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An efficient hybrid genetic algorithm to design finite impulse response filters

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ABSTRACT

Although genetic algorithms (GAs) have proved their ability to provide answers to the limitations of more conventional methods, they are comparatively inefficient in terms of the time needed to reach a repeatable solution of desired quality. An inappropriate selection of driving parameters is frequently blamed by practitioners. The use of hybrid schemes is interesting but often limited as they are computationally expensive and versatile. This paper presents a novel hybrid genetic algorithm (HGA) for the design of digital filters. HGA combines a pure genetic process and a dedicated local approach in an innovative and efficient way. The pure genetic process embeds several mechanisms that interact to make the GA self-adaptive in the management of the balance between diversity and elitism during the genetic life. The local approach concerns convergence of the algorithm and is highly optimized so as to be tractable. Only some promising reference chromosomes are submitted to the local procedure through a specific selection process. They are more likely to converge towards different local optima. This selective procedure is fully automatic and avoids excessive computational time costs as only a few chromosomes are concerned. The hybridization and the mechanisms involved afford the GA great flexibility. It therefore avoids laborious manual tuning and improves the usability of GAs for the specific area of FIR filter design. Experiments performed with various types of filters highlight the recurrent contribution of hybridization in improving performance. The experiments also reveal the advantages of our proposal compared to more conventional filter design approaches and some reference GAs in this field of application.

1. Introduction

Filters are now a key component in most electronic systems and more generally of any signal processing device. A digital filter works on sampled discrete time signals, in contrast to analog filters which operate on continuous-time analog signals. Most electronic systems contain a large number of filters that meet varied requirements. Filtering is a form of signal processing, obtained by sending the useful signal through a set of electronic circuits, which adaptively modify its frequency spectrum, phase, and hence its shape. The filter is designed to extract some information related to this signal, usually in order to return, from an incident signal, a signal that is more intelligible in terms of the information it contains and that one wants to select (Karaboğa & Çetinkaya, 2006). Filtering may eliminate or reduce unwanted noise frequencies, or isolate a complex signal in the useful frequency bands. The advantages of more efficient filters are considerable: designs can be customized, accurate and adaptable; beyond their useful function, they can be easily integrated into existing sets and can generate cost reductions in component design.

Digital filters can be classified into several different groups, depending on the classification criteria used. The two major types of digital filters are finite impulse response digital filters (FIR filters) and infinite impulse response digital filters (IIR filters) (Karaboğa & Çetinkaya, 2006). Each type has some specific advantages and disadvantages that should be carefully considered when designing a filter.

FIR filters are digital filters with a finite impulse response. They are also known as *non-recursive digital filters* as they do not have feedback, even though recursive algorithms can be used to design FIR filters. The transfer function of a FIR filter approaches the ideal one as the filter order increases, thus increasing the complexity and amount of time needed for processing input samples of the signal being filtered. FIR filters have many advantages such as

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stability, the possibility of obtaining an exact linear phase and efficient hardware implementation.

For certain signals, the phase characteristic is an essential feature. This is the case for various industrial sensors where it is necessary for a filter to have a linear phase characteristic to avoid losing important information. Linear phase refers to the condition where the phase response of the filter is a linear function of frequency. This results in the delay through the filter being the same at all frequencies. Therefore, the filter does not cause phase distortion or delay distortion. One of the drawbacks of FIR filters is that they require a high order of filter designed to meet a specific template. The order of FIR filters is considerably higher than that of IIR filters with the same frequency response.

Filter design is the process of synthesis and implementation so that the resulting filter meets the given constraints (amplitude response, phase, etc.). For reasons of physical realization and real-time use, filters will necessarily consider a causal impulse response, which means that a sample of the output signal can be calculated from input and output samples that depend only on past moments but never on the future. From a mathematical point of view, the problem of filter design can be seen as a constrained minimization problem consisting in finding a filter design which meets each of the requirements to a sufficient degree to make it useful (Milivojevic, 2009). While the science of digital filter design is very well established and researched, there are no conventional design procedures that lead to optimal designs with an acceptable Digital Filter Design, making efficient design complex (Milivojevic, 2009). A survey of relevant journals reveals that digital filter design is an active area of research seeking to develop more efficient techniques. The complexity of the design encounters the limitations of conventional design that cannot handle all the constraints of filter performances.

Evolutionary methods, especially genetic algorithms (GA) have the potential to provide answers to the limitations of more conventional methods. They are capable of performing multicriterion optimization in ways that automatically lead to performance tradeoffs between design specifications.

The implementation of an evolutionary algorithm for filter design, however, faces a number of challenges. The space of possible filters is very large, and individual parameters are tightly coupled, making it more likely for the algorithm to converge onto local, unsatisfactory sub-optima. Another point is that GAs are reputed to perform well in finding promising regions of the search space but to be inefficient in determining the local minimum in terms of convergence speed and solution quality. The field of GA applications has clearly progressed, chiefly as a result of innovation in the last ten years, and has incorporated more elaborate strategies aimed at tackling the weaknesses of GAs. However, GAs are still faced with the major issue of autonomic computing, i.e. the capacity of evolving and adapting to changing circumstances. In addition, while existing methodologies and algorithms are often sufficiently mature to handle small problems, they are unable to find the optimal solution to large space problems in a computationally tractable time, due to the resulting exponential search space. If the learning phase takes too long, GA algorithms are no longer of interest, and conventional approaches are preferred even if they are less relevant. This is the case for the field of filter design. The real challenge in GAs today is not in the search for new conceptual alternatives but rather in their usability by non-experts. Users seek stable and relevant solutions without being faced with all the evolutionary computation complexity. Another important point should be noted. An extensive analysis of studies related to the application of GAs in the field of filter design shows that it does not clearly benefit from all the advances that have been made in improving the application of GAs to real world problems.

This paper is dedicated to the application of genetic algorithms for designing optimal digital filters. It sets out to propose a hybrid genetic approach based on the best, proven genetic mechanisms and to improve the implementation of GAs. Several intelligent mechanisms are embedded and combined in the GA, which differentiates it from conventional genetic algorithms (Standard GA). To make the hybridization tractable and efficient, we propose an algorithm that consists in selecting, for the local approach, only a reduced set of chromosome prototypes that are both promising and representative of the current population. These chromosomes are more likely to converge towards different local optima. This process avoids excessive computational time costs as only a few chromosomes are concerned. Another interesting feature is the selective procedure itself. It plays the role of a clustering algorithm without its drawbacks as it is fully automatic and much faster. The hybridization and the mechanisms involved afford the GA great flexibility. The framework is a self-adaptive scheme based on a process in which the relevant parameters are implicit, i.e. they are selected by the evolutionary cycle itself. Although our proposal is conceptually general and can be extended to all types of filter, the present paper deals more specifically with finite impulse response (FIR) one dimensional (1D) filters.

The rest of the paper is organized as follows: Section 2 provides a brief literature overview of 1D FIR filter design. Related approaches followed by a summary of our contribution are presented in Section 3. Our Hybrid Genetic Algorithm (HGA) for filter design is detailed in Section 4 and design examples to illustrate the effectiveness of our HGA are given in Section 5, followed by concluding remarks.

2. FIR filter design and problem formulation

A digital filter is a filter that performs operations on a discrete-time signal sampled to remove, extract or to enhance certain aspects of that signal. Digital FIR filters can be used to perform many tasks filter and replace the role of analog filters in many applications. Among their advantages there may be mentioned the possibility of having a linear phase, the stability, the high precision and reliability, reduced physical size. Implementations of digital filters to achieve certain characteristics which are not possible with implementations of analog filters such as the linear phase, the precision and the ability to apply to the signals of very low frequency, such as those found in biomedical applications.

Any linear digital filter can be mathematically specified by a complex-numbered polynomial function, i.e. the transfer function in the Z domain. This polynomial function can be rewritten as the quotient of two product terms with the numerator specifying its zeros and the denominator specifying its poles.

$$H(z) = \frac{Y(z)}{X(z)} = \frac{\prod_{n=0}^{2N}(Z - Z_m)}{\prod_{m=0}^{k}(Z - p_n)} \quad (1)$$

There is no denominator for a FIR filter.

The transform function of a typical FIR filter can be expressed as a polynomial of a complex variable Z^{-1} depending on the filter impulse response (Lim & Oppenheim, 1988):

$$H(z) = \sum_{n=0}^{2N} h(n) * Z^{-n} \quad (2)$$

where $2N$ is the order of the filter which has $2N + 1$ coefficients. $h(n)$ is the filter impulse response calculated by applying an impulse signal at the input.

The frequency response can be derived from the transfer function by computing its values for $Z = e^{j\omega}$.

$$\widehat{H}(\omega) = \sum_{n=0}^{2N} h(n) * e^{-jn\omega} \quad (3)$$