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[Ivan Maksymov](#) *

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Article

Quantum-Tunnelling Deep Neural Networks for Sociophysical Neuromorphic AI

Ivan S. Maksymov

Artificial Intelligence and Cyber Futures Institute, Charles Sturt University, Bathurst, NSW 2795, Australia;
imakymov@csu.edu.au

Abstract: The discovery of the quantum tunnelling effect—the transmission of particles through a high potential barrier—was one of the most impressive achievements of quantum mechanics made in the 1920s. Responding to the contemporary challenges, I introduce a novel deep neural network (DNN) architecture that processes information using the effect of quantum tunnelling. I demonstrate the ability of the quantum tunnelling DNN (QT-DNN) to recognise optical illusions like a human. Hardware implementation of QT-DNN is expected to result in an inexpensive and energy-efficient neuromorphic chip suitable for applications in autonomous vehicles. The optical illusions recognition tests developed in this paper should lay foundations for cognitive benchmarking tasks for AI systems of the future, benefiting the fields of sociophysics and behavioural science.

Keywords: artificial intelligence; neuromorphic computing; quantum tunnelling; sociophysics; cognition

1. Introduction

1.1. Can AI See Optical Illusions?

How will a conscious robot [1] see us and our world? Will it understand how humans behave in natural complex environments such as oceans and space [2–4] and make decisions in virtual reality systems [5–7] and video games [8]? Speaking broadly, will a robot differentiate lie from truth in media, social networks and politics [9–11]?

Biological vision is enabled by physical, physiological and psychological processes [12]. In turn, AI employs machine vision [13] and neural network models [14] to recognise and classify objects. Hence, even though machine vision shares certain features with biological vision [15], in general AI and humans see two very different worlds [16–18].

For example, how would AI see the Necker cube [19,20] and Rubin's vase [21,22] (Figure 1a, b)? While a human looking at these paradigmatic optical illusions [19] can easily report a random switching of their perception from one possible interpretation of the figure to another [20,23] (Figure 1c), AI will struggle to produce a similar output in spite of the advances in simulation of human vision [24–30].

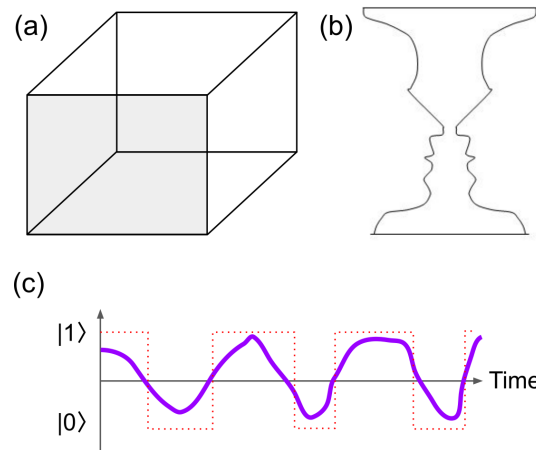


Figure 1. (a) The Necker cube: The answer to the question ‘Is the shaded face of the cube at the front or at the rear?’ will randomly switch between two stable perceptual states corresponding to the front ($|0\rangle$) and rear ($|1\rangle$) face of the cube. (b) Rubin’s vase: Do you see two people looking towards each other ($|0\rangle$) or a vase ($|1\rangle$)? (c) According to the traditional psychological theories, the change from one perceptual state to another is instantaneous (the dotted line). However, current research works demonstrate that humans might see a superposition of the states $|0\rangle$ and $|1\rangle$ (the solid curve).

1.2. AI, Psychology and Quantum Mechanics

AI cannot see optical illusions since its algorithms do not take into account peculiar psychological and neurological aspects of human vision [19,22,31,32]. Yet, although this problem has been stressed in the literature [33–36], the relevance of visual and biological complexity of natural environments to AI has not been fully appreciated [4,37,38].

Experimental studies [39–41] demonstrated that the perception of the Necker cube and other ambiguous figures may not abruptly switch between the states $|0\rangle$ and $|1\rangle$ (the dotted line in Figure 1c) but continuously oscillates between them (the solid curve in Figure 1c). Those results were interpreted as the ability of humans to see a quantum-like superposition of $|0\rangle$ and $|1\rangle$ states [20,42–44]. Indeed, in psychological experiments humans are asked to push an electric button every time their perception of the Necker cube switches between $|0\rangle$ and $|1\rangle$. While humans might see the cube in a superposition state [31,41], by pressing the button the observer ‘collapses’ the superposition to one of the possible ‘classical’ states [23]. This means that the ability of humans to access and use environmental information is limited, which may result in ambiguous interpretation. Subsequently, our perceptual system needs to disambiguate and interpret the available sensory information to construct stable and reliable percepts [45]. Yet, this suggests that AI can help humans to enhance their perception and gain access to information that our senses and brain cannot process naturally.

Further attempts to understand bistable perception using the methods of quantum mechanics [20,43,44] resulted in the suggestion to study the superposition of the perceptual states using a quantum oscillator model (QOM) [20]. Compared with Markov models [20], QOM accounts for multiple outcomes while processing input data with a large set of constraints, thus describing human mental states [43,44] more efficiently than classical models.

The predictions of QOM are in good agreement with a model based on the quantum Zeno effect [42]. Besides, the ability of QOM to simulate the perception of optical illusions was improved [23,46] by combining harmonic motion with the effect of quantum tunnelling (QT) through a potential barrier [47,48]. Since both QOM and quantum Zeno effect underpin quantum neural network models [49], the predictions made by QOM were additionally validated using a deep neural network (DNN) model [23] combined with a quantum generator of truly random numbers [50].

1.3. What is this article about?

In this work, I suggest and theoretically validate a novel neuromorphic DNN model (see Sect. 2.1 for state-of-the-art) that processes information using the physical effect of QT. I showcase the ability of the QT-DNN model to enable AI to recognise practically important optical illusions, the perception of which should pave the way for the development of machine vision system capable of recognising more complex visual effects used in fine arts and cinematography. I also demonstrate that QT-DNN can be implemented as a hardware neuromorphic chip.

My findings can be used in AI system and brain-computer interfaces aimed to enhance the performance of astronauts in long-duration spaceflight [3] and help airline pilots be aware of disorientation, loss of perspective and misinterpretation of data provided by flight instruments [51]. Interestingly enough, the algorithms proposed in this work can also help conduct research on gender since it has been demonstrated that fluidity of gender identity might be induced by optical illusions [52].

Finally, concluding the paper with a discussion of the relevance of the effect of QT to the hypothesised brain-mind link [53,54], I contribute to bridging the gap between the theories of quantum mind and decision-making [20,43] and the practically important field of sociophysics [9,11].

2. QT-DNN Architecture

2.1. Neuromorphic Quantum DNN models

DNNs—networks composed of several layers (Figure 2a) [14]—are pivotal for machine vision and human-computer interactions [13]. Yet, they are mathematically complex [55], require considerable computational resources [56] and consume significant electric power [57].

The efficiency of DNNs can be increased by constructing the network following the principles of quantum computing [58–60] and optimising their algorithms using the fundamental laws of physics [61]. DNNs can also be built using the principles of neuromorphic computing [62,63].

Neuromorphic computers mimic the operation of a biological brain [62,64]. Several neuromorphic DNN models have been demonstrated [65,66], where, instead of relying on conventional Boolean arithmetic, information is processed using nonlinear dynamical properties of a physical system [63,64]. Such DNN models can be implemented as an inexpensive and low power consuming chip [65,67] suitable for applications in AI and robotics [66].

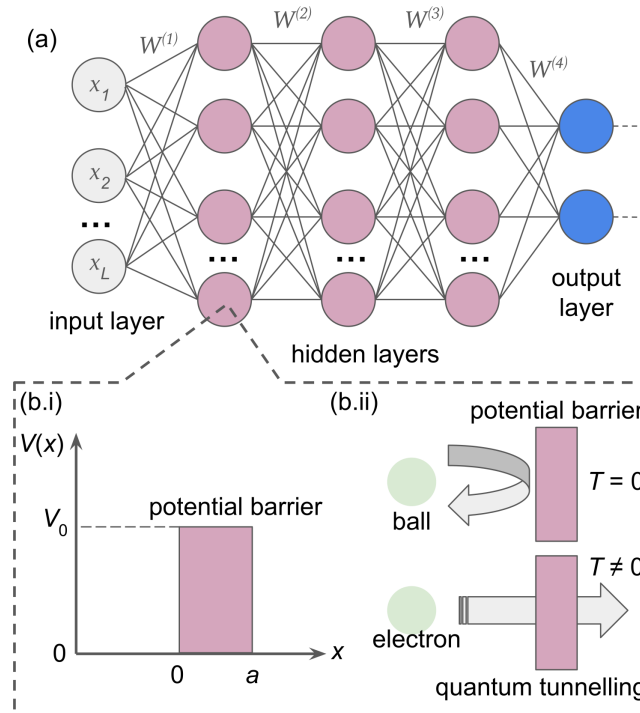


Figure 2. (a) Sketch of QT-DNN structure. $W^{(n)}$ with $n = 1 \dots 4$ are the matrices of the weights of the network connections. (b) QT-DNN model employs the physical effect of QT as the activation function of its nodes. Panel (b.i): one-dimensional rectangular potential barrier of thickness a and height V_0 . Panel (b.ii): unlike in classical mechanics, in quantum mechanics there is a non-zero probability for an electron with energy $E < V_0$ to be transmitted through the barrier.

2.2. Quantum tunnelling effect

In quantum mechanics [48], the rectangular potential barrier is a computational problem that demonstrates the phenomenon of QT (Figure 2b). The problem consists in solving a one-dimensional time-independent Schrödinger equation for an electron that encounters a rectangular potential energy barrier [47]

$$\left[-\frac{\hbar^2}{2m} \frac{d^2}{dx^2} + V(x) \right] \psi(x) = E\psi(x), \quad (1)$$

where $\psi(x)$ is a wave function, $m \approx 9.1093837 \times 10^{-31}$ kg is the mass of the electron, $\hbar \approx 1.054571817 \times 10^{-34}$ J·s is Planck's constant and E is the energy of the electron. The profile of the potential barrier (Figure 2b) is

$$V(x) = \begin{cases} 0 & \text{for } x < 0 \\ V_0 & \text{for } 0 < x \leq a \\ 0 & \text{for } x > a. \end{cases} \quad (2)$$

In classical mechanics, a counterpart of this physical system is a marble ball (Figure 2b). While a ball with energy $E < V_0$ cannot penetrate the barrier, an electron, behaving as a matter wave, has a non-zero probability of penetrating the barrier and continuing its motion on the other side. Similarly, for $E > V_0$, the electron may be reflected from the barrier with a non-zero probability.

The electron tunnelling behaviour can be quantified by finding the transmission coefficient from the solution of Eq. (1) for the potential barrier given by Eq. (2). The solution of the Schrödinger equation can be written as a superposition of left and right moving waves [47]

$$V(x) = \begin{cases} \psi_L(x) = A_1 e^{ikx} + A_2 e^{-ikx}, & x < 0 \\ \psi_C(x) = B_1 e^{i\kappa x} + B_2 e^{-i\kappa x}, & 0 < x \leq a \\ \psi_R(x) = C_1 e^{ikx} + C_2 e^{-ikx}, & x > a, \end{cases} \quad (3)$$

where i is the imaginary unit, $k = \sqrt{2mE/\hbar^2}$ and $\kappa = \sqrt{2m\alpha/\hbar^2}$ with $\alpha = E - V_0$ (the special cases $E = 0$ and $E = V_0$ are treated separately). The coefficients A, B, C are found from the boundary conditions at $x = 0$ and $x = a$, requiring that $\psi(x)$ and its derivative have to be continuous. Below, omitting the intermediate derivations [47], I present the expressions for the probability of the electron transmission through the barrier.

For electron energies smaller than the barrier height ($E < V_0$), there is a non-zero transmission probability [47]

$$T|_{E < V_0} = \left(1 - \beta \sinh^2(\kappa_1 a)\right)^{-1}, \quad (4)$$

where $\beta = \frac{V_0^2}{4E\alpha}$ and $\kappa_1 = \sqrt{-2m\alpha/\hbar^2}$. For $E > V_0$

$$T|_{E > V_0} = \left(1 + \beta \sin^2(\kappa a)\right)^{-1}, \quad (5)$$

Finally, the expression for $E = V_0$ is obtained by taking the limit of T as E approaches V_0 , resulting in

$$T|_{E=V_0} = \left(1 + \frac{ma^2 V_0}{2\hbar^2}\right)^{-1}. \quad (6)$$

2.3. Quantum Tunnelling as an Activation Function

Figure 3 shows the probability of transmission of a single electron with energy E through a potential barrier with the nondimensionalised thickness $\sqrt{2mV_0}a/\hbar$. The result predicted by the classical theory is denoted by the straight dash-dotted lines. While physical implications of these results are well-known [47], in the following I will focus only on their meaning in the context of QT-DNN.

A close inspection of the curve plotted in Figure 3 reveals that the QT transmission function T can be employed as an activation function of the nodes of an DNN, provided that the energy of the electron E is interpreted as the input value of the node. In fact, similarly to the standard activation functions used in DNNs [14], T fulfils a number of essential mathematical criteria pertinent to the field of machine learning, including nonlinearity and differentiability, thus enabling its application with gradient-based optimisation methods [14,68]. Although the negative values of E/V_0 have no strict meaning in the framework of the physical model, in the QT-DNN model they can be interpreted as the inputs that produce a zero output. The special case $E = 0$ can be avoided programmatically. It is also noteworthy that the energy of the electron can be effectively amplified (see Sect. 4.2 for technical details), which is one of the features of the computational code that accompanies this paper.

Differentiating Eqs. (4-5) with respect to E , I obtain

$$\begin{aligned}
 T'|_{E < V_0} &= -\beta \left(\frac{\sinh^2(\delta_1)}{E} + \frac{\sinh^2(\delta_1) - \delta_1 \cosh(\delta_1) \sinh(\delta_1)}{\alpha} \right) T^2|_{E < V_0}, \\
 T'|_{E > V_0} &= \beta \left(\frac{\sin^2(\delta)}{E} + \frac{\sin^2(\delta) - \delta \cos(\delta) \sin(\delta)}{\alpha} \right) T^2|_{E > V_0}, \\
 T'|_{E = V_0} &= \frac{4V_0 a^4 m^2 + 6a^2 \hbar^2 m}{3V_0^2 a^4 m^2 + 12V_0 a^2 \hbar^2 m + 12\hbar^4},
 \end{aligned} \tag{7}$$

where $\delta = \kappa a$ and $\delta_1 = \kappa_1 a$.

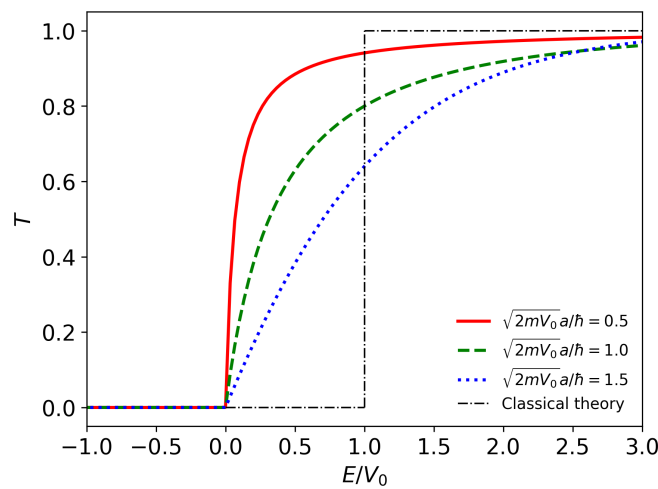


Figure 3. Transmission probability of an electron with energy E through a rectangular potential barrier with a nondimensionalised thickness $\sqrt{2mV_0}a/\hbar$. The straight dash-dotted lines denote the result predicted by the classical theory.

2.4. QT-DNN Algorithm

The QT-DNN network used in this paper (Figure 2a) consists of an input layer that has $L = 100$ input nodes, three hidden layers each of which has $N = 20$ nodes and an output layer that has $M = 2$ output nodes that are used to classify the input dataset. The weights of the connections of the network are updated using a back-propagation training algorithm [14].

The activation function ϕ_{QT} of the nodes of the hidden layers and its derivative are given by Eqs. (4-7). The output nodes are governed by the Softmax function [14]

$$\phi_{smax}(v_i) = \frac{\exp(v_i)}{\sum_{k=1}^M \exp(v_k)}, \tag{8}$$

where v_i is the weighted sum of input signals to the i th output node and M is the number of the output nodes.

The network is trained and exploited as follows. First, I construct the output nodes that correspond to the correct answers to the training datasets. Then, I initialise the weights of the neural network in the range from -1 to 1 using a random number generator. Entering the input data x_j and the corresponding training data points d_i , I calculate the error e_i between the output y_i and target d_i as $e_i = d_i - y_i$. Then, propagating the output $\delta_i = e_i$ in the backward direction of the network, I compute the respective parameters $\delta_i^{(n)}$ of the hidden nodes using the equations $e_i^{(n)} = W^{(n)\top} \delta_i$ and $\delta_i^{(n)} = \phi'_{QT}(v_i^{(n)}) e_i^{(n)}$, where the index n denotes the sequential number of the hidden layer, prime denotes the derivative

of the activation function and W^T is the transpose of the matrix of weights corresponding to each relevant layer of the network. I continue the back-propagation process until the algorithm reaches the first hidden layer and then I update the weights using the learning rule $w_{ij}^{(n)} \leftarrow w_{ij}^{(n)} + \Delta w_{ij}^{(n)}$, where $w_{ij}^{(n)}$ are the weights between an output node i and input node j of the n th layer and $\Delta w_{ij}^{(n)} = \alpha \delta_i^{(n)} x_j$.

The computational steps outlined above are sequentially applied to all training data points. Typically, to obtain convergent results it suffices to complete 1000 epochs, using the learning rate parameter $\alpha = 0.01$.

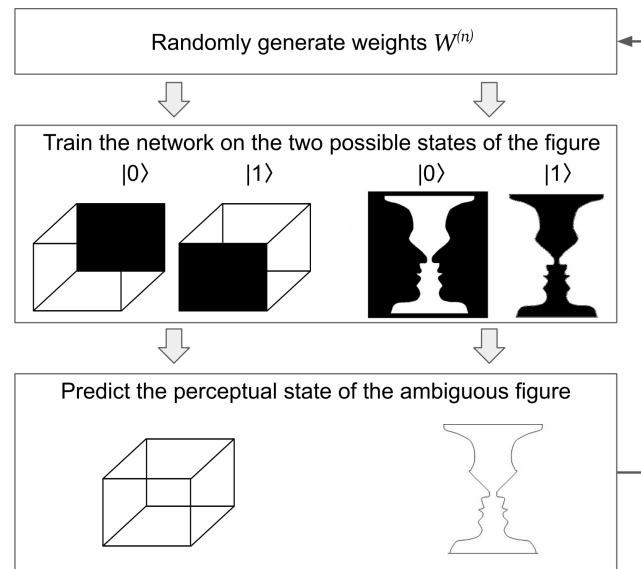


Figure 4. Neuromorphic algorithm involving the training of the network on distinguishable images of objects and its further exploitation aimed to recognise optical illusions.

2.5. Neuromorphic QT-DNN Model of Perception

A biological brain is a nonlinear dynamical system that exhibits chaotic behaviour [69]. This property has motivated the development of neuromorphic AI that mimics the operation of the brain by exploiting nonlinear dynamical properties of diverse physical systems [62–64].

The principal components of the human vision system, including the retina and visual cortex, also exhibit nonlinear dynamical properties that can be used to create neuromorphic computers [70]. The visual input to the retina is modulated by eye blinks and movements, which effectively converts spatial information in the temporal one [71], also playing an important role in cognition and visual perception [72–74]. Yet, the dynamics of eye blink is also nonlinear and it may exhibit phase changes and chaotic behaviour [75], which are the processes that underpin the perception of optical illusions [76].

Based on these facts, it was demonstrated that the introduction of chaotic changes in the architecture of a neural network enables modelling the dynamics of information perception [23–27,77]. Thus, I randomly generate the weights $W^{(n)}$, then I train QT-DNN on the 10×10 pixel unambiguous images of the Necker cube and then I exploit it to predict the perceptual state of the ambiguous Necker cube. This procedure is repeated in a loop to plot the dynamics of the perceived states (Figure 4).

Rubin's vase training images had 20×20 pixels. Although some works studying the Necker cube claim that similar results would be obtained for Rubin's vase [46], recent research demonstrated that Rubin's vase has an increased contextual complexity [22]. Hence, I train QT-QNN using the figures with the shaded faces and vase, respectively, and then exploit it using a contour version of the drawing (Figure 4). Both shaded and contour versions have been used in the literature [21] and they represent an intriguing benchmarking task, especially because the shaded training images are also ambiguous.

3. Results and Discussion

Figure 5 plots the simulated probability of perceiving $|0\rangle$ and $|1\rangle$ states of the Necker cube as a function of time (arbitrary time units are used in this work; for a relevant discussion of the cognitive timescale see Refs. [42,78]). In each panel of Figure 5, the nondimensionalised thickness of the potential barrier that is used as the activation function of QT-DNN (Figure 3) is $\sqrt{2mV_0}a/\hbar = 0.5, 1$ and 1.5 .

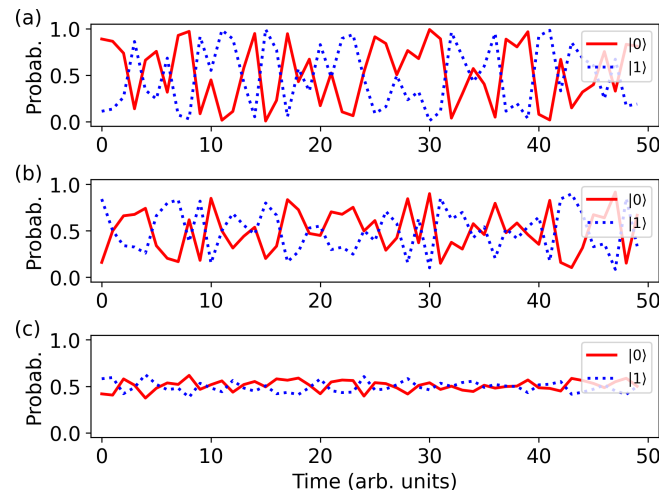


Figure 5. Perceptual switching curves produced by QT-DNN trained on the Necker cube. The data points with probability $P_{|0\rangle} = 0$ or $P_{|1\rangle} = 1$ correspond to the fundamental perceptual states of the Necker cube. The remaining data points are in a superposition of states $|0\rangle$ and $|1\rangle$ with $P_{|0\rangle} + P_{|1\rangle} = 1$.

The probability curves were obtained after 50 consecutive computational runs of the algorithm outlined in Figure 4. The states of the two output nodes of QT-DNN were recorded at the end of each run. Every pair of those data points was computed using a unique set of neural weights $W^{(n)}$. The same procedure was followed to simulate the perception of Rubin's vase (Figure 6). The same value of barrier thickness and sets of $W^{(n)}$ were used in the respective panels of Figure 5 and Figure 6.

In Figure 5a, we can observe a time-dependent switching between the fundamental perceptual states $|0\rangle$ and $|1\rangle$. The switching is not abrupt, as depicted in Figure 1c, but involves intermediate states that are a superposition of $|0\rangle$ and $|1\rangle$. A similar switching pattern is observed in Figure 5b obtained for a thicker potential barrier. Although the probability of perceiving the states $|0\rangle$ and $|1\rangle$ decreases to approximately 0.85, in this case QT-DNN can readily distinguish the two states of the Necker cube.

Further increase in the thickness of the potential well (Figure 5c) results in a smaller difference between the probabilities of perceiving $|0\rangle$ and $|1\rangle$. The so-configured QT-DNN operates similarly to perception by a human observer [78], who can quickly decode ambiguous visual information in just a few loops of recurrent biological neural activity [79], but needs much more time to decide which perceptual outcome should be reported.

In fact, I established that the same model with 2000 epochs produces a substantially more distinguishable perception pattern, which effectively means that the model requires more time to decide which perceptual state to report. Such a behaviour is beneficial for modelling the perception of illusions by different age and gender groups [80,81]. Indeed, since the dynamics of eye blink (and, therefore, the dynamics of visual information processing [71]) slows down with age [80], QT-DNN with thicker potential barriers appears to adequately model the perception of senior and visually impaired persons.

As can be seen in Figure 6, the perception switching of Rubin's vase is similar to that of the Necker cube. Yet, QT-DNN better distinguishes the two perceptual states of Rubin's vase, including in the case of a thick barrier (Figure 6c), without the need of increasing the number of epochs. This result is consistent with the hypothesis that states that Rubin's vase combines an optical illusions with the perception of background [22]. Indeed, observers may interpret this figure not only as faces-vase but

also as a white (black) vase on black (white) background, which gives them an additional point of reference that can be used to disambiguate the drawing.

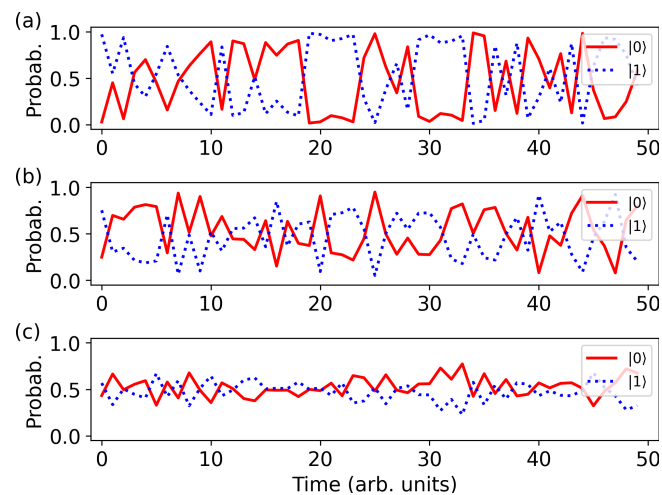


Figure 6. Perceptual switching curves produced by QT-DNN trained on Rubin's vase.

Overall, the results presented in Figure 5 and Figure 6 are in good agreement with the predictions made by the alternative quantum cognition models [20,42,46]. Below it will also be shown that the operation of QT-DNN is consistent with the broader models of brain-mind interaction.

4. Implementation and Discussion

4.1. Software

Since one of the envisioned applications of the QT-DNN model is its integration with robotic platforms and autonomous vehicles, I implemented its algorithm in Python 3 and tested the resulting software on a Raspberry Pi 4 embedded computer (1.8 GHz CPU, 8 GB RAM, Linux Ubuntu Desktop 24.04 LTS) that is often used in onboard AI systems [82,83]. Using limited embedded computational resources, QT-DNN demonstrated the ability to be trained and exploited in less than 1 second of real time, which is an encouraging result that can be considered as on-the-fly operation. It is also worth noting that the Raspberry computer consumes just 3 W of onboard power compared with more expensive GPU-based onboard computers that are required to run traditional DNN algorithms and draw 25–30 W [82]. Therefore, QT-DNN algorithm also fulfils the criterion of energy efficiency.

The advantages of QT-DNN over the traditional neural network models amplify when software that implements it runs on a high-performance workstation computer. For example, significantly lower accuracy of neural network models trained on regular images but tested on negative ones has been reported in the previous works [84]. The nominal 'vase' state of the training images of (Figure 4) is the negative image of the 'faces' state. Subsequently, since the algorithm of QT-DNN demonstrated good performance in this image recognition scenario, it is plausible to assume that QT-based activation functions can be employed in image recognition models trained on negative images. Such models have important practical applications, including ship detection and recognition in maritime environments [85] and creative arts [86].

QT-DNN can also enhance the capabilities of models employed in the emergent field of socio-physics [9]. Indeed, since the effect of QT also underpins the operation of several physics-inspired models of human opinion formation and radicalisation in social networks [10], the algorithm of QT-DNN can be adopted in the studies of fake news [11] and research on gender and racial biases [10].

4.2. Potential Hardware Implementations

The effect of QT has been exploited in semiconductor electronic devices [87–90] and different modalities of spectroscopy [91,92] and microscopy [92,93]. It has also been demonstrated that electron devices exploiting the effect of QT can serve as a building block of neuromorphic computers [94,95]. However, in those computers QT has not been exploited directly. Instead, nonlinear dynamics of the whole QT-based electron devices and circuits formed by them has been employed as a means of computation.

In practice, the architecture of QT-DNN can be implemented using tunnelling [87] and resonant tunnelling [89] diodes. Moreover, there exist neuromorphic computing schemes that exploit negative differential resistance [96,97], a prominent feature of tunnelling diodes. Importantly, systems based on tunnelling diodes and other QT-based devices consume low electric power compared with the traditional integrated electronic circuits [94].

Alternatively, QT-DNN can be embodied using the instrumentation of scanning tunnelling microscopy (STM) [93]. For example, amplifiers developed for STM operate at microwave frequencies, enabling high signal-to-noise ratios and facilitating differential conductance spectroscopy measurements [98]. Finally, QT of individual electrons was measured in quantum dots [96]—building blocks of quantum neuromorphic systems [99].

5. Conclusions and Outlook

In this paper, I pointed out the possibility of employing the effect of quantum tunnelling as an activation function of artificial neural networks. I demonstrated that the so-constructed neural networks enable accurate modelling of human perception of optical illusions. Yet, I suggested that low power consuming, hardware neuromorphic chips built using quantum tunnelling diodes or other devices and systems based on the tunnelling effect can be employed in conscious robots and autonomous vehicles. Finally, I traced a link between quantum tunnelling and sociophysical models designed to understand human behaviour in social and political groups.

So there is just one question that needs to be clarified: how can the effect of quantum tunnelling be related to cognition? This question is important because the current works on quantum models of cognition and decision-making mostly exploit the laws and methods of quantum mechanics to create phenomenological models [10,100]. While this approach has produced practically important results [9,11], addressing this question in more detail promises to attract the attention of a larger number of experts to the emergent field of sociophysical AI.

Tunnelling can be observed in all quantum systems, which explains why many Nobel prizes in physics were awarded for research involving it [101]. This physical effect is also crucial for chemical and biological evolution [102]. Most likely, it also played an essential role in the formation of the early universe and life [101,102]. Subsequently, since quantum tunnelling remains an important topic of scientific research, there have been theoretical and experimental attempts to explain the function of biological brain neurons relying on the principles of quantum mechanics [54,103] (arguably, some of those ideas could also contribute to Nobel prize-winning discoveries [104]).

Drawing on the difference between a conscious mind and a biological brain, it was suggested that the mind and brain can interact by means of quantum tunnelling [53]. Indeed, based on the cited paper and references therein, it can be said that a mental state becomes neurally effective when a large number of biological potential barriers in neurons produce high transmission probability amplitudes, which, in turn, results in a coherent action.

If proven correct, that hypothesis justifies the design of the QT-DNN model, showing that the use of tunnelling as an activation function is more than just an phenomenological mathematical approach but a model based on the fundamental principles of cognition and brain organisation. The same should be the case of the other sociophysical and quantum mind theories.

Data Availability Statement: The computational code that implements QT-DNN can be found at <https://github.com/IvanMaksymov/DeepTunnel> (accessed on 26 June 2024)

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