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Genetic algorithm for Echo cancelling

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Abstract

In this paper, echo cancellation is done using genetic algorithm (GA). The genetic algorithm is implemented by two kinds of crossovers; heuristic and microbial. A new procedure is proposed to estimate the coefficients of adaptive filters used in echo cancellation with combination of the GA with Least-Mean-Square (LMS) method. The results are compared for various values of LMS step size and different types of crossovers which are all satisfactory. Reverse SNR is used as the fitness function. It can estimate an echo path with definite length of impulse response with an adaptive filter with desired length. Results show that the proposed combined GA-LMS method operates more satisfactory than simple GA in terms of the number of generations needed to achieve a particular amount of echo cancellation. Different tests show that GAs running with heuristic crossover converge faster than GAs with microbial crossover. Results are also compared with LMS algorithm. Although LMS is faster, but its solutions are less precise and it diverges in some cases. But our proposed method always converges.

Keywords: echo cancellation, heuristic crossover, microbial crossover, genetic algorithm

1. Introduction

Echo arises due to impedance mismatch at the hybrid in Public switched telephone networks (PSTN). In case of packetized voice, the delays inherent in the network, due to jitter buffers, transport latency, etc., make remedial measures essential. Echo is not a problem by itself; however, when round-trip propagation delays become large, untended echo will significantly degrade the communication quality [1].

With the recent proliferation of packet networks for voice communications, echo cancellation requirements have changed significantly. There is now a perceived need to handle significantly longer echo tails in voice gateways that connect the packet networks with PSTN, typically of the order of 48-128 ms. At 8 KHz sampling rates, this translates to FIR filter orders of 384 to 1024. These longer tails not only lead to increased processing complexity, but also make it difficult for many of the simpler echo cancellation designs that were previously adequate, to deliver the needed performance.

Adaptive filtering is used widely to improve communication quality by eliminating line echoes [1].

In this paper, echo cancellation is done using genetic algorithm (GA). The models of echo path introduced by ITU in G.168 recommendation are used as test cases. The genetic algorithm is implemented by two kinds of crossovers; heuristic crossover and the microbial crossover. Different tests show that GAs running with heuristic crossover converge faster than GAs with microbial crossover.

In this paper a new procedure is proposed to estimate the coefficients of adaptive filters used in echo cancellation. It combines the Genetic Algorithm with Least-Mean-Square (LMS) method, i.e. in each generation of GA, after the production of new children, an LMS algorithm will be applied to these new children. The experiments are done for various values of LMS step size. This algorithm is also tested for different types of crossovers which are named above.

Reverse SNR is used as the fitness function. The power of the error signal is divided to the power of real echo to achieve the ratio of reverse SNR. This fitness function is defined in such a way that can estimate an echo path with definite length of impulse response with an adaptive filter with desired length.

Comparing the number of generations needed to achieve a particular amount of echo cancellation of the simple genetic algorithm with combined GA-LMS show that the proposed combined GA-LMS method operated more satisfactory. If the step size in our proposed increases, it finds the solution in less iterations.

Results are also compared with LMS algorithm. Although LMS is faster, but its solutions are less precise and it diverges in some cases. But our proposed method always converges and gives more precise results.

In this paper, we first introduce echo cancellation using FIR adaptive filters and LMS algorithm for estimating the coefficients of adaptive filters in section 2. In section 3, the motivations and implementations which are done with the usage of GA are described. The heuristic crossover and microbial cross over and also various feasible fitness functions are included. The proposed combined GA-LMS method is described in this section. In section 4, Experimental results based on simple GA and the proposed combined GA-LMS method are presented. In section 5, summary and conclusions are reviewed.

2. Echo cancellation using FIR adaptive filters and LMS algorithm

Echo cancellation can be done using an adaptive filter to identify an unknown echo path. In the fig.1, the unknown echo path is placed in parallel with the adaptive filter.

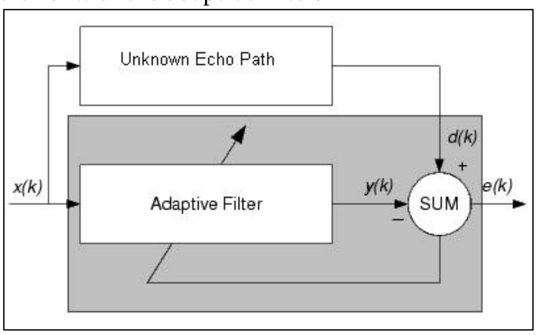

Fig.1. Using an adaptive filter to identify an unknown echo path.[2]

x(k) is the input signal of the near end speaker. d(k) is the echo signal that the near end speaker hears. This signal is the echo of x(k) which is passed through unknown echo path and is heard at near-end.

The objective is to use an adaptive filter and estimate its coefficients in such a way that the output of adaptive filter, y(k), could cancel out the echo signal, d(k). It is done via applying the same input to both adaptive filter and unknown echo path and comparing these outputs to achieve an error signal, e(k), which is desirably low. Clearly, when e(k) is very small, the adaptive filter response is close to the response of the unknown echo path.
The input fed to both the adaptive filter and the unknown is chosen Gausian white noise to cover all frequency ranges. Moreover, the training input signal should be uncorrelated, otherwise the adaptive filter may adapt to the training input signal rather than the unknown echo path.

Adaptive FIR filters have been extensively used with non-stationary signals in echo cancellation. When the adaptive FIR filter is of the form shown in (1)

$$H(z) = \sum_{n=0}^{N-1} b_n z^{-n} \tag{1}$$

The mean-squared error $E[e_k^2]$ is a quadratic function of the filter weights b_n. A number of algorithms for adjusting the filter coefficients b_n can be shown to converge to the coefficients of the filter with minimum mean-squared error [3].

2.1. Adaptive filter

Given the realization x (t) of a stochastic signal process {x (t)} an adaptive filter $F: x(t) \rightarrow \hat{y}(t)$ is defined as a system according to (2).

$$\hat{y}(t) = F[x(t)] \approx y(t) \tag{2}$$

That approximates the desired realization y(t) of a stochastic signal process {y(t)} with respect to a time-dependent optimality criterion *E(t)* (fig.2).

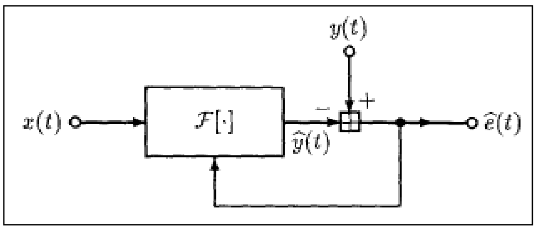

Fig.2. Adaptive filter [4]

In accordance with the method of least squares the optimality criterion requires the minimization of the moving error

$$E(t) = \sum_{\tau=0}^{L-1} w(\tau).\hat{e}^2(t-\tau) \xrightarrow{filter\,coeeff.} \text{Minimum}$$

with residual $\hat{e}(t) = y(t) - \hat{y}(t)$, window length L and weight function w(t). Minimizing $E(t)$ yields the estimated coefficients of the adaptive filter F [4].
Many algorithms for estimating the coefficients of adaptive filters have been introduced in the literature [1][5]. Among them, Least Mean Square (LMS) method has been selected to compare the results with. Also a new Genetic Algorithm sheme is introduced based on this method. In fig.3 a summary of the LMS algorithm can be seen.

Parameters:

- M=number of taps
- μ =step-size parameter

$$0 \le \mu \le \frac{2}{tap-input\,power}$$

$$tap-input\,power = \sum_{k=0}^{M-1} E\left[|u(n-k)|^2\right]$$

Initialization:
If prior knowledge on the tap-weight vector $\hat{w}(n)$ is available, use it to select an appropriate value for $\hat{w}(0)$. Otherwise, set $\hat{w}(0) = 0$.

Data:

- Given:
  $u(n) = M \times 1$ tap-input vector at time n
  $d(n)$ =desired response at time n
- To be computed:
  $\hat{w}(n+1)$ =estimate of tap-weight vector at time n+1

Computation: for n=0, 1, 2, . . . , compute

$$e(n) = d(n) - \hat{w}^H(n)u(n)$$

$$\hat{w}(n+1) = \hat{w}(n) + \mu u(n) e^*(n)$$

Fig.3. Summary of the LMS algorithm [5]

The stochastic gradient algorithms and variants such as the least-mean-square (LMS) remain the most commonly used techniques for acoustic echo cancellation because of their simplicity and low computational complexity.

While LMS method remains the lowest cost method, its convergence performance, which is already impacted by non-white inputs, is known to degrade as the filter length increases.

3. Implementations, motivations and proposed combined GA-LMS algorithm

In this section, the motivations and implementations which are done with the usage of GA are described. The heuristic crossover and microbial cross over and also various feasible fitness functions are included. The proposed combined GA-LMS method is described in this section.

3.1. Crossover

Crossover combines two individuals, or parents, to form a new individual, or child, for the next generation. Our genetic algorithm is implemented by two kinds of crossovers; the heuristic crossover and the microbial cross over. We introduce these kinds of crossovers here:

Heuristic crossover: creates children that lie on the line containing the two parents, a small distance away from the parent with the better fitness value in the direction away from the parent with the worse fitness value [2].

Microbial crossover: in this kind of crossover two parents are selected and their fitness values are compared. The parent with the better fitness will go to the next generation unchanged. The parent with the worse fitness will take a part of the better parent’s gene and replace it with its own. The procedure can be seen in fig.4.

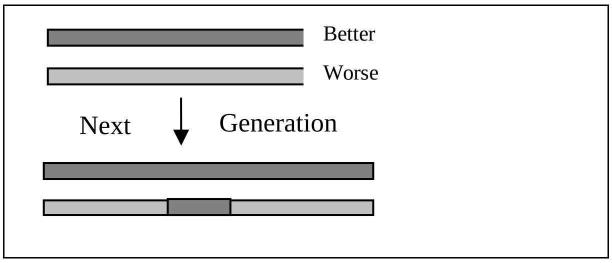

Fig.4. Microbial crossover

3.2. Combined Genetic Algorithm and LMS method

In this paper a new procedure to estimate the coefficients of adaptive filter is proposed. It combines the Genetic Algorithm with Least-Mean-Square (LMS) method, i.e. in each generation of GA, after the production of new children, an LMS algorithm will be applied to these new children. LMS algorithm will give a rough estimate of every coefficient of adaptive filter based on the results of GA. The results of LMS algorithm will construct the next generation of the GA. In other words, in this approach GA and LMS algorithms will be applied one after the other to solve the problem.

As it is well known, the main advantage of GA is that it will not remain in local minima, but is a slow process. LMS algorithm is a faster algorithm but may diverge in some cases or may remain in local minima and its results are not as accurate as GA-based procedures. The proposed approach combines the benefits of both algorithm while avoiding the very slow rate of GA and remaining in local minima which may result from LMS.

3.3. Fitness function

A suitable fitness function should be introduced to evaluate the fitness of each individual in different generations of GA. The function is defined as follows:

First a random Gaussian white noise is generated and applied to both of the echo path and the adaptive filter which tries to estimate it. The output of the echo path is the echo signal or in terms of adaptive filters, is the desired signal which we try to estimate in order to cancel out. The output of the adaptive filter is the estimated response of echo path. The more the estimated signal looks like the desired output, the better the estimation of the echo path is done.

In this function the power of the error signal, i.e. the sum of squares of the differences of the estimated echo and the real echo over different samples of outputs is divided to the power of real echo to achieve the ratio of reverse SNR. The less this value, the better the cancellation is done. It is important to note that with regard to the group delay of FIR filters, outputs with indices greater than half of the impulse response length are valid. This fitness function is defined in such a way that can estimate an echo path with definite length of impulse response with an adaptive filter with desired length. The value of the defined reverse SNR is assumed as the stopping criteria. If it reaches 10^(-7) , it means the echo is suppressed below -70db, which is meaningful with regard to quantization noise which offers an SNR with rough value of 50dB in typical cases.

Other fitness functions were tested before the one introduced above. Some of them are pointed to here:

1. A fitness which is the power of the error signal, i.e. the sum of squares of the differences of the estimated echo and the real echo over different samples of outputs but not normalized to the power of real echo.
2. A fitness which is the power of the error signal that is computed using a moving window, i.e. a particular length of output signal with some length is used to compute the error power. The location of applying window changes with consequent generations.
3. A fitness which is the power of the windowed error signal, but the length of widow is increased by the generations.

We concluded that the SNR-based fitness is the best one because it eliminates the effect of amplitude of random input. Moreover it reports the quality of operation over the complete duration of the signal, not just a part of it.

4. Experimental results

The line echo cancellation deployment and performance requirements are governed by various standards developed by the International Telecommunications Union (ITU), such as G.168 [6]. The G.168 document also includes many echo path models (8 in the most recent version) to assist in line echo cancellation performance evaluations. In this paper the first model introduced in the G.168 document is used as the test echo path. The impulse response of the first echo path model of G.168 is seen in fig.5 [6].

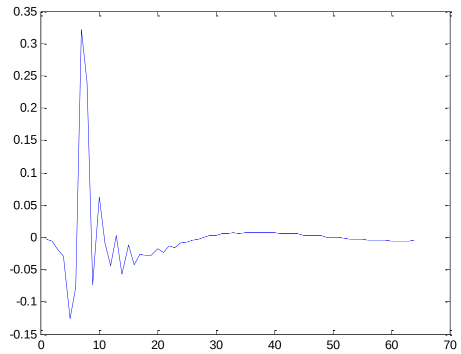

Fig.5. The first model introduced in the G.168 document used as the test echo path [6]

For solving the problem of echo cancellation using genetic algorithm, GAtool of MATLAB is used. The parameters and options needed in all cases, if not mentioned directly, are set as Table.1.

Table.1
The chosen set of parameters and options of genetic algorithm

options	values
population	
Population type	Vector double
Population size	600
Creation function	Uniform
Initial population	Random
Initial range	[-1, 1]
Fitness scaling	
Scaling function	Rank
Selection	
Selection function	Stochastic uniform
Reproduction	
Elite count	10
Crossover fraction	0.8
Mutation	
Mutation function	Gaussian
Scale	1
Shrink	1
Crossover	
Crossover function	Heuristic
Ratio	1.2
Migration	
Direction	Forward
Fraction	0.2
Interval	20
Hybrid function	
Hybrid function	None
Stopping criteria	
Generations	infinite
Time limit	infinite
Fitness limit	10^(-7) or -70dB
Stall generations	50
Stall time limit	200

This problem is solved using GA with heuristic cross over with ratio equal to 1.2, combined GA-

LMS with heuristic cross over with ratio equal to 1.2 and microbial crossover and LMS step size equal to 0.001 and 0.04. The summary of results is seen in Table.2.

Table.2
Number of generations for 50dB and 70dB echo cancellation for GA with heuristic cross over (ratio=1.2), Combined GA-LMS with heuristic cross over (ratio=1.2) and microbial crossover and LMS step size equal to 0.001 and 0.04

Algorithm	Number of generations for 50dB echo cancellation	Number of generations for 70dB echo cancellation
GA with heuristic cross over (ratio=1.2)	718	1226
Combined GA-LMS with heuristic cross over (ratio=1.2) and LMS step size=0.001	249	330
Combined GA-LMS with heuristic cross over (ratio=1.2) and LMS step size=0.04	54	68
Combined GA-LMS with microbial cross over and LMS step size=0.001	1245	2018
Combined GA-LMS with microbial cross over and LMS step size=0.04	43	57

Different tests show that in similar conditions, GAs running with heuristic crossover converge faster than GAs running with microbial crossover, because in microbial crossover near half of the next generation is the same as the previous generation.

It is also seen that our proposed combined GA-LMS method converges in so fewer iterations than simple GA.

Results are also compared with LMS algorithm. Although LMS is faster, but its solutions are less precise and it diverges in some cases. As it is seen from Table.2, the most number of iterations needed in our simulations is 2018. If we run the LMS algorithm with 600*2018 iterations, in which 600 is the Population size and 2018 is the most number of iterations needed in GA-based simulations, the measure of echo cancellation would be only 33dB. The step size was set to 0.001. It is obvious that GA-based results are more accurate.

In LMS algorithm if the step size increases, the rate of convergence increases too. But the step size should be less than the limit introduced in section 2, unless it diverges. If the step size in our proposed increases, it finds the solution in less iterations.

LMS Algorithm would diverge for some step sizes, for example, in our echo path, with step size equal to 0.04 after a fast convergence, LMS diverges. But our proposed method always converges.

5. Summary and conclusion

Echo cancellation using genetic algorithm is done. The genetic algorithm is implemented by two kinds of crossovers; heuristic crossover and the microbial crossover. Different tests showed that GAs running with heuristic crossover converge faster than GAs running with microbial crossover.

The power of the error signal, i.e. the sum of squares of the differences of the estimated echo and the real echo over different samples of outputs is divided to the power of real echo to achieve the ratio of reverse SNR which is used as the fitness function. This fitness function is defined in such a way that can estimate an echo path with definite length of impulse response with an adaptive filter with desired length.

A new procedure to estimate the coefficients of adaptive filter used in echo cancellation is proposed. It combines the Genetic Algorithm with LMS method, i.e. in each generation of GA, after the production of new children, an LMS algorithm will be applied to these new children. The experiments are done for various values for the used LMS step size. It was seen that even for large LMS step sizes which LMS algorithm would diverge, he proposed combined GA-LMS converges. This algorithm is also tested for different types of crossovers which are implemented.

Comparing the number of generations needed to achieve a particular amount of echo cancellation of the simple genetic algorithm with combined GA-LMS show that the proposed combined GA-LMS method operated more satisfactory.

Results are also compared with LMS algorithm. Although LMS is faster, but its solutions are less precise and it diverges in some cases. But our proposed method always converges.

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Appendix

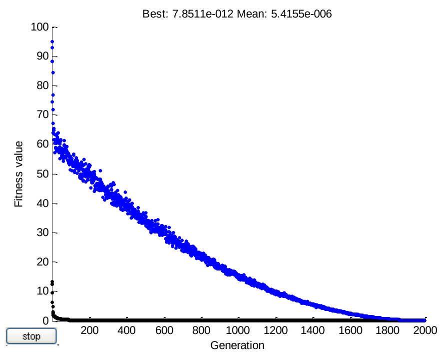

Fig.6. mean and best fitness vs. generations with heuristic crossover with error power fitness

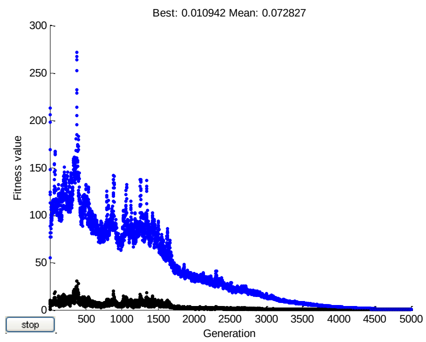

Fig.7. mean and best fitness vs. generations with heuristic crossover with error power fitness with window of length 14

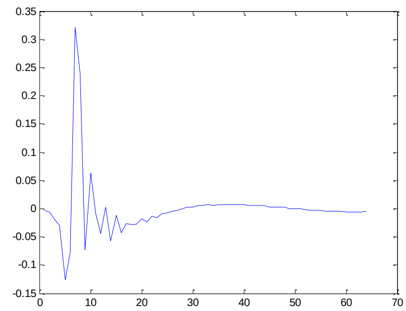

Fig.8. The echo path model 1of G.168 estimated with length of 64 with proposed combined GA_LMS method and 70 dB echo cancellation

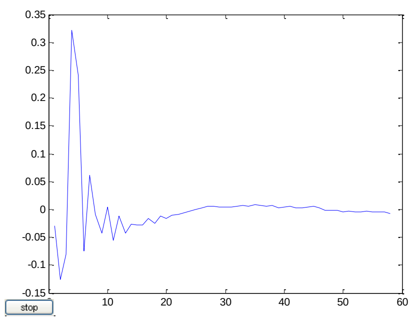

Fig.9. The echo path model 1 of G.168 estimated with desired length of 5