# Optimal bounded-error strategies for projective measurements in nonorthogonal-state discrimination

M. A. P. Touzel,\* R. B. A. Adamson, and A. M. Steinberg

Department of Physics and Centre for Quantum Information and Quantum Control, University of Toronto, 60 St. George Street, Toronto, Canada M5S-1A7

(Received 20 August 2007; published 19 December 2007)

Research in nonorthogonal-state discrimination has given rise to two conventional optimal strategies: unambiguous discrimination (UD) and minimum error discrimination. We explore the experimentally relevant range of measurement strategies between the two, where the rate of inconclusive results is minimized for a bounded-error rate. We first provide some constraints on the problem that apply to generalized measurements [positive-operator-valued measurements (POVMs)]. We then provide the theory for the optimal projective measurement in this range. Through analytical and numerical results we investigate this family of projective, bounded-error strategies and compare it to the POVM family as well as to experimental implementation of UD using POVMs. We also discuss a possible application of these bounded-error strategies to quantum key distribution.

DOI: 10.1103/PhysRevA.76.062314

#### I. INTRODUCTION

It is a well-known feature of quantum mechanics that it is impossible to discriminate perfectly between nonorthogonal states. For example, if a party is repeatedly sent one of two known, nonorthogonal states and is asked each time which of the two was sent, the set of responses based on measurements of the sent states must include either incorrect or inconclusive responses or both. Incorrect responses occur when the responding party misidentifies the state, while inconclusive ones occur when the responding party replies that he does not know what state was sent. The responding party knows only what the possible states are and with what probability each is sent. This problem, called quantum-state discrimination, has played an important role in quantum information science [1]. There are two kinds of strategies that are usually considered: the minimum error (ME) strategy and the unambiguous discrimination (UD) strategy.

A strategy that minimizes the incorrect responses with no inconclusive responses is known as the minimum error strategy. For two pure states, it is obtained through a standard projection-valued measurement (PVM). For  $|\psi_1\rangle$  and  $|\psi_2\rangle$ , with respective prior probabilities  $\eta_1$  and  $\eta_2=1-\eta_1$ , the minimum error rate as a function of the overlap between two states has an analytic form given by Helstrom [2] as

$$P_{\rm ME} = \frac{1}{2} (1 - \sqrt{1 - 4\eta_1 \eta_2} |\langle \psi_1 | \psi_2 \rangle|^2).$$
(1)

When  $\eta_1 = \eta_2 = 1/2$ , the PVM that achieves the minimum error is oriented symmetrically around the states. By the orientation of the measurement, we mean simply the orientation of the set of eigenstates of the measurement in a vector representation of the Hilbert space. We will discuss measurement elements in this way—i.e., in terms of their eigenstate vectors. Beyond two states, a general result exists for ME strategies known as Kennedy's lemma [2]. Given linearly independent pure input states, the lemma asserts that the ME strategy can always be obtained with a PVM.

PACS number(s): 03.67.-a, 03.65.Ta, 03.67.Dd

A strategy that minimizes the inconclusive rate  $P_{\text{In}}$  with no incorrect responses is known as the unambiguous discrimination strategy. The absence of errors allows for conclusive, i.e., certain, discrimination;  $P_{\text{Con}}=1-P_{\text{In}}$  is called the conclusive rate and the UD problem is often phrased as maximizing  $P_{\text{Con}}$ . For two states, after setting  $\eta_1 \ge \eta_2$  without loss of generality, the maximum conclusive rate for projective measurements is

$$P_{\rm Con}^{\rm PVM} = \eta_1 (1 - |\langle \psi_1 | \psi_2 \rangle|^2).$$
(2)

However, a generalized or positive-operator-valued measurement (POVM) is in fact optimal under the condition that  $(\eta_2/\eta_1)^{1/2} |\langle \psi_1 | \psi_2 \rangle| \ge |\langle \psi_1 | \psi_2 \rangle|^2$  [3]. Originally addressed by Ivanovic, Dieks, and Peres (IDP) [4], the measurement gives the optimal conclusive rate [3]

$$P_{\rm Con}^{\rm POVM} = 1 - 2(\eta_1 \eta_2)^{1/2} |\langle \psi_1 | \psi_2 \rangle|.$$
(3)

Unambiguous discrimination strategies are central to quantum key distribution (QKD) in quantum cryptographic protocols [5,6] and, thus, the success rate of the protocol is dependent on what type of measurement, i.e., a PVM or POVM, one chooses to implement. In the case of equal priors,  $\eta_1 = \eta_2 = 1/2$ , a POVM is the optimal measurement for any overlap. For example, when the overlap is  $1/\sqrt{2}$ , the optimal POVM performing UD gives a maximum conclusive rate of 29.3%, whereas the optimal PVM gives a maximum conclusive rate of 25%. The difference between the results for PVMs and POVMs is more pronounced in a particular three-state example of UD from Ref. [7], which we discuss later on, where the conclusive rate of the optimal POVM is more than twice that given by the corresponding optimal PVM.

The advantage that POVMs provide over PVMs in UD is related to the fact that POVM elements are *not* restricted to being orthogonal. Thus, their number can exceed the dimen-

<sup>\*</sup>max.puelmatouzel@utoronto.ca

sion of the system's Hilbert space (which we will assume throughout equals the number of input states). A positive operator is associated with each state and one extra operator is defined for inconclusive results. In contrast, PVM elements are mutually orthogonal. Since unambiguously discriminating a particular input state  $|\psi_i\rangle$  involves knowing for certain that the sent state was not any of the other input states, the respective PVM element is oriented orthogonally to all other input states so that if the outcome corresponding to that element is obtained, one knows for certain that the sent state was  $|\psi_i\rangle$ . Only one such element exists in general for PVMs and thus only one input state may be unambiguously discriminated. In this case, the projector for the orthogonal subspace corresponds to inconclusive results. Ultimately, however, if the pure input states do not form a linearly independent set-for example, when the number of input states is larger than the dimension of the Hilbert space—UD is not possible in general, regardless of the type of measurement [8]. An analogous condition holds for mixed states: UD exists if and only if the support of each input state is not completely contained in the support of the rest [9]. An equivalent matrix condition is given in Ref. [10].

In realistic quantum information processing, noisy channels are inevitable, even in UD, so a more general class of strategies where the responding party gives both inconclusive and incorrect responses becomes useful. For either the case of pure or mixed states, if a dependency exists between the input states so that UD is not possible, then indeed this approach becomes necessary. Since all outcomes are now error prone, conclusive results no longer exist. For this case, an approach that maximizes the correct rate of individual outcomes has been given in Ref. [11]. This so-called "maximum confidence" measurement gives the highest probability that the given interpretation of a result was correct. In this paper, we instead adopt the equivalent approach of minimizing the inconclusive rate, given some bounded-error rate, since we wish to consider error as a fixed parameter of the problem.

In either approach, UD and ME schemes exist as limiting cases: the latter when the inconclusive rate is 0 and the former when the error rate is 0. In between, trade-offs exist between the two rates. In the two-state case, for example, one may achieve strategies that at once give error rates less than the Helstrom bound and inconclusive rates less than the IDP bound. Zhang, Li, and Guo derive in Ref. [12] a general inequality for this intermediate range for the two input states  $|\psi_1\rangle$  and  $|\psi_2\rangle$ , given as  $P_{\text{In}1}P_{\text{In}2} \ge |P_{\text{IP}} - \sqrt{P_{\text{C1}}P_{\text{E2}}} - \sqrt{P_{\text{C2}}P_{\text{E1}}}|^2$ , where  $P_{\text{In}1}$  and  $P_{\text{In}2}$  are the inconclusive rates,  $P_{\text{C1}}$  and  $P_{\text{C2}}$ are the correct rates, and  $P_{\rm E1}$  and  $P_{\rm E2}$  are the error rates, respectively, and  $P_{\rm IP} = \langle \psi_1 | \psi_2 \rangle^M$  for the slightly more general problem of sending M copies of either  $|\psi_1\rangle$  or  $|\psi_2\rangle$  each time. In the case that each state is equally likely  $(\eta_1 = \eta_2)$  and M =1, the inequality reduces to one given in an early work on this intermediate range published by Chefles and Barnett [13]. A dependency between the input states implies a nonzero minimum error rate in both the pure- and mixed-state cases. Fiurasek and Jezek give results for the latter in Ref. [14]. In Ref. [15], Eldar formulates the mixed-state problem in terms of semidefinite programming, a branch of convex optimization. Once formulated in this way, powerful numerical techniques can be applied that readily give the optimal inconclusive rate. Applying these techniques, Eldar shows that the conditions for the optimal mixed state solution provided in Ref. [14] are necessary and sufficient; i.e., they guarantee a global optimum. These techniques scale efficiently with dimension and so are used in this work to access the more analytically difficult, higher-dimensional problems in quantum-state discrimination using POVMs.

Beyond their theoretical interest, the intermediate range of strategies in quantum discrimination is not only important in accounting for noise, but because the introduction of error can actually be beneficial. Specifically in ideal schemes, introducing error to an UD strategy allows for more correct discriminations (though, of course, by sacrificing any truly unambiguous response). Both the receiver and an eavesdropper can most likely make use of this fact in QKD [14]. For example, a recent counterintuitive result shows that the information attainable by an eavesdropper in QKD can decrease with the introduction of error [16].

Even though POVMs obtain the optimal solution in general, the projective versions of these bounded-error strategies deserve study since PVMs are still widely used in practice and the differences between the two types of measurement in this context have yet to be studied.

In the following section, we establish some constraints on the optimal solution to the problem of allowing for both inconclusive and incorrect responses. These constraints are then used in phrasing the problem of minimizing the inconclusive rate, for projective strategies, given a bounded-error rate. An instructive example of a two-state PVM solution is then presented in Sec. III, after which higher-dimensional problems are discussed in Sec. IV with an example of a three-state case based on a previous experiment [17]. Consequently, a claim made in Ref. [17] regarding the superiority of POVMs over PVMs in UD is amended. Last, by applying the bounded-error strategy to the Bennett 1992 (B92) protocol, we discuss increasing the key generation rate and summarize our results in Sec. V.

# **II. PROBLEM FORMULATION**

For the *n*-state problem, given any set of *n* input states  $|\psi_1\rangle, |\psi_2\rangle, \ldots, |\psi_n\rangle$ , with prior probabilities  $\eta_1, \eta_2, \ldots, \eta_n$ , respectively, we must find the function  $\tilde{P}_{In}(\epsilon)$  representing the minimum inconclusive response rate as a function of a bounded-error rate  $\epsilon$  defined as the largest tolerable fraction of incorrect responses out of the total number of sent states. In other words, the responding party is allowed a maximum average number of incorrect responses and, under this restriction, tries to minimize the average number of inconclusive responses.

Given an existing but not necessarily optimal strategy with some particular inconclusive rate  $P_{\text{In}_0}$  and some particular error rate  $P_{\text{E}_0}$ , consider the following two manipulations of that strategy that decrease the error rate and inconclusive rate, respectively, and provide some constraints on the problem (refer to Fig. 1).

First, the error rate  $P_{\rm E}$  may be decreased from  $P_{\rm E_0}$  by randomly calling inconclusive some fraction of the results

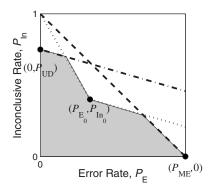


FIG. 1. Bounds on the minimum inconclusive rate function  $\tilde{P}_{In}(\epsilon)$  for the *n*-state problem with equal prior probabilities. The dash-dotted line with a slope of  $-\frac{n}{n-1}$  starting at  $(0, P_{UD})$  represents strategies where random guesses are made when inconclusive outcomes are obtained from the UD strategy. The dashed line that connects the point (0,1) to  $(P_{ME},0)$  represents strategies where results for error-prone outcomes from the ME strategy are interpreted as inconclusive. Similar strategy manipulations (shown as dotted lines) apply to any existing strategy, represented by  $(P_{E_0}, P_{In_0})$ , and so provide two constraints on the minimizing function  $\tilde{P}_{In}(\epsilon)$ : a bound on its slope (it must be less than  $-\frac{n}{n-1}$ ) and a bound on the neighboring points of the function.  $\tilde{P}_{In}(\epsilon)$  then lies somewhere in the shaded region.

obtained from error-prone outcomes (those that we interpret as a particular sent state but that are sometimes incorrect). Thus, in Fig. 1 there is a family of strategies represented by the line segment on the plot connecting the point  $(P_{E_0}, P_{In_0})$ and the point (0,1) at the upper left-hand corner. Moving from right to left along this line an increasing fraction of responses are inconclusive. When all of the responses are inconclusive the error rate is naturally zero. This property places a constraint on the values of  $P_{In}(\epsilon)$  at neighboring points. Second, the inconclusive rate  $P_{\text{In}}$  may be decreased from  $P_{\text{In}_0}$  by randomly guessing the sent state any fraction of the time an inconclusive outcome is obtained. For example, in the case of equal prior probabilities, a random guess will be correct with probability 1/n and incorrect with a probability of 1-1/n. The error rate is therefore increased above  $P_{E_0}$ by 1-1/n of the rate of guessed outcomes. Thus, the line with slope  $-\frac{n}{n-1}$  beginning at and to the right of  $(P_{E_0}, P_{In_0})$ contains strategies that differ only in the fraction of the time an inconclusive outcome is replaced by a randomly guessed outcome (see Fig. 1). For a given error rate, the optimal strategy must have an inconclusive rate less than or equal to the value along this line.

Applied to the ME and UD strategies, the above two strategy manipulations restrict the optimal solution so that it must lie at or below the line from (0,1) to the ME point ( $P_{\rm ME}$ ,0) and at or below the line from the UD point ( $0, P_{\rm UD}$ ) to  $(\frac{n}{n-1}(1-P_{\rm UD}),0)$ , which is the right-end point of a line with slope  $-\frac{n}{n-1}$  beginning at ( $0, P_{\rm UD}$ ) (see Fig. 1). The constraints displayed in Fig. 1 are satisfied by analytical results given in Ref. [13] for two states using POVMs and presumably for all POVM solutions. We now restrict ourselves to projective strategies.

An *n*-element PVM is a set of orthogonal projectors  $\{P_1, P_2, ..., P_n\}$ , where  $P_i = |p_i\rangle\langle p_i|$  for some vector  $|p_i\rangle \in \mathbb{C}^n$  and  $\langle p_i | p_j \rangle = \delta_{ij}$ , for i, j = 1, ..., n. We will continue to discuss the PVM elements in terms of these vectors onto which the elements project.

Recall that in the ME strategy, each  $P_i$  corresponds to a possible measurement outcome, which is interpreted (occasionally incorrectly) as the particular input state  $|\psi_i\rangle$  having been sent. We now formalize the idea of only making that interpretation a fraction of the time that we obtain that particular outcome; the rest of the time we call the result inconclusive.

Consider the following strategy. To each  $P_i$  associate a fraction  $w_i$  called the discrimination weight of  $P_i$ . When the projective measurement is performed many times, the outcome corresponding to  $P_i$  will be obtained many times and  $w_i$  is the fraction of those outcomes that should be interpreted as  $|\psi_i\rangle$ . The rest should be interpreted as inconclusive. A "discriminated" input state or measurement element is defined as one with  $w_i=1$ . In the ME strategy, all states are discriminated input states whereas in the UD strategy only one input state is discriminated.

Taking these discrimination weights into account, the expression for the correct rate  $P_{\rm C}$  is

$$P_{\rm C} = \sum_{i=1}^{n} w_i \eta_i |\langle p_i | \psi_i \rangle|^2 \tag{4}$$

and the expression for the error rate  $P_E$  is

$$P_{\rm E} = \sum_{i=1, j=1, i\neq j}^{n} w_i \eta_j |\langle p_i | \psi_j \rangle|^2.$$
(5)

The inconclusive rate is then defined as  $P_{\text{In}}=1-(P_{\text{C}}+P_{\text{E}})$ and the optimization problem for some bounded-error rate  $\epsilon$ is

minimize 
$$P_{\text{In}} = 1 - (P_{\text{C}} + P_{\text{E}})$$
  
subject to  $P_{\text{E}} \le \epsilon$ , (6)

over the discrimination weights  $w_1, \ldots, w_n$ , and the orientation of the PVM through  $p_1, \ldots, p_n$ . The minimal function  $\tilde{P}_{In}(\epsilon)$  is obtained by varying  $\epsilon$  from 0 to  $P_{ME}$ . On a plot of  $P_{\rm In}$  versus  $P_{\rm E}$ ,  $\tilde{P}_{\rm In}(\epsilon)$  is a curve. The region above and to the right of that curve contains points representing inconclusive rate and error rate pairs that can be obtained with a PVM strategy. At one end point of the curve is the UD strategy at  $\epsilon = 0$ , where all but one of the discrimination weights are constrained to be zero since at most one input state may be unambiguously discriminated. At the other end is the ME strategy at  $P_{\text{In}}=0$  where a discrimination is attempted for all states and so all discrimination weights are equal to 1. With increasing error from 0,  $\tilde{P}_{In}(\epsilon)$  may be obtained by optimally increasing the values of the n-1 weights from 0 to 1 while adjusting the orientation of the PVM. Now that the problem is formulated, we proceed with some examples.

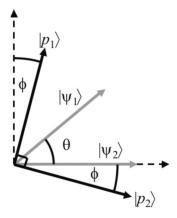


FIG. 2. The geometry of the real, two-state problem. The input states are represented by  $|\psi_1\rangle$  and  $|\psi_2\rangle$ , and the PVM elements project onto  $p_1$  and  $p_2$ . The angle  $\phi$  offsets the orientation of the PVM from the zero-error UD case where  $p_1$  is interpreted as  $|\psi_1\rangle$  and  $p_2$  is interpreted as inconclusive.  $\theta$  is the separation angle between the states.

#### **III. TWO-STATE EXAMPLE**

Consider the restricted problem where there are two states to be discriminated and all their coefficients are real. This case has a simple and instructive geometrical interpretation where the PVM is represented by a set of two orthogonal vectors  $p_1$  and  $p_2$  on the unit circle in  $\mathbb{R}^2$  whose corresponding outcomes are interpreted as the states  $|\psi_1\rangle$  and  $|\psi_2\rangle$ , respectively (see Fig. 2). We now focus on extending the two known strategies (ME and UD) into the intermediate range.

In the UD strategy where  $P_{\rm E}=0$  and assuming again without loss of generality that  $\eta_1 \ge \eta_2$ ,  $\psi_1$  is discriminated using the outcome corresponding to  $p_1$  by setting  $w_1=1$ ,  $w_2=0$ , and  $|\langle p_1 | \psi_2 \rangle|=0$ . The correct rate is then

$$P_{\rm C} = \eta_1 |\langle p_1 | \psi_1 \rangle|^2. \tag{7}$$

A discrimination is not attempted for  $|\psi_2\rangle$ , leaving the outcomes for  $p_2$  as inconclusive. Without changing the discrimination weights, this inconclusive rate may be decreased via a rotation of the PVM from the UD orientation so that the overlap between  $p_2$  and both  $\psi_1$  and  $\psi_2$  decreases. In the process, the overlap between the  $p_1$  and  $\psi_1$  increases thereby increasing the correct rate. Error is introduced in the process since there is now a nonzero overlap between the discriminated PVM element  $p_1$  and the input state to which it is not associated,  $\psi_2$ . This error rate is

$$P_{\rm E} = \eta_2 |\langle p_1 | \psi_2 \rangle|^2. \tag{8}$$

The increase in the two correct and error rates can be found using the setup in Fig. 2. Equations (7) and (8) become

$$P_{\rm C} = \eta_1 \sin^2(\phi + \theta), \quad P_{\rm E} = \eta_2 \sin^2(\phi), \tag{9}$$

respectively, where  $\phi$  is the angle of rotation that is set by the parameter  $P_{\rm E}$ . For small  $\phi$  and  $\theta$  near  $\pi/4$ , the correct rate in Eqs. (9) increases linearly and the error rate increases quadratically. Thus, near  $\phi=0$  we can obtain a significant increase in the correct response rate without a correspond-

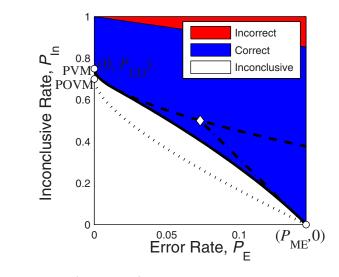


FIG. 3. (Color online) The two-state discrimination problem for  $\theta = \pi/4$  and  $\eta_1 = \eta_2 = 1/2$ . As  $P_E \rightarrow 0$ , the optimal PVM curve (solid line) approaches the dashed curve representing the less general optimization over the orientation of the PVM with  $w_2=0$ . For error approaching the ME value, the optimal PVM curve approaches the dash-dotted line representing strategies based on the ME strategy but with  $0 < w_2 < 1$ . For any value of  $\theta$ , the dashed and dash-dotted curves intersect at  $\left(\frac{P_{\text{ME}}}{2}, \frac{1}{2}\right)$  where  $w_2=0$ , shown here as a diamond marker. The optimal POVM curve for the same parameters is shown as the dotted line.

ingly large increase in the error rate (providing a maximum benefit when  $\theta = \pi/4$ ).

As  $\phi$  increases with increasing  $P_{\rm E}$ , a continuous set of pairs of inconclusive and error rate values are achieved through this freedom in the orientation of the measurement. At the curve's left-end point,  $P_{\rm E}=0$  so that  $\phi=0$  by Eq. (9) and we regain Eq. (3) as  $P_{\rm UD}^{\rm PVM} = \eta_1 [1 - \cos^2(\theta)]$ . The expression for this curve corresponding to the correct rate in Eqs. (9) as a function of the increasing error rate  $P_{\rm E}$  is

$$P_{\rm C} = P_{\rm UD} + \frac{\eta_1}{\eta_2} P_{\rm E} \left( \cos(2\theta) + \sqrt{\frac{\eta_2}{P_{\rm E}} - 1} \sin(2\theta) \right).$$
(10)

When taking the limit  $P_E \rightarrow 0$ ,  $P_C \propto \sqrt{P_E}$  and so the slope of the curve given by Eq. (10) becomes infinite. Again, there is a substantial increase (decrease) in the correct (inconclusive) rate with a small increase in error. An example of this " $w_2 = 0$ " curve is shown in Fig. 3 along with other results discussed below for the case of  $\eta_1 = \eta_2$  and  $\theta = \frac{\pi}{4}$ .

Focusing now on the ME strategy, error may be decreased from  $P_{\rm ME}$  by making use of the freedom of the discrimination weights—i.e., by calling error-prone outcomes inconclusive. This is accomplished by decreasing either of the discrimination weights  $w_1$  or  $w_2$  from 1. Taking one of them to 0 produces a linear curve on the plot in Fig. 3, shown for the case of  $\eta_1 = \eta_2$  and  $\theta = \frac{\pi}{4}$ .

The inconclusive rate function for the optimal strategy,  $\tilde{P}_{In}(\epsilon)$ , is obtained by rotating the PVM while *simultaneously* changing the discrimination weights. The optimal strategy smoothly changes from the orientation-dependent strategy at errors near 0 to the weight-dependent strategy at errors near

 $P_{\text{ME}}$ . For intermediate errors, both strategies are significant and are jointly used to achieve the optimum. The numerical solution for  $\theta = \frac{\pi}{4}$  and  $\eta_1 = \eta_2$  is shown in Fig. 3 where a maximum 10% increase in the correct discrimination rate is achieved by both rotating the PVM *and* changing the discrimination weights as compared to doing either one by itself.

Also shown in Fig. 3 is the corresponding optimal POVM curve as given in Ref. [13]. It always performs better than the PVM solution, as it must. However, even though the curves representing the two strategies are diverging as  $P_{\rm E}$  increases from 0, this trend is short lived. With increasing error, the gap between their inconclusive rates is made smaller by the use of the discrimination weight  $w_2$  in the optimal PVM strategy until the two solutions finally converge on each other at the ME values.

# IV. HIGHER-DIMENSIONAL PROBLEMS AND AN EXAMPLE

The underlying structure of the optimal strategy given above is not restricted to two states, but rather generalizes to problems with a larger number of input states. In general for *n* input states there will be *n* curves analogous to that given by Eq. (10), where each represents a family of strategies, denoted  $C_m$ , for  $1 \le m \le n$ , with a fixed, discrete number of discriminated  $(w_i=1)$  input states. Each  $C_m$  is defined by the discrimination weights:  $w_i = 1$ , for i = 1, ..., m, and  $w_i = 0$  otherwise.  $C_m$  represents the set of strategies where one always tries to discriminate the optimal subset of *m* input states with *m* projectors and interprets the remaining n-m outcomes as inconclusive. For a given set of discriminated states, i.e., for a given  $C_m$ , the error rate can be changed by reorienting the PVM, altering the overlap between the input states and PVM elements. An optimal reorientation generates, for each  $C_m$ , a continuous curve in the plane of  $P_{\text{In}}$  versus  $P_{\text{E}}$ . Each  $C_m$  has a minimum error rate  $P_{E,m}^{\min}$  that is nonzero for m > 1. All strategies that discriminate m states must have an error rate of at least  $P_{\mathrm{E},m}^{\min}$ . To obtain a lower error rate *m* must be reduced. For  $C_1$ , the minimum error is 0—i.e., in the UD case. For  $C_n$  the minimum error is that of the ME case,  $P_{ME}$ , where all weights equal 1 and  $C_n$  is in fact just the point  $(P_{\rm ME}, 0)$ . The intermediate set of strategies for 1 < m < nhave a minimum error lying between 0 and  $P_{\rm ME}$ , with  $P_{\rm E,m}^{\rm min}$  $< P_{\mathrm{E},m+1}^{\mathrm{min}}$ 

Naively, one could obtain a suboptimal set of discrimination strategies as a function of allowed error by adopting the appropriate strategies in  $C_m$  (by optimally reorienting the PVM) once  $P_E \ge P_{E,m}^{\min}$  and until  $P_E \ge P_{E,m+1}^{\min}$ . However, the *optimal* strategy also involves the continuous transformation of the discrimination weights along with the PVM reorientation and generates a continuous, smooth minimum inconclusive rate curve between 0 and  $P_{ME}$  error.

For any  $C_m$ , there will be one of the *m* discriminated states (up to symmetries in that optimal subset) that will give the worst contribution to the error. Reducing the weight for this state gives the minimal increase in the inconclusive rate for errors below  $P_{\text{E},m}^{\text{min}}$  down to  $P_{\text{E},m-1}^{\text{min}}$  at which point one is forced to reduce a weight of the remaining m-1 states to get

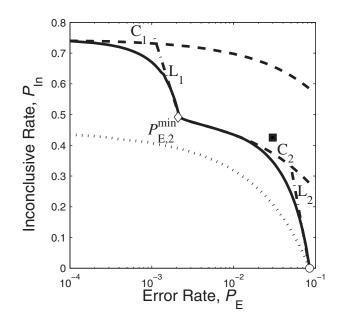


FIG. 4. State discrimination for the three states used in Ref. [17],  $|\psi_1\rangle = (\sqrt{2/3}, 0, 1/\sqrt{3})$ ,  $|\psi_2\rangle = (0, 1/\sqrt{3}, \sqrt{2/3})$ , and  $|\psi_3\rangle = (0, -1/\sqrt{3}, 0, \sqrt{2/3})$ . The optimal projective strategies are represented by the solid line. The two dashed lines C<sub>1</sub> and C<sub>2</sub> represent the strategies that discriminate one and two input states, respectively, using only the orientation of the PVM. The diamond and circular marker represent the minimum error for C<sub>2</sub>,  $P_{E,2}^{min}$ , and the minimum error  $(0, P_{ME})$  respectively. Using the PVM orientation defined at those points, L<sub>1</sub> and L<sub>2</sub> are generated by reducing the weight corresponding to the discriminate state  $(w_i=1)$  that is hardest to discriminate. The optimal PVM at 3% error gives a correct rate of 62.3% compared to the 54.5% attained by the experimental POVM in [17] shown here as a square. The optimal POVM is shown as the dotted line.

the error any lower. Just as in the two-state case, the optimal strategy is a smooth transition from the orientation-focused strategies at errors just above  $P_{\text{E},m-1}^{\text{min}}$  to the weight-focused strategies at errors just below  $P_{\text{E},m}^{\text{min}}$ . The latter can be seen in the dash-dotted lines in Figs. 3 and 4 where the weight of the respective worst state is reduced without changing the orientation of the optimal PVM at the respective  $P_{\text{E},m}^{\text{min}}$  value. Intuitively, the "worst" state is hardest to discriminate because it has the largest overlap with the rest of the states. More technically, it has the largest ratio of error rate to correct rate contribution, so reducing its discrimination weight gives the minimal increase in the inconclusive rate for a given reduction in error rate.

The optimal curve can be found numerically by solving (6) over the discrimination weights and the orientation of the PVM. The optimal projective strategies arising from the above construction may be used in a comparison with optimal POVM strategies for higher-dimensional problems, an example of which follows in the next paragraph.

What spurred interest into bounded-error projective strategies was an earlier paper from our group [17] in which an optical realization of UD was performed on a particular triplet of states,  $|\psi_1\rangle = (\sqrt{2/3}, 0, 1/\sqrt{3}), |\psi_2\rangle = (0, 1/\sqrt{3}, \sqrt{2/3}),$ and  $|\psi_3\rangle = (0, -1/\sqrt{3}, 0, \sqrt{2/3})$ , using the optimal POVM as suggested in [7]. After a comparison with the theoretical re-

sult of the corresponding optimal UD PVM, the claim was made that this POVM had demonstrated "an improvement of more than a factor of 2 over any possible projective measurement" (our emphasis). The measurement was of course accompanied by some experimental error (3% in this case, with a 2% decrease in the inconclusive rate as a result). Therefore, the legitimate comparison is between the implemented POVM and the optimal PVM, implemented or theoretical, that also gives that error rate. The family of projective strategies for a bounded error given in this paper contains such an optimal projective measurement. It is true that in any implementation these optimal projective strategies would themselves acquire experimental errors that would most likely make them less effective than the corresponding implemented UD POVM. However, it is the general claim regarding realistic POVMs and any PVM that we wish to address. Therefore, should any of these theoretically optimal PVM measurements perform better than the implemented POVM, the claim made in Ref. [17] would be invalidated. The proper comparison is shown in Fig. 4 and it is clear that the optimal PVM strategy that is wrong 3% of the time answers correctly more often than the implemented POVM in Ref. [17], represented at the 3% error it achieved in the experiment. The optimal PVM elements P<sub>1</sub>, P<sub>2</sub>, and P<sub>3</sub>, given by the vectors  $p_1 = (-0.63, 0.63, 0.45), p_2 = (0.71, 0.71, 0), \text{ and } p_3 = (0.31, 0.71, 0)$ -0.31,0.90), achieve a 62.3% correct response rate as compared to the 54.5% given by the implemented POVM.

Also shown in Fig. 4 is the optimal curve for any POVM, i.e., the one with no experimental error, found with the duality techniques described in [15] using the program YALMIP. The large advantage that the POVM solution has over the PVM solution in UD diminishes quickly with increasing error from 0 because of the ability of PVMs to make an increasingly large number of correct discriminations of a second state while introducing very little error. A logarithmic scale was used in Fig. 4 to display this fact more clearly. For example, in Fig. 4, the 25.4% correct discriminations for PVMs at 0 error jumps to over 50% at 0.0025% error. By contrast, for the POVM, the 54.5% correct discrimination rate at 0 error only goes up to 61.5% by 0.0025% error. Experimentally accessing these regions of near-zero error where POVMs give a significant advantage may prove difficult. Also, we note that the effect is even stronger in Fig. 4 than in the two-state case considered above in Fig. 3. It therefore may be true that in experiments using a large number of input states and those for which the experimental error cannot be made small, POVMs cease to give a sufficient advantage over PVMs to warrant the increased practical difficulties in their implementation.

## V. DISCUSSION AND SUMMARY

One application for optimal bounded-error strategies may lie in increasing quantum key generation rates. For example in the B92 protocol [5], Alice and Bob use the transmission and an UD measurement of two nonorthogonal states in different bases to build a cryptographic key. The key generation rate is  $R = N(1 - f_{In})[1 - H(e_b) - H(e_p)]$ , where N stands for the number of sent states measured in the same basis and  $f_{In}$ refers to the minimum inconclusive rate for the measurement, found through, for example, the convex methods mentioned in the Introduction.  $f_{In}$  is dependent only on the fixed separation between the two states and their prior probabilities. Out of all the counts that pass the procedure,  $H(e_{\rm b})$  is the fraction that are sacrificed to find the quantum bit-error rate and  $H(e_p)$  is the fraction lost in the privacy amplification process. As long as  $H(e_b)$  and  $H(e_p)$  remain within the bounds required for security, Bob is free to select a measurement that offers him the highest key generation rate through its effect on  $f_{\text{In}}$ . A bounded-error strategy will perform better in this regard than the UD measurement that is normally used. An unconditional security proof for the B92 protocol is given in [18] and provides estimates for the bounds of  $H(e_{\rm b})$ and  $H(e_p)$ . One would need only to adjust the proof by considering a bounded-error strategy instead.

In this work we have developed the general problem of the optimal PVM that interpolates between the UD and ME strategies by minimizing the inconclusive rate for some bounded-error rate. This range of strategies is more experimentally relevant since errors are inevitable and our choice of measurement is relevant since PVMs are more widely used than POVMs. We have found, in both two- and threestate examples, that a small introduction of error leads to a large decrease in the inconclusive rate for PVMs, which suggests that the substantial difference in UD results for PVMs and POVMs may not exist once realistic errors are considered.

## ACKNOWLEDGMENTS

This research was supported by NSERC and CIAR. The authors would like to thank Janos Bergou and Masoud Mohseni for useful discussions. M.P.T. also wishes to thank Peter Turner for some initial POVM MATLAB codes and Fred Fung for many digressions relating to quantum information.

- [1] A. Chefles, Contemp. Phys. **41**, 401 (2000).
- [2] C. W. Helstrom, *Quantum Detection and Estimation Theory* (Academic Press, New York, 1976).
- [3] G. Jaeger and A. Shimony, Phys. Lett. A 197, 83 (1995).
- [4] I. D. Ivanovic, Phys. Lett. A 123, 257 (1987); D. Dieks, *ibid.* 126, 303 (1988); A. Peres, *ibid.* 128, 19 (1988).
- [5] C. H. Bennett, Phys. Rev. Lett. 68, 3121 (1992).
- [6] C. H. Bennett and G. Brassard, Proceedings of the IEEE International Conference on Computers, Systems, and Signal Processing, Bangalore, India, 1984 (IEEE, New York, 1984), pp. 175–179.
- [7] Y. Sun, J. A. Bergou, and M. Hillery, Phys. Rev. A 66, 032315 (2002).
- [8] A. Chefles, Phys. Lett. A 239, 339 (1998).

- [9] Y. Feng, R. Duan, and M. Ying, Phys. Rev. A 70, 012308 (2004).
- [10] X. F. Zhou, Y. S. Zhang, and G. C. Guo, Phys. Rev. A 75, 052314 (2007).
- [11] S. Croke, E. Andersson, S. M. Barnett, C. R. Gilson, and J. Jeffers, Phys. Rev. Lett. 96, 070401 (2006).
- [12] C. W. Zhang, C. F. Li, and G. C. Guo, Phys. Lett. A 261, 25 (1999).
- [13] A. Chefles and S. M. Barnett, J. Mod. Opt. 45, 1295 (1998).
- [14] J. Fiurasek and M. Jezek, Phys. Rev. A 67, 012321 (2003).
  - [15] Y. C. Eldar, Phys. Rev. A 67, 042309 (2003).
  - [16] K. Tamaki, M. Koashi, and N. Imoto, Phys. Rev. A 67, 032310 (2003).
  - [17] M. Mohseni, A. M. Steinberg, and J. A. Bergou, Phys. Rev. Lett. 93, 200403 (2004).
  - [18] K. Tamaki, M. Koashi, and N. Imoto, Phys. Rev. Lett. 90, 167904 (2003).