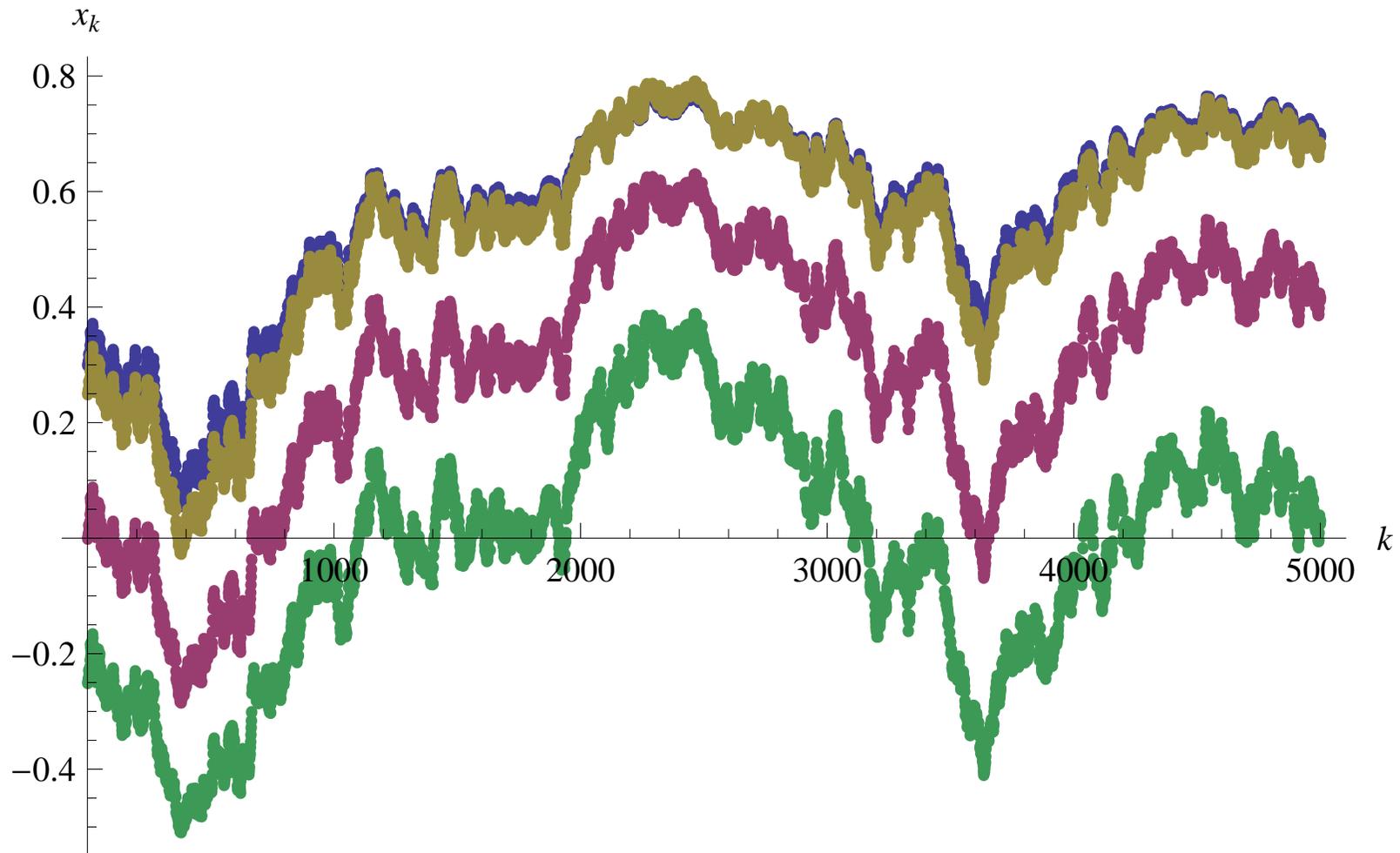
# State evolution driven by weak measurements



## ■ State evolution:

$$x_{k+1} = \left\{ \begin{array}{l} \frac{x_k + c}{1 + cx_k}, \text{ with probability } \frac{1 + cx_k}{2} : +1 \text{ measurement} \\ \frac{x_k - c}{1 - cx_k}, \text{ with probability } \frac{1 - cx_k}{2} : -1 \text{ measurement} \end{array} \right\}$$

# Example: State evolution for different $x_0$ -s



# Estimation of the initial state

- Aim: Estimation of the initial state  $x_0$
- Result: We gave 3 working methods
  - Histogram
  - Bayesian
  - **Martingale**
- Martingale property:  $\mathbb{E}(x_{k+1}) = x_k$
- For fixed value  $u, v$ , we run the process until  $u < x_k < v$ .
- Doob's optional stopping theorem:  $\mathbb{E}(x_T) = x_0$ , so

$$\mathbb{E}(x_T) = pu + (1 - p)v = x_0 \quad \Rightarrow \quad \hat{x}_0 = \hat{p}u + (1 - \hat{p})v$$

# Estimation of the process

- Aim: Estimation of the process  $x_k$  (filtering)
- Kalman filter:
  - State evolution:  $x_{k+1} = Ax_k + w_k$
  - Measurement:  $y_k = Hx_k + v_k$
  - $w_k$  and  $v_k$  are independent noises with probability distribution:  $w \sim \mathcal{N}(0, Q)$ ,  $v \sim \mathcal{N}(0, R)$
  - Kalman filter:

$$\hat{x}_{k+1} = A\hat{x}_k + K_k(y_k - H\hat{x}_k)$$

- Task: optimal choice of  $K_k$  to minimize:

$$\mathbb{E}(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T \rightarrow \min.$$

# Obtaining the state space model

## ■ State evolution:

$$x_{k+1} = x_k + Nc^2x_k(1 - x_k^2) + \omega_k \cdot c(1 - x_k^2)$$

## ■ Measurements:

$$y_k = Ncx_k + \omega_k,$$

with  $\omega_k \sim \mathcal{N}(0, N)$ .

## ■ Comparison to the classical Kalman filter settings:

- State evolution: non-linear
- Measurement: linear
- Noise: not independent (measurement feedback) and additional non-linear factor

# Related publications

- [1] L. Ruppert, A. Magyar, K.M. Hangos, *Compromising non-demolition and information gaining for qubit state estimation*, Quantum Probability and Related Topics, World Scientific, p. 212-224, 2008.
- [2] L. Ruppert, K.M. Hangos: *Martingale approach in quantum state estimation using indirect measurements*, Proceedings of the 19th International Symposium on Mathematical Theory of Networks and Systems, p. 2049-2054, 2010.
- [3] K.M. Hangos, L. Ruppert: *State estimation methods using indirect measurements*, Quantum Probability and Related Topics, World Scientific, p. 163-180, 2011
- [4] L. Ruppert, K. M. Hangos, J. Bokor, *Possibilities of Quantum Kalman Filtering*, submitted for publication

# Channel tomography

# Complementarity

- Quantum channel:  $M_n(\mathbb{C}) \rightarrow M_n(\mathbb{C})$  CPTP map
- The basis  $e_1, e_2, \dots, e_n$  is complementary to the basis  $f_1, f_2, \dots, f_n$  (also called mutually unbiased bases) if

$$|\langle e_i, f_j \rangle|^2 = \frac{1}{n} \quad (1 \leq i, j \leq n).$$

- Generalization for POVMs ( $1 \leq i \leq k, 1 \leq j \leq m$ ):

$$\left( \text{Tr} E_i F_j = \frac{1}{n} \text{Tr} E_i \text{Tr} F_j \right) \Leftrightarrow \left( E_i - \frac{\text{Tr} E_i}{n} I \perp F_j - \frac{\text{Tr} F_j}{n} I \right)$$

- We can generalize quasi-orthogonality for subspaces:

$$\mathcal{A}_1 \ominus \mathbb{C}I \perp \mathcal{A}_2 \ominus \mathbb{C}I,$$

# Parameter estimation of Pauli channels

- Let  $\mathcal{A}_1, \mathcal{A}_2, \dots, \mathcal{A}_N$  be a complementary decomposition of  $M_n(\mathbb{C})$ :

$$A_i - \frac{\text{Tr} A_i}{n} I \perp A_j - \frac{\text{Tr} A_j}{n} I, \quad \forall A_i \in \mathcal{A}_i, A_j \in \mathcal{A}_j (i \neq j)$$

- Pauli channel: contractions with  $\lambda_i$  on traceless part of  $\mathcal{A}_i$ .
- Example:  $\mathcal{A}_i := \text{span}\{I, \sigma_i\}, i \in \{1, 2, \dots, 2^n - 1\}$

$$\mathcal{E} : \rho = \frac{1}{n} \left( I + \sum_{i=1}^{2^n-1} \theta_i \sigma_i \right) \mapsto \mathcal{E}(\rho) = \frac{1}{n} \left( I + \sum_{i=1}^{2^n-1} \lambda_i \theta_i \sigma_i \right).$$

- Aim: Select input state, send through channel, measure the output, repeat many times  $\Rightarrow$  estimate  $\lambda_i$

## Parameter estimation of Pauli channels II.

- Figure of merit: Fisher information matrix of the parameters  $\lambda_i$

$$F_{ij} = \sum_{\alpha} \frac{1}{p_{\alpha}} \frac{\partial p_{\alpha}}{\partial \lambda_i} \frac{\partial p_{\alpha}}{\partial \lambda_j}$$

- Optimization:

$$\forall i : F_{ii} \rightarrow \max. \quad (\text{independently})$$

- Result: Input and measurement in the direction of  $\mathcal{A}_i$ . It depend on the algebraic structure of  $\mathcal{A}_i$ .

# Unknown channel directions

- Another problem: What if  $\sigma_i$  are unknown too?
- We gave an efficient method for the qubit case.
- channel matrix:  $A : \theta_{in} \rightarrow \theta_{out}$

$$A(\lambda_1, \lambda_2, \lambda_3, \phi_z, \phi_y, \phi_x) = R_z R_y R_x \Lambda R_x^{-1} R_y^{-1} R_z^{-1}$$

1.  $\mathbb{E} \|\hat{A} - A\|^2 \rightarrow \min.:$  in the channel directions (equivalent to the average squared distance of  $\rho_{out}$  and  $\hat{\rho}_{out}$ )
2.  $\mathbb{E} \sum (\hat{\lambda}_i - \lambda_i)^2 \rightarrow \min.:$  in the channel directions
3.  $\mathbb{E} \sum (\hat{\phi}_i - \phi_i)^2 \rightarrow \min.:$  NOT in the channel directions

# Related publications

- [1] L. Ruppert, D. Virosztek and K.M. Hangos *Optimal parameter estimation of Pauli channels*, Journal of Physics A: Math. Theor. **45**, 265305, 2012.
- [2] D. Virosztek, L. Ruppert and K. M. Hangos, *Pauli channel tomography with unknown channel directions*, submitted for publication

# State tomography

# Complementarity and DACM

- Wooters and Fields proved in 1989 the optimality of complementary measurements
- Petz, Hangos and Magyar used in 2007 the optimization

$$\det \langle \text{Var} (\hat{\theta}) \rangle \rightarrow \min .$$

for proving the optimality of complementary measurements in the qubit case.

- Baier and Petz used this quantity in 2010 to prove the optimality in a more general setting.

# Symmetric measurements

- The Bloch vector has  $n^2 - 1$  parameters, so we have at least  $n^2$  elements in POVM.
- Symmetric informationally complete POVM (SIC-POVM):

$$E_i = \frac{1}{n} P_i, \quad \text{Tr} P_i P_j = \frac{1}{n+1} \quad (i \neq j, 1 \leq i, j \leq n^2),$$

where  $P_i$  is a rank-one projection.

- Rehacek, Englert and Kaszlikowski used in 2004 the 2-dimensional SIC-POVM for state tomography.
- Scott used in 2006 the average squared Hilbert-Schmidt distance for proving the optimality of SIC-POVMs.

# Multiple von Neumann measurements

- We have a decomposition

$$M_n(\mathbb{C}) = \mathbb{C}I \oplus \mathcal{A} \oplus \mathcal{B},$$

where  $\mathcal{A} \rightarrow$  known,  $\mathcal{B} \rightarrow$  unknown parameters.

- If  $\mathcal{B}$  has  $l$  dimensions, then we have the measurements

$$(F_1, I - F_1), (F_2, I - F_2), \dots, (F_l, I - F_l)$$

**Theorem.** *If the positive contractions  $F_1, \dots, F_l$  have the same spectrum, then the determinant of the average covariance matrix is minimal if the operators  $F_1, \dots, F_l$  are complementary to each other and to  $\mathcal{A}$ .*

# Single POVMs

- We have once again the decomposition

$$M_n(\mathbb{C}) = \mathbb{C}I \oplus \mathcal{A} \oplus \mathcal{B},$$

with  $\dim(\mathcal{B}) = k - 1$ , then we have the measurement

$$(E_1, E_2, \dots, E_k)$$

- In the  $n$  dimensional case we can obtain results if  $k = n^2$ , i.e. all parameters are unknown.

**Theorem.** *If a symmetric informationally complete system exists, the optimal POVM is described by its projections  $P_i$  as  $E_i = P_i/n$  ( $1 \leq i \leq n^2$ ).*

# Single POVMs II.

- In the conditional case there are some technical issues, which we barely overcame in the qubit case.

**Theorem.** *The optimal POVM for the unknown Bloch parameters  $\theta_1$  and  $\theta_2$  can be described by projections  $P_i$ ,  $1 \leq i \leq 3$ :*

$$E_i = \frac{2}{3}P_i, \quad \text{Tr}P_iP_j = \frac{1}{4} \quad (i \neq j), \quad \text{and} \quad \text{Tr}\sigma_3P_i = 0,$$

- We get that the optimal POVM is symmetrical and complementary to the subspace of the known parameters  
 $\Rightarrow$  generalization of SIC-POVM

# Numerical algorithm

- I show the first non-trivial example of a conditional SIC-POVM

$$E_1 = \frac{1}{7} \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}, E_2 = \frac{1}{7} \begin{bmatrix} 1 & \varepsilon^6 & \varepsilon^2 \\ \varepsilon & 1 & \varepsilon^3 \\ \varepsilon^5 & \varepsilon^4 & 1 \end{bmatrix}, E_3 = \frac{1}{7} \begin{bmatrix} 1 & \varepsilon^2 & \varepsilon^3 \\ \varepsilon^5 & 1 & \varepsilon \\ \varepsilon^4 & \varepsilon^6 & 1 \end{bmatrix},$$

$$E_4 = \frac{1}{7} \begin{bmatrix} 1 & \varepsilon^4 & \varepsilon^6 \\ \varepsilon^3 & 1 & \varepsilon^2 \\ \varepsilon & \varepsilon^5 & 1 \end{bmatrix}, E_5 = E_2^\top, E_6 = E_3^\top, E_7 = E_4^\top, \text{ with } \varepsilon = \exp\left(\frac{2\pi i}{7}\right).$$

- There is a conditional SIC-POVM containing the diagonal matrix units.
- There is an example for conditional SIC-POVMs that contains projections of rank 2.
- There is an example where no conditional SIC-POVM exists.

# Conditional SIC-POVM

- From these results we obtain the precise definition of conditional SIC-POVMs:

## Definition (Conditional SIC-POVM)

$(E_1, E_2, \dots, E_k)$  forms a conditional SIC-POVM if there is a set of projections  $P_i$ ,  $1 \leq i \leq k$ , such that

$$E_i = \frac{1}{\lambda} P_i \quad \text{and} \quad \text{Tr} P_i P_j = \mu \quad (i \neq j).$$

and  $E_i$ -s are complementary to the subspace of known parameters.

- We get a SIC-POVM in the special case when  $k = n^2$ ,  $\lambda = n$  and  $\mu = 1/(n + 1)$ .

# Conditional SIC-POVM II.

- Instead of the determinant of the average covariance matrix, minimize the square of the Hilbert-Schmidt distance.

**Theorem.** *In the conditional case, the elements of the optimal POVM can be described as multiples of rank-one projections with the following properties ( $1 \leq i, j \leq k$ ):*

$$E_i = \frac{n}{k} P_i, \quad \text{Tr} P_i P_j = \frac{k-n}{n(k-1)} \quad (i \neq j)$$

$$\text{and } \text{Tr} \sigma_l P_i = 0 \quad (\forall l : \sigma_l \in \mathcal{A}).$$

- So the conditional SIC-POVM is the optimal with rank-one projections, and constants  $\lambda = \frac{k}{n}$ ,  $\mu = \frac{k-n}{n(k-1)}$ .

# Example for existence

- Let us assume that the diagonal part of  $\rho \in M_n(\mathbb{C})$  is known
- The number of POVM elements:  $k = n^2 - n + 1$

**Definition** (Difference set). *The set  $G := \{0, 1, \dots, k - 1\}$  is an additive group modulo  $k$ . The subset  $D := \{\alpha_i : 1 \leq i \leq n\}$  forms a difference set with parameters  $(k, n, \lambda)$  if the set of differences  $\alpha_i - \alpha_j$  contains every nonzero element of  $G$  exactly  $\lambda$  times.*

- A few examples for difference sets with parameters  $(k, n, 1)$ :

$$n = 2, k = 3 : D = \{0, 1\}, \quad n = 3, k = 7 : D = \{0, 1, 3\}, \quad n = 4, k = 13 : D = \{0, 1, 3, 9\}.$$

**Theorem.** *We set  $|\phi\rangle = \frac{1}{\sqrt{n}} \sum_{i=1}^n |e_i\rangle$ ,  $q = e^{2\pi i/k}$ ,  $U = \text{Diag}(q^{\alpha_1}, q^{\alpha_2}, q^{\alpha_3}, \dots, q^{\alpha_n})$ . If  $(\alpha_1, \alpha_2, \dots, \alpha_n)$  forms a difference sets with parameters  $(k, n, 1)$ , then*

$$P_i := |U^i \phi\rangle \langle U^i \phi|, \quad (i = 1, 2, \dots, k)$$

*will be an appropriate conditional SIC-POVM.*

# Application of Conditional SIC-POVM

- SIC-POVM is the BLE of a quantum state
- Conditional SIC-POVM is the BLE of a subsystem of a quantum state
- Let  $\mathcal{A}_1, \dots, \mathcal{A}_N$  be a complementary decomposition of  $M_n(\mathbb{C})$
- $E^{(i)}$  is the conditional SIC-POVM for  $\mathcal{A}_i \Rightarrow$  BLE for subsystems
- Best candidates:
  - $N = 1, \mathcal{A}_1 = M_n$ : SIC-POVM
  - $N = n + 1, \mathcal{A}_1 = \dots = \mathcal{A}_{n+1} = \mathbb{C}^n$ : MUB

# Related publications

- [1] D. Petz, K.M. Hantos and L. Ruppert, *Quantum state tomography with finite sample size*, in Quantum Bio-Informatics, eds. L. Accardi, W. Freudenberg, M. Ohya, World Scientific, p. 247-257, 2008.
- [2] D. Petz and L. Ruppert, *Efficient quantum tomography needs complementary and symmetric measurements*, Rep. Math. Phys., **69**, p. 161-177, 2012.
- [3] D. Petz and L. Ruppert, *Optimal quantum state tomography with known parameters*, Journal of Physics A: Math. Theor. **45**, 085306, 2012.
- [4] D. Petz, L. Ruppert and A. Szántó, *Conditional SIC-POVMs*, to be published, <http://arxiv.org/abs/1202.5741>