Electrocardiogram (ECG) Signal Enhancement Using Genetic Soliton Neu2qral Networks (GSNN)

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ABSTRACT

A soliton is a solitary wave whose amplitude, shape, and velocity are conserved after a collision with another soliton. Solitons, in general, manifest themselves in a large variety of wave/particle systems in nature: practically in any system that possesses both dispersion (in time or space) and nonlinearity. Solitons have been identified in optics, plasmas, fluids, condensed matter, particle physics, and astrophysics. Yet over the past decade, the forefront of soliton research has shifted to neuroscience. The Soliton model in neuroscience is a recently developed model that attempts to explain how signals are conducted within neurons. It proposes that the signals travel along the cell's membrane in the form of certain kinds of sound (or density) pulses known as solitons. The electrocardiogram (ECG) signal is generated by the rhythmic contractions of the heart. It represents the electrical activity of the heart muscles, and is usually measured by the electrodes placed on body surface. Electrocardiogram (ECG) signal has been widely used in cardiac pathology to detect heart disease. In this paper, Soliton Feed forward Neural Network (SFNN) is proposed for ECG signal enhancement. Computer simulation results demonstratedthat the proposed approach can successfully be used to model the ECG signal and remove high-frequency noise.

Keywords: Soliton Systems, Feed forward Neural Networks, Electrocardiogram (ECG).

تحسين أشارة جهاز تخطيط القلب باستخدام الشبكات العصبية الجينية ذات الموجة الانفرادية

الخلاصة

تتسم الموجة الانفرادية الـSoliton بان صفاتها من اتساع وشكل وسرعة تكون محفوظة من التغير بعد تصادمها مع موجة منفردة اخرى. تظهر الموجات الانفرادية، على العموم ، في الطبيعة على شكل تَشْكِيلة كبيرة مِن لأنظمة الموجيةِ / الجسيميةِ.اما من الناحية العملية فانها تظهر في اي نظام يمتلك خاصيتي التشتت (الزماني والمكاني) واللاخطّيةِ. لقد وجد ان الموجات الانفرادية يمكن ان تنشأفي البصريات، البلازما، الموائع، المواد المتكثفة، فيزياء الجسيمية والفيزياء الفلكية. مع كل ذلك فلقد تغيرت طليعة البحث في الموجة الانفرادية باتجاه عِلْمِ الأعصاب.ان النموذج الانفرادي للموجة في علم الاعصاب هو حاليا في طورالتطور والذي يحاول ان يوضح كيفية مرورالاشارة في داخل الخلايا العصبية. يقترح هذا النموذج بان الاشارات تنتقل بمحاذاة غشاء الخلية على شكل انواع معينه من النبضات الصوتيةوالمعروفة بالموجات الانفرادية.تتولد اشارة المخطط البياني الكهربائي لعمل القلب بواسطة التقلصات الايقاعية للقلب. حيث تمثل هذه الاشارة الفعالية الكهربائية لعضلات القلب والتي عادة ما تقاس باستخدام الاقطابكهربائية التي توضع على سطح الجسم. لقد اصبحت اشارة المخطط البياني الكهربائي للقلب مستخدمةعلى نحو واسع في علم الامراض لكشف وتحديد امراض القلب.لقد تم في هذا البحث اقتراح نموذج الشبكات العصبية بالتقنية الامامية للموجة الانفرادية من اجل تحسين اشارة جهاز تخطيط القلب ECG. لقد اظهرت نتائج المحاكاة الحاسوبية ان هذه الطريقة المقترحة يمكنها ان تمثل نموذجا ناجحا لتحسين اشارة جهاز تخطيط القلب ويتم ذلك بازالة جميع الضوضاء الناشئة عن الترددات العالية.

INTRODUCTION

Nonlinear waves have long been an interest to scientists in a variety of disciplines. A multitude of applications have been employed, ranging from fluid dynamics and plasma physics to even neuroscience and biology. Waves are omnipresent, from tsunamis in the ocean, to gamma waves and sonic booms. In fact, there are currently several wave pulses propagating through the neurons in our brain due to the firing of action potentials. The methods and results of computational wave modeling may be adapted to fit the specifics of another field [1].

Nonlinearity permeates our physical world. The evidence for nonlinear behaviors is present in so many aspects of physics, chemistry, biology, economics, etc., that it is not possible to mention them all in here. Among the most striking and aesthetically appealing manifestations of nonlinearity is the propagation of solitons or, more generally, solitary waves, spatial solitons can exist in a broad branch of nonlinear materials, such as cubic Kerr, saturable, thermal, reorientation, photorefractive, and quadratic media, and periodic systems. Furthermore, the existence of solitons varies in topologies and dimensions [2].

Artificial neural networks are viable computational models for a wide variety of problems. These include pattern classifications, speech synthesis and recognition, adaptive interfaces between humans and complex physical systems, function approximation, image compression, associative memory, clustering, forecasting and prediction, combinatorial optimization, nonlinear system modeling, and control. These networks are “neural” in the sense that they may have been inspired by neuroscience but not necessarily because they are faithful models of biologic neural or cognitive phenomena [3].

There have been some attempts to use solitary-wave descriptions to describe various biophysical phenomena. More controversially, solitary waves have recently been used in neuroscience as an alternative to the accepted Hodgkin-Huxley model to describe the traveling of signals along a cell's membrane [4].

This new theory based on observed phenomenon’s and solitonic theory provides a simpler explanation about neuron behaviors and it enhances the previous ones solving some of uncertainties carried by older models [5]. Hodgkin and Huxley were the pioneers to abstract biological neuron as an electric circuit and nerve signal as the voltage impulse. The Hodgkin-Huxley theory has set the direction and defined the goals for much of the ensuing research in biophysics. However, in 2005, T. Heimburg and A. D. Jackson, biophysicists from Copenhagen proposed a new neural theory called Soliton theory. In this theory, the nerve conduction is proposed as a density wave [6].

In this paper, Soliton theory are described and a simulation has been carried out throughout the analysis of the theories of Korteweg-deVries (KdV) equation using three layers Feedforward Neural Network (FNN) with Soliton theory as an activation function for Adapting Artificial Neural Networks to predicate the ECG signal.

SOLITON SYSTEMS

In recent years, pressure pulses of very short (picosecond) time duration have found wide application as a diagnostic tool in the semiconductor industry and in fundamental condensed matter research. Besides their outstanding present technical applications of the solitary pulses difficulties or even (sometimes) impossibility of analytic solutions to describe their propagation (due to the nonlinear character of implied media), as well as about the remarkable efficiency of the computer simulations of otherwise inaccessible scientific problems [7].

Fractals – signals that display scale-invariant or self-similar behavior are ubiquitous in nature and result from a wide variety of physical processes, including diffusion, erosion, turbulence and criticality. The traditional view that the healthy state of an organism is represented by homeostatic, regular, steady-state behavior has been challenged by the observation that many physiological signals are, in fact, non-linear, inhomogeneous and fractal [8]. Both the effects of non-linearity and dispersion produce a self-sustaining and localized density pulse with a moving segment of the nerve membrane in the gel state. This pulse is called a soliton. The solitary wave maintains its shape while it travels at a constant speed less than the sound velocity in the lipid membrane. Solitons can propagate over long distances without loss of energy. The pulse is also called as adiabatic pulse, because no energy is lost to the environment during propagation [6].

In the 1970's it was realized that several of these nonlinear PDEs yield entire families of exact solutions, and not just isolated solitons. These families contain solutions with arbitrary numbers of solitons of varying speeds andapplication in the studies of nanometer-sized structures, the propagation of these short acoustic pulses over millimeter distances at low temperatures has revealed a new field of picosecondsacoustics, amplitudes, and undergoing mutual collisions. The three most studied systems have been:

• The Korteweg-deVries equation,

$$u_t + 6uu_x + u_{xxx} = 0 \qquad \text{…(1)}$$

This is a generic equation for 'long waves' in a dispersive, energy-conserving medium, to lowest order in the nonlinearity.

• The Sine-Gordon equation,

$$f_{tt} - f_{xx} + \sin(f) = 0 \qquad \text{….(2)}$$

The name is a play on the Klein-Gordon equation, $f_{tt} - f_{xx} + f = 0$. Note that the Sine-Gordon equation is periodic under $f \longrightarrow f + 2p$

• The nonlinear Schrcodinger equation,

$$iy_t \pm y_{xx} 2|y|^2 y = 0 \qquad \text{….(3)}$$

Here, y is a complex scalar filed depending on the sign of the second term [9].

A Soliton solution of KdV equation is:

$u(x,t) = u(x - Vt)$. Then with $x \equiv x - Vt$, We have $\partial_x = \partial_x$ and $\partial_t = -V\partial x$ when acting on $u(x,t) = u(x)$. Thus we have

$$-Vu' + 6uu' + u''' = 0 \qquad \text{…..(4)}$$

Integrating once, yield

$$-Vu + 3u^2 + u'' = A \qquad \text{…. (5)}$$

Where A is a constant., integrating once more, obtaining

$$-\frac{1}{2}Vu^2 + u^3 + \frac{1}{2}(u')^2 = Au + B \qquad (6)$$
…..

Where now both *A* and *B* are constants. Assume that u and all its derivatives vanish in the limit $x \longrightarrow \pm\infty$ which entails *A=B=0.* Thus

$$\frac{du}{dx} = \pm u\sqrt{V - 2u} \qquad \text{….(7)}$$

With the substitution

$$u = \tfrac{1}{2}V \sec h^2(q) \qquad \text{… (8)}$$

We find $dq = \pm\frac{1}{2}\sqrt{V}dx$, hence the solution is

$$u(x,t) = \frac{1}{2}V \sec h^2(\frac{\sqrt{V}}{2}(x - Vt - x_o)) \qquad (9)$$
….

Where x is a distance, V velocity, t time and x is a position. Note that the maximum amplitude of the soliton is $u_{\max} = \frac{1}{2}V$, which is proportional to its velocity V . The KdV equation imposes no limitations on V other than $V \geq 0$.

SOLITON NEURAL THEORIES

T. Heimburg and A. D. Jackson proposed an alternative theoryin 2005. The theory is a thermodynamic theory of nervepulse propagation. This theory is based on the lipid characteristicof transition from a fluid to a gel state over a rangeof several degrees, slightly below the body temperature (Heimburgand Jackson, 2005, and references there in). Thatis, when a biological membrane is compressed, the fluidmembrane gradually reaches to a denser gel state. Now,a sufficient pressure/ compression either in membrane areaor volume will bring a transition to the gel state (Heimburg,2007a). This transition is associated with the releaseof heat (Heimburg, 2007a; Heimburg, 2007b) [6].

Let us firstbriefly summarize soliton model of nerve pulse proposed by Danish researchers:

1. The temperature of the axon is slightly above the critical temperature T_c for the phase transitionleading from crystal like state of the lipid layers to a liquid crystal state.
2. Variations of temperature, volume, area, and thickness and also other mechanical effects areknown to accompany nerve pulse propagation.
3. Soliton model reproduces correctly the velocity of nerve pulse inside myelin sheaths but it isnot clear to me how well the much lower conduction velocity in non-myelin sheathed regions isreproduced.
4. Soliton property predicts diabaticity.
5. The estimate for the capacitor energy density during the nerve pulse is considerably smallerthan the energy density is many times magnitude smaller than that of the acoustic wave.
6. Solitonic energy density and thecapacitor energy density as a function of time are essentially identical.[10]

The biological neuron with soliton pulse is shown in Figure (1).

ARTIFICIAL NEURAL NETWORKS (ANN)

Artificial neural networks are composed of biologically inspired neuron like elements operating in parallel. As in the human nervous system, the output of each neuron is determined by its interconnections with other neurons in the simulated nervous system. Each interconnection has a weight associated with the connected edge. It is the collective activity of multiple weighted edges that determines the behavior of the respective neuron. By adjusting the weighted connections between the respective neurons, the ANN learns to perform specific tasks for a given set of inputs [11-12]. An (ANN) is a flexible mathematical structure that is capable of identifying complex nonlinear relationships between input and output data sets. The ANN model of a physical system can be considered with *m* input neurons $X = [x_1, x_2, \mathbf{K}, x_m]$, *h* hidden neurons $Z = [z_1, z_2, \mathbf{K}, z_m]$ and *k* output neurons $Y = [y_1, y_2, \mathbf{K}, y_k]$ [3]. In this paper three-layer feed-forward neural network was proposed with *X* inputs and *Y* outputs, and *L* hidden nodes as shown in Figure (2)[13]. A neural network with supervised training is used when both the inputs and the outputs are provided. The network then processes the inputs and compares its resulting outputs against the desired outputs. The errors produced while comparing, are propagated back through the system, causing the system to adjust the weights, in order to control the network. This process occurs over and over as the weights are continually tweaked. The set of data, which enables the training, is called the "training set." During the training process of a neural network the same set of data is processed several times as the connection weights are refined. The flowchart of supervised training is shown in Figure (3)[14].

SOLITON ACTIVATION FUNCTION

Each neuron in the hidden layer uses soliton function*f*(*x*)as its threshold function, and each neuron in the output layers uses Purelinfunction *p*(*x*) as itsthreshold function. The neuron output of hidden node h ($1 \le h \le L$) and output node q ($1 \le q \le k$)can be expressed as:

$$z_h = f(W^T X) = f(\sum_{i=1}^{m} w_i x_i - d_h) \qquad (9) \ldots$$

$$y_q = p(V^T Z) = p(\sum_{i=1}^{L} v_i z_i - d_q) \qquad (10) \ldots$$

Where the superscript T stands for a vectortranspose, $W = [w_1, w_2, \mathbf{K}, w_m]$ is the weight connection vector between the input nodes and hidden node h, $V = [v_1, v_2 \mathbf{K}, v_k]$ is the weight connection vector between the hidden nodes and output node q, X is the input vector for each hidden node, and Z is the output vector of the hidden nodes. d_h and d_q are the corresponding biases for hidden node h and output node q. z_h and y_q are the output neuron responses for node h and node q, respectively. The soliton function $f(x)$ is defined as:

$$u(x,t) = \frac{1}{2} V \operatorname{sech}^2 \left(\frac{\sqrt{V}}{2}(x - Vt - x_o)\right) \qquad (12) \ldots$$

The plotting of soliton function is shown in Figure (4), and the Purelinfunction $p(x)$ is defined as:

$$p(x) = a x + b \qquad \ldots (13)$$

Where a is a non-zero constant, b is the bias. The Mean Square Error function for this neural network is described as:

$$MSE = \frac{1}{m \cdot k} \sum_{i=1}^{m} \sum_{j=1}^{k} (t_{ij} - y_{ij})^2 \qquad (14) \ldots$$

Where m and k are the number of input and output patterns respectively, t_{ij} is the target class for a specific sample and y_{ij} is the actual neuron output for the input training sample x_i at the output layer [13]. Artificial neural networks are an interesting approach in solving some difficult problems like pattern recognition, system simulation, process forecast etc. The artificial neural networks have the specific feature of "storing" the knowledge in the synaptic weights of the processing elements (artificial neurons). There are a great number of ANN types and algorithms allowing the design of neural networks and the computing of weight values[15].

RESULTS AND DISSCUSSION

This paper presents a novel method of using a Genetic Algorithm Neural Network (GSNN)with soliton transfer function to predict ECG signal. This method consists of simulating during and post-fault behaviors of the soliton system for a two soliton pulses, observing its dynamics during a few seconds. This is done by simulating the system nonlinear equations which called Korteweg-deVries (KdV) equation using three layers Feed forward Neural Network (FNN)with Genetic Algorithms for Generating and Adapting Artificial Neural Networks. Simulation results on different intervals are carried out. The proposed Mean Square Error (MSE) is 10^{-6} to check the performance of GANN. The results are obtained by using MATLAB programming.

THE PROPOSED GASNN FOR ECG SIGNAL PREDICTION

The mathematical description of the dynamic systems is not a simple task for which basic principles suffice. Not all complex systems can be modeled using basic laws to determine their dynamic behavior. An interesting alternative to solve such problems would be an experimental systems identification model. In other words, a model based on an input output system must be founded, which establishes a mathematical relation between input and output data. The assessment of a nonlinear system requires analysis of the dynamic system behavior under a prescribed set of events known as contingencies. Conventionally this is done by simulating the system nonlinear equations. Since the stability limits cannot be determined from a single simulation. More than one simulation is required. The large size of the system adds to the complexity thus two pulses of KdV equation is described as in equation (15).

$$u = A\sec h(0.5(A(x+2)))^2 + B\sec h(0.5(B(x+1)))^2 \qquad (15)$$

…

The GRSNN is a three-layer neural network with soliton transfer function that can be used to estimate and enhancement the ECG signal. It is assumed that the vectors *X* and *Y* are the input and the output of the neural network, respectively. Estimation of *Y* according to an independent input variable *X* is the most probable value for the output *Y* with respect to the input *X*. The employed hybrid algorithm for the automatic generation of neural network weights uses a direct coding scheme, and develops the following steps:

1. Create an initial population of individuals(neural network weights) with random values.
2. Select the mother and the father from the population.

3. Recombination both parents to obtain two children.
4. Mutate each child randomly.
5. Train each child using the back propagation algorithm.
6. Replace the children into the population.
7. Repeat from step 2 for a given number of generations.

Simulation of two pulses which are generated using equation (15) is shown in Figure (5a), with initial positions (-2, -1) respectively. Due to this amplitude-dependent speed, as shown in Figure(5b), a taller soliton originally placed behind a shorter one catches up with the shorter one and moves ahead of it after a collision as shown in Fig.(5c and d) . Another important set of properties is observed in this collision process. During the collision as shown in Figure (5c), the two solitons do not linearly superpose (nonlinear collision), and as a result experience a significant amount of amplitude modulation. After the collision as shown in Figure (5d) the two solitons return to their original shapes, however, they have acquired a permanent time (phase) shift due to the nonlinear collision shown by the difference in and in Figure (5d) (with no time shift, and would be equal, since the time elapse before and after the collision is the same).

The GSNN is allowed to run up to 145 training epochs. The feed forward neural network used to predict and enhancement the ECG signal has a (1-8-1) architecture, with inputs corresponding to ECG signal $(u(x,t))$ and environmental parameters. The outputs of the nodes in the three hidden neurons are processed with a soliton activation function. The output of the neuron in the output layer is processed with a Purelin function. The desired output of the feed forward neural network is proposed to be the final ECG signal as in Figure (6), if the input represented in a simulation MATLAB program with the following equation.

$$f(x) = (\frac{a_0}{2}) + \sum_{n=1}^{\infty} a_n \cos(\frac{npx}{1}) + \sum_{n=1}^{\infty} b_n \sin(\frac{npx}{1}) \qquad \ldots\ldots(16)$$

ECG signal is periodic with fundamental frequency determined by the heartbeat. It also satisfies the dirichlet’s conditions. Hence Fourier series can be used for representing ECG signal. Any periodic functions which satisfy dirichlet’s condition can be expressed as a series of scaled magnitudes of sin and cos terms of frequencies which occur as a multiple of fundamental frequency.

Training parameters of GSNN are taken to be Learning rate = 0.1, Momentum rate = 0.06, Population size = 20, Mutation rate = 0.05, Crossover rate = 0.46, Length of chromosomes = 10.

The proposed soliton activation function is shown in Figure (7).The hybrid training performance is shown in Figure (8), is the best MSE corresponding to each generation during the evolutionary training. From this figure, it can be observed the variation of best MSE represented by the best chromosome with the number of generations of the genetic algorithm. After 140 iterations of execution, the change of best MSE has become slower because of the local tuning characteristic, the relation between actual and desired output is shown in Figure (9). After training process the output of feed forward neural network is as shown in Figure (10).

CONCLUSIONS

In this paper, it's found that soliton has some properties, such as: amplitude-dependent speed, amplitude modulation during the nonlinear collision phase modulation after the nonlinear collision. The inherent difficulties that arise in estimating the parameters of soliton signals make detecting solitons a difficult task.
When the waveform shape varies significantly as a function of the unknown parameter, multiple hypotheses are used with one for each value of the parameter sampled over a prespecified range. This is often the approach used for detection of a signal of unknown frequency or unknown spatial direction. The performance of a given neural network represents its capacity to solve a nonlinear problem. The results display interesting features of nonlinear dynamical systems. Many insights were gained into the behavior of solitons, as well as into an application of nonlinear waves in neuroscience. The genetic algorithm is modifying so that it deals with a stream of continually changing training data instead of fixed training data. This requires modifying the genetic algorithm to handle a stochastic evaluation function.

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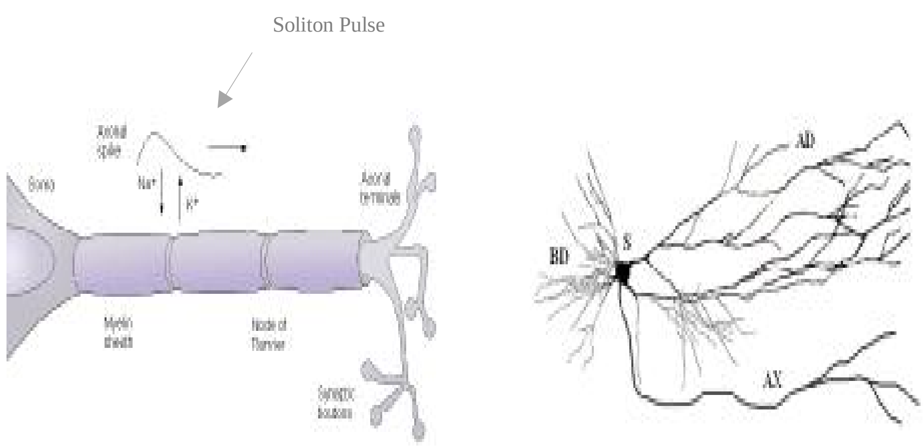

Figure (1):Axonal spike in myelinated neuron resulting from sodium and potassium ion currents across the membrane in the nodes of Ranvier.

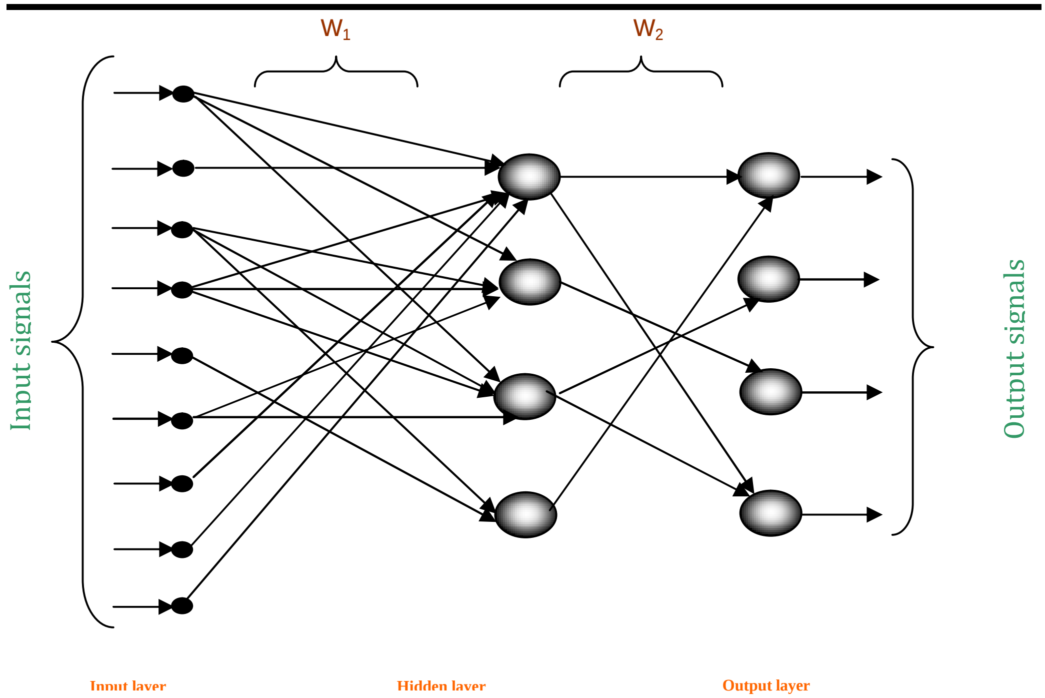

Figure (2): Neural network architecture

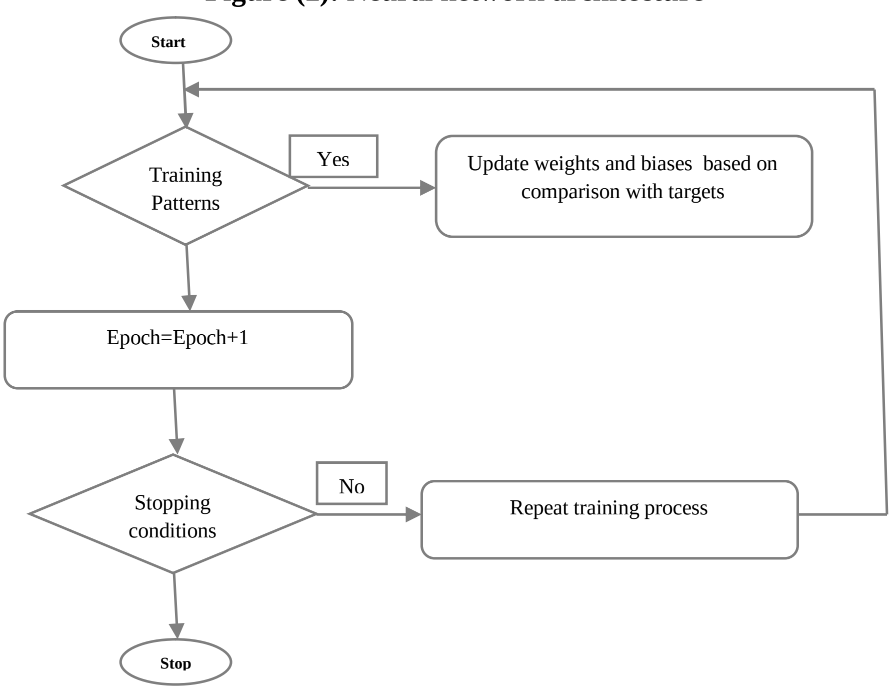

Figure (3): The flow chart of supervised training

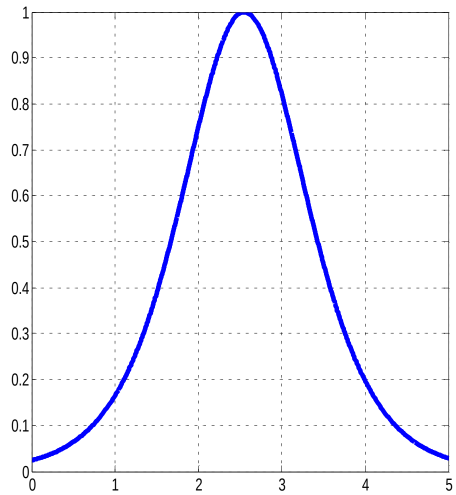

Figure (4):Soliton activation function

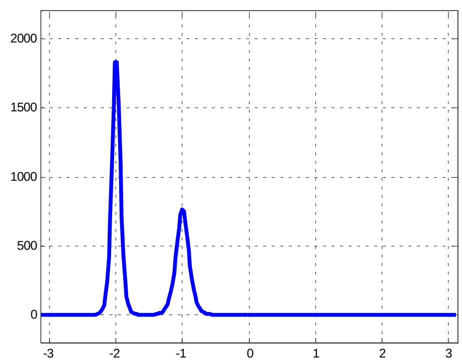

Figure (5a):Two pulses soliton

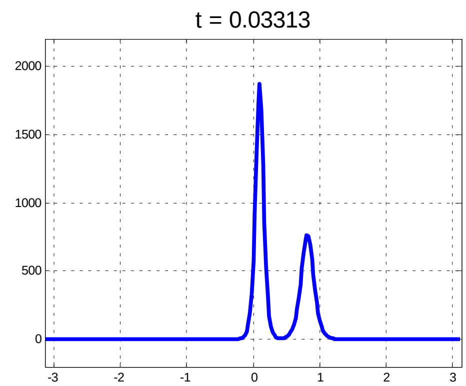

Figure (5b):Soliton dynamics after 0.03313 msec

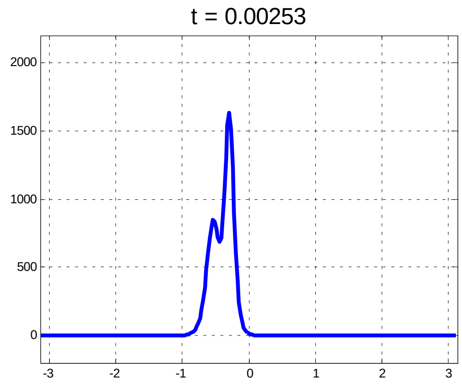

Figure (5c):Soliton dynamics after 0.00253 msec

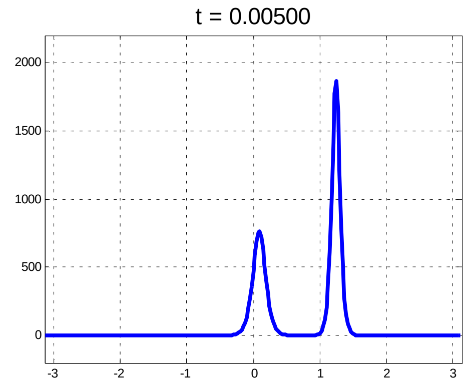

Figure (5d):Soliton dynamics after 0.005 msec

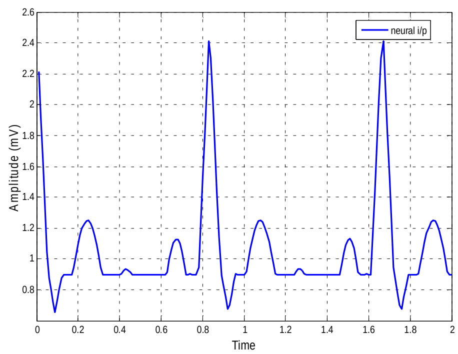

Figure (6): The desired output of GSNN

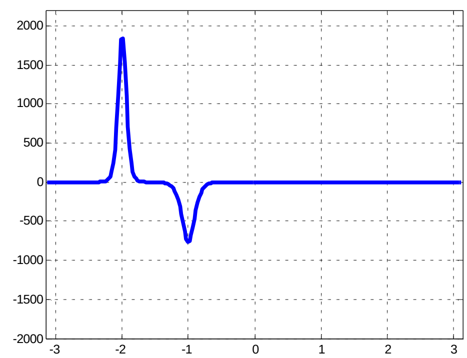

Figure (7): The proposed soliton activation function

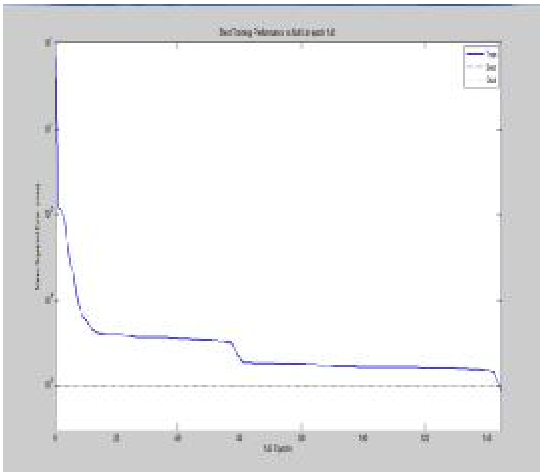

Figure (8): The hybrid training performance

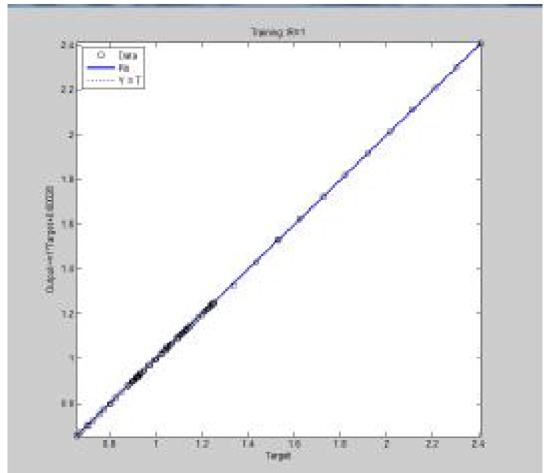

Figure (9): The relation between actual and desired output

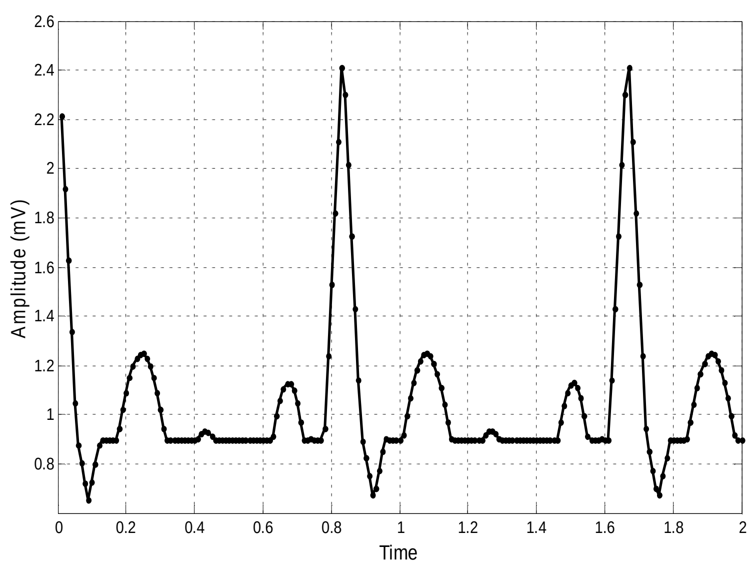

Figure (10): The actual output of GSNN