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For reference, Algorithm 1 shows the complete pseudocode of an optimization with Krotov's method, as implemented in the krotov package (https://github.com/qucontrol/krotov).

Variables are color coded. Scalars are set in blue, e.g.  $\epsilon_{ln}^{(0)}$ . States (Hilbert space states or vectorized density matrices) are set in purple, e.g.  $\phi_k^{\text{init}}$ . They may be annotated with light gray superscripts to indicate the iteration-index *i* of the control under which state was propagated, and with light gray time arguments. These annotations serve only to connect the variables to the equations of motion:  $\phi_k^{(0)}(t_n)$  and  $\phi_k^{(0)}(t_{n-1})$  are the same variable  $\phi_k$ . Operators acting on states are set in green, e.g.  $\mu_{lkn}$ . These may be implemented as a sparse matrix or implicitly as a function that returns the result of applying the operator to a state. Lastly, storage arrays are set in red, e.g.  $\Phi_0$ . Each element of a storage array is a state.

The Python implementation groups several of the algorithm's input parameters by introducing a list of N"objectives". The objectives are indexed by k, and each objective contains the initial state  $\phi_k^{\text{init}}$ , the Hamiltonian or Liouvillian  $H_k$  to be used by the propagator U and for the operators  $\mu_{lkn}$ , and possibly a "target" to be taken into account by the function  $\chi$ . In many applications,  $H_k \equiv H$  is the same in all objectives, and  $\mu_{lkn} \equiv \mu_l$  if His linear in the controls in addition.

The CPU resources required for the optimization are dominated by the time propagation (calls to the function U in lines 7, 24 37). This is under the assumption that evaluating U dominates the application of the operator  $\mu_{lkn}$  to the state  $\phi_k^{(i)}(t_{n-1})$  and the evaluation of the inner product of two states, lines 31, 34. This condition is fulfilled for any non-trivial Hilbert space dimension.

Loops over the index k are parallelizable, in particular in a shared-memory (multi-threaded) parallelization environment like OpenMP. In a (multi-process) methodpassing environment like MPI, some care must be taken to minimize communication overhead from passing large state vectors. For some (but not all) functionals, interprocess communication can be reduced to only the scalar values constituting the sum over k in lines 31, 34.

The memory requirements of the algorithm are dominated by the storage arrays  $\Phi_0$ ,  $\Phi_1$ , and X. Each of these must store  $N(N_T+1)$  full state vectors (a full time propagation for each of the N objectives). Each state vector is typically an array of double-precision complex numbers. For a Hilbert space dimension d, a state vector thus requires 16d bytes of memory, or  $16d^2$  bytes for a density matrix. Under certain conditions, the use of  $\Phi_0$  and  $\Phi_1$  can be avoided: both are required only when the second order update is used ( $\sigma(t) \neq 0$ ). When the first order update is sufficient,  $\Phi_1$  may overwrite  $\Phi_0$ so that the two collapse into a single forward-storage  $\Phi$ . The states stored in  $\Phi$  are only used for the inhomogeneity  $\partial q_b / \partial \langle \phi_k |$  in Eq. (3), and no storage  $\Phi$  of forward-propagated states at all is required if  $g_b \equiv 0$ . Thus, in most examples, only the storage X of the backward-propagated states remains. In principle, if the time propagation U is unitary (i.e., invertible), the states stored in X could be recovered by forward-propagation of  $\{\chi_k^{(i-1)}(t=0)\}$ , eliminating X at the (considerable) runtime cost of an additional time propagation.

## **Optimization Functional and Equations of Motion**

$$J[\{|\phi_k^{(i)}(t)\rangle\}, \{\epsilon_l^{(i)}(t)\}] = J_T(\{|\phi_k^{(i)}(T)\rangle\}) + \sum_l \int_0^T g_a(\epsilon_l^{(i)}(t)) \,\mathrm{d}t + \int_0^T g_b(\{\phi_k^{(i)}(t)\}) \,\mathrm{d}t \tag{1}$$

$$\frac{\partial}{\partial t} \left| \phi_k^{(i)}(t) \right\rangle = -\frac{\mathrm{i}}{\hbar} \hat{H}^{(i)} \left| \phi_k^{(i)}(t) \right\rangle \tag{2}$$

$$\frac{\partial}{\partial t} \left| \chi_k^{(i-1)}(t) \right\rangle = -\frac{\mathrm{i}}{\hbar} \hat{H}^{\dagger (i-1)} \left| \chi_k^{(i-1)}(t) \right\rangle + \left. \frac{\partial g_b}{\partial \left\langle \phi_k \right|} \right|_{(i-1)} \tag{3}$$

with 
$$\left|\chi_{k}^{(i-1)}(T)\right\rangle = -\left.\frac{\partial J_{T}}{\partial\left\langle\phi_{k}(T)\right|}\right|_{(i-1)}$$
(4)

## Algorithm 1 KROTOV'S METHOD FOR QUANTUM OPTIMAL CONTROL

- 1. list of guess control values  $\{\epsilon_{ln}^{(0)}\}$  where  $\epsilon_{ln}^{(0)}$  is the value of the *l*'th control field on the *n*'th interval of the propagation time grid  $(t_0 = 0, \ldots, t_{N_T} = T)$ , i.e.,  $\epsilon_{ln}^{(0)} \equiv \epsilon_l^{(0)}(\tilde{t}_n)$  with  $\tilde{t}_n \equiv t_n + ((t_{n+1} t_n)/2)$
- 2. list of update-shape values  $\{S_{ln}\}$  with each  $S_{ln} \in [0, 1]$
- 3. list of update step size values  $\{\lambda_{a,l}\}$
- 4. list of N initial states  $\{\phi_k^{\text{init}}\}$  at  $t = t_0 = 0$
- 5. propagator function U that in "forward mode" receives a state  $\phi_k(t_n)$  and a list of control values  $\{\epsilon_{ln}\}$  and returns  $\phi_k(t_{n+1})$  by solving the differential equation (2), respectively in "backward mode" (indicated as  $U^{\dagger}$ ) receives a state  $\chi_k(t_n)$  and returns  $\chi_k(t_{n-1})$  by solving the differential equation (3)
- 6. list of operators  $\mu_{lkn} = \frac{\partial H_k}{\partial \epsilon_{ln}}$ , where  $H_k$  is the right-hand-side of the equation of motion of  $\phi_k(t)$ , up to a factor of  $(-i/\hbar)$ , cf. Eq. (2);
- 7. function  $\chi$  that receives a list of states  $\{\phi_k(T)\}\$  and returns a list of states  $\{\chi_k(T)\}\$  according to Eq. (4);
- 8. optionally, if a second order construction of the pulse update is necessary: function  $\sigma(t)$ .

**Output:** optimized control values  $\{\epsilon_{ln}^{(\text{opt})}\}$ , such that  $J[\{\epsilon_{ln}^{(\text{opt})}\}] \leq J[\{\epsilon_{ln}^{(0)}\}]$ , with J defined in Eq. (1).

```
1: procedure KROTOVOPTIMIZATION(\{\epsilon_{ln}^{(0)}\}, \{S_{ln}\}, \{\lambda_{a,l}\}, \{\phi_k^{\text{init}}\}, U, \{\mu_{lkn}\}, \chi, \sigma)
                                                                                                                                                                                                                      ▷ iteration number
 2:
              i \leftarrow 0
              allocate forward storage array \Phi_0[1 \dots N, 0 \dots N_T]
 3:
              for k \leftarrow 1, \ldots, N do
 4:
                                                                                                                                                                                                  \triangleright initial forward-propagation
                      \begin{split} & \Phi_0[k,0] \leftarrow \phi_k^{(0)}(t_0) \leftarrow \phi_k^{\text{init}} \\ & \text{for } n \leftarrow 1, \dots, N_T \text{ do} \end{split} 
  5:
  6:
                            \Phi_0[k,n] \leftarrow \phi_k^{(0)}(t_n) \leftarrow U(\phi_k^{(0)}(t_{n-1}), \{\epsilon_{ln}^{(0)}\})
 7:
                                                                                                                                                                                                              \triangleright propagate and store
                     end for
 8:
              end for
 9:
10:
              while not converged do
                                                                                                                                                                                                                     ▷ optimization loop
                     \begin{array}{l} i \leftarrow i+1 \\ \Phi_1, \{\epsilon_{ln}^{(i)}\} \leftarrow \text{KrotovIteration}(\Phi_0, \{\epsilon_{ln}^{(i-1)}\}, \dots) \end{array}
11:
12:
                     \Phi_0 \leftarrow \Phi_1
13:
              end while

\forall l, \forall n : \epsilon_{ln}^{(\text{opt})} \leftarrow \epsilon_{ln}^{(i)}
14:
                                                                                                                                                                                                         \triangleright final optimized controls
15:
16: end procedure
```

17: procedure KROTOVITERATION( $\Phi_0, \{\epsilon_{ln}^{(i-1)}\}, \{S_{ln}\}, \{\lambda_{a,l}\}, \{\phi_k^{\text{init}}\}, U, \{\mu_{lkn}\}, \chi, \sigma$ )

 $\begin{aligned} \forall k : \phi_k^{(i-1)}(T) \leftarrow \Phi_0[k, N_T] \\ \{\chi_k^{(i-1)}(T)\} \leftarrow \chi(\{\phi_k^{(i-1)}(T)\}) \\ \text{allocate backward storage array } X[1 \dots N, 0 \dots N_T]. \end{aligned}$ 18:19:▷ backward boundary condition 20:for  $\mathbf{k} \leftarrow 1, \dots, N$  do 21:
$$\begin{split} & \mathbf{X}[k, N_T] \leftarrow \chi_k^{(i-1)}(T) \\ & \text{for } n \leftarrow N_T, \dots, 1 \text{ do} \\ & \mathbf{X}[k, n-1] \leftarrow \chi_k^{(i-1)}(t_{n-1}) \leftarrow U^{\dagger}(\chi_k^{(i-1)}(t_n), \{\epsilon_{ln}^{(i-1)}\}, \Phi_0) \end{split}$$
22:23:▷ backward-propagate and store 24:end for 25:end for 26:allocate forward storage array  $\Phi_1[1 \dots N, 0 \dots N_T]$ 27: $\begin{aligned} \forall k : \Phi_1[k, 0] \leftarrow \phi_k^{(i)}(t_0) \leftarrow \phi_k^{\text{init}} \\ \text{for } n \leftarrow 1, \dots, N_T \text{ do} \\ \forall k : \chi_k^{(i-1)}(t_{n-1}) \leftarrow X[k, n-1] \\ \forall l : \Delta \epsilon_{ln} \leftarrow \frac{S_{l,n-1}}{\lambda_{a,l}} \operatorname{Im} \sum_k \left\langle \chi_k^{(i-1)}(t_{n-1}) \middle| \mu_{lkn} \middle| \phi_k^{(i)}(t_{n-1}) \right\rangle \end{aligned}$ 28: $\triangleright$  sequential update loop 29:30: 31: ▷ first order if  $\sigma(t) \neq 0$  then 32:  $\triangleright$  second order  $\begin{aligned} &\forall k : \Delta \phi_k^{(i)}(t_{n-1}) \leftarrow \phi_k^{(i)}(t_{n-1}) - \Phi_0[k, n-1] \\ &\forall l : \Delta \epsilon_{ln} \leftarrow \Delta \epsilon_{ln} + \frac{S_{l,n-1}}{\lambda_{a,l}} \operatorname{Im} \sum_k \frac{1}{2} \sigma(\tilde{t}_n) \langle \Delta \phi_k^{(i)}(t_{n-1}) \big| \mu_{lkn} \big| \phi_k^{(i)}(t_{n-1}) \rangle \end{aligned}$ 33: 34: $\begin{array}{l} \mathbf{end if} \\ \forall l: \epsilon_{ln}^{(i)} \leftarrow \epsilon_{ln}^{(i-1)} + \Delta \epsilon_{ln} \\ \forall k: \mathbf{\Phi}_1[k,n] \leftarrow \phi_k^{(i)}(t_n) \leftarrow U(\phi_k^{(i)}(t_{n-1}), \{\epsilon_{ln}^{(i)}\}) \end{array}$ 35:▷ apply update 36:37:  $\triangleright$  propagate and store end for 38: if  $\sigma(t) \neq 0$  then 39:40: Update internal parameters of  $\sigma(t)$  if necessary 41: end if 42: end procedure

## Notes:

- The index k numbers the independent states to be propagated, respectively the independent "objectives" (see text for details), l numbers the independent control fields, and n numbers the intervals on the time grid.
- The optimization loop may be stopped if the optimization functional or the change of functional falls below a pre-defined threshold, a maximum number of iterations is reached, or any other criterion.
- The braket notation in lines 31 indicates the (Hilbert-Schmidt) inner product of the state  $\chi_k^{(i-1)}(t_n-1)$  and the state resulting from applying  $\mu_{lkn}$  to  $\phi_k^{(i)}(t_{n-1})$ . In Hilbert space, this is the standard braket. In Liouville space, it is tr  $(\chi_k^{\dagger} \mu_{lkn}[\phi_k])$  with density matrices  $\chi_k$ ,  $\phi_k$  and a super-operator  $\mu_{lkn}$ .
- For numerical stability, the states  $\chi_k^{(i-1)}(T)$  in line 19 may be normalized. This norm then has to taken into account in the pulse update, line 31.
- In line 24, the storage array  $\Phi_0$  is passed to  $U^{\dagger}$  only to account for the inhomogeneity due to a possible statedependent constraint,  $\partial g_b / \partial \langle \phi_k |$  in Eq. (3). If  $g_b \equiv 0$ , the parameter can be omitted.