Adaptive Filters Realized with Nano-scale VLSI Circuit Technology

C. Radhakrishnan and W. K. Jenkins
Department of Electrical Engineering
The Pennsylvania State University
University Park, PA
jenkins@engr.psu.edu

D. J. Krusienski
Department of Electrical Engineering
University of North Florida
Jacksonville, FL
d.krusienski.59536@unf.edu

Abstract - **This paper investigates design strategies for achieving reliable performance in VLSI adaptive filters that are prone to transient errors due to increasingly smaller feature dimensions and supply voltages of the CMOS circuits. First it will be shown that stochastic search algorithms (e.g. Particle Swarm Optimization) have a natural resistance to transient errors. It is then shown how modular hardware based on residue number system (RNS) coding can be designed to more effectively manage transient errors in adaptive filters with stochastic search algorithms.**

I. INRODUCTION AND BACKGROUND

To achieve higher speed, higher density, and lower power dissipation MOS VLSI circuits continue to be scaled down in terms of feature sizes and power supply voltages, resulting in an increase of radiation induced (soft) errors in logic circuits [1]. In addition reducing supply voltages is a common method of reducing power consumption. This requires threshold voltages to be scaled down, causing higher leakage currents and high power density. Reducing supply voltages to reduce power consumption in DSP systems also causes increased gate delays in critical paths [2], which also leads to an increase of transient error rates.

Reducing threshold voltages requires reducing the oxide layer thickness, which in turn results in increased leakage currents, larger quiescent power consumption, and increased operating temperatures. Increased temperature has a substantial impact on the key figures of merit (performance parameters) of a VLSI circuit, including circuit speed, lifetime, and power dissipation. Chip temperature is set by the power dissipation in the substrate and interconnects as well as the physical layout, routing resources, and power distribution network in the chip. The following temperature effects were reported in [3]:

- Logic gate delay change is about 4% with 40 C. temperature difference in a 130-nm industrial process.
- Delay change for wire resulted in about 5% for 40 C. temperature changes.
- Clock skew can be increased by as much as 10% of the clock cycle time when the junction temperature changes in the substrate by as much as 40 C.

When adaptive echo cancellers, channel equalizers, noise cancellers, and LPC data compressors are implemented in nano-scale VLSI circuits there is a concern about how such systems will perform in the presence of transient errors. Previous work has shown that in many circumstances transient errors have the effect of resetting the system to arbitrary initial conditions. In this case the adaptive system will re-adjust to meet the minimum MSE criterion and thereby bring the system back to a converged condition. However, there are other circumstances when transient errors can drive the system into instability, resulting in permanent system failure.

Figure 1 shows an example of an adaptive FIR filter responding to a transient (soft) coefficient error. A transient error at iteration 100 temporarily forces the filter to a non-converged state as evidenced by the large jump in the MSE. The filter then re-adapts toward the global minimum error condition, suggesting that an adaptive filter will likely be tolerant to transient errors that occur during the calculation and storage of the filter coefficients.

Section II reviews the principles of the Particle Swarm Optimization (PSO) algorithm and discusses how this type of stochastic search algorithm achieves inherent fault tolerant behavior. Section III introduces fault tolerance for soft errors through hardware and arithmetic modularity via residue number system (RNS) arithmetic. It is shown how the error magnification property of redundant RNS coding enhances the ability of the PSO strategy to maintain fault tolerance. Finally Section IV presents some experimental examples that demonstrate the fault tolerant behavior of PSO-based adaptive filters operating with RNS arithmetic.

II. INHERENT TRANSIENT ERROR RESISTANCE OF STRUCTURED STOCHASTIC SEARCH ALGORITHMS

Recently the Particle Swarm Optimization (PSO) algorithm has been researched for use in adaptive filters that have ill-conditioned mean squared error (MSE) surfaces [4]. The conventional PSO algorithm begins by initializing a random swarm of M particles, each having R unknown parameters to be optimized. At each epoch, the fitness of each particle is evaluated according to the selected fitness function (MSE). The algorithm stores and progressively replaces the most fit parameters of each particle ($pbest_i$, i=1,2,... M) as well as a single most fit particle (*gbest*) as better fit parameters are encountered. The parameters are updated at each epoch (n) according to:

$$\overline{vel_i}(n) = w * \overline{vel_i}(n-1) + acc_1 * diag[e_1, e_2, ..., e_R]_{i1} * (gbest - p_i(n-1)) + acc_2 * diag[e_1, e_2, ..., e_R]_{i2} * (pbest_i - p_i(n-1)) \quad (1)$$

$$p_i(n) = p_i(n-1) + \overline{vel_i}(n) \quad (2)$$

where $\overline{vel_i}(n)$ is the velocity vector of the i^{th} particle, e_r is a vector of random values within in the interval (0,1), acc_1 and acc_2 are the acceleration coefficients toward *gbest* and $pbest_i$ respectively, and *w* is the inertia weight. It has been shown that premature stagnation can be overcome by adding the enhancements of *mutation*, *re-randomization*, and *adaptive inertia* into the PSO algorithm, resulting in the Modified PSO (MPSO) algorithm shown in figure 2 [4].

The structure of the MPSO algorithm makes it inherently fault tolerant to transient errors in the updating of the parameters according to equations (1) and (2), and also to transient errors that might occur in the filter calculations for each member of the population. Transient errors introduce effects that are similar to re-randomization about *gbest*, as well as to the mutation of selected members of the population. If a transient error does not significantly damage the fitness of a particular particle, that particle continues to influence the swarm as the stochastic search progresses. However, if a transient error produces a seriously unfit particle its influence is eliminated from the search process since the erroneous particle will not be selected in subsequent search updates.

III. FAULT TOLERANT DESIGNS BASED ON MODULAR HARDWARE

Additional fault tolerance can be introduced into VLSI chip designs through the use of residue number system (RNS) coding. A general class of RNS arithmetic is constructed as a direct sum of simple modular structures (either fields or rings) that have moduli that are pairwise relatively prime integers (i.e. no two have a non-unity common factor). If R(M) is a modular ring that defines the computational range of a particular signal processing task, where $M = m_1 m_2 \ldots m_L$ and $\boldsymbol{M} = \{m_1, m_2, \ldots, m_L\}$ is the moduli set, then the arithmetic within the RNS is defined by:

$$(x_1, \ldots, x_L) * (y_1, \ldots, y_L) = (z_1, \ldots, z_L) \quad (3a)$$

$$\text{where: } z_i = (x_i * y_i) \bmod m_i \text{ for } i = 1, \ldots, L \quad (3b)$$

where $*$ denotes addition, subtraction, or multiplication. Since z_i is determined entirely from x_i and y_i, RNS arithmetic is carry-free in the sense that there is no propagation of information from the i^{th} digit to the j^{th} digit for $i \neq j$. The lack of carry propagation in residue arithmetic systems means that an error occurring in one digit cannot be propagated into other digit position during subsequent operations of addition, subtraction, or multiplication. Therefore the modularity of the arithmetic provides error isolation that limits the propagation of errors between the RNS modules [5].

In order to enable RNS error detection redundancy is constructed by including extra moduli that provide dynamic range beyond what is needed for the actual computation. Suppose that one redundant modulus is appended to the original moduli set, creating a total of L+1 moduli. All of the L+1 moduli must be pairwise relatively prime to ensure a unique representation for each state in the RNS code. It is well established that the addition of one redundant modulus, such that $m_{L+1} > m_i$, i = 1, . . . L, is necessary and sufficient to provide error detection capability for all single residue digit errors [5].

Error detection is typically implemented by converting an RNS number to an associated radix representation $a_L \ldots a_1$, where the a_i's are defined by:

$$x = a_L(m_{L-1} \cdots m_1) + \ldots + a_2 m_2 + a_2 \quad (4)$$

If no errors occur x will be constrained to the legitimate range [0, M-1]. However if any one of the RNS digits is corrupted an error the result will be mapped into the illegitimate range [M, M_r-1], where $M_r = m_{L+1}M$. (see figure 3). Therefore single RNS digit error detection is achieved through single digit redundancy (SDR) and a simple check (via mixed radix conversion or otherwise) to determine if the resulting calculation overflows the legitimate range of the RNS system.

Modularity induced by an RNS arithmetic code introduces three important properties that aid in managing the effects of transient errors [7,8]:

i) *Hardware modularity* - RNS arithmetic is executed in short word length modules that tend to break long delay paths into shorter parallel paths. The negative effects of increased gate delays due to supply voltage scaling are mitigated. The basic building blocks of an RNS module consist of a short word length ripple carry adder and a small ROM, both of which are relatively insensitive to the ill effects of parameter scaling [9].

ii) *Arithmetic modularity* - results in the lack of error propagation among modules and facilitates error detection strategies that are not so easily implemented in conventional long (2's-complement) word length processors.

iii) *Error magnification* – error magnification results from the fact that all single digit errors map the result to large values that will make the erroneous result appear as an unfit member of the population, and hence will have little influence on the stochastic search algorithm.

IV. EXPERIMENTAL EXAMPLES

To illustrate error magnification in a redundant RNS an example of a 233-tap FIR notch filter is presented in figure 4. This filter is used to eliminate noise from the frequency band 1.2 – 1.3 MHz. in a random noise radar system [6]. The filter was implemented in a redundant RNS with moduli {71, 79, 83, 89, 97}, where 97 was defined to be the redundant modulus. In figure 4a the output of the RNS-SDR filter is shown operating on a noisy input signal without the occurrence of transient errors. In figure 4b the output of the filter is shown with RNS single digit transient errors occurring at iteration n = 1000 and held in the same error condition for 100 iterations. During the occurrence of the error the output of the filter is magnified (i.e. it is mapped into the illegitimate range), thereby revealing that a single digit error has occurred.

Experimental results showing the fault tolerant behavior of an adaptive filter using the PSO adaptive algorithm implemented in a redundant RNS arithmetic code are presented in figures 5 – 9. In these experiments each of the particle filters was implemented in RNS arithmetic, although the updates were implemented in 2's-complement binary arithmetic [9]. These experiments all used a population of 10 and were implemented in the same RNS system used in the previous FIR filter example. Figure 5 shows the baseline learning curve for a length N = 4 FIR adaptive filter used in the system identification configuration to identify an FIR system with a unit pulse response of $\mathbf{h} = [2.0, -0.5, 0.5, 1.0]^T$. In this case no transient errors were injected. The learning curve of the PSO-RNS combination is seen to achieve rapid convergence.

In figure 6 the previous experiment was repeated but with a single RNS digit error introduced in gbest at iteration 10. This represents a severe error condition because the erroneous gbest suddenly moves the entire swarm of particles to a new location in the parameter space. After a serious transient response in the learning curve the adaptation rapidly recovers as the erroneous value of gbest is replaced with new values. Figure 7 shows an extreme case where an error was created at iteration 10 in the pbest associated with the most fit particle. In this case there is a smaller transient in the learning curve after which the adaptation rapidly recovers.

Finally, figure 8 shows two additional experiments where 5-out-of-10 and 8-out-of-10 of the values of pbest are corrupted at iteration 10 by single digital errors. Figure 9 shows two similar cases where transient errors were made in the particles themselves (rather than in gbest or the pbest's). In all cases the PSO-RNS learning curves show modest disturbances due to injection of transient errors. In all cases examined rapid recovery occurred in the adaptation process due to the modular structure of the RNS arithmetic and the error magnification property provided by RNS single digit redundancy.

REFERENCES

[1] R. C. Baumann, "Radiation–Induced Soft Errors in Advanced Semiconductor Technologies," *IEEE Transactions on Device and Materials Reliability*, Vol. 5, No. 3, pp 305-316, September 2005.

[2] R.Hegde and N.R. Shanbhag, "Soft digital signal processing," *IEEE Trans. On Very Large Scale Integration (VLSI) Systems*, vol. 8, no. 4, pp 813-823, Dec 2001.

[3] M. Pedram and S. Nazarian, "Thermal modeling, analysis, and management in VLSI circuits: Principles and methods," *Proceedings of the IEEE*, Special Issue on On-chip Thermal Engineering, vol. 94, no. 8, pp 1487-1501, August 2006.

[4] D. J. Krusienski and W. K. Jenkins, "A modified particle swarm optimization algorithm for adaptive filtering" *Proceedings of the International Symposium on Circuits and Systems*, Kos, Greece, May 2006.

[5] M. A. Soderstrand, W. K. Jenkins, G. A. Jullien, and F. J. Taylor (eds.), *Modern Applications of Residue Number System Arithmetic to Digital Signal Processing*, IEEE Press, New York, NY, 1986.

[6] S. C. Surender and R. M. Narayanan, "Covert netted wireless noise radar sensor: OFDMA-BASED communication architecture," *IEEE Military Communications Conference,* MILCOM 2006.

[7] W. K. Jenkins, C. Radhakrishnan, S. Pal, andJ. Sabarad, "Fault tolerant signal processing for nano-scale VLSI Circuit Technology," *Proceedings of the 40th Annual Asilomar Conference on Signals, Systems, and Computers,* Pacific Grove, CA, pp 926-930, October 2006.

[8] W. K. Jenkins, C. Radhakrishnan and S. Pal, "Fault tolerant signal processing for masking errors in VLSI signal processors," *Proceedings of the International Symposium on Circuits and Systems*, New Orleans, LA, pp 2570-2573, May 2007.

[9] G. L. Bernocchi, G. C. Cardarilli, A. Del Re, A. Nannarelli and M. RE, "Low power adaptive filter based on RNS components," *Proceedings of the International Symposium on Circuits and Systems*, New Orleans, LA, pp 3211-3214, May 2007.

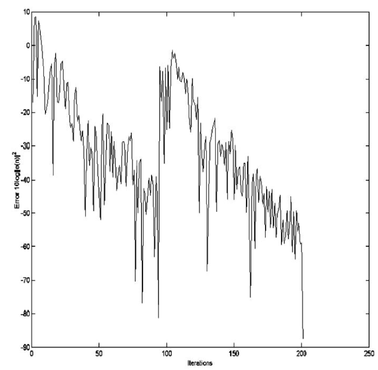

Figure 1. Learning curve for a 4-tap FIR filter with a transient (soft) coefficient error occurring at iteration 100.

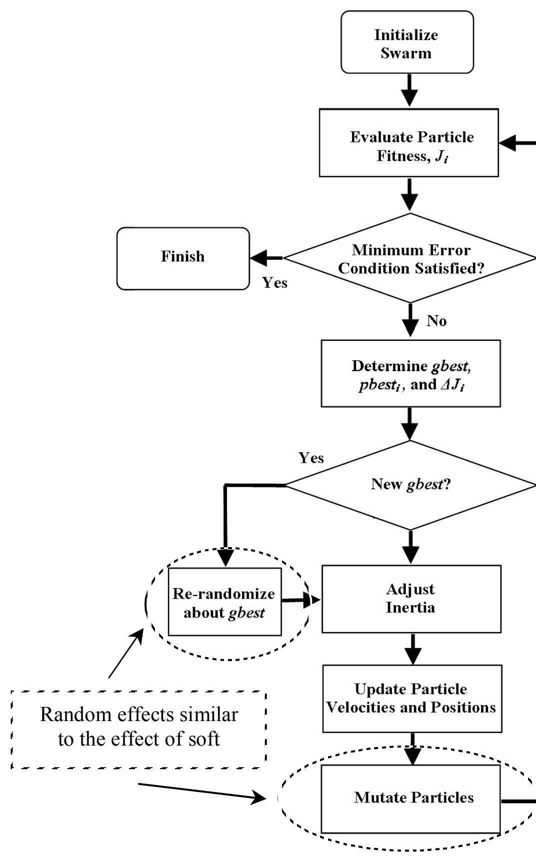

Figure 2. Flow chart for the Modified PSO algorithm.

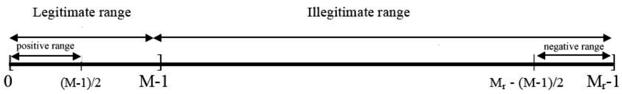

Figure 3. Various ranges of a redundant RNS

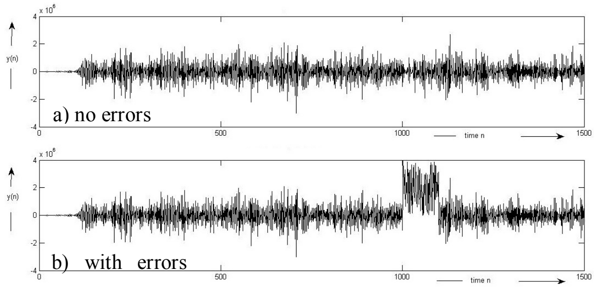

Figure 4. Error magnification of transient errors in a 233-tap FIR notch filter used in a random noise radar (notch from 1.2 - 1.3 MHz).

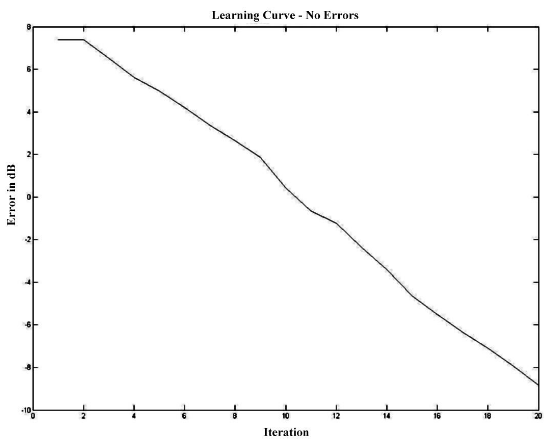

Figure 5. Baseline learning curve for the PSO-RNS algorithm.

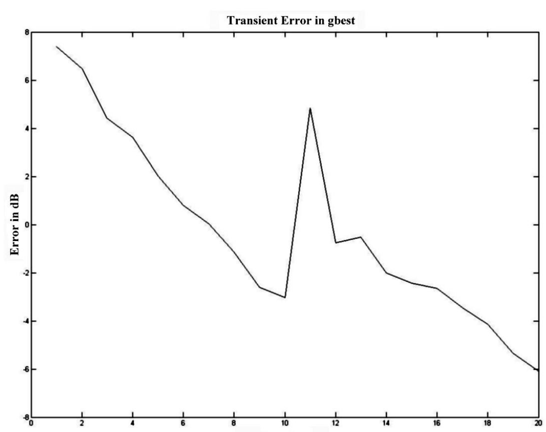

Figure 6. PSO-RNS algorithm with an error in gbest.

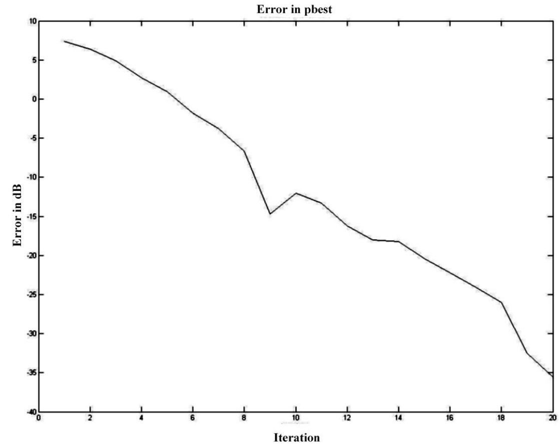

Figure 7. RNS - PSO algorithm with an error in pbest of the most fit particle.

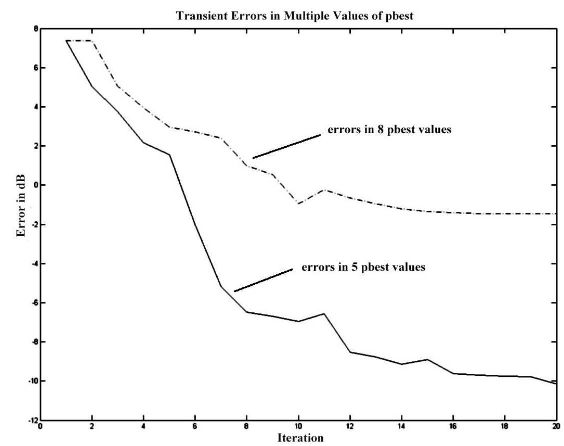

Figure 8. RNS – PSO with multiple errors in pbests.

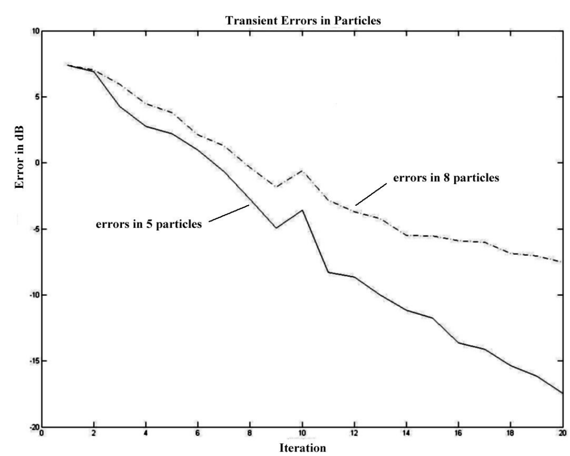

Figure 9. PSO-RNS algorithm with multiple particle errors.