

# Quantum Computation

## Particle and Wave Aspects of Algorithms

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The driving force in the pursuit for quantum computation is the exciting possibility that quantum algorithms can be more efficient than their classical analogues. Research on the subject has unraveled several aspects of how that can happen. Clever quantum algorithms have been discovered in recent years, although not systematically, and the field remains under active investigation. Richard Feynman was one of the pioneers who foresaw the power of quantum computers. In this issue dedicated to him, I give an introduction to how particle and wave aspects contribute to the power of quantum computers. Shor's and Grover's algorithms are analysed as examples.

Richard Feynman's primary area of research was quantum field theory and particle physics. But he had many other interests beyond that (some of them outside science), his refreshingly original approaches to analysing different problems, and colourful ways of presenting the results to novices as well as to the general public. He had a life-long interest in computers, dating back to the Manhattan Project at Los Alamos while still a graduate student. There he was put in charge of the IBM group calculating the energy release during the implosion of the plutonium bomb, and he figured out parallel computation techniques to speed up the work. In his later years, he became interested in potentialities and limitations of computers, as determined by the laws of physics, specifically quantum physics. In the early 1980's, when I was a graduate student at Caltech, he taught a course titled 'The Physics of Computation', together with John



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Hopfield and Carver Mead. The syllabus of that course was vague, and the lecturers covered various topics in a rather chaotic manner, often without knowing what would come next. Still many of us attended the course for the fun of it, especially because we knew that with Feynman as an instructor, there would always be some surprises. A refined version of what was taught in that course, and the exciting ideas that developed from it, is now available as two excellent books [1, 2]. In particular, the concept of quantum computers formulated there has now become a thriving field of research [3, 4].

### 1. Quantum Computation

Any physical system – with some initial state, some final state, and some interactions in between – is a candidate for an information processing device, i.e., a computer. One only needs to construct a suitable map between the physical properties of the system and the desired abstract mathematical variables. The initial state becomes the input, the final state becomes the output, and the interactions provide appropriate logic operations. Most of the development in theoretical computer science has been in the framework of ‘particle-like’ discrete digital systems. The simplest digital language is the binary one; the digits are the bits represented by ‘off’ and ‘on’ in electronic circuits, and by ‘0’ and ‘1’ in mathematical notation. (Note that a language with only one letter is not versatile enough to encode any information, but a language with two letters can encode everything.) The outstanding advantage of a digital language is that any value can be broken up into a sequence of digits, each one picked from a finite set. Then  $N$  possible values can be represented using only  $n = \log_2 N$  bits, which is an exponential reduction in the required resources compared to the situation where every value is represented by a different physical state. Mathematically this structure is known as a ‘tensor product’, and I will refer to a similar break-up of computational algorithms as

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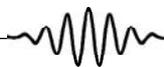


‘factorisation’.

The growth in semiconductor technology has been so explosive – doubling the number of transistors on a chip every 18–24 months according to Moore’s law – that many choices made in constructing the theoretical framework of computer science (see for example, [5]) were almost forgotten over the years. Computer architecture became essentially synonymous with digital electronic circuits implementing Boolean operations, pushing aside other models of computation. It is well known that ‘wave-like’ analogue computation can also be carried out, e.g., for solving differential equations using RLC circuits. But that has not been explored as intensively, even though algorithms for solving differential equations on digital computers are cumbersome due to lack of infinitesimal variables. A specific operation may be easier to implement in the digital mode than in the analogue mode, or vice versa, but its physical implementation is not chosen solely by considerations of computational complexity. Any physical device cannot avoid noise and disturbances from the environment, and hence the criteria for hardware stability also play an important role in the choice of physical implementation. There the discrete variables win hands down – they allow a degree of precision, by implementation of error-correction procedures for the finite alphabet, that continuous variables cannot provide.

The situation of having to choose between digital and analogue computation changed with the advent of quantum computation. First came the realisation that with shrinking size of its elementary components, sooner or later, the computer technology will inevitably encounter the dynamics of the atomic scale [6]. The laws that apply at the atomic scale are those of quantum mechanics and not those of electrical circuits. The computational framework needs reanalysis, because quantum objects display both ‘particle-like’ and ‘wave-like’ features at

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the same time – the discrete eigenstates that form the Hilbert space basis as well as the superposition principle that allows for simultaneous existence of multiple eigenstate components. In what way would this combination alter the axioms of the classical information theory? How will the analysis of computational complexity change? Many investigations in quantum information theory are addressed to such questions. It is worthwhile to observe that this step was precipitated by technological progress; earlier pioneers such as von Neumann, well-versed in both quantum mechanics and computer science, had not paid any attention to it.

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The next step was automatic. In classical physics, ‘particle’ and ‘wave’ behaviour are mutually exclusive concepts. With both ‘particle-like’ and ‘wave-like’ behaviour at their disposal, quantum algorithms can only improve upon their classical counterparts based on only one of them. Note that we are classical creatures, and the inputs and the outputs of all the computational problems we investigate are always classical (or are uniquely mapped to classical states). At the most a quantum computer may solve a problem by a simpler non-classical algorithmic route compared to the classical one. We clearly understand that the concept of what is computable and what is not does not change in going from classical to quantum computation. The scaling rules characterising how efficiently a problem can be solved are altered, however, and the important question is to what extent. Explorations using several toy examples have demonstrated that the improvement provided by a quantum solution, relative to the corresponding Boolean logic solution, depends on the problem. The extraordinary feature is that in certain cases the difference is large enough to challenge the conventional complexity classification of computational problems. In what follows, we want to track down which algorithmic advantages are due to ‘particle-like’ features and which



ones are due to ‘wave-like’ features. We use the famous algorithms constructed by Peter Shor for factoring large integers [7], and by Lov Grover for database search [8], as the test cases for our analysis. Hopefully, the insight gained would help in developing new quantum algorithms for other interesting computational problems.

## 2. Factorisation and Superposition

The analysis of classical computational complexity is routinely done in the digital framework. As mentioned earlier, when the computation can be fully factorised as a tensor product of bits, one reduces the spatial resources needed by a factor  $N/\log_2 N$ . This is the maximum gain achievable in ‘particle-like’ implementations; when the algorithm does not factorise completely, the factor gained is smaller.

The characteristic property of waves useful in computation is superposition, which means having multiple signals at the same position at the same time. That allows the simplest type of parallel computation paradigm, i.e., SIMD (Single Instruction Multiple Data), whereby all the superposed components undergo identical transformations. Parallel computation generically reduces the time complexity at the expense of the space one. For an SIMD algorithm, the advantage depends on the number of components that can be efficiently superposed. When a tensor product structure exists in the Hilbert space, an exponentially large number of components can be superposed using only polynomial resources. For instance, with  $n$  qubits and  $n$  rotations, one can create a uniform superposition of  $N = 2^n$  components:

$$|0\rangle^{\otimes n} \longrightarrow \left( \frac{|0\rangle + |1\rangle}{\sqrt{2}} \right)^{\otimes n} = 2^{-n/2} \sum_{i=0}^{2^n-1} |i\rangle, \quad (1)$$

where we have denoted the quantum states using Dirac’s notation. Thus a single run of a quantum algorithm can take  $2^n$  superposed inputs to  $2^n$  superposed outputs.

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The caveat is that the final measurement can extract only one of the output components (by interference, amplification or otherwise), while erasing all the rest. This is analogous to the situation that one can listen to only a single radio or television programme at a time from the superposition of a large number of available broadcast signals. The advantage inherent in superposition is therefore useful only in those computational problems, where many different inputs need to be processed by the same instructions, but only one specific property of the possible outputs is desired at the end.

The gain provided by ‘wave-like’ superposition is in the temporal resources. Once again, the  $N/\log_2 N$  gain, arising from superposition of  $N$  components using  $\log_2 N$  effort, is maximal. When the algorithm uses a smaller number of superposed components, or when the needed superposition cannot be created as efficiently, the factor gained is smaller.

In a general algorithm, the advantage provided by factorisation may or may not overlap with that of superposition. One has the best of the two worlds when the two are independent, and the gain reduces when the two overlap. Although quantum dynamics can implement both factorisation and superposition together, classical dynamics has to make a choice between the two, and the digital Boolean algorithms use the former. Then the extra gain possible in quantum algorithms, over their best Boolean counterparts, is due to the parallelism of superposition. The superiority of a quantum algorithm thus depends on how much superposition can be included on top of factorisation.

In the computational complexity analysis, the problems that can be solved with all resources polynomial in the input size are considered easy, and they form the class P. Alan Turing’s<sup>1</sup> classic work showed that a universal computer can simulate any other computer. Subsequent

<sup>1</sup> See *Resonance*, Vol.2, No.7, 1997.



analysis quantified that the conversion cost is at most a polynomial overhead. That separated the polynomial problems from the super-polynomial ones, irrespective of the type of computer. Many super-polynomial problems of practical interest belong to the class NP (Non-deterministic Polynomial), i.e., those whose solutions can be verified with polynomial resources. Turing's analysis did not include superposition, and the arguments above show that superposition can provide an exponential advantage to breach the barrier between the classes P and NP. That would imply that the quantum complexity analysis of computational problems differs from the classical one. Indeed, a lot of research effort has been directed towards discovering problems whose Boolean solution is in the class NP, while the quantum solution would need only polynomial resources, i.e., belong to the class BQP (Bounded error Quantum Polynomial time). A rigorous instance of this highly plausible conjecture has not yet been found. But even in cases where the advantage provided by superposition is not maximal, the quantum improvement in the scaling rules of the algorithms can be substantial enough for practical applications.

We now look at Shor's and Grover's famous quantum algorithms in this general framework.

### 3. Shor's Algorithm [7]

Shor's algorithm first classically reduces the problem of factoring integers to a period finding problem, and then solves the latter using efficient quantum implementation of Fourier transform. The discrete Quantum Fourier Transform (QFT) can be expressed as a unitary change of basis,

$$\sum_x f(x)|x\rangle = \sum_y \left( \frac{1}{\sqrt{N}} \sum_x e^{2\pi ixy/N} f(x) \right) |y\rangle, \quad (2)$$

again using Dirac's notation for the quantum states.

Superposition can provide an exponential advantage to breach the barrier between the classes P and NP.



The period-finding problem requires only one result, i.e., the period, from multiple evaluations of  $f(x)$ .

Writing the integers  $x$  and  $y$  in binary notation, e.g.,  $x = x_{n-1} \cdot 2^{n-1} + \dots + x_1 \cdot 2 + x_0$ , the non-trivial fractional part of the exponent can be decomposed as

$$\text{frac}\left(\frac{xy}{N}\right) = y_{n-1}(.x_0) + y_{n-2}(.x_1x_0) + \dots + y_0(.x_{n-1} \dots x_0). \quad (3)$$

Then the unitary rotation of the QFT factorises as

$$|x\rangle \rightarrow \frac{1}{\sqrt{N}} \sum_y e^{2\pi i xy/N} |y\rangle = \frac{(|0\rangle + e^{2\pi i(.x_0)}|1\rangle)}{\sqrt{2}} \times \frac{(|0\rangle + e^{2\pi i(.x_1x_0)}|1\rangle)}{\sqrt{2}} \dots \frac{(|0\rangle + e^{2\pi i(.x_{n-1} \dots x_0)}|1\rangle)}{\sqrt{2}}, \quad (4)$$

where the sum over  $y$  has been expanded in terms of the two values of each of its  $n$  bits. The factorisation has converted the sum over  $N$  different values of  $y$  to a product of  $n$  single qubit rotations. This is the familiar classical trick used for implementing the Fast Fourier Transform (FFT), albeit written in a quantum notation. Complete factorisation of the transform provides the maximal  $O(N/\log_2 N)$  gain, as expected.

The next step is to evaluate the transform for different values of  $x$ , which can be implemented in parallel. Individual evaluations of  $f(x)$  for each value of  $x$  are not needed, however. The ‘period finding’ problem requires only one result, i.e., the period, from multiple evaluations of  $f(x)$ . That is possible with maximal quantum superposition of  $x$  values, and a single run of QFT. Thus period finding using QFT gains another factor of  $N/\log_2 N$  in complexity. Since the parallelism over  $x$  is totally independent of the factorisation over  $y$ , both the  $N/\log_2 N$  gains can be achieved simultaneously, whereby the classical and the quantum algorithms differ exponentially in complexity.

To summarise, Fourier transform requires multiplication of an  $N \times N$  matrix with an  $N$ -component vector, which



is an  $O(N^2)$  problem. The FFT factorisation reduces the operations to  $O(N \log_2 N)$ . Furthermore, in case of period finding, the QFT superposition cuts down the operations to  $O((\log_2 N)^2)$ .

#### 4. Grover's Algorithm [8]

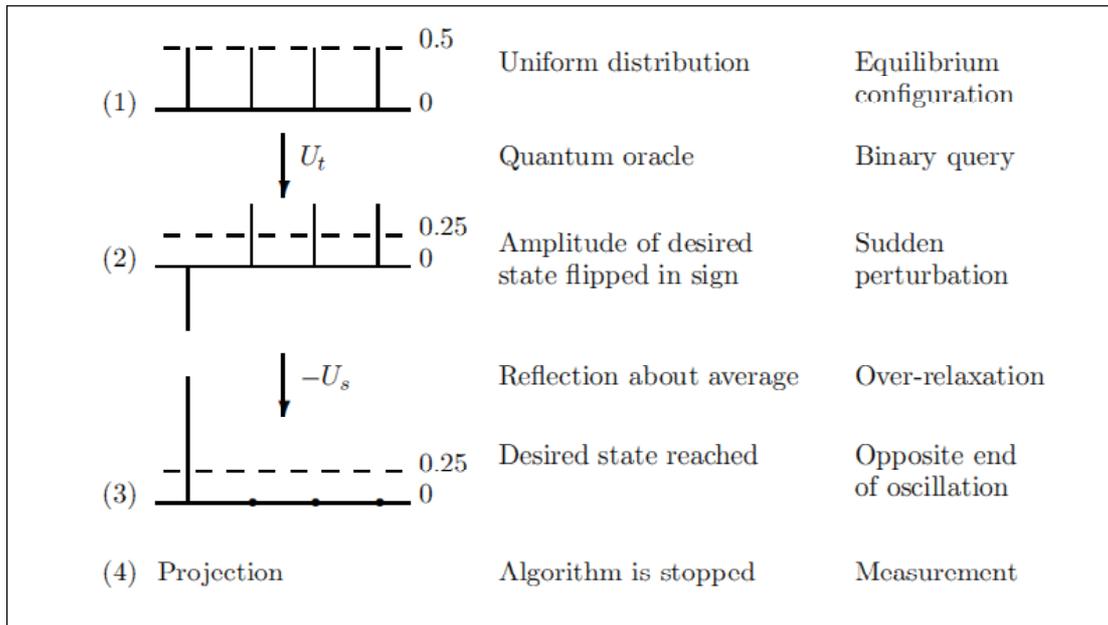
Grover's algorithm concerns searching for a specific object in a database, using binary oracle queries, i.e., questions of the type "Does the selected object have the specified property?" with only "yes or no" answers. This is a relativised problem, where the design of the oracle is not a concern, and the optimal algorithm uses the minimum number of oracle queries to locate the desired object. In absence of any structure in the database, random pickings are as good as any other selection scheme. Then for a database of  $N$  items, each query has a success probability of  $1/N$ , and on the average one requires  $\langle Q \rangle = N$  queries to locate the desired object.

The digital strategy for improving the search process is to factorise the oracle query into smaller parts, and then sort the database in the order of the query parts. The sorted order allows, for every query, separation of the objects corresponding to the 'yes' answer from those corresponding to the 'no' answer. For example, while looking for a word in a dictionary, one first locates the first letter, then the second letter, and so on. With discrete labels, a single binary query can uniquely identify only two objects. A binary search tree therefore achieves maximal factorisation, allowing the desired object to be found using  $Q = \log_2 N$  queries. Note that sorting requires significant effort, i.e.,  $O(N \log_2 N)$  operations for a database of size  $N$ . It is the exponential change in the number of queries for all subsequent searches that makes the laborious process of sorting worthwhile, to be carried out once and for all.

After the oracle query factorisation, superposition can be used to speed up the quantum search process further.

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**Figure 1.** The steps of the quantum database search algorithm for the simplest case of 4 items, when the first item is desired by the oracle. The left column depicts the amplitudes along the 4 basis vectors, with the dashed lines showing their average values. The middle column describes the algorithmic steps, and the right column mentions their physical implementation in the wave language.

But that parallelism can only be over the possibilities addressed by each query factor, and not over different query factors. Wave dynamics allows unique identification of four objects using a single binary query, as illustrated in *Figure 1*. So the additional gain provided by superposition is just  $\log_2 4 = 2$ . Superposition is commutative, however, and that offers another advantage that the quantum search process does not need prior sorting of the database according to a particular order.

Grover actually solved the quantum search problem for the situation where the oracle query cannot be factorised. The non-factorisation restriction makes the gain that can be achieved from superposition explicit. The individual objects are mapped to the basis vectors of an  $N$ -dimensional Hilbert space. The algorithm evolves the initial unbiased uniform superposition state (1) to a final state where all but the desired components vanish. It achieves this goal by applying two reflection operations in an alternating sequence: (i) the binary oracle query reversing the amplitude of the desired object, and (ii) the reflection-in-the-average operation typical of a wave



oscillating about its average value. The smallest solution, i.e.,  $Q = 1$ , is depicted in *Figure 1*, while more generally

$$(2Q + 1) \sin^{-1}(1/\sqrt{N}) = \frac{\pi}{2}, \quad (5)$$

and asymptotically  $Q = \frac{\pi}{4}\sqrt{N}$ .

Grover's algorithm does not have the SIMD structure for processing  $N$  different amplitudes. Rather it needs a clever interference among the amplitudes so that only the desired one survives at the end. The advantage of superposition is then limited to  $O(\sqrt{N})$ , and is not  $N/\log_2 N$ . This square-root speed-up happens to be the best one can do, as can be inferred from the following two features of the algorithm: (i) The evolution is restricted to the two-dimensional subspace of the Hilbert space, formed by the initial and the final states, and hence proceeds along the shortest path (i.e., geodesic great circle on the unitary sphere). (ii) The largest step one can take in a given direction during any unitary evolution is reflection, and the algorithm uses only such steps.

The superposition advantage of Grover's algorithm can be exhibited by classical wave systems that do not have digital structure, e.g., a set of coupled oscillators. Such systems reduce the temporal complexity (i.e., number of queries), but the spatial complexity remains  $N$  in absence of digitisation. On the other hand, in classical digital systems with  $\log_2 N$  spatial complexity, the temporal complexity of unstructured search remains  $N$ . Note that when factorised oracle queries are available, Grover's algorithm can use them to reduce the database size in steps, e.g.,  $N \rightarrow N/4 \rightarrow N/16 \rightarrow \dots$  in case of maximal factorisation,

To summarise, unlike the period finding problem, the search problem does not have two factors of  $N$  in its complexity that can be improved upon independently

The superposition advantage of Grover's algorithm can be exhibited by classical wave systems that do not have digital structure.



by factorisation and superposition. Factorisation can produce the maximal gain, but superposition cannot. The overlap between the two limits the maximal gain to  $2N/\log_2 N$ , which can be looked upon as either  $N/\log_2 N \times 2$  (factorisation followed by superposition) or  $N/\sqrt{N} \times \sqrt{N}/\log_2 \sqrt{N}$  (superposition followed by factorisation).

## 5. What Else?

The preceding two examples illustrate the advantages to be gained from ‘particle-like’ factorisation and ‘wave-like’ superposition, as well as their interplay. The same type of analysis and inferences help in understanding the following also.

### 5.1 *Simulation of Quantum Systems*

An important area where quantum computation has a lot to offer is the study of quantum models that are simplified versions of real physical systems. Such models often help us correlate observable phenomena with appropriate theoretical ingredients. Frequently, exact solutions are not available even for the simplified models, and it has become commonplace to study such models using computer simulations. Now, quantum dynamics results from the interference among multiple quantum evolution paths – the famous double-slit experiment being the prototype system. Classical digital simulations either evaluate these paths one by one or approximate their sum using importance sampling methods. It was obvious to Feynman that, for many-body quantum systems and quantum field theories, a quantum computer can sum over these evolutionary paths by implementing their SIMD structure as superposition [1]. That provides an exponential gain in complexity beyond what classical digital computers can achieve, and so would be an attractive application for a quantum computer.

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### 5.2 *Spatial Search*

This is the problem where the database to be searched



is spread over a number (say  $N$ ) of distinct locations instead of being all in one place, and there is a locality restriction that one can proceed from any location to only its neighbours while inspecting the objects using a binary oracle query. The problem is interesting when the oracle query cannot be factorised, because the locality restriction then constrains both the global operations of sorting and superposition. The best digital classical algorithm has to inspect all the locations one by one, which is a directed walk in some order on the network of locations and requires  $O(N)$  effort. A quantum algorithm can do better by superposing a number of walks, but that is restricted by how fast the walks spread. The spread obviously depends on the geometry and the connectivity of the network, characterised for example by its dimension.

The typical method for exploring an unstructured discrete space, with the constraint of local movements, is the random walk. In the ‘particle’ form, that describes a diffusion process, which spreads according to the rule  $distance \propto \sqrt{time}$  associated with the dispersion relation  $E \propto k^2$ . On the other hand, the coherent ‘wave’ form spreads quadratically faster, according to the rule  $distance \propto time$  associated with the dispersion relation  $E \propto |k|$ . Quantum spatial search algorithms obviously use the latter, also called the quantum random walk, and hence have the lower bound  $\Omega(N^{1/d})$  for spreading over a  $d$ -dimensional network. To put it differently, the best spatial search algorithms arise in a setting that combines unitarity of quantum dynamics with finite propagation speed of special relativity, i.e., relativistic quantum mechanics.

Another lower bound on quantum spatial search algorithms follows from the fact that they cannot outperform Grover’s optimal algorithm which has no restriction on movement. Combining the two bounds, the complexity of quantum spatial search is  $\Omega(N^{1/d}, \sqrt{N})$ . Numerical

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simulations verify that these bounds can indeed be reached. It also follows that [9]: (i) the requirement of locality weakens with increasing  $d$  and Grover's algorithm is the  $d \rightarrow \infty$  limit, (ii) the clash between the two bounds in the critical dimension  $d = 2$  produces logarithmic corrections to the  $\Omega(\sqrt{N})$  scaling behaviour, familiar from critical phenomena in statistical mechanics, and (iii) the locality constraint is the strongest in  $d = 1$ , where quantum spatial search cannot improve upon classical spatial search.

### 5.3 Role of Entanglement

The classical initial and final states of our computational problems can be digitally factorised in a specific basis. The superposition of many such factorised states is an entangled quantum state. When the superposed components evolve independently, e.g., in the SIMD mode as in (4), the computational complexity gain is maximal. When the superposed components have to interfere with each other during the course of evolution, e.g., as in Grover's algorithm, the gain is smaller. In the design of best quantum algorithms, therefore, what is important is the non-mixing of the superposed components during evolution and not the amount of entanglement. The considerations of entanglement are relegated to the ends of the algorithms – the production of the initial superposed state, e.g., as in (1), and the final choice of the measurement basis that extracts appropriate results from the superposed outcomes.

## 6. Conclusion

To conclude, we have observed that each of 'particle-like' digital factorisation and 'wave-like' parallelism of superposition can provide a computational complexity gain upto  $N/\log_2 N$ . Traditional computer science has extensively explored the former, but not the latter. Quantum algorithms need to combine the two, and we do





**Figure 2.** The author with Richard Feynman, on his graduation day at Caltech in 1984.

not yet have a general framework to do that for arbitrary problems. But we believe that the study of pure ‘wave algorithms’ is an excellent stepping stone to identify problems amenable to efficient quantum computation.

### Suggested Reading

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