A Note About Claw Function with a Small Range

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– Abstract

In the claw detection problem we are given two functions $f: D \to R$ and $g: D \to R$ (|D| = n,|R| = k, and we have to determine if there is exist $x, y \in D$ such that f(x) = g(y). We show that the quantum query complexity of this problem is between $\Omega(n^{1/2}k^{1/6})$ and $O(n^{1/2+\varepsilon}k^{1/4})$ when $2 \le k < n.$

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1 Introduction

In this note we study the CLAW problem in which given two discrete functions $f: D \to R$ and $q: D \to R$ (|D| = n, |R| = k) we have to determine if there is a collision, i.e., inputs $x, y \in D$ such that f(x) = q(y). In contrast to the ELEMENT-DISTINCTNESS problem, where the input is a single function $f: D \to R$ and we have to determine if f is injective, CLAW is non-trivial even when k < n. This is the setting we focus on.

Both CLAW and ELEMENT-DISTINCTNESS have wide applications as useful subroutines in more complex algorithms [5, 12] and as a means of lower bounding complexity [10, 1].

CLAW and ELEMENT-DISTINCTNESS were first tackled by Buhrman et al. in 2000 [8] where they gave an $O(n^{3/4})$ algorithm and $\Omega(n^{1/2})$ lower bound. In 2003 Ambainis, introducing a novel technique of quantum walks, improved the upper bound to $O(n^{2/3})$ in the query model [4]. It was soon realized that a similar approach works for CLAW [9, 13, 15]. Meanwhile Aaronson and Shi showed a lower bound $\Omega(n^{2/3})$ that holds if the range $k = \Omega(n^2)$ [2]. Eventually Ambainis showed that the $\Omega(n^{2/3})$ bound holds even if k = n [3]. The same lower bound has since been reproved using the adversary method [14]. Until now, only the $\Omega(n^{1/2})$ bound based on reduction of searching was known for CLAW with k = o(n) [8].

We consider quantum query complexity of CLAW where the input functions are given as a list of their values in black box. Let Q(f) denote the bounded error quantum query complexity of f. For a short overview of black box model refer to Buhrman and de Wolf's survey [7]. Let [n] denote $\{1, 2, \ldots, n\}$. Let $\operatorname{CLAW}_{n \to k} : [k]^{2n} \to \{0, 1\}$ be defined as

$$CLAW_{n \to k}(x_1, \dots, x_n, y_1, \dots, y_n) = \begin{cases} 1, & \text{if } \exists i, j \, x_i = y_j \\ 0, & \text{otherwise} \end{cases}.$$

Our contribution is a quantum algorithm for $CLAW_{n \to k}$ with quantum query complexity $Q(\operatorname{CLAW}_{n\to k}) = O(n^{1/2+\varepsilon}k^{1/4})$ and a lower bound $Q(\operatorname{CLAW}_{n\to k}) = \Omega(n^{1/2}k^{1/6})$. In section 2 we describe the algorithm, and in section 3 we give the lower bound.



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2 Results

▶ Theorem 1. For all $\varepsilon > 0$, we have $Q(CLAW_{n \to k}) = O(n^{1/2 + \varepsilon} k^{1/4})$.

Proof. Let $X = (x_1, \ldots, x_n)$, $Y = (y_1, \ldots, y_n)$ be the inputs of the function. We denote $k = n^{\varkappa}$.

Consider the following algorithm parametrized by $\alpha \in [0, 1]$.

a. Select a random sample A = {a₁,..., a_ℓ} ⊆ [n] of size ℓ = 4 · n^α · ln n and query the variables x_{a₁},..., x_{a_ℓ}.
Denote by X_A = {x_a | a ∈ A} the set containing their values. Do a Grover search for

Denote by $X_A = \{x_a \mid a \in A\}$ the set containing their values. Do a Grover search for an element $y \in Y$ such that $y \in X_A$. If found, output 1.

b. Select a random sample $A' = \{a'_1, \ldots, a'_\ell\} \subseteq Y$ of size ℓ and query the variables $y_{a'_1}, \ldots, y_{a'_\ell}$.

Denote by $Y_{A'} = \{y_{a'} \mid a' \in A'\}$ the set containing their values. Do a Grover search for an element $x \in X$ such that $x \in Y_{A'}$. If found, output 1.

- 2. Run $\operatorname{CLAW}_{4b \ln n \to k}$ algorithm (with the value of b specified below) with the following oracle:
 - a. To get x_i : do a pseudorandom permutation on x_1, \ldots, x_n using seed *i* and using Grover's minimum search return the first value x_j such that $x_j \notin X_A$.
 - **b.** To get y_i : do a pseudorandom permutation on y_1, \ldots, y_n using seed *i* and using Grover's minimum search return the first value y_i such that $y_i \notin X_{A'}$.

Let $B = \{i \in [n] \mid x_i \notin X_A\}, B' = \{i \in [n] \mid y_i \notin Y_{A'}\}$ be the sets containing the indices of the variables which have values not seen in the steps 1a and 1b. We denote $|B| = b = n^{\beta}$.

Let us calculate the probability that after step 1a there exists an unseen value v which is represented in at least $n^{1-\alpha}$ variables, i.e., $v \notin X_A \wedge |\{i \in [n] \mid x_i = v\}| \geq n^{1-\alpha}$. Consider an arbitrary value $v^* \in [k]$ such that $|\{i \mid x_i = v^*\}| \geq n^{1-\alpha}$. For $i \in [\ell]$, let Z_i be the event that $x_{a_i} = v^*$. $\forall i \in [\ell] \operatorname{Pr}[Z_i] \geq \frac{n^{1-\alpha}}{n}$. Let $Z = \sum_{i \in [\ell]} Z_i$. Then $\mathbb{E}[Z] = \ell \cdot \mathbb{E}[Z_1] \geq$ $4 \cdot n^{\alpha} \cdot \ln n \cdot \frac{n^{1-\alpha}}{n} = 4 \ln n$. Using Chernoff inequality (see e.g. [11]),

$$\Pr[Z=0] \le \exp\left(-\frac{1}{2} \mathbb{E}[Z]\right) \le \exp(-2\ln n) = \frac{1}{n^2}.$$

The probability that there exists such $v^* \in [k]$ is at most $\frac{n^{\varkappa}}{n^2} = o(1)$. Therefore, with probability 1 - o(1) after step 1a, every value $v \in X_B$ is represented in the input less than $n^{1-\alpha}$ times. The same reasoning can be applied to step 1b and the set B'. Therefore, with probability 1 - o(1) both b and b' are at most $k \cdot n^{1-\alpha} = n^{\varkappa+1-\alpha}$.

Similarly, we show that with probability 1 - o(1) each $x \in B$ appears as the first element from B in at least one of the permutations of the oracle in step 2. Let W_i^x be the event that $x \in B$ appears in the *i*-th permutation as the first element from B. $\mathbb{E}[W_i^x] = \frac{1}{b}$. Let $W^x = \sum_{i \in [4b \ln n]} W_i^x$. $\mathbb{E}[W^x] = 4b \ln n \cdot \frac{1}{b} = 4 \ln n$. $\Pr[W^x = 0] \le \exp(-2\ln n) = \frac{1}{n^2}$. $\Pr[\exists x \in B : W^x = 0] \le \frac{n}{n^2} = \frac{1}{n} = o(1)$. The same argument works for B'. Therefore, if there is a collision, it will be found by the algorithm with probability 1 - o(1).

We also show that with probability 1 - o(1), in all permutations the first element from B appears no further than in position $4\frac{n}{b}\ln n$ (and similarly for B'). We denote by $P_{i,j}$ the event that in the *i*-th permutation in the *j*-th position is an element from B. $\mathbb{E}[P_{i,j}] = \frac{b}{n}$. We denote $P_i = \sum_{j \in [4 \cdot \frac{n}{b} \ln n]} P_{i,j}$. $\mathbb{E}[P_i] = 4 \cdot \ln n$. $\Pr[P_i = 0] \leq \exp(-2\ln n) = \frac{1}{n^2}$. $\Pr[\exists i \in [4b \ln n] : P_i = 0] \leq \frac{4b \ln n}{n^2} \leq \frac{4n \ln n}{n^2} = o(1)$. Therefore, the Grover's minimum search will use at most $\tilde{O}(\sqrt{\frac{n}{n^\beta}})$ queries.

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The steps 1a and 1b use $\tilde{O}(n^{\alpha})$ queries to obtain the random sample, and $O(\sqrt{n})$ queries to check if there is a colliding element on the other side of the input. The oracle in step 2 uses $\tilde{O}(\sqrt{\frac{n}{n^{\beta}}})$ queries to obtain one value of x_i or y_i .

Therefore the total complexity of the algorithm is

$$\tilde{O}\left(n^{\alpha}+n^{\frac{1}{2}}+Q(\operatorname{CLAW}_{4b\ln n\to k})\cdot n^{\frac{1}{2}-\frac{1}{2}\beta}\right).$$

By using the $O(n^{2/3})$ algorithm in step 2,

$$Q(\operatorname{CLAW}_{4b\ln n \to k}) \cdot n^{\frac{1}{2} - \frac{1}{2}\beta} = n^{\frac{2}{3}\beta + \frac{1}{2} - \frac{1}{2}\beta}$$
$$= n^{\frac{1}{2} + \frac{1}{6}\beta}$$
$$\leq n^{\frac{1}{2} + \frac{1}{6}(\varkappa + 1 - \alpha)}$$
$$= n^{\frac{4 + \varkappa - \alpha}{6}},$$

and the total complexity is minimized by setting $\alpha = \frac{4+\varkappa}{7}$. However, we can do better than that. Notice that the $O(n^{2/3})$ algorithm might not be the best choice for solving $\operatorname{CLAW}_{4b \ln n \to k}$ in step 2.

Let \mathcal{A}_0 denote the regular $O(n^{2/3})$ CLAW_{$n \to k$} algorithm. For i > 0, let \mathcal{A}_i denote a version of algorithm from Theorem 1 that in step 2 calls \mathcal{A}_{i-1} . Then we show that for all n and all $0 \le \varkappa \le \frac{2}{3}$,

$$Q(\mathcal{A}_i) = \tilde{O}\Big(n^{T_i(\varkappa)}\Big),$$

where $T_i(\varkappa) = \frac{(2^{i-1})\varkappa + 2^{i+1}}{2^{i+2}-1}$.

The proof is by induction on *i*. For i = 0, we trivially have that $Q(\mathcal{A}_0) = \tilde{O}(n^{2/3})$. For the inductive step, consider the analysis of our algorithm. Let us set $\alpha = T_i(\varkappa)$. First, notice that $T_i(\varkappa)$ is non-decreasing in \varkappa and $T_i(\frac{2}{3}) = \frac{2}{3}$ for all *i*. Thus for all $\varkappa \leq \frac{2}{3}$, we have $T_i(\varkappa) \leq \frac{2}{3}$, hence $\alpha \leq \frac{2}{3}$ and $\frac{\varkappa}{1-\alpha+\varkappa} \leq \frac{2}{3}$. Second, since the coefficient of \varkappa is $\frac{2^i-1}{2^{i+2}-1} \leq 1$ the function $T_i(\varkappa)$ is above \varkappa for $\varkappa \leq \frac{2}{3}$, establishing $\alpha - \varkappa \geq 0$. This confirms that $\alpha = T_i(\varkappa)$ is a valid choice of α .

It remains to show that the complexity of step 2 does not exceed $\tilde{O}(n^{T_i(\varkappa)})$. By the inductive assumption and analysis of the algorithm, the complexity (up to logarithmic factors) of the second step is n to the power of $(1 - \alpha + \varkappa) \cdot T_{i-1}\left(\frac{\varkappa}{1-\alpha+\varkappa}\right) + \frac{\alpha-\varkappa}{2}$. Finally, we have to show that

$$(1 - T_i(\varkappa) + \varkappa) \cdot T_{i-1}\left(\frac{\varkappa}{1 - T_i(\varkappa) + \varkappa}\right) + \frac{T_i(\varkappa) - \varkappa}{2} \le T_i(\varkappa).$$

By expanding $T_{i-1}(\varkappa)$ and with a slight rearrangement, we obtain

$$\frac{(2^{i-1}-1)\varkappa+2^i(1-T_i(\varkappa)+\varkappa)}{2^{i+1}-1} \leq \frac{T_i(\varkappa)+\varkappa}{2}.$$

We can further rearrange the required inequality by bringing $T_i(\varkappa)$ to right hand side and everything else to the other. Then we get

$$\frac{(2^{i-1}-1+2^i-\frac{2^{i+1}-1}{2})\varkappa+2^i}{2^{i+1}-1} \le T_i(\varkappa) \bigg(\frac{1}{2}+\frac{2^i}{2^{i+1}-1}\bigg).$$

After simplification we obtain $\frac{(2^{i}-1)\varkappa+2^{i+1}}{2^{i+2}-1} \leq T_i(\varkappa)$, which is true. Since $\lim_{i\to\infty} \frac{2^{i}-1}{2^{i+2}-1} = \frac{1}{4}$ and $\lim_{i\to\infty} \frac{2^{i+1}}{2^{i+2}-1} = \frac{1}{2}$, the result follows.

3 Lower Bound

We show a $\Omega(n^{1/2}k^{1/6})$ quantum query complexity lower bound for $\operatorname{CLAW}_{n\to k}$.

▶ Theorem 2. For all $k \ge 2$, we have $Q(CLAW_{n \to k}) = \Omega(n^{1/2}k^{1/6})$.

Proof. Let $PSEARCH_m : (* \cup [k])^m \to [k]$ be the partial function defined as

$$PSEARCH_m(x_1, x_2, \dots, x_m) = \begin{cases} x_i, & \text{if } x_i \neq *, \forall j \neq i : x_j = * \\ \text{undefined}, & \text{otherwise} \end{cases}$$

Consider the function $f_{n,k} = \text{CLAW}_{k \to k} \circ \text{PSEARCH}_{\lfloor n/k \rfloor}$. One can straightforwardly reduce $f_{n,k}(x,y)$ to $\text{CLAW}_{n \to k+2}(x',y')$ by setting

$$x'_{i} = \begin{cases} x_{i}, & \text{if } x_{i} \neq * \\ k+1, & \text{if } x_{i} = * \end{cases}$$

and

$$y'_i = \begin{cases} y_i, & \text{if } y_i \neq * \\ k+2, & \text{if } y_i = * \end{cases}$$

Now we show that $Q(f_{n,k}) = \Omega\left(k^{2/3}\sqrt{n/k}\right) = \Omega\left(n^{1/2}k^{1/6}\right)$. The fact that $Q(\text{CLAW}_{k\to k}) = \Omega\left(k^{2/3}\right)$ has been established by Zhang [16]. Furthermore, thanks to the work done by Brassard et al. in [6, Theorem 13] we know that for PSEARCH_m a composition theorem holds: $Q(h \circ \text{PSEARCH}_m) = \Omega(Q(h) \cdot Q(\text{PSEARCH}_m)) = \Omega(Q(h) \cdot \sqrt{m})$. Therefore,

$$Q(\operatorname{CLAW}_{n \to k}) \ge Q\left(\operatorname{CLAW}_{k-2 \to k-2} \circ \operatorname{PSEARCH}_{\lfloor \frac{n}{k-2} \rfloor}\right) = \Omega\left(k^{2/3}\sqrt{\frac{n}{k}}\right) = \Omega\left(n^{1/2}k^{1/6}\right).$$

4 Open Problems

Can we show that $Q(\operatorname{CLAW}_{n \to n^{2/3}}) = \Omega(n^{2/3})$? In particular, our algorithm struggles with instances where there are $\frac{n^{2/3}}{2}$ singletons only two (or none) of which are matching and the remaining variables are evenly distributed with $\Theta(n^{1/3})$ copies each, such that none are matching. Thus our algorithm then either has to waste time sampling all the high-frequency decoy values or have most variables not sampled by step 2. If this lower bound held, it would imply a better lower bound for evaluating constant depth formulas and Boolean matrix product verification [10, Theorem 5].

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