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DCNN oscillator design, implementation, and performance evaluation

***Abstract**. FPAAs technology are the ideal solution for creating an analog system. FPAA describes and implements the architecture of a simple CNN model used to build a delayed cellular neural network (DCNN) oscillator in this letter. Matlab simulation was carried out in order to analyze the proposed system. The attraction spectrum with different initial conditions, as well as Lyapunov's motives, were used to investigate the fundamental characteristics of the proposed system. The effect of noise on the proposed system was investigated. The promising results obtained encourage the application of the proposed model in secure communication systems.*

Streszczenie.** Technologia FPAA jest idealnym rozwiązaniem do stworzenia systemu analogowego. W tym liście FPAA opisuje i implementuje architekturę prostego modelu CNN używanego do budowy oscylatora opóźnionej komórkowej sieci neuronowej (DCNN). W celu analizy proponowanego systemu przeprowadzono symulację w Matlabie. Widmo przyciągania z różnymi warunkami początkowymi, a także motywy Lapunowa zostały wykorzystane do zbadania podstawowych cech proponowanego systemu. Zbadano wpływ hałasu na proponowany system. Uzyskane obiecujące wyniki zachęcają do zastosowania proponowanego modelu w bezpiecznych systemach komunikacyjnych.* (Projekt, implementacja i ocena oscylatora DCNN***)

Keywords: DCNN, FPAA, Chaotic signal , Lyapunov exponents
Słowa kluczowe:generator DCNN, .sygnał chaotyczny

Introduction

In the past few years, information safety has induced a potent interest in the improvement of information technology [1]. Because of its long-term predictability, initial useful sensitivity, and pseudo-noise, the chaotic signal is appropriate for secure communication technology [2-5]. Previously, it was believed that complex systems like those seen in neurology, mechanics, fluid dynamics, and oceanography were the only ones capable of exhibiting chaotic behavior [6]. Edward Lorenz, however, disproved the prevalent theories in the area in 1963 by identifying the more prevalent chaotic system while simulating weather patterns using a three-dimensional model of atmospheric convection [7-8]. A chaotic system, which is mathematically simpler than the Lorenz system, was proposed by Rössler in 1976 [8]. Several chaotic systems followed, such as Sprott system[9] the Arneodo system[10], Chen system[11], Lü-Chen chaotic generator[12], Cai system[13], Tigan system[14], Vaaidyanathan system[15], and Pehlivan system were developed[16]. CNNs are a subcategory of dynamic neural networks, and because of their nonlinear properties, they are extremely effective in image processing as well as chaotic signal production [17-19]. Automatic control, disease detection, pattern-discrimination artificial intelligence, and network design are just a few of the many uses for cellular neural networks [20].

Chaos signals have random properties, which results in a very powerful Chaos algorithm. If the chaotic feature is combined with the characteristics of ANN, then ANN's efficiency will evolve unbelievably [21]. Chua and Yang suggested a cellular neural network (CNN) for signal processing in actual time, which is composed of a combination of basic components named cells [22-24].Cellular neural networks have received a lot of attention through the many research and experimental studies of CNN's in the literature since their debut [25]. Barış et al. suggested building a random number generator based on chaotic CNN. It was implemented on a Field Programmable Gate Array (FPGA) [26]. G. Grassi provides a model of the synchronization of two CNN's consisting of cells expressed by the dynamics of the Chua circuit [27]. B. Karakaya et al. display the implementation of a Delayed CNN on an FPGA. The network has two cells, and an unconventional attractor has been discovered in a system explained by a differential equation [28]. Wei-Feng-Shi suggested using local recurrent chaotic neural networks for marine synchronous generator modeling with a marine real-time simulator. A dynamic BP learning algorithm is applied in the network training of generator modeling [17]. Jia Lin et al. suggested a picture encryption algorithm based on CNN and compressive sensing (CS) [29]. Scientists and researchers in recent years have taken an interest in the topic of chaotic image encryption [30-33]. Enis Günay et al. proposed a Lorenz-like system based on CNN's[4]. The issue that needs to be solved in this work is how to create low-power consumption DCNN oscillators using the advantages of programmable analog devices, much like FPGAs have done for digital. First introduced was the theoretical mathematical model of the DCNN system. Second, the suggested model is represented using Matlab or Simulink through an account of the Lyapunov exponent in the presence of AWGN, a key tool in the study of chaotic signals, power spectrum analysis, a method to compute the chaotic signal's frequency spectrum; and strange attractor for variable initial conditions. This enables the researchers to more thoroughly explore the suggested system. Third, a description of the DCNN system's experimental implementation follows. The generated results are then displayed to demonstrate the effort put into employing the model developed for this study. The essay's remaining sections are arranged as follows. The mathematical formulation and Simulink Matlab models of the DCNN oscillator are covered in Section 2. Section 3 describes the hardware implementation of the DCNN system based on FPAA. The findings of the software and hardware are described in the fourth component of the proposed system. The conclusion of our contribution completes section No. 5.

Related works

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Methology

The basic building block of CNN is the cell. Every cell is comparable to a nonlinear 1-order circuit. Figure 1 illustrates a CNN neuron's block diagram [34]. A CNN is created by connecting and positioning identical cell neurons in a predictable pattern in space. Each neuron is only connected to its eight closest neighbors, and unconnected cells can still influence connected cells through dynamic spreading effects. There are distinct input and output states for every neuron [2]. CNN-OST, is a simple variation of these networks that only uses two neurons as described by Zou and Nossek [34].

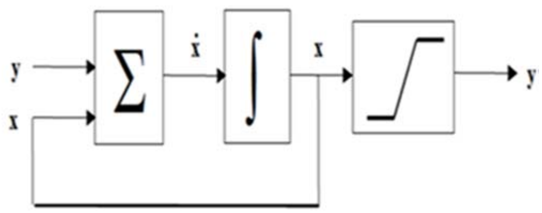


Fig. 1. Block diagram of a CNN cell

Equation for DCNN of N*M cells can be defined as:

$$\dot{x}(t) = -x(t) + A_0 y(t) + A_\tau y(t-\tau) + u \tag{1}$$

where n = N*M and x, y, and u represent the state, output, and input vectors in R^n, respectively,

$$y_i(t) = 1/2\left(\left|x_i(t)+1\right| - \left|x_i(t)-1\right|\right), i = 1,2, \ldots, n \tag{2}$$

$A_{(0)}$=[a_i j] is the feedback matrix, is the delayed feedback matrix and τ > 0 is the delay [35].

Our suggested approach consists of two parts. In the first one, the sensitivity of the system is investigated by investigating the sensitivity of the DCNN using the Lyapunov exponent, which is a key component in categorizing the chaos produced by dynamical systems, and the power spectral density, which explains the distribution of energy in the frequency components that make up the chaotic transmissions. The proposed system building is shown in the second section using FPAA technology.

1- The simulink Matlab mode

Wireless communication system simulation frequently makes use of Simulink. A dynamic/chaotic oscillator's mathematical model from equation (1) is put into practice using Matlab Simulink. Figure 2 describes the two DCNN cell-based model. To produce the chaotic signal, two integrators with changing beginning conditions are required. All weighted inputs are sent into two sum units, two transportable delays, and a few amplifier units before the piecewise linear activation.

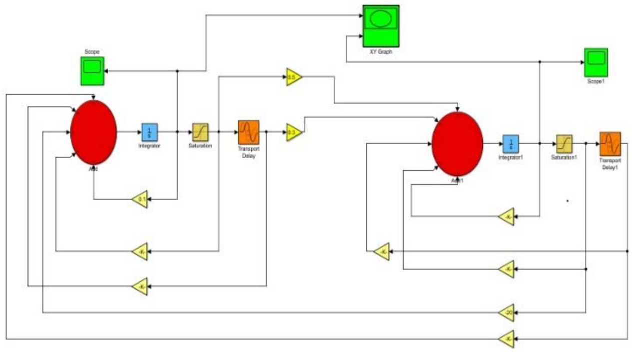


Fig. 2. DCNN Matlab simulink model

2-Largest Lyapunov exponen

Lyapunov exponents are now used in secure communication and chaotic encryption [36]. A system must have one positive Lyapunov exponent in order to be chaotic[37]. The sensitive dependence on the beginning conditions is quantitatively estimated by the Lyapunov exponent. The mean rate of divergence or convergence of two adjacent trajectories in the state-space is determined by the Lyapunov exponent [38]. Lyapunov exponents (LE) are real quantities that can be used to distinguish between chaotic and non-chaotic attractors [39].

The spectrum of Lyapunov exponents refers to this arrangement of Lyapunov exponents from the majorette to the minarets. For this reason, the majorette exponent, also known as the Maximal or Largest Lyapunov Exponent (MLE or LLE), defines the capacity of a dynamical system to predict the future. The following relationship can be used to determine Lyapunov exponents:

$$\lambda_i = lim_{t\to\infty} \frac{1}{t} \log_2 \frac{p_i(t)}{p_i(0)} \tag{3}$$

Where the λ_i is reneged from the major to minor and i-th Lyapunov exponent is determined over the main ellipsoidal axis $p_i(t)$. For a limited t, ʎ is also label a local Lyapunov exponent . The combination of Lyapunov exponents is named the spectrum of Lyapunov exponents, and the major exponent is named the Maximal or Largest Lyapunov Exponent (MLE or LLE) [40].

3-Power spectrum analysis

The power spectrum analysis offers a fresh viewpoint on the properties of chaotic systems. It seems challenging to distinguish between chaos and noise since chaotic systems have vast frequency bands and their tails exponentially decompose at high frequencies. These qualities assist in revealing the turmoil. The only systems that appear to have a persistent power spectrum are chaotic ones. The signal's power spectrum illustrates how the contrast of the data is dispersed across the frequency range.

Experimental implementation of DCNN system

Programs for the examination of analog and mixed-signal circuits employing experiential typical or preliminary models currently make heavy use of the Anadigm Inc. FPAAs [41]. One of the primary components of the FPAA is an adaptive analog block (CAB), which is constructed from the fundamental analog processing blocks that make up the FPAA and is coupled to other CAB devices via the routing network [42]. Some tasks and factors can be reformatted using the FPAA's dynamic adjustment capability without requiring reconstruction. The FPAA makes it possible to adapt to many conditions and situations [43]. FPAA chips are always supported with a software-programmed development tool for designing and investigating analog circuits based on the initial model in the chip. The program provides several CAMs like filters, summing amplifiers, mixers, and differentiated that can be utilized to implement numerous of the tasks of a circuit [44] .

Figure 3 shows the completed DCNN oscillator construction based on the FPAA AN231E04 chip. Two-cell DCNN models were used to implement figure 3, which requires four Sum/Difference units with quadrant input including adjusted gains in the range of 0.01–77.

Two integrators with an integration constant 1/µsec in the range of 0.04-15.7, and two S/H systems act as a delay unit. Two comparators with variable reference, two low pass filters with a corner frequency in the range of 4.4-400 kHz for smoothing the output signal. The Comparator unit acts as a Programmable Activation Function to implement the various activation functions and interconnections among units.

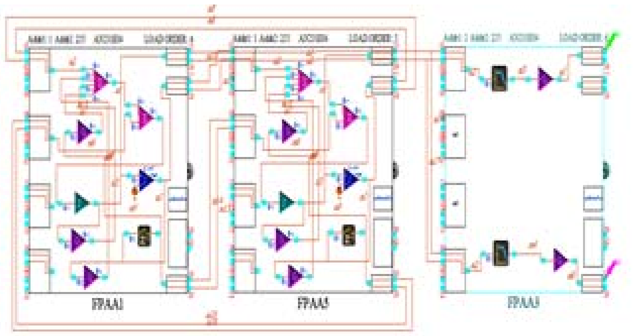


Fig. 3. Realization of the FPAA-based DCNN oscillator structure

Result's and Discussion

In this work, the outcomes achieved from the trained DCNN model are debated. This indicates if the model is eligible to produce an unlimited number of chaotic signals and is sensitive to its initial condition.

1- DCNN strange attractor

If an attractor has a curve or geometric shape that has the same statistical character as the whole, it is said to have a weird shape. When the dynamics within it are chaotic, this is frequently the state. Utilizing the integrators' initial values, the performance of the dynamic/chaotic oscillator system shown in figure 4 was evaluated (0.1-0.5-0.7).

Figures 5 demonstrate the simulation for a DCNN oscillator with varying beginning circumstances, characterization of the exotic attractant product.

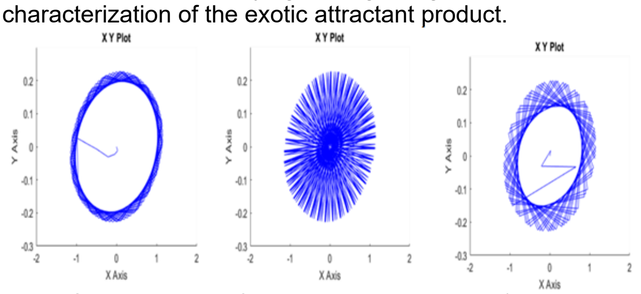


Fig. 4. Strange attractor for variable initial condition (A=0.1, B=0.5, & C=0.7)

2-Lyapunov exponent measurements

For the symmetrical data series signals X1 & X2, chaotic systems with two positive Lyapunov exponents (1, 2) are calculated using sampling frequency fs = 10. Three rates of the LLE are obtained by repeatedly estimating the LLE with different arbitrary initial weights and biases. The intermediate rate is then obtained, and figure 6 show the curve of the intermediate rate for 0 to 300 seconds.

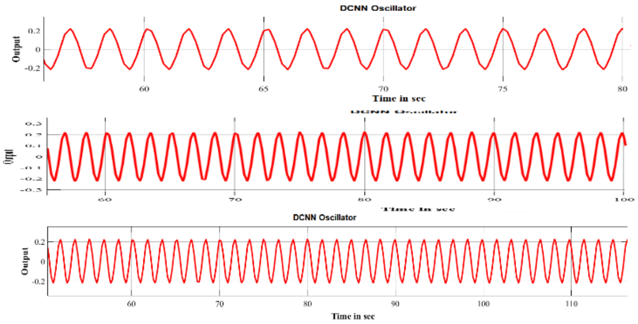
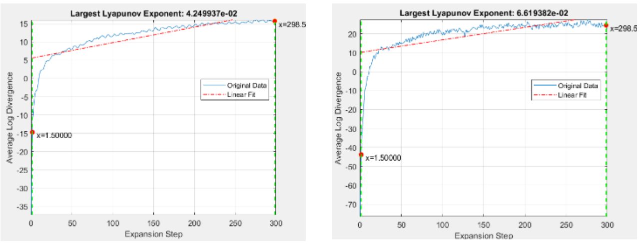


Fig.5.Strange attractor for variable initial condition (a=0.1, b=0.5, & c=0.7)



a-Λ_1 b-Λ_2

Fig. 6. Computed value of the LLE for the DCNN system at time delay =5

The cephalic green line on the left, which is largely dashed, denotes the minimum number of steps used to compute the expansion range, while the cephalic green line on the right, which is solid, denotes the maximum number of steps used.

Cephalic lines that are lower and higher, perform the expansion range. Within the expansion range, the data's linear fit line is indicated by the dashed red line. Noise has an effect on all systems. Noise can occasionally have an impact that cannot be ignored. In this study, the real signal is blended with Gaussian white noise. To calculate the impact of noise on the LLE value, the given signal-to-noise ratio (SNR) per sample is used. The DCNN system adds the three signals sequentially to the Gaussian white noise values (0 dB). The results are shown in figure 7.

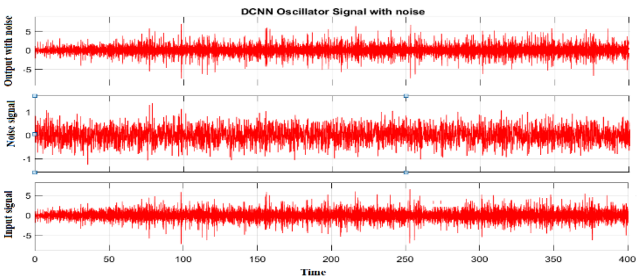


Fig. 7. DCNN oscillator signal for SNR=0

Figures 8 illustrate how noise affects the value of the greatest Lyapunov exponent, which can be used to distinguish between chaos and no chaos. The Estimate LLE is overwhelmingly positive for weak noise. However, when noise is included, the LLE estimate shrinks, especially when there is strong noise present.

3-Power spectrum analysis

An innovative viewpoint on the properties of chaotic systems is provided by power spectrum analysis. Chaos has vast frequency ranges and exponential decomposition of its tail at high frequencies, making it difficult to distinguish it from noise. These qualities are assisting in revealing the turmoil. The only systems that appear to have a persistent power spectrum are chaotic ones. The signal's power spectrum shows how the contrast of the data is dispersed throughout the frequency range. Figures 9 display power spectral density (PSD) evaluated using 3563 samples. These simulations of calculations allow us to conclude that the signal energy is still intense in the low-frequency region of the spectrum. The system is more stable and the PSD is getting close to 0 dB.

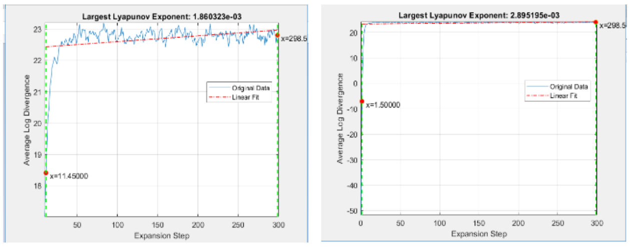


Fig.8. Computed value of the LLE for the DCNN system at SNR = 7 dB

The value of PSD increases, when the LE is positive, because the path is unstable and chaotic. The higher the PSD of the chaotic signals produced, the higher the rate of an LE. This indicates that the greater PSD of the chaotic signals is produced at an enhanced rate of an LE.

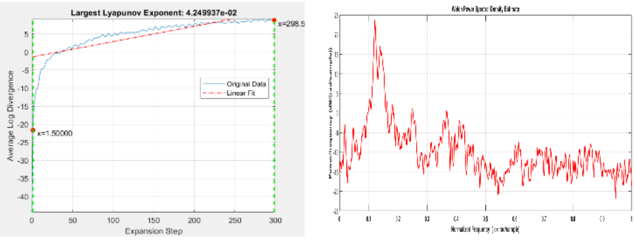


Fig. 9. PSD estimated for positive LE value

4-Experimental results

An efficient Anadigm Designer 2 software tool is used to study the dynamic properties of the prototype in figure 3. Simulation models are used to map the various factors in the proposed system in addition to using the remote system to replicate the results and also obtain a variety of dynamics collection by specifying the circuit specificity. The output of the DCNN oscillator is connected to the upper and lower output of the FPAA3 see figure 3. Different activation functions and initial conditions are given in Table I for the current DCNN oscillator circuit that has been tested. The results obtained from figure 10-11 in both practical and simulation terms, indicate that an infinite number of the oscillator output signals can be obtained by simply varying the initial condition or activation function, and this specification qualifies this type of oscillator for use in secure communication systems.

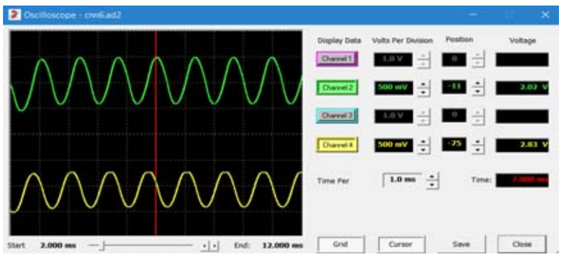


Fig. 10. DCNN oscillator signal output for initial condition (0.1) & activation function (± 0.5)

Conclusions

In this study, FPAA technology was used to construct a DCNN system with two cells that had different topologies and compositions. It was discovered that the proposed system behaved chaotically for a variety of factors, including the initial condition, Lyapunov exponents, and power spectral density, after being examined using Matlab Simulink over a wide range of factor values. There were Matlab-Lyapunov exponents to validate the hypothesized system's chaotic dynamics. The output signal of the suggested system continued to behave chaotically when Lyapunov exponents were computed with AWGN present.
Conclusions

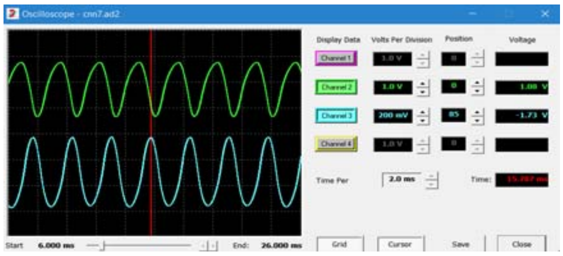


Fig. 11. DCNN oscillator signal output for initial condition (0.7) & activation function (±2)

Table 1. Activation functions and initial conditions for DCNN oscillator

Initial condition	Activation function	output signal
0.1	± 0.5	648 Hz
0.5	± 1	882 Hz
0.7	± 2	1490 z

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