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ADAPTIVE NOISE CANCELLATION BASED ON NLMS ALGORITHM

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Abstract

The main goal of this paper is to present an adaptive filter system using NLMS (normalized least mean square) algorithm for noise cancellation. The proposed algorithm has less computational complexity and better convergence property than the former algorithms like spectral subtraction algorithm. We use TIMIT criterion voice and Noisex-92 for the experiment. The experimental result shows the feasibility of our algorithm can filter noise from voice effectively.

I. Introduction

Noise cancellation is a variation of optimal filtering that involves producing an estimate of the noise by filtering the reference input and then subtracting this noise estimate from the primary input containing both signal and noise [1]. Widrow et al. presented LMS algorithm which could be widely used in field of automatic control, radar and signal processing [2].

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The initial convergence speed, steady state maladjustment and tracking performance are three important technology indicators that determine the superiority and inferiority of the adaptive algorithm. Since the disturbing noise exists inevitably in the input signal, LMS algorithm will generate additive noise [3]. In order to solve this problem, various step-size LMS algorithms have been researched to achieve both fast convergence and small steady-state error [4]. The variable-step-size LMS (VSS-LMS) algorithm is using some value provided in the adaptive processing as a standard measure and adjusts the step-size.

Section II presents the theory and structure of NLMS filter and Section III explains the experimental results. Finally Section IV gives conclusion and the future works.

II. NLMS Algorithm

The least mean square algorithm is a widely used algorithm for adaptive filtering. It has been extensively analyzed in the literature, and a large number of results on its steady state maladjustment and its tracking performance has been obtained. Figure 1 is the basic block diagram of LMS adaptive filter [4].

The algorithm is described by the following equations (1), (2), (3):

$$y(n) = W^T(n)X(n), \tag{1}$$

$$e(n) = d(n) + v_0 - y(n), \tag{2}$$

$$W(n+1) = W(n) + 2\mu e(n)X(n). \tag{3}$$

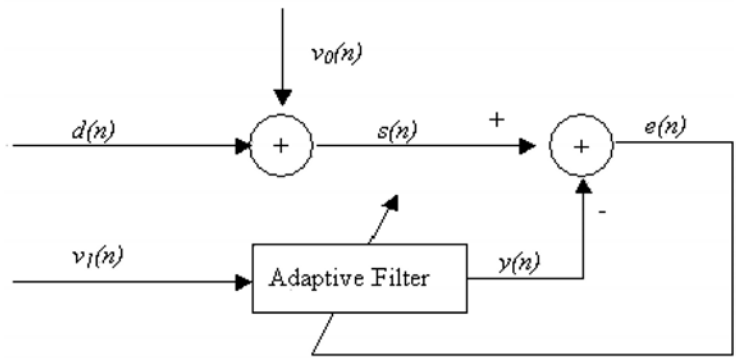

Figure 1. LMS filter diagram.

Equation (1) calculates the output $y(n)$ of adaptive filter, $X(n)$ is the input vector. Equation (2) calculates the error, $d(n)$ is the desired output. Equation (3) shows the weight iteration, $W(n)$ is the weight coefficient vector of adaptive filter in time *n*, μ is the step-size parameter which controls the stability and convergence speed of the LMS algorithm.

The main drawback of the LMS algorithm is sensitive to scaling of its input $X(n)$. This makes it very hard to choose a learning rate μ that guarantees stability of the algorithm [5]. The normalized least mean squares filter (NLMS) is a variant of the LMS algorithm that solves this problem by normalizing with the power of the input. The NLMS algorithm can be summarized as:

$$W(n+1) = W(n) + \frac{\mu}{\varepsilon + X^T(n)X(n)} e(n)X(n). \tag{4}$$

Equation (4) has been improved by equation (3) and it is the step-size iteration equation. In this equation: ε is a constant, usually $\varepsilon \approx 0.01$ for preventing the undersize of $|X(n)|^2$ from causing the oversize of step-size μ, resulting in the divergence. Respect to the LMS algorithm, the only difference is the coefficient updating equation.

III. Experimental Results

In this section, we evaluate the performance of NLMS algorithms and compare it with LMS filters. The NLMS adaptive filter uses the desired signal and the reference signal, to automatically match the filter response. As it converges to the correct filter model, the filtered noise is subtracted and the error signal should only contain the original signal [6]. In our experiment, the desired signal is composed of some colored noises and voice signals. We use the noise sampling from Noisex-92 database [7], testing with the TIMIT standard voice database, use the sampling FAKS0_SA1.WAV, sampling frequency $f_s = 16$ kHz. We separately mix the original signal with different kinds of noises: white noises and babble noises. In these noises, white noises are stationary noises, babble noises are non-stationary noises, respectively [8]. Figure 2 shows the behavior of the LMS algorithm and the NLMS algorithm in a stationary environment with the white noise signal. The NLMS algorithm has reduced the tradeoff between maladjustment and convergence rate [9].

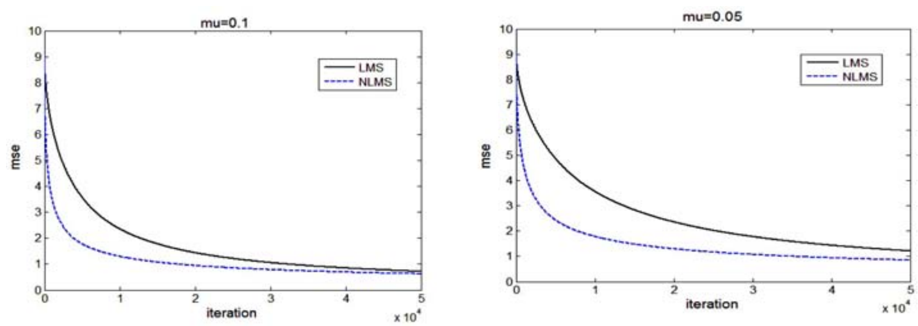

Figure 2. Comparison of smoothed MSE of LMS and NLMS algorithm when $mu = 0.1$ and $mu = 0.05$.

We use the signal to noise ratio (SNR) and test the mean opinion score (MOS) value by the perceptual evaluation of speech quality (PESQ) for analyzing the noise cancellation performance [10, 11].

We select white noise and babble noise to do the PESQ test. The input SNR of white noise and babble noise is 12.139 dB and 4.287 dB. The performance comparison result of LMS algorithm, NLMS algorithm and spectrum subtraction is showed in Table 1. The mixed signals with the voice signals and white noise signals are for test 1 in Table 1 and the mixed signals with the voice signals and the babble noise signals are for test 2. We can see that the proposed algorithm outperforms any other algorithm in stationary and non-stationary noisy environments.

Table 1. The PESQ MOS test result

	Spectrum subtraction	LMS	NLMS
Test 1	2.7321	2.6865	2.9045
Test 2	3.0812	3.1596	3.2379

IV. Conclusions

In this paper, we analyzed a NLMS algorithm and tested the noise cancellation program in stationary and non-stationary noisy environment using this algorithm. Compared with other filter, the result shows NLMS algorithm has faster convergence speed, better tracking performance, and adjusts the step-size more effectively. In future work, by utilizing the findings of this study, new variable-step size algorithms can be developed in order to optimize filter performances.

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