# Min. Error Disc. of Linearly Independent Pure States Analytic Properties of Optimal POVM

### Tanmay Singal<sup>1</sup> Sibasish Ghosh<sup>1</sup>

<sup>1</sup>Optics and Quantum Information Group Institute of Mathematical Sciences Chennai

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#### The Ensemble

•  $\{p_i > 0, \rho_i\}_{i=1}^m$   $\rho_i \in \mathcal{B}(\mathcal{H})$  where dim $\mathcal{H} = n$ 

The m POVM

• 
$$\{\Pi_i\}_{i=1}^m$$
  $\Pi_i \ge 0$   $\sum_{i=1}^m \Pi_i = \mathbb{I}$ 

Avg. Probability of Success: P<sub>s</sub> = Σ<sup>m</sup><sub>i=1</sub> p<sub>i</sub> Tr(ρ<sub>i</sub>Π<sub>i</sub>)
 Avg. Probability of Error: P<sub>e</sub> = Σ<sup>m</sup><sub>i,j=1</sub> p<sub>i</sub> Tr(ρ<sub>i</sub>Π<sub>j</sub>)

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- Necessary Condition: Π<sub>j</sub>(p<sub>j</sub>ρ<sub>j</sub> − p<sub>i</sub>ρ<sub>i</sub>)Π<sub>i</sub> = 0, ∀1 ≤ i, j ≤ m (Given by Holevo)
- SDP Necessary and Sufficient Conditions:
- $\operatorname{Min}_{Z=Z^{\dagger}}\operatorname{Tr}(Z) \ni Z \ge p_i \rho_i \forall 1 \le i \le m$
- Complementary Slackness Conditions (given by Yuen):  $(Z - p_i \rho_i) \prod_i = \prod_i (Z - p_i \rho_i) = 0, \forall 1 \le i \le m$

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## Some Important Ensembles Solved So Far

- When  $\operatorname{Supp}(\rho_i) \perp \operatorname{Supp}(\rho_j) \forall i, j$  $\Pi_i = \operatorname{Projector on } \operatorname{Supp}(\rho_i) \forall i$
- Any ensemble of two states (by Helstrom)
- When  $\sum_i p_i \rho_i = \frac{1}{m} \mathcal{I}$
- Equiprobable ensemble when  $\rho_i$  lie on the orbit of some unitary:  $\rho_{i+1} = U \ \rho_i \ U^{\dagger}$
- For three qubits (recently)

- The problem we look at is MED when  $\rho_i \rightarrow |\psi_i\rangle\langle\psi_i|$ and {  $\psi_i$  } are linearly independent.
- In this case dim $(\mathcal{H}) = m$
- Kennedy showed that  $\Pi_i \rightarrow |v_i\rangle \langle v_i|$ , where  $\langle v_i | v_j \rangle = \delta_{i,j} \forall 1 \le i, j \le m$ . i.e. Optimal m-POVM is rank-one projective measurement
- Case when m = 2 has been solved, but not for m = 3.

## A Special Representation

- Ensemble:  $\{p_i, |\psi_i\rangle\langle\psi\rangle i|\}_{i=1}^m$  where  $|\psi_i\rangle$  are LI.
- Define:  $|\widetilde{\psi}_i\rangle = \sqrt{p_i}|\psi_i\rangle$
- $|\tilde{\psi}_i\rangle$  are LI  $\Rightarrow \exists \{|\tilde{u}_i\rangle\} \ni \langle \tilde{\psi}_i|\tilde{u}_j\rangle = \delta_{i,j}$
- Let G be gram matrix of {  $|\psi_i\rangle$ } i.e.  $G_{ij} = \langle \tilde{\psi}_i | \tilde{\psi}_j \rangle$ which implies and is implied by  $G_{ij}^{-1} = \langle \tilde{u}_i | \tilde{u}_j \rangle$
- Let  $\{|v_i\rangle\}$  be any ONB. Then  $|v_i\rangle = \sum_{j=1}^{m} (G^{\frac{1}{2}}U)_{j,i} |\tilde{u_j}\rangle$  where U is some unitary.

• Holevo's Necessary Condition:

$$\Rightarrow \langle v_j | (|\widetilde{\psi}_j \rangle \langle \widetilde{\psi}_j | - |\widetilde{\psi}_i \rangle \langle \widetilde{\psi}_i |) | v_i \rangle = 0, \ \forall \ 1 \le i, j \ \le m$$

$$\Rightarrow \ (\mathsf{G}^{\frac{1}{2}}\widetilde{U})_{ii}(\mathsf{G}^{\frac{1}{2}}\widetilde{U})^*_{ij} \ = \ (\mathsf{G}^{\frac{1}{2}}\widetilde{U})_{ji}(\mathsf{G}^{\frac{1}{2}}\widetilde{U})^*_{jj} \ \forall \ 1 \le i,j \le m$$

• Add a phase 
$$\longrightarrow |v_i\rangle \longrightarrow e^{i\phi_i}|v_i\rangle$$
 so that  $(G^{\frac{1}{2}}\widetilde{U})_{i,i} \ge 0$ 

• Let 
$$D = Diag((G^{\frac{1}{2}}\widetilde{U})_{11}), (G^{\frac{1}{2}}\widetilde{U})_{22}), \cdots, (G^{\frac{1}{2}}\widetilde{U})_{mm})$$

• Then the matix  $G^{\frac{1}{2}}\widetilde{U}D^{-1}$  is hermitian.

$$\mathsf{G}^{\frac{1}{2}}\widetilde{U}\mathsf{D}^{-1} = \left(\begin{array}{ccc} 1 & \frac{(\mathsf{G}^{\frac{1}{2}}\widetilde{U})_{1,2}}{(\mathsf{G}^{\frac{1}{2}}\widetilde{U})_{2,2}} & \cdots \\ & \frac{(\mathsf{G}^{\frac{1}{2}}\widetilde{U})_{2,1}}{(\mathsf{G}^{\frac{1}{1}}\widetilde{U})_{1,1}} & 1 & \cdots \\ & \vdots & \ddots & \vdots \end{array}\right)$$

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Consider the equation:

$$D^{-1}\widetilde{U}^{\dagger}G^{\frac{1}{2}} G^{-1} G^{\frac{1}{2}}\widetilde{U}D^{-1} = D^{-2}$$

- Note that the RHS is diagonal.
- Now, let m=3 and the states |ψ<sub>i</sub>⟩ be real ⇒ everything is real (gram matrix, optimal POVM, |u<sub>i</sub>⟩ states etc). So we can work in the real domain without having to worry about complex numbers.
- The matrix equation upstairs is then given by<sup>1</sup>:

$$\begin{pmatrix} 1 & \alpha & \beta \\ \alpha & 1 & \gamma \\ \beta & \gamma & 1 \end{pmatrix} \begin{pmatrix} (G^{-1})_{11} & (G^{-1})_{12} & (G^{-1})_{13} \\ (G^{-1})_{21} & (G^{-1})_{22} & (G^{-1})_{23} \\ (G^{-1})_{31} & (G^{-1})_{32} & (G^{-1})_{33} \end{pmatrix} \begin{pmatrix} 1 & \alpha & \beta \\ \alpha & 1 & \gamma \\ \beta & \gamma & 1 \end{pmatrix} \\ = \begin{pmatrix} (D_{11})^{-2} & 0 & 0 \\ 0 & (D_{22})^{-2} & 0 \\ 0 & 0 & (D_{33})^{-2} \end{pmatrix}$$

 $^1 Note$  again that the elements  $({\rm G}^{-1})_{ij}$  are known and that  $\alpha,\beta,\gamma,D_{ii}$  are unknowns.

We get 6 equations in the matrix elements:

$$\begin{split} &\alpha^2(\mathsf{G}^{-1})_{12} + \alpha((\mathsf{G}^{-1})_{11} + (\mathsf{G}^{-1})_{22} + (\mathsf{G}^{-1})_{13}\beta + (\mathsf{G}^{-1})_{23}\gamma) \\ &+ (\mathsf{G}^{-1})_{33}\beta\gamma + (\mathsf{G}^{-1})_{23}\beta + (\mathsf{G}^{-1})_{13}\gamma + (\mathsf{G}^{-1})_{12} = 0 \\ &\beta^2(\mathsf{G}^{-1})_{13} + \beta((\mathsf{G}^{-1})_{11} + (\mathsf{G}^{-1})_{33} + (\mathsf{G}^{-1})_{23}\gamma + (\mathsf{G}^{-1})_{12}\alpha) \\ &+ (\mathsf{G}^{-1})_{22}\alpha\gamma + (\mathsf{G}^{-1})_{12}\gamma + (\mathsf{G}^{-1})_{23}\alpha + (\mathsf{G}^{-1})_{13} = 0 \\ &\gamma^2(\mathsf{G}^{-1})_{23} + \gamma((\mathsf{G}^{-1})_{22} + (\mathsf{G}^{-1})_{33} + (\mathsf{G}^{-1})_{13}\beta + (\mathsf{G}^{-1})_{12}\alpha) \\ &+ (\mathsf{G}^{-1})_{11}\alpha\beta + (\mathsf{G}^{-1})_{12}\beta + (\mathsf{G}^{-1})_{13}\alpha + (\mathsf{G}^{-1})_{23} = 0 \end{split}$$

The above are quadraitc in  $\alpha, \beta, \gamma$ . Typically this set has 8 different solutions of which only one corresponds to the optimal POVM. Some solutions are complex and hence discarded. The remaining solutions correspond to projective measurements where  $P_s$  is stationary in the space of projective measurement.

$$\begin{split} (\mathsf{G}^{-1})_{22}\alpha^2 &+ (\mathsf{G}^{-1})_{33}\beta^2 + 2\alpha\beta(\mathsf{G}^{-1})_{23} + 2\alpha(\mathsf{G}^{-1})_{12} + 2\beta(\mathsf{G}^{-1})_{13} \\ &+ (\mathsf{G}^{-1})_{11} = (\mathsf{D}_{12}^{-2}) \\ (\mathsf{G}^{-1})_{11}\alpha^2 &+ (\mathsf{G}^{-1})_{33}\gamma^2 + 2\alpha\gamma(\mathsf{G}^{-1})_{13} + 2\alpha(\mathsf{G}^{-1})_{12} + 2\gamma(\mathsf{G}^{-1})_{23} \\ &+ (\mathsf{G}^{-1})_{22} = (\mathsf{D}_{22}^{-2}) \\ (\mathsf{G}^{-1})_{11}\beta^2 &+ (\mathsf{G}^{-1})_{22}\gamma^2 + 2\beta\gamma(\mathsf{G}^{-1})_{12} + 2\beta(\mathsf{G}^{-1})_{13} + 2\gamma(\mathsf{G}^{-1})_{23} \\ &+ (\mathsf{G}^{-1})_{33} = (\mathsf{D}_{33}^{-2}) \end{split}$$

We solve for  $(\alpha, \beta, \gamma)$  from the three equations and substitute in the three equations below to obtain t he values for  $D_{ii}$ s.

A closed form solution for the equations above is very difficult to obtain. It's worth mentioning that solving the m=3 case in other methods yields polynomial equations (but often in greater number of u

nknowns). This is due to the fact there are multiple stationary points in the space of projective measurements, =

### Analytic Properties of Optimal POVM Inspired by Representation from Last Section

$$DG^{\frac{1}{2}}\widetilde{U} = \begin{pmatrix} (G^{\frac{1}{2}}\widetilde{U})_{11}^{2} & (G^{\frac{1}{2}}\widetilde{U})_{11}(G^{\frac{1}{2}}\widetilde{U})_{12} & \cdots \\ (G^{\frac{1}{2}}\widetilde{U})_{21}(G^{\frac{1}{2}}\widetilde{U})_{22} & (G^{\frac{1}{2}}\widetilde{U})_{11}^{2} & \cdots \\ \vdots & \ddots & \cdots \end{pmatrix}$$

Hence  $DG^{\frac{1}{2}}\widetilde{U}$  is hermitian. Now

$$(\widetilde{U}^{\dagger}G^{rac{1}{2}}D)(D^{-1}G^{-1}D^{-1})(DG^{rac{1}{2}}\widetilde{U})=\mathbb{I}$$

 $DG^{\frac{1}{2}}\widetilde{U}$  is a hermitian square root of DGD. Note that until now we have only used Holevo's necessary conditions. What Carlos Mochos<sup>2</sup> and Belavkin<sup>3</sup>, proved, proves that  $DG^{\frac{1}{2}}\widetilde{U}$  is a positive square root of DGD.

<sup>3</sup>P. Belavkin, âOptimal multiple quantum statistical hypothesis testing.â Stochastics 1, 315-345 (1975).

<sup>&</sup>lt;sup>2</sup>Phys. Rev. A 73, 032338 (2006)

From previous slide we have the equation:

$$(DG^{\frac{1}{2}}\widetilde{U})^2 - DGD = 0$$

#### Implicit Function Theorem

Implicit Function Theorem: Let  $\{y_i\}_{i=1}^N$  be N functions (real or complex) of the independent variables -  $\{t, f_i\}$ where the variables  $\{f_i\}_i$ , which are N in number too. Let  $(\tau, \phi_i)$  be a point such that  $y_i(\tau, \phi_i)=0 \forall 1 \le i \le N$ . If the Jacobian matrix  $J_{i,j} = \frac{\partial y_i}{\partial f_j}$  is invertible at  $(\tau, \phi_i)$  then there exists some open neighbourhood of  $\tau$ , T for which there exists open neighbourhoods  $S_i$  around  $\phi_i$  such that  $f_i: T \longrightarrow S_i$  can be defined, so that  $y_i(t, f_i(t))=0 \forall 1 \le i \le N$ . That is

 $\{(t,f_i)\in T\times S|y(t,f_i)=0\}=\{(t,f_i(t))|t\in T \text{ and } y(t,f_i(t))=0\} \text{ where } S=S_1\times S_2\times\cdots\times S_N.$ 

Analytic Implicit Function Theorem: Furthermore if  $y_i$  is an analytic function in the variables  $f_i$  then the implicit dependence of  $f_i$  on t will be analytic too.

- Here  $a_i = \sqrt{(\sqrt{G}\tilde{U})_{ii}} = D_{ii}$ ,  $f_{ij} = (\sqrt{G}\tilde{U})_{ij}$ ,  $y_{ij} = ((D\sqrt{G}\tilde{U})^2 DGD)_{ij}$ ,  $y_{ij}$  is analytic in  $f_{ij}$  and  $a_i$ .
- Consider a trajectory of gram matrix: G(t)
  Objective: That a<sub>i</sub>, f<sub>ij</sub> depend implicitly on t so that y<sub>ij</sub>=0 ∀t∈[0,1].
- Unable to prove that the Jacobian is non-singular at every point. But we know the functions  $f_{ii}(t)$  and  $a_i(t)$  exist.
- Thus the function exists and is continuous. Since y<sub>ij</sub> is polynomial in the variables f<sub>ij</sub> and a<sub>i</sub>, f<sub>ij</sub>(t) and a<sub>i</sub>(t) are analytic in t.

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# Dragging the Solution from One Point to Another

- Using implicit function theorem we get differential equations:  $\frac{dy_{ij}}{dt} = \zeta_{ij}(t; a_k(t), f_{kl}(t), \frac{da_k(t)}{dt}, \frac{df_{kl}(t)}{dt}) = 0 \quad \forall \ 1 \le i, j \le m$ These are non-linear coupled ordinary differential equations.
- Let the starting point (initial conditions) the equiprobable orthogonal ensemble. Gram matrix corresponding to this ensemble is: G(0)=<sup>1</sup>/<sub>m</sub>I The trajectory we employ is linear in t: G(t)=(1-t)<sup>1</sup>/<sub>m</sub>I+t G where G is the gram matrix of the system which we want to solve MED for.
- We use RK4 to solve this system of coupld differential equations
  - Interval:  $h=10^{-3}$  No. of iterations: 1000
  - RK4 Local Truncation Error (expected):  $O(h^5) \sim -15$ RK4,Total Accumulated Error(expected):  $O(h^4) \sim -12$
  - RK4 Avg. Local Truncation Error( Randomly generated for m=5): O(-16)
  - RK4 Avg. Total Accumulated Error(Randomly generated for m=5): O(-15)

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#### As an illustration,

$$G = \begin{pmatrix} 0.3 & \sqrt{0.06}(0.2+i0.1) & \sqrt{0.06}(0.1) & \sqrt{0.045}(0.1) & \sqrt{0.045}(0.1) \\ \sqrt{0.06}(0.2-i0.1) & 0.2 & 0.06 & \sqrt{0.03}(0.2+i0.2) & \sqrt{0.03}(0.1) \\ \sqrt{0.06}(0.1) & 0.06 & 0.2 & \sqrt{0.03}(0.2+i0.05) & \sqrt{0.03}(0.3+i0.2) \\ \sqrt{0.045}(0.1) & (0.2-i0.2)\sqrt{0.03} & \sqrt{0.03}(0.1-i0.05) & 0.15 & (0.15)(0.2+i0.3) \\ \sqrt{0.045}(0.1) & (0.1)\sqrt{0.03} & (0.3-i0.3)\sqrt{0.03} & (0.15)(0.2-i0.3) & 0.15 \end{pmatrix}$$

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y- axis :Log of Error, x-axis: No. of iterations. One can see the gradual increase in the error from -16.8 when  $1 \le x \le 10$  to -15.7 for  $980 \le x \le 1000$ . This shows that the truncation error is  $10^{-16}$  and the total accumulated error is  $\sim 10^{-15}$  which shows a pretty good performance for RK4.

Figure: Error vs Iteration No.