# Energy Landscape of Optimizing Symmetric Phase Factors in Quantum Signal Processing 

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## Applications of Quantum Signal Processing

Construct quantum algorithms for many numerical problems with a proper set of phase factors.

- Quantum linear system problem, $x^{-1}$,
- Hamiltonian simulation, $e^{-i t x}$,
- Thermal state preparation problem, $e^{-\beta x}$


Fig: Polynomial approximation of $\frac{1}{x}$.

## Quantum Signal Processing(QSP)

Given a sequence of phase factors $\Phi:=\left(\phi_{0}, \cdots, \phi_{d}\right) \in[-\pi, \pi)^{d+1}$, define

$$
\begin{equation*}
U(x, \Phi):=e^{\mathrm{i} \phi_{0} Z} e^{\mathrm{i} \arccos (x) X} e^{\mathrm{i} \phi_{1} Z} e^{\mathrm{i} \arccos (x) X} \ldots e^{\mathrm{i} \phi_{d-1} Z} e^{\mathrm{i} \arccos (x) X} e^{\mathrm{i} \phi_{d} Z} . \tag{1}
\end{equation*}
$$

where $x \in[-1,1], X:=\left(\begin{array}{cc}0 & 1 \\ 1 & 0\end{array}\right), Z:=\left(\begin{array}{cc}1 & 0 \\ 0 & -1\end{array}\right)$ are Pauli matrices.

- The real component of the upper-left matrix element ${ }^{1}$

$$
\begin{equation*}
g(x, \Phi):=\operatorname{Re}\left[U(x, \Phi)_{11}\right] \tag{2}
\end{equation*}
$$

can be any real polynomial with parity $(d \bmod 2)$ and of degree $\leq d$ up to scaling.

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## How to find phase factors

Recent progress:

- Gilyén-Su-Low-Wiebe [STOC'19],
- Haah [Quantum'19],
- Dong-Meng-Whaley-Lin [Phys.Rev.A'21],
- Chao-Ding-Gilyén-Huang-Szedegy [arXiv:2003.02831].
- The first two methods are constructive, but need to find the roots of high degree polynomials to high precision.
- The third method is an optimization based method and imposes the symmetry constraint on the phase factors.


## Optimization problem

Given a polynomial $f \in \mathbb{R}[x]$ of degree $d$, with parity $(d \bmod 2)$ and $\max _{x \in[-1,1]}|f(x)| \leq 1$, the optimization problem is

$$
\begin{equation*}
\Phi^{*}=\underset{\substack{\Phi \in[-\pi, \pi)^{d+1}, \\ \text { symmetric }}}{\operatorname{argmin}} F(\Phi), F(\Phi):=\frac{1}{\widetilde{d}} \sum_{k=1}^{\tilde{d}}\left|g\left(x_{k}, \Phi\right)-f\left(x_{k}\right)\right|^{2}, \tag{3}
\end{equation*}
$$

where $\widetilde{d}:=\left\lceil\frac{d+1}{2}\right\rceil$ and $x_{k}=\cos \left(\frac{2 k-1}{4 \tilde{d}} \pi\right), k=1, \ldots, \widetilde{d}$ are positive Chebyshev nodes of $T_{2 \tilde{d}}(x)$.

- The selection of $T_{2 \tilde{d}}(x)$ is enough, because it matches the degree of freedom. For convenience, we choose the first half of phase factors $\left(\phi_{0}, \cdots, \phi_{\tilde{d}-1}\right)$ as free variables.
- Usually scale the $L^{\infty}$ norm of $f$ to be less than 1 in order to enhance numerical stability.


## Symmetric phase factors

## Theorem 1 (Existence and uniqueness)

There exists a unique set of symmetric phase factors $\Phi:=\left(\phi_{0}, \phi_{1}, \cdots, \phi_{1}\right.$, $\left.\phi_{0}\right) \in R_{d}$ such that

$$
U(x, \Phi)=\left(\begin{array}{cc}
P(x) & i Q(x) \sqrt{1-x^{2}}  \tag{4}\\
i Q(x) \sqrt{1-x^{2}} & P^{*}(x)
\end{array}\right)
$$

if and only if $P \in \mathbb{C}[x]$ and $Q \in \mathbb{R}[x]$ satisfy

1. $\operatorname{deg}(P)=d$ and $\operatorname{deg}(Q)=d-1$.
2. $P$ has parity $(d \bmod 2)$ and $Q$ has parity $(d-1 \bmod 2)$.
3. Normalization condition: $\forall x \in[-1,1],|P(x)|^{2}+\left(1-x^{2}\right)|Q(x)|^{2}=1$.
4. If $d$ is odd, then the nonzero leading coefficient of $Q$ is positive.

Here, $R_{d}:= \begin{cases}{[0, \pi)^{k} \times[-\pi, \pi) \times[0, \pi)^{k}} & \text { if } d=2 k, k \in \mathbb{N}^{*}, \\ {[0, \pi)^{d+1}} & \text { otherwise } .\end{cases}$

## Global minimizer of the optimization problem

- There is a bijection between the global minimizer and the pair of $(P, Q)$ satisfying the conditions 1-4 in Theorem 1.
- The global minimizer is not unique.


$$
\begin{aligned}
& f(x)=x^{2}-\frac{1}{2} \\
& \left\{\begin{array}{l}
P_{\operatorname{Im}}= \pm \frac{\sqrt{3}}{2}\left(2 x^{2}-1\right) \\
Q= \pm 2 x
\end{array}\right. \\
& \left\{\begin{array}{l}
P_{\operatorname{Im}}= \pm \frac{\sqrt{3}}{2} \\
Q= \pm x
\end{array}\right.
\end{aligned}
$$

Fig: The contour of the objective function.

## Find all global minimizers

- We notice that Haah's method and GSLW method can be modified for symmetrical phase factors, but provide only the global minimizer around $\left(\frac{\pi}{4}, 0, \cdots, 0\right)$.
- We propose the generalized versions of both methods which are able to find all global minimizers to the optimization problem.



## Characterize all global minimizers

## Theorem 2

Given $f(x) \in \mathbb{R}[x]$ with $\max _{x \in[-1,1]}|f(x)|<1, P \in \mathbb{C}[x]$ and $Q \in \mathbb{R}[x]$ satisfy

1. $P_{\operatorname{Re}}(x)=f(x)$,
2. the conditions 1-4 in Theorem 1, if only if there exists a multiset $\tilde{\mathcal{D}}$ such that
3. $\tilde{\mathcal{D}} \uplus \tilde{\mathcal{D}}^{-1}=\mathcal{S}$, where $\mathcal{S}$ contains all roots of $1-f\left(\frac{z+z^{-1}}{2}\right)^{2}$ with multiplicity and $\tilde{\mathcal{D}}^{-1}:=\left\{z^{-1}: z \in \tilde{\mathcal{D}}\right\}$,
4. $\tilde{\mathcal{D}}$ is closed under complex conjugation and additive inverse,
5. $P_{\operatorname{Im}}\left(\frac{z+z^{-1}}{2}\right)=c_{1} \frac{e(z)+e\left(z^{-1}\right)}{2}$ and $Q\left(\frac{z+z^{-1}}{2}\right)=c_{2} \frac{e(z)-e\left(z^{-1}\right)}{2\left(z-z^{-1}\right)}$, where

$$
e(z):=z^{-d} \prod_{r \in \tilde{\mathcal{D}}}(z-r) \text { and } c_{1}^{2}=c_{2}^{2}=\frac{1-f\left(\frac{z+z^{-1}}{2}\right)^{2}}{e(z) e\left(z^{-1}\right)} \in \mathbb{R}_{+}
$$

4. If $d$ is odd, then $c_{2}>0$.

## Existence of local minimizer

The local minimizer exists for $d \geq 3$. Here is an example.

$d=4$
Objective value: $1.33 e-2$
Eigenvalues of Hessian matrix:
(0.1075, 4.4849, 7.7454)

Fig: The contour of the objective function on the hyperplane spanned by the eigenvectors corresponding to the two largest eigenvalues.

## Others

- The global energy landscape is bad.
- However, the optimization problem is locally strong convex around $\left(\frac{\pi}{4}, 0, \cdots, 0\right)$ thanks to the symmetry constraint.
- This accounts for the good performance of optimization algorithms around that point.


Different convergence limit
class $0:\left(\frac{\pi}{4}, 0,0,0\right)$
class $1:\left(\frac{\pi}{4}, 0, \frac{\pi}{4},-\frac{\pi}{2}\right)$
class $2:\left(\frac{\pi}{4}, 0,-\frac{\pi}{4}, \frac{\pi}{2}\right)$
class $3:\left(\frac{\pi}{4}, \frac{\pi}{4}, 0,-\frac{\pi}{2}\right)$
Fig: The convergence rate of different global minimizers corresponding to $0.1^{k} f(x)$ with $f(x)=\frac{1}{4} x^{6}+\frac{5}{4} x^{4}+\frac{1}{8} x^{2}$ $-\frac{1}{8}$.

## Thank you!


[^0]:    ${ }^{1}$ A. Gilyén, Y. Su, G. H. Low, and N. Wiebe, Quantum singular value transformation and beyond: exponential improvements for quantum matrixarithmetics, 2018.

