

Algebraic Reduction and Numerical Optimization Methods for Solving Quantum Control Sum of Squares Problems

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The Problem

Quantum control: find $E(t) = \sum_k x_k t^k$ that drives a system to a target unitary U^*

$$\min \operatorname{Tr}(M^\dagger M), \quad M = U(T) - U^* \approx e^{\Lambda_n/2} - e^{-\Lambda_n/2} U^*$$

Unitary, $U(T)$ approximated via **Magnus expansion** (ODE solution) + **Chebyshev expansion** (matrix exponential):

$$e^{\alpha \Lambda_n} \approx J_0(\alpha) \mathbf{1} + 2 \sum_{k=1}^p J_k(\alpha) T_k$$

Result: the objective becomes a polynomial in x_k — solvable globally via Sum of Squares programming.

The Problem

Quantum control: find $E(t) = \sum_k x_k t^k$ that drives a system to a target unitary U^* given control Hamiltonian, V and drift Hamiltonian, H_0

$$\begin{aligned} &\text{minimize} && \text{Tr}(M^\dagger M) \\ &\text{subject to} && \partial_t U(t) = A(t)U(t) \\ & && U(0) = \mathbb{1} \\ & && A(t) = -i(H_0 + E(t)V) \end{aligned}$$

$$M \approx e^{\Lambda_n/2} - e^{-\Lambda_n/2} U^*$$

Result: the objective becomes a polynomial in x_k — solvable globally via Sum of Squares programming.

The Problem

- This can be written as a sum of squares program solved using semidefinite programming!

$$\begin{array}{ll}\text{minimize} & [x]_d^T Q [x]_d \\ \text{subject to} & Q \in S_+^d\end{array}$$

- We solve for the polynomial control coefficients, Q and choose an appropriate basis, $[x]_d$
- Even for small quantum systems (e.g. 3x3), SDPs become intractable quickly!

Symmetry Reduction:

`SymbolicWedderburn.jl`

Block-diagonalize the SDP via Wedderburn decomposition over the Symmetric Group:

$$V = \bigoplus_{i=1}^r V_i \quad \Rightarrow \quad 4 \text{ independent, smaller SDPs}$$

Affine constraints become per-block:

$$A^i = \sum_j V_i^j, \quad b^i = \alpha \cdot V_i^j$$

Reconstruct the full solution as: $\sum_i V_i X V_i^T$

27× variable reduction before the solver even starts — and better numerical conditioning as a bonus.

Face Reduction

ConicSolveFR.jl

Symmetry reduction alone leaves **structural degeneracy** — the solution lives on a lower-dimensional face of the cone. **Interior point solvers stall without this.**

Algorithm (Permenter 2017): iteratively expose the minimal face via TSVD:

```
while SDP(*) feasible:
    solve SDP(*) → get  $\tilde{X}$ 
    update face:  $\tilde{X} = U_r \Lambda_r U_r^T$  (truncated SVD)
return minimal face  $F$ 
```

Solve the reduced problem, then invert: $X_{n-1} = UX_k U^T$

⚠ TSVD threshold η_λ is the key tuning parameter — too small: stalls; too large: diverges from original problem.

The QCSOS Pipeline

```
""" * `ε`: absolute tolerance
* `η_eps`: absolute tolerance to determine exposed face (using duality gap)
* `η_lambda`: absolute tolerance to remove near redundant constraints
* `p`: order of Chebyshev expansion for approximating matrix exponential """
function run_test(ε = 1e-2, η_eps = 1e-3, η_lambda = 1e-3, p = 2)
    # define optimization problem
    U_target, problem = get_qc_problem()
    problem = QuantumUnitaryFixedTimeProblem(U_target, problem, p)
    qcsos_solver = QCSOS_Solver(p, problem, ε, η_eps, η_lambda)
    solve!(qcsos_solver)

    # get solution
    solution = get_solution(problem.program)

    # evaluate solution
    coefficients = get_control(problem, solution)
    H_result = get_unitary_from_control(problem, coefficients)
    infidelity = get_infidelity(U_target, H_result)
    return U_target, H_result, problem, solution
end
```

ConicSolve.jl — symmetric self-dual interior point solver: - Euclidean-Jordan algebra structure; **no autodiff (AD) needed** - QR + Cholesky for KKT system, equilibration + regularization - Native support for symmetry & face reduction inputs

```
function QuantumUnitaryFixedTimeProblem(U_target, problem, order=2)
    exp½Ω = est_unitary(problem, order)
    A = exp½Ω' * U_target - exp½Ω
    f = get_hilbert_schmidt_inner_product(A)
    n = problem.n

    cone_qp = ConeQP()
    program = define_program(cone_qp,
        minimize(f),
        f ∈ ConicSolve.SymmetricGroup(n))

    build_program(program)
    problem.program = program

    return problem
end
```

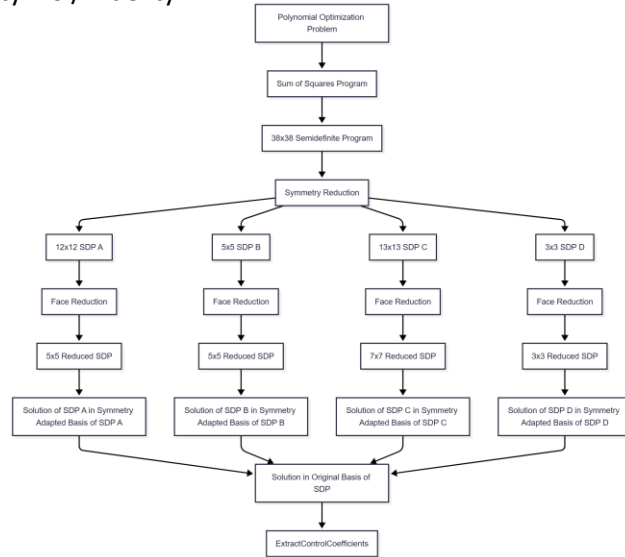
QCSOS Pipeline In Action

What do we want?

(Dual, Primal, Cent.) Res. ≈ 0

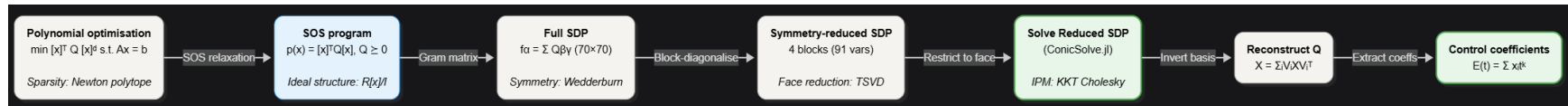
Duality gap ≈ 0

Infidelity ≈ 0 / Fidelity ≈ 1



```
Info: Performing face reduction on cone 5 of 5
Info: Subproblem constructed of size 91
Info: Iter. | Dual Res. | Primal Res. | Cent. Res. | Dual. Gap | Primal Obj. | Dual Obj. | Step size | b'y |
Info: 10 | 1.2222 | 2.7607e-16 | 166.072 | 0.114093 | 0.0 | -1.14080e-9 | 0.0296663 | 1.09935e-9 |
Info: Constraint already feasible, nothing to reduce
Info: Nothing reduced
Info: Subproblem feasible
Info: Subproblem reduced
Info: Optimize called
Info: Solver parameters
Info: Objective limit: -Inf
Info: Limit solution: 0.0
Info: Max iterations: 10
Info: Num constraints: 140
Info: Num threads: 1
Info: Preferred device: CPU
Info: Iterative Refinement Max iterations: 1
Info: Iterative Refinement Trigger Mode: NO_ITERATIVE_REFINEMENT
Info: Presolve Regularization Method: none
Info: Presolve Scaling (Equilibration) Method: ruiz
Info: System Solver KKT method: QR and Cholesky
Info: Time limit (seconds): 1800000
Info: Tolerance gap absolute: 0.0001
Info: Tolerance gap relative: 0.0001
Info: Tolerance optimality: 0.01
Info: Performing Ruiz Equilibration
Info: solving for primal dual starting points
Info: Executing main optimization loop
Info: Iter. | Dual Res. | Primal Res. | Cent. Res. | Dual. Gap | Primal Obj. | Dual Obj. | Step size | b'y |
Info: 1 | 3.6855 | 4.082479999999999e-31 | 7.69185e-16 | 1.0 | 0.0 | 0.000328976 | 0.732622 |
Info: 2 | 1.01933 | 7.89854e-16 | 1.36866 | 0.282705 | 0.0 | -1.38152e-9 | 0.182095 |
Info: Slow progress...
Info: 3 | 1.34468 | 7.65259e-16 | 0.28123 | 0.0 | -1.38242e-9 | 0.00821025 |
Info: 4 | 1.45453 | 6.23237e-16 | 25.8466 | 0.276814 | 0.0 | -1.7389e-9 | 0.182095 |
Info: Slow progress...
Info: 5 | 1.52599 | 6.33857e-16 | 1.29276 | 0.276575 | 0.0 | -4.5288e-11 | 4.96927e-5 |
Info: 6 | 1.63113 | 6.18324e-16 | 338.699 | 0.272053 | 0.0 | -2.17593e-10 | 0.0102004 |
Info: 7 | 1.67295 | 4.0018e-16 | 1.3818 | 0.188906 | 0.0 | -8.44292e-10 | 0.484499 |
Info: 8 | 1.09964 | 2.59768e-16 | 0.723022 | 0.116047 | 0.0 | -1.10313e-9 | 0.467991 |
Info: Slow progress...
Info: 9 | 1.11866 | 2.71525e-16 | 3694.3 | 0.116005 | 0.0 | -1.0981e-9 | 0.000375714 |
Info: 10 | 1.14028 | 2.88731e-16 | 163.137 | 0.111972 | 0.0 | -1.19215e-9 | 0.0321183 |
Info: Solver finished
Info: Exit status: ITERATION LIMIT
Info: Primal objective value: 0.0
Info: Number of iterations: 10
Info: Time elapsed: 0.028469160800000004
Info: Iter. | Dual Res. | Primal Res. | Cent. Res. | Dual. Gap | Primal Obj. | Dual Obj. | Step size | b'y |
Info: 10 | 1.14028 | 2.88731e-16 | 163.137 | 0.111972 | 0.0 | -1.19215e-9 | 0.0321183 | 1.05974e-9 |
Info: Solved reduced problem
Info: Reproject iterate
Info: Reproject iterate
Info: Reproject iterate
Info: Reproject iterate
Info: Face reduction completed
Info: WARNING: no result from subprogram, skipping
Info: Numerical rank of solution (Ideally 1) with tolerance 0.0001 is 93
Info: Extracted control coefficients
Info: Infidelity: 0.10637362880070156
```

The QCSOS method computational pipeline

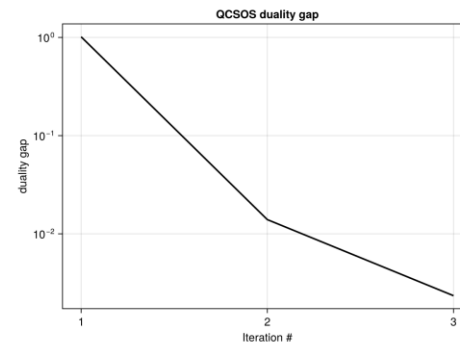
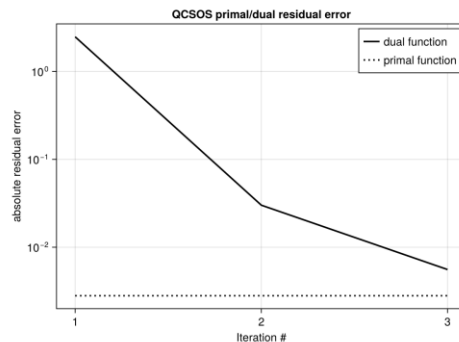
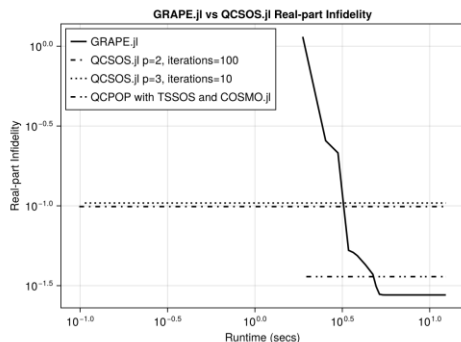


Achieve global convergence via
Structural exploitation -> better numerical stability and efficiency -> faster
convergence and tighter numerical guarantees

Results: QCSOS vs GRAPE.jl and QCPOP

For a Three-level system

Performance Measure	GRAPE.jl	QCPOP with TSSOS + COSMO.jl	QCSOS.jl
Infidelity	0.0277	0.036	0.099
Runtime (seconds)	53.2	1.97	0.1



QCSOS is ~500× faster at ~1e-1 infidelity compared to GRAPE.jl

GRAPE plateaus at iteration ~10. QCSOS reaches its solution in **single-digit iterations** — no local minima to escape.

Discussion & Future Work

What's working: - Layered algebraic reduction without relaxing the original problem - Composable Julia packages — drop-in preprocessing for existing solvers

Current limitations: - Numerically brittle — careful parameter tuning required - Residuals plateau at physics model ceiling (Magnus/Chebyshev truncation)

Next steps: - Alternate polynomial bases (e.g. Chebyshev) for better numerical stability - Partial face reduction to reduce overhead of multiple face-exposing SDPs - Scaling to larger quantum systems for safety-critical applications

Thank You!

Step	Julia Package	Contribution
Symmetry reduction	<code>SymbolicWedderburn.jl</code>	2485 $\rightarrow$ 91 variables
SDP solve + face reduction	<code>ConicSolve.jl</code>	Degeneracy-robust IPM
Full pipeline	<code>QCSOS.jl</code>	215 $\times$ speedup, 7 $\times$ infidelity

 `github.com/alexander-leong/QCSOS.jl`

 `toshibaalexander@gmail.com`

*Thanks to QNumerics 2025 for
inspiring this work.*

Link to Paper =>

