A Feed-forward Switched Adaptive Filtering configuration for Underwater Acoustic Signal Denoising Technique with low-complexity

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***Abstract*—The Underwater acoustic communication is difficult by virtue of the noise that exists undersea. This can be caused by both natural phenomena, like waves and currents, as well as artificial sources such as ships and boats. In order to reduce or eliminate this interference, it is necessary to process the signal before further processing. One way of doing this is through denoising. However, because noise constantly fluctuates in intensity, predicting its future behavior becomes almost impossible. To address this problem, we propose a new method for filtering underwater communications using an superlative feed-foward switched adaptive filter model using Signed Error variant of Least Mean Square (SELMS) and Signed Data variant of Least Mean Square (SDLMS) algorithm that takes into account signed form LMS values. The effectiveness of the filter is tested using a clean fish sound that has been tainted by noises from underwater vessels from the ShipsEar database.**

***Index Terms*—SELMS, SDLMS, Least Mean Square, adaptive noise cancellation,**

I. Introduction

Reducing human noise remains the foremost obstacle in transmitting signals underwater [1] . The objective of this research is to explore the effectiveness of utilizing the adaptive noise cancellation method, a prevalent approach in telecommunications for signal denoising [2], with feedforward switched adaptive filters in order to denoise underwater signals. The most effective noise-cancelling method for signal denoising is a feed forward switched adaptive filter due to their ability to automatically adjust filter coefficients using adaptive algorithms based on output error signals without requiring any specialized knowledge, adaptive filters are suitable for a wide range of applications, such as telephone echo cancellation [3], noise cancellation [4], channel equalization, and biomedical signal enhancement [5]. By employing suitable algorithms, like LMS and its variations, enhances the effectiveness of the filter. Despite the fact that the LMS algorithm [6] delivers gradational confluence and requires smaller computations, to attain a fast confluence rate, a change in filter structure has been suggested by certain experts to address steady-state MSE. By adding multiple stages with distinct step-sizes automatically, a quicker convergence of the mean squared error (MSE) can be achieved using Multistage SDLMS Adaptive Filter model [7] suggested by Hannah et al. A predictor for lossless audio coding is created by cascading high order of LMS filters and low order of Recursive Least Square (RLS) filters, as put forward by Yu et al. [8].Ahmed et al. proposed a cascaded predictor utilizing Recursive Least Square-Least Mean Square, which offers quicker convergence and improved prediction gain. [9], improved line amplifier output SNR. The Finite Impulse Response (FIR) or the non-recursive filter cascaded structure suggested by Prandoni et al. [10], the application of adaptive linear prediction demonstrates that a recursive model achieves the convergence to an ideal predictor at a faster rate when compared to a single-stage filter. To improve the quality of speech that contains significant power fluctuations, a new adaptive speech denoising algorithm has been introduced, which is based on the adaptive least mean square method [11]. Artefacts from ambulatory Electrocardiogram (ECG) impulses are successfully eliminated by a multistage adaptive filter design. Optimum MPEG-lossless audio coding reduction ratio [13] is achieved with a cascaded RLS-LMS predictor. Utilizing adjustable filters based on the Least Mean Square algorithm to separate the foetal phonocardiogram from the abdominal signal mixture [14].In regards to SNR, the two [15] and three-stage [16] LMS adaptive filter designs proposed for adaptive noise cancellation exhibit superior performance to that of standard LMS adaptive filters. An adjustable recursive filter is suggested in narrow band active noiseless mode using the filtered variant of least square [17]. The cascade model has been shown to have faster convergence and reduce noise more effectively. The underwater picture restoration using diffraction-bounded images [18]. Enhancing the image to remove noise from it [19]. An ideal adaptive filter structure that determines the most accurate estimation of the desired signal using the least mean square (LMS) and normalised LMS (NLMS) algorithms [20]. Effectively denoising and recovery of the PCG data using an Adaptive Noise Cancellers-based filter model [21].

Based on the aforementioned experiments, the multi-stage adaptive filter model outperforms the adaptive filter with a solitary stage, as is commonly used traditionally in several applications, including signal augmentation, noise cancellation, echo cancellation, channel equalization, system identification, and speech processing, among other. Feed-forward filters and the related algorithm are constantly updated to get the best performance in the feed-forward adaptive filter model approach that we propose in this research to denoise the signal. The given filtering model denoises underwater audio signals using the sign data LMS and sign error LMS method, which involves the fewest calculations.

II. PROPOSED FEED-FORWARD SWITCHED FILTER

The primary attributes of the suggested filter model are the automatic modification of the feed forward filters and the selection of the appropriate algorithm for each filter. The noisy signal for stage I ANC's initial input is represented by $d_1(k) = s(k) + c(k)$, whereas the reference input is represented by noise signal $c^{'}(k)$. The erroneous signal from the prior ANC serves as the beginning input for the future ANC , while the noise from the previous ANC is used as the current stage's input for reference noise. The suggested feed forward SDLMS and SELMS adaptive filter design is depicted in Figure (1). The parameters for the suggested filter model may be found in the following:

$$d_1(k) = s(k) + c(k). \tag{1}$$

$$x_1(k) = c^{'}(k). \tag{2}$$

$$e_1(k) = d_1(k) - y_1(k) \tag{3}$$

is the error from stage I ANC's first stage, with $y_1(k)$ standing for the filter output, and expressed as

$$\begin{aligned} y_1(k) &= \mathbf{weight}_1^T(k)\mathbf{x}_1(k) \\ &= \mathbf{weight}_1^T(k)\mathbf{c}^{'}(k) = \hat{c}(k), \end{aligned} \tag{4}$$

where $\mathbf{weight}_1(k) = [weight_1, weight_2, ...weight_K]^T$ is the filter coefficient and $\mathbf{x}_1(k) = [x_1(k), x_2(k-1), ...x_L(k-L+1)]^T$ is one of the steps of the filter and the filter's sequence is represented as L. The weights of the filter are adjusted through update using the Sign Data LMS and is given by

$$\mathbf{weight}_1(k+1) = \mathbf{weight}_1(k) + \mu_{1SDLMS} e_1(k) sgn[\mathbf{x}_1(k)]. \tag{5}$$

For updating its weights, which are provided by the Sign Error LMS filter algorithm is given by

$$\mathbf{weight}_1(k+1) = \mathbf{weight}_1(k) + \mu_{1SELMS} sgn[\mathbf{e}_1(k)]\mathbf{x}_1(k). \tag{6}$$

The first stage ANC's main and second stage ANC's secondary inputs are

$$d_2(k) = e_1(k). \tag{7}$$

Substituting equations (1),(3) and (4) in (7)

$$\begin{aligned} d_2(k) &= s(k) + c(k) - \hat{c}(k) \\ &= s(k) + \Delta c(k). \end{aligned} \tag{8}$$

To remove the noise $\Delta c(k)$ from $d_2(k)$, we use the reference signal that is linked to $\Delta c(k)$ at step II filter given by

$$x_2(k) = x_1(k) - y_1(k) \tag{9}$$

Substituting equations (2) and (4) in (9) we get

$$\begin{aligned} x_2(k) &= c^{'}(k) - \hat{c}(k) \\ &= \Delta c^{'}(k) \end{aligned} \tag{10}$$

As a result, stage II's output error is

$$e_2(k) = d_2(k) - y_2(k) \tag{11}$$

Substituting equations (8) and (13) in (11) we get

$$\begin{aligned} c_2(k) &= s(k) + \Delta c(k) - \Delta \hat{c}(k) \\ &= s(k) + \delta c(k), \end{aligned} \tag{12}$$

where

$$\begin{aligned} y_2(k) &= \mathbf{weight}_2^T(k)\mathbf{x}_2(k) \\ &= \mathbf{weight}_2^T(k)\Delta \mathbf{c}^{'}(k) = \Delta \hat{c}(k), \end{aligned} \tag{13}$$

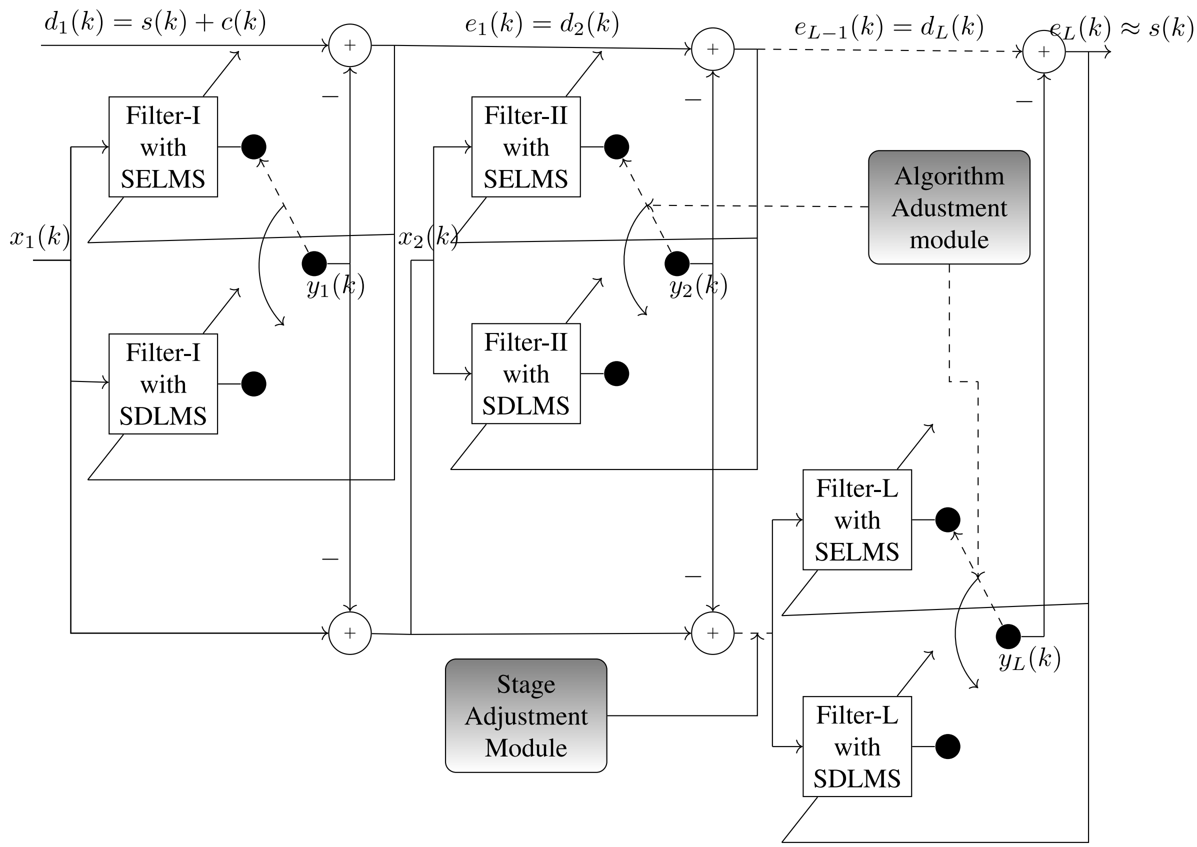

Fig. 1. Feed-forward Switched architecture

The formula for the Stage II of the Signed Data variant of LMS filter has been updated, as described

$$\textbf{weight}_2(k+1) = \textbf{weight}_2(k) + \mu_{2SDLMS} e_2(k) sgn[\mathbf{x}_2(k)]. \tag{14}$$

Error Stage II Sign Update of the LMS filter value is provided by

$$\textbf{weight}_2(k+1) = \mathbf{w}_2(k) + \mu_{2SELMS} sgn[\mathbf{e}_2(k)]\mathbf{x}_2(k). \tag{15}$$

The error from the preceding phase, $e_{i-1}(k)$, and the difference between the output and the input of the preceding stage filter, $y_{i-1}(k), x_{i-1}(k)$ respectively, are used to determine reference signal $x_i(k)$ and the source $d_i(k)$ to the following stage. Control of stage addition is automatic and determined by a certain criterion based on the link between output error of the i^{th} stage, $c(k)$ the standard noise and $e_i(k)$. When there is a minimal correlation between $e_i(k)$ and $c^{'}(k)$ ($\approx$ 0), additional stage is not necessary. For ANC to advance to its final level, the optimal situation is for there to be no correlation between $e_i(k)$ and $c^{'}(k)$. As a result of this not being feasible, very little noise is retained at the output in the end. The step size is modified as well in accordance with the inbound signal's autocorrelation. The inputs to the filter are at stage L, the final level are

$$d_L(k) = e_{L-1}(k) = s(k) + \rho c(k), \tag{16}$$

and

$$x_L(k) = x_{L-1}(k) - y_{L-1}(k) = \rho c^{'}(k). \tag{17}$$

At stage M the output error is

$$\begin{aligned} e_L(k) &= d_L(k) - y_L(k) \\ &= s(k) + \rho c(k) - \rho \hat{c}(k) \approx s(k), \end{aligned} \tag{18}$$

and the outputs are

$$\begin{aligned} y_L(k) &= \textbf{weight}_L^T(k)\mathbf{x}_L(k) \\ &= \textbf{weight}_L^T(k)\rho\mathbf{c}^{'}(k) = \rho\hat{c}(k). \end{aligned} \tag{19}$$

The SDLMS algorithm is utilized to update the filter's weights as

$$\textbf{weight}_L(k+1) = \textbf{weight}_L(k) + \mu_{LSDLMS} e_L(k) sgn[\mathbf{x}_L(k)]. \tag{20}$$

(21)

And using SELMS as

$$\textbf{weight}_L(k+1) = \textbf{weight}_L(k) + \mu_{LSELMS} sgn[\mathbf{e}_L(k)]\mathbf{x}_L(k). \tag{22}$$

III. Results and Discussion

The effectiveness of the suggested filter model is assessed by testing its capacity to remove noise from a fish sound that has been distorted by ship noise and obtained from the ShipsEar database [3]. Figure 2 illustrates signal denoising using a feed-forward filter, and Table 1 demonstrates that the feed-forward filter performs better. The proposed filter's capacity to denoise signals is shown in Figure 2. It should be mentioned that the suggested filter model demonstrates effective denoise capability for underwater test signal that has been tainted by underwater noise signals. The table presents a comparison between the output of the proposed filter and that of other filters. The proposed filter is capable of effectively distinguishing between ship noise signals and fish sounds at an astonishingly fast and precise rate. Table I provides a analytical comparison between the considered filter and several other filters in terms of mean square error, signal-to-noise ratio and average noise reduction. As indicated in Table I, the suggested filter model exhibits outstanding performance in eliminating underwater noise signals. The suggested filter model's ability to require few computations is its distinguishing quality. The computational complicacy is calculated by the combined count of multiplications and additions required for a single iteration. Table II presents the computative requirements of the filter. The SELMS and SDLMS method requires the fewest additions and multiplications possible, as shown in the Table. [3].

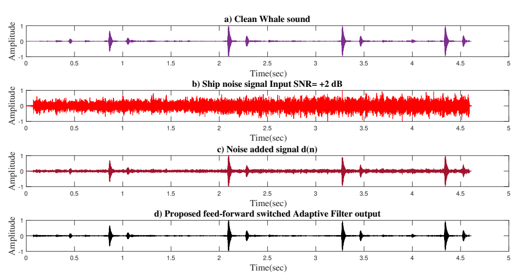

Fig. 2. Noise removal from fish sound corrupted by underwater vessel noise (a) Fish sound (b) Vessel Noise (c) Fish+Vessel signal (d) Feed-forward filter output

Filter Model	MSE	SNR(dB)	ANR(dB)
LMS (1-Stage) filter	5.90E-04	22.1029	24.5004
LMS (2-stage)filter [4]	4.13E-04	25.6693	26.7744
LMS (3-stage) filter [5]	3.45E-04	27.4776	28.5827
Feed-forward filter	4.89E-05	47.1498	47.0108

TABLE I

Comparison of SNR,ANR and MSE performance

Figure 2 depicts the signal denoising by employing the feed-forward filter and Table 1 shows that the feed-forward filter gives better performance.

IV. Conclusion

In this paper, an effective underwater noise reduction method is presented. The Multistage SDLMS and SELMS Adaptive Filter model is a highly effective approach for speeding up the convergence of MSE. This is achieved by combining multiple stages, each with a distinct step-size. According to the simulation, the suggested multistage SELMS and SDLMS Adaptive Filter shows better performance compared to other adaptive filter architectures, offering hardware that is less expensive to minimise noise in the ocean.

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