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Synthesis of optimal digital shapers with arbitrary noise using a genetic algorithm

Alberto Regadío [a,b,*], Sebastián Sánchez-Prieto [a], Jesús Tabero [b], Diego M. González-Castaño [c]

[a] Department of Computer Engineering, Space Research Group, Universidad de Alcalá, 28805 Alcalá de Henares, Spain
[b] Electronic Technology Area, Instituto Nacional de Técnica Aeroespacial, 28850 Torrejón de Ardoz, Spain
[c] Radiation Physics Laboratory, Universidad de Santiago, 15782 Santiago de Compostela, Spain

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ABSTRACT

This paper presents structure, design and implementation of a novel technique for determining the optimal shaping, in time-domain, for spectrometers by means of a Genetic Algorithm (GA) specifically designed for this purpose. The proposed algorithm is able to adjust automatically the coefficients for shaping an input signal. Results of this experiment have been compared to a previous simulated annealing algorithm. Finally, its performance and capabilities were tested using simulation data and a real particle detector, as a scintillator.

1. Introduction

In spectroscopy, the value of energy of incident particles can be extracted from the peak amplitude of the input pulses coming from particle detectors. This method is called Pulse Height Analysis (PHA) and provides a value of energy proportional to the incident particle energy. Thus, identical particles with the same energy must generate identical peak values. The ability of a given measurement to resolve fine details in the incident energy of the radiation is improved as the width of the response function becomes smaller. This feature is called resolution. Nowadays, this property remains determining for all spectroscopy systems [1–4].

The resolution of these measurements is affected by noise. This noise has a spectral density that depends on the type of detector and the features of the spectroscopy system. To mitigate this type of noise, spectroscopy systems have filters at the output of particle detectors called shapers.

The shaper's effectiveness in a spectroscopy system depends on the spectral density of noise. However, finding the optimal shaper is a problem with multiple degrees of freedom. This fact implies that optimal shapers should be selected using numerical and/or iterative procedures (e.g. [3,5–8]).

This paper describes the development of an algorithm based on a GA for providing the optimal shaping for spectroscopy systems. The paper is structured as follows. Section 2 presents the fundamentals of the GA. Section 3 provides details of the GA used and the cost functions. Section 4 presents the theoretical and experimental results of this algorithm. Finally, Section 5 covers the conclusions and the future work.

2. Genetic algorithms

In the computer science field of artificial intelligence, a GA is a heuristic search that tries to imitate the process of natural selection and mutations. This heuristic is used to generate useful solutions to optimization and searching problems [9,10]. GAs belong to the larger class of evolutionary algorithms, which generate solutions to optimization problems using techniques inspired by the natural evolution, such as inheritance, mutation, selection, and crossover.

In a genetic algorithm, a population of candidate solutions (called individuals or phenotypes) to an optimization problem is evolved toward better solutions. Each candidate solution has a set of properties (its chromosomes or genotype) which can be mutated and altered. Traditionally, solutions are represented as strings of information, usually in binary format [11].

* Corresponding author at: Department of Computer Engineering, Space Research Group, Universidad de Alcalá, 28805 Alcalá de Henares, Spain.
E-mail addresses: regadioca@inta.es (A. Regadío), sebastian.sanchez@uah.es (S. Sánchez-Prieto), taberogj@inta.es (J. Tabero), diego.gonzalez@usc.es (D.M. González-Castaño).

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The evolution process usually starts from a population of randomly generated individuals. The population in each iteration is called *generation*. In each generation, the fitness of every individual in the population is evaluated; the fitness is usually the value of the objective function in the optimization problem being solved. The individuals best suited are stochastically selected from the current population and selected individual's genome is modified (recombined and possibly randomly mutated) to form a new generation. The new generation of candidate solutions is then used in the next iteration of the algorithm. Finally, the searching process terminates when either a maximum number of generations have been produced or a satisfactory fitness level has been reached for the population.

Interest in such algorithms is intense because some important combinational optimization problems can be solved exactly in a reasonable time.

3. Proposed genetic algorithm

A typical genetic algorithm requires (a) a cost function to evaluate the candidate solutions and (b) chromosomic representation of the solution domain.

A combinational optimization problem is aimed at finding among many configurations the one which minimizes a given function which is usually referred to as the *cost function*. This function is a measurement of goodness of a particular configuration of parameters. The selection of an appropriate cost function is crucial for achieving good results using this algorithm.

In this work, and in order to reduce the searching space and the processing time, we assume that the chromosomic representation is a monotonically increasing function until it reaches the maximum level, and then it follows a monotonically decreasing function. Thus, for each individual,

$$\mathbf{I} = \{x_1, x_2, \ldots, x_{N/2} : 0 \le x_1 \le x_2 \le \cdots \le x_{N/2} = 1\} \tag{1}$$

where N is the shaper order. From these individuals, a symmetrical shaper can be obtained

$$\mathbf{S} = \left\{\mathbf{I}, \mathbf{I}^R\right\} = \{x_1, x_2, \ldots, x_{N/2} = 1, \ldots, x_2, x_1\} \tag{2}$$

where $\mathbf{I}^R$ is $\mathbf{I}$ reversed.

For all the considered shapers, the flat-top duration is equal to T_s. As in [8], when flat-tops with a duration of τ_t clock cycles, an additional constraint must be included with a number of ones equal to $L = \tau_t/\tau_s$ added in the middle of $\mathbf{S}$. In this case, the new equation is

$$\mathbf{S} = \left\{\mathbf{I}, 1\cdots1, \mathbf{I}^R\right\} = \{x_1, x_2, \ldots, x_{N/2-L/2} = 1, \ldots, x_{N/2+L/2} = 1, \ldots, x_2, x_1\} \tag{3}$$

The shaper $\mathbf{S}$ works as a digital Finite Impulse Response (FIR) filter. Thus x_n are the coefficients of the FIR filter.

Once both genotype and phenotype are defined, a GA proceeds to initialize a population of shapers, and then to improve it through repetitive application of the mutation, crossover and selection operators according to a cost function. Thus, in order to get an optimal shaper, the following steps are to be taken:

1. Establish the sampling period T_s of the input signal, the maximum shaping time $\tau_{\max}$ and the maximum shaper order $N_{\max}$. The relationship among these parameters is
$$N_{\max} = \frac{\tau_{\max}}{T_s} \tag{4}$$
2. Establish the number of generations G (i.e. iterations), the population P for each generation and the cost function. If mutations are desired, set p_m (probability of mutation) and S_n mutation maximum value.
3. Create a population of P shapers. Each shaper shall have a random integer N where $N \in [1, N_{\max}]$ to try different values of shaping time.
4. For each generation:
   (a) Generate a new population based on the crossover between the set that had got the best score (based on the cost function) in the present population. For this algorithm, the crossover is given by the following equation:
   $$\mathbf{I}_{\text{new}} = \frac{\varphi \mathbf{I}_1 + (1-\varphi)\mathbf{I}_2}{\max(\varphi \mathbf{I}_1 + (1-\varphi)\mathbf{I}_2)} \tag{5}$$
   where $\mathbf{I}_1$ and $\mathbf{I}_2$ are two individuals $\mathbf{I}_{new}$ the resulting individual from the crossover and $\varphi \in [0, 1]$ is a real number to set the weight of $\mathbf{I}_1$ and $\mathbf{I}_2$ proportional to the score of both individuals according to the following equation:
   $$\varphi = \frac{\text{score}(\mathbf{I}_1)}{\text{score}(\mathbf{I}_1) + \text{score}(\mathbf{I}_2)} \tag{6}$$
   (b) Include within the population the individual of the past generation that get the best score.
   (c) For each value of $\mathbf{I}_{\text{new}}$, add mutations randomly with a probability p_m. If a mutation occurs, the new value of $x_n \in \mathbf{I}_{\text{new}}$ is now equal to $\tilde{x}_n$ in this way
   $$\tilde{x}_n = x_n + \chi S_n \tag{7}$$
   where $\chi \in [-1, 1]$ is a real random number.
   (d) Generate a shaper $\mathbf{S}$ for each individual $\mathbf{I}$ (see Eq. (2)) and test it.
   (e) Evaluate $\mathbf{S}$ according to a cost function previously selected (see Section 3.1). Assign a score to each shaper based on the evaluation.
5. At the end of the process, the optimal shaper will be the final best shaper.

In specific environments, it can be interesting the execution of this algorithm at a certain intervals. For instance, in space systems, the GA could be executed at regular intervals to counter the effects of radiation damages as was proposed in [12].

3.1. Cost functions

In this work, the cost function used for simulation experiments (Section 4.1) is the Equivalent Noise Charge (ENC), calculated using the noise indices [13], whereas for real test, the cost function is the Signal/Noise Ratio (SNR). In the experimental tests (Section 4.2), the Full Width at Half Maximum (FWHM), as a percentage, was used to measure the quality of the final shaper, but it has not been used as a cost function due to the enormous burden of calculation and time taken to generate a histogram for each individual in the population.

3.1.1. ENC

To evaluate the results of simulation experiments, noise indexes have been used as a cost function. Noise indexes in analog domain were introduced by Goulding in [13]. The noise indexes, calculated in time-domain, are inversely proportional to the SNR, and they can be used to calculate the ENC [14]. This noise analysis is valid for any detector/preamplifier/analog filtering/ADC/PHA combination.

The noise indexes for serial (white) noise N_Δ^2, parallel (red or brownian) noise N_S^2 and $1/f$ series (pink) noise N_F^2 were adapted to