Efficient estimation of nearly sparse many-body quantum Hamiltonians

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We develop an efficient and robust approach to Hamiltonian identification for multipartite quantum systems based on the method of compressed sensing. This work demonstrates that with only $O(s \log(d))$ experimental configurations, consisting of random local preparations and measurements, one can estimate the Hamiltonian of a $d$-dimensional system, provided that the Hamiltonian is nearly $s$-sparse in a known basis. We numerically simulate the performance of this algorithm for three- and four-body interactions in spin-coupled quantum dots and atoms in optical lattices. Furthermore, we apply the algorithm to characterize Hamiltonian fine structure and unknown system-bath interactions.

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I. INTRODUCTION

The dynamical behavior of multipartite quantum systems is governed by the interactions amongst the constituent particles. Although, the physical or engineering considerations may specify some generic properties about the nature of quantum dynamics, the specific form and the strength of multi-particle interactions are typically unknown. Additionally, quantum systems usually have an unspecified interaction with their surrounding environment. In principle, one can characterize quantum dynamical systems via “quantum process tomography” (QPT) [1–8]. However, the relationship between relevant physical properties of a system to the information gathered via QPT is typically unknown. Alternatively, knowledge about the nature of inter- and intra- many-body interactions within the system and/or its environment can be constructed by identifying a set of (physical or effective) Hamiltonian parameters generating the dynamics [9–18]. Currently, a scalable approach for efficient estimation of a full set of Hamiltonian parameters does not exist.

The dynamics of a quantum system can be estimated by observing the evolution of some suitable test states. This can be achieved by a complete set of experimental configurations consisting of appropriate input states and observables measured at given time intervals. Knowledge about the dynamics may then be reconstructed via inversion of the laboratory data by fitting a set of dynamical variables to the desired accuracy. Estimating Hamiltonian parameters from such a procedure faces three major problems: (1) The number of required physical resources grows exponentially with the degrees of freedom of the system [1–8]. (2) There are inevitable statistical errors associated with the inversion of experimental data [1–8]. (3) The inversion generally involves solving a set of nonlinear and non-convex equations, since the propagator is a nonlinear function of Hamiltonian parameters [9–18]. The first two problems are always present with any form of quantum tomography, but the last problem is specific to the task of Hamiltonian identification as we wish to reconstruct the generators of the dynamics. Many quantum systems involve two-body local interactions, so the goal is often to estimate sparse Hamiltonians with effectively a polynomial number of unknown parameters. Unfortunately, quantum state and process tomography cannot readily exploit this potentially useful feature.

The highly nonlinear feature in the required inversion of laboratory data was studied in Ref. [9] in which closed-loop learning control strategies were used for the Hamiltonian identification. In that approach one estimates the unknown Hamiltonian parameters by tailoring shaped laser pulses to enhance the quality of the inversion. Identification of time-independent (or piece-wise constant) Hamiltonians have been studied for single-qubit and two-qubit cases [13, 14] to verify the performance of quantum gates. Estimation of these Hamiltonians is typically achieved via monitoring the expectation values of some observable, e.g. concurrence, which are time periodic functions. Through Fourier transform of this signal the identification task is reduced to finding the relative location of the peaks and heights of the Fourier spectrum [13, 14]. Bayesian analysis is another method proposed for robust estimation of a two-qubit Hamiltonian [15]. The difficulty with these methods is then scalability with the size of the system. A symmetrization method for efficient estimation of the magnitude of effective two-body error generators in a quantum computer was studied in [16] by monitoring quantum gate average fidelity decay. Recently, it was demonstrated that direct or selective QPT schemes could be used for efficient identification of short-time behavior of sparse Hamiltonians [17] assuming controllable two-body quantum correlations with auxiliary systems and the exact knowledge of the sparsity pattern. Another scheme for the determination of the coupling parameters in a chain of interacting spins with restricted controllability was introduced in Ref. [18].

In this work, inspired by recent advances in classical signal processing known as compressed sensing [19], we use random local input states and measurement observables for efficient Hamiltonian identification. We show how the difficulties with the nonlinearity of the equations can be avoided by either a short time or a perturbative treatment of the dynamics. We demonstrate that randomization of the measurement observables enables compressing the extracted Hamiltonian information into an exponentially smaller set of outcomes. This is accomplished by a generalization of compressed sensing to
utilize random matrices with correlated elements. This approach is applicable for Hamiltonians that are nearly sparse in a known basis with an arbitrary unknown sparsity pattern of parameters. The laboratory data can then be inverted by solving a convex optimization problem. This algorithm is highly tolerant to noise and experimental imperfections. The power of this procedure is illustrated by simulating three- and four-body Hamiltonians for neutral atoms in an optical lattice and spin-coupled quantum dot systems, respectively. Furthermore, we directly apply the algorithm to estimate Hamiltonian fine structure and characterize unknown system-bath interactions for open quantum systems.

II. QUANTUM DYNAMICAL EQUATIONS

The time evolution of a quantum system in a pure state is governed by the Schrödinger equation, \( \frac{d}{dt} |\psi(t)\rangle = -iH |\psi(t)\rangle \). The solution of this equation for a time-independent Hamiltonian can be simply expressed as \( |\psi(t)\rangle = \exp(-itH) |\psi(0)\rangle \). In principle, the Hamiltonian of the system \( H \) can be estimated by preparing an appropriate set of test states \( \{ |\psi_k\rangle \} \) and measuring the expectation value of a set of observables \( \{ M_j \} \) after the system has evolved for a certain period of time. The expectation value of these observables can be expressed as

\[
p_{jk} = \langle M_j | \psi_k \rangle = \langle \psi_k | e^{itH} M_j e^{-itH} | \psi_k \rangle \tag{1}
\]

Equation (1) implies that the experimental outcomes \( \{ p_{jk} \} \) are nonlinear functions of the Hamiltonian parameters. To avoid the difficulties of solving a set of coupled nonlinear equations we consider the short time behavior of the system. Monitoring the short time dynamics of the system is valid when the relevant time scales of the system evolution satisfy \( t \ll K^{-1} \) where, for positive operator-valued measure (POVM) operators \( \{ M_j \} \), the constant \( K \) equals \( 2|H|_{\text{spec}} \). The general expression of \( K \) is given in appendix B, also see appendix A for definition of the norms. This yields the linearized form of the Eq. (1)

\[
p_{jk} = \langle \psi_k | M_j | \psi_k \rangle + it \langle \psi_k | [H, M_j] | \psi_k \rangle + O(K^2t^2) \tag{2}
\]

The linear approximation contains enough information to fully identify the Hamiltonian and the higher order terms do not provide additional information. The short-time approximation implies prior knowledge about the system dynamical time-scale or the order of magnitude of \( |H|_{\text{spec}} \). This prior knowledge is available from generic physical and engineering considerations. For example, in solid-state quantum devices the time-scale of single qubit rotations is typically on the order of 1-10 ns. The switching time for exchange interactions varies among different solid-state systems from 1ps to 100ps, (for more details see appendix B.)

We expand the Hamiltonian in an orthonormal basis \( \{ \Gamma_{\alpha} \} \), where \( \text{Tr}(\Gamma_{\alpha}^{\dagger} \Gamma_{\beta}) = \delta_{\alpha,\beta} \); \( H = \sum_{\alpha} h_{\alpha} \Gamma_{\alpha} \). Here \( d \) is the dimension of the Hilbert space. In this representation the Hamiltonian parameters are the coefficients \( h_{\alpha} \). The expanded form of the above affine equation (2) is

\[
\bar{p}_{jk} = it \sum_{\alpha} \langle \psi_k | [\Gamma_{\alpha}, M_j] | \psi_k \rangle h_{\alpha} \tag{3}
\]

Here we introduce the experimental outcomes as \( \bar{p}_{jk} = p_{jk} - \langle \psi_k | M_j | \psi_k \rangle \), since \( \langle \psi_k | M_j | \psi_k \rangle \) is apriori known. The relation (3) corresponds to a single experimental configuration \( (M_j | \psi_k) \). For a d-dimensional system, the total number of Hamiltonian parameters \( h_{\alpha} \) is \( d^2 \). Thus, one requires the same number of experimental outcomes, \( p_{jk} \) that leads to \( d^2 \) linearly independent equations. For a system of \( n \) qubits, this number grows exponentially with \( n \) as \( d = 2^n \). In order to devise an efficient measurement strategy we will focus on physically motivated nearly sparse Hamiltonians.

A Hamiltonian \( H \) is considered to be \( s \)-sparse if it only contains \( s \) non-zero parameters \( \{ h_{\alpha} \} \). More generally, a Hamiltonian \( H \) is termed nearly \( s \)-sparse, for a threshold \( \eta \), if at most \( s \) coefficients \( h_{\alpha} (H = \sum h_{\alpha} \Gamma_{\alpha}) \) have magnitude greater than \( \eta h_{\text{max}} \) where \( h_{\text{max}} = \max(h_{\alpha}) \). By definition, the sparsity is basis dependent. However, for local interactions, the basis in which the Hamiltonian is sparse is typically known from physical or engineering considerations.

III. COMpressed HAMILTONIAN ESTIMATION

Our algorithm is based on general methods of so-called compressed sensing that recently have been developed in signal processing theory \cite{19}. Compressed sensing allows for condensing signals and images into a significantly smaller amount of data, and recovery of the signal becomes possible from far fewer measurements than required by traditional methods.

Compressed sensing has two main steps: encoding and decoding. The information contained in the signal is mapped into a set of laboratory data with an exponentially smaller representation. This compression can be achieved by randomization of data acquisition. The actual signal can be recovered via an efficient algorithm based on convex optimization methods. Compressed sensing has been applied to certain quantum tomography tasks. Standard compressed sensing has been directly used for efficient pseudothermal ghost imaging \cite{20,21}. Recently, a quadratic reduction in the total number of measurements for quantum tomography of a low rank density matrix has been demonstrated using a compressed sensing approach \cite{22}.

Here, we first describe how the Hamiltonian information is compressed into the experimental data. The output of a single measurement is related to the unknown signal (Hamiltonian parameters) through the relation (3). Suppose we try \( m \) different experimental configurations (i.e., \( m \) different pairs of \( (M_j, |\psi_k\rangle) \)). This yields a set of linear equations

\[
\frac{1}{\sqrt{m}} \vec{p} = \Phi \vec{h} \tag{4}
\]

where \( \Phi \) is a \( m \times d^2 \) matrix with elements \( \Phi_{jk,\alpha} = \langle \psi_k | [\Gamma_{\alpha}, M_j] | \psi_k \rangle \) (A factor \( 1/\sqrt{m} \) is included for simplifying the proofs, appendix C). In general \( m \) has to be
The inequality (6) is defined for any exponential reduction in the minimum number of the required  
this inequality, and how small the value of  
\( \Phi \) preserves the distance between \( h_1 \) and \( h_2 \) to a good approximation:  
\[
(1 - \delta_s)||h_2 - h_1||^2_2 \leq ||\Phi(h_2 - h_1)||^2_2 \leq (1 + \delta_s)||h_2 - h_1||^2_2
\]
for a constant \( \delta_s \in (0, 1) \). A smaller \( \delta_s \) ensures higher distinguishability of \( s \)-sparse Hamiltonians. The inequality relation (5) is termed a restricted isometry property (RIP) of the matrix \( \Phi \). We now discuss how to construct a map \( \Phi \) satisfying this inequality, and how small the value of \( m \) can be made.

The RIP (5) for a matrix \( \Phi \) can be established by employing the measurement concentrations of random matrices. In each experiment the test state and the measurement observable can be drawn randomly from a set of configurations \( \{ M_j, j \} \) realizable in the laboratory. The independent selection of \( \{ j \} \) and \( M_j \) leads to a matrix \( \Phi \) with independent rows but correlated elements \( \Phi_{jk} \) in each row. Thus the standard results from compressed sensing theory are not applicable here (appendix C).

In contrast, here we derive a concentration inequality for a matrix with independent rows and correlated columns as the backbone for the RIP of our quantum problem in appendix C. Using Hoeffding’s inequality, we show that for any Hamiltonian \( h \) and a random matrix \( \Phi \) with column only correlations, the random variable \( ||\Phi h||^2 \) is concentrated around \( ||h||^2 \) with a high probability, i.e. \( \forall 0 < \delta < 1 \)
\[
\text{Prob.}\left( ||\Phi h||^2_2 - ||h||^2_2 \geq \delta ||h||^2_2 \right) \leq 2e^{-mc_0(\delta + c_1)^2}
\]
for some constants \( c_0 \) and \( c_1 \).

Using the above inequality, now we can show how an exponential reduction in the minimum number of the required configurations can be achieved for Hamiltonian estimation. The inequality (6) is defined for any \( h \) while the inequality in the definition of RIP, Eq. (5), is for any \( s \)-sparse \( h \). As shown in Ref. [24], there is an inherent connection between these two inequalities. It is proved that any matrix \( \Phi \) satisfying (6) has RIP with probability greater than \( 1 - 2 \exp(-mc_0(\delta^2 + c_1)^2 + s[log(d^4/s) + log(12e/\delta^2)]) \). In addition, whenever \( m \geq c_2s \log(d^4/s) \), for a sufficiently large constant \( c_2 \) one can find a constant \( c_3 \geq 0 \) such that the likelihood of the RIP to be satisfied converges exponentially fast to unity as \( 1 - 2 \exp(-c_3m) \).

The set of experimental configurations defined by Eq (4), and the concentration properties given by Eq (5) and (6) can be understood as encoding the information of a sparse Hamiltonian into a space with a lower dimension. Next we need to provide an efficient method for decoding in order to recover the original Hamiltonian. The decoder is simply the minimizer of the \( l_1 \) norm of the signal \( h \). Implementing this decoder is a special convex optimization problem, which can be solved via fast classical algorithms, yet not strictly scalable. Furthermore, the encoding/decoding scheme is robust to noisy data as \( ||p' - \Phi h||_2 \leq \epsilon \) where \( \epsilon \) is the noise threshold. Note that \( \epsilon \) includes the error of linearization (see Eq (2)) that is \( O(\sqrt{mK/\ell^2}) \). Denote \( h_0 \) as the true representation of the Hamiltonian. For a threshold \( \eta \), \( h_0(s) \) is an approximation to \( h_0 \) obtained by selecting the \( s \) elements of \( h_0 \) as those that are larger than \( \eta h_{\text{max}} \) and setting the remaining elements to zero. Now we state our main result:

IV. ALGORITHM EFFICIENCY

If the measurement matrix \( \Phi \in \mathbb{C}^{m \times d^4} \) is drawn randomly from a probability distribution that satisfies the concentration inequality in (5) with \( \delta_s < \sqrt{2} - 1 \), then there exist constants \( c_2, c_3, d_1, d_2 > 0 \) such that the solution \( h^* \) to the convex optimization problem,
\[
\begin{align*}
\text{minimize} & \quad ||h||_{l_1} \\
\text{subject to} & \quad ||p' - \Phi h||_2 \leq \epsilon,
\end{align*}
\]
satisfies,
\[
||h^* - h_0||_2 \leq \frac{d_1}{\sqrt{s}} ||h_0(s) - h_0||_{l_1} + d_2 \epsilon
\]
with probability \( \geq 1 - 2e^{-mc_3} \) provided that,
\[
m \geq c_2s \log(d^4/s),
\]
where the performance of a \( l_1 \) minimizer, Eq. (3), and the necessary bound \( \delta_s < \sqrt{2} - 1 \) are derived by Candès in Ref. [25].

As an example, for a system consisting of \( n \) interacting qubits, the exponential number of parameters describing the dynamics, \( 2^{2n} \), can be estimated with a linearly growing number of experiments \( m \geq c_2s(8 \log(2)n - \log(s)) \). The second term, \( d_2 \epsilon \), indicates that the algorithmic performance is bounded by the experimental uncertainties. Consequently, for fully sparse Hamiltonians and \( \epsilon = 0 \) the exact identification of an unknown Hamiltonian is achievable. The properties of the ensemble from which the states and measurement observables are chosen would determine the parameter \( \delta_s \) and consequently the performance of the algorithm. The linear independency of the \( \Phi \) matrix rows for a random set of local state preparations and observables can be guaranteed by a polynomial level of computational overhead before conducting the experiments.

A certification for the nearly sparsity assumption can be obtained from Eqs. (8) and (9) as follows: Suppose \( h^*_{m} \) is the algorithm’s outcome for \( m \) configurations. The nearly sparsity assumption is certified on the fly during the experiment, if the estimation improvement \( ||h^*_{m+1} - h^*_{m}|| \) converges to zero for a polynomially large total number of configurations.

V. PHYSICALLY NEARLY SPARSE HAMILTONIAN

Although physical systems at the fundamental level involve local two-body interactions, many-body Hamiltonians often
describe quantum dynamics in a particular representation or in well defined approximate limits. The strength of the non-local \( k \)-body terms typically is much smaller than the two-body terms with strength \( J \) and decreases with the number \( k \). For a fixed sparsity threshold \( \eta, k_\eta \) is defined as the largest number \( k \) for which \( k \)-body terms have strength larger than \( \eta J \). Then the number of the elements of a \( \eta \)-sparse approximation of a \( n \)-body Hamiltonian grows linearly as \( \mathcal{O}(n g(k_\eta)) \), where the \( g(k_\eta) \) is determined by the geometry of the system.

A general class of many-body interactions arises when we change the basis for a bosonic or fermionic system expressed by a (typically local) second-quantized Hamiltonian to a Pauli basis, e.g., via a Jordan-Wigner transformation. For fermionic systems the interactions are imposed physically from Coulomb’s force and Pauli exclusion principle. The second-quantized Hamiltonian for these systems can be generally written as:

\[
\hat{H} = \sum_{p,q} b_{pq} \hat{a}_p^\dagger \hat{a}_q + \sum_{p,q,r,s} b_{pqrs} \hat{a}_p^\dagger \hat{a}_q^\dagger \hat{a}_r \hat{a}_s,
\]

where the annihilation and creation operators (\( \hat{a}_j \) and \( \hat{a}_j^\dagger \) respectively) satisfy the fermionic anti-commutation relations: \( \{ \hat{a}_i, \hat{a}_j^\dagger \} = \delta_{ij} \) and \( \{ \hat{a}_i, \hat{a}_j \} = 0 \). For example, in chemical systems the coefficients \( h_{pq} \) and \( h_{pqrs} \) can be evaluated using the Hartree-Fock procedure for \( N \) single-electron basis functions. The Jordan-Wigner transformation can then be used to map the fermionic creation and annihilation operators into a representation in terms of Pauli matrices \( \hat{\sigma}^x, \hat{\sigma}^y, \hat{\sigma}^z \). This allows for a convenient implementation on a quantum computer, as was demonstrated recently for the efficient simulation of chemical energy of molecular systems [27]. An important example of a Coulomb based Hamiltonian is the spin-coupled interactions in quantum dots which has the following Pauli representation:

\[
H = \sum_{i,j,k,\cdots} b_{ij,k,\cdots} \sigma_A^i \otimes \sigma_B^j \otimes \sigma_C^k \cdots,
\]

where \( A, B, C, \cdots \) indicate the location of the quantum dots, \( \sigma_A^i, \sigma_B^j, \sigma_C^k \) are Pauli operators, and \( b_{ij,k,\cdots} \) generally represents a many-body spin interacting term. In practice, these Hamiltonians are highly sparse or almost sparse due to symmetry considerations associated with total momentum [28]. For example the Hamiltonian for the case of four quantum dots (\( A, B, C, D \)) takes the general form [28]:

\[
H_{\text{exchange}} = J \sum_{A \leq i < j \leq D} \sigma_i \sigma_j + J' \{(\sigma_A \sigma_B)(\sigma_C \sigma_D) \} + \{(\sigma_A \sigma_C)(\sigma_B \sigma_D) \} + \{(\sigma_A \sigma_D)(\sigma_B \sigma_C) \}.
\]

Another class of effective many-body interactions often emerge in a perturbative and/or short time expansion of dynamics, such as effective three-body interactions between atoms in optical lattices [29] that we study in this work.

Next, we simulate the performance of our algorithm for estimation of such sparse many-body Hamiltonians in optical lattices [29] and quantum dots [28].

### A. Three-body interactions in optical lattices

An optical lattice is a periodic potential formed from interference of counterpropagating laser beams where neutral atoms are typically cooled and trapped one per site. Consider four sites in two adjacent building blocks of a triangular optical lattice filled by two species of atoms [29]. The interaction between atoms is facilitated by the tunneling rate \( J \) between neighboring sites and collisional couplings \( U \) when two or more atoms occupy the same site. For each site an effective spin is defined by the presence of one type of atom as the up-state \( \uparrow \) and the presence of the other type as the down-state \( \downarrow \). Three-body interactions between atoms in a triangular optical lattice can be significant. The effective Hamiltonian for this system is studied in Ref. [29]. The on-site collisional interaction \( U \), and tunneling rates \( J = J^\uparrow = J^\downarrow \) are taken to be the same in all sites, also \( U = U_{\uparrow \uparrow} = U_{\downarrow \downarrow} = 2.12 U_{\uparrow \downarrow} = 10 k H z \). The effective Hamiltonian of the 4-spin system is

\[
H_{\text{opt-latt}} = \sum_{j,\alpha=x,y,z} b_{1j}^\alpha \sigma_j^\alpha \sigma_{j+1}^\alpha + b_{2j}^\alpha \sigma_j^\alpha \sigma_{j+1}^\alpha \sigma_{j+2}^\alpha
\]

where \( \{b_{1j}^\alpha, b_{2j}^\alpha\} \) are functions of \( \{J, U\} \) and their explicit forms are given in appendix D. The ratio \( \eta = \text{\text{g}} / \text{\text{r}} \)]] quantifies the sparsity level. For a fixed value of \( U \), a smaller \( J \) leads to weaker three-body interactions and therefore a higher level of sparsity. As expected, this enhances the algorithm performance.

We assume that the system can be initialized in a random product state \( |\psi_k\rangle = |\psi_k^x\rangle \otimes \cdots \otimes |\psi_k^z\rangle \), where \( |\psi_k^x\rangle \) are drawn from the Fubini-Study metric induced distribution. The required observables for the algorithm are uniformly selected from single qubit Pauli operators \( \{ \sigma_x^i, \sigma_y^i, \sigma_z^i \} \). This choice of states and observables allows for \( \delta_\text{\text{g}} \approx 0.37 < \sqrt{2} - 1 \). Let us denote the extracted Hamiltonian and the true Hamiltonian by \( \text{\text{g}} \) and \( H_{\text{true}} \), respectively. Here, the performance of the algorithm is defined by the relative error \( 1 - ||H^\text{\text{g}} - H_{\text{true}}||_{\text{\text{Fro}}} / ||H_{\text{true}}||_{\text{\text{Fro}}} \). The results for different number of configurations are depicted in Fig. [1], for various values of \( J \). As evident in Fig. [1], performance accuracy of above 94\% can be obtained with only 80 settings significantly smaller than approximately \( 6 \times 10^4 \) configurations required in QPT.

The robustness of this scheme was also investigated for 10% random error in simulated experimental data leading to about a 5% reduction in the overall performance.

### B. Four-body interactions in quantum dots

Another important class of effective many-body Hamiltonians can be obtained for electrons in quantum dots coupled through an isotropic (Heisenberg) or anisotropic exchange interaction. For example the Hamiltonian for the case of four quantum dots (\( A, B, C, D \)) takes the general form Eq. (12).

The first term in the summation is a two-body Heisenberg exchange interaction and the last three terms are four-body spin interactions. In certain regimes, the ratio \( J / J^\prime \) can reach up...
to the random and independent selection of error bars demonstrate the standard deviation of the performance due only for different tunneling rates, $J$, and collisional coupling $U = 10kHz$. The error bars demonstrate the standard deviation of the performance due to the random and independent selection of $m$ configurations (shown only for $J = 5kHz$). Performance accuracy of above 90% with only 60 settings is achievable for $J = 1kHz$, which is significantly smaller than about $6 \times 10^5$ required experimental configurations in QPT.

Here we use an efficient modification of signal recovery referred as “reweighted $l_1$-minimization” which is described in appendix E. The performance of this algorithm is demonstrated in Fig. 2 that shows a significant reduction of the required number of settings in contrast to the standard QPT.

VI. V. CHARACTERIZATION OF HAMILTONIAN FINE STRUCTURES AND SYSTEM-BATH INTERACTIONS

A. Hamiltonian fine estimation

In many systems a primary model of the interactions is often known through physical and/or engineering considerations. Starting with such an initial model we seek to improve our knowledge about the Hamiltonian by random measurements. Let’s assume the initial guess about the Hamiltonian $H_0$ is close to the true form $H_{true}$ that is $||\Delta = H_{true} - H_0|| \ll ||H_{true}||$. Therefore for a perturbative treatment we demand $t||\Delta|| \ll 1$, which is a much weaker requirement compared to $t||H_{true}|| \ll 1$. We can approximate Eq. (1) in the paper to find

$$p_{jk} \approx \langle \psi_k | M^0_j | \psi_k \rangle + i \langle \psi_k | \int_0^t e^{i\varepsilon H_0} \Delta e^{-i\varepsilon H_0} ds, M^0_j | \psi_k \rangle,$$  

where $M^0_j = e^{itH_0} M_j e^{-itH_0}$ \([31]\). This equation is linear in $\Delta$, consequently, in a similar fashion as above, the compressed sensing analysis can be applied for efficient estimation of the fine structure of Hamiltonians.

B. Characterizing system-bath interactions

The identification of a decoherence process is a vital task for quantum engineering. In contrast to the usual approach of describing dynamics of an open quantum system by a Kraus map or a reduce master equation, here we use a microscopic Hamiltonian picture to efficiently estimate the system-bath coupling terms generating the overall decoherence process. However since we consider a full dynamics of the system and bath, this method can be applied to a finite size environment such as a spin bath, or a surrogate Hamiltonian modeling of a infinite bath. In the latter case a harmonic bath of oscillators is approximated by a finite spin bath \([32]\).

Consider an open quantum system with a total Hamiltonian:

$$H = H_S \otimes I_B + I_S \otimes H_B + H_{SB}$$  

and

$$H_{SB} = \sum_{p,q} \lambda_{p,q} S_p \otimes B_q$$  

where $H_S$ ($H_B$) denotes the system (bath) free Hamiltonian and $H_{SB}$ is the system-bath interaction with coupling strengths $\{\lambda_{p,q}\}$, and a complete operator basis of the system and bath being $\{S_p\}$ and $\{B_q\}$, respectively.

We develop a formalism to estimate $\lambda_{p,q}$ parameters in the weak system-bath coupling regime and with the sparsity assumption that a few number of $\lambda_{p,q}$ have a significant value.

The Liouvillian dynamical equation is

$$\frac{d}{dt} \rho_{SB}(t) = (\mathcal{L}_0 + \sum_{pq} \lambda_{pq} \mathcal{L}_{pq}) [\rho_{SB}(t)]$$
where $L_0[.] = -i[H_S \otimes I_B + I_S \otimes H_B, .]$ and $L_{pq}[.] = -i[S_p \otimes B_q, .]$. In the regime of weak coupling to a finite bath, $\|H_{SB}\| \ll \min\{\|H_S\|, \|H_B\|\}$, the Liouvillean equation \cite{17} can be solved perturbatively if time $t$ satisfies $t\|H_{SB}\| \ll 1$.

For an initial system density state $\rho_k$, using the matrix identity given in Ref. \cite{31} we find the measurement outcomes as

$$p_{jk} \approx tr(\rho_k M_j) \quad (18)$$

$$+ \sum_{pq} \lambda_{pq} tr(\{ \int_0^t ds e^{(t-s)\mathcal{L}_0} \mathcal{L}_{pq} e^{s\mathcal{L}_0} \rho_k \}, M_j)$$

where $M_j$ is a system only observable. This affine function between the outcomes $p_{jk}$ and coupling parameters $\{\lambda_{pq}\}$ is similar to Eq.(2) in the paper for Hamiltonian estimation.

Consequently, the compressed sensing algorithm can be employed for computing $\{\lambda_{pq}\}$.

VII. OUTLOOK

We have introduced an efficient and robust experimental procedure for the identification of nearly sparse Hamiltonians using only separable (local) random state preparations and measurements. There are a number of future directions and open problems associated with this work. It is not known how the performance of the algorithm depends on the distribution of the ensemble from the states and measurement observables are drawn. Also, a general closed-loop learning approach for updating the knowledge of sparsity basis of an arbitrary Hamiltonian is an interesting open problem that will be of importance for generic compressed system identification. The presented method for Hamiltonian estimation is promising for drastic reduction in the number of experimental configurations. However the classical resources for post-processing is not scalable. A fully scalable Hamiltonian estimation method might be achievable via a hybrid of compressed sensing and DMRG (Density-Matrix Renormalization Group) methods \cite{33}. A compressed tomography method can also be developed for nearly sparse quantum processes \cite{34}.

VIII. ACKNOWLEDGEMENT

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Appendix A: vectors and operator norm

In this paper we use the following different norms: For a vector $x$,

$$\|x\|_2 = \sqrt{x^\dagger x}, \|x\|_1 = \sum_i |x_i|. \quad (A1)$$

For a matrix $A$,

$$\|A\|_{\text{spec}} = \sqrt{\lambda_{\text{max}}(A^\dagger A)} \quad (A2)$$

where $\lambda_{\text{max}}$ means largest eigenvalue.

$$\|A\|_{\text{fro}} = \sqrt{\text{trace}(A^\dagger A)} \quad (A3)$$

Appendix B: Analysis of the short time approximation

The short time monitoring of the system’s dynamics requires a prior knowledge of the dynamical time scales. In the solid-state quantum devices, in particular in the context of quantum control and quantum information-processing, the time-scale of single qubit rotations is typically on the order of 1-10 ns. The switching time for exchange interactions varies among different solid-state systems. For superconducting phase qubit the duration of a swap gate is about 10 ns \cite{35}. For electron-spin qubits in quantum dots and in donor atoms (Heisenberg models) \cite{36,37}, and also for quantum dots in cavities (anisotropic exchange interactions) \cite{39} the coupling time is between 10-100ps, while for exciton-coupled quantum dots (XY model) and Förster energy transfer in multichromophoric complexes the relevant time scale is in the order of 1ps. Next we rigorously derive bound on the evolution time $t$ that guarantees the validity of the short time approximation.

For an input state $|\psi_k\rangle$, the expectation value of an observable $M_j$ is

$$p_{jk} = \langle \psi_k(t) | M_j | \psi_k(t) \rangle = \langle \psi_k | e^{itH} M_j e^{-itH} | \psi_k \rangle \quad (B1)$$

Considering the expansion of the propagator $e^{-itH} = I - itH - \frac{t^2}{2} H^2 + ...$, we find

$$p_{jk} = \langle \psi_k | M_j | \psi_k \rangle + it \langle \psi_k | [H, M_j] | \psi_k \rangle - \frac{t^2}{2} \langle \psi_k | [H, [H, M_j]] | \psi_k \rangle + ... \quad (B2)$$

Therefore, for the linearization assumption, it is sufficient to have for the $l$’th term

$$t^l \min_j \langle \psi_k | [H, [H, [... M_j]]] | \psi_k \rangle \leq \frac{t^l}{l!} ||[H, [H, [... M_j]]]||_{\text{spec}} \ll 1, \forall l. \quad (B3)$$

A tighter bound can be found for operators $\{M_j\}$ from a POVM as

$$||[H, [H, [... M_j]]]||_{\text{spec}} \leq 2^l ||H||_{\text{spec}}^l \quad (B4)$$

To derive this we use

$$||[A, B]||_{\text{spec}} \leq ||AB||_{\text{spec}} + ||BA||_{\text{spec}} \leq 2 ||A||_{\text{spec}} ||B||_{\text{spec}} \quad (B5)$$

and $||A||_{\text{spec}}^2 = ||AA^\dagger||_{\text{spec}}$.

This gives a single bound sufficient for linearization: $t \ll \frac{1}{2} ||H||_{\text{spec}}^{-\frac{1}{2}}$. 

\[ \]
Appendix C: RIP from a concentration inequality

In this work, we generalize the standard compressed sensing algorithm such that the necessity for independent randomness in all elements of the measurement matrix \( \Phi \) can be avoided. A common approach to establish RIP (\( \mathbb{E} \)) for a matrix \( \Phi \) is by introducing randomness in the elements of this matrix. This approach benefits from measure concentration properties of random matrices. In classical signal processing each element \( \Phi_{jk,\alpha} \) can be independently selected from a random distribution such as Gaussian or Bernoulli. Whereas in the quantum states and observables of a finite dimensional system, there is no freedom for independent selection of the \( \Phi \) matrix elements.

Here we prove the concentration inequality that we employed for establishing the restricted isometry property.

Though \( \Phi \) is a random matrix, because it is constructed from quantum states and observables of a finite dimensional system, it is bounded. Thus we are able to apply Hoeffding’s concentration inequality: If \( v_1, \ldots, v_m \) are independent bounded random variables such that \( \text{Prob.}\{v_i \in [u_i, b_i]\} = 1 \), then for \( S = \sum_i v_i \),

\[
\text{Prob.}\{S - \mathbb{E}(S) \geq t\} \leq e^{-2t^2/\sum_i (b_i - u_i)^2} \\
\text{Prob.}\{S - \mathbb{E}(S) \leq -t\} \leq e^{-2t^2/\sum_i (b_i - u_i)^2}
\]

(C1)

for any \( t > 0 \). (Here \( \mathbb{E} \) denotes the expectation value.) Set \( v_i = ||\phi_i^0||^2 \) for a row \( \phi_i \). Then with \( S = \sum_i v_i = ||\Phi x||^2 \), we get \( \forall x, \)

\[
v_i = x^\dagger (\phi_i^0 \phi_i^0) x \in [1/m] [w_l, w_u] ||x||^2
\]

\[
\mathbb{E}(S) = \mathbb{E} ||\Phi x||^2 \in [f, g] ||x||^2
\]

(C2)

for constants \( w_l, w_u, f, g \). Note that \( f \) and \( g \) are the min and max singular values of \( \mathbb{E} (\Phi^\dagger \Phi) \). From (C2) we find \( \forall t > 0 \) and \( \forall v \),

\[
\text{Prob.}\{S - g ||x||^2_2 \geq t_+\} \leq \text{Prob.}\{S - \mathbb{E}(S) \geq t_+\}
\]

\[
\text{Prob.}\{S - f ||x||^2_2 \leq -t_-\} \leq \text{Prob.}\{S - \mathbb{E}(S) \leq -t_-\}
\]

These together with (C1) and (C2), and the choice of \( t_+ = (\delta + 1 - g) ||x||^2_2 \) and \( t_- = (f - 1 + \delta) ||x||^2_2 \) yields

\[
\text{Prob.}\{||\Phi x||^2_2 - ||x||^2_2 \geq \delta ||x||^2_2\} \leq 2e^{2m(\delta + e)^2}
\]

(C3)

with \( e = \min\{1 - g, f - 1\} \). To ensure that \( t_+, t_- > 0 \), we need \( 1 - \delta < f \leq g < 1 + \delta \). Since the observable \( M \) can be scaled by any real number, a sufficient condition is \( g/f < (1 + \delta)/(1 - \delta) \). For the simulations in this paper, this ratio becomes 2.176.

Appendix D: 4-sites optical lattice Hamiltonian

Let us consider four sites in two adjacent building blocks of a triangular optical lattice filled by two species of atoms, \( \uparrow \) and \( \downarrow \). Atoms interact by tunneling between neighboring sites, \( J^\uparrow \) and \( J^\downarrow \), and through collisional couplings in the same site, \( U \). The Hamiltonian for such system can be written as [29]:

\[
H_{\text{opt-latt}} = \sum_j \left( 0.03 \frac{J_j^\uparrow + J_j^\downarrow}{U} - 0.27 \frac{J_j^\uparrow + J_j^\downarrow}{U^2} \right) \sigma_j^x \sigma_j^y
\]

\[
- \left( 2.1 \frac{(J_j^\uparrow + J_j^\downarrow)J_j^\uparrow J_j^\downarrow}{U^2} + \frac{J_j^\uparrow J_j^\downarrow}{U} \right) (\sigma_j^x \sigma_j^y + \sigma_j^y \sigma_j^x)
\]

\[
+ \sum_j \left( \frac{0.14}{U^2} (J_j^\uparrow - J_j^\downarrow) (\sigma_j^x \sigma_{j+1}^x \sigma_{j+2}^x + \sigma_j^y \sigma_{j+1}^y \sigma_{j+2}^y) \right)
\]

(D1)

where \( \sigma_j^{x,y,z} \) are Pauli operators.

Appendix E: Reweighted \( l_1 \)-minimization

In order to simulate our algorithm performance for estimating the above Hamiltonian we use an iterative algorithm that outperforms the standard \( l_1 \) norm minimization [30]. This procedure entails initializing a weight matrix \( W = I_{d^2} \) and a weight factor \( \sigma > 0 \), and repeating the following steps until convergence is reached:

1. Solve for \( h \), minimize \( ||W h||_{l_1} \) subject to \( ||p' - \Phi h||_{l_2} \leq \epsilon \).
2. Update weights

\[
W = \text{diag}(1/(||h||_1 + \sigma), ..., 1/(||h||_d + \sigma)).
\]

(E1)

where \( h = \text{vec}(h_i) \) is the Hamiltonian vectorized form. \( \Phi \) is the measurement matrix and \( p' \) is the experimental data with a noise threshold \( \epsilon \).

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