# Nonlinear Function Optimizations Based on Clonal Selective Principle for Hardware Implementation

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***Abstract*** **- The artificial immune algorithms are implemented by the human immune system. They inspired a technique that has the ability to find optimal solutions in a nonlinear search space. This kind of technique increases the computing speed and converges faster than the genetic algorithms. In this paper is presented an application of artificial immune algorithms in order to optimize the transfer function of a sigma delta modulator to be implemented in hardware structure. It is also presented the base method which can perform the adjustment coefficients, in decimal, of the sigma delta modulator.**

***Keywords-*** **artificial immune system, clone selection principle, optimization methods, sigma-delta modulation, signal/noise ratio.**

## I. INTRODUCTION

Various aspects of biology have always been an inspiration to the development of new computer models that are used to solve complex problems. The immune system is the one that has been recently spotted the result being the creation of a new field called Artificial Immune System. It gives very useful information in several types of applications such as: pattern recognition, optimization, learning, etc.

The immune system is – by all means – very complex and presents a new and rich field to be thoroughly investigated by researchers. In the field of artificial intelligence only some of its operating modes are taken into account – the only ones that could be understood and applied in numerical calculation [1,2]. These methods are: the mechanism of negative selection, immune network theory and the clone selection principle.

Clone selection principle inspiration needs a great source for finding new improved techniques [3] in problem optimizations for nonlinear functions but at the same time to mitigate the effects of quantization when digital systems are involved in the calculation. For this reason it is proposed to adapt this technique to optimize the coefficient's noise transfer function of a sigma delta modulator in the digital domain for digital signal processing. The significant advantage is that the sigma-delta modulator converting signals at high resolution using oversampling technique. Moreover, sigma-delta converters are successfully implemented in VLSI Technology (Very Large Scale Integration) implementation involving far less hardware.

Also, the sigma delta modulator is implemented in digital structure as Programmable hardware structures, especially Field Programmable Gate Array (FPGA) devices that are useful for implementing the prototype because offer high performance hardware at a reduced cost in comparison with Application specific Integrated Circuits (ASIC). Currently, FPGA devices are composed from complex functional blocks, offering a variety of functions as multipliers, distributed RAM memory; block RAM, digital clock manager (DCM) and some structures contain even processor cores immersed. In many applications, in offer good processing performance data that can change the algorithm in terms of hardware and the ability to be connected to high speed as peripheral devices with special function tot systems with microprocessors that don't have these features.

Sigma delta modulators are nonlinear and, in order to approximate their behavior the white noise model of quantization error is used and its quantizer is replaced with a stochastic random process. Although it delivers relevant results on signal-noise ratio performance, this model fails to explain the emergence of limit cycles that appear in the spectrum of the output signal. Higher order modulators have some stability problems that are not handled by this model [4,5,6,7,8].

## II. A NON LINEAR FUNCTION

As non-linear function was chose a sigma-delta modulation and is based on a negative feedback loop in which a low quality quantization is performed at a high sampling frequency, and a big amount of the quantization noise is moved into a superior area of the input signal frequency band [9]. In this paper, the quantization error white noise model is used, which simplifies the analyses of sigma-delta modulators and gives important information upon the system functionality. The model replaces the quantizer with an independent input stochastic randomize process; it can use the conventional theory of linear systems

When more the order modulator increases, more noise is shifted to higher area. There is not difficult to obtain the high order sigma-delta modulator, but some aspects appear as the limit cycles in the spectrum of output signal or some stability problems that affects the modulator.

Only some models have been agreed for higher order sigma-delta modulators in digital structure. There are a lot of different ways to realize a sigma-delta modulator in the digital implementation. In order to spread the position of the zeros, we are tempted to introduce many multiplications coefficients. These structures however would be very difficult to be achieved with the currently used hardware, as a large number of multiplications consume too much space area.

For this reason we are concentrating on a structure with fewer multiplications [4]. The fourth-order low pass sigma delta modulator has the advantage of using a low number of multiply coefficients, where $a_1$, $a_2$, $a_3$ and $a_4$ are on the feed-back and take a ±1 value. if the sigma delta modulator has the quantizer only on single bit, then the multiplication operations of coefficients in the feedback are with one or minus one. in this case, the multiply operation needs a minimal number of logic cells into the hardware structure.

The fourth order low pass sigma-delta modulator is shown in fig. 1. The transfer functions are low pass filter and identical as in following relation:

$$H_1(z) = H_2(z) = H_3(z) = H_4(z) = \frac{z^{-1}}{1 - z^{-1}}$$

(1)

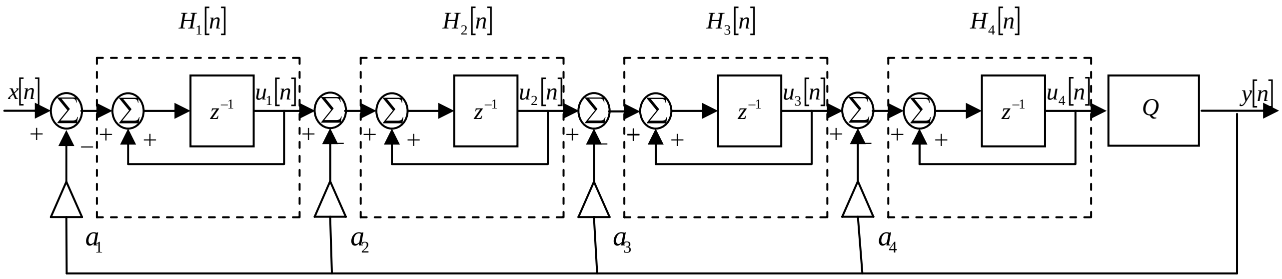


Fig. 1. Block diagram of fourth order sigma-delta modulator

The quantization process will be on a single bit. After the computation in discrete time of the differential equations of the fourth order sigma-delta modulator we can determinate the signal transfer function (2) and the noise transfer function as (3) given in the following relations:

$$STF = \frac{z^{-4}}{1 + z^{-1}(-4 + a_4) + z^{-2}(6 - 3a_4 + a_3) + z^{-3}(-4 + 3a_4 - 2a_3 + a_2) + z^{-4}(1 - a_4 + a_3 - a_2 + a_1)} \qquad (2)$$

$$NTF = \frac{1 - 4z^{-1} + 6z^{-2} - 4z^{-3} + z^{-4}}{1 + z^{-1}(-4 + a_4) + z^{-2}(6 - 3a_4 + a_3) + z^{-3}(-4 + 3a_4 - 2a_3 + a_2) + z^{-4}(1 - a_4 + a_3 - a_2 + a_1)} \qquad (3)$$

## III. Clonal selective principle

The immune system detects foreign elements and acts to eliminate them. Such elements are prerequisites of the immune system like bacteria, viruses, etc. and are found as the antigen. Detection elements of the immune system in vertebrates are distributed in the body and interact with elements considered intruders by the immune system. For some detectors there are mechanisms to improve their recognition performance. Affinity maturation process consists of an iterative process of generating clones, variation and selection and will still participate in the process of evolution. The best detectors resulting from clone selection are retained in memory cells.

The process of cloning is lymphocytes proliferation that recognizes the antigens. Lymphocytes interaction with the antigens is the result of their activation. When an antigen activates a lymphocyte, it just does not make antibody to bind antigen and clones are moved to have a better affinity with the antigen detected. The latter process is called somatic hyper mutation. The repetitive exposure to antigen of the immune system helps it to learn to adapt itself to various forms of antigen. This process is called clone selection theory [12].

Clone selection algorithm it's important for studies on immune system and it is able to generate optimization process. It is always trying to find an optimal solution but it can be stopped after a number of cycles predefined by the user.
Selective cloning algorithm follows these steps [11]:

1. Generates a set (P) of candidate solutions, composed of the subset of memory cells (M) added to the remaining (Pr) population (P = Pr + M);
2. Determines (Selects) the n best individuals of the population (Pn), based on an affinity measure;
3. Reproduces (Clones) these n best individuals of the population, giving rise to a temporary population of clones (*C*). The clone size is an increasing function of the affinity with the antigen;
4. Submits the population of clones to a hypermutation scheme, where the hypermutation is proportional to the affinity of the antibody with the antigen. A maturated antibody population is generated (*C**);
5. Re-selects the improved individuals from *C** to compose the memory set M. Some members of P can be replaced by other improved members of *C**;
6. Replaces d antibodies by novel ones (diversity introduction). The lower affinity cells have higher probabilities of being replaced.

## VI. Results

Evaluation functions were done after the signal-noise ratio. In order to obtain the comparable result a sinusoidal input signal was chosen, with 0.75 amplitude and a sampling rate of 32. To execute the clonal selection algorithm the following initial configurations were necessary:

*Clonal selection algorithm*

- A cell contains four subdivisions, each subdivision representing one modulator's coefficient
- Populations consisted of 30 cells
- For each generation there is formed a population with 20 clone cells
- In every evolution the last two cells with less fitted are replaced by another two randomly generated.
- 1000 evolutions were made.

Data obtained by running the three methods are given in table 1.

TABLE I. RESULTS OF CLONAL SELECTION ALGORITM

| Methods | Coefficients | Signal/noise ratio | Time of execution |
|---|---|---|---|
| Clonal Selection Principle | 0.489432<br>0.417479<br>0.492517<br>0.762137 | 68.991dB | 0'57" |

Evolution of the implementation of the clone selection algorithm is shown in Fig. 2.

As we can notice from Fig. 2, the clone selection algorithm is able to optimize and further solutions have been found.

In fig. 3 is shown the power spectral density obtained for the clonal selection principle.

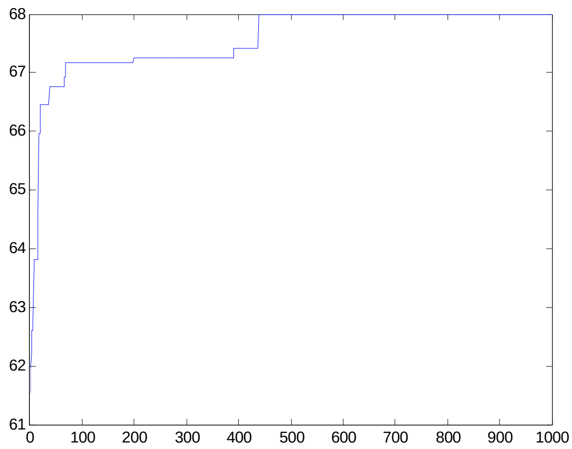

Fig. 2. Fitness evolution of clonal selective principle

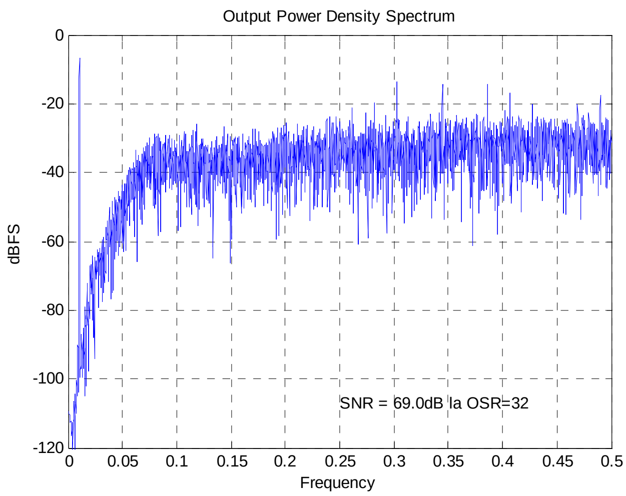


Fig. 3. Output power spectrum density for clonal selective principle

In Fig. 4 there are represented the obtained transfer functions (STF and NTF) for the clonal selection principle.

Note that the transfer functions obtained by cloning selection algorithm were modeled to find the optimum input signal frequency.

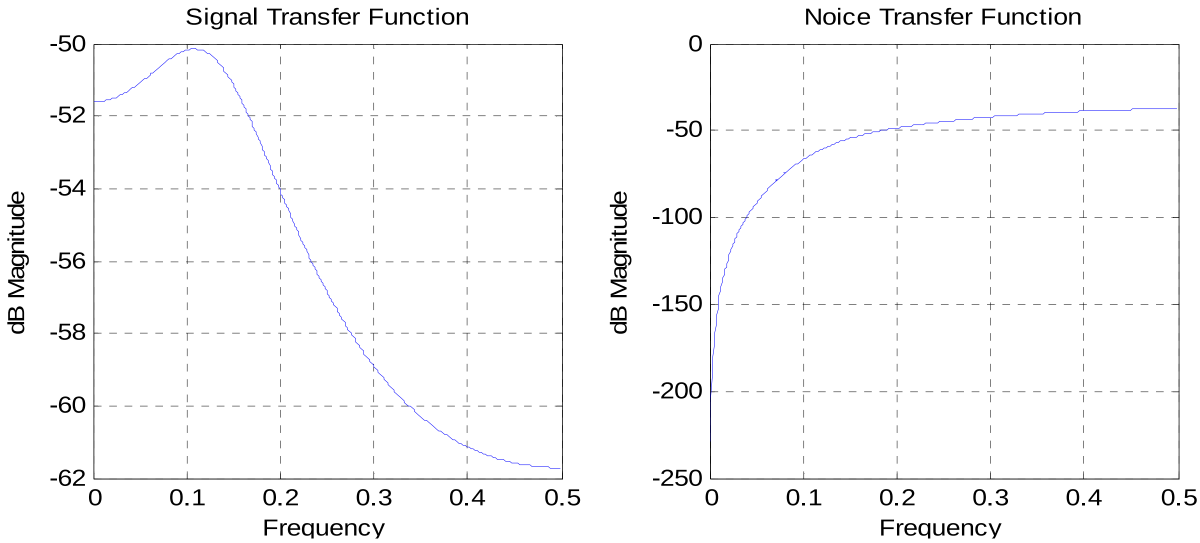


Fig. 4. STF and NTF obtained with clonal selection principle

## V. CONCLUSIONS

The algorithm based on the principle of clone selection was applied to optimize a fourth degree order sigma-delta modulator with a structure easily applied to digital systems, where a minimum number of multipliers are desired. Coefficients calculation was performed for its transfer function to highlight the advantages of clone selection algorithm. It was noticed that the clone selection algorithm reaches an optimal level in less time and it is able to optimize a better solution compared to the genetic algorithms [5]. The selective cloning principle it's supposed to start from the relatively known solutions inmate data system, according to the profile literature. To obtain the best possible optimization performance, a lot of clones have been generated and a hypermutation process has been performed followed by the replacement of the less fitness cells

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