Design and Analysis of Interval Adaptive Filter Applied to Active Noise Cancellation

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***Abstract*— This paper proposes a unique approach to active noise cancellation system, which provides an efficient and effective non-intrusive solution for reducing the disturbing snore signal in the room. An interval analysis based adaptive algorithm is developed which is optimized for the different kinds of snore signals. In this work, we are replacing the input-signal's auto-correlation matrix with an approximate estimate, by assuming of input-signal matrix is Toeplitz. In the proposed work, the multiplication of R ^{1}x is replaced with the update of its matrix in the frequency domain. The stability of the algorithm is increased as interval matrices handle the bounded values. The main objective of this work is to increase stability by reducing the mean square error. The results obtained prove to show that the implementation with interval arithmetic is more accurate ruling out the rounding errors which are unavoidable in the traditional floating point approach. On the other hand, as there are two values (infimum, supremum) in interval analysis, the computational complexity increases.**

Index Terms—Keywords— ANC (active noise cancellation), ALMS (Least Mean Square), snore signal, interval arithmetic, quasi-Newton adaptive algorithm.

I. INTRODUCTION

Snoring, is directly related to quality and quantity of sleep, especially with a person sleeping with snorer [1]–[3]. Night deprived snoring can cause substantial physical, emotional, and economic problems. It is necessary to find the solution for snore signal suppression using non-intrusive methods. The least mean square algorithm and its improved versions are applied in several applications which has single or multiple input/output. When the input signal has a higher degree of correlation and is band-limited, the LMS and steepest decent family converge very slowly. Such algorithms are not able to track non-stationaries, and performance deteriorates. In such cases, it is required to use more sophisticated algorithms such as extended interval analysis based analysis [4]-[5]. In an adaptive filter, the inverse of the input-signal auto-correlation matrix is required in order to update the weights. In quasi-Newton method, the algorithm avoids the calculation of the auto-correlation matrix by directly updating the inverse of the auto-correlation matrix, which has high computational complexity. In such algorithms, the approximate update of the inverse matrix is calculated. But when the input is uncertain because of sensor limitations and noise, more accurate weights are needed. In such cases, interval analysis can be used [4], [6], [7]. Interval analysis consists of two values, i.e. lower and upper bound [8]. IA gives the guaranteed results, irrespective of rounding of floating point numbers, approximation and uncertainties in the data because of sensor limitations. Interval analysis based algorithms produce sharp bounds on the solution to a computational problem[9]–[11]. Extended interval arithmetic is proposed in [5] when there is a zero included in the interval bounds. In [12] the discussion is on the accuracy and precision of the filter co-efficient and effects on the frequency response. The Interval size approach is used to analyse the order of the filter and frequency response. In [13], [14], an extended interval Kalman filters used to estimate the values related to localization and mapping. Interval Kalman filter obtains the bounds on the estimated value. The actual estimates are computed at each time step, which is the weighted average. The system instability can be controlled by this trained method and can be used for tracking missions [15], [16]. Interval analysis based global optimization methods are also used to determine the coefficients of McClellan transformation and 1-D filter [17], [18]. The feasibility of interval analysis method is used to verify 2-D fan filter's correctness. In [19], the IIR filter is designed by using interval optimization methods, which will increase the accuracy of the design of higher-order filters. The optimally bounded Kalman filter is designed in [20], and is used in the uncertainties of sensor inputs in terms of observations and noises. System identification for unmanned marine vehicles is designed by using IA, so that the problem of accurate estimation is solved by intervals instead if real values [21], [22]. The system is bounded under parameter uncertainties so that the gain matrix and its co-variance matrix is optimized to give minimal error boundary [23], [24]. The state estimation problems are solved by using interval analysis based optimization algorithms. It is observed that the bound of IA encloses all types of solutions, with respect to the primitive Kalman filter. In [25], [26], the constrained optimization method is used to solve uncertain matrices. The differential evolution algorithm is used in this method. It is used to solve the uncertainties in structural optimization problems. The effectiveness of the method is pre-sented in mechanical engineering applications. In [18], [27], the drawback of extended Kalman filter, applied to nonlinear GPS/IMU system with huge uncertainties is resolved by using interval Kalman filter. In [28], [29], the calculations related to interval matrices, such as, inverse of a interval matrix, symmetric interval matrix, eigenvalue, eigenvalue bounds is discussed. The filtering method is proposed, which iteratively improves the approximation. The article [30], an appropriate dynamic filter for computational geometry is discussed. Many floating point based adaptive filters are also proposed and are applied to active noise cancellation of indoor acoustics, snore signal cancellation, wireless telephony and hand held telephony etc. Speech signal analysis and synthesis model for full-band

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harmonic model is proposed in [31]. II. ACTIVE NOISE CANCELLATION OF SNORE SIGNALIn order to suppress the snore signal, active noise cancellation (ANC) system can be used. This is an effective way to reduce the low frequency snoring noise by using destructive interference (i.e. by superimposing 1800 phase shifted signal) as shown in Figure 1.

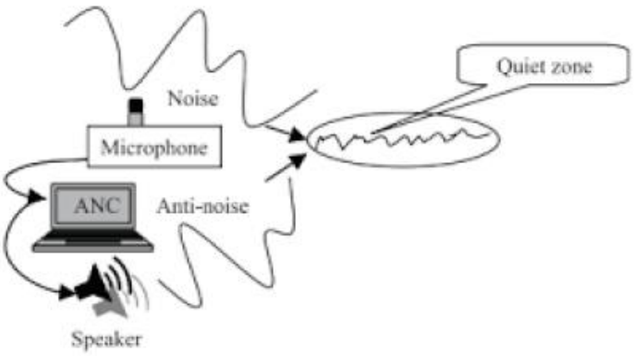

Figure.1 Principal of operation for a ANC system.

In order to develop an algorithm for snore cancellation, it is important to examine the power spectrum of the snoring signals and also the frequency domain characteristics of all kinds of snore signals. In the literature [39], the power spectrum of the snoring signal is studied. Snore signals of men, women and kids are analyzed. It is observed that the major power content is below 2500Hz and the main frequency band lies from 150Hz to 1500Hz. In [1], [3] the snore signals of men, women and children of all age groups are collected. These samples are used for experimentation. A typical snore signal is as shown in Figure 2, which includes inspiration and expiration. Figure 3 shows the 3D view of snore signal spectrum, which shows non stationary characteristic.

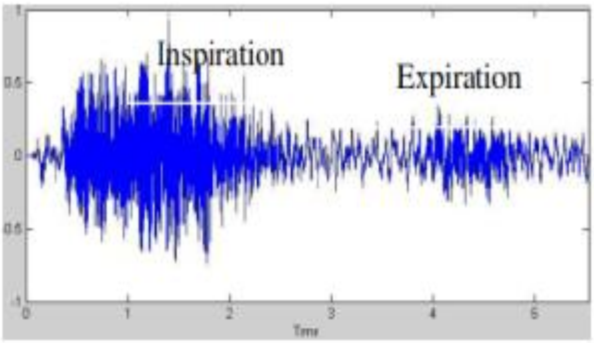

Figure. 2. Typical snore signal showing inspiration and expiration

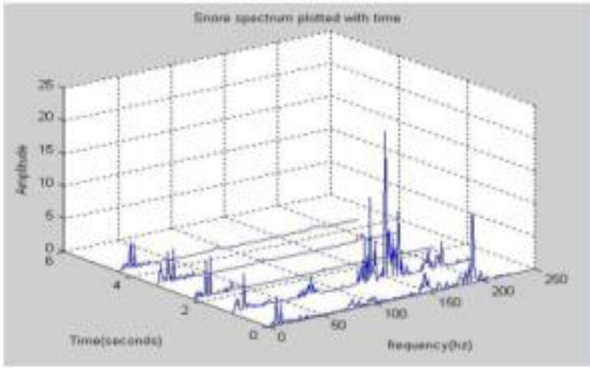

Figure. 3. 3D View of snore spectra as a function of time and frequency showing non-stationary characteristics

III. CONVENTIONAL FLOATING POINT FILTERS TO INTERVAL ADAPTIVE FILTERS

Basically IA deals with intervals (infimum, supremum) of real number instead of real number themselves [40]. The real number number [x]=[xl, xu] is defined in the closed subset of real number R where x represents the lower bound (infimum), x represents the upper bound (supremum). The center or the mid-point is defined by mid([x])=[xl+xu]/2 and the width of an interval is defined by wid([x])=[xl - xu]/2. For any interval numbers, the basic elementary operations (+, -, *, /) is denoted by [x] Ѳ[y] = {} The basic operations of interval arithmetic are, for two intervals a = [al, au] and bI = [bl, bu] that are subsets of the real line (-∞, ∞).

1) [al, au] + [bl, bu] = [al+ bl, al + bu]
2) [al, au] − [bl, bu] = [al − bu, au − bl]
3) [al, au] ∗ [bl, bu] = [min(al ∗ bl, al ∗ bu, ai ∗ bu, al ∗ bu), max(al ∗ bu, al ∗bu, al ∗ bu, al ∗ bu)]
4) [al, au]/[bl, bu] = (al ÷ bu, al ÷ bu) when 0 ∈/ [b, b]

IV. PROBLEM FORMULATION

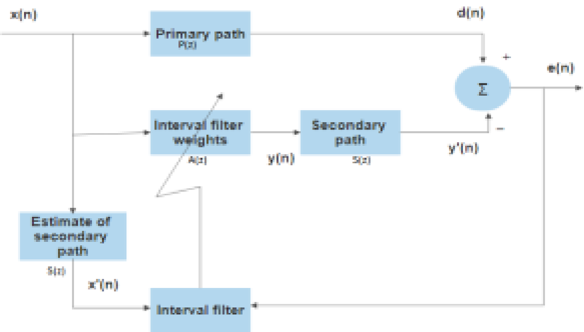

Figure 4. System model of IAF used for masking snore signal

The system model of multi-channel (J*M*K) adaptive filter is as shown in Figure 4 [33]. J denotes reference microphones, K denotes secondary sources and M denotes error microphones for picking error signals. The signal from the microphone 'J' can be shown as,

$$x(n) = [x_1(n), x_2(n), ..x_J(n - L + 1)]^T \qquad (1)$$

where $xj(n)^T$ is the jth reference signal of length L. The secondary microphones have K channels,

y(n) = [y1 (n), y2 (n), ...yK (n − L + 1)]T ,----- (2)
where yk (n) is the signal of kth output channel at n. The error signals have M channels and can be represented as
e(n) = [e1 (n), e2 (n), ...eM (n − L + 1)]T , ------(3)
The nonlinear function used in interval adaptive filter is given as shown in figure 5.

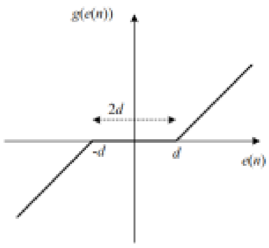

Figure. 5. Non-linear function used in interval adaptive filters

$$g(x) = \left\{ \begin{array}{ll} x - d, & \text{for } x \geq d \geq 0 \\ 0, & \text{for } -d \leq x \leq d \\ x + d, & \text{for } x \leq -d \end{array} \right\}$$

where d is the threshold value. The samples below this value can be neglected, which reduces the computational complexity. This can be adjusted according to the variance of input signal. The interval weights are updated by using the equation, Updated weight co coefficients are calculated using equation 9. In this algorithm with a interval step size the optimal weights of the system are identified which reduces the MSE. The proposed algorithm is compared with existing algorithms, like VSS-LMS, NLMS, FxLMS etc. The pseducode of interval adaptive filter is shown in algorithm 2.

Algorithm 2 Interval adaptive filter

function INTADAPTIVEFILTER($\mu^I \in [0,1], p \in \mathbb{N}$)
  Initialize: w^I=[initial box], $R^I(k)$, $P^I(k)$, ϵ
  for $k \leftarrow 1$ to n **do**
    measure: e^I // an estimate will suffice
    $y^I = (w^T)^I * x^I$
    find w_k^I
    while W^I is not empty **do**
      calculate e^I
      if $e^I \leq \epsilon$ **then**
      end if
      if $e^I \geq \epsilon$ **then**
        discard w^I
        generate w_1^I and w_2^I
        such that w is split into two boxes
        insert w_1^I, w_2^I into w_{out}
      end if
    end while
    interchange w_{in} and w_{out}
  end for
  calculate y^I
end function

1) Comparison of computational complexity and performance parameters:

In the IAF algorithm, the computational complexity is very high as summarized in table I. The memory requirement per iteration is also doubled as interval analysis consists of two values.

TABLE I
COMPARISON OF COMPLEXITY OF LMS, NLMS, VSS LMS AND IAF ALGORITHMS

Algorithm	mul/div	add/sub	memory consumption
LMS	$3N+2$	$2N$	4N
NLMS	$3N+2$	$3N$	6N
$VSSLMS$	$4N+2$	$3N+4$	8N
IAF	$4(N^2+4N+1)$	$6(2N^2+N)$	32N

V. RESULT AND DISCUSSION

In order to test the performance of the algorithm the test database is taken from [1], [3]. The different types of snore signals of a child, men and women of different variance are selected. The comparison is done with the least mean square, normalized least mean square and variable step size LMS algorithm. The dimension of ANC system was assumed to be 1*2*2. The output signal y0 (n) and the masked snore signal (error) e(n), are plotted in time and frequency domain, as shown in figure 6 and 7. Mid values are used to plot the graphs. is set to 10^{-3} , filter tap weight=128, and μI = [0.1, 0.4]. It is observed that when active noise cancellation is on, the system effectively reduces the snore signal. Also the algorithm was simulated for single tone frequency sine wave and combination of frequencies as input signals. The different types sine wave and its combinations are generated. The μI is also varied to test the convergence speed. In the table II, the average snore signal reduction is given for frequencies ranging from 50Hz to 1500Hz. It is observed that average input power is 26.16dB and in the secondary path average power is 24.87dB is achieved. Finally it is noted that, output at the error microphone was 1.8dB. The reduction in power depends on the location of the primary and secondary microphones in real time applications.

TABLE II
NOISE POWER REDUCTION IN DB FOR SINGLE TONE FREQUENCIES

Frequency (Hz)	**Power in dB**		
	Input signal power	**Secondary path Y'(n)**	**Error**
50	9	8	1
100	20	18.2	1.8
200	42	39	3
300	51	48	3
400	45	43	2
500	31	29	2
600	28	26.5	1.5
700	15	12.4	2.6
800	10	9.6	0.4
900	6	5	1
1000	27	25	2
1500	30	28	2
	26.1666	**24.8**	**1.8**

Later, with several real time snore signals the algorithm was tested. The spectra of error signal with ANC on and off are plotted in Figure 8. It is observed that average noise reduction of 15dB to 13dB is achieved. The variation error in time and the spectra of sample test signal is plotted in Figure 6. In the table III, the average reduction of snore signals (men, women, kid) for various algorithms is given. It is observed that IAF

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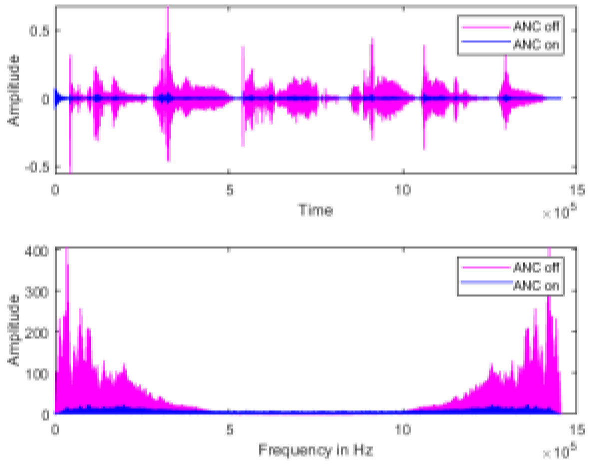

Figure 6. Snore signal cancellation of IAF algorithm: (upper) Time domain waveform of input snore signal and the output error. (Lower) The spectrum of input and the error signal

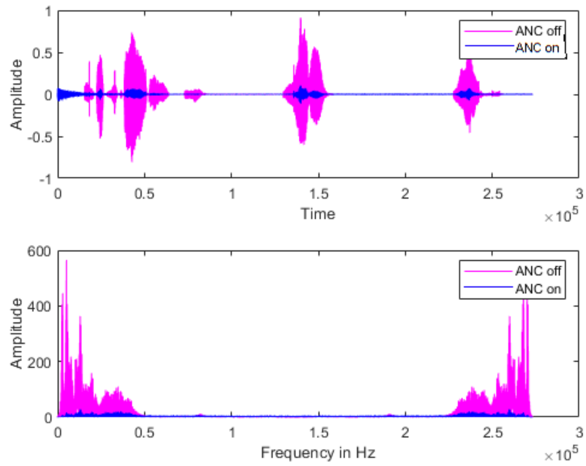

Figure. 7. Snore signal cancellation of IAF algorithm: (upper) Time domain waveform of input snore signal and the output error. (Lower) The spectrum of input and the error signal

TABLE III
COMPARISON OF AVERAGE MSE WHEN ANC IS ON, FOR DIFFERENT ALGORITHMS

	Average MSE (dB) when ANC is on
LMS	4.6
NLMS	3.9
V SS/LMS	2.8
IAF	1.38

gives better performance compared to other algorithms. The weight vectors are calculated using different algorithms and variation of error is plotted in Figure 9. It is illustrated that the IAF gives the minimum error by choosing the optimal weights. The average mean square error for twenty different snore signals of men, women and kid versus different µ values are plotted in Figure 10. It is observed that the optimal µ value can be selected depending on the MSE threshold value.

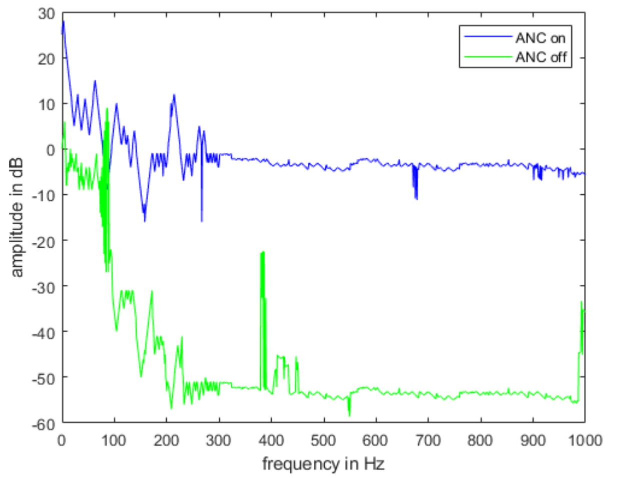

Fig. 9. Figure 8 :Frequency domain plot of snore signal with ANC on and ANC off

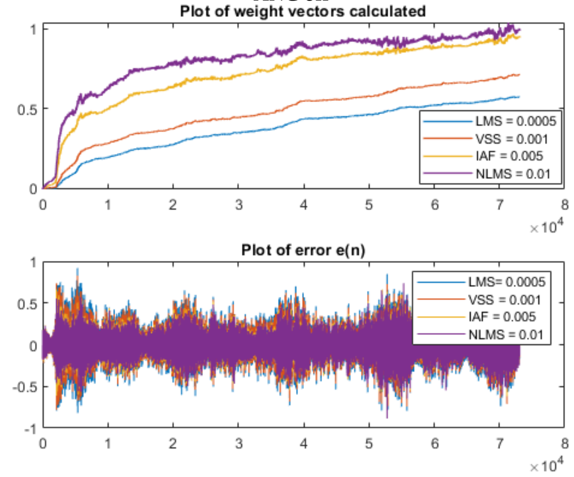

Figure 9. The weight vectors calculated using LMS, IAF, VSS LMS, NLMS

the IAF gives the minimum error by choosing the optimal weights. The average mean square error for twenty different snore signals of men, women and kid versus different μ values are plotted in Figure 11. It is observed that the optimal μ value can be selected depending on the MSE threshold value.

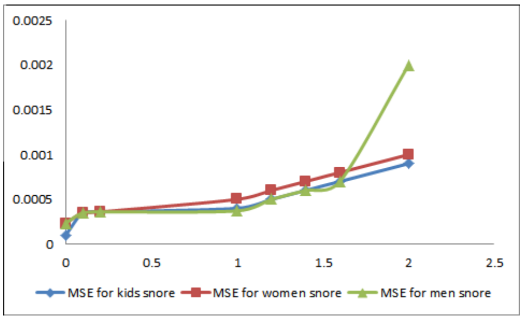

Figure 10. Plot of average (20 test signals) MSE and μ for different types of snoring signals

VI. CONCLUSION

In this paper, the snore signal cancellation using interval ANC is proposed. The algorithm is replacing the calculation of inverse of a matrix with the auto correlation matrix in frequency domain. Using interval analysis the bounds of weight vectors are calculated. The performance of IAF is compared with several other algorithms. The proposed algorithm shows better masking of snore signal with lower mean square error at the ANC output (1.38dB). But the computational complexity and memory consumption is increased four times, as interval values have bounds. The computer simulation shows that this can be used in real time applications for masking sound signals. In future work, The real time experiments can be done using multiple microphone setup. In order to decrease the computational time, GPU processors can be used. Audio integration like river stream and nature sounds can be added so that the residual signal is also masked.

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