# A Quantum Multilayer Self Organizing Neural Network For Binary Object Extraction From A Noisy Perspective

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***Abstract-*** Binary object extraction from a noisy perspective is a challenging proposition in the computer vision community. Various research initiatives based on different methodologies have been entrusted on this aspect over the decades. The multilayer self-organizing neural network (MLSONN) architecture implemented by a fuzzy measure guided backpropagation of errors is one of the best accomplishments in this direction. In this article, a quantum multilayer self-organizing neural network (QMLSONN) architecture is proposed to achieve the same objective. Quantum computation plays a remarkable role in the proposed architecture. The proposed architecture operates using single *qubit* rotation gates. Here different nodes and interconnection weights act as vital components for this intention. The proposed QMLSONN architecture comprises three processing layers specified as input, hidden and output layers. The nodes in the processing layers are represented by *qubits* and the interconnection weights are represented by quantum gates. A quantum measurement at the output layer destroys the quantum states of the processed information thereby inducing assimilation of linear indices of fuzziness as the network system errors used to adjust network interconnection weights through a proposed quantum back propagation algorithm. Results of application of the QMLSONN are established on a synthetic and a real life spanner image with various degrees of Gaussian noise and uniform noise. Comparative study with the classical MLSONN architecture reveals the time efficiency of the presented QMLSONN architecture. Moreover, the QMLSONN architecture also restores the shape of the extracted objects to a great extent.

***Keywords-*** Multilayer self-organizing neural network, binary object extraction, quantum computing, quantum back propagation quantum multilayer self-organizing neural network.

## I. Introduction

According to the computer vision research community, accurate extraction of binary objects from a noisy background is a challenging proposition. Several research initiatives have been invested on this aspect over the decades. Neural networks have often been employed by researchers for dealing with the tasks of extraction [1], [2], [3], classification [4], [5], [6] of



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pertinent object specific information from redundant image information bases and identification and recognition of binary objects from an image scene [7], [8], [9]. Several neural network architectures, both self-supervised and unsupervised, are reported in the literature, which have been evolved to produce outputs in real time.

Kohonen's self-organizing feature map [10] is centered on preserving the topology in the input data by subjecting the output data units to assured neighborhood constraints. The Hopfield's network [11] proposed in 1982, is a fully connected network architecture with capabilities of auto-relationship. A photonic execution of the Hopfield network is also reported in [12], where a winner-take-all algorithm is used to imitate the state transitions of the network.

Numerous attempts have also been reported [13] where self organizing neural network architectures have been used for object extraction and pattern recognition. Several neighborhood based network architectures like the multilayer self organizing neural network (MLSONN) [14] are used for similar jobs. The fundamental loom is centered on employing a fully connected multilayer network architecture with each neuron of one layer connected to its neighboring neurons in the previous layer. Such a network architecture, upon stabilization leads to the detection and extraction of objects by ways of self supervision of inputs. The MLSONN [14] architecture is a feedforward network architecture and resorts to some fuzzy measures of the image information so as to derive the system errors. Quantum Computation has evolved from the theoretical studies of Feynman (1982), Deutsch (1985), and others, to an intensive research field since the innovation of a quantum algorithm, which can solve the problem of factorizing a large integer in polynomial time by Shor (1994). Matsui *et al.* [15] projected a Qubit Neuron Model which exhibits quantum learning abilities. This model resulted on a quantum multi-layer feed forward neural network proposal [16] which implements Quantum Mechanics (QM) effects, having its learning efficiency proved on non-linear controlling problems [17]. Aytekin *et al.* [18] proposed an automatic object extraction procedure based on the quantum mechanical principles. Matsui *et al.* [15] anticipated a Qubit Neuron Model which exhibits quantum learning abilities. Ezhov [19] proposed a new model of quantum neural network to solve classification problems. It is based on the extension of the model of quantum associative memory and also utilizes Everetts principle of quantum mechanics. Quantum entanglement is liable for the associations between input and output patterns in the proposed architecture. In the field of artificial neural networks (ANN), some pioneers introduced quantum computation into analogous discussion such as quantum associative memory, parallel learning and empirical analysis [20], [21], [22], [23]. They constructed the establishment for further study of quantum computation in artificial neural networks. Menneer developed her Ph. D. thesis in which deeply discussed the application of quantum theory to ANN and established that QANNs are more efficient than ANNs for classification tasks [24]. Ventura and Martinez developed a quantum associative memory, its structure and learning manner in quantum version [25]. Weigang tried to develop a parallel-SOM and mentioned the once learning manner in quantum computing environment [26]. He also proposed an Entanglement Neural Networks (ENN) on the base of the quantum teleportation and its extension with smart sense. In AI and quantum computing, there is more recent review from Hirsh *et al.* [27], [28], [29], [30]. According to Perus, quantum wave function collapse "is very similar to neuronal-pattern-reconstruction from memory. In memory, there is a superposition of many stored patterns. One of them is selectively brought forward from the background if an external incentive triggers such a reconstruction" [31], [32].

A quantum neural computer consists of an ANN where quantum processes are supported. The ANN is a self-organizing type that becomes a different measuring system based on associations triggered by an external or internally generated stimulus. [21]. A quantum learning system might acquire some form of intentionally, and begin the bridging of the physical/mental gap. Menneer and Narayanan (1995) have applied the multiple universes view from quantum theory to one-layer ANNs. In 1997, Lagaris *et al.*, [33] developed Artificial Neural Networks for Solving Ordinary and Partial Differential Equations. The use of quantum parallelism is often connected with consideration of quantum system with massive dimension of state space. The applications described further are used with some other properties of quantum systems and they do not stipulate such enormous number of states. The term "image recognition" is used here for several broad class of problems [34]. Quantum computation uses microscopic quantum level effects to perform computational tasks and has created results that in some cases are exponentially faster than their classical counterparts. The unique characteristics of quantum theory may also be used to create a quantum associative memory with a capacity exponential in the number of neurons [25]. Quantum Artificial Neural Networks (QANNs) are more efficient than Classical Artificial Neural Networks (CLANNs) for classification tasks, in that the time required for training is much less for QANNs. (Menneer and Narayanan, 1998). The repetition is not required by QANNs, since each component network learns only one pattern causing the training set to be learned more quickly. Perus reported this as a basis for Quantum Associate Networks [35]. Quantum systems can realize content addressable associative memory [36]. Hu [37] developed a research about Quantum computation via neural networks applied to image processing and pattern recognition. He proved that the error in measurement produced by quantum principle is half the error produced by a classical approach.

## II. Quantum Computing Fundamentals

Quantum Computing is concerned with creating computational devices based on the principles of quantum



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mechanics. It defines quantum mechanical operations like superposition, entanglement [38] on them. Superposition is the property of quantum mechanics. Due to the linear dynamics the linear combination of each possible solution in a quantum mechanical system is also a solution. Entanglement is the property which generally gives rise to non-local interaction among bipartite correlated states. These properties have some profound implications. Problems like large integer factorization which is one of the cornerstones of today's digital security, is rendered solvable in reasonable amount of time by a quantum computer whereas it was practically impossible to track on a standard classical computer.

A quantum computer would not just be a traditional computer built out of different parts, but a machine that would exploit the laws of quantum physics to perform certain information processing tasks in a spectacularly more efficient manner. One demonstration of this potential is that quantum computers would break the codes that protect our modern computing infrastructure the security of every Internet transaction would be broken if a quantum computer were to be built. This prospective has made quantum computing a national security concern. Yet at the same time, quantum computers will also revolutionize large parts of science in a more benevolent way. Simulating large quantum systems, something a quantum computer can easily do, is not practically possible on a traditional computer. From exhaustive simulations of biological molecules which will advance the health sciences, to aiding research into narrative materials for harvesting electricity from light, a quantum computer will likely be an fundamental tool for future progress in chemistry, physics, and engineering.

*A. Concept of Qubits*

The most basic element of Quantum Computer is a *qubit*. It is represented as a linear superposition of two *eigenstates* $|0\rangle$ and $|1\rangle$. It is represented as

$$|\phi\rangle = \alpha|0\rangle + \beta|1\rangle \tag{1}$$

where, $\alpha$ and $\beta$ are the probability amplitudes subject to the normalization criteria

$$|\alpha|^2 + |\beta|^2 = 1 \tag{2}$$

The fundamental operations on these *qubits* are represented as unitary operators in the Hilbert space. These unitary transformations can be used to appreciate various logic functions.

These are the basic quantum gates [16] and contain the quintessence of quantum computation.

*B. Single qubit rotation gate* The single qubit rotation gate is defined as

$$R(\theta) = \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \tag{3}$$

This operates $R(\theta)$ on a single *qubit* to renovate it to

$$[ \; =- \; ] \times [ \; ] \; \cos\theta \; \sin\theta \; \cos\phi_0 \; \sin\theta \cos\theta \sin\phi_0 \tag{4}$$

$$= \left[ \begin{matrix} \cos(\theta + \phi \;) \\ \sin(\theta + \phi \;) \end{matrix} \;\; {}_{00} \right]$$

*C. Quantum Measurement*

In quantum mechanics a system is described by its quantum state. In mathematical languages, all possible pure states of a system form a complete abstract vector space called Hilbert space, which is characteristically infinite-dimensional. A pure state is represented by a state vector (or precisely a ray) in the Hilbert space. In the experimental aspect, once a quantum system has been prepared in laboratory, some measurable quantities such as position and energy are measured. That is, the dynamic state of the system is already in an eigenstate of some measurable quantities which is probably not the quantity that will be measured. For pedagogic reasons, the measurement is usually assumed to be ideally perfect. Hence, the dynamic state of a system after measurement is assumed to "collapse" into an eigenstate of the operator corresponding to the measurement. Repeating the same measurement without any significant evolution of the quantum state will lead to the same result. If the preparation is continual, which does not put the system into the previous eigenstate, subsequent measurements will likely lead to different result. That is, the dynamic state collapses to different eigenstates.

The values obtained after the measurement is in general described by a probability distribution, which is determined by an "average" (or "expectation") of the measurement operator based on the quantum state of the prepared system. The probability distribution is either continuous (such as position and momentum) or discrete (such as spin), depending on the quantity being measured. The measurement process is frequently considered as random and indeterministic. However, there is considerable dispute over this issue. In some interpretations of quantum mechanics, the result merely appears random and indeterministic, whereas in other interpretations the indeterminism is core and irreducible. A significant element in this disagreement is the issue of "collapse of the wave function" associated with the change in state following measurement. In any case, our descriptions of dynamics involve probabilities and averages. For measurement purpose, we introduce the von Neumann measurement strategy which establishes one of a set of basis participating states as output. To continue this process, we first select a basis at random and ensure that the system exists in



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the basis states. Quantum computing initiates some probabilistic measurement procedure that transforms the states in superposed form to a specific state required. To accomplish multi-qubit measurement, a succession of single-qubit measurements in the defined basis are performed. Suppose, at initial, the system is in the state $|\psi\rangle$, then the probability of finding the state $\phi$ will be $|c_\phi|_2$.

## III. Multilayer Self Organizing Neural Network Architecture (Mlsonn)

MLSONN [14] is a self-supervised architecture efficient in extracting binary objects from a noisy and blurred background. It comprises several layers, viz. the input layer, any number of hidden layers and an output layer for obtaining the final processed output. The interconnection strategy employed between the layers follows a second order neighborhood topology. The network is characterized by forward propagation of incident information and subsequent processing at the hidden layers and the output layer. The network system errors are calculated at the output layer using the linear indices of fuzziness of the intermediate outputs obtained. These errors are used to adjust the network interconnection weights through the standard backpropagation algorithm. These intermediate outputs are fed back to the input layer for further processing. This process is continued until the network errors stabilize. Details regarding the operation and dynamics of the network can be obtained in [14].

## IV. Quantum Multilayer Self Organizing Neural Network Architecture (QMLSONN)

As QMLSONN is the quantum version of the MLSONN architecture [14], the processing nodes of the different layers are simply *qubits* like

$$\begin{pmatrix} \langle\alpha_{11}| & \langle\alpha_{12}| & \langle\alpha_{13}| & \dots & \langle\alpha_{1n}| \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \langle\alpha_{m1}| & \langle\alpha_{m2}| & \langle\alpha_{m3}| & \dots & \langle\alpha_{mn}| \end{pmatrix}$$

$$\begin{pmatrix} \langle\beta_{11}| & \langle\beta_{12}| & \langle\beta_{13}| & \dots & \langle\beta_{1n}| \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \langle\beta_{m1}| & \langle\beta_{m2}| & \langle\beta_{m3}| & \dots & \langle\beta_{mn}| \end{pmatrix}$$

$$\begin{pmatrix} \langle\gamma_{11}| & \langle\gamma_{12}| & \langle\gamma_{13}| & \dots & \langle\gamma_{1n}| \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \dots & \dots & \dots & \dots & \dots \\ \langle\gamma_{m1}| & \langle\gamma_{m2}| & \langle\gamma_{m3}| & \dots & \langle\gamma_{mn}| \end{pmatrix}$$

The interconnection weights are in the form of rotation gates and also follow a second order neighborhood topology. A schematic of the QMLSONN is shown in Figure 1.



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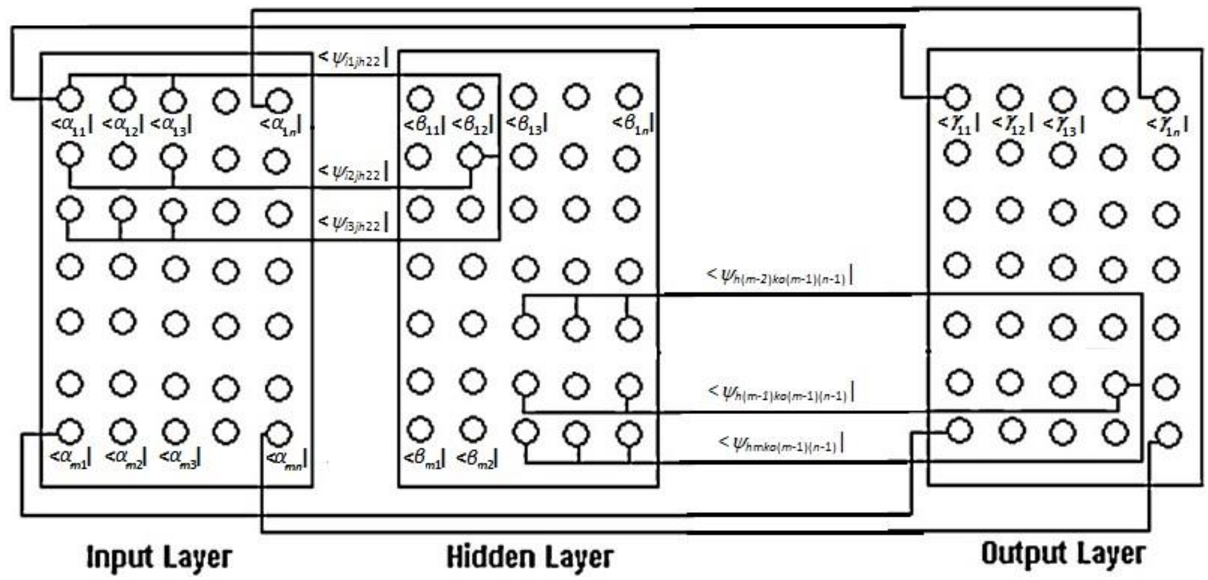


Fig. 1. Schematic of a QMLSONN. Only few interconnections are shown for the sake of clarity.

*A. Dynamics of operation*

When input data ($input_i$) is given into the network, the input layer first converts the fuzzified input value [0, 1] into the phase [0, $\frac{\pi}{2}$] in quantum states.

$$y_i^I = \frac{\pi}{2}(input_i) \tag{5}$$

Here, ($input_i$) are general inputs and $y_i^I$ are quantum inputs.

Since we have input neurons $i$ = 1 to $l$ and hidden neurons $j$ = 1 to $m$, so [39]

$$u_{hj} = \sum_{i=1}^{l} f(\psi_{ipjhll}) f(y_{il}) - f(\lambda_{hj}) \tag{6}$$

where, $\psi_{ipjhll}$ are the connection weights between input and hidden layer and $\lambda^h{}_j$ is the threshold of $j^{\text{th}}$ hidden neuron. From equation 6, we get [39],

$$u_{hj} = \sum_{i=1}^{l} f(\psi_{ipjhll}) f(y_{il}) - f(\lambda_h) = \sum_{i=1}^{l} e^{i(\psi_{ipjhll}+y_{il}) - f(\lambda_{hj})} \tag{7}$$

$$= cos(\psi_{ipjhll} + y_{il}) + isin(\psi_{ipjhll} + y_{il}) - cos(\lambda_{hj}) - isin(\lambda_{hj}) \tag{8}$$

Now,

$$y_j^h = \frac{\pi}{2} g(\delta_j^h) - arg(u_j^h) \tag{9}$$

$$= \frac{\pi}{2} g(\delta_j^h) - tan^{-1} \frac{\sum sin(\psi_{ipjhll} + y_i^I) - sin\lambda_j^h}{\sum cos(\psi_{ipjhll} + y_i^I) - cos\lambda_j^h} \tag{10}$$

$$= \frac{\pi}{2} g(\delta_j^h) - tan^{-1}(z_h) \tag{11}$$

where, $z_h = \frac{\sum sin(\psi_{ipjhll}+y_i^I) - sin\lambda_j^h}{\sum cos(\psi_{ipjhll}+y_i^I) - cos\lambda_j^h}$. Here $arg(u^h{}_j)$ means the phase extracted from a complex number $u$ and $\delta_j^h$ is the reversal parameter of $j^{\text{th}}$ hidden neuron. Similarly [39],

$$u_k = \sum_{j=1}^{m} f(\psi_{hqkoll}) f(y_j^h) - f(\lambda_k) \tag{12}$$

where, $\psi_{hqkoll}$ are the connection weights between hidden and output layer and $\lambda_k$ is the threshold of $k^{\text{th}}$ output neuron. Thus [39],

$$u_k = \sum_{j=1}^{m} e^{i\psi_{hqkoll}} e^{iy_{jh}} - e^{i\lambda_k} = \sum_{j=1}^{m} e^{i(\psi_{hqkoll} + y_{jh})} - e^{i\lambda_k} \tag{13}$$

$$= cos(\psi_{hqkoll} + y_{jh}) + isin(\psi_{hqkoll} + y_{jh}) - cos(\lambda_k) - isin(\lambda_k) \tag{14}$$

Now,

$$y_k = \frac{\pi}{2} g(\delta_k) - arg(u_k) \tag{15}$$

where $g(\delta_k)$ is the sigmoidal activation function.



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$$= \frac{\pi}{2}g(\delta_k) - tan^{-1}\frac{\sum sin(\psi_{hqkoll} + y_j^h) - sin\lambda_k}{\sum cos(\psi_{hqkoll} + y_j^h) - cos\lambda_k} \qquad (16)$$

$$= \frac{\pi}{2}g(\delta_k) - tan^{-1}(z_k) \qquad (17)$$

where, $z_k = \frac{\sum sin(\psi_{hqkoll}+y_j^h)-sin\lambda_k}{\sum cos(\psi_{hqkoll}+y_j^h)-cos\lambda_k}$.

In this way, the outputs are generated at the output layer of the QMLSONN architecture. A quantum measurement destroys the quantum states of the outputs at the output layer and convert the same to either 0 or 1 depending on a probability. However, since these outputs are to be further processed, these are retained in a safe custody. The probability amplitudes of the quantum states are compared with 1's and 0's using the linear indices of fuzziness to compute the system errors. These errors are used in a quantum backpropagation algorithm (to be discussed next) to regulate the interconnection weights of the network layers. The retained outputs are fed back to the input layer for further processing. This process is repeated until the network system errors fall below a certain reasonable limit whence the object gets extracted from the noisy background.

*B. Quantum Backpropagation Algorithm*

In this section the quantum backpropagation error adjustment algorithm is discussed and generalized for any number of layers [40]. For this purpose, the probability amplitude of $|0\rangle$ is attached to the real part and that of $|1\rangle$ to the imaginary part.

Two kinds of parameters exist in this neuron model: the phase parameter of weight connection $\theta$ and threshold $\lambda$, and the reversal parameter $\delta$.

The network error is represented as

$$E_{total} = \frac{1}{2}\sum_{p}^{P}\sum_{n}^{N}(t_{n,p} - output_{n,p})^2 \qquad (18)$$

Here $P$ is the number of learning patterns. $t_{n,p}$ is a target signal for the $n^{th}$ neuron and $output_{n,p}$ means an $output_n$ at the $p^{th}$ pattern. The error gradient is given by

$$\frac{\partial E}{\partial \theta_{jk}} = t_{n,p} - output_{n,p}\frac{\partial output}{\partial \theta_{jk}} \qquad (19)$$

$$= -t_{n,p} - output_{n,p}[2sin(y_k)cos(y_k)\frac{\partial y_k}{\partial \psi_{hqkoll}}] \qquad (20)$$

$$= \;= t_{n,p} - output_{n,p}[2sin(y_k)cos(y_k)\frac{1}{1+z_k^2}] \frac{cos(\psi_{hqkoll} + y_j^h)Re(u_k) + sin(\psi_{hqkoll} + y_j^h)Im(u_k)}{Re(u_k)^2} \qquad (21)$$

Thus, the weight update equation takes the form

$$\psi_{hqkoll}^{new} = \psi_{hqkoll}^{old} - \eta\frac{\partial E}{\partial \psi_{hqkoll}^{old}} \qquad (22)$$

where, $\eta$ is the learning coefficient. So,

$$\frac{\partial E}{\partial \delta_k} = -[(t_{n,p} - output_{n,p})(2sin(y_k)cos(y_k)\frac{\partial y_k}{\partial \delta_k}] \qquad (23)$$

$$\frac{\partial E}{\partial \delta_k} = (t_{n,p} - output_{n,p})[(2sin(y_k)cos(y_k)\frac{\pi}{2}\frac{e^{i\delta_k}}{(1+e^{i\delta_k})^2} \qquad (24)$$

Therefore,

$$\delta_k^{new} = \delta_k^{old} - \eta\frac{\partial E}{\partial \delta_k^{old}} \qquad (25)$$

So,

$$\frac{\partial E}{\partial \lambda_k} = (t_{n,p} - output_{n,p})\frac{\partial output}{\partial \lambda_k}] \qquad (26)$$

$$\frac{\partial E}{\partial \lambda_k} = (t_{n,p} - output_{n,p})(2sin(y_k)cos(y_k)\frac{\delta y_k}{\delta \lambda_k} \qquad (27)$$

$$\frac{\partial E}{\partial \lambda_k} = -(t_{n,p} - output_{n,p})(2sin(y_k)cos(y_k)\frac{1}{1+z_k^2} (\frac{1}{Re(u_k)^2}))[cos(\lambda_k)Re(u_k) + sin(\lambda_k)Im(u_k)] \qquad (28)$$

Similarly,

$$\lambda_k^{new} = \lambda_k^{old} - \eta\frac{\partial E}{\partial \lambda_k^{old}} \qquad (29)$$

Using chain rule,

$$\frac{\partial E}{\partial \psi_{ipjhll}} = \frac{\partial E}{\partial y_j^h} \times \frac{\partial y_j^h}{\partial \psi_{ipjhll}} \qquad (30)$$

where,

$$\frac{\partial E}{\partial y_j^h} = -(t_{n,p} - output_{n,p})[2sin(y_k)cos(y_k)\frac{\partial y_k}{\partial y_j^h}] \qquad (31)$$

$$\frac{\partial E}{\partial y_j^h} = [\frac{(t_{n,p} - output_{n,p})2sin(y_k)cos(y_k)}{1+z_k^2}] [\frac{cos(\psi_{hqkoll} + y_j^h)Re(u_k)}{Re(u_k)^2}] + [\frac{sin(\psi_{hqkoll} + y_j^h)Im(u_k)}{Re(u_k)^2}] \qquad (32)$$

Now,



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$$\frac{\partial y_j^h}{\partial \psi_{ipjhll}} = -[\frac{1}{1+z_j^2}] [\frac{cos(\psi_{ipjhll}+y_i^I)Re(u_j^h)}{Re(u_j^h)^2}] +[\frac{sin(\psi_{ipjhll}+y_i^I)Im(u_j^h)}{Re(u_j^h)^2}] \quad (33)$$

Similarly,

$$\psi_{ipjhll}^{new} = \psi_{ipjhll}^{old} - \eta \frac{\partial E}{\partial \psi_{ipjhll}^{old}} \quad (34)$$

Now, using chain rule, one gets,

$$\frac{\partial E}{\partial \lambda_j^h} = \frac{\partial E}{\partial y_j^h} \times \frac{\partial y_j^h}{\partial \lambda_j^h} \quad (35)$$

where,

$$\frac{\partial y_j^h}{\partial \lambda_j^h} = -[\frac{1}{1+(z_h)^2}] [\frac{cos(\lambda_j^h)Re(u_j^h)+sin(\lambda_j^h)Im(u_j^h)}{Re(u_j^h)^2}] \quad (36)$$

Again,

$$\lambda_j^{new} = \lambda_j^{old} - \eta \frac{\partial E}{\partial \lambda_j^{old}} \quad (37)$$

Using chain rule,

$$\frac{\partial E}{\partial \delta_j^h} = \frac{\partial E}{\partial y_j^h} \times \frac{\partial y_j^h}{\partial \delta_j^h} \quad (38)$$

where,

$$\frac{\partial y_j^h}{\partial \delta_j^h} = \frac{\pi}{2} \frac{e^{-\delta_j^h}}{(1+\delta_j^h)^2} \quad (39)$$

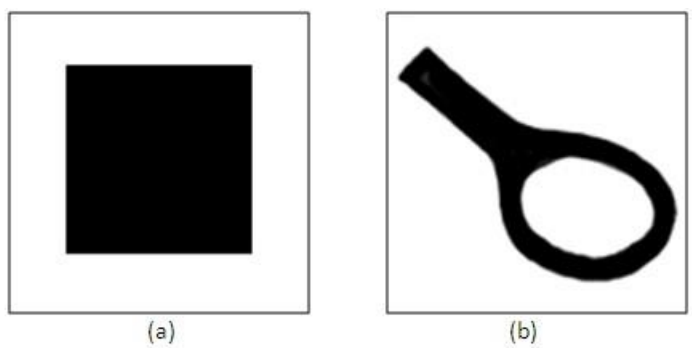


Fig. 2. Original images (a) Synthetic image (b) Real life Spanner image

## V. EXPERIMENTAL RESULTS

The application of the proposed QMLSONN has been established on a synthetic image and a real life spanner image (Figure 2) affected with various degrees of Gaussian noise of zero mean and standard deviation of $\sigma$=8, 10 and 12 and uniform noise with varied degrees $\epsilon$=64%, 100%, 144%, 196% and 256%. The noisy versions of the images are shown in Figures 3 and 4. The same test images were considered with the conventional classical MLSONN architecture. The extracted Gaussian and uniform noise affected images with the MLSONN architecture are shown in Figures 5 and 6. The respective extracted outputs obtained with the QMLSONN architecture are shown in Figure 7 and 8. From Figures 5, 6, 7 and 8 it is evident that QMLSONN restores the shape of the objects much better after extraction. We have also computed the percentage of correct classification of pixels (*pcc*) [14] for the extracted images. In addition, we have also computed the times of extraction for the two architectures. Table I lists the *pcc* values and the times of extraction ($t$) for the two images obtained with the two architectures for the Gaussian noise. Table II lists the corresponding values for *pcc* and the times of extraction ($t$) for the two images for the uniform noise. It is evident from Tables I and II that QMLSONN outperforms its classical counterpart as far as both the time complexity and the quality of the extracted images.

Table I
Comparative Performance Results Of Qmlsonn And Mlsonn On The Test Images Affected With Gaussian Noise

| QMLSONN | | | MLSONN | |
|---|---|---|---|---|
| Synthetic image | | | | |
| $\sigma$ | $t$(secs) | *pcc* | $t$(secs) | *pcc* |
| 8 | 12 | 99.5361 | 63 | 91.5710 |
| 10 | 15 | 98.7548 | 63 | 91.4550 |
| 12 | 21 | 98.3093 | 65 | 91.2597 |
| 14 | 39 | 97.0520 | 68 | 89.4409 |
| 16 | 40 | 94.0917 | 92 | 83.9111 |
| Real life image | | | | |
| $\sigma$ | $t$(secs) | *pcc* | $t$(secs) | *pcc* |
| 8 | 12 | 92.2851 | 44 | 85.3468 |
| 10 | 18 | 91.9494 | 42 | 84.8937 |



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| | | | | |
|---|---|---|---|---|
| 12 | 19 | 91.5344 | 41 | 84.5397 |
| 14 | 37 | 90.6921 | 67 | 78.3386 |
| 16 | 67 | 83.5815 | 94 | 73.3459 |

Table 2
Comparative Performance Results of Qmlsonn And Mlsonn On The Test Images Affected With Uniform Noise

| QMLSONN | | | MLSONN | |
|---|---|---|---|---|
| Synthetic image | | | | |
| $\epsilon$ | $t$(secs) | *pcc* | $t$(secs) | *pcc* |
| 64% | 3 | 99.9146 | 5 | 95.4285 |
| 100% | 3 | 99.5911 | 6 | 95.1294 |
| 144% | 3 | 99.1455 | 7 | 94.1406 |
| 196% | 4 | 98.3887 | 7 | 92.4927 |
| 256% | 8 | 96.2219 | 7 | 88.2690 |
| Real life image | | | | |
| $\epsilon$ | $t$(secs) | *pcc* | $t$(secs) | *pcc* |
| 64% | 1 | 92.2974 | 2 | 89.1907 |
| 100% | 2 | 92.2424 | 4 | 88.3972 |
| 144% | 2 | 91.8518 | 5 | 87.2376 |
| 196% | 4 | 90.5029 | 7 | 83.6548 |
| 256% | 6 | 87.3169 | 8 | 80.5969 |

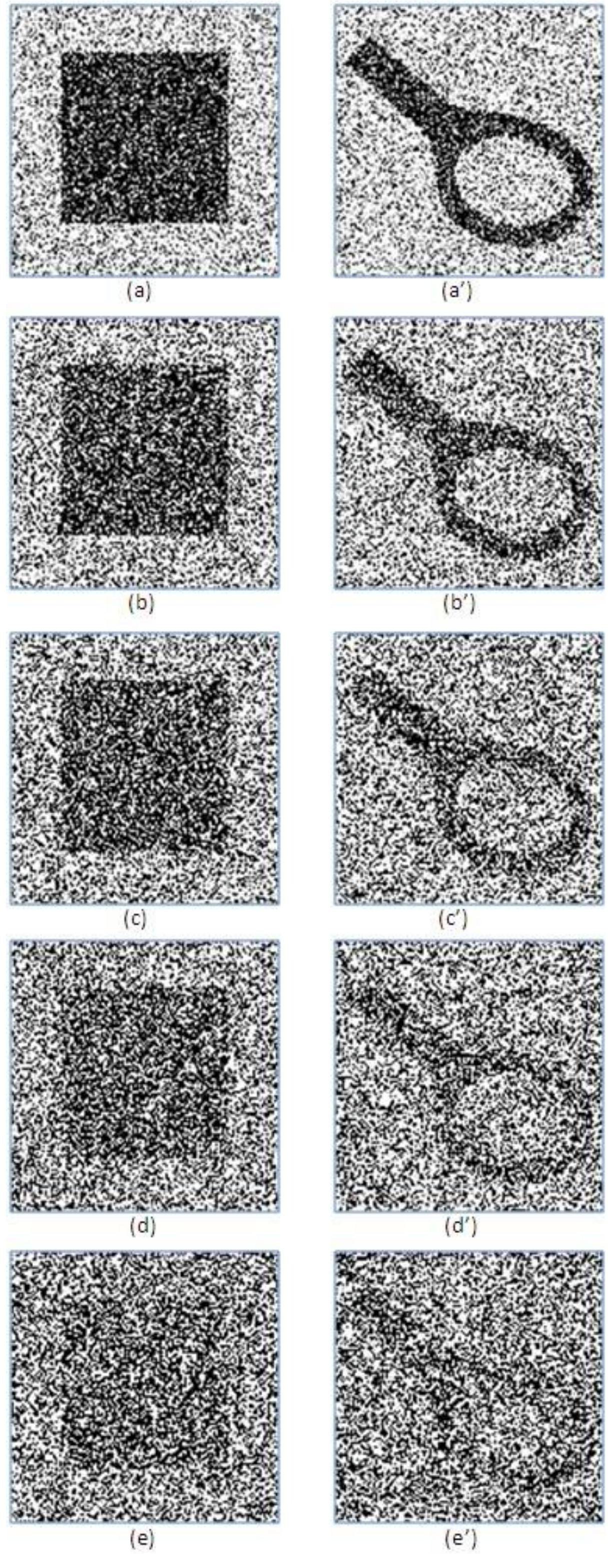


Fig. 3. Gaussian noise affected images (a)(b)(c)(d)(e) Synthetic image at $\sigma$=8, 10, 12, 14 and 16; (a′)(b′)(c′)(d′)(e′) Real life Spanner image at $\sigma$=8, 10, 12,



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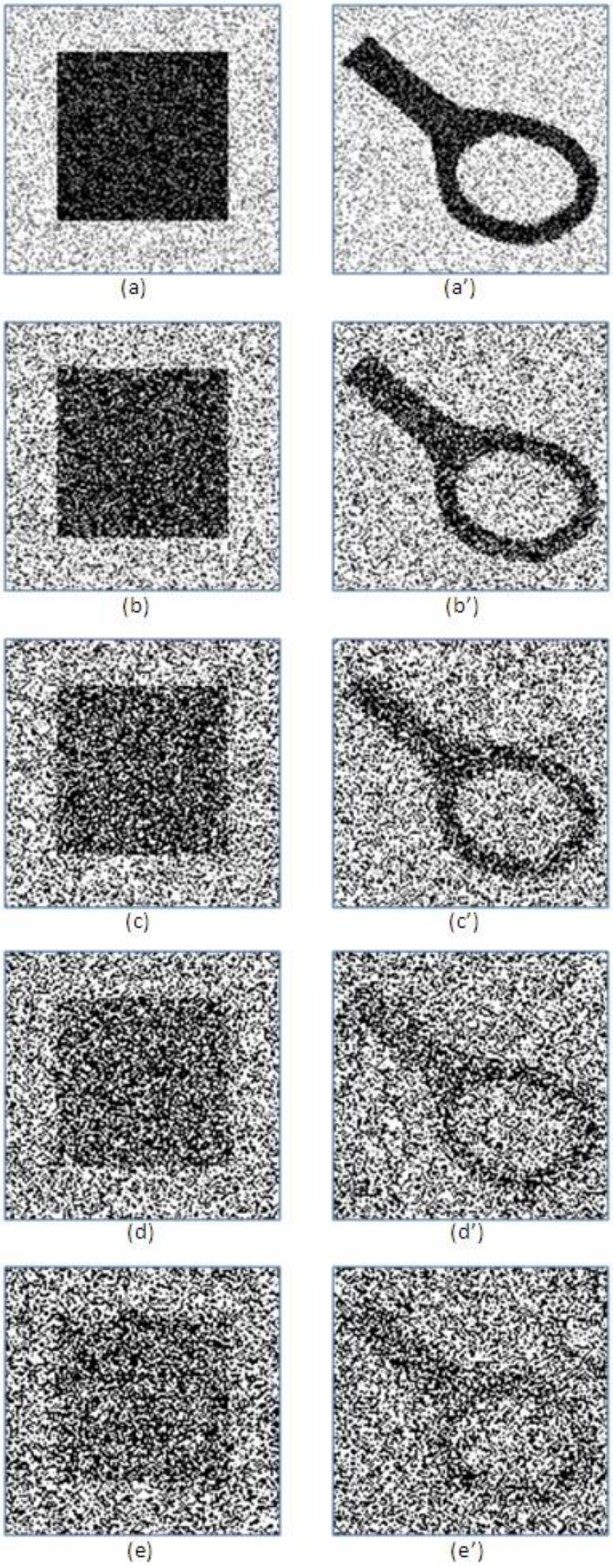


Fig4. Uniform noise affected images (a)(b)(c)(d)(e) Synthetic image at $\epsilon$=64%, 100%, 144%, 196% and 256%; (a′)(b′)(c′)(d′)(e′) Real life Spanner image at $\epsilon$=64%, 100%, 144%, 196% and 256%

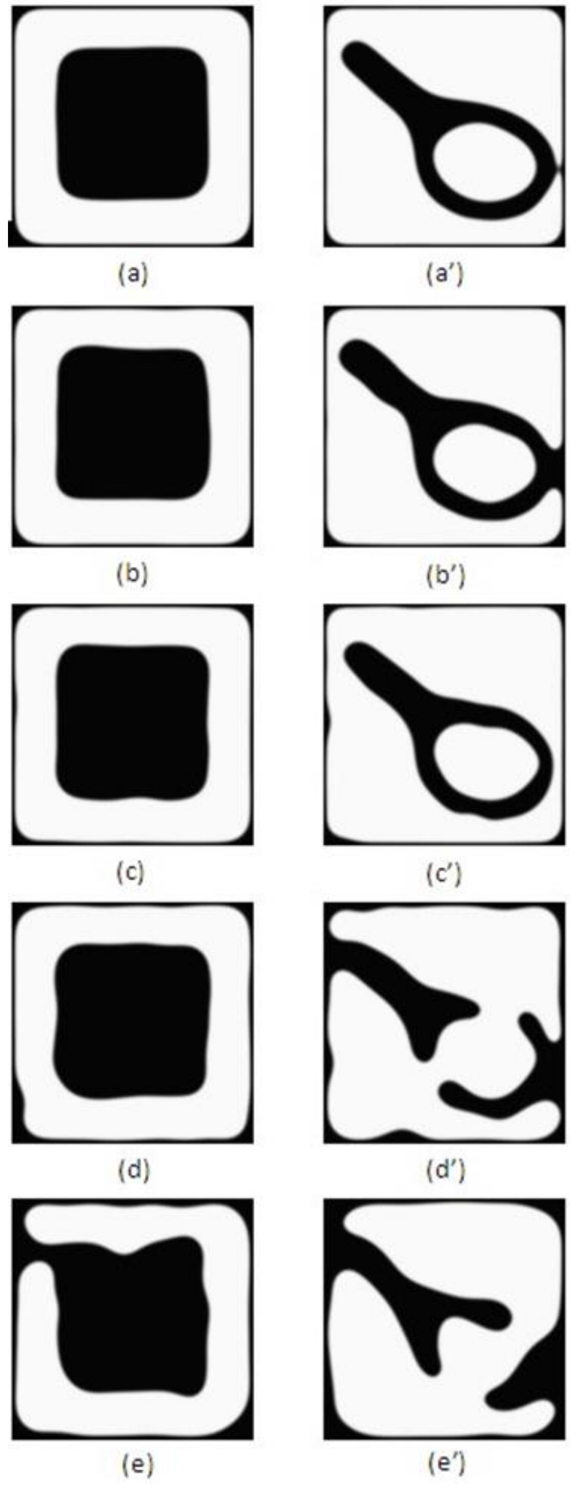


Fig.5. Uniform noise affected images (a)(b)(c)(d)(e) Synthetic image at $\epsilon$=64%, 100%, 144%, 196% and 256%; (a′)(b′)(c′)(d′)(e′) Real life Spanner image at $\epsilon$=64%, 100%, 144%, 196% and 256%



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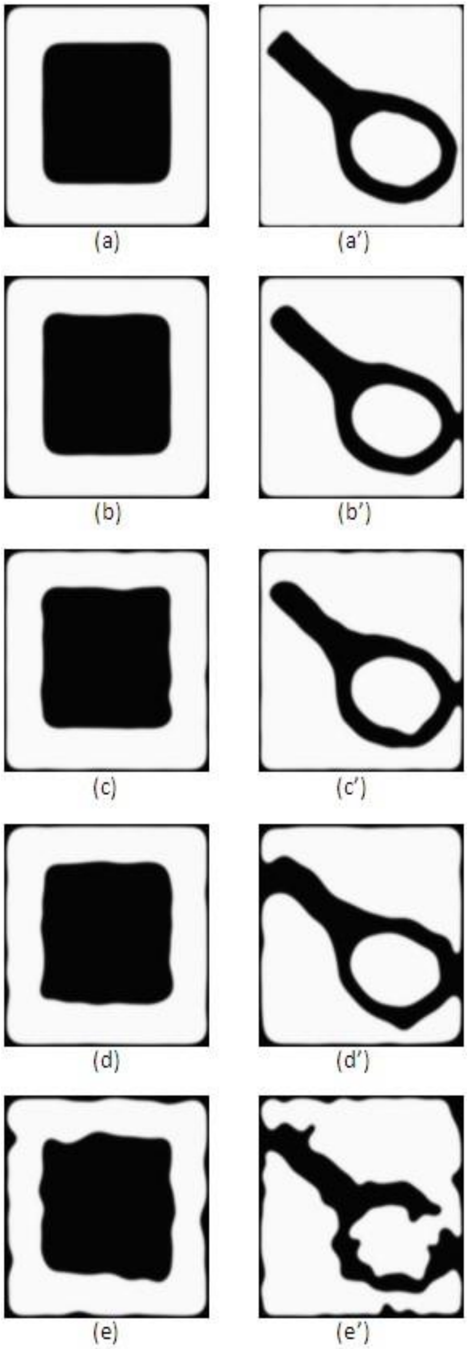


Fig.6. Extracted uniform noise affected images using MLSONN (a)(b)(c)(d)(e) Synthetic image at $\epsilon$=64%, 100%, 144%, 196% and 256%; (a′)(b′)(c′)(d′)(e′) Extracted Gaussian noise affected images using MLSONN (a)(b)(c)(d)(e) Synthetic image at $\sigma$=8 10, 12, 14 and 16; (a′)(b′)(c′)(d′)(e′) Real life Spanner image at $\sigma$=8, 10, 12, 14 and 16.

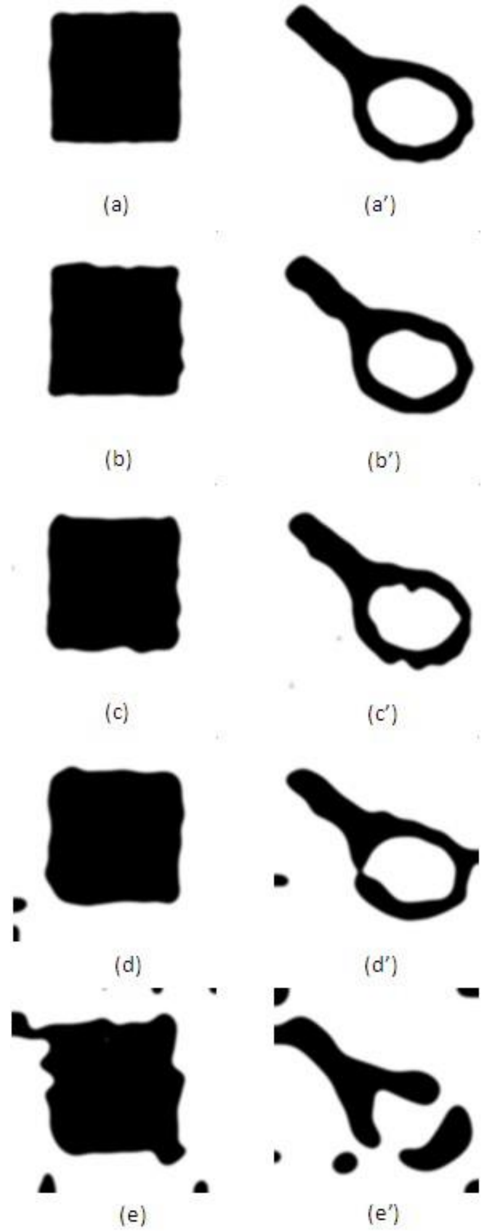


Fig.7. Extracted Gaussian noise affected images using QMLSONN (a)(b)(c)(d)(e) Synthetic image at $\sigma$=8, 10, 12, 14 and 16; (a′)(b′)(c′)(d′)(e′) Real life Spanner image at $\sigma$=8, 10, 12, 14 and 16



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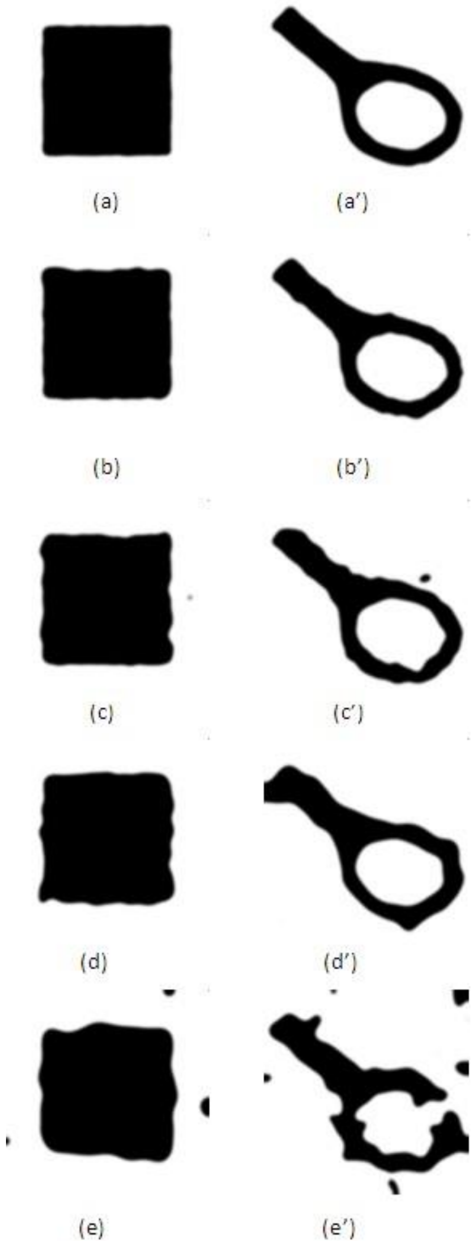


Fig.8. Extracted uniform noise affected images using QMLSONN (a)(b)(c)(d)(e) Synthetic image at $\epsilon$=64%, 100%, 144%, 196% and 256%; (a′)(b′)(c′)(d′)(e′) Real life Spanner image at $\epsilon$=64%, 100%, 144%, 196% and 256%

## VI. Discussions and Conclusion

A quantum version of the MLSONN architecture is proposed in this article. The architecture operates using *qubits* and rotation gates. The dynamics of operation of the proposed QMLSONN network and the corresponding quantum backpropagation is discussed.

The proposed QMLSONN network is found to outperform the classical MLSONN counterpart as regards to the time complexity as well as the extraction quality of the extraction process. Methods remain to investigate the application of the QMLSONN to the segmentation of multilevel images. The authors are currently engaged in this direction.

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