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Adaptive Genetic Modification of FIR LPF for Rich Audio Environment

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ABSTRACT

This abstract offers a digital filter design for use with digital hearing aids. The technique used in this instance is to create a filter to eliminate background noise. The filter's construction is made up of several parallel FIR (Finite Impulse Response) Low Pass Filters. This study demonstrates how FIR filters can provide good results in digital hearing aids with low levels of complexity, resulting in low hardware resource requirements and low power consumption for VLSI design. The optimization process using a genetic algorithm (GA) will yield the filter coefficients for these FIR filters. GA will reduce the discrepancy between the desired magnitude response and the actual magnitude response. Now, an adaptive algorithm is applied to the filter, making it dynamic and responsive to changes in the noise in the speech stream.

Keywords: Genetic Algorithm, Adaptive Algorithm, LMS Algorithm

1. INTRODUCTION

The last 50 years have seen tremendous advancement in the field of adaptive filtering. Additionally, it is still growing today. Due to this, adaptive filters could be used in a wide range of applications, including system identification, echo cancellation, noise cancellation, equalization, control, de convolution, change detection, smart antennas, speech processing, data compression, radar, sonar, biomedicine, seismology, etc. There is no doubt that this would not have been achievable without the VLSI technology required to meet the computing needs of these applications. When a new sample of the signals is made available, a filter becomes adaptive when its coefficients are updated (using a specific method). The selected method should, in theory, be able to track the development of the system being investigated. In doing so, the adaptive filter gains the capacity to work in real time and enhances its performance without requiring human input.

Elements that are fundamental to building an adaptive filter:

Definition of the objective function form:

The objective function can be represented by a variety of metrics, including Mean Squares Error (MSE), Least Squares (LS), Weighted Least Squares (WLS), Instantaneous Square Value (ISV), and Mean Absolute Error. (MSA). Given that it incorporates the expectation operator in its formulation, the MSE is strictly speaking simply a theoretical value because it must be computed from a "infinite number" of single samples. In real life, the LS, WLS, or ISV can come close to this ideal objective function. Given that the objective function is considerably simplified, they differ in terms of implementation complexity and convergence qualities. The LS is practical for usage in static situations. The WLS, on the other hand, is useful in situations when the environment changes gradually or where the measurement noise is not white.

Error signal definition: The definition of the algorithm depends heavily on the error signal selection. Since it may have an impact on a number of traits, such as robustness, convergence speed, and computational complexity.

The minimization algorithm's definition:

The primary focus of optimisation theory, this factor largely influences the rate of convergence and computing complexity of the adaptive process. While using a second-order approximation results in Newton's algorithm, using a first-order approximation results in the gradient search algorithm. When estimating the Hessian, Quasi-Newton's techniques are employed. However, because of the recursive structure employed to estimate the inverse hessian matrix, they are prone to instability issues. In these techniques, the step size regulates the process's general stability, convergence speed, and some aspects of the residual error. Newton's algorithm is produced by second order approximation, but the gradian search algorithm is produced by first order approximation. As a result, it serves as the optimisation theory's major topic. In order to solve these instability issues, an inverted hessian matrix is created.

MAIN CONTRIBUTIONS OF THE RESEARCH:

The primary goal of the research is to develop shadow approaches for combinational algorithms in adaptive filters for the enhancement of voice signal.

The main contributions of the work is as follows:

1.Application of adaptive filters with a fixed LMS algorithm, for the enhancement of speech.

2. Combinational adaptive algorithms are applied to basic adaptive filters to increase the effectiveness of the filters used to process voice signals.

3. improving the overall performance of the Adaptive filters by adding the shadow method to the combinational adaptive algorithms.

4. Combinational adaptive algorithms with a single adjustable parameter may be made more generic by using hybrid approach, both with and without a shadow mechanism.

ORGANIZATION OF THE THESIS:

We divide the thesis into six chapters. The first chapter is the Introduction, which consists of Elements that are fundamental to building an adaptive filter, Main contributions of the research and Organization of the Thesis. Chapter Two contains digital filter types, design of LPF

And its response, Methods to design a FIR Filter and Types of window functions. In Third chapter it contains Adaptive Filter, And its different configurations and Its groups. And its also contains Least Mean Squares(LMS) Algorithm and How to create an adaptive filter with a fixed LMS. The Fourth Chapter contains Genetic Algorithm and Traditional Discrete Generic Algorithm (DGA) Block diagram. The Fifth Chapter contains Results. In which has without using Genetic Algorithm Simulation results and with using genetic Algorithm Simulation results. In Final Chapter, It contains Conclusion and the References that we are used in our project.

2. DIGITAL FILTER DESIGN

The process of creating a signal processing filter that fulfils a number of requirements, some of which may be in conflict, is known as filter design. The goal is to locate a filter implementation that sufficiently satisfies each condition to be helpful. Each need in the filter design process adds to an error function that needs to be reduced, making it an issue involving optimisation. Certain steps in the design process can be automated, but for the majority of cases, a skilled electrical engineer is required to provide quality work.

Digital filters may be divided into two types:

1.The expression for each output sample in finite impulse response (FIR) filters is the weighted sum of the previous N input samples, where N is the order of the filter.

Since FIR filters are often non-recursive and don't employ feedback, they are by nature steady.

The equation for FIR is

$$Y(n) = \sum_{k=0}^{n-1} \mathrm{h(K)x(n-k)}$$

2. IIR filters, also known as infinite impulse response filters, are analogue filters digital equivalent. A linear combination of the prior inputs and outputs determines the output and the subsequent internal state of a filter like this.

The equation for IIR is

$$Y(n) = \sum_{k=0}^{\infty} \mathrm{h(k)x(n-k)}$$

DESIGN OF LOW PASS FILTER:

Specification:

1)cut-off-frequency:0.2π

2)Filter order:25

The desired transfer function of filter is

$$h_d(n) = \frac{\sin 0.2\pi n}{\pi n}$$

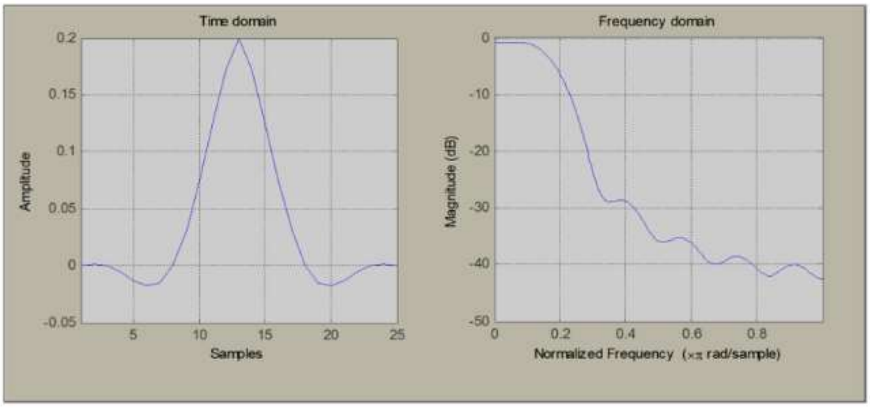

Fig: Frequency response of Low pass filter

By multiplying the desired transfer function with window we can get transfer function of FIR band reject filter i.e.

$h(n) = h_d(n) * w(n)$

METHODS TO DESIGN FIR FILTER:

- Fourier series method
- Frequency Sampling method
- Window method

The majority of these design methods have some sort of flaw, some of them cannot provide optimum designs in any sense, others lack generality, and some require extensive computational effort.

TYPES OF WINDOW FUNCTIONS:

1. Rectangular Window:

The simplest window is rectangular, which simulates the waveform seeming to abruptly switch on and off by replacing all except N values in a data stream with zeros.

W (n) = 1

The weighted function is applied to the M point rectangular window, which corresponds to the Fourier series' direct truncation.

W_r (n) = 1, for(M-1) /2≤n≤ (M-1)/2

= 0, otherwise

2. Triangular window:

Triangular windows are given by:

$$w(n) = 1 - \left| \frac{n - \frac{N-1}{2}}{\frac{L}{2}} \right|$$

Where **L** can be N, N+1, or N-1. The triangular window is the 2nd order *B*-spline window and can be seen as the convolution of two half-sized rectangular windows, giving it twice the width of the regular windows.

3. Bartlett Window:

By tapering the rectangular window sequence linearly from the middle to the ends, we then obtain the M point triangular window given by

W_T (n) = 2n / (M-1) for 0≤n≤ (M-1)/2

= 2-2n / (M-1) for (M-1)/2<n≤ (M-1)

= 0, Otherwise

4. Raised Cosine Windows:

Another class of windows is raised cosine windows that, compared with the triangular window, are smoother at the ends, but closer to one at the middle. The smoother taper at the ends should reduce the side-lobe levels, while the broader middle section reduces distortion of the desired pulse response bound n = 0. To reduce the side-lobe level further, we can consider an even more gradual taper at the ends of the window sequence by using the raised cosine sequence. The various windows in this category are:

1. Hanning window:

Hanning windows are frequently employed with random data because, when compared to the impacts of other windows, they have a minor impact on the frequency resolution and amplitude accuracy of the resultant frequency spectrum. The function, with length L and amplitude 1/L, is given by

$$w_0(x) \triangleq \begin{cases} \frac{1}{L}\left(\frac{1}{2}+\frac{1}{2}\cos\left(\frac{2\pi x}{L}\right)\right) = \frac{1}{L}\cos^2\left(\frac{\pi x}{L}\right), & |x| \leq L/2 \\ 0, & |x| > L/2 \end{cases}$$

2. Hamming Window:

Since there is no limit to the quantity of data points that computers can process, all transmissions are terminated at either end. This is what generates the peak's visible ripple on each side. The frequency spectrum of the original signal is more precisely depicted thanks to the hamming window's reduction of this ripple. Hamming window is given by

$$Wh(n) = 0.54 - 0.46\cos\left(\frac{2\pi n}{M} - 1\right), \qquad for\ 0 \leq n$$

$$= 0 \qquad otherwise$$

3.Blackman window:

In the resultant FIR filter, the Blackman window displays an even smaller maximum stopband ripple than the Hamming window does. Blackman window is given by

$$Wh(n) = 0.42 - 0.5\cos\left(\frac{2\pi n}{M-1}\right) + 0.08\cos\left(\frac{4\pi n}{M-1}\right), \qquad for\ 0 \leq n \leq (M-1)$$

$$= 0 \qquad otherwise$$

3. ADAPTIVE FILTER

Digital filters with self-adjusting features are referred to as adaptive filters. It has the ability to use an adaptive algorithm to automatically modify its filter coefficients to the input signal. Modern digital signal processing (DSP) devices use adaptive filters extensively in applications such active noise control (ANC), adaptive control systems, telephone echo cancellation, noise cancellation, communications channel equalisation, and biomedical signal amplification.

Generally speaking, adaptive filters can adapt to signal-changing surroundings, spectral overlap between noise and signal, and unknown or time-varying noise.

An adaptive filter typically comes in four different configurations:

1. system identification
2. noise cancellation
3. equalization
4. adaptive prediction

In communications, control, and many other applications where the statistical properties of the signals to be filtered are either unknown a priori or, in some circumstances, slowly time varying, adaptive filtering is widely used. There have been numerous proposals for adaptive filtering algorithms, and they can be broadly divided into two groups

- Least Mean Squares (LMS) algorithm
- Recursive Least Squares (RLS) algorithm

LEAST MEAN SQUARES ALGORITHM(LMS):

The LMS algorithm typically converges slowly despite having a low computing complexity of O(L) (where L is the number of taps in the adaptive filter). On the other hand, the RLS algorithm, which has a complexity of O, has a quick convergence but is more expensive computationally (L2). Various strategies have been put forth to enhance the LMS algorithm's convergence property and to simplify the RLS algorithm

The standard LMS algorithm displays steady-state tracking behavior that is comparable to a linear first-order learning filter when tracking a time-varying signal

How to create an adaptive filter with a fixed LMS:

1. Produce or capture a voice signal.

2. Produce or capture a signal of noise.

3. Use a low pass filter to corroborate noise.

4. Combine the actual noise signal with the noise signal.

5. Using the Fixed LMS Algorithm, send this combined signal to the adaptive filter.

6. Determine the error e (n) Adjust the weight equation with (n) Until error is minimized.

7. repeat step 6 and determine adaptive output y(n).

8. Determine the input and output SNR.

4. GENETIC ALGORITHM

A population of possible alternatives to an optimization problem (referred to as individuals, creatures, organisms, or phenotypes) is evolved towards better solutions in a genetic algorithm.

Traditionally, solutions are represented in binary as strings of 0s and 1s, although other encodings are also feasible. Each possible alternatives have a set of properties (its chromosomes or genotype) that can be changed and modified. By relying on biologically inspired operators like mutation, crossover, and selection, genetic algorithms are frequently employed to produce high-quality solutions to optimization and search problems. The population in each iteration of the evolution is referred to as a generation, and the process typically begins with a population of randomly created individuals. Each generation evaluates each member of the population in terms of their fitness, which is often the value of the objective function in the optimization problem being solved.

Generally, a genetic algorithm needs

1.Genetic representation of problem domain,

2.fitness function to quantify the scope of the.

After the genetic representation and fitness function have been established, a GA starts by creating a population of solutions and then continuously using the mutation, crossover, inversion, and selection operators to enhance it

- Initialization: Depending on the nature of the issue, the population can range from few hundred to thousands of potential solutions. The beginning population is frequently produced at random, allowing for all conceivable resolutions.
- Selection: For each succeeding generation, some of the current population is chosen to reproduce for that generation. Individual solutions are chosen using a fitness-based method, where fitter solutions are often more likely to be chosen (as determined by a fitness function). The fitness function, which is computed over the genetic representation, assesses the effectiveness of the solution that is represented. Always subject to problem dependence is the fitness function.
- Genetic operators: Mutation and crossover are the genetic operators. The next stage is to create a second generation population of solutions from the ones that were chosen using a combination of the genetic operators crossover (also known as recombination) and mutation.
- Heuristics: To make the calculation quicker or more reliable, additional heuristics may be used in addition to the main operators mentioned above. The speciation heuristic restricts crossover between candidate solutions that are too similar; this promotes population variety and helps avoid premature convergence to a less ideal solution.
- Termination: This generational process is carried out repeatedly until a termination condition is met.

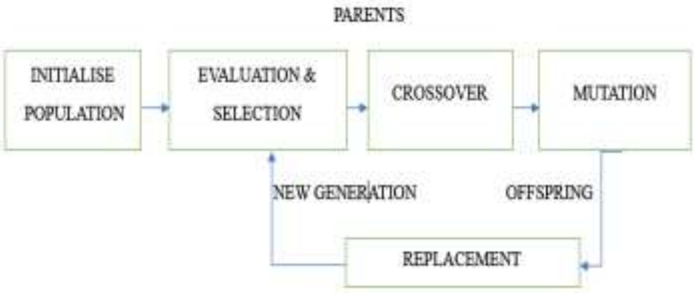

Fig: Traditional Discrete Generic Algorithm (DGA) Block

5. RESULTS

Without using Genetic Algorithm:

Here, we used voice and noise to the adaptive filter to get the simulation results. We used a genetic algorithm to create filter coefficients, which we then applied to the adaptive filter in order to enhance performance in the following stage.

Simulation Results:

The Simulation results obtained by passing speech and noise signal to the adaptive filter are as shown below.

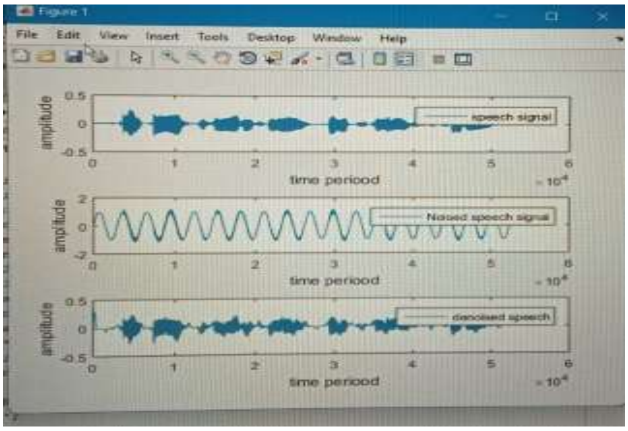

Fig: Simulation results without GA

Parameters:

Input SNR in dB = 0.0017

Output in dB = 60.4580

Mean square Error = 0.5005

With Genetic Algorithm:

FITNESS FUNCTION:

The fitness function provides a way for the GA to analyse the performance of each chromosome in the population. Since the fitness function is the only relation between the GA and the application itself, the function must be chosen with care. The fitness function must reflect the application appropriately with respect to the way the parameters are to be minimized.

Fitness function is:

(n)[(0.6875)-((sin(0.6875*pi*n))/(pi*n))]

Generation	f-count	f(x)	f(x)	Generations
31	800	2.638e-05	0.08157	2
32	825	2.638e-05	0.1359	3
33	850	1.64e-05	0.1067	0
34	875	1.64e-05	0.08082	1
35	900	1.64e-05	0.07122	2
36	925	1.64e-05	0.1163	3
37	950	1.64e-05	0.06085	4
38	975	1.64e-05	0.05703	5
39	1000	1.64e-05	0.03138	6
40	1025	1.64e-05	0.04814	7
41	1050	1.64e-05	0.096	8
42	1075	1.64e-05	0.06336	9
43	1100	1.64e-05	0.0975	10
44	1125	1.64e-05	0.02686	11
45	1150	1.64e-05	0.05129	12
46	1175	1.64e-05	0.03797	13
47	1200	4.265e-07	0.02886	0
48	1225	4.265e-07	0.07087	1
49	1250	4.265e-07	0.07603	2
50	1275	4.265e-07	0.08699	3
51	1300	4.265e-07	0.07626	4

Fig: Filter Coefficients

FITNESS FUNCTION OUTPUT:

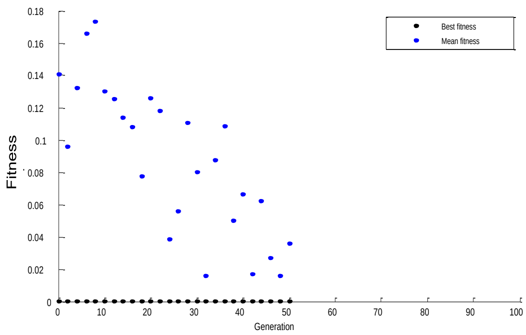

Fig: Fitness function output plot

SIMULATION RESULTS:

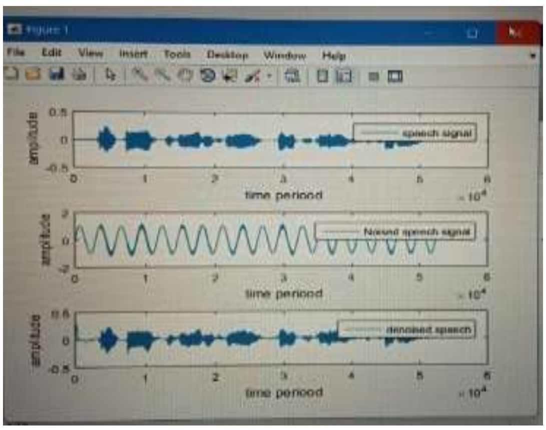

Fig: Simulation results with GA

Fig: Mean Square Error Performance

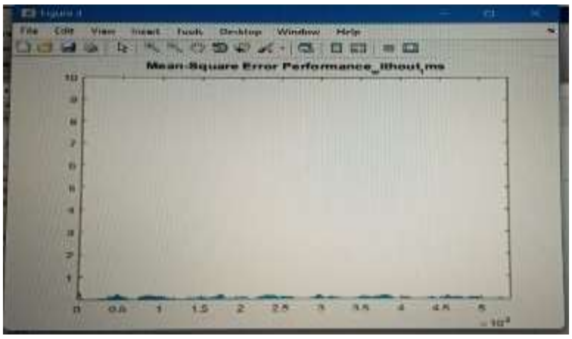

Fig: Mean Square Error Performance Without RMS

Parameters:

Input SNR in dB = 0.0017

Mean Square Error for FIR filter = 0.0027

Output SNR in dB = 61.1973

Mean square Error for GA FIR = 0.0010

6. CONCLUSION

The article has outlined the numerous methods used to create FIR filters. The MATLAB software package's filter design techniques are offered in an appendix as well. The outcomes of the Function Approximation problem simulation show that the Genetic Algorithm outperforms alternative approaches of optimization for both unimodal and multimodal functions. Real Coded GA and Differential Evolution GA developed a system model that was exactly in line with the output of the known plant. Consequently, this paper provides a summary of a number of recent advancements in genetic algorithms. It covers both theoretical elements of genetic algorithms and their variations as well as some potential uses for genetic algorithms.

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